AI-Based Defect Detection Model Development to Enable Zero Defect Manufacturing in Ethiopian Steel Industries

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Authors' Declaration

I hereby declare that the work which is being presented in this PhD dissertation entitled "*AI-Based Defect Detection Model Development to Enable Zero Defect Manufacturing in Ethiopian Steel Industries*" is original work of my own, has not been presented for a degree of any other university and all the source of materials used for this dissertation have been duly acknowledged.

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Abstract

Product quality stands as the primary competing factor in manufacturing industries, especially in the rapidly evolving digital landscape of the current era. Zero Defect Manufacturing (ZDM) has emerged as a state-of-the-art quality enhancement framework in response to Industry 4.0 technologies. This data-centric approach encompasses four crucial strategies: detection, prediction, repair, and prevention. Detection, the cornerstone of ZDM, operates through two distinct methods. The physical method relies on direct product measurements to identify defects, while the virtual approach, known as virtual metrology, conducts quality inspections without physical contact. This novel technology is revolutionizing quality inspection practices in the steel industry on a global scale. Ethiopian steel industries are facing a persistent challenge of producing a significant volume of defective products due to their reliance on manual inspection methods, a practice that is both costly and time-intensive.

The successful integration of virtual detection relies entirely on data accessibility (via robust data infrastructure) and advanced analytics. The pivotal components for achieving virtual defect detection in industries are organizational shifts toward digitalization and the adoption of standardized data analytics (DA) practices. Current literature on ZDM overlooks crucial factors related to industrial digital readiness and fails to analyze the interconnected impact of these factors on the digitization of manufacturing industries. While various digital maturity (DM) models are in use in industrial contexts, there is a lack of analysis regarding the intricate relationships among MM dimensions. Furthermore, the absence of a standardized approach to data analytics poses challenges. Although numerous data analytics frameworks exist beyond ZDM, customizing these methods for ZDM applications can complicate the development of effective AI models. Hence, the primary objective of this dissertation is to develop an AI-driven defect detection model. This will be achieved by initially addressing the challenges outlined in industrial digital readiness and standardized data analytics framework enabling the implementation of virtual defect detection.

To achieve the primary goal, a multi-stage research methodology is employed, encompassing diverse analytical dimensions to tackle different aspects of the research problem. The work begins with an exploration of the theoretical underpinnings of zero-defect manufacturing, leading to the identification of challenges in effective industrial data analytics in ZDM and the proposition of a standardized DA framework. Subsequently, it proceeds to identify the crucial factors for digital readiness in ZDM implementation, utilizing structural equation modeling (SEM) to explore the connections among these factors using Statistical Package for the Social Sciences (SPSS) and Analysis of Moment Structures (AMOS) as a tool. A digital maturity assessment of industries is then conducted to devise a robust ZDM strategy. Causal relationship analysis of the digital readiness factors has been performed by collecting a

data from a sample of 149 steel industries in Ethiopia, while a detailed assessment of digital maturity is carried out on a specific industry case, employing a well-established assessment framework and the six maturity levels identified in recent publications. Finally, an AI-based defect detection model is developed and validated using one year of time-series quality inspection data collected from the case industry, using R programming language with RSTUDIO as a tool and three ensemble learning algorithms.

The finding from the relationship analysis of DM factors reveals that people and expertise play a crucial mediating role between the adoption of digital technology and digital maturity, underscoring the significance of human capital in digital transformation in manufacturing. The evaluation of digital readiness at the industry level indicates that the industry is presently positioned at level 2, representing the initial phase of connectivity (having attained computerization). The assessment exposes a notable digital maturity gap concerning people and expertise. Another significant empirical aspect of this dissertation is the development of a defect detection model, which exhibits enhanced accuracy in defect identification through the incorporation of comprehensive quality parameters. The modified Gradient Boosting model outperforms the other two ensemble learning models, which are Bagging and Random Forest in predicting the quality of the considered steel product (Rebar output quality parameters) based on the following R^2 values: 0.9538 for Yield Load, 0.9726 for Yield Stress, 0.9751 for Ultimate Load, 0.9718 for Tensile Strength, 0.9614 for Elongation after Fracture, 0.983 for Tensile strength to Yield strength ratio, and 0.964 for Bend Test. Comparative analysis with existing literature also demonstrates that this study achieves superior levels of prediction accuracy across most output variables.

The DD model developed in this dissertation tackles the shortcomings of manual quality inspection techniques leveraging AI and machine learning on recorded QI data. Traditional methods (physical inspection), resulting in high costs, time inefficiencies, and inconsistencies, especially when detecting concealed defects. Unlike these approaches, the AI-based DD model autonomously learns and detects defects. Prior to delving into model development, the dissertation also explores key prerequisites for effective AI implementation and propose solutions to realize virtual defect detection: industrial digital maturity assessment and the adoption of standardized data analytics. These enable steel industries to shift systematically from manual quality inspections to a data-driven method and progress towards the implementation of each ZDM strategies.

The research contributes to filling gap in the current literature of DM models by critically analyzing the relationships among the existing DM models dimensions. This enables industries to focus on the critical factors which highly contribute to DM. The proposed assessment guide provides practitioners with the tool to accurately determine their DM index and implement the appropriate ZDM strategy. The novel DA framework proposed also enables the development of AI model standardized (considering key elements of

product quality control) which were fragmented in the ZDM literature. The developed AI-driven defect detection model addresses the current challenge for the steel industries quality inspection activities assisting operators in accurately estimating the occurrence of defects. Lastly, the proposed ZDM Continuous Improvement Cycle (CIC) provides a clear framework for continuous improvement, aligning the ZDM strategy with the industry's current digital maturity level. This approach enables industries to systematically progress through the four ZDM strategies, starting with detection as the baseline to prediction and prevention.

Key words: Zero defect manufacturing; Defect detection; Quality control; Quality inspection; Virtual defect detection; Data analytics; Industrial digital readiness; Digital maturity model; Artificial intelligence

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List of Acronyms and Abbreviations

AI	Artificial Intelligence
AU	African Union
ASRIC	African Science Research and Innovation Counsel
CIC	Continuous Improvement Cycle
CRISP-DM	Cross Industry Standard Processor for Data Mining
DA	Data Analytics
DD	Defect Detection
DM	Digital Maturity
DR	Digital Readiness
GRU	Gated Recurrent Unit
GA	Genetic Algorithm
GBM	Generalized Boosted Regression Modeling
IC	Inclusion Criteria
I4.0	Industry 4.0
IOT	Internet of Things
IIOT	Industrial Internet of Things
ML	Machine Learning
MIDI	Metal Industry Development Institute
MM	Maturity Model
MP	Mathematical Programing
MSE	Mean Squared Error
OES	Optical Emission Spectrometer
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QA	Quality Assurance
QC	Quality Control
QI	Quality Inspection
RF	Random Forest
RMSE	Root Mean Squared Error
RT	Real Time
SI	Steel Industry
SEM	Structural Equation Modeling
SVM	Support Vector Machine
UTM	Universal Testing Machine
VM	Virtual Metrology
WS	Work Station
ZDM	Zero Defect Manufacturing

Chapter One

Introduction and Background

1.1. Introduction

As the focus on sustainable manufacturing grows, industries are under pressure to deliver high quality products at lower costs while also limiting the resource utilization (P. Wang et al., 2023). Prioritizing product quality is crucial for gaining a competitive edge since better quality often translates to cost savings through reduced rework, fewer errors, and minimal delays (Lario et al., 2024). The rise of digitalization and Industry 4.0 in the 2010s has opened up possibilities for a new age of digitally enhanced quality control in manufacturing (Powell et al., 2022). In the current industrial landscape (Industry 4.0), manufacturing industries are continuously adjusting and refining their production systems to accommodate the production of customized products in smaller batches and shorter timeframes (Martinez et al., 2022; Dreyfus et al., 2022). This adaptation generates a huge volume of data encompassing the entire production processes, which holds significant potential to enhance product quality (T. Zheng et al., 2020).

In response to this, quality control practices in manufacturing have undergone a significant evolution, transitioning from traditional methodologies to data-driven approaches (Eichenseer & Winkler, 2024; Babalola et al., 2023). This evolution underscores the critical importance of defect detection, prediction and prevention throughout the production process. Central to this shift is the emergence of Zero-Defect Manufacturing (ZDM) as a cutting-edge quality improvement framework. This framework aimed at leveraging data-driven techniques to ensure defect free production (Gauder, Gölz, et al., 2023). As a technology-centric concept, ZDM gained a great attention upon the existence of a huge amount operational data in industries (Getachew, Beshah, & Mulugeta, 2024).

The evolution of ZDM has been shaped by both technological and policy milestones (Powell et al., 2022). Technology integration in 2015 established ZDM as a cornerstone of smart manufacturing, enabling data-driven precision. Building on this, EU initiatives in 2018 strategically prioritized ZDM to enhance competitive quality, supported by substantial funding to accelerate its industrial adoption. Current trends (2020–present) emphasize digital transformation and predictive analytics, promoting proactive quality control through real-time monitoring and AI-driven decision-making. The future of ZDM lies in aligning its frameworks with global sustainability goals, optimizing waste reduction and resource efficiency.

The main difference between classical quality control frameworks (e.g., TQM, Six Sigma) and ZDM lies in their approach to variability, and use of data-driven proactivity. Classical frameworks primarily rely on manual processes and reactive corrections, addressing quality issues after they occur within stable, predictable mass-production environments (Shi, 2023). Conversely, ZDM embraces variability as inherent to modern manufacturing and leverages operational data proactively to anticipate and prevent defects before they occurred (Dreyfus et al., 2022; Y. Zhang et al., 2024; Psarommatis, Sousa, et al., 2022a). This shift transforms product quality control from corrective oversight to predictive prevention.

ZDM embodies a holistic approach that integrates traditional quality control tools with the technological advancements of Industry 4.0.. Psarommatis et al. (2022b) clearly define ZDM as "a holistic approach to ensure both process and product quality by reducing defects through corrective, preventive, and predictive techniques, utilizing data-driven technologies to guarantee that no defective products leave the production site, aiming at higher manufacturing sustainability."

Moving beyond manual inspections, data-driven quality control harnesses the power of data analytics and automation (Mateo-Casalí et al., 2023). By analyzing vast amount of quality inspection data, manufacturing industries can proactively identify potential defects, facilitating a more agile and responsive approach to quality assurance (Getachew, Beshah, & Mulugeta, 2024) (Azamfirei et al., 2023). Through the implementation of ZDM strategies (detection, prediction, repair and prevention), industries strive for seamless production processes by eliminating defects at their source, thereby reducing waste, and fostering a culture of continuous improvement (Caiazzo et al., 2022).

Detection, being the fundamental aspect of ZDM, stands out as the most extensively studied strategy in existing literature (Psarommatis et al., 2020). It is often an enabler for the implementation of the remaining strategies (Azamfirei et al., 2023). Defect detection involves analyzing data from the quality attributes of already manufactured products (Dreyfus et al., 2022).

This process differs with prediction, which focuses on predicting the quality of a product before its production (Maitra et al., 2024).

The integration of defect detection models into manufacturing quality control enables manufacturers to enhance production speed, minimize defects, and improve overall production efficiency (Dreyfus et al., 2022). These advanced technologies work in harmony with human workers, empowering them to focus on complex tasks and quality decision-making while the model efficiently handles repetitive and time-consuming defect detection processes (Konstantinidis et al., 2022). This integration plays a pivotal role in driving the progression towards Industry 5.0, where human-machine collaboration and the optimization of production processes are key objectives (Konstantinidis et al., 2022).

Defect detection operates through two distinct ways, the physical method relies on direct measurements from the product to verify defects, while the virtual approach, also known as virtual metrology, assesses product quality without direct physical measurement (Dreyfus et al., 2022; Xie et al., 2024). Artificial intelligence (AI) and its subfield machine learning (ML) have appeared as invaluable data-driven tools for effective implementation of virtual metrology (Getachew, et al., 2024). These techniques facilitate the efficient control of product quality by taking the full advantage of the shop floor data captured by different sensor systems and metrology instruments (Foivos & Gokan, 2022).

This dissertation focuses on investigating methods to transform prevailing industry practices, which heavily depend on manual physical inspections without integrating defect detection or prediction model. This approach overlooks the potential benefits of leveraging advanced data-driven techniques, leading to the underutilization of a significant portion of quality inspection records and related data. By harnessing advanced data analytics, the aim is to automate the quality inspection process and strive towards achieving zero defects.

1.2. Research Background

In the rapidly evolving landscape of Industry 4.0 technologies and digitalization, quality control, a fundamental aspect of manufacturing processes, has emerged as a transformative force, marking the critical role of data-driven methodologies in enhancing product quality.

The steel manufacturing industry, a subset of the broader metal industry, is recognized as one of the largest and most vibrant sectors on a global scale, serving as the foundation of the remaining manufacturing domain (Y. bao Zhao et al., 2023). It is a cornerstone of modern society, providing the primary input material for construction, transportation, machinery, and many other sectors (Guo et al., 2019). Its significance extends to national economies, as steel production and consumption are often used as indicators of industrial and economic growth of the nation.

Advancing quality control practices within the steel industry can have intense implications for the broader industrial domain. This advancement can not only enhance the sector's own performance but also contribute to bolstering the reliability, sustainability, and competitiveness of downstream industries reliant on steel product(Xu et al., 2023).

The strength (load bearing capacity), precise dimensions, and appearance of steel products are crucial parameters that determine their quality (Chazhoor et al., 2024). Failure to meet customers' requirements and standards due to defects renders the product unacceptable to end users. Therefore, there is a considerable motivation to identify defects early in the manufacturing process to prevent the rejection of products upon completion of production.

The importance of Zero-Defect Manufacturing in steel quality assurance is recognized by many scholars (Yu et al., 2024; Kusuma & Huang, 2023; Takalo-Mattila et al., 2022; Xu et al., 2023). This potential is underscored by the abundance of unutilized data within steel quality control processes (Jeong et al., 2023). Within these operations, a huge amount of data is routinely collected through offline or real-time systems (depending on the existing digital infrastructure) related to various quality parameters of steel products. Employing AI in the quality control process, utilizing the abundant data collected, to replace manual inspection with virtual techniques, presented as an opportunity for the industry by cutting down both the time and costs linked to physical inspection.

Ethiopia, the second most populous country in Africa, is currently undertaking numerous high-value infrastructure projects that have led to a significant increase in the demand for steel. Historically a major importer of steel products, the government is now implementing measures to encourage local iron processing and steel production industries. It's substantial infrastructural upgrades are set to propel the sector to double in size (Fente et al., 2024). Meeting the total national market demand involves a combination of imported virgin steel and locally produced steel through scrap recycling. Steel and iron consumption surged to 200,000 tons in 2024, with projections signaling 300,000 tons by 2030 *(https://app.indexbox.io, visited on 17 Sep 2024)*.

The country owns approximately 241 Iron and Steel manufacturing industries, each with varying production capacities (Fente et al., 2024). Ensuring the supply of high-quality steel products is crucial to establish sustainable business within the competitive landscape of the steel industries.

1.3. Problem Statement

The core motivation of ZDM is to guarantee that no defective products leave the industry. Virtual defect detection is transforming quality inspection in the global steel industry, achieving defect rates of less than 2% (Jeong et al., 2023; Xu et al., 2023). Steel manufacturers are becoming capable to detect defects and measure critical dimensions with high precision, harnessing shopfloor data and advanced analytics technologies like AI. As steel products quality control involves numerous complex quality parameters that are challenging for human inspectors to simultaneously consider and analyze. This innovation not only reduces human error but also enhances the overall quality control process, ensuring that only the high-quality steel products reach the market.

Ethiopian steel industries are facing a persistent challenge of high defect rates in their products, with a reported 15% defect rate (Case Industry, 2023). This issue primarily stems from their reliance on manual physical inspection methods. In response, defective products are commonly melted down into scrap steel for reprocessing. This approach is costlier, as reprocessing finished defective steel incurs expenses that are 10 times higher than detecting defects early in the production process (Leberruyer et al., 2023).

This inefficient cycle not only results in significant financial investments in steel processing but also hampers the industry's ability to deliver high-quality steel products efficiently. From the total manufacturing time, 20-25% is consumed by QI operation (Case Industry, 2023). The visual inspections and dimensional measures take 1.5 minutes per sample on average. For more complicated tests like mechanical properties test, 30-140 min per sample may be required. The longer it takes to inspect and identify defects, the higher the chances of defective products reaching customers, thereby compromising the goal of achieving zero defects. The QI costs are another drawback to the inspection as much of the quality tests including the mechanical properties test are measured with significant number of samples and 57% of the test involves destructive tests where value imparted in samples will be lost. Addressing these challenges associated with quality inspection is crucial to optimize production processes, minimize costs, and enhance the overall journey towards ZDM.

Successful implementation of virtual detection is completely dependent on access to data and advanced analytics. Applying this technology is not a straightforward process and have some requirements which are still a challenge for the industry. The first one associated with industrial digital readiness. Embracing zero defects requires organizational changes towards digitalization that impact strategic management decisions and day-to-day manufacturing operations. Hence, evaluating and enhancing digital readiness becomes crucial for the successful adoption of ZDM. Digital readiness or maturity refers to: "The extent to which an organization has successfully adopted and integrated digital technologies into its operations and processes" (Lassnig et al., 2018). As ZDM heavily relies on digital technologies and data-driven approaches, organizations with higher digital maturity and data analytics capabilities are likely to be better positioned to implement and leverage ZDM effectively. Identifying the critical factors to industrial digital readiness and analyzing the correlated impact of these factors is critical towards digitalizing manufacturing industries. While several digital maturity models (MM) in industrial use cases already exist, the complex relationship among the MM dimensions are not yet been analyzed specifically, for ease of AI implementation in industry remain open.

The other challenge is the lack of a standardized approach to data analytics. Often there exists multiple data analytics frameworks outside of ZDM, but customizing the existing methods taking the case of ZDM leads to a difficulty in developing an effective AI model. Creating data analytics frameworks for a specific domain involves a thorough exploration of specific requirements to extract insights from data effectively. In the context of ZDM, this process initiates with grasping the industries' quality control data ecosystem, identify data sources, and evaluating according to the ZDM strategies. And defining the quality control stage whether in preproduction, during production, or post-production and aligning these with analytical techniques like detective, predictive, and prescriptive analytics, tailored to ZDM strategies such as detection, prediction, repair, and prevention. This data analytics procedure encompasses data preparation, integration, model development, and interpretation, enabling industries to harness data efficiently and implement ZDM strategies seamlessly.

The mentioned limitations compel steel industries to persist with manual physical quality inspection methods, causing extended inspection times and high inspection costs. This underscores the necessity for enhanced technological integration and data-driven approaches to streamline inspection procedures and enable ZDM

1.4. Research Questions

Four research questions have been outlined to address the general objective of this dissertation, split into two fundamental research questions exploring theoretical concepts and two additional questions concentrating on applied research to tackle practical challenges and address specific issues prevalent in the steel industry.

1. What are the current trends and challenges of data analytics in the field of zero-defect manufacturing?
2. What factors influence digital readiness of manufacturing industries and how do they collectively affect digital maturity?
3. What is the current state of readiness of Ethiopian steel industries to adopt zero defect manufacturing?
4. How can an AI model be developed and validated to enhance defect detection effectiveness in Ethiopian steel industries?

1.5. Research Objective

General objective

The general objective of this research is to develop and validate AI-based defect detection model to enable virtual quality inspection and ZDM in Ethiopian steel industries.

Specific objectives

1. To examine the current trends and challenges of data analytics in ZDM.
2. To identify, and subsequently analyze factors affecting the digital readiness of manufacturing industries towards the successful implementation of ZDM.
3. To evaluate the current state of digital readiness of Ethiopian steel industries to adopt ZDM, in terms of digital infrastructure, data management and analytics.

4. To develop and validate an AI-based defect detection model facilitating an effective quality inspection in Ethiopian steel industries.

1.6. Significance

The emergence of the fourth industrial revolution has compelled the manufacturing sector to transition towards digitalization and the utilization of artificial intelligence to effectively implement zero defect manufacturing. The significance of this study can be seen from two broad perspectives:

First, it serves to elicit steel manufacturing industries to embark on their digital transformation journey, encompassing the establishment of a robust digital infrastructure, effective data management, and analytics. Digital readiness, which refers to the extent to which an organization has successfully integrated digital technologies into its operations and workflows, is crucial for the successful adoption of Zero-Defect Manufacturing. Given that ZDM heavily relies on digital tools and data-centric methodologies, organizations with higher digital maturity are poised to better implement and leverage ZDM. This research offers a pathway for evaluating and enhancing digital readiness for the industries.

Second, the study validates the efficacy of artificial intelligence in assisting the quality inspection processes within the industry. AI emerges as a key solution for minimizing quality defects. Through powerful algorithms, AI can promptly analyze vast datasets and discern patterns across many quality parameters. While humans are capable of such analyses, AI performs them at a significantly accelerated time and lower cost, relying solely on data. The research contributes by utilizing AI for quality control in manufacturing settings facilitating the way towards zero defect. The significance of the detection model introduced in this chapter lies in its direct applicability to the industry. It explores comprehensive quality parameters including dimensional measures, specifically addressing a distinct requirement within the steel rebar manufacturing sector. By incorporating these essential quality parameters alongside other relevant parameters, this research makes a valuable contribution to the advancement of defect detection techniques within an industrial environment.

1.7. Scope

While ZDM can be applied across various manufacturing sectors and industries, this research specifically focuses on the steel industries, which falls under the umbrella of the metal manufacturing sector. Within the domain of steel products, the data collection for defect detection model development is centered on reinforcement bars (rebar) with grade B500BWR. This grade serves as an example that can be extended to other steel products and even other sector through a reassessment of other quality parameters.

Although the ZDM implementation framework highlighted in the introduction section indicates the incorporation of various Industry 4.0 technologies (including big data, cyber-physical systems, IoT, cloud computing, machine learning, and artificial intelligence) into the four ZDM strategies, this study limits its scope to the utilization of artificial intelligence, specifically, machine learning.

1.8. Limitations

The research encountered three major limitations. The first limitation of this research is the possibility of bias during the content analysis of some studies and the potential for subjective judgments when evaluating their content. These factors may raise concerns about the applicability of the findings, as the studies reviewed might not be universally applicable to all contexts or domains. To address this limitation and enhance the credibility of the literature content analysis, the researcher's took measures such as clearly defining the criteria used for analysis and conducting multiple crosschecks to ensure consistency and minimize bias.

The second challenge arises from the scarcity of defect data to train the model. The data collected contained few defect instances which limited the model learning. Out of the total observations used for training and testing the model, only 202 instances represent defects, while the remaining 5878 instances are non-defective. This significant class imbalance can negatively impact the model's ability to learn and accurately identify defects. To address these challenges, an iterative improvement process (a for-loop iteration) has been implemented to select the most informative samples.

The last limitation pertains to interpreting the quality estimation made by the model. Ensemble models, despite their reputation for high quality prediction accuracy, are often labeled as "black box" models; implying that the internal workings and decision-making processes of these models are not easily explainable or transparent to human interpretation (Kusiak & Kusiak, 2024). To mitigate this challenge, the model's interpretation has been approached through feature importance analysis. Additionally, the input and insights of the existing literature and domain experts have been sought to interpret the significance of various features within the model.

1.9. Dissertation organization

This section offers an overview of the dissertation's framework. The dissertation consists of seven (7) chapters, each sequentially addressing specific problems and objectives while establishing a logical connection between the research problem, related research questions, and the central research question of the dissertation. Additionally, a concise summary highlighting the primary focus of each chapter is included.

Chapter two: Involves a comprehensive literature review, employing various methodologies. It starts by examining existing literature review articles in ZDM to highlight the broad overview of the field. Subsequently, a systematic literature review is carried out using the PRISMA framework to analyze ZDM papers from a data analytics perspective. Moreover, an analysis of current digital maturity models is performed to extract digital readiness factors. Another aspect of content analysis focuses on steel defect detection models to identify gaps in the existing models. By the end of this chapter, the research addresses the initial two research questions.

Chapter three: Presents the research design and methodology, providing a coherent structure and understanding of the methods employed in the study. This chapter elaborates on the research design, data collection methods, and data analysis techniques.

In Chapter four: An examination of the factors influencing the digital readiness of industries to implement ZDM has been conducted. This analysis involves both the direct and indirect effects, considering factors that may mediate the relationship with digital readiness. This chapter addresses a segment of research question 2.

Chapter Five presents the development of a defect detection model, drawing on insights from the digital maturity assessment of the case steel industry (addressing Research Question 3) to answer Research Question 4. Prior to model development, an assessment was conducted to evaluate the progress of steel industries in digitalization. This evaluation supports the alignment of industries with appropriate ZDM strategies.

Chapter Six: Discusses the results of the entire analysis derived from the key findings of the analysis, including both theoretical and practical insights. A ZDM continuous improvement cycle has also been proposed.

Chapter seven: Concludes the primary findings of the study and gives recommendations to the industries with feature research directions.

Chapter Two

Literature Review

2.1. Introduction

This chapter first conducts a focused analysis of AI-driven defect detection, explicitly excluding prediction, repair, and prevention. This prioritization addresses a focused literature review at the dissertation's core aim. The next section presents ZDM's strategies through the lens of data analytics (the broader concept). This sequence establishes detection as the critical enabler for the comprehensive view of the remaining ZDM strategies. As the limitation on having defect detection model constrain an effective prediction and prevention goals of ZDM. Lastly, a literature review on industrial digital readiness for ZDM has been given, as these barriers directly impact effective AI implementation. The literature gaps identified in each subsection are outlined at the end of the chapter under the summary section. Moreover, contribution from the literature review is demonstrated through the proposal of a standardized framework to implement data analytics in ZDM, based on the identified implementation challenges and presented at the end of the content analysis.

2.2. AI-Based Defect Detection

Defect detection is the foundational pillar of ZDM transforming quality control from reactive inspection to proactive intervention (Y. Zhang et al., 2024). It is the automated process of identifying physical deviations from specifications in products during manufacturing, using virtual (data-driven) methods (Maitra et al., 2024). This technology can be realized by utilizing extensive quality control datasets or records and advanced data-driven algorithms. According to Psarommatis et al., (2023), techniques such as AI and ML play a crucial role in achieving ZDM. The accumulation of vast amounts of data from shop floors necessitates the use of appropriate tools to extract valuable insights and knowledge (Psarommatis, May, et al., 2020a).

Machine learning, a powerful and widely adopted data-driven approach, is particularly prominent in this context (Psarommatis, Sousa, et al., 2022a). All the strategies in ZDM, including defect detection, heavily rely on machine learning and data mining techniques (Dreyfus et al., 2022). The ability of machine learning to handle complex and large-scale datasets surpasses that of traditional data analytics tools (Rai et al., 2021; Farahani et al., 2023). Machine learning algorithms, which find application in various domains, can be broadly categorized into classical learning, deep learning, reinforcement learning, and ensemble learning (Dong et al., 2020).

Ensemble learning algorithms operate by combining multiple weak models/learners in to one model to reduce bias and improve accuracy (Dong et al., 2020; Escobar et al., 2021). Bagging, boosting and stacking are the three most common types of ensemble learning. For any machine learning project, selecting the most suitable model for a particular problem is crucial. The decision regarding the appropriate ML technique relies on factors such as the dataset's specific characteristics, the problem's nature, and the computational resources at hand (Tercan & Meisen, 2022). In this regard, ensemble learning techniques have gained wide acceptance in the ZDM research due to their proven detection capacity. In the following paragraphs, some notable research studies that have leveraged these algorithms are presented.

In their recent study, Xin et al., (2023) introduced an approach for defect detection in laser sintering using ensemble models based on convolutional neural networks (CNNs). Specifically, they utilized two types of CNN ensembles: bagged CNN and boosted CNN on a powder bed image data and achieve 95.1% quality estimation accuracy from the bagged model, highlighting the effectiveness of the proposed ensemble-based methodology.

Koo et al., (2023) also conducted a comparative analysis between single models, including decision tree (DT), random forest (RF), logistic regression (LR), Bayesian network (BN), and artificial neural network (ANN), and ensemble models, specifically bagging and boosting. The objective was to detect the factors that influence weight defects in injection-molded products. The results of their investigation revealed that ensemble models surpass the detection accuracy achieved by the individual models.

In a related study, Sariyer et al., (2022) introduced a model for estimating the cost of defects using a clustering-based classifier ensemble method, incorporating principles of bagging and voting. The proposed ensemble-based model achieved an accuracy rate of approximately 89% when evaluated on the test dataset. Dengler et al., (2021) also propose a quality control system for the pharmaceutical industry. This system utilizes an ensemble method, Support Vector Machines (SVM) and Convolutional Neural Networks (CNN). The proposed system aims to detect all defective products and achieves100% detection of defects.

Moreover, there are research efforts devoted to achieve ZDM strategies that employ diverse techniques of ML. In a recent study by Konstantinidis et al. (2023), a four-layer architecture was presented specifically designed for the inspection of dairy products. This system utilizes machine vision to gather data, and employs artificial intelligence to analyze the input data and generate quality estimation, leveraging the concept of digital twin technology.

Although ML have a wide application domain in ZDM, this study specifically focuses on the defect detection strategy within the context of steel manufacturing. Thus, in the subsequent subsection, the authors present an overview of relevant models employed for steel defect detection.

2.2.1. Defect detection in steel quality control

Many defect detection models have been developed in the steel industry to ensure the production of high-quality steel products. These studies have addressed various quality concerns prevalent in the industry. For this particular research, a selection was made among the most pertinent studies, resulting in the inclusion of 16 relevant papers. These papers were analyzed and summarized based on 8 key parameters for defect detection model development, as presented in Table 2.1.

Table 2. 1: Content analysis of the existing steel defect detection models (Source: Authors)

Reference	Data points	No. of input variable	No. of output variables	Dimensional features included	Model explainability considered	Sufficient defect data	Alternate solution proposed for scarce of defect data	ML technique
(X. Li et al., 2023)	Real-time	24	3	_	_	+	_	General causality analysis, stacking
(Amin & Akhter, 2020)	12568	_	2	_	_	+(5902)	_	U-NET and Deep Residual U-NET
(Kusuma & Huang, 2023)	72	15	1	_	_	_	_	Deep neural network
(Y. bao Zhao et al., 2023)	4501	15	3	_	_	_ (247)	_	ERT, Factor analysis
(Xin et al., 2023)	8514	_	1	_	_	_	_	Bagged CNN and boosted CNN
(W. Zhao et al., 2021)	1800	_	6	_	_	+ (300)	_	Faster R-CNN
(Takalo-Mattila et al., 2022)	225,461	89	1	_	+	_	_	Gradient boosting

(S. Li et al., 2021)	3350	69	1	_	_	_ (205)	_	DBN-ELM
(Murta et al., 2021)	2340	18	4	_	_	_	_	LR, ANN
(Q. Xie et al., 2021)	11,101	27	4	_	_	_	_	DNN
(Guo et al., 2019)	63,137	27	3	_	_	_ (890)	_	OLS, SVM, RT, RF
(Boto et al., 2022)		18	1	_	_	_	_	RF, gradient boosting, xgboost and NN
(Xu et al., 2023)	Real-time	12	4	_	_	_	_	LSTM, GRU, GPR
(Ji et al., 2022)	1268	41	1	_	+			HC, GA, GLR
(Chen et al., 2023)	Real-time	29	1	_	_	_	_	LR, SMOreg, MP, KNN, RF
(Feng et al., 2022)	4878	12	1	_	_	_ (110)	_	SVR, RF, BPNN

The initial literature analysis pertains to the quantity of data points used for training and testing the model. This includes both streaming data, which is continuously received, and batch historical data. From the analysis, the volume of data points considered differs encompassing both large and relatively smaller datasets. Machine learning algorithms, being inherently reliant on data, benefit from having a substantial amount of data for training and testing, generally enhances the accuracy of the model's detection capabilities.

Some of the studies have employed an unsupervised machine learning approach. In such a case, the determination of input variables is not predefined. Instead, it relies on the data itself and is dictated by the dataset's dimensionality during the analysis. The remaining studies adopt a supervised learning approach, where input variables are predetermined and linked to corresponding labeled outputs.

Regarding the number of output variables, much of the studies have opted for a binary classification approach, grouping all defect types into a single category of either normal or defective (labeled as 1 in table 2.1). This approach has a drawback as it fails to provide insights into the specific reasons behind rejections. The underlying causes for the rejects often remain unnoticed. On the other hand, other studies have examined each output quality parameter or defect type individually, analyzing the detection accuracy for each specific parameter.

In terms of including dimensional measures as input quality parameters, previous steel defect detection studies have generally overlooked these parameters, despite their critical importance as input features.

In steel product quality control, precise measurement and control of dimensional errors are key factors in enhancing overall quality standards and positively influencing mechanical properties (Poudel et al., 2013). Parameters such as weight, diameter, cross-sectional area, rib height, rib spacing, transverse-rib inclination, and transverse-rib flank inclination are the major features in dimensional measures. Even minor deviations in these dimensions can trigger significant effect, potentially leading to losses and deviations in mechanical properties. Such deviations hold the power to alter the stress-strain behavior of the steel product and consequently impact the offset yield strength (Murta et al., 2021).

In terms of model explainability, most of the papers, with the exception of two studies, do not focus on advancing the understandability of how the model operates or detect defects. Model explainability is a crucial aspect, especially for industries that prioritize problem-solving over algorithmic intricacies. Many of the other models are generally considered black box models, lacking the inherent nature of explainability.

When considering the availability of sufficient defect data for model training, only two studies have taken into account an adequate number of defective product samples. This poses a significant challenge, particularly for supervised learning methods that heavily rely on labeled data. This aspect presents a challenge in many studies, as insufficient defect data can adversely affect model performance. It may result in lower detection accuracy and higher rates of false positives or false negatives.

However, none of the previous studies have proposed an alternative solution to overcome this challenge under the steel defect detection domain. Hakami, (2024) proposes the use of synthetic data as a potential solution to predict machine failure under the constraint of limited machine failure data. Nevertheless, to customize to the steel defect, synthetic data might not encompass the wide array of quality parameters and defects types that can manifest in steel products. This shortfall could lead to models being inadequately trained to identify all defect types encountered in real industrial settings. Therefore, there is a need for a robust approach that addresses the challenges of defect data scarcity which can overcome entire dependence in sensor and other metrology data and even synthetic data.

2.3. Introduction to ZDM and previous review articles

A well-structured framework for ZDM implementation, which serves as a foundation of modern ZDM is given by Psarommatis et al., (2020). This framework effectively consolidated previously scattered concepts related to zero defects, providing a cohesive approach. The framework is built upon the principles of Industry 4.0 technologies and encompasses four key quality strategies namely: detection, prediction, repair, and prevention. The first two as a triggering factor and the last two as an action strategy. These are generally implemented in three pairs of strategies according to the following combinations: Detect – Repair, Detect – Prevent and Predict – Prevent (Babalola et al., 2023). Following this framework, different research outputs have been produced dealing in each of the four strategies.

Moreover, ZDM can be implemented through two approaches: product-oriented and process-oriented (Powell et al., 2022). A product-oriented ZDM focuses on identifying defects in the actual products, whereas the process-oriented approach focuses on eliminating defects in the manufacturing equipment, often aligned with the concept of predictive maintenance (Psarommatis et al., 2020). Both approaches ultimately contribute to ZDM, albeit with different starting points. A product-centered approach prioritizes product quality, derived from the product's quality parameter data (Dreyfus et al., 2022; Y. Zhang et al., 2024). The process-oriented approach on the other hand harnesses maintenance related dataset, including machine performance data, failure data, maintenance records, maintenance cost data, and more (Christou et al., 2022). In both approaches, data-driven technologies facilitate an effective implementation of ZDM strategies (Foivos & Gokan, 2022).

Previous literature review articles have evaluated and achieved a significant facet of ZDM, as outlined in table 2.2. The table highlights discoveries from 10 pertinent literature reviews that delve into various subjects encompassed within the domain of zero-defect manufacturing as a core topic. The major ZDM aspect covered, the attributes used for content analysis and the key contributions are summarized. By doing so, this sub-section provides an overview of the primary subject matters that have been explored so far in ZDM research domain.

Although, the advancements in industry 4.0 technologies and data analytics techniques offer a substantial opportunity to amplify the impact of ZDM, there is a gap on review article for such a topic. The table highlights the importance of exploring the field from the data analytics perspective.

Table 2. 2: Subjects covered in previous literature reviews on ZDM and key contributions (source: Authors)

S. N	***Literature review papers on the field of ZDM***	***Research domain under ZDM***	***Limited to process/product centric***	***Attributes used for content analysis***	***Key contribution***
1	*(Psarommatis, May, et al., 2020a)*	*State-of-the-art in ZDM*	*No*	*ZDM strategies category, Industrial sector, Manufacturing process, Level of automation, Industrial setting, manufacturing stage*	*New framework for ZDM implementation proposed*
2	*(Psarommatis, Prouvost, et al., 2020)*	*Position paper*	*No*	*-*	*Propose a clear and widely used definition for ZDM*
3	*(Psarommatis, Sousa, et al., 2022b)*	*State-of-the-art review*	*Yes (quality)*	*Tools used for quality improvement, enabling factors, benefits, and barriers to implement*	*Provide critical discussions on the evolution of traditional quality tools to ZDM*
4	*(Azamfirei et al., 2023)*	*In-line quality inspection*	*No*	*Process domain, level of automation, inspection actuators, type and condition of inspection equipment, method for data analysis, contribution to ZDM strategies and dedicated improvements*	*Adapted quality inspection framework for ZDM proposed*
5	(Foivos & Gokan, 2022)	*Digital twin (DT)*	*Yes (quality)*	*Type of DT implementation, quality tool used, industry and purpose domain, application domain, technologies used*	*Standardized DT design methodology provided*
6	*(Dreyfus et al., 2022b)*	*Virtual metrology (VM)*		*Analyze and discuss VM elements*	*VM framework proposed*

7	*(Powell et al., 2022)*	*State-of-the-art in ZDM*	*No*	*Scope, focus, type, hierarchical level, enabling technology*	*Framework proposed*
8	*(Psarommatis, May, et al., 2023)*	*Maintenance 5.0*	*Yes (maintenance)*	*Identifies key trends in advanced maintenance techniques in ZDM*	*Introduce Maintenance 5.0 framework*
9	(Caiazzo et al., 2022)	*State-of-the-art in ZDM*	*No*	*ZDM strategies, techniques used to attain each strategy*	-
10	(Y. Zhang et al., 2024)	*Virtual metrology*	*No*	-	*VM development framework proposed*

2.4. Data analytics in zero defect manufacturing

Data analytics (DA) in ZDM involves utilizing data and advanced analytics techniques to detect and predict defects throughout the entire product lifecycle (Psarommatis et al., 2021). It starts from design phase to manufacturing of final products or operation phase. As shown in Figure 2.1, each phase is interconnected and contribute to ensuring consistent product quality. Data from various sources at the shopfloor level is analyzed, cleaned, and processed to build accurate and reliable models (Dreyfus et al., 2022b). Models provide insights into potential quality issues and guide the design process by evaluating design options, predict product performance, and assess the impact of design choices on quality. Previous design data, the domain knowledge and the product lifecycle documentations can assist on defect-free product design process by analyzing and extracting useful insights from the data (P. Wang et al., 2023). The goal is to proactively identify and address potential quality issues during the design phase, reducing the likelihood of defects in the operation phase. perspective by conducting an in-depth content analysis using key data analytics attributes.

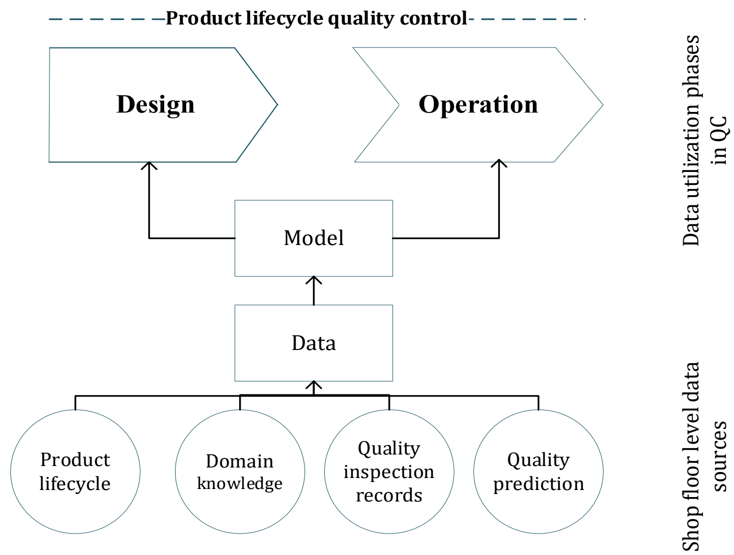


Figure 2. 1: Product lifecycle quality control, (Source: (Psarommatis et al., 2021))

Data analytics has a significance role in advancing quality control processes, across both phases, within product-oriented ZDM strategies. Utilizing data from the shop floor level in manufacturing operations plays a key role in optimizing the production phase, enhancing product quality, and ultimately achieving the objective of zero defects (Chiarini & Kumar, 2021). Additionally, data analytics enables the analysis of customer feedback, market trends, and historical data to accurately understand and define product requirements even before actual production commences. These approaches necessitate extensive datasets and the application of cutting-edge data analytics techniques such as AI and machine learning to proactively prevent defects and effectively implement the ZDM strategies. Consequently, the interest among scholars and practitioners is immense in data-driven strategies that empower companies to improve their manufacturing quality through the analysis of data gathered throughout the entire product life cycle.

Models are also used in the operation phase for real-time and offline quality control serving as the basis for establishing quality parameters, predict potential quality issues, and guide decision-making to maintain consistent product quality (Caiazzo et al., 2022). In the operation phase, quality control encompasses activities that are carried out during the production stages (Azamfirei et al., 2023). Data analytics conducted at this phase includes quality control checks, inspections, and testing at various points in the production process to detect and prevent defects. Quality control process at this stage leverages a huge amount of data collected from different sources at the shop floor level majorly, the quality inspection records at different production stages and predictions.

The sequence of literature search activities is depicted in Figure 2.2. The bibliometric and content analysis results have been presented subsequently.

Article identification: To ensure a thorough and comprehensive systematic literature review and access to pertinent research, a combination of the Scopus database, Web of Science, and IEEE Xplore were utilized to search for scientific articles. These three databases, are recognized for their wide-ranging coverage of international journals, offering a wide range of view of research output across diverse domains. Furthermore, they are renowned for their stringent selection criteria and indexing of influential, peer-reviewed journals. Keyword assumption is another important requirement in the data identification phase. Given that the research focuses on exploring data analytics in the context of zero-defect manufacturing, specific query keywords of "Zero defect manufacturing" OR "zero defect" AND "manufacturing" OR "zero defect manufacturing" OR "defect detection" OR "defect prediction" OR "defect prevention" have been employed to ensure relevant data retrieval.

Article screening: Once the papers had been collected from each of the databases, relevant articles were selected based on the following four inclusion criteria (IC) or exclusion criteria (EC).

1. Publication year: Only academic papers published starting from the year where Industry 4.0 emerged (2011- January 2024) were included.
2. Scientific discipline: The articles' subject area has to align with the academic fields taken into consideration (Engineering and Computer Science).
3. Document type: Only research articles and conference papers were included not (books, book chapters, and reports).
4. Language: The article should be written in English.

Eligible article selection:

1. Subject relevance: All the papers had to respect product-oriented ZDM (not process-oriented).

2. Contribution: The reviewed papers were selected according to whether they contribute to the development and application of data analytics methods and algorithms in the ZDM domain.

Included articles: The final inclusion criterion (IC) is the papers' availability without a subscription. Following all the steps of the PRISMA framework, the remaining 188 were downloaded and stored in Mendeley reference management software for in-depth content analysis.

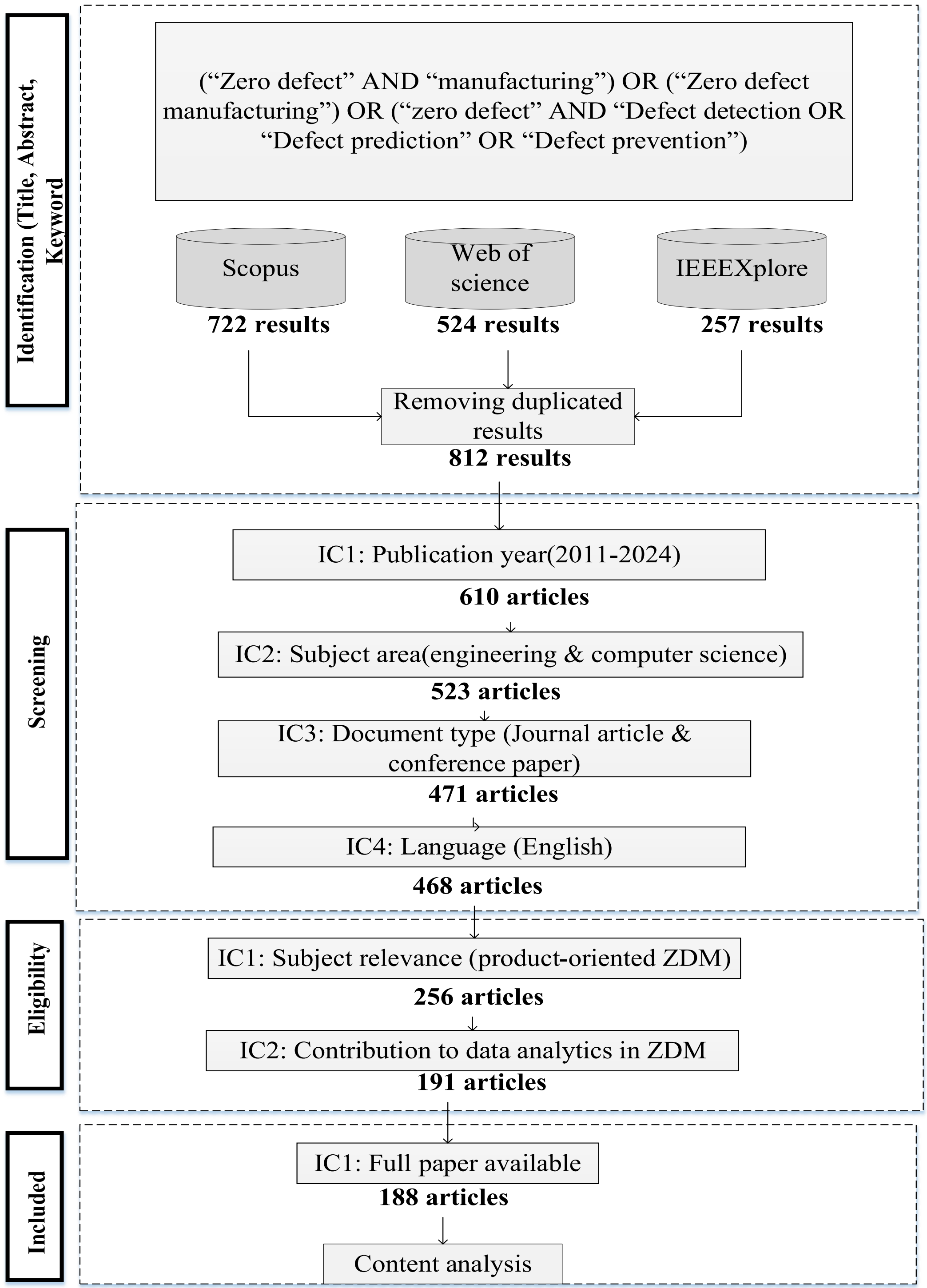


Figure 2. 2: The PRISMA framework, IC, inclusion criteria (Source: Authors)

2.4.1. Descriptive statistics of the selected papers

The distribution of the articles (publications per year) is shown in Figure 2.3. Starting from the year 2016 up to 2023, the figure reveals a clear and steady upward trend of ZDM publication. Of the total papers produced from 2011- January 2024, 31%, or around 152 papers were published in the year 2022 and 2023. This trend is reasonable as more industry experts and researchers are understanding the need for an alternative, more efficient quality improvement framework specially to prevail the goal of sustainable manufacturing.

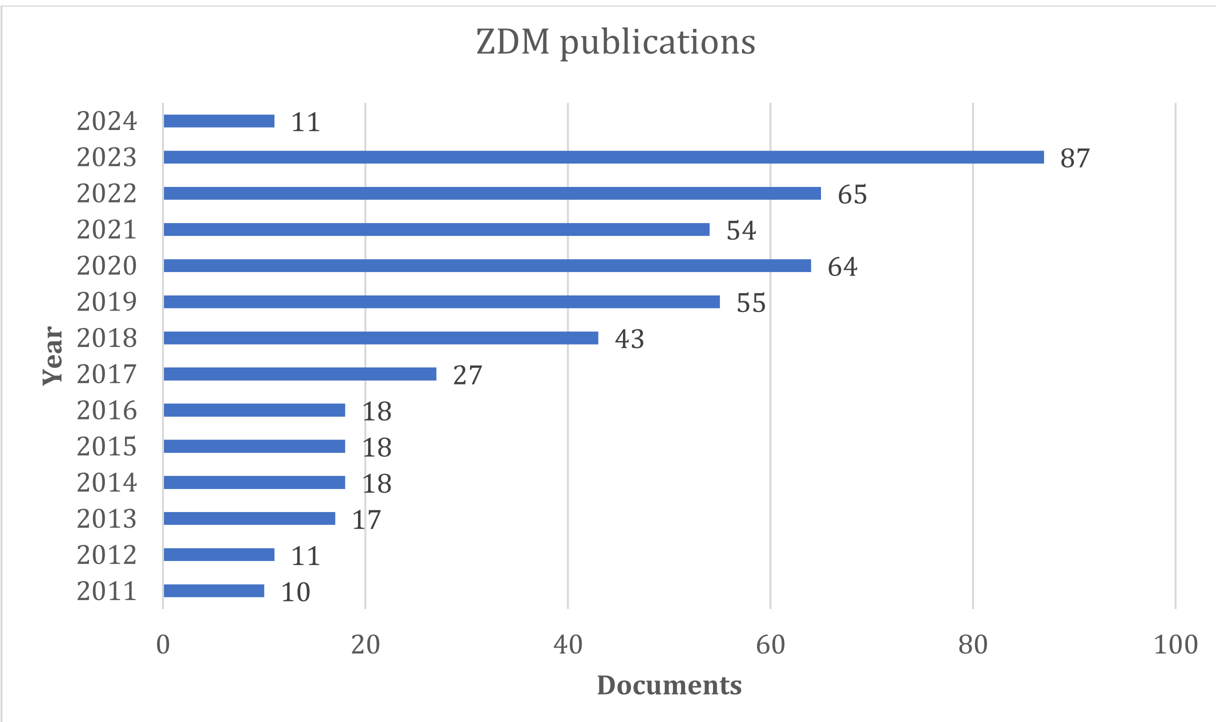


Figure 2. 3: Publications on zero defect manufacturing, from 2011 until January 2024 (Source: Authors)

Figure 2.4 shows the leading authors that have made the largest contribution to the field of zero-defect manufacturing. Foivos Psarommatis is the most productive author in the field with 27 publications. Dimitris Kiritisis is the second most productive author on the list with 22 publications. Marcello Colledani and Gokan May are the third productive authors each having 14 publications.

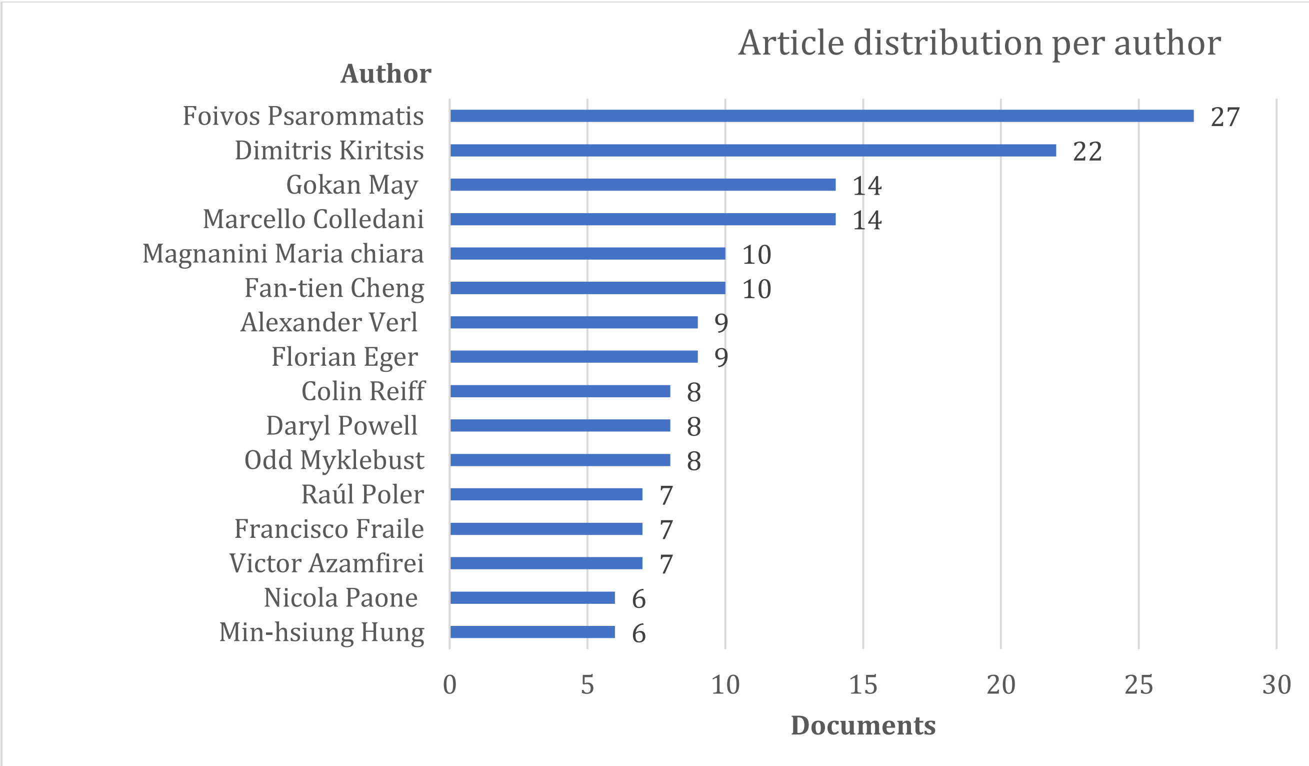


Figure 2. 4: Article distribution per author (Source: Authors)

In Figure 2.5, the collaborative relationships between authors who have published research papers in ZDM is presented. It shows the prominent authors who have collaborated extensively with others and the clusters or groups of authors who frequently collaborate.

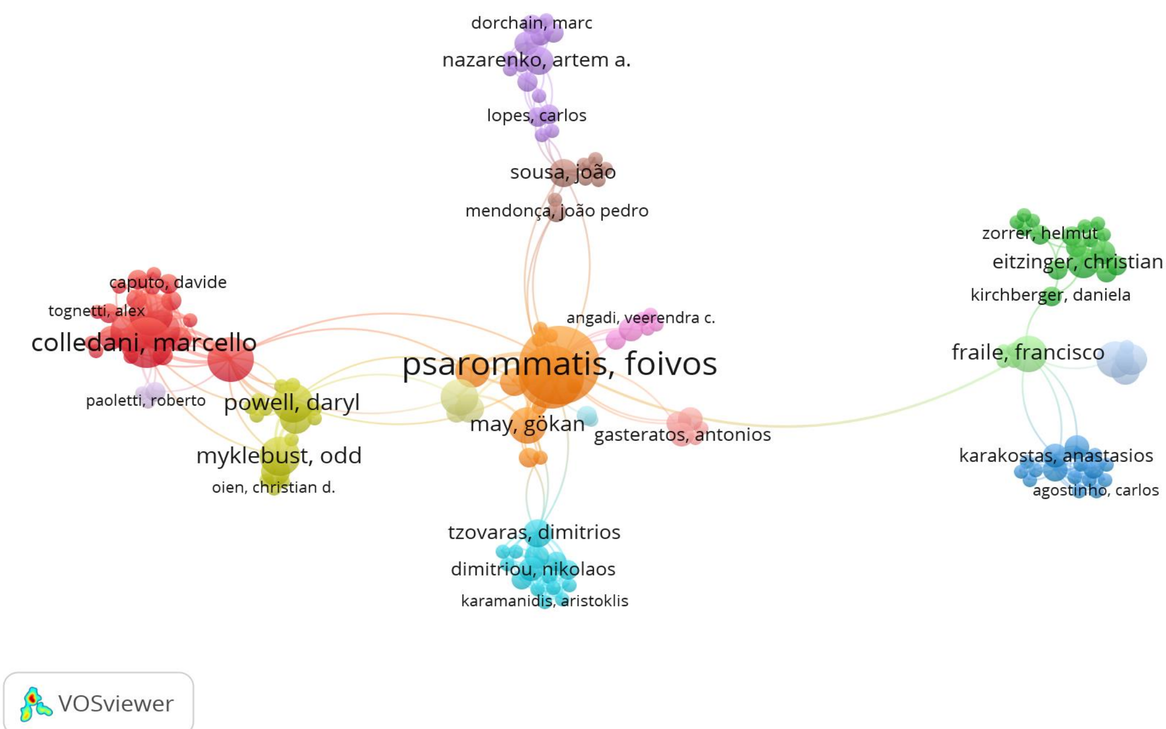


Figure 2. 5: Authors co-authorship map in the field of zero-defect manufacturing (Source: Authors)

2.4.2. Content analysis and synthesis of the reviewed papers

In this section, the selected n=187 articles (Appendix B) were analyzed using six key attributes (listed below). The analysis and classification of papers for each attribute and the associated challenges for implementing DA in ZDM is presented in the following sub-sections.

1. *Data utilization phases in product quality control: design and operation.*
2. *Manufacturing stage to which data analytics is implemented: Pre-process, in-process, or post-process.*
3. *Shop floor level data infrastructure (data source): data from the manufacturing sensors, industrial cameras (image and video data), inspection machine, product/process knowledge and specification, and knowledge from the experts/operator.*
4. *Data analytics condition: real-time or offline.*

5. *Data analytics types and techniques: the enabling data analytics methods.*

6. *Targeted ZDM strategy enabled by data analytics techniques: Detection, Prediction, Repair, and Prevent.*

2.4.2.1. Data utilization phases

In this section, a literature analysis is presented, focusing on the various stages of data utilization in product lifecycle quality control (Figure 2.6). In the context of product quality control, data utilization can be categorized into two phases: the design phase and the operational phase (Psarommatis et al., 2021). The literature analysis reveals that a significant majority of the papers examined (69%) are centered around the operational phase. This phase involves leveraging data related to quality inspections, historical records, and quality predictions throughout different stages of product manufacturing to ensure product quality. On the other hand, a mere 3.7% of the total papers analyzed address the utilization of data in the design phase. The design phase data utilization primarily involves leveraging previous design data, domain knowledge, and product lifecycle documentation. The analysis also reveals that 9.5% of the papers reviewed fails to specify the specific phase in which data is collected and analyzed. This lack of clarity regarding the phase being addressed further highlights the need for a more comprehensive and well-defined approach when considering data collection and analysis for quality control purposes.

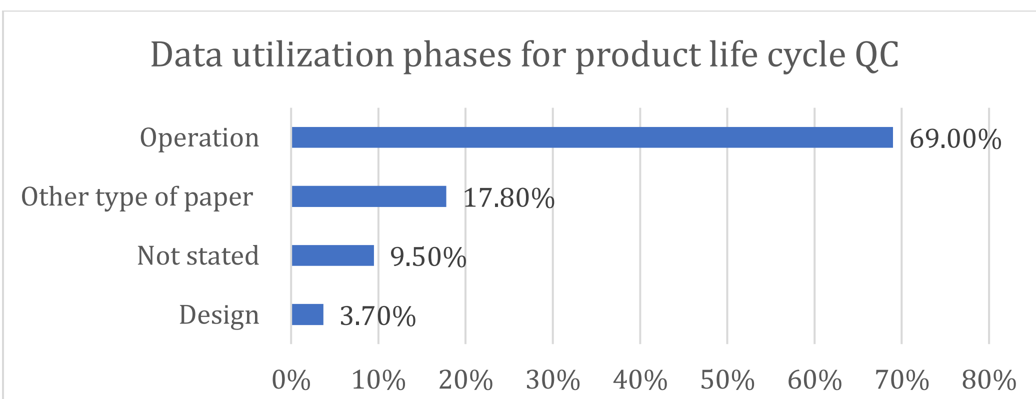


Figure 2. 6: Data utilization phases for design and production quality control (Source: Authors)

2.4.2.2. Manufacturing stage

In this sub-section, the reviewed papers are classified according to the manufacturing stage in which they refer to implement data analytics towards ZDM: pre-process (beginning), in-the process (middle), or post-process (end) (Psarommatis *et al.*, 2020; Bousdekis *et al.*, 2022). From Figure 2.7, it is seen that in-process or quality inspection during the production process is the most dominant stage to take measurements of quality in ZDM. It is preferable as it enables identification and avoidance of defects at each value-added process on the production line (Azamfirei et al., 2023).

In different works of literature, in-process is named, in-situ, in-line, and on-machine. Unlike this, very few papers have been found for quality inspection at the beginning of the production phase. This stage can be seen in two aspects: pre-production or product configuration is the phase before the start of production: usually includes raw material and design quality check. Two papers were found in this regard (Pinto and Silva, 2017); (Pradal & Yakubov, 2018). Even though it is a critical stage demanding quality measures, especially for the customized products; used to eliminate the delivery of defective products in the consecutive production stages, it is not well-explored in the current ZDM research.

The other papers were found as quality check at the initial production phase (Beckert et al., 2023); (Mourtzis *et al.*, 2021); (Leberruyer et al., 2023a). In both cases, limited papers have been found and more research is expected scoping the beginning phase of manufacturing. Finally, compared to the in-process stage, a limited number of papers has been found dealing with the end-of-line quality control stage. Similar to the beginning phase, end of line phase is researched in two aspects; the end (post-production) phase (Martínez et al., 2022); (Psarommatis & Kiritsis, 2022); (Armendia *et al.*, 2021); (Egera, F., Reiffa, C., Tempelb, P., Magnaninic, M. C., Caputod, D., Lechlera, A., 2020); (Eitzinger & Eitzinger, 2019); (Llanos et al., 2016); (Colledani et al., 2015); (D'Addona *et al.*, 2015b). And on the actual finished product (Su et al., 2022); (Baghbanpourasl *et al.,* 2021); (Tiwari & Khan, 2021); (Konstantopoulos *et al.*, 2020); (Pagani et al., 2020); (J. Schmitt et al., 2020); (Lee *et al.*, 2018); (Dimla, 2018); (Vafeiadis et al., 2017); (Caggiano et al., 2016); (D'Addona, Matarazzo, Sharif Ullah, et al., 2015); (Llanos *et al.,* 2014).

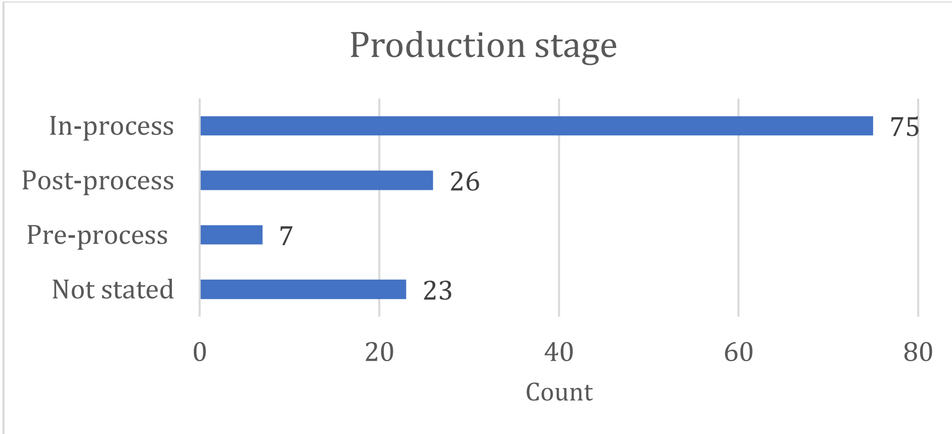


Figure 2. 7: Classification of papers per the manufacturing stage (Source: Authors)

2.4.2.3. Shop floor level data infrastructure

All the quality inspection data is usually generated from the shop floor, in which it is the cornerstone for accurate analytics towards zero defect (C. W. Zhang et al., 2020). This data could be gathered from different sources each having a different form. In industry, it is a prevalent practice to deploy diverse metrology instruments throughout the production line, each dedicated to collecting quality inspection data (Zhong et al., 2015). These instruments encompass an array of sources, such as manufacturing sensors, industrial cameras, inspection machines, product/process documentation, and insights from domain experts.

The ultimate objective of all the devices is to capture information about the product quality but differ in their functionality and purpose. Sensors provide raw data of different physical quantities of a product, including light, temperature, pressure, motion, or proximity in the form of electrical signals or digital values. Industrial cameras on the other hand provide visual information (image or video) commonly used in industry for computer vision applications. Inspection machines also play a crucial role in ensuring the dimensional accuracy of products and conducting inspections based on the design specifications. Commonly used metrology instruments in industry include Coordinate Measuring Machine (CMM), optical comparators, profilometers, surface roughness testers, hardness testers, and laser scanners.

The manufacturing environment in general could be explained by the insert able/measured data or the domain knowledge (Lindström et al., 2020). In addition to the above discussed data collection devices, knowledge captured from quality experts or experienced operators is a principal source of data to identify signals for defects or non-conformities. Integrating or combining different sources of data to get an insight into the product quality status and predict the future is a key element one can leverage from the recent technological advancements.

From the analysis, sensors are the dominant source of data that are mostly utilized in the shopfloor (Figure 2.8). Sensors may provide real-time or non-real-time data about the product parameters depending on the network infrastructure.

Besides, industrial cameras are another widely used source of data for quality inspection in ZDM. These devices are quickly replacing human inspection and positively affecting the speed and accuracy of inspection providing high resolution image and video data. Moreover, knowledge from the operators and quality experts has not been widely exploited. In general, every production line already offers access to data (especially in case of multi-stage). Thus, collecting and recording all the possible quality related data of the parts has the outmost importance to flourish zero defect. To do so, advancing the data infrastructure in industry by deploying many sensor systems, automated inspection machine and cameras across the entire manufacturing stage is required (Chiara et al., 2019).

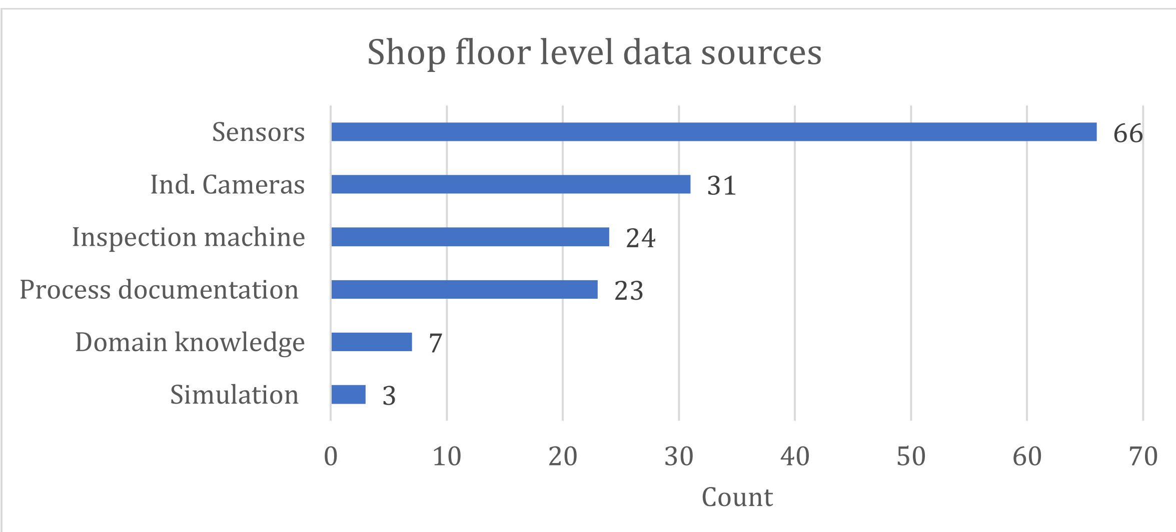


Figure 2. 8: Classification of papers per the data sources used (Source: Authors)

The utilization of combined data sources can help detect or predict and prevent defects that may be missed when relying on a single source of data (Eger et al., 2022). Nonetheless, many of the extant data analytics models (73%) are developed to process data from a single source (Figure 2.9). Utilizing data from multiple data sources (historical data, real-time data, and contextual data) enhances the accuracy of the model. In this regard, Leberruyer *et al.*,(2023) ; (Martínez et al., 2022); (Psarommatis & Kiritsis, 2022); Grobler-Dębska *et al.,* (2022); (Dias et al., 2021); (Egera, F., Reiffa, C., Tempelb, P., Magnaninic, M. C., Caputod, D., Lechlera, A., 2020); Christian *et al.*, (2019); Eger *et al.*, (2018) offered a model for the success of ZDM utilizing a diverse data sources from the shop floor.

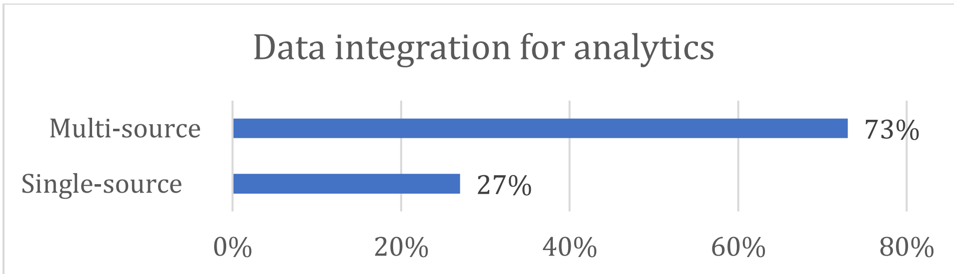


Figure 2. 9: Classification of papers per the data integration strategy (Source: Authors)

2.4.2.4. Data analytics condition

The terms real-time and offline used in this review is to indicate the time when the data is collected to undertake a quality inspection. Real-time data analytics is performed in real-time or near real-time (online streaming data) as data is generated, while the other one is performed after data has been collected and stored (historical batch data). From the literature review, real-time data processing has started to catch greater attention in recent years as much of the ZDM research is conducted based on real-time analytics. However, from the generic view, 68% of the reviewed papers deal with offline data analytics models (Figure 2.10). In addition, nearly 31% of the papers fail to explicitly mention whether the data analyzed pertains to real-time or offline conditions.

The emergence of advanced data collection devices with internet connection in modern industries has led to increasing demand for real-time systems in recent years (Lepenioti *et al.*, 2020). Technologies like Digital twins, which are virtual representations of physical objects, have also the potential to be combined with real-time analytics. These technologies work hand in hand, enabling continuous data collection from various sources and processing it through advanced analytical algorithms (X. Zheng et al., 2022; Psarommatis & May, 2023). Apart from the technical requirements (sensor-driven information systems), there is also the need to build algorithms for data analytics, that can process data in real-time. Real-time analytics is an urgent need since the minimized time interval between the prediction and the decision is the outmost importance of data analytics.

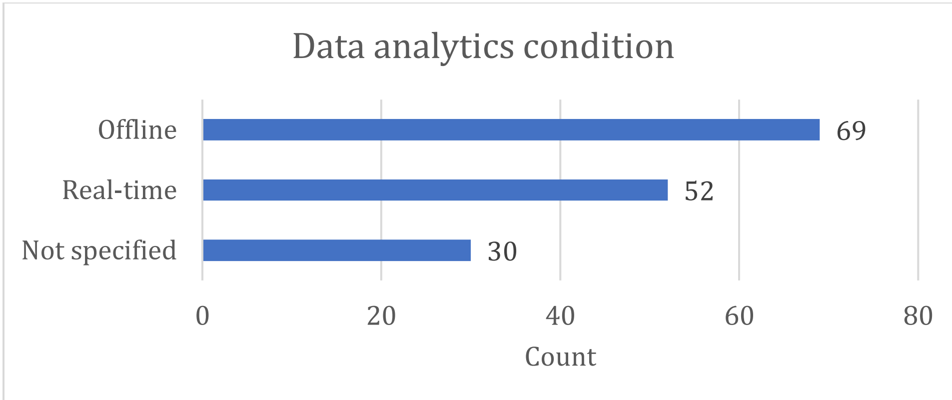


Figure 2. 10: Classification of research per data analytics condition (Source: Authors)

Moreover, further analysis has been conducted to determine whether the papers explicitly distinguish between the production stage (inline or in-process) and the condition of data analytics (real-time), or if such distinctions are absent. The analysis unveils the identification or lack thereof of a distinct separation between in-process and online (real-time) quality control, as depicted in Figure 2.11. In-process quality control is associated with the stages of the manufacturing process, whereas online quality control involves real-time monitoring and intervention during production to control product quality.

Out of the analyzed papers, approximately 67% clearly state the differentiation between data collection and analysis conditions (real-time or offline) and the corresponding stage of quality control (preprocess, in-process, or post-process). However, it is worth noting that the remaining 33% of the papers lack clarity, as they inconsistently use these terms without establishing a clear distinction. It is important to recognize that the entire data analytics process and the corresponding techniques differ significantly between these two approaches.

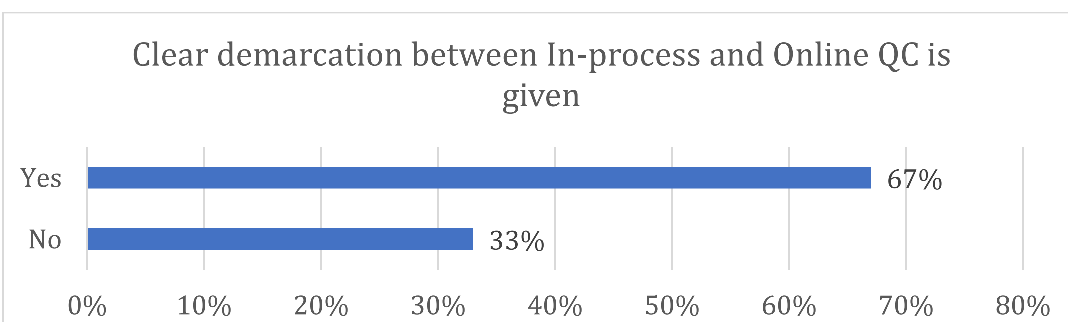


Figure 2. 11: Classification of papers based on their clear differentiation between the in-process and online quality control (QC) approaches (Source: Authors)

2.4.2.5. Data analytics types and techniques

Here the papers are classified according to the type of data analytics tools used for each analytics type (Figure 2.12). Often, defect detection is the starting point for ZDM implementation (Dreyfus et al., 2022a). After each defect is detected, the system learns from it to predict the future (Psarommatis, May, et al., 2020b). In more detail term, the data gathered by the defect detection model is mostly used to specifically design algorithms for prediction. Prescriptive analytics can be integrated into either of the two methods of data analytics discussed above. It is an advanced data analytics type next to predictive analytics; dedicated to realizing optimized decision-making, answering the question 'What should be done?' and 'Why?' (Frazzetto et al., 2019).

Papers presented with paired ZDM strategy shows an interplay of detective/predictive analytics with prescriptive analytics aiming to execute defect detection/prediction and optimal decisions are considered as an integration of detective/predictive analytics with prescriptive analytics.
To classify the techniques for each data analytics type, the paper by Lepenioti *et al.*, (2020) has been referred to. This paper is selected since it is a highly cited paper in the area of data analytics techniques.

The techniques employed for detective and predictive analytics are classified into three categories: probabilistic models (PM), machine learning/data mining (ML/DM), and statistical analysis (SA). The techniques associated with prescriptive analytics are classified into six categories: probabilistic models (PM), machine learning/data mining (ML/DM), mathematical programming (MP), evolutionary computation (EC), simulation (SM), and logic-based models (L-BM).
Machine learning/ data mining algorithms have been mostly used in the context of defect detection and prediction. Nonetheless, it is not well exploited in prescriptive analytics. It is found that only four paper relies entirely on machine learning algorithms both for the application of triggering and action strategies (Leberruyer et al., 2023a); (Petrillo et al., 2022); (Martínez et al., 2022); (Vafeiadis et al., 2017).

Machine vision (deep learning algorithms) is a widely exploited machine learning method especially to process image data to detect defects (Konstantinidis, Myrillas, et al., 2023). Herranz *et al.*, (2019) have used a clustering-based method of machine learning for the segmentation of near real-time data coming from sensors to detect defects. Statistical analysis has also been widely used to develop a predictive model. Under this method, different regression and correlation methods have been explored to develop detective and predictive models. Probabilistic models, on the other hand, are not well exploited in ZDM. Verna *et al.*, (2021) have developed a probabilistic model to determine the quality inspection effectiveness by calculating the likelihood of defect occurrence instead of monitoring actual data to search for defects; Colledani *et al.*, (2018) have also developed a probabilistic model using continuous time-discrete state Markov chain to predict the product status. The trend for the utilization of simulation models for all three types of analytics seems to have decreased in recent years since all the papers found were published in the earlier years (Eitzinger & Eitzinger, 2019); (Pradal & Yakubov, 2018); (Pinto & Silva, 2017); (Llanos et al., 2016) (Meier & Georgiadis, 2014).

Mathematical Programming has been widely used in ZDM in the context of prescriptive analytics with major coverage of optimization methods and algorithms (Psarommatis *et al.*, 2022b); (Groen et al., 2020); (Egera, F., Reiffa, C., Tempelb, P., Magnaninic, M. C., Caputod, D., Lechlera, A., 2020); (Colledani et al., 2018); (Colledani et al., 2014). Most of the papers considered cost as an objective function to be minimized. Here, as ZDM is key to achieving manufacturing sustainability, other sustainability dimensions (social and environmental) also have to be incorporated while defining an objective function. Evolutionary computation on the other hand gets less coverage as a prescriptive analytics tool: only one study (Dias et al., 2021) has used it to develop a decision support system. Logic-based Models, particularly rule-based systems, have been used to develop the decision support system in ZDM literature to automate the action strategies. Most of the papers incorporate expert knowledge into the prescriptive models (Psarommatis and Kiritsis, 2022); (Grobler-Dębska *et al.,* 2022); (Anaya et al., 2020); (Zorrer *et al.*, 2019).

In regards to the combination of categories of methods, machine learning algorithms with statistical analysis (statistical machine learning method) are widely integrated into defect prediction/predictive analytics. As statistics has played a major role in the science of quality control for several years, its integration with recent methods like machine learning is advisable. Methods labeled as 'other' are papers with no specific data analytics approaches including sensor monitoring (Linares et al., 2015); (Centobelli *et al.,* 2015); (Teti, 2015); (Caggiano et al., 2015) in which it involves monitoring a wide variety of product/process parameters directly from the sensors without an explicit data analytics algorithms.

The other trending technology for data analytics in ZDM, particularly for defect detection is virtual metrology (VM). It is distinctly crucial for manufacturing industries with multiple production stages and many complex process parameters in which 100% physical inspection is time-consuming and uneconomical (Dreyfus et al., 2022a). Semiconductor manufacturing is an exemplary sector to indicate complex processes in which VM is well implemented. It is typically used in real-time process control i.e.; it relies on the availability of real-time data from the manufacturing process to make predictions as the virtual metrology model is trained using real-time data of the parameters. This strengthens the discussion in section 2.2.3.4 about the importance of the availability of real-time data. Generally, the authors have the same argument as Azamfirei et al., (2023) that more publications of VM are expected in the future ZDM research as it is a promising method for data analytics advancement.

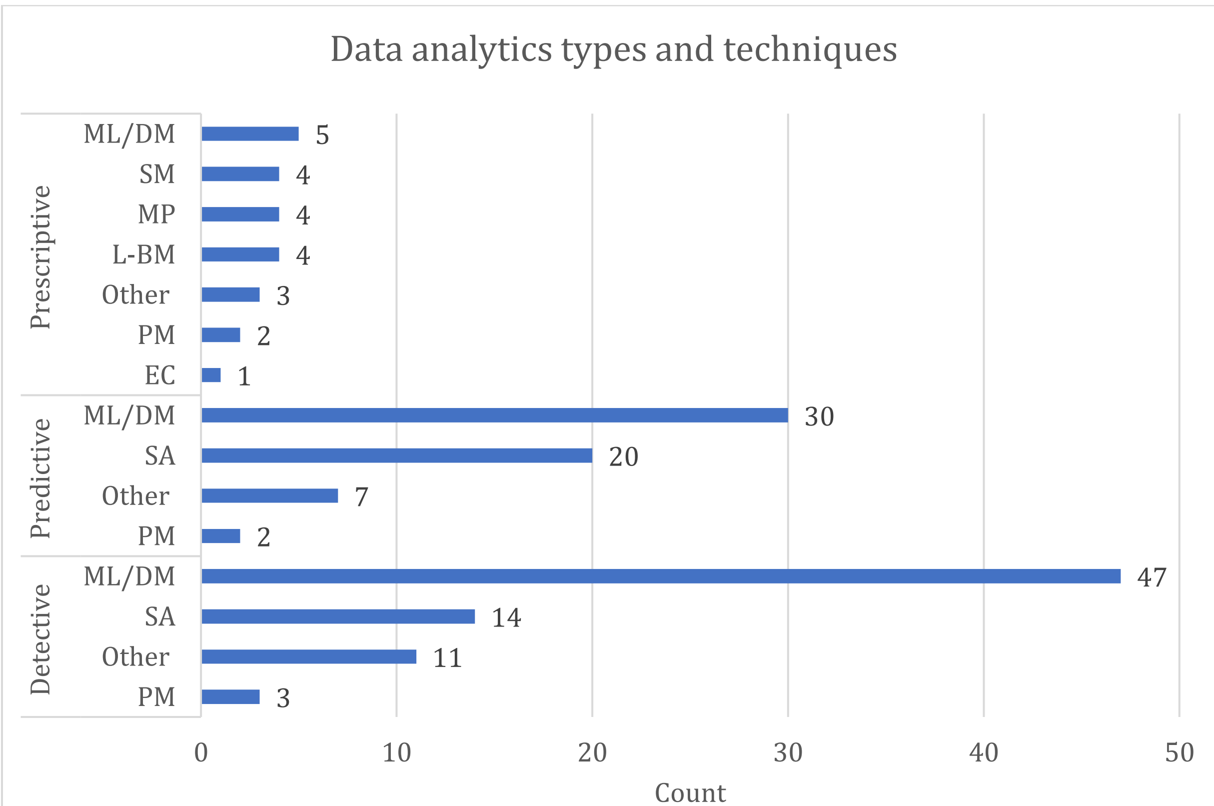


Figure 2. 12: Classification of papers according to the data analytics type and techniques (Source: Authors)

ML/DM=Machine learning/Data mining, L-BM=logic-based model, SA=Statistical analysis, PM=Probabilistic models, MP=Mathematical programming, EC=Evolutionary computation, SM=Simulation

2.4.2.6. Targeted ZDM strategy enabled by data analytics techniques

The process of analyzing data derived from the quality features or parameters of already manufactured products is known as defect detection (Dreyfus et al., 2022). On the other hand, prediction involves calculating the expected quality of a product before it is manufactured (Psarommatis, Sousa, et al., 2022b). Among the four strategies, defect detection is extensively studied in ZDM as a means of achieving zero defects (Figure 2.13), which aligns with previous research findings by (Psarommatis *et al.*, 2020a). Prediction, is gaining importance as a significant triggering strategy in recent ZDM studies. The existing literature on ZDM primarily focuses on detection and prediction strategies in general, whereas the action strategies; repair and prevention are relatively less explored.

Repair and prevention measures are crucial components implemented based on defect detection and prediction, serving to rectify existing defects and prevent potential future defects. It is evident that the majority of publications, including recent ones, predominantly concentrate on realizing a single strategy (84%) rather than fully integrating both triggering and action strategies.

According to the review paper by Psarommatis *et al.*, (2020a), it is evident that 93.73% of the papers focused on a non-paired approach. Figure 2.14 further indicates limited progress in recent years regarding the presentation of triggering and action strategies for product-oriented ZDM in a single model. A recent research trend in the field of data analytics in manufacturing is the adoption of a "smart predict-then-optimize" approach or a decision support system that combines prediction/detection with prescription (Lorenz et al., 2022). Consequently, there is an expectation of increased research output concerning a paired ZDM strategy that integrates predictive and prescriptive analytics. Additionally, there are papers in the literature that do not explicitly specify which ZDM strategy they address or focus on.

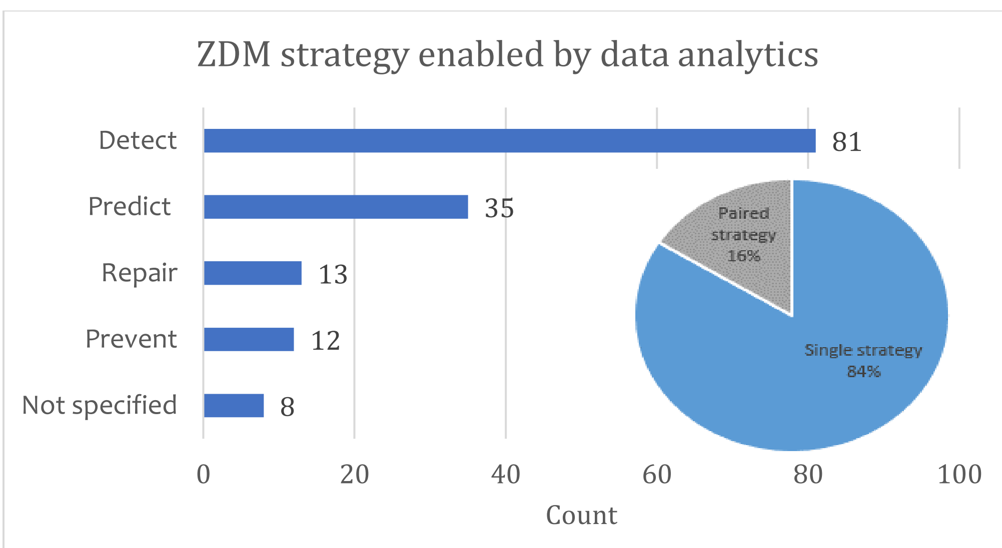


Figure 2. 13: Classification of papers according to the ZDM strategy (Source: Authors)

2.4.2.7. Combinations of data analytics techniques to the paired ZDM strategies

In addition, the reviewed works assigned to each pair of ZDM strategies and the associated data analytics techniques implemented are presented in Table 2.3.

Detect-repair strategy, the authors identified a total of four papers that employed machine learning (ML) techniques to build models for both detection and repair. Additionally, three papers adopted a synergistic approach by combining ML with logic-based model (L-BM). Another paper utilized a hybrid model comprising statistical analysis (SA), machine learning (ML), and logic-based methods (L-BM). Lastly, one paper relied on statistical analysis (SA) and simulation (SM) techniques.

Detect-prevent strategy, from the literature content analysis, no papers specifically addressing the Detect-Prevent strategy in the product-oriented ZDM research domain were found. The Detect-Prevent strategy involves utilizing product quality data from production processes to proactively avoid future defects. However, there is a lack of integration between these strategies, and no data analytics efforts have been conducted to combine them in the context of product-oriented ZDM.

Predict-repair strategy, it is logically untenable, and therefore, no papers were found in support of it.

Predict-prevent strategy, has emerged as a highly promising approach in the field of ZDM, garnering increasing attention in recent literature. To achieve this strategy, researchers have employed a combination of various data analytics techniques, as depicted in Table 2.3.

Table 2. 3: Combinations of data analytics techniques to achieve the paired ZDM strategies (Source: Authors)

		Triggering strategies	
		Detect	**Predict**
Action strategies	**Repair**	*4(ML &ML);3(ML&L-BM); 1(SA,ML&,L-BM);1(SA&SM);*	___________
	Prevent	___________	*2(ML&ML);2(SA&MP);1(ML&EC);1(SA&L-BM);1(ML,SA&MP);1(PM&MP);1(SA,ML&ML)*

2.4.2.8. Taxonomy of the data sources to data analytics condition and data analytics type

Data analytics advancement in ZDM critically depends on the manufacturing infrastructure to collect data in real-time. Real-time data can be used to improve predictive and detective analytics by providing more up-to-date information, which greatly helps to detect/predict defects early in the production process. It is also equally important for prescriptive analytics to provide quick and timely decisions. Access to real-time data directly depends on the source of the data and the network infrastructure. As the network infrastructure is not under the scope of this study, only the source of data is synthesized. Real-time data can be generated from sensors, machines, and other devices that are connected to a network. The availability of real-time data depends on the type of devices that are used. Figure 2.14 provides a bubble chart showing the data analytics condition (i.e. real-time or offline) for each data source (i.e. sensors, industrial camera, inspection machines, product documentation, and operator/experts) and for each data analytics type (i.e. detective, predictive, prescriptive). For each point, it indicates the number of papers that are associated with the aforementioned dimensions.

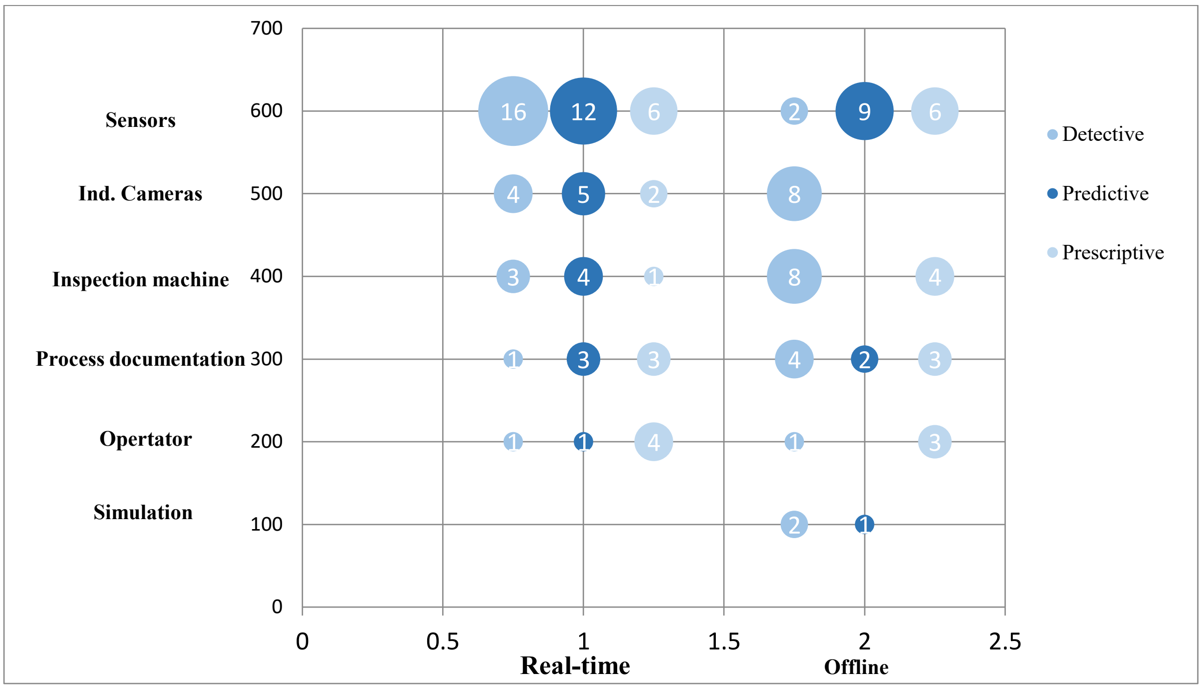


Figure 2. 14: Taxonomy of the data sources to data analytics condition and data analytics type (source Authors)

2.4.3. Challenges to implement data analytics in ZDM

Some of the challenges that have been identified from the reviewed papers in applying data analytics to ZDM are discussed below.

Unbalanced product lifecycle phase consideration: the quality control (QC) process is an integral part of the product lifecycle, encompassing both the design and manufacturing stages. A thorough analysis of the existing ZDM literature reveals an excessive emphasis on quality control during manufacturing and post-production activities. A significant majority (69%) of the literature is directed towards controlling product quality during production, carrying out detections, repairs, and managing warranty costs. This focus overlooks the importance of ensuring product design quality, which only receives a mere 3% of attention. Ideally, both phases should undergo thorough scrutiny and improvement by leveraging advanced data analytics techniques and utilizing data from every stage of product development. However, the distribution of research findings exhibits a noticeable imbalance. Furthermore, a portion of the reviewed papers (9.5%) fails to explicitly specify the phase in which the quality control process takes place.

To address these challenges, it is crucial to have a framework with clear data extraction procedure, presenting the specific product development phases from which data is collected and analyzed. By doing so, a more balanced and holistic data analytics process can be achieved throughout the product lifecycle quality control in pursuit of ZDM.

Lack of clarity between in-line and online quality control: in manufacturing, two approaches, namely in-line (in-process) and online quality control, are employed to ensure product quality. A content analysis of the literature reveals that 37% of the papers lack a clear distinction between these terms and use them interchangeably. Nevertheless, they differ in terms of timing, location, and purpose. In the case of in-line quality control, quality checks are performed at specific intervals during various stages of production process as it progresses through different manufacturing stages. Online quality control on the other hand involves continuous real-time monitoring of product quality during the manufacturing process using Internet of Things (IoT) technologies and sensors to collect and analyze data in real-time. This lack of clarity in explaining the production stage considered and the corresponding data analytics approach makes it challenging to comprehend how the proposed QC model work.

Difficulties in terms of merging large and heterogenous source of data: while data collection devices or sensors are becoming increasingly accessible and affordable for deployment at each manufacturing stage, the integration of data from multiple sources to enable accurate analytics and improved predictions remains a challenge in implementing data analytics for ZDM. Out of all the papers analyzed, 73% solely rely on data from a single source to develop a detective or predictive models.

Difficulties in selecting the best analytics techniques based on the data type and streaming condition: understanding the data's characteristics and requirements is essential when choosing the most suitable algorithms and analytics techniques for effective data analysis. For instance, streaming data typically demands real-time analytics techniques like stream processing, complex event processing, or online machine learning. On the other hand, historical recorded data, which is well-organized and defined, often benefits from traditional statistical methods and machine learning algorithms (Sharma et al., 2021). Data types such as images or audio necessitate techniques like natural language processing, computer vision, or audio processing. In industries, expertise in data analytics, alongside quality experts, plays a crucial role in facilitating the selection and application of appropriate methods for data analytics.

In general, in the past decade, there has been a notable surge in publications focusing on the utilization of diverse data analytics techniques to accomplish the four strategies of ZDM: detection, prediction, repair, and prevention. These studies have often been conducted independently, employing varying approaches to structure the data analytics process. As a result, the existing ZDM literature remains fragmented in terms of data analytics procedure and remains with the above listed challenges. This brings a conclusion that there is need for a standardized method for identifying use cases, extracting and processing data, and conducting analyses for an effective quality control process. In the next subsection, the developed DA framework along with the details of each component is presented.

2.5. Proposed framework of data analytics in ZDM

A six-step data analytics framework is proposed for implementing a product-oriented ZDM approach (Figure 2.15). Multiple standard data analytics frameworks have been proposed in various research domains outside of zero-defect manufacturing (Sahoo, 2022; Massmann et al., 2020; J. Wang et al., 2021). Within the specific context of product-oriented zero-defect manufacturing, this dissertation takes a pioneering approach proposing a standardized data analytics framework for ZDM. It is developed to tackle the identified challenges (2.4.4) from existing literature.

The data analytics process first has to start with clearly identifying potential use cases for quality control. Ensuring product quality throughout its entire life cycle, encompassing design and manufacturing, is a crucial element in achieving zero-defect. If the Product design phase is the focus, it involves conceptualizing and refining a product before it moves into production. While for the manufacturing phase, the stages involved in manufacturing the product, ensuring quality throughout each production stage is considered. Thus, it is important to precisely identify the relevant phases to focus on. Table 2.4 presents the divisions of each components considered to develop the framework. Additionally, it is essential to clearly identify the use cases associated with each phase of product quality control and also targeting the most suitable ZDM strategy. This systematic approach aids in determining the precise sources from which data should be extracted and collected, facilitating accurate analytics and implement the right ZDM strategy.

Another important aspect of the framework involves establishing a well-defined process for data acquisition and integrating data from diverse sources, ensuring its readiness for analysis. This step, as shown in Table 2.4, encompasses three key elements: extraction, transformation, and loading of data. However, it is important to adapt different approaches for real-time and offline data, taking into account the streaming condition of the data. Data is extracted from various sources, (vary between the design and operation phases).

The extracted data undergoes cleaning, standardization, and transformation to meet to a standardized format using techniques like data cleaning, normalization, aggregation, and ontology-based approaches for data type conversions. Finally, the transformed data is loaded into a designated system, such as a data warehouse or a data lake to be utilized for analytics. Failing to utilize the appropriate analytical techniques can result in underutilizing the potential value of preprocessed and cleaned data. This inefficiency in extracting insights undermines the efforts invested in data preparation. Therefore, selecting the most suitable analytics technique and model procedure is a critical aspect of any data analytics. The final step involves implementing or deploying the proposed data analytics solution and ensuring continuous follow-up to monitor its performance and effectiveness.

Table 2. 4: Component and the corresponding divisions of the framework (source: Authors)

Components	Divisions
Product design stages	Design concept (ideation), prototype and design feedback
Production stages	Beginning of manufacturing line, In-line and end of line
On which product	On 100% of products or sample products
ZDM strategy	Detect, predict, repair, prevent/detect-repair, detect-predict, predict-prevent
Sourcing and extraction of data (for design phase)	Design data, domain knowledge, customer feedback, evolution of product, market information
Sourcing and extraction of data (for production phase)	Industrial sensors and cameras, inspection records, shop floor operator, detection results, process documentations
Data accusation (integration and preprocessing)	Extract, transform, load
Data analytics type	Detective, predictive, prescriptive

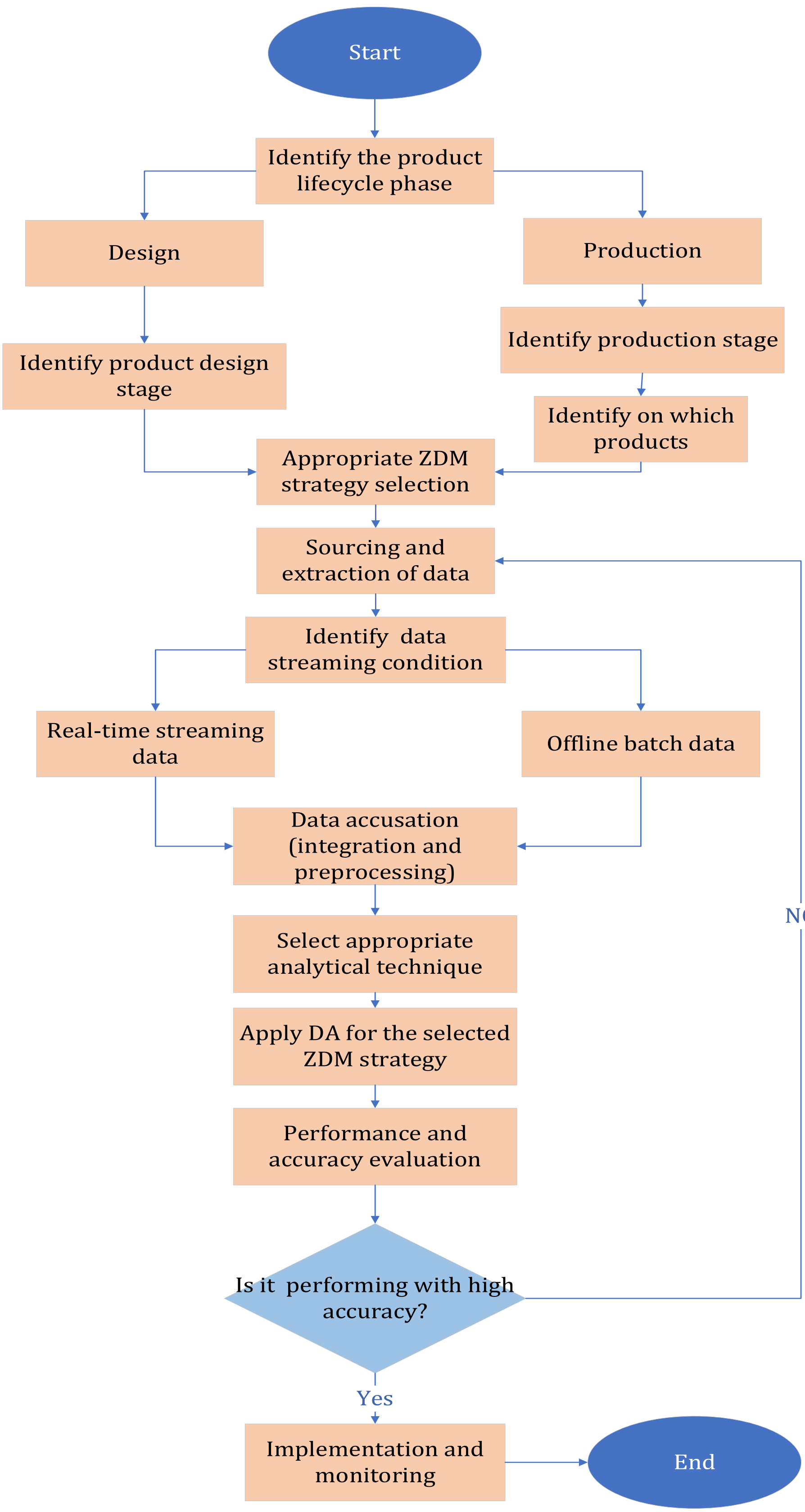


Figure 2. 15: Proposed framework for data analytics in product-oriented ZDM (source: Authors)

2.6. Industrial readiness for zero defect manufacturing

ZDM has become a critical tool for global enterprises grappling with the complexities of the fourth industrial revolution, characterized by networking and digitization. By combining advanced data analytics with cutting-edge technologies, ZDM enables proactive quality assurance, anticipating and preventing defects before they occur.

Embracing zero defects requires organizational and technological changes that impact strategic management decisions and day-to-day manufacturing operations. Hence, evaluating and enhancing digital readiness becomes crucial for the successful adoption of ZDM making it important for organizations to consider their digital maturity level.

Digital maturity refers to the extent to which an organization has successfully adopted and integrated digital technologies into its operations and processes. As ZDM heavily relies on digital technologies and data-driven approaches, industries with higher digital maturity (already established a foundation of digital infrastructure and data analytics capabilities) are likely to be better positioned to implement and leverage ZDM effectively.

2.6.1. Digital maturity

Like other sectors, industry 4.0 brings a potential benefit for manufacturing quality and ZDM as well (Hermann et al*,* 2020). For successful entry into Industry 4.0, manufacturing industries need to define a specific digital transformation strategy and evaluate the digital maturity level (Machado et al., 2021; Morteza Ghobakhloo, 2018; Rachinger et al., 2019). In this regard, Pirola et al., (2020) briefly discussed the three-stage digital transformation process. First, creating a plan second, strength and weakness analysis to deploy the digital transformation strategy, and third, changing strategies into action. Thus, it is observed that the second stage requires an examination of the company's current digital maturity to outline future steps fittingly. To achieve this, maturity models are the most crucial tools.

Kırmızı and Kocaoglu, (2022) define maturity as "the state of being at the desired level". They describe digital maturity as "the desired level of the application of digital technologies and techniques on organizational and economic conditions". To reach the desired level of maturity, a progressive evolution in achieving a target, from an initial to the desired end stage, is required (Pirola et al*,* 2020*)*. Therefore, maturity models greatly help in the evaluation of a company's position and answer questions, about what needs to be measured and how to assign a level of maturity (Gökşen and Gökşen, 2021; Demeter et al., 2021). In this regard, the maturity model has an incremental level that includes different hierarchical maturity levels aiming to measure the ongoing progress through the maturation process. Maturity levels are defined as "the increase in the capabilities of digital technologies and can be evaluated either qualitatively or quantitatively" (Kırmızı & Kocaoglu, 2022). In the next subsection, some of the existing digital maturity models that have emerged in recent years are reviewed.

2.6.2. Digital maturity models

Maturity models provide a comprehensive framework used to evaluate a company's status from different maturity model dimensions and help to plan a development roadmap. Some scholars contributed to proposing a new digital maturity model and advancing the existing ones. For a review of recent developments in digital maturity models the readers are referred to Gökşen & Gökşen, (2021); Hizam-hanafiah et al., (2020); Kiraz et al., (2020); Rajnai & Kocsis, (2018); Rossmann, (2018); Schumacher et al., (2016); Şener et al., (2018); Steinlechner et al., (2021), Kammerlohr et al., (2022); Machado et al., (2021); Pirola et al., (2020); Santos & Martinho, (2020); Kırmızı and Kocaoglu, (2022). There is a considerable amount of ongoing research on the development and application of digital maturity models. In this particular literature review, the authors aggregated the review papers on maturity models conducted so far. This review has contributed by providing a recent and thorough view of the industry 4.0/digital maturity models collected from different review papers devoted to discussing the commonly incorporated model dimensions. See Table 2.5.

Table 2. 5: Summary of the digital maturity models review papers

S.n	Source	# of MM reviewed	Gaps identified	Review outcome	Model dimensions	Maturity levels
1	(Sener 2018)	7	Scarce of MMs for the manufacturing industry	Propose new model	Asset management, data governance, application management, process transformation, organizational alignment	6 levels of digital capability
2	(Rajnai & Kocsis, 2018)	2		-		
3	(Pirola et al., 2020)	13	Lack of focus on SMEs and models' rigidity	Propose new model	Strategy, people, process, technology integration	5 levels maturity
4	(Hizam-hanafiah et al., 2020)	30		-		
5	(Santos & Martinho, 2020)	3	Integrate the 3 models to maintain the natural process of continuous improvement over time	Propose new model	Organizational strategy, structure, and culture, workforce, smart factories, smart processes, smart products, and services	5 levels of maturity
6	(Steinlechner et al., 2021)	11	Less investigation of employee competency in the existing models	Propose new model	Digital content, human-machine, human-human, personal	4 levels of digital competency of the employee
7	(Gökşen & Gökşen, 2021)	10		-		
8	(Kırmızı & Kocaoglu, 2022)	21	Lack of maturity model development framework	Propose new model	Synergy and governance, organization and corporate culture, Smartness, employee, process, customer	5 levels; Awareness, pilot, engagement, integration, optimization

The major concern of the eight review papers presented in Table 2.5 is to identify the existing digital maturity models and extract the common maturity model dimensions). Five out of eight papers proposed a new maturity model (briefly discussed in the next subsection). Among the papers, Hizam-hanafiah et al., (2020) have presented the highest number of models and dimensions (30 models and 158 dimensions). The review of reviewed models suggests that each model is different with diverse model dimensions. In terms of the number of dimensions, some models are broad having many dimensions and others are narrow with a few dimensions. Among others, the five pertinent models have been discussed in the following paragraphs.

Sener et al., (2018) have proposed a new maturity model known as the industry 4.0 maturity model after reviewing seven existing maturity models systematically. The gap that initiates the authors to propose a new model is the scarcity of maturity models for the manufacturing industry. The model consists of 5 dimensions (see Table one) and 6 maturity levels of each dimension.

Pirola et al., (2020) have proposed another maturity model known as the Digital Readiness Level 4.0 Model. They developed the model to overcome the two major limitations commonly found in the existing models; those are lack of focus on SMEs and models' rigidity. Strategy, people, process, and technology integration are the model dimensions considered. In addition, five digital maturity assessment levels are considered for the model. They are, not involved in Industry 4.0 pilot initiatives, including Industry 4.0 into its strategic orientation, formulated an Industry 4.0 strategy and investing to promote, already implementing an Industry 4.0 strategy, and already implemented its Industry 4.0 strategy and continuously monitoring.

Santos and Martinho, (2020) have proposed another maturity model based on the gap in the existing models. The model consists of two additional components which are transformation capabilities and the measurement instrument in addition to model dimensions and maturity levels. Unlike the other models focused only on maturity assessment, the model by these authors is capable of identifying the current stage of maturity, revealing the causes of non-attainment of the desired maturity, and monitoring the development of actions that enhance their technical and managerial capabilities. In that way, a continuous improvement of the industry 4.0/digital maturity can be sustained.

Steinlechner et al., (2021) have presented a maturity model known as a digital competence maturity model (DigiCoM). The model they proposed consists of four dimensions (as indicated in

Table 2.5) and focused on digital maturity assessment at the individual employee level. The gap they identified from the reviewed models is ignorance or less investigation of employee competency in digitalized working conditions.

Lastly, Kırmızı and Kocaoglu, (2022) suggest a novel maturity model development framework based on design science and develop a digital maturity model by following the proposed framework. In this particular paper, the concept of descriptive and prescriptive types of maturity models is also highlighted. It is thus emphasized that the descriptive types of maturity models (measures the current state of maturity or serve as a diagnostic tool) need to advance to the prescriptive type of maturity model (able to provide improvement measures). There is a bit related concept to the model by Santos and Martinho, (2020) which integrates the elements of identifying the causes of non-attainment of the desired maturity and continuous monitoring. However, this issue needs further research.

2.6.3. The digital readiness factors and sub-factors

Besides the above discussion, the major intent of this sub topic is to identify the potential/commonly implemented digital maturity model factors and sub-factors. In this regard, from the eight digital maturity review articles, it is clearly understood that Technology, Digital operation, Digital product, Management commitment, People and expertise, and Culture are the most commonly incorporated digital maturity model dimensions. List of the digital maturity model dimensions and the corresponding sub-dimensions are presented in (Table 2.6). Interested readers who want to in-depth understand the table can refer to the eight summarized review papers. Moreover the six digital maturity levels (Table 2.6) are given by (Gökalp & Martinez, 2021)which are directly used in this research.

Table 2. 6: Prominent factors and sub-factors affecting digital maturity of manufacturing industries (Source: the eight review papers)

1. Management Commitment
Available resource (people and budget) for realization of digital strategy
Company's road map for the planning of digital activities
New business models adopted driven by digitalization
The management understand the concept of digitalization
The management introduce/promotes digitalization
Management empowers active employees with digital technologies
There is a management competences and central coordination for digitalization

2. Digital Operation Decentralized processes Modelling and simulation implemented to assist production process Interdisciplinary working process Interdepartmental collaboration via data accessibility 3. Culture Significant value of Internet/ICT in a company Strong approach for knowledge sharing Good approach for open-innovation and cross company collaboration Continuous change as part of corporate culture Decisions within the firm are based on data and transparent to employees 4. Digital Product Individualized/customized products using customer data Product commercialization through digital technologies Good customer experience impact on digital products Direct added value created by the progressive digitization of products of the company 5. People and Expertise A good condition of ICT competences and openness for new technologies of employees Availability of sufficient experts on digital core issues Availability of further education opportunities for digital core topics Implementation of comprehensive measures to strengthen digital literacy development Creation of new job profiles for employees with expertise in digital core topics 6. Technology An existence of ICT infrastructure in the company Usage of digital platforms for day-to-day collaboration Usage of large amounts of operational data to detect, predict and optimize processes and products Usage of tools for digital modeling, automation and control of production processes Implementation of enterprise-wide digital workplace concepts Utilization of machine-to-machine communication 7. Digital maturity L-1: Computerization L-2: Connectivity L-3: Visibility L-4: Transparency L-5: predictive capacity L-6: Adaptability

From section 2.2, one can understand how the study on maturity models is getting evolved. The authors appreciated the devotion of scholars who are introducing new maturity models by identifying and adding new model dimensions, and incorporating untouched issues into the models (refer to Table 2.5).

2.7. Summary of the literature review and gaps identified

In this chapter, a theoretical exploration has been undertaken across three primary focus areas. key gaps identified are summarized in this subsection and novel conceptual framework is proposed. The gaps addressed by this dissertation and those that remain open for future research are both presented, highlighting areas of potential investigation. Distinctly utilizing review and research articles in specific contexts has been important in achieving some of the chapter's aims. The literature review process starts with highlighting the existing literature review papers within ZDM aiding in capturing the relevant subjects which are already explored.

Looking prominent literature review articles in the domain of ZDM enables authors to identify that there has no previous effort on analyzing the ZDM papers from the data analytics point of view. This analysis fosters an exploration of the domain from a data analytics perspective by conducting a systematic literature review, utilizing key content analysis attributes. Additionally, the chapter delved in depth into steel defect detection studies, crucial for identifying gaps in the existing defect detection models. Unlike prior approaches, this subsection focused on examining existing empirical studies, excluding literature review papers, to understand the model development process, quality parameters considered, quantity of data points for ML model training, utilized ML algorithms, and related aspects.

While significant research has been undertaken in developing defect detection model within the steel manufacturing, there still remains a need for advancement in certain aspects. The analysis reveals a significant research gap in three specific areas. First, there is a lack of emphasis on incorporating dimensional measures as input parameters. Second, there is a need for further efforts in developing explainable models. Lastly, exploration of alternative solutions to address the challenges associated with limited defect sample data require more exploration within the field. In light of these considerations, this study tackles the first gap (incorporation of dimensional measures associated with steel products as an input quality parameter). And, the study identifies the remaining two research gaps as potential areas for future investigation.

Another key area of this chapter was to identify the factors influencing the digital readiness of manufacturing industries in adopting ZDM. This section initiated the literature review by exploring existing articles on maturity models within manufacturing sector. Again, empirical studies were not the primary focus since, the aim was to identify key digital maturity factors and sub-factors. This effort led to the identification of six widely recognized digital maturity factors and 32 sub-factors, enhancing understanding of existing maturity models and their progression by integrating a range of factors and sub-factors.

From the literature review, it is understood that the digital maturity model research is following the trend; investigating the existing models, adding/reducing contributing factors, and measuring the digital maturity level of industries. Indeed, it is a great contribution to the acceleration of the entry of industries into the fourth industrial revolution. Understanding the complex relationship of each dimension greatly helps the industries to easily deploy the digital strategy and implementation, which is overlooked in the existing literature. Only one paper by Kiraz et al., (2020) has been found that dealt with analyzing the factors affecting the industry 4.0 tendency with a structural equation model. However, the factors identified in the mentioned paper do not have a strict connection with digital maturity model dimensions. In consideration of this, more research effort is required in the analysis of the relationship between the digital maturity model dimensions/constructs and their impact on the digital maturity level which it is not yet been studied thoroughly.

In general, based on the analysis of the selected papers, a considerable portion of the ZDM literature lack a clarity in some key aspects of data analytics. These include properly specifying the data extraction procedure, production stage to which data analytics is applied, defining the data analytics condition, identifying the data sources used and integration of data from multiple sources, and determining the most effective tool for analytics. There is also a vagueness (31% of the papers) to distinguish between real-time and offline analytics, despite the fact that these two approaches require distinct methods for data processing and analysis. Although the existing literature on ZDM exhibits the challenges associated with data analytics as highlighted in this subsection, no previous attempts have been found to propose a framework for the implementation of data analytics in ZDM.

Therefore, there is a need for a standardized framework to guide data analytics in ZDM. Such a framework ensures uniformity across the different elements of AI based product quality control procedure in data collection, analysis, and interpretation across different phases and manufacturing stages. It simplifies data analytics for quality control activities, benefiting both industry professionals and academia. It also facilitates scalability, enabling its consistent application across quality control processes for various products, manufacturing lines, and even different industry sectors.

Chapter Three

Research Methodology

3.1. Introduction

Zero Defect Manufacturing strives to eliminate defects throughout the manufacturing process by utilizing proactive quality control strategies and data-driven techniques. The integration of virtual defect detection (one element of ZDM) revolutionizes quality inspection by surpassing traditional physical methods, enhancing accuracy, efficiency, and reducing human errors. Ethiopian steel manufacturers are facing with challenges related to producing defective items and maintaining customer confidence. This is happened due to their complete reliance on traditional manual inspection methods. These methods, known by prolonged inspection processes, can result in inspector fatigue and reduced attentiveness. This increases the risk of defects being overlooked or increase errors occurring during inspection. Additionally, due to high inspection costs, especially destructive tests, manufacturers reduce the frequency of inspections or samples to save money, potentially missing defects that would have been caught with more thorough inspections. Also, some of steel quality inspections that require longer duration can lead to bottlenecks in production, creating pressure to rush through inspections and increasing the chances of ignoring defects.

This challenge prompts the need for a new quality control paradigm embracing digital capabilities and data-driven techniques effectively. The primary objective of this dissertation is therefore to develop an AI-driven defect detection model to integrate virtual quality inspection in Ethiopian steel manufacturing industries and assist ZDM. This central objective is accomplished through employing a multi-stage research methodology. Implying that the research framework is designed Incorporating various dimensions of analysis to address different aspects of the research problem.

3.2. Research design

The overall research procedure is designed having four consecutive stages. Problem formulation and literature review, data Collection and organization, data analysis methods and tools, discussion, conclusions and future research directions. It starts with an exploration of the theoretical foundations of zero-defect manufacturing. Subsequently, it delves into identifying the factors essential for digital readiness in implementing ZDM and examines the complex relationships among these factors. An evaluation of the digital maturity of the industries is conducted to formulate an effective ZDM strategy. Causal relationship analysis of the digital readiness factors has been performed collecting a data from a sample of 149 steel industries in Ethiopia, while a detailed digital maturity assessment is carried out on a single industry case. Finally, an AI-based defect detection model is created and validated based on the findings of the digital maturity assessment. The research framework is illustrated in figure 3.1

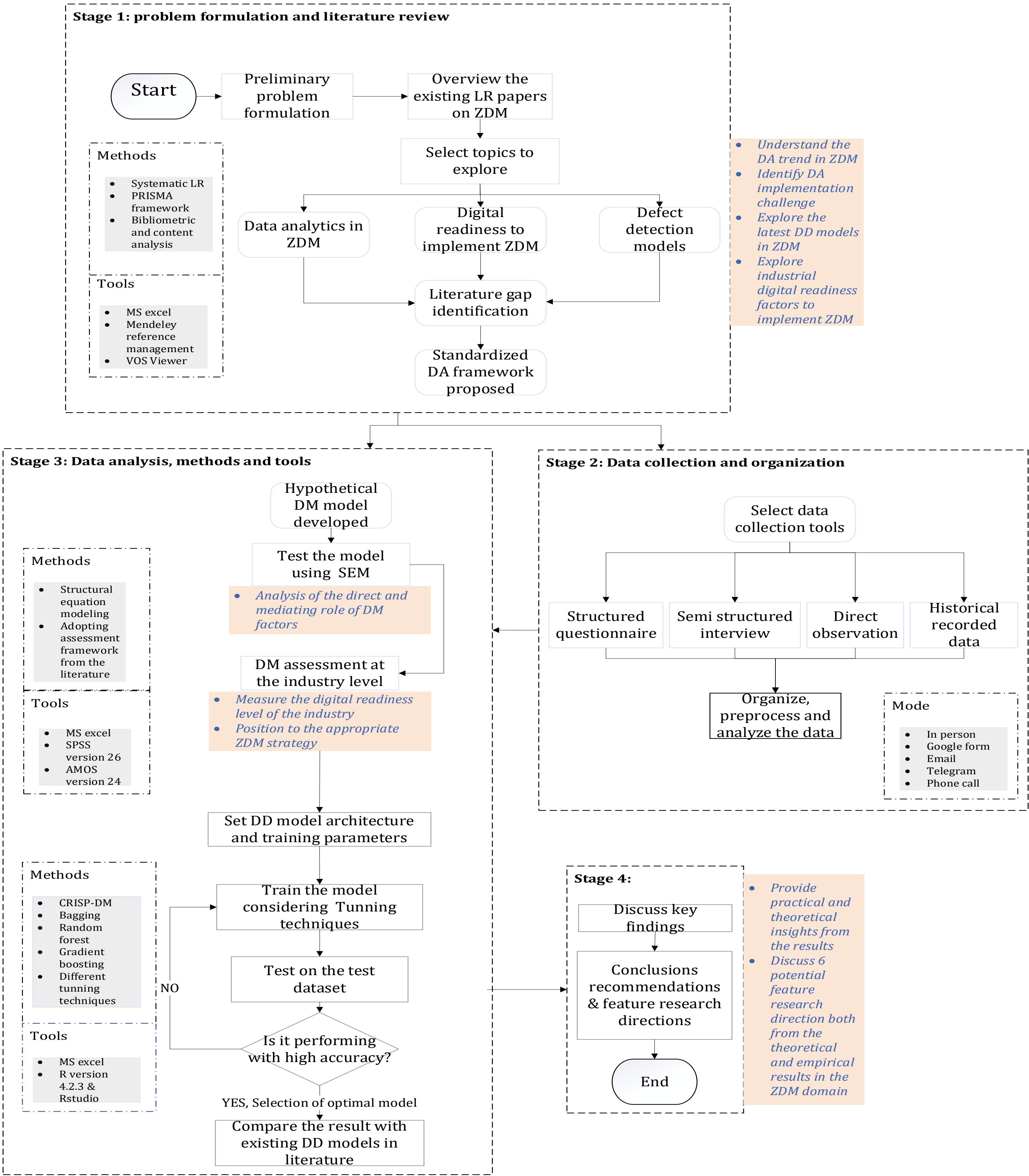


Figure 3. 1: The research procedures (Source: Authors)

3.2.1. Stage I: Initial problem formulation and literature review

A well-defined research path has been established through an initial problem definition. The focal point has centered on transitioning steel industries from manual physical quality inspection activities to the innovative technology of virtual defect detection (virtual metrology). This involves leveraging advanced data analytics methods and drawing insights about the product quality status from historical quality inspection data obtained from both shopfloor and laboratory tests. This technology minimizes the human input in analyzing product state and output quality aiding real metrology in product quality inspection. The primary objective is to steer the steel industry towards achieving ZDM. The research starts with an in-depth literature review exploring key topics including, the data analytics trends and challenges in ZDM through a systematic review, state-of-the-art defect detection models, and industrial digital readiness for the successful ZDM implementation.

Data extraction, analysis, and discussion in this stage follow a systematic methodology to identify, select, and document relevant articles from reputable academic research databases (majorly Scopus, Web of science and IEEEXplore). Utilizing structured data extraction forms based on the Preferred reporting items for systematic review and meta-analysis (PRISMA) methodology, the research captures relevant studies using an appropriate key word. The PRISMA framework is used since it is a well-structured model for conducting systematic reviews and strengthening the transparency and reporting of relevant articles (Page et al., 2021). After a diligent screening process to align the selected studies with predefined inclusion criteria, more than 236 recently published articles undergo analysis and synthesis to reveal trends in data analytics (188), recent machine learning-based detection models (26) and digital readiness factors (22). Each subject underwent a detailed content analysis focusing on carefully chosen attributes. Following this, the outcomes from bibliometric analysis (visualized through MS Excel and VOS Viewer) and content analysis (Appendix B) are presented and discussed in the systematic literature review section, providing a thorough exploration of Zero-Defect Manufacturing aligned with the specific aims of this research.

Within this review, critical gaps in existing literature were identified for each area of focus. The initial gap, the absence of a standardized data analytics framework for ZDM, has been addressed through the introduction of the proposed data analytics framework. The second gap, which pertained to the lack of relationship analysis among digital readiness factors, has been filled by the development and validation of a hypothesized digital readiness model. Lastly, the third gap identified from the review of defect detection models specifically the oversight of a crucial quality parameter in the defect detection studies has been dealt in this study through the incorporation of this parameter in the development of a novel defect detection model.

3.2.2. Stage 2: Data Collection and organization

Both qualitative and quantitative data were collected in this study to capture theoretical and practical insights into the research topic and the state of the case steel industry. The data sources encompass both primary and secondary sources. Secondary data, sourced from journal articles, books, registered quality complaints and related quality control process activities. Primary data relevant to achieving the research objectives was gathered through structured questionnaire (Appendix E), semi-structured face-to-face interview with industry experts (Appendix F), and direct observations within the case industry.

Questionnaire:

A close-ended questionnaire was designed to collect primary data related to factors affecting digital maturity. The goal is to analyze the direct and mediated relationship among the digital readiness factors. As the model is reflective, all the questions are positive (e.g. strongly agree is supposed for positive agreement). The questionnaire contains the most frequently used digital maturity measuring factors or model dimensions from the literature. The questions for measuring items (sub-factors) were also directly taken from Rossmann, (2018). Some of the questions were modified by improving only the clarity of the questions (the way that particular item was asked). The questionnaire was filled out by directors, team leaders, IT managers, and other experts in the company. The result of the reliability analysis showed a Cronbach's alpha value greater than 0.76 and above, which is above the acceptable cut-off point. The data collection was conducted in the time frame of October 2021 to January 2022 via email, google form and by reaching to them physically.

Observation:

Primary data was collected through direct observation of a single steel manufacturing industry to understand the broader steel manufacturing process and the quality control and inspection practices employed within the industry.

Interview:

An Interview session that lasted from 20 to 50 min each were organized. These interviews targeted shop floor workers, process coordinators/supervisors, quality engineers, quality managers and inspectors. The aim is to understand the background of the case industry in general and existing quality inspection practices and the QI technologies employed in particular. Moreover, to understand the quality control challenges it is currently facing. Results from the interview were combined with the organizational technical documents review and direct observations. Key quality complaints registered and related process activities were rectified by combination of the data sources.

Secondary data from the industry QC database:

Finally, a significant amount of data (6080 data points across 28 quality parameters) of quality inspection records was obtained from secondary sources to develop the defect detection model. The data was extracted directly from the quality control databases of the case steel industry, collected over a one-year time series from diverse sources such as sensors, metrology instruments, and laboratory tests.

3.2.3. Sample size determination

According to the MIDI report on 2023, Ethiopia has approximately 241 steel manufacturing industries, encompassing a mix of large, medium, and small-scale operations. Which are engaged in producing different steel products including; hot rolled steel, cold rolled steel, galvanized steel, rebar, beams, angles, and wire rods for nails and cables, pipes and tubes. Considering Yamane sample size formula (Chanuan et al., 2021), with a 95% confidence interval as shown in Equation 3.1.

$$n = \frac{N}{1+N(e)2} \quad \ldots\ldots\ldots\ldots\ldots (3.1)$$

Where:

- n = Required sample size
- N = Total population size
- e= Margin of error (95%confidence interval in the current case)

An optimal sample of 149 steel industries has been considered for data collection (two responses from each industry has been collected). This sample size is large enough to encompass a variety of steel industry profiles, potentially reflecting different scales of operation, technologies used, and market positions.

Moreover, a digital maturity assessment was conducted within the selected steel industry, drawing insights from evaluations by 10 industry experts. In this evaluation, a stratified random sampling approach was employed. Respondents within the industry were stratified into two groups: those from the Quality Control department and those from other department (IT, data and infrastructure management). A total of 5 respondents each were randomly selected from the quality control department and the remaining departments for the assessment.

3.2.4. Stage 3: Data Analysis, methods and tools

The process of data analysis and organization is divided into three key components. These include understanding the relationship among digital readiness factors, evaluating the level of digital readiness in the case steel industry, and creating and validating a defect detection model. Each stage of data analysis is interconnected: the initial stage assists in identifying the direct and mediating effects of digital readiness factors on overall digital readiness, which is followed by the direct assessment of the industry's readiness. Completing these two steps offers industries a clear pathway towards digital transformation, with the first stage outlining the roles of the factors and the second stage highlighting existing digitalization gaps in the industry. Lastly, the development of the model is contingent upon empirical assessments within the industry, aiding in aligning with a suitable ZDM strategy based on its readiness level.

I. Understanding the complex relationship of digital readiness factors

To comprehend the complex relationship of digital readiness factors, an initial step involved developing a hypothesized digital readiness model. Drawing upon factors extracted from the literature, these were clustered into basic enablers and organizational adaptability. Subsequently, the direct and mediating impacts of each factor on digital maturity were examined through a Structural Equation Model (SEM). The validity of the instruments was assessed using SPSS version 26, while the SEM model was analyzed and tested using AMOS version 23.

II. Digital readiness assessment of the case steel industry

After analyzing the direct and indirect impact of digital readiness factors, the evaluation of digital readiness within the case steel industry was done which entails a direct empirical assessment of its readiness. The optimal Maturity model was selected for this assessment to position the industries current state of digitalization to align with the appropriate ZDM. This process facilitates the AI-based model development process fitting to the existing digital readiness.

Digital maturity model selection:

A comparison of 4 digital maturity models in the context of product quality control have been made by Elibal & Özceylan, (2021). They determined seven quality related criteria and 33 sub-criteria and mapped to the industry 4.0 concepts (digital technologies). To determine which maturity model mostly fits manufacturing quality principles, they used fuzzy TOPSIS and fuzzy Decision-Making Trial and Evaluation Laboratory (fuzzy DEMATEL) method for criteria weighting and they found the model of (Schumacher et al., 2016), Equation (3.2). with the highest score among the compared models. In this research, the researcher has used the first prioritized MM proposed by Elibal & Özceylan, (2021).

The maturity level (MD) of each dimension is determined by computing the weighted average of all maturity items (MDIi) within the respective dimension. The local weighting factor (gDIi) and the corresponding average agreement rating provided by all 10 experts for each item is considered.

$$MD = \sum_{i=1}^{n} MDI,i * WDI,i \div \sum_{i=1}^{n} WDI,i \ldots\ldots\ldots\ldots\ldots\ldots \quad (3.2)$$

M	…	Maturity
D	…	Dimension
I	…	Item
W	…	Weighting Factor
N	…	Number of Maturity Item

Additionally, the six-maturity level index outlined by (Gökalp & Martinez, 2021) were used. Level 1 signifies the least supportive attributes for digital maturity, while level 6 denotes the most advanced stage of digitalization with all necessary technologies in place.

III. Model development and validation

The third stage of data analysis involves the development and validation of a defect detection model through the application of machine learning techniques. The model was designed to correlate a comprehensive set of input and output quality parameters of steel products. To make the model development process comprehended and ensure clarity, the CRISP-DM framework was used. Moreover, the entire analysis was conducted using the R programming language within R version 4.2.3, utilizing its integrated working environment, RStudio.

Data was preprocessed before training the model. The Z-score method was employed to achieve data normalization using the "scale" function on R. It works based on the formula given in Equation 3.3.

$$z = (x - \mu) / \sigma \ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \quad (3.3)$$

Where, z is the z-score, x is the value to be normalized, μ is the mean of the observation and σ is the standard deviation of the observation.

Ensemble learning algorithms including Bagging, Random Forest, and Gradient Boosting were employed to train the model. Feature importance analysis has also been conducted. The "importance" function of a bagging/RF model in R utilizes different metrics for regression and classification cases to assess the importance of a variable. In regression model, there are two indicators for feature importance. First, the mean decrease of accuracy in estimation on out-of-bag samples is examined when the variable is excluded from the model (%IncMSE) using Equation 3.4.

$$\%IncMSE = ((MSE\_excluded - MSE\_included) / MSE\_included) * 100 \ldots.. \quad (3.4)$$

Where, "MSE_excluded" is the mean squared error when the variable is excluded from the model and "MSE_included" is the mean squared error when the variable is included in the model. Second, the total decrease in node impurity resulting from splits over that variable is evaluated. The node impurity is quantified using training Residual Sum of Squares (RSS) for regression trees (Equation 3.5).

$$RSS = \Sigma(x_i - yi)^2 \ldots\ldots\ldots\ldots.. \quad (3.5)$$

Where, x_i is the actual values of the output variable and y_i is the estimated values of the output variable obtained from the regression model. Equation 3.6 and 3.7 are utilized to measure variable importance in the classification bagging model, employing the metrics of Mean Decrease Accuracy

(MDA) and Mean Decrease Gini (MDG). Mean Decrease Accuracy (MDA) is calculated as the average difference in accuracy across all features:

$$MDA = (1/n) * \Sigma(diff\_i) \text{ ………….. (3.6)}$$

And Mean Decrease Gini (MDG) given that n number of total features is calculated as the average reduction in Gini impurity across all features:

$$MDG = (1/n) * \Sigma(Gini\_i) \text{ …………… (3.7)}$$

The boosting algorithm calculates the importance of each variable using a "relative influence" function. It considers how often a feature is used for splitting in the weak models and the improvement in the loss function achieved by those splits as given in Equation 3.8. Features with higher relative importance are considered more influential in making estimations, while those with lower importance are considered to have less impact.

Relative Influence = (Weighted Training Error Reduction) / (Sum of Weighted Training Error Reductions) ……….. (3.8)

Weighted Training Error Reduction represents the reduction in training error achieved by a particular base learner, weighted by its contribution or importance in the boosting process. Sum of Weighted Training Error Reductions is the sum of the weighted training error reductions for all base learners in the boosting model.

The validation of the machine learning model includes assessing its representation of the underlying data and its ability to provide accurate predictions on new dataset. This study employs two model validation approaches. The first approach utilizes hyperparameter optimizations to secure the most precise model, ensuring it does not overfit the training data and can generalize effectively for accurate predictions in real industrial applications. Therefore, the model accuracy evaluation has been assessed using various metrics, as detailed in the following paragraphs.

For the regression ensemble learning model, if $x_1, x_2, ..., x_t$ represent the actual measured values and $y_1, y_2, ..., y_t$ represent the corresponding estimated values, the Equations from 3.9- 3.13 are used to evaluate the accuracy of each model: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), R-squared (R^2), and Mean Absolute Percentage Error (MAPE).

$$MAE = (1/T) * \Sigma|xi - yi| \text{ ……………….. (3.9)}$$

$$RMSE = sqrt((1/T) * \Sigma(xi - yi)2) \ldots\ldots\ldots\ldots\ldots\ldots (3.10)$$

$$MAPE = (1/T) * \Sigma(|(xi - yi)/xi|) * 100 \ldots\ldots\ldots\ldots\ldots\ldots (3.11)$$

$$R2 = 1 - (SSR / SST) \ldots\ldots\ldots\ldots\ldots\ldots (3.12)$$

On the other hand, the commonly used metrics for binary classification is Accuracy using the confusion matrix (Vujović, 2021). It is a tabular representation that summarizes the performance of a binary classification model by showing the counts of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). This metrics is used to measure the defect detection performance of the classification model for bend test (BT). By examining the aforementioned values in the confusion matrix, quality estimation accuracy can be calculated using Equation 3.13.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \ldots\ldots\ldots\ldots\ldots\ldots (3.13)$$

The second approach involves comparing the model's predictive performance with the existing literature, allowing for an evaluation of its effectiveness and reliability by benchmarking its predictive capabilities against established steel defect detection models in the literature.

3.2.5. Stage 4: Discussions, Conclusions and Future research directions

In this stage, the outcomes obtained from the complete analysis are deliberated upon, with the objective of offering an in-depth insight into its implications on practical implementations within the steel industry and theoretical progressions within ZDM detection strategies.

Also, the results from the three ensemble learning modes, along with the findings of the fine-tuned gradient boosting model, are discussed. Additionally, the results of the feature importance analysis, outlining the significance of each quality parameter in determining the output quality parameters, are also addressed. The theoretical and practical implications of these results are also outlined.

The overall impact of the virtual defect detection model on the progression of the remaining ZDM) strategies, particularly in prediction and prevention, and its specific role in optimizing the quality inspection process within the steel industry are discussed. These discussions lay the ground for recommendations aimed at aiding steel manufacturing industries in leveraging AI and their shop floor data to bolster their quality control processes.

Drawing conclusions from the obtained results, suggestions are put forth on how steel industries can advance their digital transformation efforts and implement data-driven techniques to optimize their entire manufacturing process, specifically focusing on enhancing their quality control procedures, thus leading towards achieving zero-defect manufacturing. The adaptability of the model to other products or manufacturing sectors is noted, requiring adjustments to the input and output parameters. Furthermore, potential future research avenues are identified based on the gaps identified through a thorough exploration of the literature and empirical analyses within the ZDM domain.

Chapter Four

Digital Maturity and Readiness Factors Analysis

4.1. Introduction

This chapter presents an empirical evaluation of core constructs within the dissertation framework. It focuses on analyzing causal relationships among digital readiness factors to elucidate their complex interplay and collective impact on digital maturity. To establish theoretical grounding, the authors first examine widely recognized digital maturity indices (levels) and prominent factors identified in Chapter 2. Building on this foundation, the analysis formulates a hypothesized causal maturity model, subsequently tested through structural equation modeling (SEM).

4.2. Digital maturity levels in manufacturing

The sub-section presents the six consecutive stages of the digital maturity index (Figure 4.1), delineated by Gökalp & Martinez, (2021) , through which manufacturers progress as they enhance their digital capabilities.

Stage 1, Computerization, industries utilize digital tools such as CNC machining. However, these tools function independently without integration. Coordination between these tools requires manual intervention, and the production data collected remains isolated, siloed, and accessible only post-production completion. Stage 2, Connectivity, industries progress by establishing connections between their digital solutions. Connecting machines to the internet. While some communication between machines becomes feasible, it often proves sluggish and inefficient. These connections lack the flexibility to match real-time production events, creating a disconnect between data and the actual occurrences on the factory floor.

Stage 3, Visibility, manufacturers surpass previous limitations and gain a 'digital twin' of their factory, enriched with extensive real-time data. This data provides detailed insight into ongoing activities within the factory, yet may lack the required organization for seamless comprehension. Consequently, the mere presence of data becomes the primary criteria at this point. Stage 4, Transparency, the focus of digital advancement transitions from enhancing technical capabilities to utilizing analytics. To reach this stage, manufacturers must acquire the skills to interpret and comprehend the data they have gathered. Typically, shop floor control software conducts this analysis automatically, organizing and presenting relevant data upon user requests.

Stage 5, Predictive Capacity, manufacturers utilize real-time data to forecast the future of their production capabilities. This entails predicting occurrences like potential work stoppages, quality control issues, energy-saving opportunities within the facility, and other key insights. Shop floor control software remains pivotal in facilitating these predictive analyses. Stage 6, Adaptability, digital systems within the facility acquire autonomy through their analytic and predictive capabilities. They can autonomously adjust to evolving conditions, arranging staff assignments to manage regular operations, emergencies, and emerging challenges.

The key takeaway from the six digital maturity levels is the critical role of initial digital investment in generating large-scale operational data. This data must then be organized and made readily accessible to facilitate efficient data analytics. The next stage involves leveraging AI and machine learning to process data and extract valuable insights. Ultimately, the goal is to achieve fully autonomous decision-making, where machines operate independently without human intervention. This index, in addition to determining an industry's current digital maturity level, it also provides a clear direction for advancing to the higher stages.

This dissertation focuses on the implementation of one of the strategies in ZDM. ZDM is fundamentally a data-driven approach where its effectiveness is determined by industrial digital capabilities. All the four strategies; Detection, Prediction, Repair, and Prevention are completely dependent on high volume shop floor data. Each necessitates a different level of digital readiness. Taking the "Detection" strategy as an example, the initial and crucial requirement is access to historical data. In this scenario, having real-time data access and integrating machines is not essential. An effective model for defect detection can be created using historical time-series quality inspection data. This indicates that industries at levels 1 and 2 can effectively implement and take advantage of this strategy.

The next strategy, "Prediction," involves forecasting future defects in products that have not yet been manufactured. This requires both historical and real-time data. Implementing this strategy demands the next level of digital readiness (Level 3), including real-time data access and efficient machine integration with the production line. The remaining ZDM strategies, "Repair" and "Prevent," are decision-making strategies that can be paired with either "Prediction” or

"Detection." These advanced approaches of ZDM can be realized by progressing toward higher levels (level 5 and 6) of digital maturity, ultimately leading to autonomous data-driven decision-making.

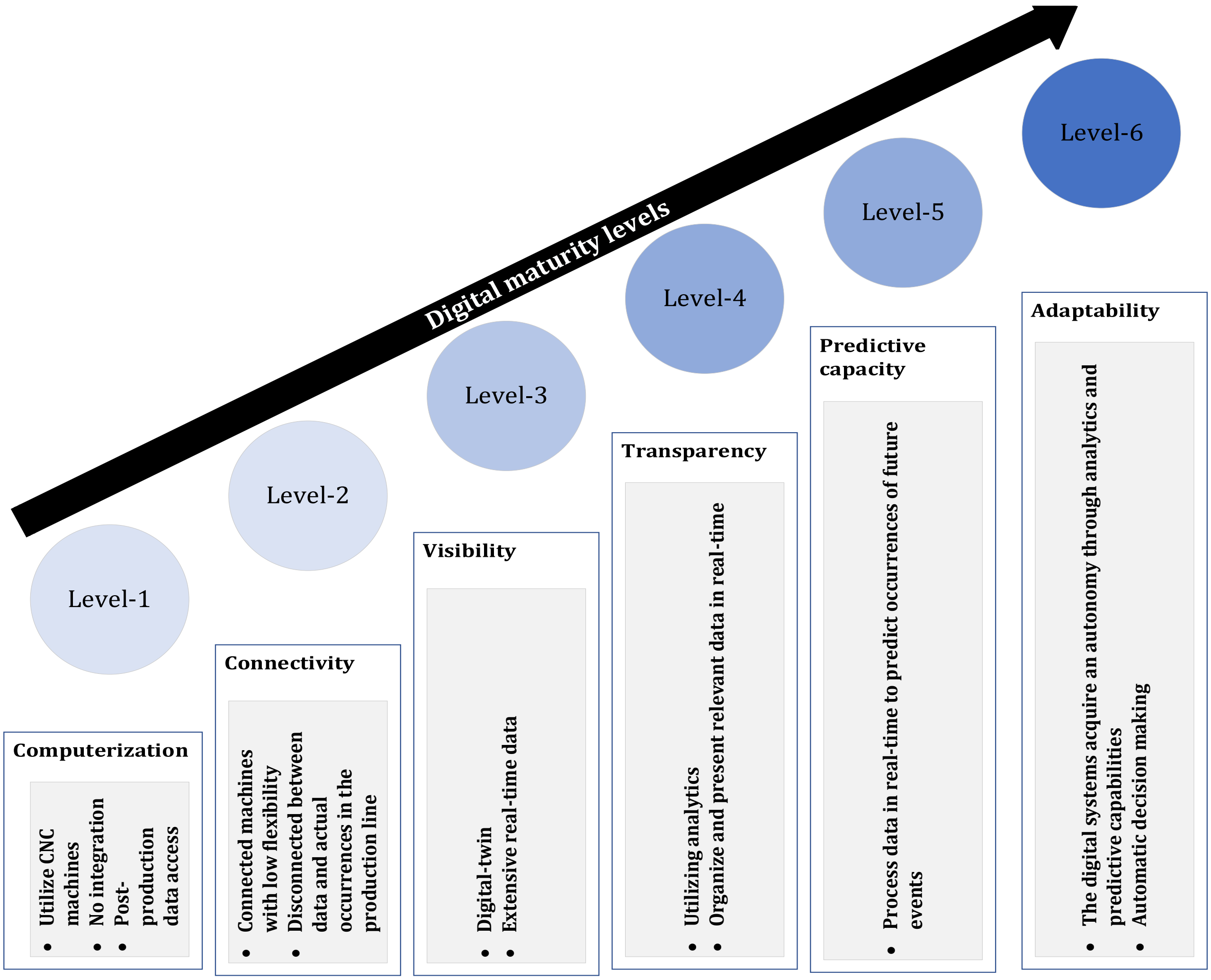


Figure 4. 1: Digital maturity levels in manufacturing; Source: Gökalp & Martinez, (2021)

4.3. Hypothesis formulation

A hypothesized causal relationship among the digital readiness factors identified in chapter two and six-level maturity index (Figure 4.1) has been established, drawing insights from a variety of scholarly articles. Schumacher et al., (2016) categorize the dimensions of the digital maturity model as basic enablers and organizational adaptability. In the mentioned paper, constructs considered basic enablers are technology, digital product, and digital operation. Based on Gökşen & Gökşen, (2021); Hizam-hanafiah et al., (2020); Santos & Martinho, (2020); Kalender & Žilka,

(2024) finding, technology is the dimension that needs to be emphasized more intensively in digital maturity models. The systematic review by Hizam-hanafiah et al., (2020) depicts that 70 (44%) out of the total 158 total unique dimensions of Industry 4.0 pertain to the assessment of technology alone.

This is because, Industry 4.0/digitalization is a concept based on nine pillars of technology (Big Data, Industrial Internet, Horizontal and Vertical Integration, Simulation, Augmented Reality, Additive Manufacturing, Cyber Security, and Advanced Manufacturing) (Klingenberg et al., 2021). Thus, technology in Industry 4.0 could go to one or many of the above-mentioned nine pillars. According to many of the scholar's arguments, digital product and digital operation are also basic enablers as they directly affect the digital maturity of industries (Lassnig et al., 2018).

This establishes the conclusion that organizations need to largely improve their technology, digital product, and digital operation to strengthen their digital maturity. Therefor the first hypothesis is formulated assuming that digital maturity can directly be affected by the basic enablers.

1. *The basic enablers (Technology, Digital product, and Digital operation) have a positive impact on the digital maturity of the industry.*

Management commitment, people and expertise, and culture on the other hand are considered as organizational adaptability (Schumacher et al., 2016). The model assumes that digital maturity can directly be affected by these factors. Strong leadership and commitment from management are essential for driving digital transformation initiatives (Kirmizi & Kocaoglu, 2024). When the management actively support and invest in digital initiatives, organizations are more likely to achieve higher levels of digital maturity. Also, skilled employees, continuous learning, and a workforce that embraces digital technologies are fundamental to digital maturity specifically in manufacturing (Sukrat & Leeraphong, 2024). Organizations that prioritize digital workforce development and expertise enhancement are better positioned to adapt to digital changes. A culture that fosters innovation, agility, and openness to change is also a critical enabler of digital maturity (Kalender & Žilka, 2024). Organizations with an adaptive and digitally inclusive culture are more resilient and capable of leveraging digital advancements effectively. Based on the above assumptions the second hypothesis is formulated as;

2. *Organizational adaptability (Management commitment, People and Expertise, and Culture) has a positive impact on digital maturity of the industry*

Though the three dimensions under organizational adaptability are commonly mentioned digital maturity model dimensions from the reviewed maturity models, it is believed that they have an indirect impact on the digital maturity of the industry. In other words, improvement of the organizational culture for digitalization may not directly enhance digital maturity. Rather, it may impact one of the basic enabler dimensions so that the digital maturity level of the company could be affected. People and expertise are another major digital maturity model dimension (Rossmann, 2018; Flores et al, 2020). Similarly, it has an indirect impact on digital maturity without basic enablers and the same goes for management commitment. Accordingly, the authors of this research deliberately structured these three dimensions as mediating factors. It is to mean that they have a mediating role between basic enablers and digital maturity.

Thus, the authors assumed that digital maturity can indirectly be affected by basic enablers through a mediating effect of organizational adaptability. Based on the above assumptions the third hypothesis is formulated as.

3. *The basic enablers for digital maturity (Technology, Digital product, and Digital operation) have a positive impact on digital maturity through organizational adaptability (Management commitment, Culture, People, and expertise).*

The causal relationships between digital maturity levels represented by six different levels (Table 2.3) and the six maturity model dimensions are constructed. Both the direct and indirect effect of the dimensions/latent constructs is considered. A direct effect represents the effect of an independent variable (exogenous) on a dependent variable (endogenous), Whereas an indirect effect represents the effect of an independent variable on a dependent variable through a mediating variable (Berhan, 2020). Figure 4.2 shows the conceptual framework developed.

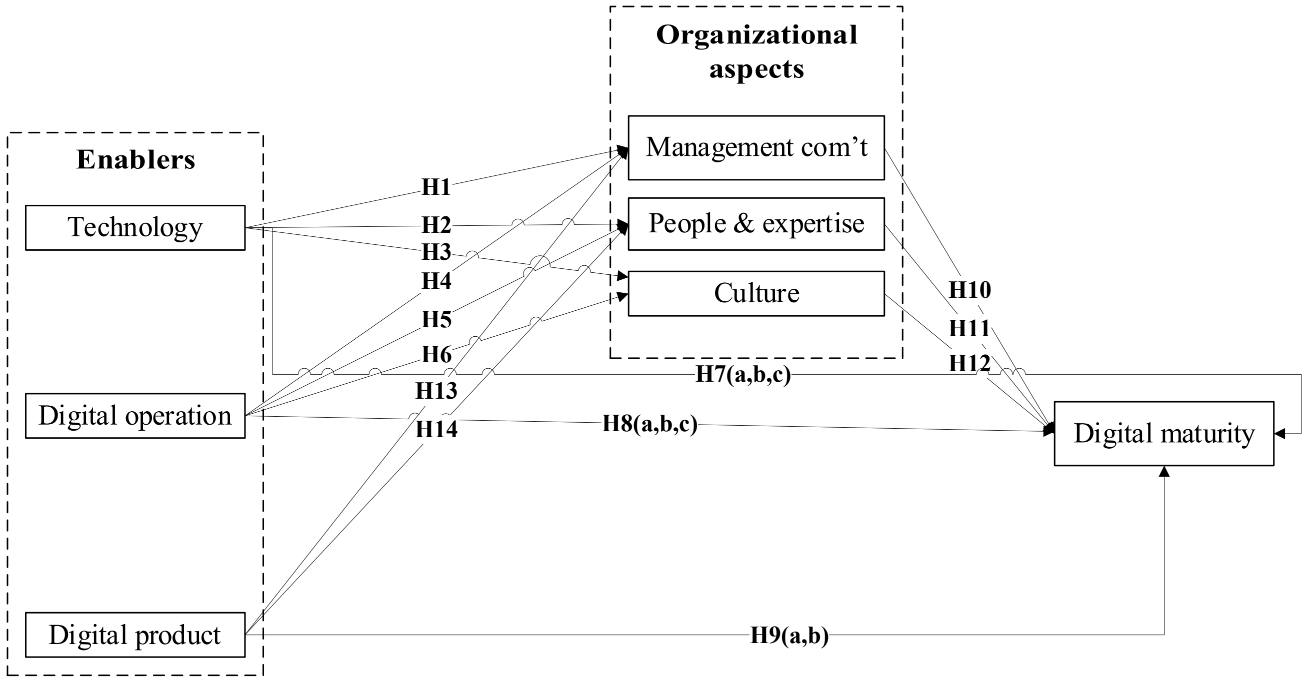


*Figure 4. 2: Digital maturity hypothesized causal model, (**Source:** Authors)*

4.4. Causal relationship analysis of digital readiness factors

Digital readiness factors are important elements in the manufacturing as they empower companies to adjust to and leverage digital technologies. Enhancement in these dimensions facilitate shopfloor data gathering, processing, and analysis, enabling manufacturers to predict trends and make well-informed decisions. The proposed causal digital readiness model presented in section 4.1 is validated in this subsection. This addresses a gap in knowledge where there have been no previous efforts to analyze the combined effects of digital maturity model dimensions or the causal connections between digital maturity factors.

Structural Equation Modeling (SEM) has been chosen as the analytical tool. SEM stands out among other modeling techniques due to its ability to test specific hypotheses derived from theoretical assumptions and data, thereby determining whether the data supports the proposed relationships. Furthermore, unlike other techniques which are able to analyze only the direct relationship, SEM can distinguish between factors directly impacting digital maturity and those influencing it indirectly through a mediation of other variables, aiding in the identification of key factors of digital maturity within the industry. It also supports the quantification of the strength and direction of relationships between digital maturity factors, enabling an assessment of how one factor influences another.

Understanding the causal links between digital maturity factors holds significant implications for policy-making within the industry. Organizations can leverage insights from SEM analysis to tailor interventions aimed at enhancing digital maturity effectively and implement the ZDM strategies.

4.4.1. Demographic description of the data

As the nature of the respondents is the critical aspect for the reliability of the responses, some demographic data have been taken. The larger group of work experience of the respondent were above six years (145 respondents) and between 2-6 years (133 respondents), below two years (19 respondents). Their level of education was 146 respondents with a BSc. /BA, 132 respondents MSc. /MA and college diploma 13 respondents. Many of the respondents working positions were, team leaders (132 respondents), general managers (9 respondents), directors (80 respondents), IT managers (22 respondents), and other positions (56 respondents). Thus, it is believed that they can understand the term digitalization and digital technologies and properly represent their company.

4.4.2. Construct validity and reliability

Confirmatory factor analysis was performed to assess the reliability and validity of the constructs and scales used. To do this, a measurement model was estimated, consisting of seven latent factors and 34 measurement items (removing 3 items, one from digital maturity and two from management commitment those having low factor loading). The outcome of this is presented in Table 4.1.

Table 4. 1: Confirmatory factor model fit, reliability and validity assessment (Source: Authors)

Constructs and measurement items	FL	Alpha	CR	AVE	Mean	SD	P-value	TLI	CFI	RMSEA
1. Management Commitment		0.844	0.870	0.584	2.7837	0.78434	2.027(0.155)	0.981	0.998	0.070
The company uses a road map for the planning of digital activities.	0.722									
The company adopts new business models driven by digitalization.	0.847									
The management introduces/promotes digitalization.	0.427									
Management empowers active employees with digital technologies.	0.933									
There is management competence and central coordination for digitalization.	0.795									
2. Digital Operation		0.856	0.848	0.594	3.7163	0.87024	2.047(0.152)	0.986	0.998	0.071
In the company, processes are decentralized.	0.523									
Our company implements modeling and simulation for the production process.	0.717									
In the company, the working process is interdisciplinary.	0.996									
In the company, there is an interdepartmental collaboration.	0.772									
3. Culture		0.787	0.813	0.474	3.9288	0.69528	3.568(0.168)	0.976	0.995	0.062
Internet/ICT has a significant value in a company.	0.535									
Our company has a strong approach to knowledge sharing.	0.853									
Our company has a good approach to open innovation and cross-company collaboration.	0.788									
Continuous change is part of our corporate culture.	0.540									
Decisions within our firm are transparent to our employees.	0.665									
4. Digital Product		0.821	0.843	0.584	2.9591	0.83775	4.916(0.086)	0.976	0.992	0.084
Products are Individualized/customized using customer data.	0.472									
Products are commercialized through digital technologies.	0.772									

Digital products of our company create a significant impact on customer experience.	0.839									
There is a direct added value created by the progressive digitization of products of our company (e.g., cost reductions, increased productivity, better customer experience, customer differentiation)	0.901									
5. People and Expertise		0.816	0.837	0.524	2.7731	0.79299	2.897(0.089)	0.966	0.997	0.096
In the company, ICT competencies and openness to new technologies of employees are in good condition.	0.411									
Within our firm, there are sufficient experts on digital core issues.	0.642									
Within our firm, further education opportunities for digital core topics are available.	0.818									
Within our firm, comprehensive measures to strengthen digital literacy development are implemented	0.968									
Within our firm, new job profiles have been created for employees with expertise in digital core topics	0.658									
6. Technology		0.76	0.843	0.491	3.2260	0.63572	9.026(0.060)	0.963	0.990	0.078
There is an existence of ICT infrastructure in the company.	0.742									
Digital platforms are used for day-to-day collaboration.	0.887									
Our firm uses large amounts of data to optimize strategies, processes and products.	0.825									
Within our firm, we use tools for digital modeling, automation and control of business processes.	0.574									
Our firm has implemented enterprise-wide digital workplace concepts	0.310									
There is utilization of machine-to-machine communication	0.708									
7. Digital maturity		0.824	0.855	0.559	2.3846	0.92279	4.433(0.351)	0.999	0.999	0.023
Connectivity	0.512									
Visibility	0.464									
Transparency	0.779									
predictive capacity	0.949									
Adaptability	0.900									

Model fit was evaluated using χ2/df=2.77 (p≤0.001), Tucker–Lewis index (TLI) =0.95, comparative fit index (CFI) =0.96, and root mean square error of approximation (RMSEA) =0.06, mean and standard deviation (Berhan, 2020; Cangur & Ercan, 2015). The model estimated shows a good fit with the data, as most of the fit indices indicated above fall within the acceptable cut-off limits (Boateng, 2019). The standardized factor loadings of all the measurement items for each construct are also detailed in Table 4.1. Most of the factor loading in the table is greater than 0.5 (except 5 items), satisfying the requirements for acceptability (Bagozzi & Yi, 2012; Hair Jr. et al., 2014).

To determine the reliability of the seven constructs their composite reliabilities (CR) were extracted. These ranged from 0.813 to 0.870, exceeding the prescribed criterion of 0.6 and above (Bagozzi & Yi, 2012). To test the inter-item reliability, Cronbach's α values were considered all of which exceeded the suggested criteria of 0.70, as presented in Table 4.1. To evaluate the construct validity, the convergent and discriminant validities were each examined.

For the discriminant validity, both Fornell and Larcker criterion and Hetrotrait, Monotrait (HTMT) ratio are used (Henseler et al., 2015). Regarding convergent validity, the average variance extracted (AVE) for each construct was examined. Five of the constructs out of seven were found to be above 0.5 (Table 4.2), indicating convergent validity (Bagozzi & Yi, 2012). For discriminant validity using Fornell and Larcker criterion, the average variance extracted (AVE) values for each construct are compared with the squared individual inter-construct correlations based on Ab Hamid et al., (2017), as presented in Table 4.3.

Table 4. 2: Correlational matrix of each construct (Source: Authors)

Correlations

	MC	**DO**	**CL**	**DP**	**PE**	**TG**
MC						
DO	.553**					
CL	.445**	.820**				
DP	.303**	.565**	.639**			
PE	.557**	.532**	.591**	.631**		
TG	.406**	.747**	.821**	.707**	.575**	
DM	.436**	.513**	.522**	.666**	.722**	.652**

(Note):. Correlation is significant at the 0.01 level (2-tailed).**

It indicates that most of the AVE values were greater than the square of each inter-construct correlation except two, culture with the digital operation (0.92) and culture with technology (0.81) and thereby; satisfying the criteria for discriminant validity.

Using Heterotrait-monotrait (HTMT) ratio, HTMT values close to 1 indicate a lack of discriminant validity with a suggested threshold of 0.9 (Ab Hamid et al., 2017). The results indicate all (except one, digital operation and culture having 0.95) the values are below the threshold (0.9) as shown in Tables 4.3. The same is true for the results obtained from Fornell and Larcker Criterion (Table 4.4). Thus, the discriminant validity is satisfied.

Table 4. 3: Discriminant validity using Fornell and Larcker Criterion (Source: Authors)

	AVE	DM	MC	DP	TG	PE	CL	DO
DM	0.559	**0.747663**						
MC	0.584	0.421	**0.764199**					
DP	0.584	0.441	0.266	**0.764199**				
TG	0.491	0.37	0.245	0.677	**0.700714**			
PE	0.524	0.686	0.647	0.603	0.39	**0.723878**		
CL	0.474	0.313	0.434	0.648	0.81	0.537	**0.688477**	
DO	0.594	0.351	0.585	0.614	0.63	0.548	0.92	**0.770714**

Table 4. 4: Discriminant validity using HTMT Ratio (Source: Authors)

	DP	TG	PE	DO	CL	MC	DM
DP							
TG	0.715023						
PE	0.627405	0.422862					
DO	0.61741	0.660187	0.566383				
CL	0.61741	0.883047	0.576487	0.954356			
MC	0.278521	0.268214	0.696857	0.608449	0.46962		
DM	0.423618	0.370518	0.677324	0.342472	0.310148	0.418287	

4.4.3. The direct role of basic enablers and organizational adaptability on digital maturity

In this subsection, the first two hypotheses have been empirically examined. The first hypothesis sets that the basic enablers; Technology, Digital product, and Digital operation directly enhance the digital maturity level of an industry. The second hypothesis assumes that Organizational adaptability, comprising Management commitment, People and Expertise, and Culture, positively influences the digital maturity of the industry.

The causal relationships between the predictor and output variables were explored as hypothesized using SEM. Separate structural models were estimated to assess the direct relationships. The results of these tests for direct relationships are found in Table 4.5 and are visually represented in both the conceptual model (Figure 4.2) and structural model (Figure 4.3).

These summarize the findings of the tests for H1 to H14, where each hypothesis (H1 to H14) represents a separate dimension. In the framework, these dimensions are grouped under clusters; however, the actual analysis treats each dimension individually, resulting in 14 distinct connections. Among all, seven of the hypotheses were supported (H4, H14, H12, H6, H7, H9, H11). This outcome substantiates the work of scholars including, Rossmann, (2018); Şener et al., (2018); Hizam-hanafiah, Soomro and Abdullah, (2020); Kiraz et al., (2020); Gökşen and Gökşen, (2021); Machado et al., (2021) .

On the other hand, digital operation was found to have a significant positive effect on management commitment (β=0.456, p=0.001). Digital product on people and expertise and digital maturity (β=0.414, p=0.001) and (β=0.233, p=0.001) respectively. Technology and digital operation were found to have a significant positive influence on culture (β=0.471, p=0.001) and (β=0.469, p=0.001) respectively. Technology, digital product and people and expertise have a significant positive effect on digital maturity (β=0.433, p=0.001), (β=0.233, p=0.001) and (β=0.390, p=0.001) respectively.

The negative effect of digital operation on digital maturity (β=-0.004, p=0.954) becomes a surprise; given that digital operation has been found and is expected to contribute positively to enhancing digital maturity Schumacher et al., (2016); Rossmann, (2018); Hizam-hanafiah et al., (2020); Soomro and Abdullah (2020); Gökşen and Gökşen, (2021). Similar to digital operation, culture is found to have a negative relationship with digital maturity (β=-0.122, p=0.166) which is far from the previous findings by Schumacher et al., (2016) and the researcher's hypothesis. The rest of the five relationships were found to be insignificant as seen in Table 4.5. In general, the model shows a good fit, with χ2/df=1.627, IFI=0.999, TLI=0.989, CFI=0.999, and RMSEA=0.055 according to Cangur and Ercan, (2015).

Table 4. 5: Direct path analysis (Source: Authors)

Path description	Hypothesis	Standardized estimate	Results
PeopleExpertise <---DigitalOpration	H5	0.199(0.011)	Not supported
ManagmentComt <--- Technology	H1	0.213(0.020)	Not supported
ManagmentComt <--- DigitalOpration	H4	0.456(***)	**Supported**
ManagmentComt <--- DigitalProduct	H13	0.049(0.507)	Not supported
PeopleExpertise <--- DigitalProduct	H14	0.414(***)	**Supported**
PeopleExpertise <--- Technology	H2	0.135(0.138)	Not supported
Culture <--- Technology	H12	0.471(***)	**Supported**
Culture <--- DigitalOpration	H6	0.469(***)	**Supported**
DigitalMaturity <--- Technology	H7	0.433(***)	**Supported**
DigitalMaturity <--- DigitalOpration	H8	-0.004(0.954)	Not supported
DigitalMaturity <--- ManagmentComt	H10	0.041(0.447)	Not supported
DigitalMaturity <--- Culture	H12	-0.122(0.116)	Not supported
DigitalMaturity <--- DigitalProduct	H9	0.233(***)	**Supported**
DigitalMaturity <--- PeopleExpertise	H11	0.390(***)	**Supported**

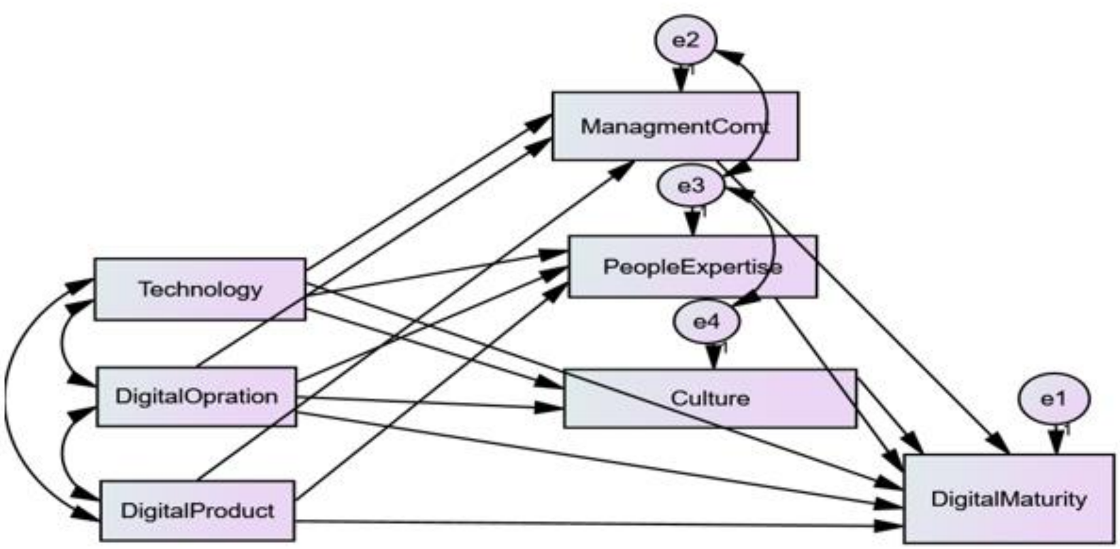


Figure 4. 3: Structural model, (Source: Authors)

4.4.4. The mediating role of organizational adaptability on digital maturity

A mediation analysis was subsequently conducted using a bootstrap sample of 2,000. It can be observed from table 4.6 that, technology affects digital maturity with their direct relationship. Through the two mediators (management commitment and culture), failed to have a significant indirect effect; thereby failing to provide support for H7(a &c). The result of this path contrasts with what VanBoskirk, (2016) and Rajnai and Kocsis, (2018) proposed where this two dimensions contributes to digital maturity for the industrial setting where digital technologies are in place.

Contrary to many existing maturity models that heavily emphasize technology as a foundational factor for digital maturity, this study underscores the critical importance of people and expertise (employee competency) alongside technological enablers for enhancing digital maturity within steel industries. Demonstrating that, "people and expertise" partially mediates technology and digital maturity supporting H7(b).

Various researchers including Schumacher et al, (2016); Rajnai and Kocsis, (2018); Rossmann, (2018); Şener, Gökalp and Eren, (2018); Hizam-hanafiah et al, (2020); Kiraz et al., (2020); Gökşen and Gökşen, (2021); Steinlechner et al, (2021); Lassetnig et al., (2018); Pirola, et al., (2020); Santos and Martinho, (2020) have highlighted the significance of "technology" as a key driver of digital maturity in steel industries. The research puts that these industries remain susceptible to digital disruptions unless they focus on cultivating digitally adept employees and fostering a mindset conducive to embracing new ways of working. Therefore, "People and expertise" are positioned as a key dimension in the digital maturity model, running parallel to "technology".

While the substantial influence of digital operations on digital maturity was anticipated based on previous research emphasizing the positive impact of digital operations such as process decentralization, modeling, interdisciplinary collaboration, and more, this study reveals an unexpected finding. Digital operations alone do not significantly affect digital maturity in industries unless mediated by people and expertise. This supports the assertions made by Abdallah et al., (2022), who suggest that the adoption of digital products and operations is not a guarantee of industry digital maturity. The absence of a direct impact of digital operations on digital maturity disproves the argument made by many scholars that industries actively engaged in digital operations are the ones achieving digital maturity.

Furthermore, the research uncovers that the relationship between culture and technology lacks significance without the mediation of people and expertise, emphasizing once more the critical role of digital competency in driving digital maturity, particularly within steel industries. People and expertise not only mitigate negative relationships between digital operations and digital maturity but also align with the argument proposed by (Schumacher et al., 2016). regarding the pivotal role of human intelligence and expertise in the digital transformation journey. This section contributes valuable insights into the multifaceted dynamics that shape digital maturity within the context of steel industries, emphasizing the essential role of human intelligence alongside technological advancements in achieving organizational digital readiness and resilience in the face of digital disruptions.

Digital operation has a negative relationship with digital maturity (of their direct relationship) but, through the mediation of people and expertise, it has a significant relationship. Thus, people and expertise (excluding the rest two mediators, culture and management commitment) fully mediate the relationship between digital operation and digital maturity. Thus, providing support for H8(b). Additionally, the direct path from digital product to digital maturity, and the indirect path through people and expertise are both significant. This signifies that people and expertise partially mediate the relationship between digital product and digital maturity, as predicted in H9b. These findings are consistent with the previous research (Kiraz et al., 2020). Taking management commitment as a mediating factor, the relationship is insignificant implying that has no indirect effect on the relationship between digital product and digital maturity.

Table 4.6 highlights the outcome of this analysis, indicating the presence of all No, Partial and Full mediation relationships. The distinction given as "No Mediation" and "Full Mediation" is determined by analyzing the direct and indirect effects. No Mediation is remarked when the indirect effect is not statistically significant, and the direct effect remains significant, mediation is not supported. Suggesting that the independent variable directly influences the dependent variable without the mediation path playing a significant role. On the other hand, Full Mediation is remarked if the indirect effect is statistically significant while the direct effect becomes nonsignificant when the mediator is included, full mediation is established. This indicates that the independent variable influences the dependent variable entirely through the mediator. "Partial mediation" occurs when the indirect effect is significant (or at least close to significance). The direct effect remains significant even after including the mediator.

Table 4. 6: Mediation Analysis (Source: Authors)

Relationship	Hypothesis	Direct effect	Indirect effect	Mediation type
Technology – ManagementComt-DigitalMaturity	H7a	0.433***	0.012	No mediation
Technology – PeopleExpertise – DigitalMaturity	H7b		0.071**	**Partial mediation**
Technology – Culture – DigitalMaturity	H7c		-0.077	No mediation
DigitalOperation – ManagementComt – DigitalMaturity	H8a	-0.004(0.954)	0.018	No mediation
DigitalOperation – PeopleExpertise – DigitalMaturity	H8b		0.077**	**Full mediation**
DigitalOperation – Cultuer – DigitalMaturity	H8c		-0.056	No mediation
DigitalProduct – ManagmentComt – DigitalMaturity	H9a	0.233***	0.002	No mediation
DigitalProduct – PeopleExpertise – DigitalMaturity	H9b		0.165***	**Partial mediation**

In general, this section sought to examine the connection and influence of basic enablers; digital technologies, digital operation and digital product on digital maturity level; and how these relationships are mediated by organizational adaptability; management commitment, people and expertise and organizational culture within steel industries in Ethiopia. The SEM analysis largely supports the hypothesized relationships outlined in the conceptual model (Figure 4.3, Tables 4.5 and 4.6)

4.5. Summary

This chapter presents an empirical analysis of industrial digital maturity for implementing ZDM. It explores the impact of fundamental enablers; digital technologies, digital operations, and digital products on the digital maturity level within steel industries in Ethiopia. It investigated how these relationships are influenced by organizational adaptability management commitment, people and expertise, and organizational culture. The results highlight the key role of employee competency alongside digital technology in driving digital maturity in industry. Notably, there exists a strong correlation (0.077**) with digital operations, (0.071**) with technology and an even stronger correlation (0.165***) with digital products. This contrasts with prior studies that overly emphasize the impact of digital technology on digital maturity.

The findings underscore that industries must prioritize cultivating digitally skilled employees to navigate digital disruptions effectively. Moreover, the research reveals that while digital operations are vital, their impact on digital maturity hinges on the mediation of people and expertise, challenging conventional approach. The study also emphasizes the link between culture, technology, and employee competency in fostering digital maturity, revealing the significance of human capital in digital transformation journeys within steel industries. Overall, the research sheds light on the interconnections of digital maturity dimensions, stressing the critical synergy between technological advancements and human expertise in achieving organizational digital readiness.

Chapter-Five

AI-Based Defect Detection Model Development and Validation

5.1. Introduction

This chapter details the development of a machine learning (ML)-based defect detection model for steel manufacturing. Prior to model development, selecting a ZDM strategy aligned with the industry's digital readiness level is essential. Therefore, an actual digital maturity assessment of the steel manufacturing industry is conducted. This evaluation aims to ascertain the industry's digital readiness status and decide on the viable ZDM strategy, thereby guiding the industry towards digital transformation and the creation of an effective AI-based quality control system. The rationale for adopting a *detection-focused* ZDM strategy is also outlined followed by presenting the AI model.

5.2. Digital maturity assessment of the case steel industry

Digitalization is a relatively new concept in the manufacturing industry, but it is gaining momentum as time goes on (Kırmızı & Kocaoglu, 2022). Smart digital transformation has the ability to give industries unprecedented insight into the finer points of their day-to-day operations. With this level of insight comes great opportunity, a digital factory has the ability to optimize virtually every moment of production and minimizing defects. The digital solutions simply make the necessary information more accessible (Gökalp & Martinez, 2021).

Industries aiming to effectively transition into Industry 4.0 and seamlessly integrate advanced operational frameworks such as ZDM into their processes must first assess their digital maturity levels (Zonnenshain & Kenett, 2020). Maturity models play a key role in assessing the digital maturity of an industry (Gökşen & Gökşen, 2021). These models serve as essential tools for evaluating a company's position from various sector-specific or disciplinary perspectives. This section focuses on actual measurement or assessment of the digital maturity level of the case steel industry.

The 6 MM factors and 31 subfactors identified in the previous chapter are presented in Table 5.1 along with their local and global weights. The table also displays the corresponding six maturity levels. The 5-level Likert scale questionnaire responses were used as input data for an MS Excel software tool to calculate and depict the maturity level. According to the analysis by Elibal and Özceylan (2021), each items significance were evaluated and weighted with local and global weights, indicating that not all items carry the same weight in progressing towards a digitally mature industry. Therefore, each item's contribution to the corresponding maturity dimension is different and they confirmed its practicality.

For instance, within the 'Technology' dimension, the presence of "ICT infrastructure" may contribute differently to "digital maturity" compared to the "use of digital platforms for daily collaboration". As a result, the given local weights and the mean values from the ten respondents were integrated into the assessment process.

To elaborate the assessment and calculation, the first dimension, named as "Management commitment (M1)" contains seven measuring items is presented in detail. The company self-assessed the seven criteria with each contained 7 measuring items. The analysis is done according to (Schumacher et al., 2016).

- → M1/1 (Available resource for realization of digital strategy) =3, W=0.041
- → M1/2 (Company's Road map for the planning of digital activities) =2 W=0.031
- → M1/3 (New business models adopted driven by digitalization) =2 W=0.025
- → M1/4 (The management understand the concept of digitalization) =2 W=0.022
- → M1/5 (The management introduce/promotes digitalization) =3 W=0.015
- → M1/6 (Management empowers active employees with digital technologies) =2 W=0.024
- → M1/7 (There is a management competences and central coordination for digitalization) =2 W=0.012

The related weight for each measuring item is presented in the respective row of the item as shown in the table 5.1. Using Equation 3.2, the maturity level is calculated for each measuring items of each dimension. For instance, for the first dimension "management commitment" (M1), the result obtained was 2.3 based on the Likert scale.

$$M1= ((3*0.041) + (2*0.031) +(2*0.025) +(2*0.022) +(3*0.015) +(2*0.024) +(2*0.012))/ (0.041+0.031+0.025+0.022+0.015+0.024+0.012) =\boldsymbol{2.3}$$

The overall maturity index for M1, calculated at 2.3, reflects the weighted contributions of each measuring items. This score suggests that management in the industry has made some progress in digital transformation but remains in the early stages. Specifically, the lower score in planning (M1/2), despite its higher weight of 0.031 (approximately 19% of the total contribution from all seven items), indicates a need for greater focus on planning digital activities. Additionally, while the high score for resources (M1/1) shows readiness, the scores for model adoption (M1/3) and digitally active employee empowerment (M1/6) point to significant areas needing improvement. Overall, the result of 2.3 for "management commitment" (M1) indicates a level below what is considered moderate. The same interpretation can be made for the remaining dimensions.

The same analysis has been performed for each of the remaining dimensions and subdimensions, as presented in Table 5.1. Finally, the aggregated result is obtained by averaging all the weighted results from each six dimension (Equation 3.2).

$$MD = (M1*W1) + (M2*W2) + (M3*W3) + (M4*W4) + (M5*W5) + (M6*W6)$$

$$\text{Total weighted maturity score} = ((2.3*0.17) + (2.2*0.16) + (2.3*0.13) + (2.5*0.18) + (1.4*0.22) + (1.6*0.16)) = \boldsymbol{2.056}$$

The result 2.056 or approximately 2.1 indicates the maximum possible digital maturity score. To align this result with the six maturity levels, it is possible to divide the Likert range (1–5) into 6 equal intervals as follows:

→ Level 1(Computerization): $1.0 \leq \text{Score} < 1.67$

→ Level 2(Connectivity): $1.67 \leq \text{Score} < 2.33$ ⟵ *The current result falls under this range*

→ Level 3(Visibility): $2.33 \leq \text{Score} < 3.0$

→ Level 4(Transparency): $3.0 \leq \text{Score} < 3.67$

→ Level 5(Predictive capacity): $3.67 \leq \text{Score} < 4.33$

→ Level 6(Adaptability): $4.33 \leq \text{Score} \leq 5.0$

Table 5. 1: Digital maturity/readiness level of the case steel manufacturing industry (Source: Authors)

Main Criteria	*Weight*	*Sub-criteria*	*Local Weights*	*Global Weights*	*Average response*	*Weighted score*	*Maturity result*
Management Commitment	*0.17*	Available resource (people and budget) for realization of digital strategy	*0.25*	*0.041*	*3*	*0.123*	*2.3*
		Company's road map for the planning of digital activities	*0.19*	*0.031*	*2*	*0.062*	
		New business models adopted driven by digitalization	*0.15*	*0.025*	*2*	*0.050*	

		The management understand the concept of digitalization	*0.1*	*0.022*	*2*	*0.044*	
		The management introduce/promotes digitalization	*0.12*	*0.015*	*3*	*0.045*	
		Management empowers active employees with digital technologies	*0.1*	*0.024*	*2*	*0.048*	
		There is a management competences and central coordination for digitalization	*0.09*	*0.012*	*2*	*0.024*	
Digital Operation	*0.16*	Decentralized processes	*0.289*	*0.040*	*3*	*0.120*	*2.2*
		Modelling and simulation implemented to assist production process	*0.245*	*0.044*	*2*	*0.088*	
		Interdisciplinary working process	*0.119*	*0.034*	*2*	*0.068*	
		Interdepartmental collaboration via data accessibility	*0.347*	*0.042*	*2*	*0.084*	
Culture	*0.13*	Significant value of Internet/ICT in a company	*0.270*	*0.044*	*3*	*0.132*	*2.3*
		Strong approach for knowledge sharing	*0.146*	*0.018*	*3*	*0.054*	
		Good approach for open-innovation and cross company collaboration	*0.126*	*0.024*	*2*	*0.024*	
		Continuous change as part of corporate culture	*0.157*	*0.013*	*2*	*0.026*	
		Decisions within the firm are based on data and transparent to employees	*0.301*	*0.031*	*2*	*0.062*	
Digital Product	*0.18*	Individualized/customized products using customer data	*0.317*	*0.057*	*2*	*0.114*	*2.5*
		Product commercialization through digital technologies	*0.286*	*0.050*	*3*	*0.150*	
		Good customer experience impact on digital products	*0.199*	*0.039*	*3*	*0.117*	
		Direct added value created by the progressive digitization of products of the company	*0.198*	*0.034*	*3*	*0.068*	
People and Expertise	*0.22*	A good condition of ICT competences and openness for new technologies of employees	*0.390*	*0.065*	*2*	*0.065*	*1.4*
		Availability of sufficient experts on digital core issues	*0.203*	*0.045*	*1*	*0.045*	
		Availability of further education opportunities for digital core topics	*0.20*	*0.044*	*1*	*0.044*	

		Implementation of comprehensive measures to strengthen digital literacy development	*0.12*	*0.034*	*2*	*0.068*	
		Creation of new job profiles for employees with expertise in digital core topics	*0.11*	*0.032*	*3*	*0.096*	
Technology	*0.16*	An existence of ICT infrastructure in the company	*0.200*	*0.037*	*2*	*0.074*	*1.6*
		Usage of digital platforms for day-to-day collaboration	*0.112*	*0.031*	*3*	*0.093*	
		Usage of large amounts of operational data to detect, predict and optimize processes and products	*0.225*	*0.030*	*1*	*0.030*	
		Usage of tools for digital modeling, automation and control of production processes	*0.140*	*0.026*	*1*	*0.026*	
		Implementation of enterprise-wide digital workplace concepts	*0.123*	*0.014*	*2*	*0.028*	
		Utilization of machine-to-machine communication	*0.200*	*0.022*	*3*	*0.066*	
	Average of all dimensions						
Digital maturity level	*Six levels*	L-1: Computerization					
		L-2: Connectivity	*The current position*				
		L-3: Visibility	-				
		L-4: Transparency	-				
		L-5: Predictive capacity	-				
		L-6: Adaptability	-				

The analysis of the assessment positioned the case industries at level 2, defined as connectivity. These results were assessed according to the six digital maturity levels given by Gökalp & Martinez, (2021). Moreover, the identification of dimensions requiring potential further development was provided to facilitate a successful digital transformation of the case steel industry.

At the operational and managerial levels, the case industry incorporates computerization. For example, it employs several computer numerical controls (CNC) machines and computers. However, these machines operate independently without integration or connectivity. Manual intervention is necessary to link these machines, and production data gathered is siloed across various departments and machines, accessible only on post-production completion. Currently, the industry is advancing by linking its machines to the internet. Nevertheless, the communication efficiency is lacking, lacking the flexibility to align with real-time production events, thus resulting in a disconnection between data and actual shop floor production. The remaining levels of digital maturity; transparency (leveraging analytics), predictive ability (real-time analytics), and adaptability (autonomous decision-making) remain unattained within the case industry. This highlights the pressing need for significant attention and effort towards digital transformation.

Furthermore, when looking for the dimensions which further requires improvements, there is approaches to moderate level of management commitment to digital transformation (Figure 5.1). The digital operational aspects also seem to be at a developing stage. This dimension could benefit from enhancements in processes, automation, and efficiency gains through digital technologies. The industry's digital culture is relatively strong. There is a positive attitude towards digital innovation and adoption within the organizational culture. Moreover, it is excelling in terms of digital product offerings. There is a need to focus on developing innovative digital products to cater to market demands and stay competitive.

A potential area of concern is regarding the expertise and skills of people within the industry on digital technologies (Table 5.1). Capacity building and upskilling programs could be beneficial in this regard. The technology dimension also indicates a lower level of digital technology integration within the steel industry (A gap is seen in terms of utilizing operational data for process optimization, detection and prediction of events. There is an opportunity to further leverage advanced data-driven technologies to enhance operational efficiency. The results are further depicted in a radar chart, visually representing the company's current digital maturity across the six dimensions (Figure 5.1). Figure 5.2 specifically represents on the company's current digital maturity level from the perspective of a single dimension (technology).

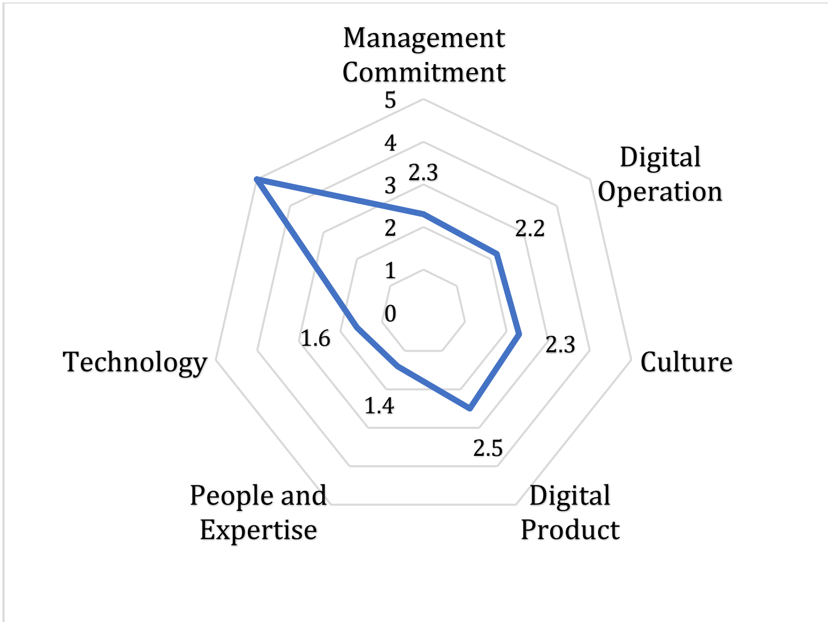


Figure 5. 1: Digital maturity across six dimensions within the case industry

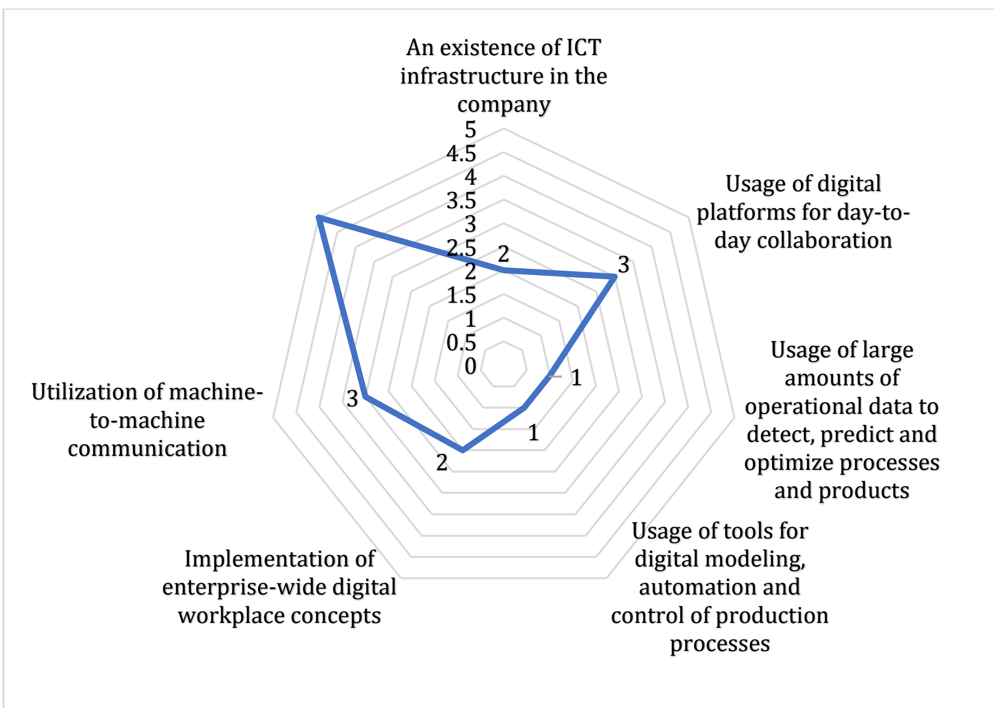


Figure 5. 2: Digital maturity of a specific dimension ("Technology") within the case industry

5.3. Appropriate ZDM strategy selection

Each ZDM strategy (Detection, Prediction, Repair and Prevention) requires a different level of digital readiness within an industrial setting. Implementing the "Detection" strategy; the first and fundamental step in ZDM requires access to existing historical data. In this case, real-time data access and machine integration are not mandatory. An effective defect detection model can be developed using historical time-series quality inspection data, thereby confirming that industries classified at digital maturity level 1 and 2 can adopt and leverage this strategy.

Hence, the suitable ZDM strategy identified is detection. The detection strategy can be implemented in both offline and real-time scenarios, depending upon the network infrastructure and digital readiness of the industry. Within the case industry context, there exists a huge amount of historical data stored within computer systems, enabling the development of defect detection model. This involves offline defect detection or offline analytics utilizing historical recorded data and machine learning algorithms. Real-time defect detection involves monitoring and analyzing data as it is generated in real-time. Although it enables quick decision-making and intervention to repair defect or prevent occurrence of defects, it requires real-time and highly flexible integration of machines. Offline defect detection on the other hand involves analyzing historical data that has been collected and stored for analysis at a later time. It is less resource-intensive compared to real-time detection and allows for in-depth analysis of past inspection data to identify accurate pattern.

Therefore, a defect detection model is developed utilizing machine learning techniques. This model takes into account the mechanical properties of steel as an output quality parameter and integrates a comprehensive set of input variables from each stage of production including dimensional measures. The model has taken full advantage of mass time-series data generated in a steel rebar production process.

5.4. CRISP-DM based defect detection model

This section presents a defect detection model, which has been developed based on the CRISP-DM framework and tailored to align with the objectives of this research (Figure 5.3). A very recent version of this framework has been discussed by Bokrantz et al., (2023) having six well-defined stages. Which are: 1. Business understanding: involves determining the business problem and the goal. 2. Data understanding: focused on collecting and exploring available data. 3. Data preparation: making the data ready and suitable for analysis including cleaning, integration and transformation. 4. Modeling: this is choosing the appropriate algorithm and building the model. 5. Evaluation: assessing the model performance using different matrices so as to select the best performing model to make it ready for the last stage. 6. Deployment: installing the chosen model to the operational environment.

The model framework for this study is explained in detail within each subsection, focusing on the steel rebar production process as a use case. It comprises five consecutive stages, starting with the study of rebar manufacturing process and the quality inspection activities, followed by defining the challenges associated with the current quality inspection process. Another crucial aspect of the model is the identification of key input and output quality parameters. Additionally, the model framework represents the data sources and historical records related to each quality parameter. The subsequent step involves collecting, describing, and cleaning the data. The modeling stage encompasses activities such as selecting an appropriate algorithm, fine-tuning optimal hyperparameters, and training the data. Finally, the framework includes the performance and accuracy evaluation of the defect detection model as the last step.

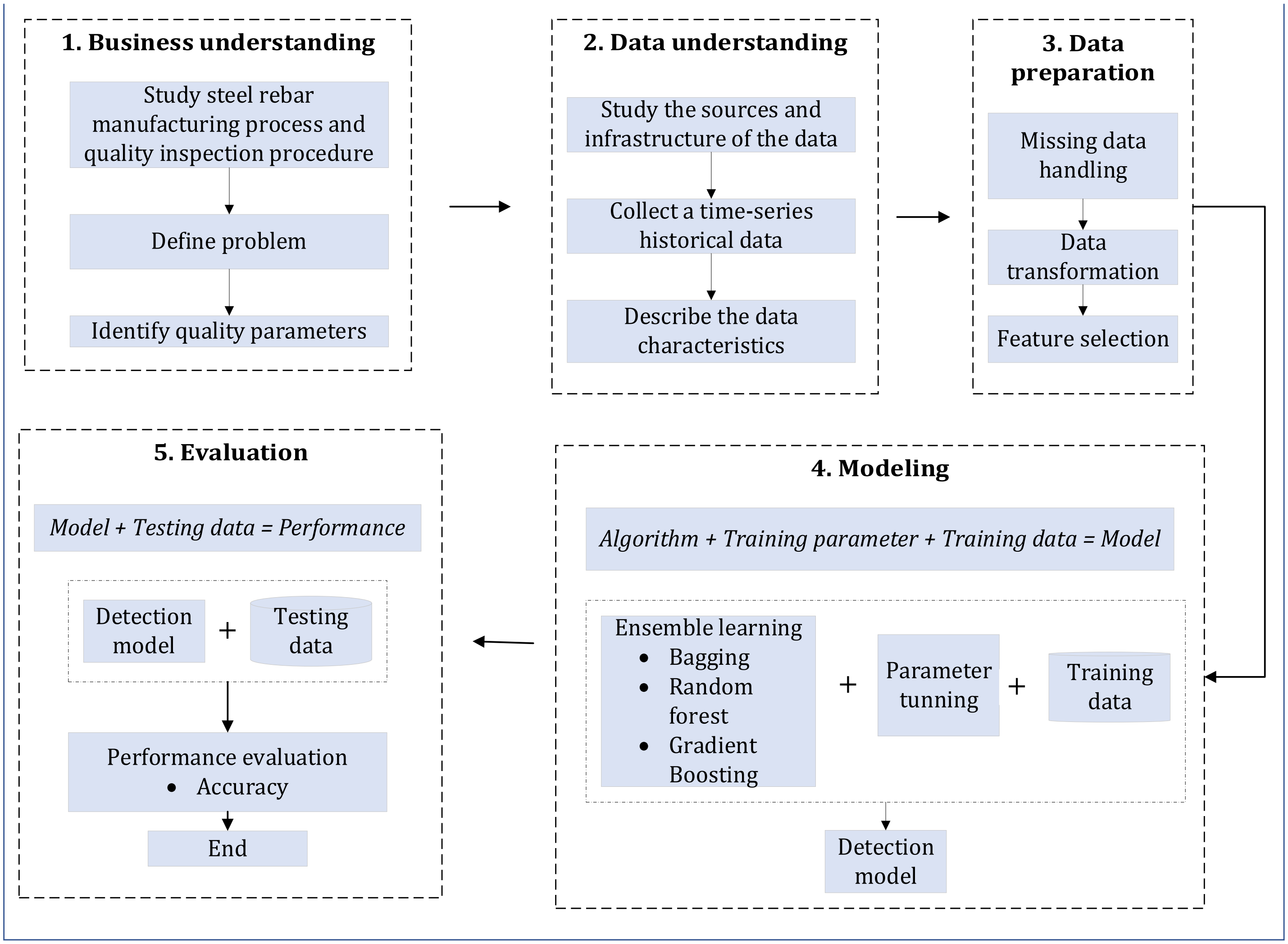


Figure 5. 3: Defect detection model framework (source: Authors)

5.4.1. Quality control in steel rebar production process

Rebar manufacturing process as one of steel product in the sector, encompass multiple production stages, including continuous casting, heating and reheating, rolling, cooling, and cutting. The quality of steel rebar is primarily determined by its mechanical properties, including yield strength, ultimate tensile strength, and elongation (Xu et al., 2023). Achieving the desired mechanical properties requires strict control over the chemical composition and process parameters during each stage of manufacturing.

Dimensional measures also play a crucial role in determining the desired mechanical properties. These measures include weight, diameter, cross-sectional area, rib height, rib spacing, transverse-rib inclination, and transverse-rib flank inclination. Small deviations in dimensions can lead to a subsequent loss, causing an increase in mechanical property deviation. This, can affect the stress-strain behavior of the rebar and impact the offset yield strength. Statistical findings within the case industry reveal a relationship between dimension deviation and the extent of mechanical property deviation in steel rebar. Specifically, for every 1 mm reduction in dimension deviation, there is a corresponding increase of 0.1% in the offset yield strength (a method used to determine the yield strength of rebar). It signifies the stress level at which the rebar begins deformation. This determination involves subjecting the rebar to a 0.1% strain and measuring the stress required to achieve that specific strain providing insight into the rebar's ability to withstand applied loads.

The production of steel rebar begins by melting scrap steel in a chosen furnace as shown in Figure 5.4. The molten steel undergoes refining, where various alloying elements are added to eliminate impurities. Following this, the steel enters the continuous casting stage. Here, the molten steel is poured into a water-cooled mold, transforming it into a solid material called a billet. It is at this stage that the initial quality inspection is conducted. A sample is extracted from the billet for chemical composition analysis, ensuring that the steel adheres to the specified standards.

The third stage of production is the reheating and rolling or the hot rolling process. During this stage, the solidified billets are heated once again on the reheating furnace with the initial rolling temperature of 900-1200℃ and then passed through a series of rolling mills. The rebar has to be maintained in an average rolling temperature between 900-1100 ℃ during the rolling process. The purpose of this process is to decrease the cross-sectional area of the billets and elongate them into slender, straight bars. The rolling process will continue until the desired shape and dimension is found. At this stage the rebar has to be maintained with the final rolling temperature between 800-1000℃. This belongs to the second quality inspection point where the dimensional check (cross-sectional area, weight, diameter, rib height, rib spacing, transverse-rib inclination, and transverse-rib flank inclination) is conducted.

The rebar will then be involved in additional heat treatment process to improve its mechanical properties. This process is quenching the rebar using water pressure (between 2bar to 5bar) and consistent water flow between 200-500 L/min to quickly cool it followed by tempering or reheating at a lower temperature between 300-600℃.

The final stage of rebar manufacturing involves cutting it into the desired lengths. This process marks the last step before the rebar is ready to be packed. At this stage, the last quality inspection takes place to ensure that all the required mechanical properties have been achieved. This includes conducting tensile testing, bend testing, and impact testing. These tests are crucial in assessing the rebar's strength, ductility, and ability to withstand dynamic loading conditions.

All the quality parameters starting from the initial chemical composition analysis, to process parameters and dimensions at each three stages of quality inspection significantly influences the final mechanical properties of the rebar.

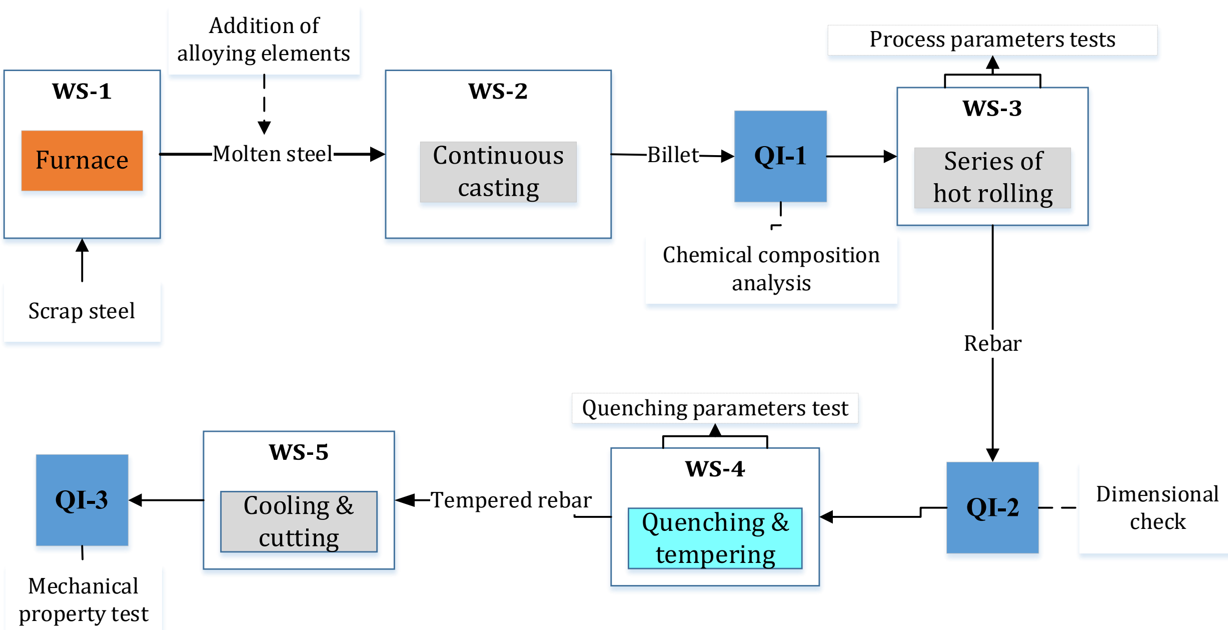


Figure 5. 4: Rebar production process and quality inspection points (QI, quality inspection; WS, work station) (Source: Authors)

5.4.2. Understanding the problem associated with quality inspection

The quality inspection operation of the case steel manufacturing industry is an integral part of the production process in which QI is performed continuously throughout each stage of production. Two distinct challenges prevail from the extensive physical inspections.

Time for quality inspection; though, quality inspection is an important process in manufacturing, at the same time it is a very time-consuming activity. From the total manufacturing time, 20-25% is consumed by QI operation. Each stage of the quality inspection process requires a considerable amount of time ranging from few minutes to several hours per sample. The estimated time per sample can vary depending on the following factors; testing complexity, sample size, testing equipment and inspector experience. For instance, the visual inspections and dimensional measures take 1.5 minutes per sample on average. However, for more complicated tests like mechanical properties test, 30-140 min per sample may be required. The longer it takes to inspect and identify defects, the higher the chances of defective products reaching customers, thereby compromising the goal of achieving zero defects.

Costs associated with quality inspection: The major aim of zero-defect manufacturing initiative is to ensure the manufacturing process attains to achieve zero defects while maintaining economic viability. It involves implementing strategies and practices that optimize resource utilization and reduce costs. In this regard, the case industry is being investing a significant amount of money for QI. Much of the quality inspection tests including the mechanical properties test are measured with significant number of samples and 57% of the quality inspection task involves destructive tests where value imparted in samples will be lost. Reducing a destructed and non-destructed sample to a minimum using data driven techniques reduces the associated quality control costs.

5.4.3. Data understanding

A data associated with key steel rebar quality parameters were collected consisting of 6080 data points with 28 features as shown in Table 5.2. Considering the data's characteristics, out of the 28 variables, only one variable (bend test) is categorical, with values represented as "pass" and "fail." The remaining 27 variables are numeric in nature. The data is recorded for each measurement of the sample and documented as a daily quality record. All the records from different sources are then continuously collected and stored to the central database through offline system and managed by the quality control department. In addition, the steel rebar represented in this study is grade B500BWR. The standard followed for quality assurance of steel rebar of grade B500BWR is based on ISO 6935-2:2007 as shown in Table 5.3.

The raw data of rebar quality inspection were identified and sourced from sensors and different metrology instruments. The chemical composition analysis typically conducted in the chemical test laboratories using optical emission spectrometer (OES). It has a capability to identify and quantify the elements present in the sample steel billet. Most of the mechanical property tests are performed using the universal testing machine (UTM). The data related to process parameters or the temperature data were measured by thermocouples or temperature sensors. It records data by attaching it to the rebar or embedded in the surrounding of hot rolling process to monitor and record temperature changes during various stages of rolling. This includes initial, average and final rolling and also during quenching, tempering, and cooling processes of the steel rebar. Finally for dimensional measures, different metrology instruments including calipers (to measure the diameter and rib spacing), weighing scale (to measure weight), profile gauge (to measure rib height), pitch angle gauge (to measure degree of rib inclinations) are used.

Table 5. 2: Statistical description of the quality parameters or features (Source: data from the case industry)

	Feature	Mean	S.D.	Range	Q_{25}	Q_{75}
Chemical composition (wt.%)	C	0.19975	0.02621115	(0.15,0.27)	0.1800	0.2200
	Si	0.2189211	0.03454715	(0.15,0.33)	0.2000	0.2400
	Mn	0.5453816	0.05534191	(0.43,0.72)	0.5000	0.5900
	P	0.04166316	0.006693808	(0.03,0.059)	0.03800	0.04200
	S	0.03756053	0.00826261	(0.022,0.052)	0.03100	0.04500
	Cr	0.1181579	0.0327381	(0.07,0.21)	0.0900	0.1500
	Cu	0.2913184	0.08904609	(0.003,0.51)	0.2800	0.3300
	Sn	0.02914474	0.008085094	(0.016,0.05)	0.02300	0.03300
Thermo-mechanical properties	IRT(°C)	1069.08	37.65909	(968,1200)	1045	1100
	MRT(°C)	948.6592	44.56602	(815,1101)	915.0	980.0
	FRT(°C)	868.6908	32.24083	(800,975)	845.0	886.0
	QWP(Bar)	2.133737	0.1474266	(2,2.7)	2.060	2.200
	QWF(L/min)	342.2868	31.96617	(300,440)	314.0	350.0
	QT(°C)	446.2171	37.54943	(400,560)	415.0	474.0
Dimensional measures	CSA(mm^2)	47.53855	0.8280809	(46.12,50.1)	46.88	48.03
	WGHT(kg/m)	0.3731776	0.006500435	(0.362,0.394)	0.3680	0.3770
	DMTR(mm)	7.861	0.4589698	(6.210,8.96)	7.428	8.300
	RH(mm)	0.3904513	0.03919715	(0,0.45)	0.3710	0.4150
	RS(mm)	4.625	0.6137956	(3,6.2)	4.200	5.000
	TRI(degree)	44.6	7.29733	(4,65)	40.0	48.0
	TRFI(degree)	48.54342	9.962626	(5,70)	43.00	53.00
Mechanical Properties	YL(KN)	26.24	1.207385	(23.38,29.26)	25.45	27.01
	YS(N/mm^2)	552.0	25.57096	(477.4,620.3)	533.5	571.2
	UL(KN)	31.10026	2.229474	(24.1,40.8)	29.9	32.3
	TS(N/mm^2)	654.3118	46.90924	(504.5,882.3)	625.4	680.3
	EAF (%)	22.22	1.576311	(18,33)	21.00	23.14
	TS/TY (ratio)	1.1854	0.06492054	(0.884,1055)	1.1511	1.2114
	BT(pass/fail)	5878pass/202fail				

IRT= Initial rolling temperature; MRT= Middle rolling temperature; FRT= Final rolling temperature; QWP= Quenching water pressure; QWF= Quenching water flow; QT= Quenching temperature; CSA= Cross-sectional area; WGHT= Weight; DMTR= Diameter; RH= Rib height; RS= Rib spacing; TRI= Transverse-rib inclination or the pitch angle; TRFI= Transverse-rib flank inclination; YL= Yield load; YS= Yield stress; UL= Ultimate load; TS= Tensile strength; EAF= Elongation after fracture; TSTY= TS/TY ratio; BT= Bend test

Table 5. 3: ISO standard for the corresponding quality parameters of steel rebar grade B500BWR (Source: case industry)

Variable	C	Si	Mn	P	S	Cr	Cu	Sn	IRT	MRT	FRT	QWP	QWF	QT
ISO 6935-2:2007 Standard	0.16-0.22	0.15-0.30	0.55-0.65	0.050max	0.050max	0.20max	0.40max	0.050max	900-1200	900-1100	800-1000	2-4	200-500	300-600
Variable	CSA	WGHT	DMTR	RH	RS	TRI	TRFI	YL	YS	UL	TS	EAF	TSTY	BT
ISO 6935-2:2007 Standard	46.276-54.324	0.3634-0.4266	7.36 - 8.64	0.05(diameter) min	0.5(diameter) min and 0.7(diameter) max/ 4 - 5.6	35-90, 45 average	45 minimum	-	-	-	-	-	1.12-1.55	P/F

5.4.4. Data preparation

Data preprocessing was performed to enhance the data's quality and suitability for analysis. The major tasks undertaken included missing data handling, data transformation and feature selection. These steps aimed to improve the data's integrity and optimize its compatibility with the selected ML algorithms before training the model.

Missing data handling: Handling missing data is crucial in any data analytics endeavor. In the current dataset, some features have missing data that follows a pattern of being completely at random (MCAR). To determine the appropriate technique for handling missing data, it is essential to assess whether the data contains outliers. Descriptive statistics such as mean, median, standard deviation, and range have been employed for this purpose (Table 5.2). Based on the descriptive statistics, the data distribution did not show any outliers. Consequently, the missing values have been replaced by the mean values using the mean imputation technique. The "mice" package from the R library has been utilized for this task.

Data transformation: As the data has one categorical variable (the bend test, represented by a “pass” and “fail”) it is transformed into numeric variable by encoding as a binary distribution as “1” and “0” respectively. Moreover, many of the features within the dataset exhibit diverse scaling or measurement units, necessitating normalization of the data. This becomes an especially crucial task when working with algorithms that assume a normal distribution. Indeed, the tree-based algorithms used in this study are capable of handling data with different scale. But still, it is one part of data preparation and will maintain the Gaussian nature of the data.

Feature selection: Each input variables cannot be equality important to estimate the output variable. Thus, the most influential features for estimating each output variable are carefully selected to enhance the model's performance. Different ML algorithms have different ways of measuring or determining the importance of features. The algorithms examined in this study come equipped with their own feature importance measures, accessed using the "importance" and “relative influence” functions on R. As a result, these measures are seamlessly incorporated into the modeling stage.

5.4.5. Modeling

The modeling stage aims to create a mapping function that can be used to estimate the target variable based on the input features. A supervised ML approach is followed and both a regression and classification models are considered because the response variables, which represent steel rebar mechanical properties, are given as both categorical and numeric values. The detection was made using three categories of input features: chemical compositions, process parameters, and dimensional measures.

The study employed advanced multiple tree models utilizing three ensemble learning methods namely; Bagging, random forest (RF) and boosting or the generalized boosted regression modeling (GBM). The aforementioned ensemble learning techniques generally function by combining multiple weak models/learners in to one model to reduce bias and variance (Khayyati & Tan, 2022). Each ML algorithms are experimented and compared on the data aiming to reduce the possibility of overfitting and improve the quality estimation accuracy of the testing dataset.

The main R packages used to run the three ensemble learning methods are “random forest” and “gbm” or the generalized boosted regression model. The bagging is a special case in RF and does not require a new package. Moreover, the dataset has been divided into; 70% (4,256 observations) for training and the remaining 30% (1,824 observations) for testing. This 70/30 split is a commonly adopted ratio in machine learning to ensure a sufficient amount of data for training while retaining enough data for accurate testing and validation of the model's estimation performance (Cha et al., 2021; Sahin, 2020; Singh et al., 2021).

5.4.6. Feature importance analysis

Gaining insights into the connections between features and the target variable is facilitated by feature importance analysis (Maiti & Muthuswamy, 2024). The comprehension and interpretation of metrics play a key role in discerning the importance of input variables within a model. This understanding enables informed decisions regarding feature selection, model optimization, and identifying the primary variables influencing the outcomes (Khayyati & Tan, 2022).

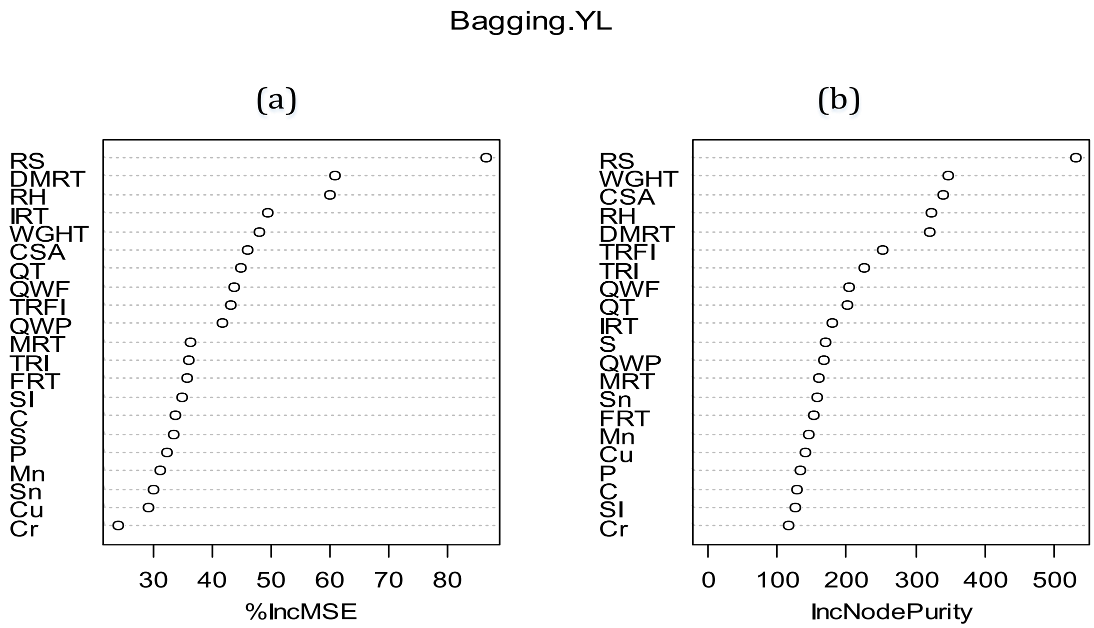
5.4.6.1. Feature importance results from the Bagging model

The analysis of feature importance was conducted for each of the three models. Figure 5.5 shows the result obtained on the order of significance of each input features on estimating the corresponding output variable obtained from the bagging model. As the bagging and random forest models employed similar metrics, the results from the RF are found in Appendix C.

The case of regression:

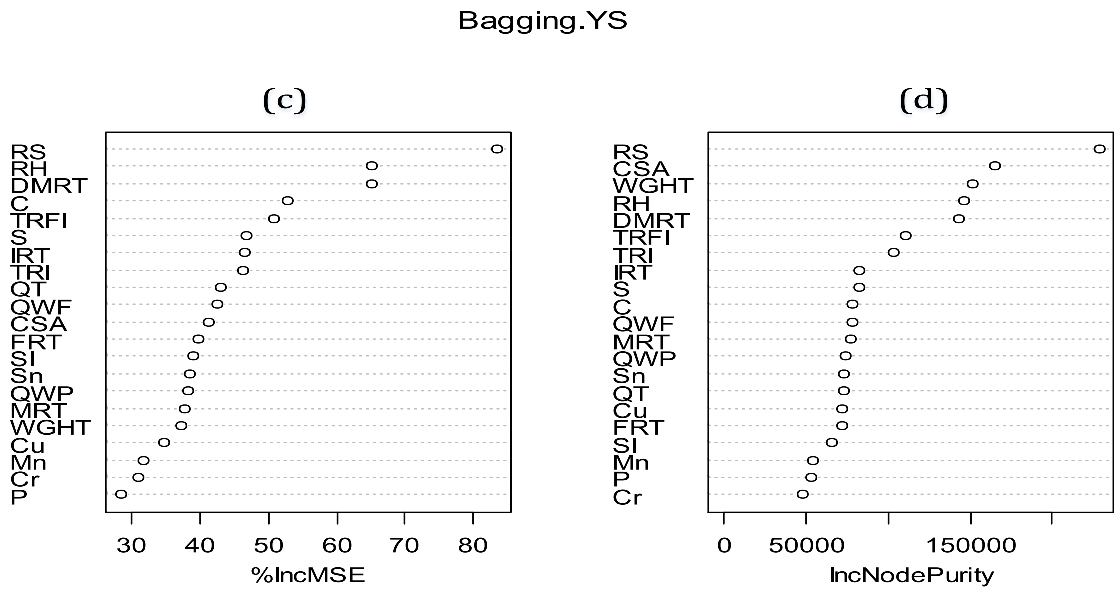
In a regression model, a higher %IncMSE (Mean Decrease of Accuracy) value suggests that excluding a variable decreases accuracy, emphasizing its importance in determining the output. Reversely, a lower %IncMSE value indicates the variable's lesser role in determining the output. Likewise, a significant decrease in node impurity (Inc Node Purity) in regression models indicates the variable's crucial role in reducing impurity during model splits, showcasing its importance. Conversely, a minor decrease suggests the variable's limited contribution to impurity reduction during node splits.

In Figure 5.5 (A-L), the significance of the 21 input variables in detecting the 6 output variables from the regression model is depicted. Figure 5.5 (a) showcases the 'bagging YL' model, which forecasts the yield load utilizing %IncMSE. Within the input variable categories (refer to Table 5.2 for category specifics), dimensional measures stand out as the most influential feature. Chemical composition variables are rated lowest, with thermomechanical properties variables falling in-between. Additionally, Figure 5.5 (b) presents the 'bagging YL' model using Inc Node Purity metrics. Among the dimensional measures category, 'Rib spacing,' 'Weight,' and 'Cross-sectional area' presented as the top three significant variables, followed by thermomechanical properties and then chemical compositions.



Both feature importance metrics consistently presented dimensional measures as the primary quality parameters for predicting yield load and across all other output variables in regression models (Figure 5.5(c)-(l)).

Although there is a slight variance in specific variables highlighted by %IncMSE and Inc Node Purity, the categories remained largely consistent in both cases. The key finding from this analysis was the significant influence of dimensional measures on the mechanical properties of steel rebar. These quality parameters of steel products can have an impact on the mechanical properties, including yield strength and tensile strength. For instance, variations in thickness can lead to disparities in material characteristics throughout the product, thereby impacting the yield strength. Areas with uneven thickness profiles may develop stress concentrations under loads, affecting the overall tensile strength. Similarly, irregularities in width can create localized stress points, influencing the product's load-bearing capacity and, consequently, its tensile strength. Moreover, defects related to flatness, such as buckling, or warping, and rib dimension inaccuracies have the potential to introduce additional stresses into the material, influencing the yield strength.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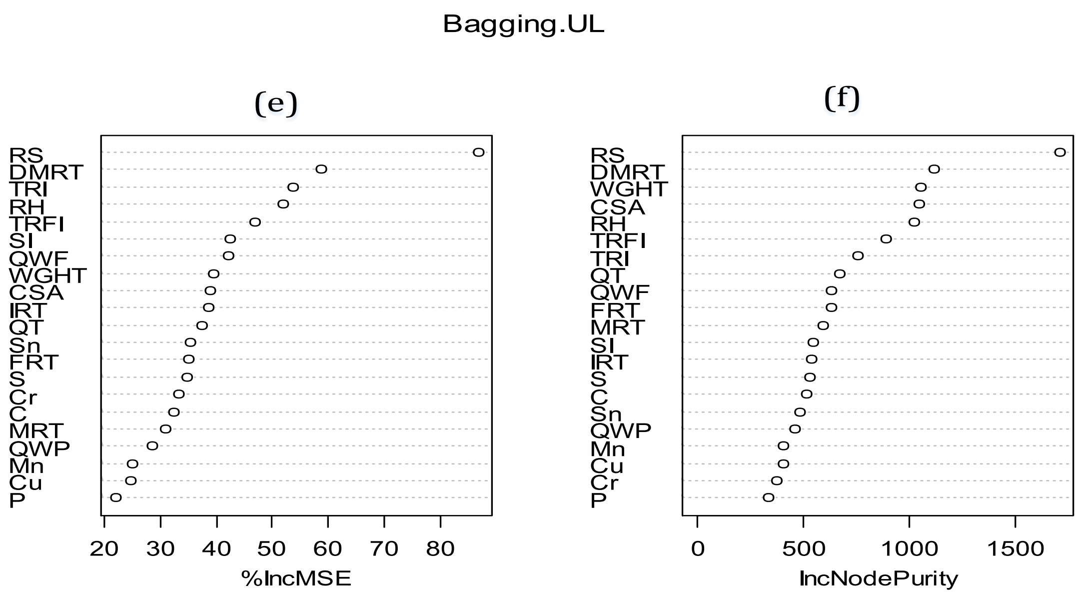
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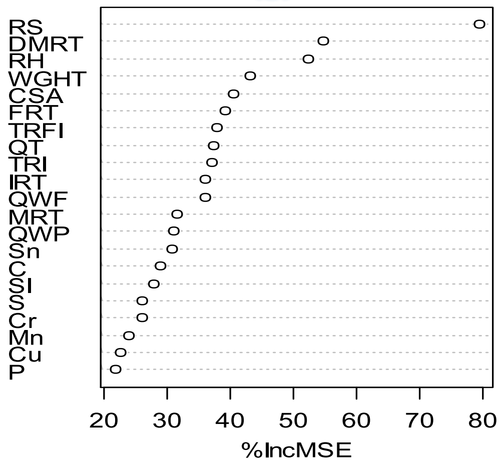

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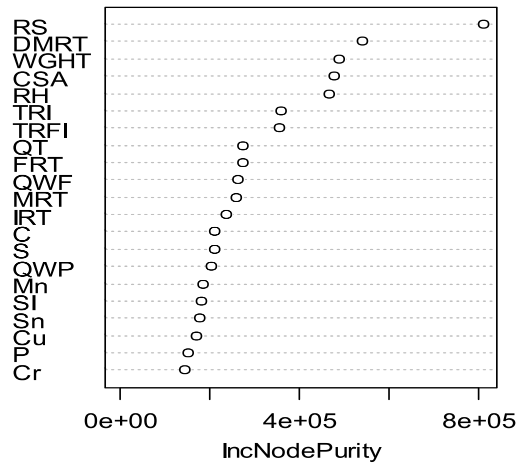

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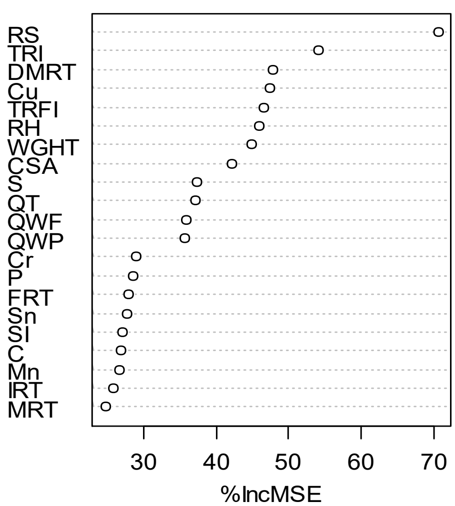

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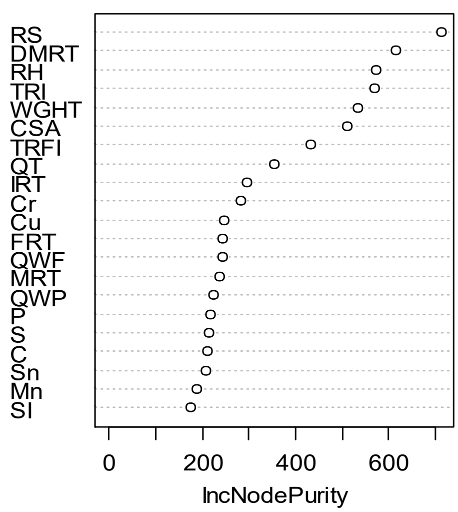


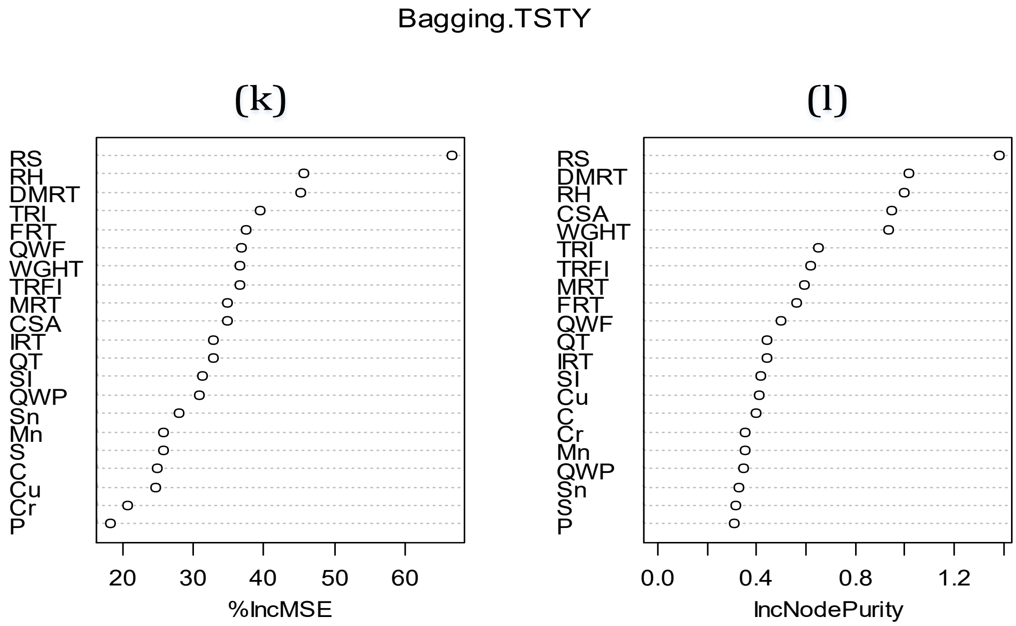


Figure 5. 5: Feature importance of each input variables from the regression bagging model

The case of classification:

Regarding the classification models, the interpretations of the feature importance metrics is represented by MDA (Mean Decrease Accuracy) and MDG (Mean Decrease Gini). A higher MDA value indicates that removing the feature leads to a more significant decrease in accuracy across all features, suggesting its importance in classification. And lower MDA value implies that the feature might be less crucial in improving the overall accuracy of the classification model. Higher MDG (Mean Decrease Gini) value indicates that the feature contributes more to reducing Gini impurity across all features, emphasizing its importance in class separation. And a lower MDG value signifies that the feature has less impact on reducing Gini impurity during splits.

Figure 5.6(a) and 5.6(b) shows the 'bagging BT' model, which estimates the bend test utilizing MDA and MDG respectively. Similar with the regression model, dimensional measures stand out as the most influential feature in both case of metrices. However, there is a slight difference on the chemical composition variables and thermomechanical properties which are presented as mixed as middle and lower without having a pattern. This implies that regression and classification models often prioritize features differently. Features that are important for predicting continuous outcomes in regression may not hold the same importance when predicting categorical outcomes in classification, and vice versa.

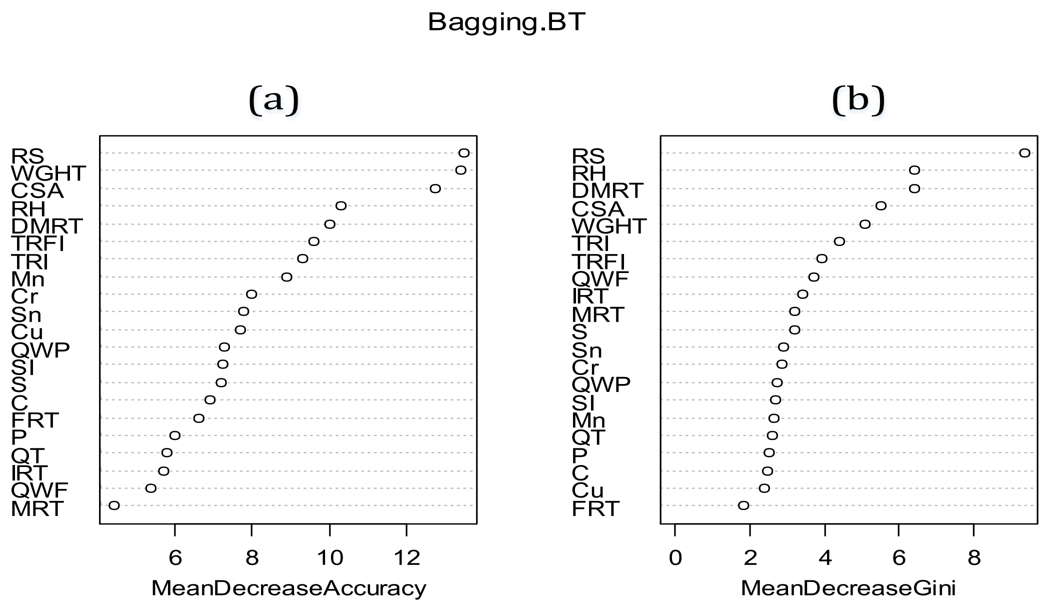


Figure 5. 6: Feature importance of each input variable from the classification bagging model

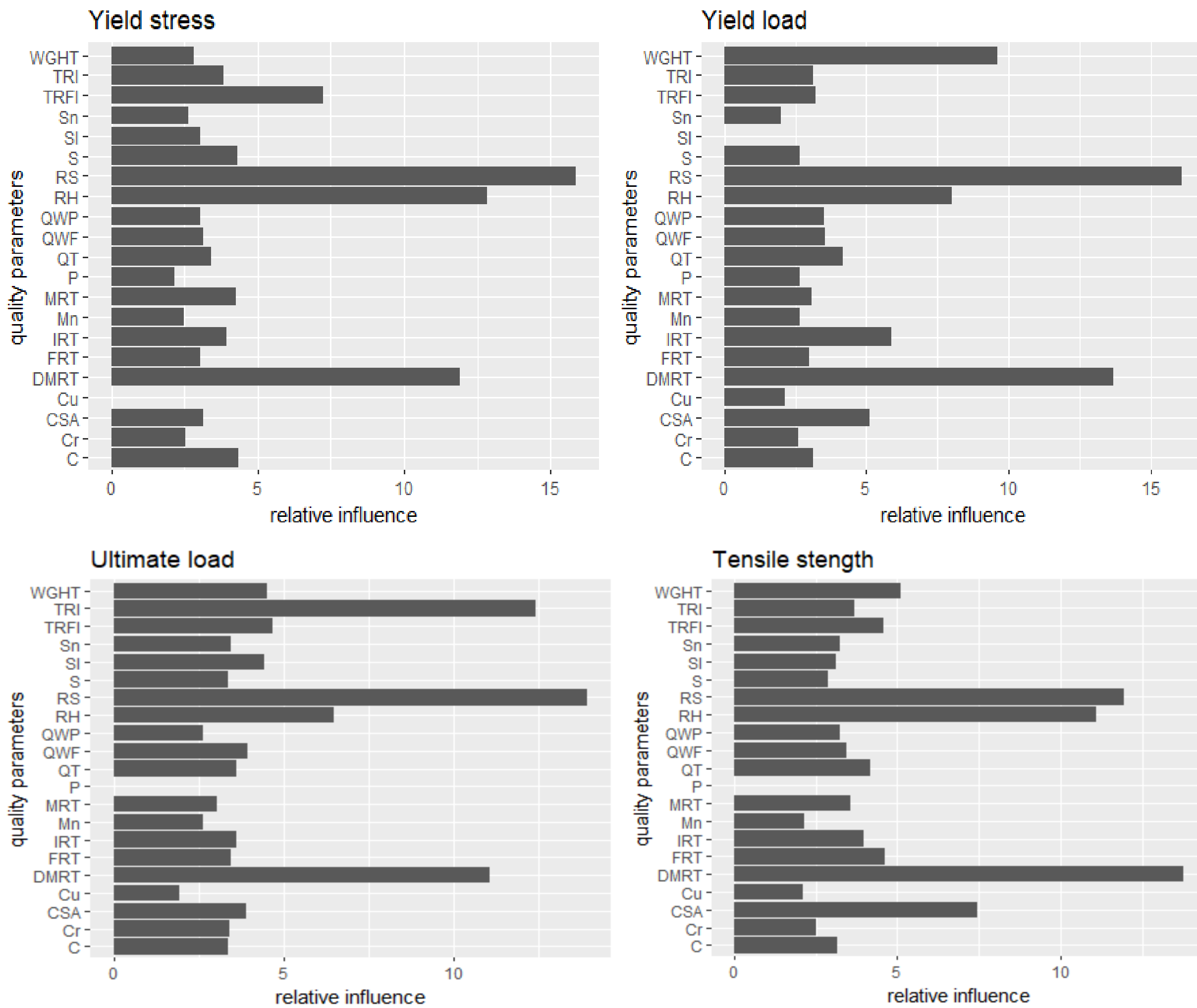
5.4.6.2. Feature importance results from the Boosting model

In boosting models, the feature importance metric used is Relative Influence. Features with higher relative influence are more frequently employed for splitting in weaker models, leading to substantial improvements in the loss function and playing a critical role in accurate predictions. Oppositely, features with lower relative influence are used less frequently for splitting, contributing less to reducing training error, indicating their lesser importance in the model.

Figure 5.7 illustrates the relative influence from the boosting algorithm of each input quality parameter on the corresponding output parameter. Despite the distinctions in ensemble learning techniques between bagging and boosting algorithms, they yield similar rankings for feature importance, as shown in Figures 5.5, 5.6, 5.7 and Appendix C.

This outcome suggests that the importance of features is not heavily reliant on the specific algorithm employed, thereby instilling confidence in the reliability of the feature importance analysis. It also indicates that the data and relationships between the input features and output variable exhibit a notable level of stability and consistency. As a result, these features are likely to serve as robust and reliable indicators for each output variable.

The convergence of feature importance rankings also facilitates the interpretation of the model's behavior and decision-making process, allowing for a better understanding of the patterns and relationships within the data. Moreover, similar to Figure 5.5 and 5.6, the findings from Figure 5.7 underscore the significance of incorporating quality features derived from dimensional measures in estimating the mechanical properties of steel products.



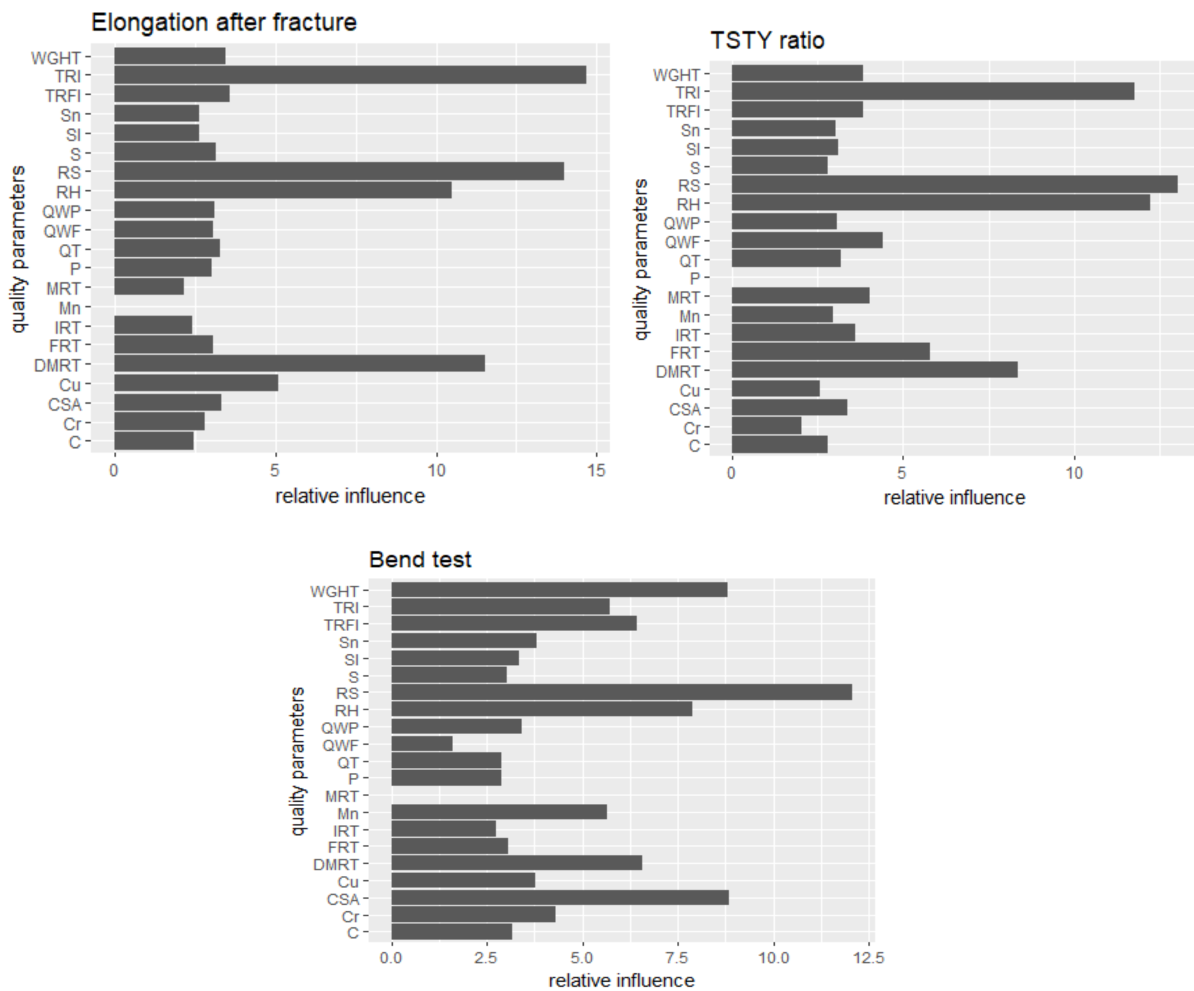


Figure 5. 7: Feature importance of each input variables from the boosting model

5.4.7. Model accuracy evaluation

Model accuracy evaluation allows to determine the model's goodness of fit to the data (detection capabilities) and enables for comparisons between different models to facilitate model selection (Dessain, 2022). The major difference between regression and classification models is on their accuracy evaluation. In this research, both the models are utilized, and as a result, both accuracy evaluation metrics are employed. In both cases, the “caret” package from R library is implemented.

5.5. Model Validation

In machine learning, model validation is referred as the process where the performance of a trained model is evaluated with a testing data set. The testing data set is a separate portion of the same data set from which the training set is derived. The main purpose of using the testing data set is to test the generalization ability of a trained model. Together with model training, model validation aims to find an optimal model with the best performance (Bertolini et al., 2021). Thus, various hyperparameter optimizations have been employed to obtain the best model with accurate estimation.

5.5.1. Validation through hyperparameters optimization

The models considered are trained using the selected set of hyperparameters (Figure 5.8). These hyperparameters are optimized to achieve the highest possible quality estimation performance for each model. It allows to control the learning process of each ensemble learning methods. The optimizing parameters are arbitrarily defined by the authors before starting the training phase. The optimization process is carried out using the "caret" package and "tune grid" function in R, which systematically explores the hyperparameter space to find the best combination for maximizing model performance.

In the Bagging (Bootstrap Aggregating) model, bootstrap resampling creates unique datasets for each round of model training, yielding different results while keeping parameters constant. This method effectively randomizes the dataset, but when strong features dominate, the resulting tree structures may remain similar. As a result, aggregating these trees can lead to limited variation and potential overfitting.

To address this, the Random Forest (RF) model adds an extra layer beyond bootstrap resampling by defining the structure of randomized trees. It determines the number of features used for each split, enhancing randomization and reducing overfitting compared to bagging. The goal is to identify the optimal number of variables sampled at each split for improved performance.

To achieve this, a for-loop iteration is conducted through all the 21 input features, inputting one feature at a time into the RF model. The model's performance is assessed by calculating the mean square error (MSE) for each split. The loop gradually incorporates more features, storing the MSE for each iteration. This process continues until all features are used, allowing the identification of an optimal number of variables to be sampled as candidate at each split (mtry) by analyzing the MSE values.

There is further potential for optimization in the boosting model. It constructs multiple trees, but unlike random forests, it does not utilize bootstrap resampling. Instead, it creates trees by applying various splits to the existing data, resulting in trees of varying sizes based on the specified number of trees. Each split contributes to the final outcome, capturing the influence of even minor subdivisions. Therefore, a for-loop iteration is performed to tune three key parameters of boosting model: learning rate, number of trees, and interaction depth. The hyperparameters tuned for each of the three ensemble methods is summarized in Figure 5.8.

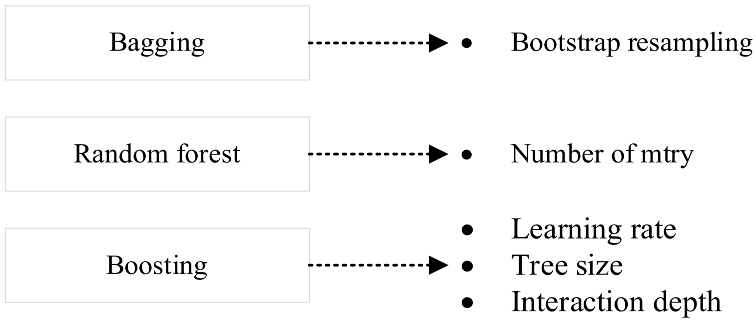


Figure 5. 8: Hyperparameter tuning summary for the three ensemble methods

5.5.2. Results of the optimal hyperparameters

A series of model training experiments is conducted on a consistent dataset in order to obtain the most accurate model for estimating the quality of steel rebar. Table 5.4 provides the hyperparameters that have been tuned for each ensemble learning model. The table includes a description of each hyperparameter, along with the resulted optimal range of values obtained from the tuning process.

Table 5. 4: The resulted optimal hyperparameters of the three ensemble learning models

	Ensemble learning methods	**Hyperparameters**	**Meaning**	**Optimal hyperparameter**
1	Bagging	n_estimators	The number of decision trees to be created in the ensemble	500
		max_depth	The maximum depth of each decision tree in the ensemble	1
		max_features	The number of variables randomly sampled as candidate at each split	In bagging, all the input features have to be considered; mtry=21
		random State	The random seed value for reproducibility.	1
2	Random forest	n_estimators	Similar with bagging	Optimal mtry with min MSE / Output variable: 5 – YL 3 – YS 3 – UL 4 – TS 5 – EAF 4 – TSTY
		max_depth	Similar with bagging	
		max_features	Different optimal mtry to each output variables	
		min_samples leaf	minimum number of samples required to be at a leaf node	

				6 | BT
3	Boosting	Distribution	The probability distribution used to model the target variable in the training data.	Gaussian for regression (for all the target variables except BT) Bernoulli for binary classification (for BT)
		Number of trees	The total number of weak models or decision trees that are sequentially added to the ensemble during the boosting process.	5000
		Interaction depth	The depth of the feature interactions captured by the boosting model	4
		Learning rate	Contribution of each individual model (weak learner) in the boosting process	Lambda (L=0.001)

The initial learning experiment involved using default parameter values for each model. For the bagging model, the number of decision trees considered was 500, the maximum depth of each tree to 1, and randomly sampled 21 variables at each split. In the case of the random forest model, similar parameter settings were employed as the bagging model, with the exception of the number of variables sampled at each split of the tree.

In the gradient boosting model, the default settings were utilized for the total number of weak models sequentially added to the ensemble, which was 5000. Additionally, the depth of feature interactions captured by the boosting model was seated as 4, and the learning rate, also known as the Lambda value, to 0.001.

On the second learning experiment aiming to improve the defect detection accuracy of the models, a hyperparameter optimization was conducted. In the case of the bagging model, since all 21 variables were resampled at each split of the tree, no additional modifications were made. However, for the random forest model, the number of mtry, which represents the optimal number of input variables at each split of the tree, was considered as a tuning parameter. To determine the optimal value for mtry, for-loop iteration was employed to explore different values and identify the one with minimum MSE. From the for-loop iteration, for each seven output variables different optimal number of mtry is obtained as shown in Table 5.4. The performance adjustment results for the boosting or GBM model are shown in Table 5.5. The analysis took into account three important tuning parameters: learning rate, tree size, and interaction depth.

Table 5. 5: The optimal hyperparameters obtained through the tuning process of boosting model (Source: Authors)

Output variable	Optimal Lambda value with min MSE	Optimal tree size with min MSE	Optimal interaction depth with min MSE
YL	0.20000	8000	4
YS	0.15000	8000	4
UL	0.10000	8000	4
TS	0.15000	9000	4
EAF	0.10000	4000	4
TSTY	0.20000	8000	3
BT	0.15000	5000	4

From Table 5.5, the configuration with the minimum MSE value for each parameter is observed, and this refined set of parameters was then used to train the model. Similar to the random forest model, for-loop iteration is conducted to each tuning parameter. The primary parameter employed is the learning rate. To explore its effect, different Lambda values of 0.00001, 0.0001, 0.001, 0.01, 0.1, 0.15, and 0.2 were examined. The crucial tuning consideration is whether it is more beneficial to decrease the learning rate, thereby slowing down the learning process, or to increase it for improved results. The second vital tuning parameter in boosting is the tree size. To determine the optimal tree size, a range of 50 to 5000 trees was iterated to find the best-performing configuration. The third parameter tuned is the interaction depth. It has been tuned using the values 1, 2, 3, and 4. Table 5.5 provides the optimal values obtained through the tuning process.

5.5.3. Detection performance results

Utilizing the model training configurations presented in section 5.5, each trained model was evaluated using the testing dataset, yielding various results. A summary of accuracy of estimation results obtained from the three methods is given in Table 5.6.

Table 5. 6: Results of the best performing ensemble learning technique

	ML algorithm	Output variables	R^2	MAE	RMSE	MAPE
1	Bagging	Yield load (YL)	0.904	0.09289	0.2641	0.3542
		Yield stress (YS)	0.927	0.07438	0.37205	0.2432
		Ultimate load (UL)	0.9246	0.15963	0.39218	0.5150
		Tensile strength (UTS)	0.922	0.1062	0.2617	0.237

		Elongation after fracture (EAF)	0.922	0.1173	0.29218	0.5350
		TS/TY ratio	0.93	0.00433	0.01066	0.37019
		Bend test (BT)	Accuracy, 0.923			
2	Random forest	Yield load (YL)	0.898	0.1037	0.2730	0.39597
		Yield stress (YS)	0.91	0.07438	0.37205	0.2432
		Ultimate load (UL)	0.90	0.06149	0.2620	0.237
		Tensile strength (UTS)	0.912	0.1062	0.2617	0.237
		Elongation after fracture (EAF)	0.921	0.1281	0.2859	0.5846
		TS/TY ratio	0.92	0.00526	0.0116	0.4473
		Bend test (BT)	Accuracy, 0.9245			
3	Improved Boosting	Yield load (YL)	0.9538	0.06149	0.2620	0.237
		Yield stress (YS)	0.9726	0.8482	4.0365	0.15530
		Ultimate load (UL)	0.9751	0.07438	0.37205	0.2432
		Tensile strength (UTS)	0.9718	0.1062	0.2617	0.237
		Elongation after fracture (EAF)	0.9614	0.1062	0.2617	0.4788
		TS/TY ratio	0.9830	0.00199	0.0090	0.1704
		Bend test (BT)	Accuracy,0.964			

The results presented in Table 5.5 provide an evaluation of the prediction performance of the three different models using key regression and classification metrics. The visual representation of the results has also been given. In Figure 5.9, visual illustration is given for the performance of the initial learning of the three models in estimating single output variable "yield load". The results from for the remaining output variables on the RF and Bagging model are given in Appendix D.

Bagging **RF** **Gradient Boosting**

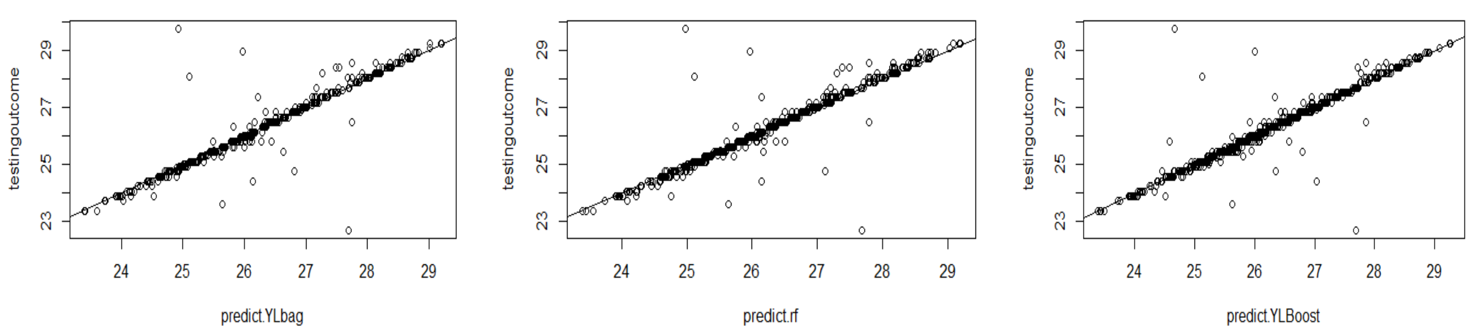


Figure 5. 9: Performance of the three ensemble models in estimating single output variable "yield load"

When comparing the RF and bagging models, the initial bagging model demonstrates superior performance compared to nearly all the seven variables. One interesting result from the bagging concept is that variable sampling cannot always be a model optimization technique. The RF model chooses a subset of variables and leads to reduced performance compared to bagging, where all variables are considered. Moreover, since RF has a bagging algorithm behind itself, it can be interpreted that the boosting idea (reducing bias) is more fitting for the current data set than that of the bagging (reducing variance). Figure 5.10 and Appendix D provides a visual representation of the detection performance of the initial learning and the modified boosting models respectively.

Although all the three ensemble models perform well on the test data set, the best performing model is the modified/optimized Gradient Boosting or generalized boosted regression algorithm by exhibiting the highest level of detection accuracy for all output variables (Figure 5.10).

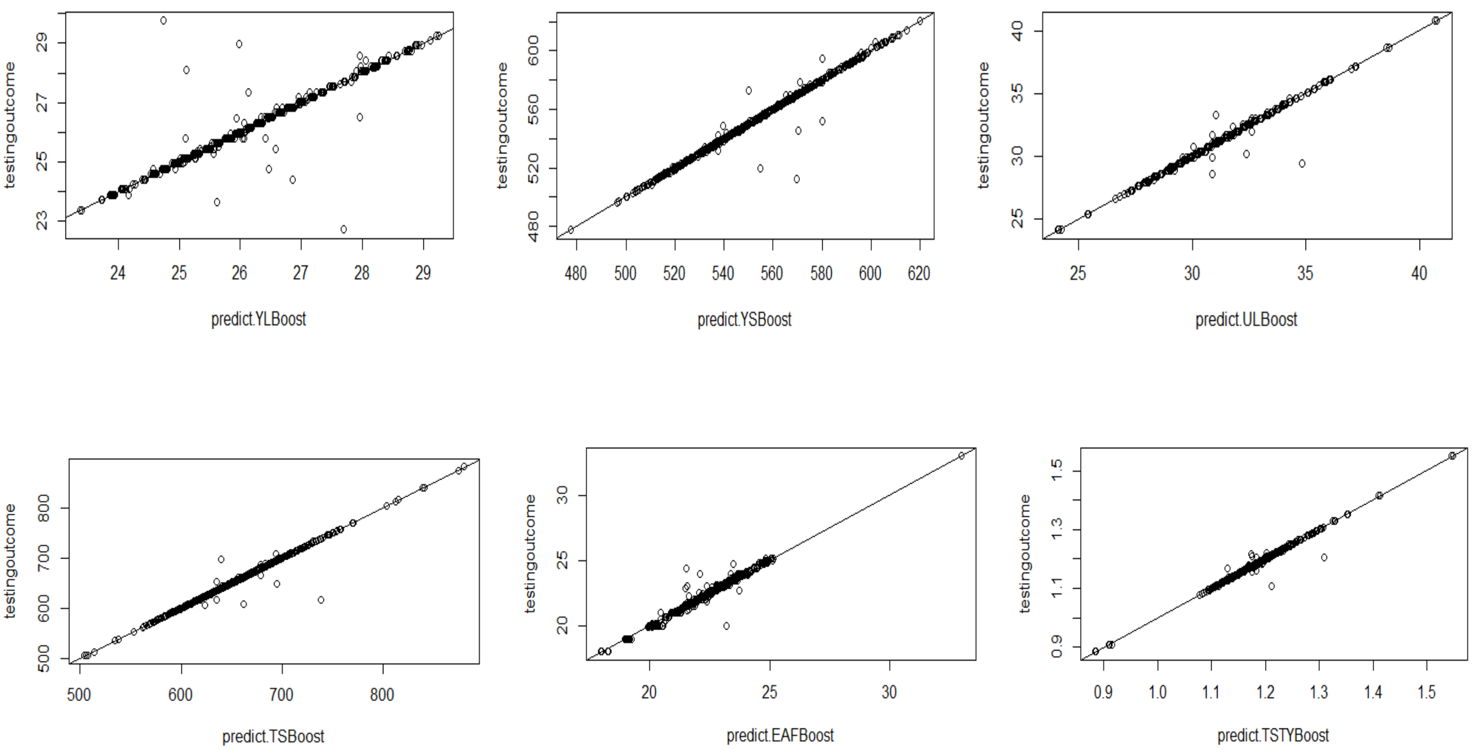


Figure 5. 10: The improved quality estimation performance of Boosting model after parameter optimization

The values indicate that the model captures most of the variance in the data while maintaining minimal detection errors. Under the Boosting model, the highest accuracy with an R^2 value of 0.983 and low error values across MAE (0.00199), RMSE (0.0090), and MAPE (0.1704) has been achieved for the output variable TS/TY ratio. Training the boosting model with a specific set of hyperparameters utilizing for-loop iteration allows to evaluate its performance based on the error metric, MSE. This metric provides insights into how well the model performs with different hyperparameter settings allowing to improve the estimation accuracy of the boosting model significantly.

5.6. Result comparison with previous findings

Lastly, in addition to comparing the model performances considering various hyperparameter tunning techniques, detection accuracy comparison was also made with the results of the reviewed steel quality detection studies. This broader analysis aimed to comprehensively analyze the quality estimation performance of the current research and different steel quality detection models and to provide a complete understanding of the advancements and findings in the field and also highlighting the key contributions of this work. Table 5.7 presents this comparison.

Table 5. 7: Comparison of detection accuracy of this study with the reviewed steel quality detection studies

Reference	Best accuracy of estimation achieved
(X. Li et al., 2023)	R^2 0.942, 0.958, 0.987
(Kusuma & Huang, 2023)	MAPE 8.90%
(Y. bao Zhao et al., 2023)	R^2 93.20, 97.62, 96.6
(Takalo-Mattila et al., 2022)	_
(S. Li et al., 2021)	R^2 0.9956
(Murta et al., 2021)	R^2 0.8599, 0.6868, 0.9170, 0.7436
(Q. Xie et al., 2021)	RMSPE 4.7%, 2.9%, 7.7%, 16.2%
(Guo et al., 2019)	R^2 0.972, 0.8259, 0.969
(Boto et al., 2022)	R^2 0.98
(Xu et al., 2023)	R^2 0.949, 0.956, 0.975, 0.928
(Ji et al., 2022)	MSE, 0.0177
(Chen et al., 2023)	R^2 0.9255
(Yu et al., 2024)	R^2 85.40
(Feng et al., 2022)	R^2 0.9419
(W. Zhao et al., 2021)	R^2 0.501, 0.791, 0.792, 0.874, 0.649, and 0.905
Current study	**R^2 0.9538, 0.9726, 0.9751, 0.9718, 0.9614, 0.9830, 0.964**

Based on the findings presented in Table 5.7, it is evident that the current study attains higher levels of quality estimation accuracy across the majority of the output variables. This achievement can be attributed to several key contributions, including the utilization of a substantial volume of data, a wide range of input and output variables, and the application of diverse ensemble learning techniques. It is worth noting that prior studies in the literature employ both large datasets (relatively big data) and limited data points to demonstrate their models. The current study leverages a relatively large dataset with a substantial number of features from the entire production stages, which enhances the comprehensiveness of the analysis.

5.7. Summary

This chapter explores an actual digital readiness assessment for the case industry, identify an appropriate ZDM strategy, and develop the AI model. The assessment is carried out utilizing the MM model proposed by Elibal & Özceylan,(2021), which aligns closely with the concept of quality control and is derived from the model developed by (Schumacher et al., 2016). Additionally, the six maturity levels established by Gökalp & Martinez, (2021) is employed to position the industry's current state of digital readiness. Analysis of the results reveals significant gaps across all six dimensions, falling within the range of 1.7-3.3 out of five, factoring in the assigned weights for each dimension. A distinct gap is particularly evident in the "people and expertise" dimension, recognized as a crucial mediating factor for digital maturity.

As per the assessment, the industry presently resides in the initial phase of connectivity (level 2). This signifies the successful transition through the initial stage of computerization, wherein all operational data are stored within computer systems. The connectivity phase, involving the integration of machines and data sources with an internet system, has started but remains at an initial stage. It has yet to reach the capability to integrate with real-time analytics due to a disconnection between data and actual shop floor production.

Based on the assessment, the detection strategy of ZDM has been selected. To realize this, a machine learning model using ensemble learning technique was developed and evaluated for its ability to estimate the mechanical properties of grade B500BWR steel rebar. The model considers the chemical composition, process parameters, and dimensional measures as an input quality features. The data used in the study consisted of 21 input features, 7 target variables, and a total of 6080 data points.

CRISP-DM framework has been followed to develop the model, ensuring a systematic approach at each stage. This includes thoroughly understanding the industry's existing problem related to quality inspection, collecting, describing, and preprocessing the data, as well as building and evaluating the model. The Bagging (Bootstrap aggregating), Random Forest, and Gradient Boosting/Generalized Boosted Regression algorithms were trained and compared.

From the feature importance analysis, the bagging and boosting algorithms produce nearly similar rankings. Suggesting that the importance of features is not heavily reliant on the specific algorithm employed. It is also concluded that features related to dimensional measures have a significant influence on the mechanical properties of steel rebar.

On the model training and validation phase, various parameters that impact the ensemble learning process, including the maximum number of features, number of trees, interaction depth, and learning rate, were fine-tuned and analyzed using a for-loop iteration. The objective was to identify the optimal values for each tuning parameter with minimum MSE.

The modified Gradient boosting model outperforms the highest accuracy of quality estimation over the bagging and random forest model with an R2 =0.9538, 0.9726, 0.9751, 0.9718, 0.9614, 0.983, 0.964 for Yield load, Yield strength, Ultimate load, Tensile strength, Elongation after fracture, TSTY ratio and Bend test respectively. The comparative analysis with the existing literature also shows that the current study achieves higher levels of quality estimation accuracy for most of the output variables.

Chapter Six

Discussions and Improvement Strategy Development

6.1. Introduction

This chapter discusses the practical and theoretical implications of the study's findings, examining their dual impact on operational applications in steel manufacturing and theoretical contributions to ZDM detection methodologies. An improvement strategy is proposed to guide industries toward higher digital maturity levels and comprehensive ZDM strategy implementation. Recognizing quality as both an outcome and a continual process, the research introduces a ZDM Continuous Improvement Cycle designed to evolve with technological and operational advancements.

6.2. A strategic guide for industries to leverage digital maturity assessment

The major prerequisite for the industries to implement new quality control approaches like ZDM is dependent on industrial digital readiness (data generation, utilization and digitally skilled workers). This readiness involves improved access to operational data for informed decision-making, achieved through robust data infrastructure, data management, and advanced analytics capabilities. From part of this research, industries can gain a deeper understanding of the critical components that contribute to digital maturity. It explores how the selected digital maturity model dimensions inform the development of a digital maturity level.

A digital maturity assessment is a crucial prerequisite for developing an effective digital strategy. This section provides a framework (Figure 6.1) that helps industries to conduct a structured digital maturity assessment and ensures they focus on changes that maximize the value derived from digital technologies.

Figure 6. 1: Industrial digital maturity assessment strategic guide, (Source: Authors)

To effectively conduct a digital maturity assessment, awareness of digital maturity and a strong commitment are essential. The assessment process involves attending workshops, completing questionnaires, and evaluating results. Also, it is not advisable to assess an entire industry's digital maturity all at once; instead, piloting the assessment in a specific part of the organization can yield more accurate and focused results, reducing the risk of generic assessments and vague scoring. Using the production or IT department as a pilot is recommended. In the current research, both the QC and IT departments were selected for assessment, as the goal was to introduce a new quality control approach to the industry.

Industries can either design or select an existing maturity model for their assessment. The most commonly referenced assessment dimensions in the literature include digital technology, digital product, digital operation, management commitment, culture, and people and expertise. Companies have the flexibility to adapt this model by adjusting the weight assigned to each dimension or sub-dimension in relation to their focus. Alternatively, they may choose to create and validate a new assessment model by adding or removing dimensions as needed. A variety of assessment tools are available, including one-on-one meetings, group discussions, journey mapping, questionnaires, service mapping, observation, and participation. Some methods require specific skills, while others demand experience. The choice of tool depends on the focus of the assessment and the time available.

The next step is to determine the target maturity level. Various indexing approaches are outlined in the literature. While these indexes differ, most digital maturity frameworks share a common progression: starting with "data generation," moving to "analytics," and ultimately reaching "autonomous decision-making." In this research, the six-level maturity index found from the literature is utilized. As with the selection of a maturity model, it is important to choose a digital maturity index that aligns with the specific nature and goals of the industrial setting.

After establishing the model, assessment technique, and maturity level index, following action is to analyze the assessment results. This can be accomplished by conducting a survey using a 5- or 7-point Likert scale. As mentioned earlier, a weighted average can be used to analyze the average scores. For instance, in a 5-point scale, high scores (4-5) indicate strong maturity in that dimension, while low scores (1) reflect lower maturity. Finally, summarize the scores for each maturity dimension to create an overall maturity profile, confirming the current maturity level alongside the targeted index.

6.3. Actions for industries based on digital maturity: A ZDM strategy perspective

Industries can tailor their actions based on their specific levels of digital maturity to effectively implement a ZDM strategy. For organizations at a lower maturity level, focusing on foundational technologies and basic data collection methods is essential to establish a robust digital infrastructure. As companies progress to a moderate maturity level, they can enhance their capabilities by integrating advanced analytics and automation tools. At a higher maturity stage, organizations should leverage real-time data analytics and digital twin to predict defects and improve quality control dynamically.

An effective execution of all the four strategies of ZDM; Detection, Prediction, Repair, and Prevention are highly dependent on high volume shop floor quality control data. However, each necessitates a different level of digital maturity. Taking the "Detection" strategy as an example, the initial and crucial requirement is access to historical data. In this scenario, having real-time data access and integrating machines is not imperative. An effective model for defect detection can be created using historical time-series quality inspection data from the manufactured product. In this case data collected from various devices can be collected and stored to the central database using offline system. This suggests that industries at levels 1 and 2 can successfully adopt and benefit from this strategy. At these stages, industries are primarily required to implement digital tools such as CNC machines. However, integrating all machines with the internet and collecting real-time streaming data across the entire system is not yet expected.

The next strategy, "Prediction," focuses on forecasting potential defects in products that have not yet been manufactured. This strategy requires a combination of historical and real-time data. Implementing it necessitates reaching Level 3 of digital maturity, where industries can generate real-time data about the products being produced through an effective integration of machines with the production line. Level 3 serves as a prerequisite for Levels 4 and 5 of digital maturity. At Level 3, industries adequately generate and present data in real time, while Level 4 enhances this capability by utilizing analytics to predict the future state of the product. The remaining ZDM strategies, "Repair" and "Prevent," involve decision-making that can be paired with either

"Prediction" or "Detection." Automating these strategies can be achieved by progressing to Level 6 of digital maturity, ultimately leading to autonomous data-driven decision-making.

In this dissertation after a carful digital maturity assessment of the case industry, a defect detection model has been developed. The model offers significant improvements to the quality inspection process in the steel industry based on its existing digital capabilities, and expected to result in notable reductions in time and cost of manual quality inspection activities. Approximately 20-25% of the total manufacturing time was consumed by quality inspection operations, with 57% of these tasks involving destructive tests that generate substantial waste. The production steel involves numerous complex quality parameters that are challenging for human inspectors to simultaneously consider and analyze.

In this regard, the model generates valuable information about the interconnectedness of these quality parameters, enabling more accurate defect detection. By implementing the proposed model, this burden of quality inspection can be reduced, leading to enhanced throughput rates and quality product. This, in turn, helps quality experts develop a deeper understanding of the intricate interrelation between the parameters, leading to more informed decision-making.

Furthermore, the model demonstrates relatively higher accuracy in detecting defects by incorporating dimensional measures such as rebar weight, diameter, cross-sectional area, rib height, rib spacing, transverse-rib inclination, and transverse-rib flank inclination. Previously, the lack of a mechanism to estimate the impact of dimensional measure deviations on the mechanical properties of steel rebar posed a challenge for the industry. The model addresses this gap by providing insights into the relationship between dimensional measures and mechanical properties of steel rebar, enabling more advanced quality control procedures.

Finally, the data analytics framework proposed can serve as a guiding tool for practitioners in developing an effective AI/ML-based model. This is particularly important because quality control operations have unique requirements that differ from other shop floor processes. By adopting this framework, industries can effectively determine the relevant product lifecycle phase, define the appropriate production stage for model implementation, carefully assess related data, select suitable analytics techniques, and align their strategies with ZDM objectives. This enables them to focus on early defect detection and prevention (starting from the product design phase) rather than relying on post-production inspections. The implementation challenges associated with data analytics in ZDM identified in this research are also useful to anticipate and address potential obstacles during the AI model development process.

A comprehensive implementation guide is presented in Table 6.1. Industries must assess their current digital status and develop a ZDM strategy accordingly. At the core of this process is a standardized data analytics framework essential for creating an AI-based model. This dissertation explores the “pre-implementation requirements” for ZDM, the “implementation of an AI-driven ZDM quality strategy,” and provides a “forward look.” The work concludes with a holistic implementation framework that integrates digital maturity, the data analytics framework for the AI detection model, and the execution of the ZDM strategy, ultimately addressing the general objective.

Table 6. 1: A comprehensive ZDM implementation guide

<table>
<tr><th>Pre-ZDM requirement</th><th colspan="2">ZDM implementation</th><th>Forward look</th></tr>
<tr><td rowspan="9">Digital maturity assessment

Input: The 7-step DM assessment strategic guide

Output: Confirmand maturity level</td><td colspan="2">Input:
• Standardized data analytics framework
• Confirmed digital maturity level</td><td rowspan="9">• Progress on the DM levels and ZDM strategies
• Continuous data collection and Fine tune the model</td></tr>
<tr><td>DM levels</td><td>ZDM strategies</td></tr>
<tr><td>Computerization</td><td rowspan="3">Defect detection</td></tr>
<tr><td>Connectivity</td></tr>
<tr><td>Visibility</td></tr>
<tr><td>Transparency</td><td rowspan="2">Defect prediction</td></tr>
<tr><td>Predictive capacity</td></tr>
<tr><td>Adaptability</td><td>Repair and Prevention</td></tr>
<tr><td colspan="2">Output: AI-based QC model</td></tr>
</table>

6.4. Theoretical implications

Throughout the research journey and analysis, significant scholarly implications have been deliberated upon. The development and testing of a hypothesized causal digital readiness model contribute to the advancement of industrial digital readiness research. By addressing a literature gap regarding lack of complex relationship analysis among the digital maturity model dimensions, this study enhances the theoretical framework and offers valuable insights into industrial readiness for digital change. The validation of structural equation modeling in this context strengthens the methodological rigor of future studies.

Utilization of AI techniques for quality inspection, aiming to advance the detection strategy of ZDM was the central aim of this research. The proposed ensemble learning model encompasses data collection, preprocessing, analysis of important quality parameters, hyperparameter optimization, model training, testing, and evaluation. These contributions enrich the understanding of the standard procedure for constructing defect detection models, benefiting academicians in the field. The research focuses on identifying a comprehensive set of product quality parameters and analyzing inspection records associated with these parameters. Incorporating a wide range of quality parameters enhances the model's accuracy and enables a more thorough analysis of steel defects. Diverse parameters increase the model's sensitivity in detecting various types and sizes of defects. By including dimensional measures as additional parameters, the model becomes more adept at identifying complex defects that may be overlooked with a limited set of variables.

The study also addresses the theoretical challenges and requirements related to defect detection model development including, data collection, emphasizing the importance of representative inspection data. This includes maintaining an adequate representation of both defective and normal samples, which is essential for developing a model with high estimation accuracy. Furthermore, the significance of explainable models is highlighted, explaining their role in bridging the gap between theoretical constructs and algorithmic complexity. These insights contribute to the advancement of defect detection model theory, offering a structured methodology that can be relevant across different study fields.

The content analysis conducted on the topic of data analytics provides a clear understanding of the current state of data analytics implementation in ZDM, including the phases of data utilization, implementation stages, data sources, analytics conditions, analytics types, and targeted ZDM strategies. This enables researchers to identify the prevailing trends and practices in the field. The insights gathered from the content analysis and implementation challenges identified pave the way to propose a standardized framework for realizing data analytics in ZDM. It integrates six important elements to consider while doing DA, advances existing scattered approach by providing a holistic and structured approach to implementing data analytics. It expands the understanding of how these elements interact and influence the effectiveness of data analytics in quality control.

Moreover, scholars can collaborate on the development of advanced analytics techniques tailored for ZDM. These techniques can address the implementation challenges encountered in data analytics for ZDM. Collaborative research efforts can focus on areas such as real-time data analytics, data fusion and integration, explainable machine learning algorithms, artificial intelligence, and optimization methods that are applicable to ZDM scenarios. By exploring and advancing these techniques, scholars can enhance the capabilities and effectiveness of data analytics in ZDM, ultimately contributing to improved quality control in manufacturing processes.

6.4.1. Defect detection model as a guide to the repair strategy

While it is crucial to prioritize the development of efficient inspection techniques, equal importance has to be placed on considering the potential implications that the detection model would have on the repair strategy. Defect detection model offers the potential for an effective repair strategy providing insights into the parameters that contribute to defects. It allows for the early identification of defects in the manufacturing process, overcoming the limitations of conventional approaches that often struggle due to the complex interdependencies among quality parameters at various stages of production. It facilitates early identification and repair of the underlying causes of quality issues, where deviations from the initial stages of production can be addressed and compensated for throughout the production process. This sequence of actions has been supported by a review of relevant literature, demonstrating that the ZDM detection strategy guides the repair of defects (Psarommatis et al., 2020; Dreyfus et al., 2022). This transition can be considered as from insight into detection to foresight into repair.

6.4.2. Detection as a transition to predict and prevent defects

Defect detection often serves as the initial step in the implementation of ZDM (Dreyfus et al., 2022). Once a defect is detected, the system learns from it to make predictions for the future. Specifically, the data collected by the defect detection model is primarily used to develop a model for prediction (X. Zheng et al., 2022). Therefore, an effective defect detection mechanism allows manufacturers to create predictive models and preventive measures resulting in reduction of quality inspection costs (Lario et al., 2024). This event has been supported by literature, demonstrating that the ZDM detection strategy facilitates repair in 56% of cases, prediction facilitates prevention in 37% of cases when paired ZDM strategies are employed (Psarommatis, May, et al., 2020a). This transition from detection to prediction and prevention strategies plays a vital role in realizing the ultimate objective of ZDM.

6.5. The ZDM continuous improvement cycle

Drawing on practical insights from the model and previous theoretical understanding of the sequence of actions involved in ZDM strategies (discussed on 6.4.1 and 6.4.2), the ZDM continuous improvement cycle is proposed with the defect detection model as its foundation. This cycle encompasses defect detection (or identification), followed by repair through localization and root cause analysis, prediction alongside repair, and continuous improvement through prevention, the DRPP cycle (Figure 6.2).

Detection (Defect Identification): The detection model identifies defects by analyzing quality parameters and complex relationships. This step ensures that defects are recognized early and accurately, setting the stage for repair.

Repair (Defect Localization and Root Cause Analysis): Defect localization involves identifying the exact production stages in a production process where defects arise. This process utilizes insights from a defect detection model, which examines the relationships between quality parameters and defects through feature importance analysis. The model determines which parameters have the greatest impact on defect occurrence. Once key features are identified, they can be associated with specific manufacturing stages. For instance, in steel quality control, high dimensional quality parameters are evaluated. If the model highlights that the defect is related to “Yield strength” and if "Carbon proportion" is considered as a critical factor in determining the yield strength from the feature importance analysis, it becomes straightforward to localize the defect to the “chemical composition analysis” stage, where Carbon proportion is crucial.

This targeted information aids in developing effective strategies to tackle root causes, allowing for a focused problem scope. By concentrating on the specific stage where the defect is detected, root cause analysis can examine both the equipment and quality parameters specific to that stage, rather than the entire production line. This approach enables targeted repairs to address localized issues efficiently, minimizing unnecessary effort and reducing downtime.

Prediction and Repair as an Integrated Process: Based on the detection model outputs, and the system predicts potential failures for the future production from the expected performance. Similar to the detection process, the repair method (localization and root cause analysis) is informed by these predictions, allowing for proactive interventions.

Prevention (Continuous Improvement): Insights from the prediction step are used to implement preventive measures, optimizing critical quality parameters. The Continuous Improvement process comes into play, as feedback from detection, repairs and prediction is integrated into the model. Over time, the detection model improves its ability to identify defects (via continuous data collection and model training and tuning), guide repairs, asset in building accurate prediction, and prevent recurrence creating a robust and self-improving quality control system.

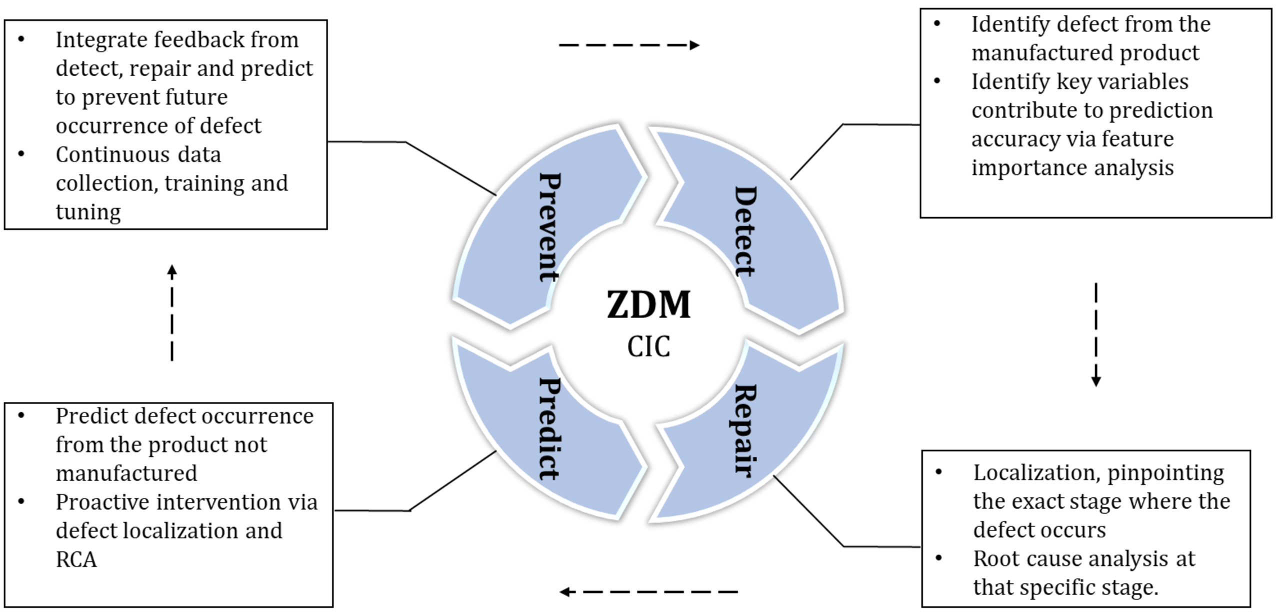


Figure 6. 2: The DRPP cycle (CIC: continuous improvement cycle), (Source: Authors)

Chapter Seven

Conclusions, Recommendations and Future Research Directions

7.1. Conclusions

Zero Defect Manufacturing primarily focuses on data and analytics to detect and prevent defects. Worldwide, the rise of virtual defect detection, a key component of ZDM, is revolutionizing quality inspection activity in steel industries. It is rapidly replacing manual inspection solely depending on data and bringing a promising detection accuracy result. Ethiopian steel industries face challenges of significant number of defective products due to manual inspection methods, which is costly and time consuming and leading to the waste of reprocessing of already manufactured product.

An initial aspect for the successful implementation of ZDM in steel industries is their digital readiness, encompassing components such as data generation from integrated machines, utilization through AI and machine learning, and a digitally skilled workforce. To achieve this, industries must enhance access to operational data through robust data infrastructure, effective data management, and advanced analytics capabilities. The identification of key digital readiness factors and their interconnections, as explored in this research, aids industries in understanding the basis critical to digital maturity. This study examines the direct and mediating effects of digital readiness factors. The findings highlight that employees' digital skills play a crucial mediating role in the relationship between digital technology adoption and digital maturity, statistically significant value (0.077**) have been found. This underscores the importance of enhancing digital competencies in parallel with other digital maturity dimensions to maximize the benefits of technological advancements and drive organizational digital transformation particularly in the steel industry. Also, the DM framework can serve as a tool for self-assessment.

Digital maturity is not about reaching a final destination or ultimate level; rather, it is about taking the initial steps to embark on the journey. Industries at the early stages of digital maturity have the opportunity to adopt advanced, data-driven operational frameworks. Therefore, conducting maturity assessments is crucial for shaping effective ZDM strategies or implementing AI-based quality monitoring systems. Additionally, understanding digital readiness enables a smoother transition to advanced technologies by identifying essential foundational steps. Before integrating

AI models, industries must first strengthen their data collection and management capabilities. Improved connectivity and integration between machines to facilitate seamless data sharing, together with investments in real-time analytics technologies, are recommended. By emphasizing digital maturity level increment, industries can progress to a successful implementation of ZDM strategies.

This research is crucial in establishing a clear understanding of how digital maturity directly influences the effective implementation of ZDM strategies. By linking maturity assessments with tailored ZDM strategies, leads industries to initiate their zero-defect journey, deploy AI and machine learning based models.

The assessment of the case industry identified the current maturity level as Level 2 (Connectivity). The result highlights a substantial digital maturity gap concerning people and expertise. When contextualizing these findings for Ethiopian industries and other developing economies, several unique challenges emerge beyond just digital expertise. Many industries in these regions grapple with limited resources, deficiencies in digital infrastructure, and a shortage of digitally skilled personnel. A maturity assessment can assist these industries in prioritizing their investments in technology and training, enabling them to concentrate on areas that will provide the most significant advantages.

Based on the assessment result, the decision was made to opt for a suitable ZDM strategy focused on detection. This involves the development of an AI-driven model utilizing quality inspection data from previously manufactured steel product. This model promises huge enhancements to virtual quality inspection process within the steel industry, particularly for the time and cost burdens brought from manual inspections. By incorporating this model, industries can streamline their quality inspection operations, resulting in improved throughput rates and higher-quality products. Steel product manufacturing involves intricate quality parameters that pose challenges for human inspectors; the model addresses this complexity by providing valuable insights into the interconnectivity of these parameters, facilitating more accurate defect detection and informed decision-making.

Furthermore, the model demonstrates enhanced defect detection accuracy, achieving scores of 0.9538, 0.9726, 0.9751, 0.9718, 0.9614, 0.983, and 0.964 across its output variables, by incorporating a comprehensive range of input quality parameters. These parameters directly influence the mechanical properties of steel, making them critical for ensuring final product quality. The model's ability to predict the influence of dimensional measure deviations on mechanical properties fills a crucial industry gap, enabling advanced quality control procedures. As detection is a foundational approach, it plays a key role in achieving the remaining strategies of ZDM, namely repair, prediction and prevention. In this context, insights have been provided on how defect detection, can be leveraged to establish a continuous improvement cycle within ZDM.

Standardized data analytics frameworks are needed for adequate field specific AI model development. In this regard, there was a gap in the literature concerning a standardized approach to data analytics in ZDM, as independent studies employ diverse methods to structure the data analytics process. Unbalanced product lifecycle phase consideration (design or operation), lack of clarity between in-line and online quality control, difficulties in terms of merging large and heterogenous source of data and difficulties in selecting the best analytics techniques based on the data type and streaming condition are the key challenges identified for the implementation of data analytics in ZDM. Based on these challenges, a generic framework for data analytics in product-oriented ZDM has been proposed and discussed in this dissertation.

7.2. Recommendations

This study has demonstrated how AI, particularly machine learning, can revolutionize quality control in manufacturing, with ZDM as a fundamental framework. Based on the findings, the recommendations are structured into three key areas: pre-ZDM implementation requirements for the industry, implementation of the AI-based ZDM quality strategy, and ZDM as a continuous improvement approach.

→ *Pre-ZDM implementation requirements from the industry:* steel industries in Ethiopia are currently at Level 2, implemented basic connectivity but still need to move to the next levels and be able to implement ZDM strategy beyond defect detection. The following 4 recommendations are given for this.

- Adopt advanced data collection technologies, such as sensors and cameras, along with the classical metrology instruments for real-time tracking of product quality parameters on the shop floor.

- Set up a centralized data center to store and manage large volumes of quality control data in real-time.

- Facilitate connectivity among machines for smooth shopfloor data sharing.

- Recognize the critical role of people and expertise in digital transformation. Implement ongoing training programs covering technical skills need to leverage digital technologies like data management, analytics, and AI.

→ *Implementation of the AI-based ZDM quality strategy:* the following 3 points are recommended to successfully integrate the proposed defect detection model.

- Continuously train and improve the model's defect detection capabilities, particularly by ensuring that there are sufficient samples of defective products to accurately estimate the occurrences of defects.

- The model helps to understand and localize the impact of each input quality parameters on the final product. Industries are recommended to leverage model's insights for early repair or prevention of defects.
- Industries are also recommended to implement the proposed data analytics framework to guide the integration of data analytics into ZDM practices.

→ *ZDM as a continuous improvement approach*

- Utilize the proposed digital maturity assessment guide to continuously conduct an assessment and adjust to the fitting ZDM strategy.
- Adopt a culture of continuous improvement where output from the first strategy (detection) is used as an input for the subsequent strategy (repair), and this process continues through all four strategies and make sure on its sustainability.

7.3. Future research directions

From the entirety of the research content, the subsequent critical avenues for future research have been identified and discussed to amplify the influence of the field of ZDM.

- *Real-time predictive model for industries beyond level 2:* Real-time data requires a completely different processing approach from batch (off-line) data. Thus, predictive model capable of processing data in real time for industries that have achieved level 3 and above can be a potential future research direction.

- *Integrating predictive and prescriptive analytics algorithms to realize paired strategies of ZDM.*
- *Developing a robust data fusion model to utilize all the shop floor level data:* The proper fusion of data from multiple data sources increases the insights gained in all aspects. Therefore, future research on ZDM may focus on developing a robust data integration/fusion model.
- *Integrate interpretability into the ML model:* Combining evolutionary algorithms with ensemble learning techniques. By employing these approaches, the model can achieve defect detection performance similar to that of black-box models, while still retaining interpretability.
- *Developing semi-supervised or active learning approaches:* That intelligently utilize labeled data along with unsupervised techniques to overcome the challenges with limited labeled defect data.
- *Consider other sectors:* Including leather industry, textile industry, and chemical industry.
- *Finally, the study focused on a developing economy Ethiopia*: Comparably internet infrastructure and penetration are just in its infant stage. Thus, many new digital technologies are yet to catch up with industries. It is, therefore, likely that a future study in a country that exhibits a higher use of digital technologies.

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Appendix A: Major Accomplishments during the PhD Study period

Journal Articles Published

- Mehret et. al., (2024). "Data analytics in zero defect manufacturing: A systematic literature review and proposed framework". *International journal of production research. DOI: 10.1080/00207543.2024.2382379*
- Mehret et. al., (2024). "Application of artificial intelligence to enhance manufacturing quality and zero-defect using CRISP-DM framework". *International journal of production research. DOI: 10.1080/00207543.20242407919*

Conference Paper Presented and Published

- Mehret & Eshetie (2023). "Analysis of Factors affecting the Digital Maturity of Manufacturing Industries: Evidence from the Metal Sector in Ethiopia." *ASRIC Journal on Engineering Sciences Vol.4(1), 1-14. ISSN 2795-3548 (online), 2795-3556 (print),* presented on 6TH ASRIC conference held in Rabbat, Morrocco from November 12 – 15, 2023.

Courses Delivered

Assist 2 Post Graduate Courses

- Project management (two semesters), (for Ethio telecom technical staffs)
- Research methods (for MIDI staffs)

Co-Advising

- 6 MSc theses (4 successfully completed)

Short term research visit

- A three-month research visit to University Technische Hochschule Nürnberg NCT research center, Germany on the year 2023/2024.

Professional Memberships

- International Society for Industrial Engineering and Operations Management (IEOM), Membership Type: Student Member, Duration: 2023 – 2025, Involvement: Actively participated in annual IEOM conferences papers revision and contributed to industrial engineering study field.

Peer Review

- Reviewed 2 conference papers for the "*5th International Conference on Industry 4.0 and Smart Manufacturing",* held in Lisbon Portugal, from November 22, 2023 - November 24, 2023
- Reviewed 1 article for "*The international journal of production research"*

Appendix B: A systematic literature review content analysis

No	**Author**	**Industry**	**Data utilization phases**		**Manufacturing condition**		**Triggering (detective, predictive)**	**Action (prescriptive)**	**Method (triggering)**	**Method (action)**	**Production phase**			**Data infrastructure**
			Design	Operation	Real-time	offline					Preprocess	In process	Post process	
1	(Kumar et al., 2024)	Additive manufacturing		*	*		Detection		DL\ML			*		Industrial camera
2	(Psarommatis & May, 2024)	Comparative analysis												
3	(Apostolou et al., 2024)			*		*	Detection		ML				*	Sensors
4	(Taatali et al., 2024)			*	*		Detection		ML			*		Industrial camera
5	(Y. Zhang et al., 2024)	LR												
6	(Zeiser et al., 2023)	Additive manufacturing		Not sta	*		Detection		ML			*		Industrial camera
7	(L. P. Zhao et al., 2023)	Metal		*	*		Prediction	Prevention	SA/ML	ML			Not	Inspection machine\historical data
8	(Sen et al., 2023)	General		*	*		Prediction		ML			*		Sensor
9	(Fragapane et al., 2023)	LR												
10	(Leberruyer et al., 2023a)	Automotive	*		*		Detection	Repair	ML	ML	*			Process documentation, operator, sensors

11	(Verna et al., 2023)	Metal	*			Not s	Prediction		PM				*	Process documentation
12	(Afolaranmi *et al.*, 2023)	Food and beverage		*	*		Prediction		ML			*		Inspection machine, sensors
13	(Psarommatis, *et al.*, 2023)	LR												
14	(Ghibaudo et al., 2023)	Steel		*	*		Prediction		SA			*		Industrial camera
15	(Moliner-Heredia *et al.*, 2023)	General		Not st		*	Prediction		SA					Inspection machine, operator knowledge
16	(Araújo et al., 2023)	Metal		*	*		Detection		SA			*		Inspection machine
17	(Gauder, Bott, et al., 2023)	Metal		*		*	Detection		SA			*		Sensors
18	(Yeh & Chen, 2023)	Semiconductor		*		*	Predict		SA			*		Process documentation
19	(Lanza et al., 2023)	Metal		*		*	Predict		SA			*		Simulation data
20	(Jung et al., 2023)	Metal		*		*	Detection		ML			*		Simulation data
21	(Manivannan, 2022)	Additive manufacturing		Not st		Not s	Detection		ML				Not st	Cameras
22	(Y. Zhang & Yan, 2023)	LR												
23	(Beckert et al., 2023)	Metal	*		*		Prediction/ detection	Compensation /prevent	ML	AI	*			Sensors and industrial cameras
24	(Wan & Leirmo, 2023)	LR												
25	(Venanzi et al., 2023)	General		*	*		Predict		ML				*	Sensors
26	(Azamfirei *et al.*, 2023)	LR												

27	(Dellarre et al., 2023)	Additive manufacturing		Not st		Not	Detection						Not st	cameras
28	(X. Liu et al., 2023)	Electronics		*		Not	Detection		ML			*		Inspection machine
29	(S. Li et al., 2023)													
30	(Mateo-Casalí et al., 2023)	Maturity model												
31	(Gauder, Gölz, et al., 2023)	Metal		*		*	Detection		ML/SM			*		Sensor
32	(Babalola et al., 2023)	Metal/welding		*	*		Detection		ML			*		Sensor
33	(Lv et al., 2023)	Metal		*	*		Detection		ML/DT			*		Sensor
34	(Discepolo et al., 2023)	Metrology system					Detection		Other					Sensor, camera
35	(Pasquinelli et al., 2023)	Metrology system					Detection		SM					Camera
36	(Medici et al., 2023)	Thermal		*	*		Detection		Other				Not	Sensor
37	(Vojtko et al., 2023)	General		Not st		Not							Not	
38	(Hsieh et al., 2023)	Metal		Not st	*		Detection		SA/TS				Not	Sensor
39	(Viet Que et al., 2023)	General		Not st		Not							Not	
40	(Ghansiyal et al., 2023)	Metal		*		*	Detection		ML			*		Industrial camera
41	(X. Li et al., 2023)	Metal			*		Prediction		ML					Sensors
42	(H. Zhang et al., 2023)	Metal		*		*	Detection		ML			*		Industrial camera
43	(Caiazzo et al., 2022)	LR												

44	(Trebuna et al., 2022)	System design												
45	(Psarommatis & May, 2022)	Framework												
46	(Gladines et al., 2022)	Additive manufacturing		*		*	Detection		MV			*		Industrial cameras
47	(Petrillo et al., 2022)	General manufacturing		Not st	Not		Detection	Repair	ML	ML			*	Sensors
48	(Spantideas et al., 2022)	Printing industry		*		*	Detection		ML			*		Process documentation
49	(Martínez et al., 2022)	Food and beverage		*	*		Predict	Prevent	ML	ML			*	Process documentation, operator, camera, sensor
50	(Psarommatis & Kiritsis, 2022)	Semiconductor		*		*	Detect	Repair	ML	DSS(L-BM)			*	Process documentation and sensor
51	(Catalucci et al., 2022)	LR												
52	(Foivos & Gokan, 2022)	LR												
53	(Dreyfus et al., 2022a)	LR												
54	(Kronauer et al., 2022)	Steel industry		*	Not		Prediction		SA			*		Process documentation
55	(Sousa *et al.,* 2022)	Steel		Not st	*		Detection (VM)		SA				Not st	Sensors
56	(Psarommatis & Bravos, 2022)	Conceptual FW												
57	(Grobler-Dębska *et al.,* 2022)	Metal industry		*		*	Detection	Repair	ML	L-BM		*		Inspection Machin, sensors

58	(Psarommatis *et al.*, 2022a)	Metal		*	*		Predict	Prevent	SA	MP		*		Process documentation
59	(Eger et al., 2022)	Metal		*		*	Detect		ML			*		Sensor, process/product documentation
60	(Danishvar *et al.*, 2022)	Semiconductor		*	*		Predict		ML			*		Sensor
61	(Su et al., 2022)	Metal		*		Not	Detection		MV/DL				*	Industrial camera
62	(Christou et al., 2022)	Fashion industry		*		*	Prediction		ML			*		Sensor
63	(Stavropoulos, 2022)	Metal		*	*		Prediction		DT			*		Sensor
64	(Subramaniam *et al.*, 2022)	Metal		*		Not	Detection		ML			*		Industrial camera
65	(Cavone et al., 2022)	Automotive		*	*		Prediction		DT			*		Sensors
66	(Psarommatis *et al.*, 2022b)	LR												
67	(Leonhardt *et al.*, 2022)	General		*		*	Prediction		ML			*		Sensor
68	(Powell et al., 2022)	LR												
69	(Margetis et al., 2022)	System design												
70	(Psarommatis, Danishvar, et al., 2022)	Metal		*	*			Repair		SA/MP				Historical data/process documentation
71	(Ye & Liu, 2022)	Semiconductor		*	*		Not		SA				Not st	Sensor
72	(Bousdekis et al., 2022)	LR												

73	(Martinez et al., 2022b)	Steel	*		*		Predict	Repair, prevent	SA			*		Sensor, process data
74	(Udphzrun, 2021)	Framework			Not									
75	(Powell *et al.*, 2021)	LR												
76	(Azamfirei *et al.*, 2021)	LR												
77	(Konstantinidis *et al.*, 2021)	Automotive		*		*	Detection		ML/MV			*		Industrial camera
78	(Levichev *et al.*, 2021)	Metal		*	*		Detection		ML/MV			*		Industrial camera
79	(Menoncin *et al.*, 2021)	Automotive		*		*	Detection		Other			*		Process documentation
80	(Armendia *et al.*, 2021)	Wind energy		Not st		*	Detection		SA				*	Sensors
81	(Papageorgiou et al., 2021)	LR												
82	(Gramegna, 2021)	Metal		Not st	*		Prediction		DT				Not st	Sensors
83	(Dias et al., 2021)	Wood		*		*	Prediction	Prevent	ML/AI	EC		*		Sensor, process documentation
84	(Plakhotnik et al., 2021)	Metal		*		*	Detection		DT			*		Process documentation, simulation
85	(Psarommatis, 2021)	System design & development			Not									
86	(Caccamo et al., 2021)	System design & development												
87	(Fraile et al., 2021)	System design &development			Not									

88	(Verna et al., 2021)	Additive manufacturing		*		*	Detection		PM			*		Inspection machine
89	(Tiwari & Khan, 2021)	General		*	*								*	
90	(Baghbanpourasl *et al.*, 2021)	Metal		*	*		Detection		SA				*	Sensors
91	(Balzategui *et al.*, 2021)	Electronics manufacturing		*	*		Detection		ML			*		Industrial camera, sensor
92	(Re et al., 2021)	System design												
93	(Sølvsberg *et al.*, 2021)	Metal		*	*		Detection		ML			*		Inspection machine, sensor
94	(Mourtzis *et al.,* 2021)	Metal	*			*					*			
95	(Psarommatis & Kiritsis, 2021)	LR												
96	(Pang et al., 2021)	Metal		Not st		Not s	Detection		ML/DL				Not st	Inspection machine
97	(Weichhart et al., 2021)	System design												
98	(Vali et al., 2021)	Steel		*		*	Detection		ML			*		Industrial camera
99	(Antunes & Jesus, 2021)	Stone industry		*		Not	Detection					*		Camera
100	(Escobar et al., 2020)	General					Detection		ML			*		Process documentation
101	(Anaya et al., 2020)	Framework		*		Not s	Prediction	Prevent	SA	L-BM		*		Sensor
102	(Fabrizioli et al., 2020)	Automotive		*		*	Detection		AI/ML/DT			*		Sensor
103	(Konstantopoulos *et al.*, 2020)	General		*		*	Prediction		ML/AI				*	

104	(J. Wang et al., 2020)	Aerospace		*		*	Detection		ML/AI			*		Inspection machine
105	(Reiff et al., 2020)	System design				Not								
106	(Lindström et al., 2020)	Framework												
107	(Groen et al., 2020)	Steel industry		*		*	Prediction	Prevent	ML&SA	MP		*		Sensor
108	(Pagani et al., 2020)	Metal		*	*		Prediction		DL/ML				*	Industrial camera
109	(Ou et al., 2020)	Metal		Not st		Not	Detection						Not st	
110	(Nazarenko et al., 2020)	System design												
111	(Egera, F., Reiffa, C., Tempelb, P., Magnaninic, M. C., Caputod, D., Lechlera, A., 2020)	Aerospace industry		*		*	Prediction	Prevent	SA	MP			*	Sensor, inspection machine
112	(Campbell et al., 2020)	Framework												
113	(Psarommatis, May, et al., 2020b)	LR												
114	(Editor, 2020)	Electronics manufacturing		*	*		Prediction		ML(SVM/DT)			*		Industrial camera
115	(J. Schmitt et al., 2020)	Electronics manufacturing		*		*	Prediction		ML/ECC			*	*	Sensor
116	(Brito et al., 2020)	General				Not s	Prediction		ML/RL				Not st	Sensor
117	(G. Liu, 2020)	LR												
118	(Yuan et al., 2020)	Semiconductor		*		*	Prediction		SA				Not st	Process data

119	(Jacobs et al., 2020)	General		Not st		*	Detection		Other				Not st	
120	(Herranz et al., 2019)	Metal industry		Not st	*		Detection		ML/clustering				Not st	Sensors and Process knowledge and specifications
121	(Lee et al., 2019)	Electronics		*		*	Prediction					*		Operator
122	(Magnanini et al., 2019)	Framework/architecture				Not								
123	(Eger et al., 2019)	System design and development				Not								
124	(Stief et al., 2019)	Electronics industry		Not st		*	Prediction		SA				Not st	Sensor
125	(Grevenitis et al., 2019)	Framework												
126	(Chiara et al., 2019)	Metal		*		*	Detection		SA			*		Inspection machine
127	(Zorrer *et al.*, 2019)	Aerospace industry		*	*		Detection	Rework	ML	L-BM		*		Sensor & Industrial camera
128	(Teti *et al.*, 2019)	Aerospace industry		*	*		Detection					*		Inspection machine
129	(Gambardella et al., 2019)	Steel industry		*		*	Detection		ML/CNN			*		Industrial camera
130	(Eitzinger & Eitzinger, 2019)	Aerospace industry		*	*			Rework		SM			*	Sensor
131	(Psarommatis & Kiritsis, 2019)	Framework					Detection	Other		Other				
132	(Eitzinger & Eitzinger, 2019)	General		*		*		Rework		SM		*		Sensor & operator

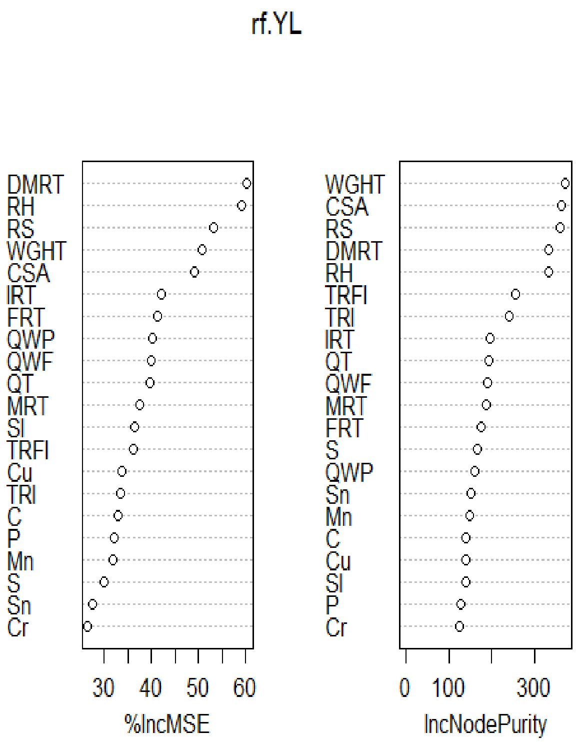
133	(Lin et al., 2019)	Automotive		*	*		Detection		Not spec.				*	Inspection machine
134	(Hsieh et al., 2019)	Fiber manufacturing		*	*		Detection		Not spec				Not st	Process documentation, sensor
135	(Baghbanpourasl et al., 2019)	Metal		*	*		Prediction		ML				*	Process documentation, sensor
136	(Udood et al., 2019)	Metrology system		*		Not	Detection						Not st	
137	(Eger *et al.*, 2018a)	Aerospace, railway, medical		*	*		Detection	Rework	SA & ML	SM		*		Sensor, operator, camera
138	(Chiariotti, 2018)	Electronics industry		*	*		Detection		ML			*		Sensor
139	(Eger *et al.*, 2018b)	General		*		*	Detection		ML			*		Sensor/inspection machine
140	(Leitão et al., 2018)	System design				Not								
141	(Cirp et al., 2018)	Framework				Not								
142	(Lee *et al.*, 2018)	Metal industry		*		*	Detection						*	Inspection machine
143	(Rocha et al., 2018)	Electronic motor		*		*	Detection		ML			*		Sensor/operator/inspection machine
144	(Peres et al., 2018)	Electronic industry		*		*	Detection		ML			*		Sensor/operator/inspection machine
145	(Colledani et al., 2018)	Automotive industry		*	*		Prediction	Prevent	PM	MP		*		Inspection machine
146	(Pradal & Yakubov, 2018)	Automotive industry	*		*		Prediction		Simulation		*			Inspection machine

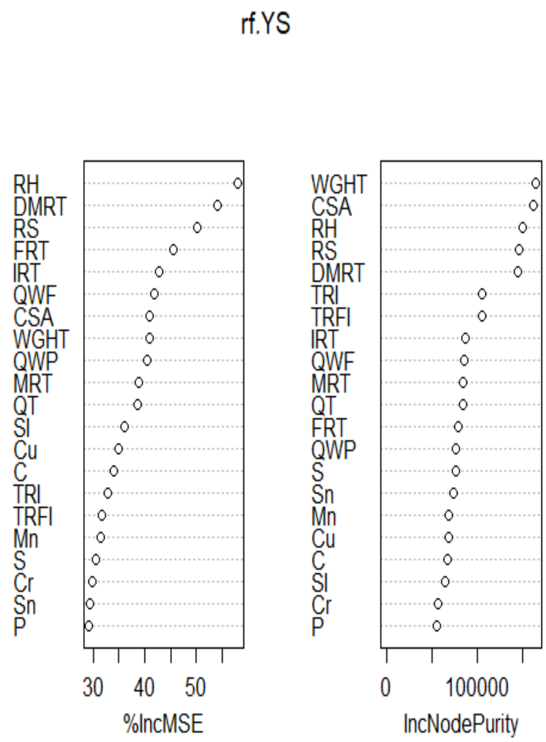
147	(Stavropoulos et al., 2018)	Automotive industry		*		*	Detection		MV/ML			*		Industrial cameras
148	(Huang et al., 2018)	Semiconductor industry		*	*		Detection/prediction		ML/AI			*		Process knowledge and specification
149	(Geczy et al., 2018)	Metal industry		*		*	Detection		MV			*		Industrial camera/sensor
150	(Dimla, 2018)	Metal industry		*	*		Prediction		ML				*	Sensor
151	(Colosimo, 2018)	General		*		*	Prediction		ML			*		Cameras, sensors
152	(Barbosa et al., 2018.)	General		Not st		Not s	Detection		Not spec				Not st	Not
153	(B & Ba, 2018)					*	Not spec		Not spec				Not st	Not
154	(Pinto & Silva, 2017)	Automotive industry	*			*	Detection		Simulation		*			Process knowledge and specification
155	(Alexopoulos & Packianather, 2017)	Pharmaceutical industry		*		*	Detection		ML			*		Process knowledge and specification
156	(Vafeiadis et al., 2017)	General		*	*		Prediction	Prevent	Statistical & ML	ML			*	Sensor
157	(Kiraci et al., 2017)	Automotive industry		*	*		Detection		Statistical			*		Sensor
158	(Abell et al., 2017)	LR												
159	(Siew *et al.*, 2016)	Printing industry		*	*		Prediction		Statistical & ML			*		Inspection machine
160	(Caggiano et al., 2016)	Electronic industry		*		*	Detection		ML				*	Sensor
161	(Ngo & Schmitt, 2016)	Framework				Not								

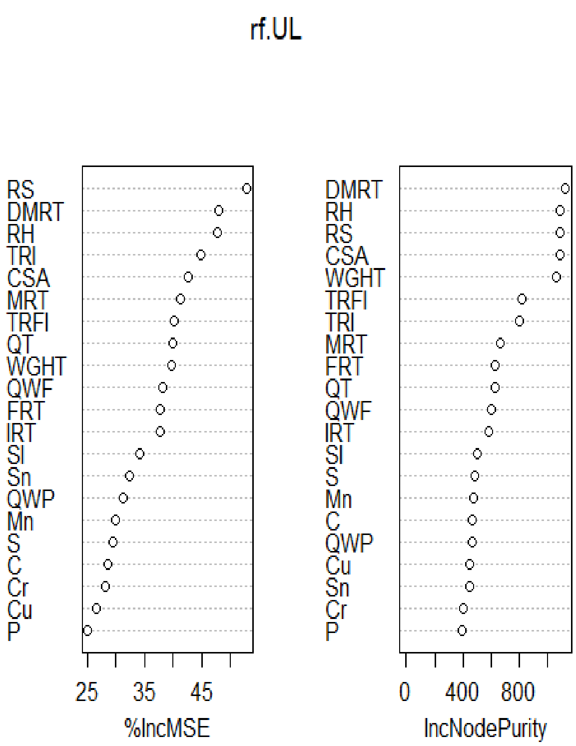
162	(Llanos et al., 2016)	Steel industry		*		*	Detection	Repair	SA	Simulation			*	Inspection machine
163	(Colledani *et al.,* 2016)	General		*	*							*		Inspection machine
164	(Eleftheriadis & Myklebust, 2016)	Framework				Not								Sensor
165	(Liedtke & Ph, 2016)	LR												
166	(Caggiano et al., 2015)	Metal industry		*	*		Detection		Sensor monitoring			*		Sensor
167	(Teti, 2015)	Steel industry		*		*	Detection		Sensor monitoring			*		Sensor
168	(D'Addona, Matarazzo, Sharif Ullah, et al., 2015)	General		*	*		Prediction		ML				*	Industrial camera
169	(Colledani et al., 2015)	Automotive industry		*		*	Detect		Other				*	Inspection machine
170	(Zoesch *et al.,* 2015)	Automotive industry		*		*	Detection		Statistical			*		Sensor
171	(Centobelli *et al.,* 2015)	Aerospace industry		*		*	Detection		Sensor monitoring			*		Sensor
172	(D'Addona *et al.,* 2015b)	Ceramic industry		*	*		Prediction		ML				*	Sensor & Process knowledge and specification
173	(Vinod et al., 2015)	LR												
174	(Linares et al., 2015)	Metal industry		*		*	Detection		Sensor monitoring			*		Industrial camera
175	(Llanos *et al.,* 2014)	Metal industry		*		*	Detection	Repair					*	Inspection machine

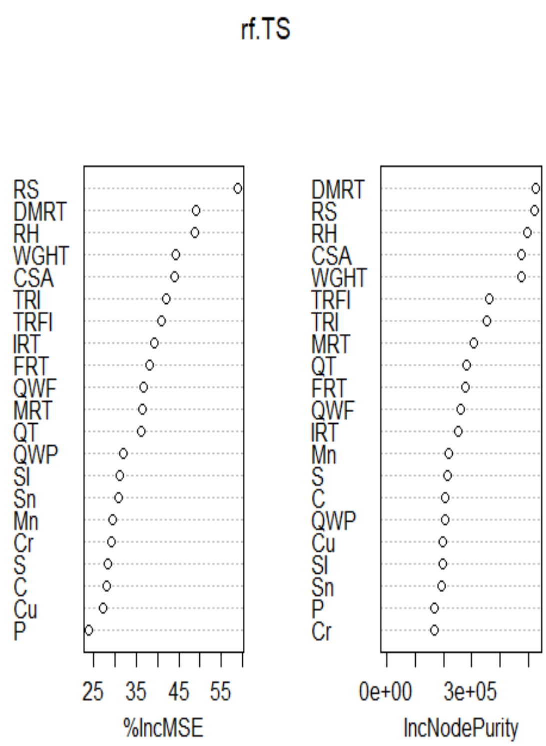
176	(R. Schmitt et al., 2014)	Framework												
177	(Myklebust *et al.*, 2014)	System design				Not								
178	(Georgiadis *et al.*, 2014)	Metal industry		*		*	Detection		Other			*		Inspection machine & sensor
179	(Meier & Georgiadis, 2014)	Metal industry		*		*	Detection		Simulation			*		Sensor
180	(Colledani et al., 2014)	Automotive industry		*		*		Repair		Optimiz ation		*		Process knowledge and specification
181	(Ferretti et al., 2013)	Framework				Not s								
182	(Qian *et al.*, 2013)	Metal industry		*		*		Prevent				*		Sensor
183	(Ransing et al., 2013)	Metal industry		*		*	Predict		ML			*		Process knowledge and specification
184	(Myklebust, 2013)	System design												
185	(Di Foggia & D'Addona, 2013)	Framework												
186	(K. S. Wang, 2013)	Framework												
187	(Schmidt & Hanitzsch, 2012)	Framework												
188	(Yuan et al., 2011)	Electronics		Not st		*	Prediction		ML				Not st	Historical data, process documentation

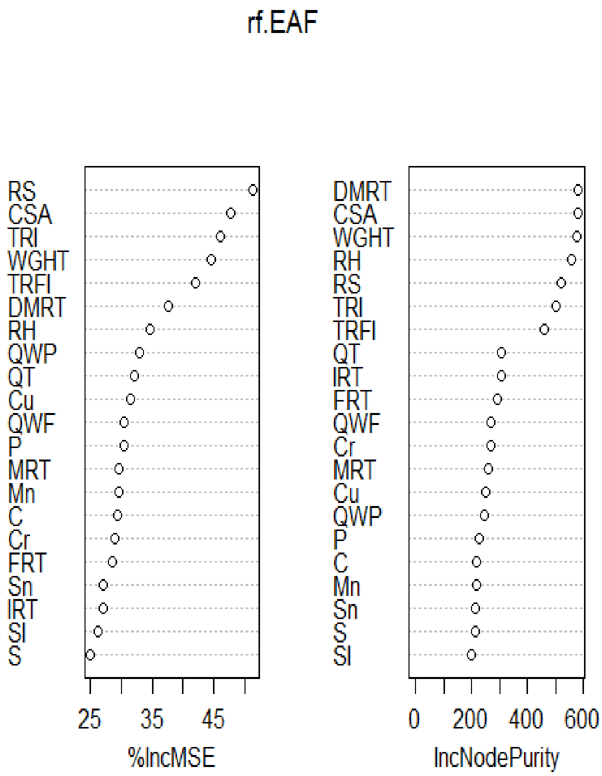
Appendix C: Feature importance analysis results of each output variables from the random forest mode model











rf.EAF
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WGHT
TRFI
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QWP
QT
Cu
QWF
P
MRT
Mn
C
Cr
FRT
Sn
IRT
SI
S
25
35
45
%IncMSE
DMRT
CSA
WGHT
RH
RS
TRI
TRFI
QT
IRT
FRT
QWF
Cr
MRT
Cu
QWP
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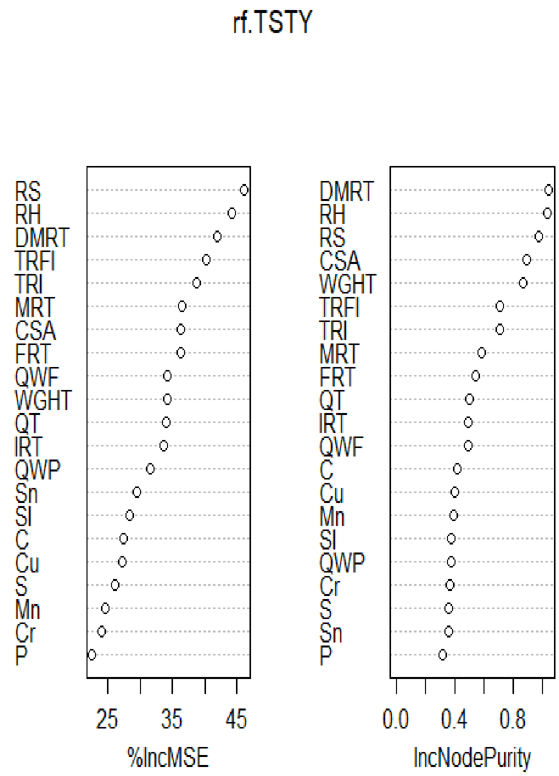
C
Mn
Sn
S
SI
0
200
400
600
IncNodePurity



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C
Cu
S
Mn
Cr
P
25
35
45
%IncMSE
DMRT
RH
RS
CSA
WGHT
TRFI
TRI
MRT
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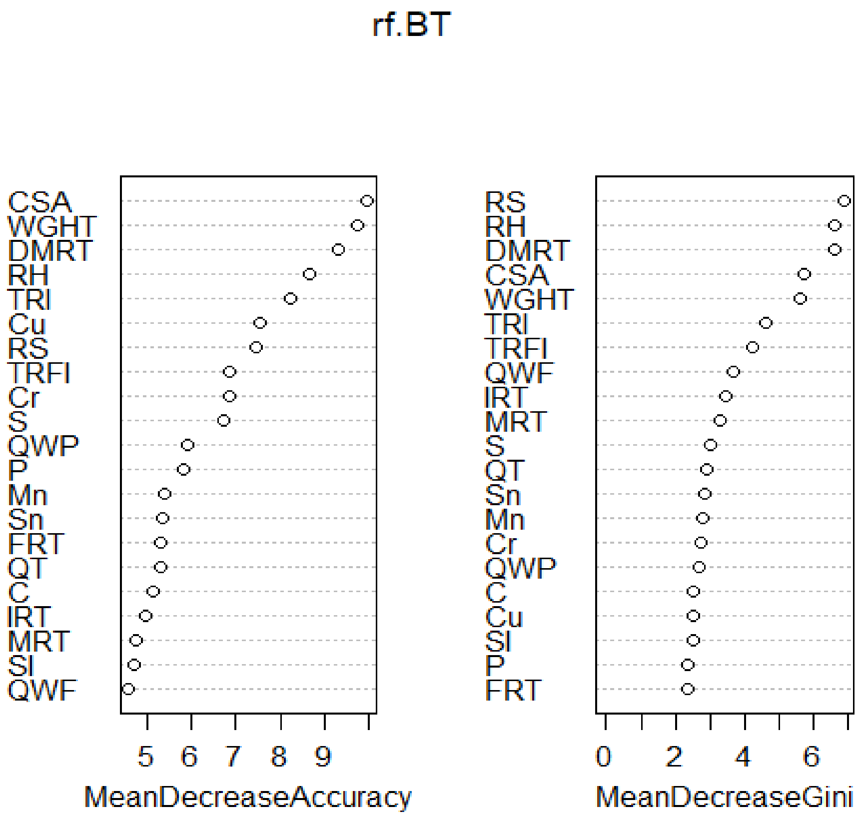
0.8
IncNodePurity


rf.BT
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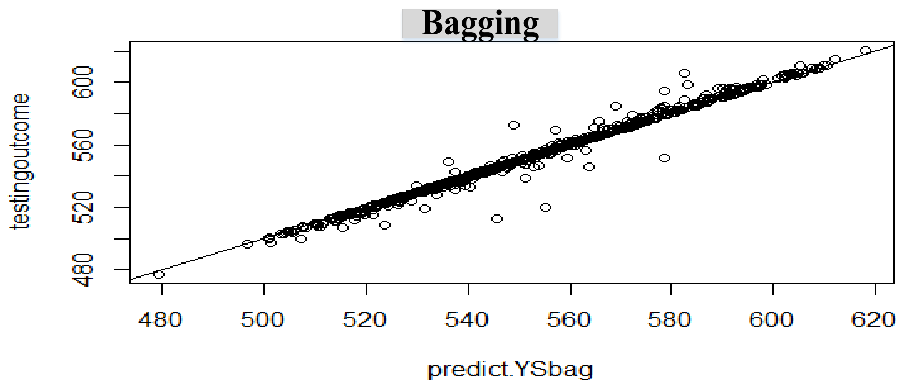
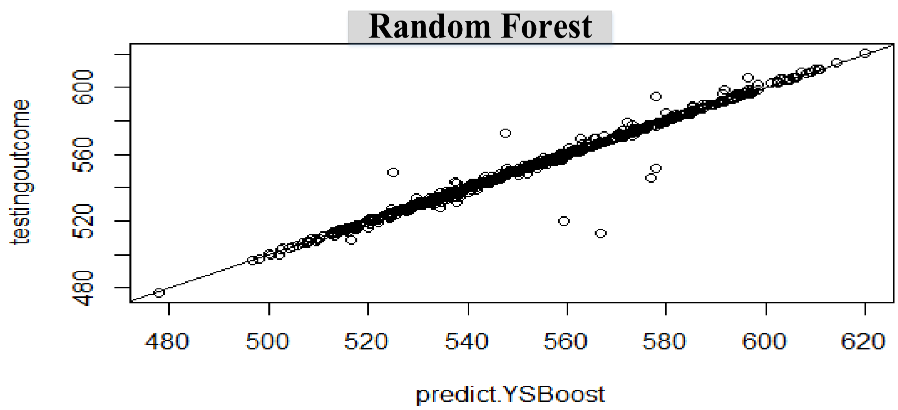
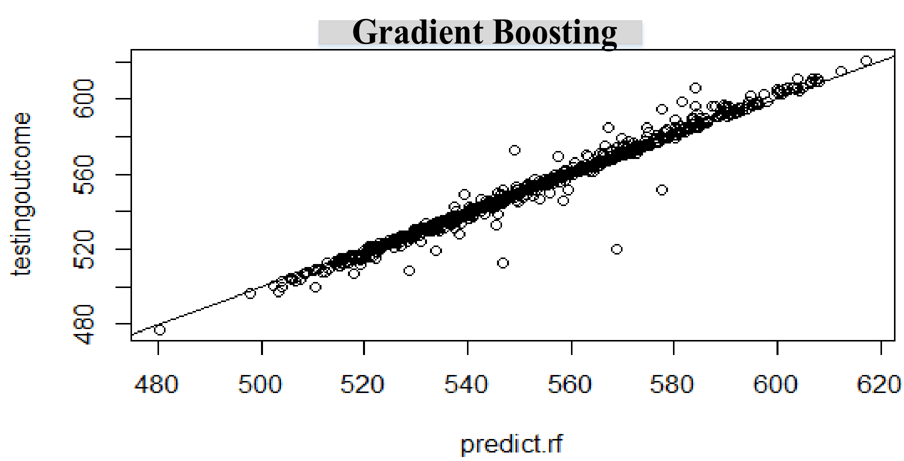
RH
TRI
Cu
RS
TRFI
Cr
S
QWP
P
Mn
Sn
FRT
QT
C
IRT
MRT
SI
QWF
5 6 7 8 9
MeanDecreaseAccuracy
RS
RH
DMRT
CSA
WGHT
TRI
TRFI
QWF
IRT
MRT
S
QT
Sn
Mn
Cr
QWP
C
Cu
SI
P
FRT
0 2 4 6
MeanDecreaseGini

Appendix D: Detection results of each output variables from the three ensemble methods

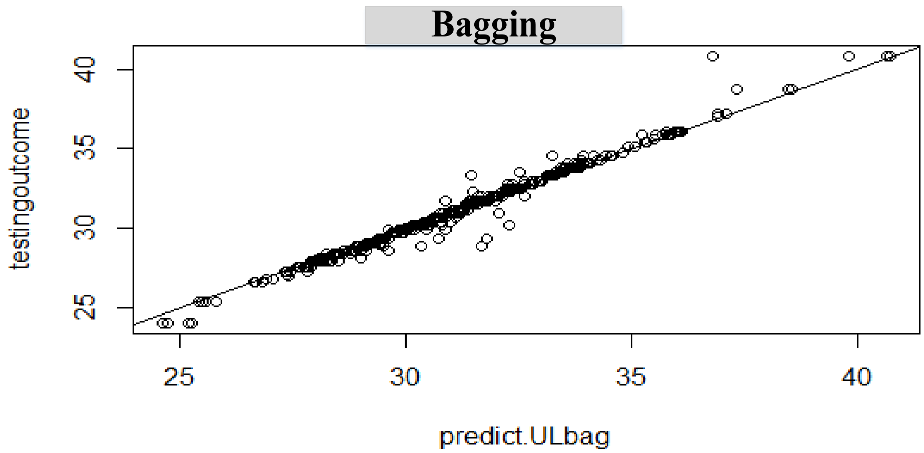
Yield Stress (N/mm^2)

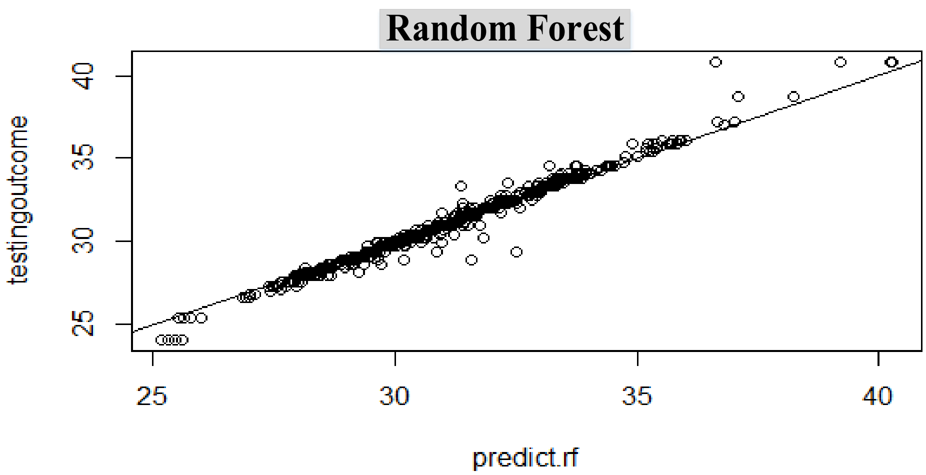


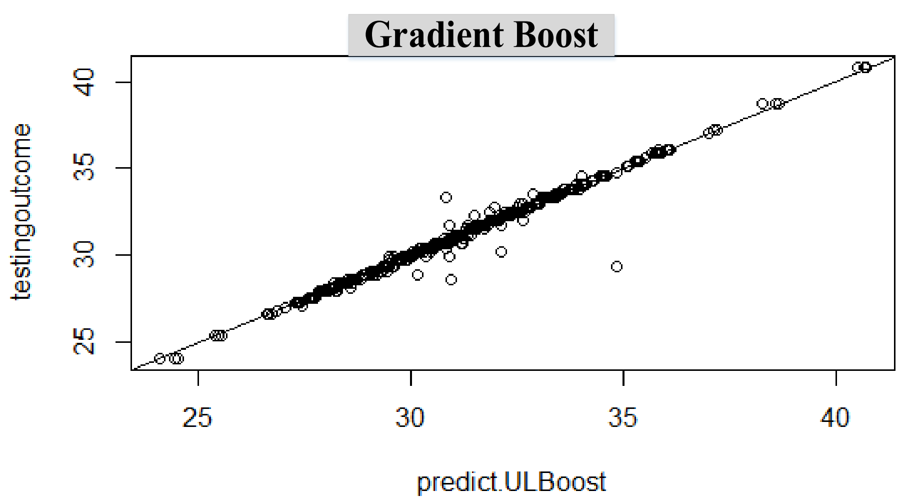




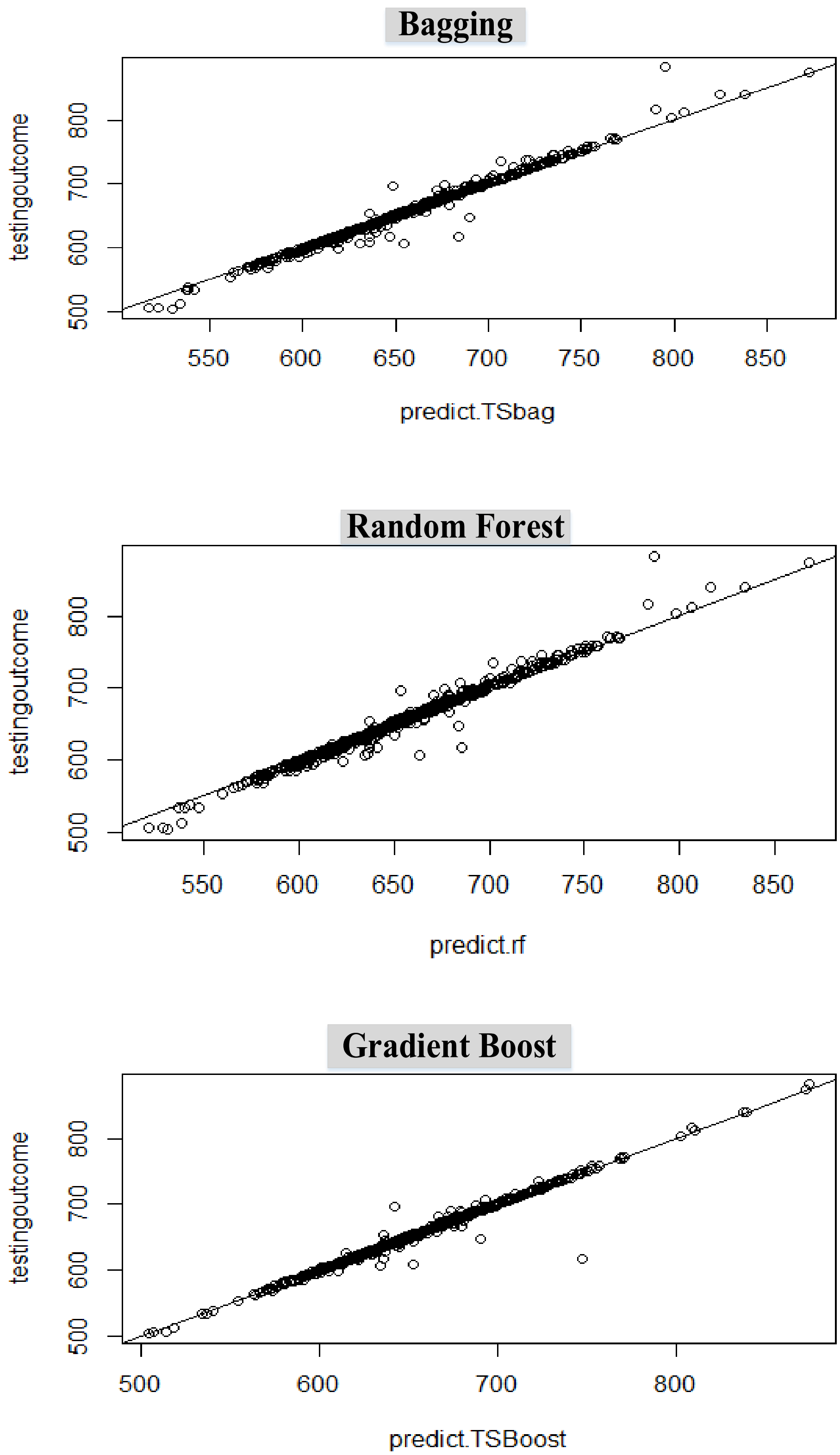
Ultimate Load (KN)



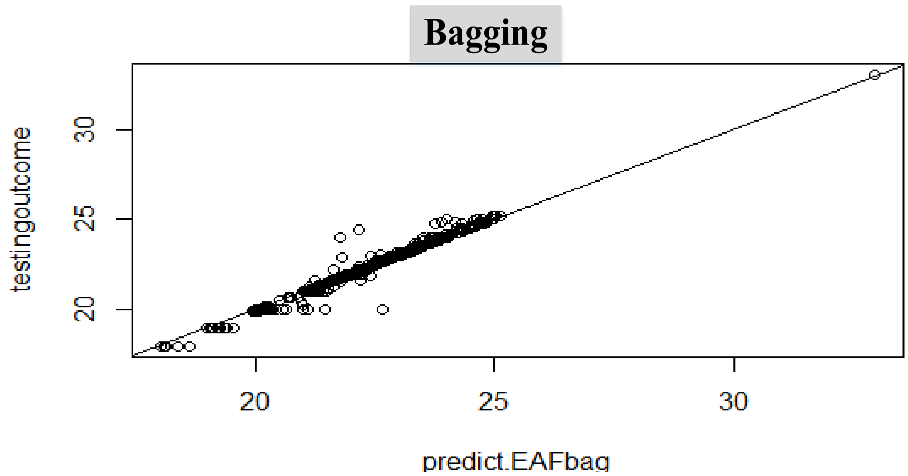


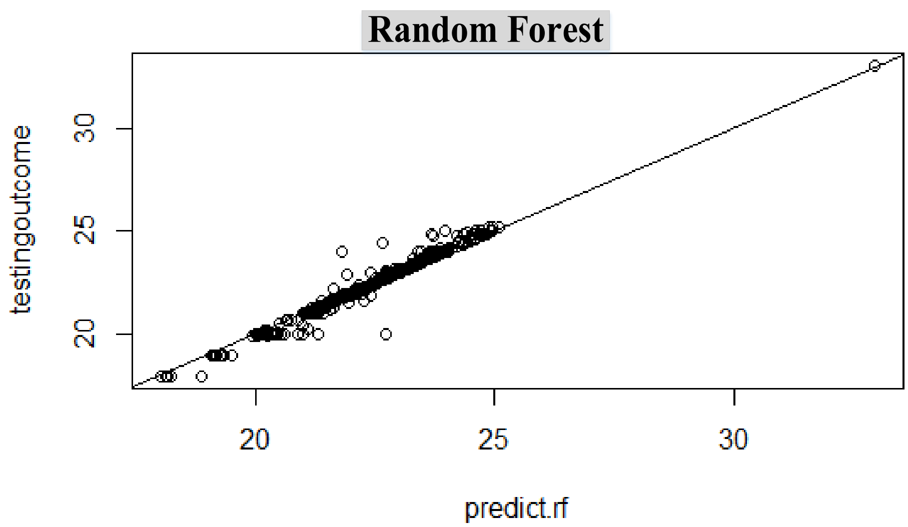


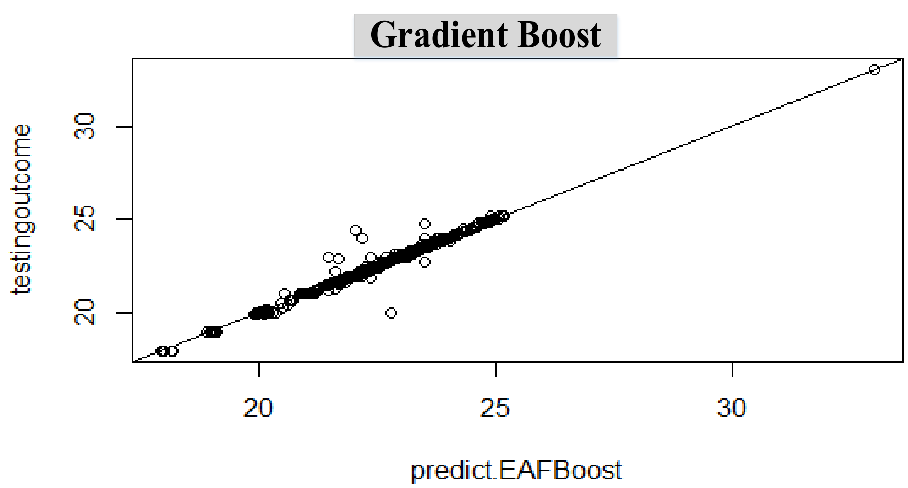
Tensile Strength (N/mm²)



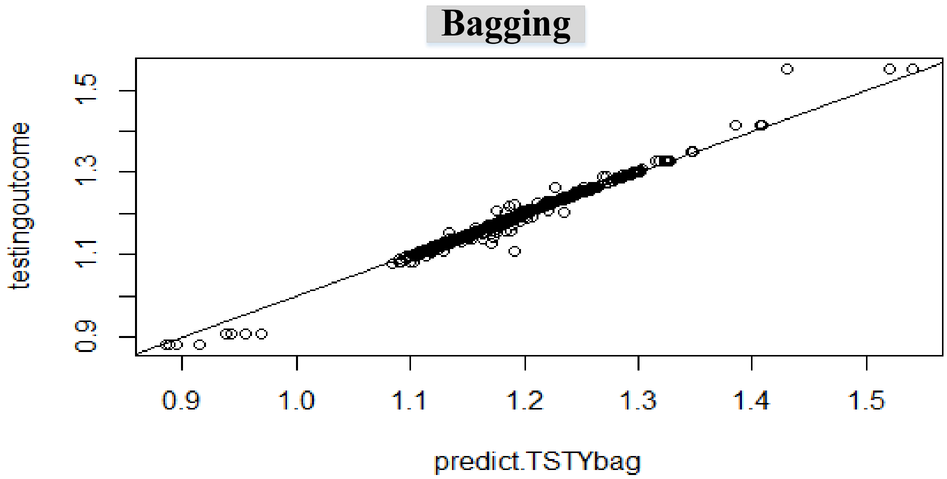
Elongation After Fracture (%)

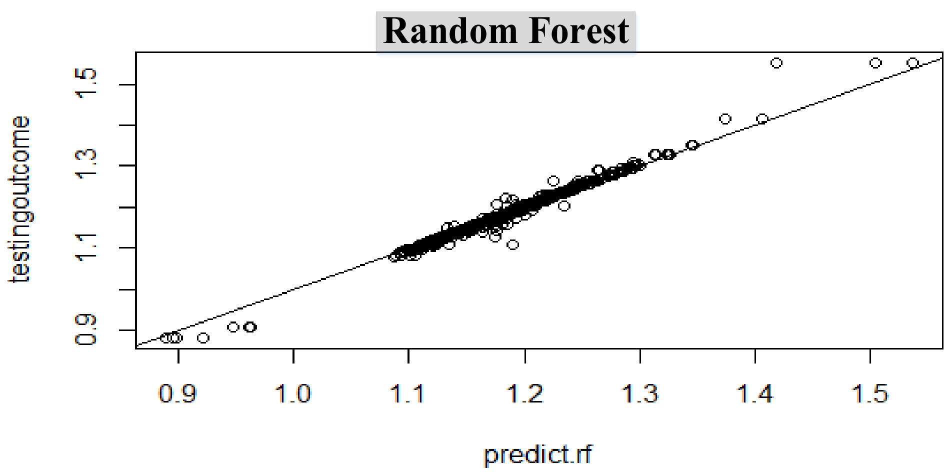


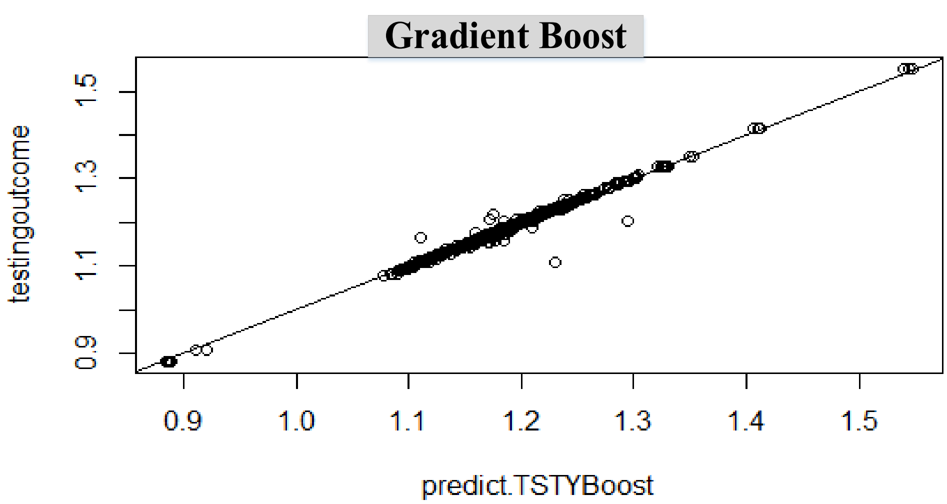




Tensile Strength-to-Yield Strength ratio(TS/TY)







Appendix E: Close-ended questionnaire for Data Collection from Selected Steel Industries

Greetings from the Addis Ababa University! With the approval of College of Technology and Built Environment, I am conducting research for the fulfillment of the PhD degree program in Industrial Engineering under the supervision of Dr. Birhanu Beshah (Associate professor). **The purpose of this research is to study the digital readiness/ maturity of the steel manufacturing industries in Ethiopia**. Industries digitalization plays an important role in increasing competitiveness in all aspects and accelerates the digital economy of the country. Therefore, I would like to request you to participate in this research because I believe that your experience in the sector would help me much. Please answer the questions freely **every information provided will be treated in the strictest confidence**. Closely look at all the close ended questions and score your preference putting a check mark on the space provided. Your genuine responses are essential to build an accurate picture of the issues that are of utmost importance for this research.

For any enquiry, please contact:

PhD Student: Mehret Getachew +251-943-65 10 37
Email: mihretgetachew2015@gmail.com

Thank you in advance for your time and genuine response!

Gender: Female ☐ Male ☐

Level of education: College Diploma ☐ BSc. /BA ☐ MSc. /MA and above ☐

Your position in the company: Director ☐ Team Leader ☐ IT manager ☐

Your work experience in the company: Below 2 years ☐ Between 2-6 ☐ Above 6 years ☐

1. **Management Commitment**

1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree						
		1	**2**	**3**	**4**	**5**
1	Our company has available resource (people and budget) for realization of digital strategy.					
2	Company uses a road map for the planning of digital activities.					
3	Company adopts new business models driven by digitalization.					
4	The management understands the concept of digitalization.					
5	The management introduce/promotes digitalization.					
6	Management empowers active employees with digital technologies.					
7	There is a management competences and central coordination for digitalization.					

2. **Digital Operation**

		1	**2**	**3**	**4**	**5**
1	In the company, processes are decentralized.					
2	Our company implements modelling and simulation for the production process.					
3	In the company, the working process is interdisciplinary.					
4	In the company, there is an interdepartmental collaboration.					

3. **Culture**

		1	**2**	**3**	**4**	**5**
1	Internet/ICT has a significant value in a company.					
2	Our company has strong approach for knowledge sharing.					
3	Our company has a good approach for open-innovation and cross company collaboration.					

4	Continuous change is part of our corporate culture.					
5	Decisions within our firm are transparent to our own employees.					

4. Digital Product

		1	**2**	**3**	**4**	**5**
1	Products are Individualized/customized using customer data.					
2	Products are commercialized through digital technologies.					
3	Digital products of our company create a significant impact on customer experience.					
4	There is a direct added value created by the progressive digitization of products of our company (e.g., cost reductions, increased productivity, better customer experience, customer differentiation)					

5. People and Expertise

		1	**2**	**3**	**4**	**5**
1	In the company, ICT competences and openness for new technologies of employees is in a good condition.					
2	Within our firm, there are sufficient experts on digital core issues.					
3	Within our firm, further education opportunities for digital core topics are available.					
4	Within our firm, comprehensive measures to strengthen digital literacy development are implemented					
5	Within our firm, new job profiles have been created for employees with expertise in digital core topics					

6. Technology

		1	**2**	**3**	**4**	**5**
1	There is an existence of ICT infrastructure in the company.					
2	Digital platforms are used for day-to-day collaboration.					
3	Our firm uses large amounts of data to optimize strategies, processes and products.					
4	Within our firm, we use tools for digital modeling, automation and control of business processes.					
5	Our firm has implemented enterprise-wide digital workplace concepts					

6	There is utilization of machine-to-machine communication					

7. **Digital maturity**

		1	**2**	**3**	**4**	**5**
L-1: Computerization	The company utilize digital tools such as CNC machining without integration					
L-2: Connectivity	Industries progress by establishing connections between their digital solutions					
L-3: Visibility	Enriched with extensive real-time data					
L-4: Transparency	Transitions to utilizing analytics, organizing and presenting data upon requests					
L-5: predictive capacity	Utilize real-time data to predict the future of production					
L-6: Adaptability	Decisions are based on predictive analytics supported by IOT					

Appendix F: Semi-structured Interview questions to quality control experts in the studied steel industry

1. Can you describe the current steel production process in your facility, from raw materials to finished products, and highlight key quality control checkpoints along the way?
2. How do you ensure product quality and compliance with standards throughout the steel production process?
3. What are the most common types of defects or quality issues encountered during steel production, and how are they currently addressed?
4. How do you monitor and evaluate the performance of quality control measures at different stages of the steel production process?
5. What technologies or tools are currently utilized for quality inspection in your steel production operations, and are there any limitations or areas for improvement identified?
6. How do you handle defective or non-conforming products discovered during quality control inspections?
7. Can you discuss any recent advancements or changes in quality control practices within your company, and their impact on overall product quality?