Addis Ababa University
Addis Ababa Institute of Technology
School of Mechanical & Industrial Engineering

Predicting Sand Casting Defects using a Data-Driven Supervised Machine Learning Approach: A Case Study of Akaki Basic Metals Industry

Thesis Submitted to the School of Graduate Studies of Addis Ababa Institute of Technology, Addis Ababa University in partial fulfillment for the Degree of Master of Science in Mechanical Engineering (Manufacturing Engineering)

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DECLARATION

I hereby declare that the work which is being presented in this thesis entitled **"Predicting Sand Casting Defects using a Data-Driven Supervised Machine Learning Approach: A Case Study of Akaki Basic Metals Industry"** is original work of my own, has not been presented for a degree of any other university and all the resource of materials used for this thesis have been duly acknowledged.

Demewez Demeke   Date

This is to certify that the above declaration made by the candidate is correct to the best of my Knowledge.

Dr. Mesfin Gizaw (Advisor)   Date

Mr. Henok Zewdu (Co-Advisor)   Date

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ABSTRACT

This research investigates supervised machine learning to predict sand casting defects and its severity, aiming to enhance product quality and reduce costs in metal casting. Effective quality control is essential for maintaining structural integrity, energy efficiency, and environmental sustainability.

Defects such as porosities, inclusions, shrinkages, cracks, and blowholes increase energy consumption and environmental impact. Rework, scrap, and product rejection due to defects gain significant production costs and reduce profitability.

The study identifies and mitigates defects in bronze, steel, and cast iron products weighing from 15 kg to 16,800 kg. Using a dataset of 1001 samples with 37 features, it evaluates machine learning algorithms: Decision Tree, K-Nearest Neighbors, Gradient Boosting, Random Forest, XGBoost, SVC, Ensemble methods, and NN. XGBoost is most effective, with 87% accuracy in defect type prediction and 94% in severity classification. Specifically, the ensemble XGBoost model achieves 93.07% accuracy in defect severity and 86.67% in defect types.

The Neural Network also performs well but shows signs of overfitting due to the small dataset. Severity is classified into severe, minor, and moderate; defect types include non-defect, porosity, shrinkage, and others (misrun, blowhole inclusion, crack, and metal penetration).

User-friendly tools based on these models are accessible via URLs (https://scdp-dt.streamlit.app/ and https://scdp-severity.streamlit.app/), aiding defect assessment and decision-making in sand casting. In conclusion, machine learning enhances operational efficiency and product quality while promoting sustainability. It also reduces energy use, minimizes rework costs, and enhances quality control, aligning with global environmental goals.

Keywords: Machine learning, Quality control, Sand casting defects, Supervised algorithms, Sustainability, XGBoost

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LIST OF ABBREVIATIONS AND ACRONYMS

ABMI	Akaki Basic Metals Industry
ANN	Artificial Neural Network
CAE	Computer-Aided Engineering
CNN	Convolutional Neural Network
DT	Decision Tree
ET	Extremely Randomized Trees
GB	Gradient Boosting
IoT	Internet of Things
KNN	K-Nearest Neighbors
LR	Logistic Regression
MAE	Mean Absolute Error
MATLAB	Matrix Laboratory
ML	Machine Learning
MSE	Mean Squared Error
NDT	Non-Destructive Testing
NN	Neural Network
PFI	Permutation Feature Importance
R^2	R-squared
RF	Random Forest
RMSE	Root Mean Squared Error
SHAP	SHapley Additive exPlanations
SMOTE	Synthetic Minority Over-sampling Technique
SVC	Support Vector Classifier
SVM	Support Vector Machine
XGBoost	Extreme Gradient Boosting

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the Research

For centuries, manufacturing sector especially metal casting has been the backbone of world production, supplying vital parts for wide range of uses in the machinery, automobile, aerospace, and construction industries. For these businesses to operate safely and effectively, cast metal components dependability and quality are essential [1]. Sand casting, a cost-effective method, is a global economic force in metal component production, supporting various industries. Green and dry sand casting are pivotal methods in ferrous and non-ferrous metal component production. Dry sand casting involves using chemically bonded sand molds, offering precision and dimensional stability while green sand casting depend on naturally bonded sand, given that flexibility and cost-effectiveness in creating complicated parts for different industries [2].

In the production of cast metal components, quality control is essential for maintaining structural integrity as well as energy and environmental sustainability. In these product defects include porosities, inclusions, shrinkages, cracks, and blowholes, can increase energy consumption and have an adverse effect on the environment in addition to compromising the structural integrity of the components. Rework, scrap, rejection of products and environmental damage causes come at a large production cost and decrease profitability [3], [4]. Growing the demand on the manufacturing sector to minimize its environmental impact and cut down on energy use in a world where environmental sustainability is of maximum importance. Energy efficiency in the production process and material waste reduction have emerged as crucial factors affecting business competitiveness and global environmental objectives [5].

Machine learning (ML) has recently expanded immense attention due to its ability to effectively determine the relationship between the input features and the dependent variable in a complex system. It is considered as a powerful technique to solve different manufacturing engineering problems [6]. The recent development of machine learning gives a chance to address these complex issues. Machine learning models can be created to predict, diagnose, and categorize defects in finance, health and manufacturing industries [7], [8]. From types of ML supervised learning approach utilizes input data to predict outcomes based on historical patterns, divided into regression for numerical predictions and classification for categorization select techniques based on the problems [9].

With a large datasets and processing techniques, different algorithms such as Decision Tree, K-Nearest Neighbors, Gradient Boosting, Random Forest, XGBoost, Support Vector Classifier (SVC), Ensemble, and Neural Network (NN) can be utilized for prediction purpose. These algorithms examine data patterns to uncover links between process factors and defect occurrence, helping decision-making in sand casting production [10], [11].

Akaki Basic Metals Industry, a leading Ethiopian foundry under the Ethio Engineering Group, dry sand cast products such as Scrapper plate, mill roller, flange roller, old boiler ash door with its frame, trash plate and other for Ethiopian sugar industry, Ethio telecom, construction sectors, electric power and utility etc. However, it actively addresses rejection and defects in its cast products. These issues not only lead to customer dissatisfaction but also result in increased remanufacturing (rework) costs, decreased quality, profitability, and competitiveness. Usually producing products from material cast iron, bronze, and steel by understanding materiel properties and sand-casting process parameters, this indicates limitations of conventional quality control procedures due to manual inspection, and labor-intensive, slow, and prone to human error constraints not only impact operational effectiveness extend to sustainability and environmental energy efficiency. The developed supervised ML models predict sand casting defect type and its severity used as proactive approach to quality control to establish industry-leading standards in quality control, and also helps to minimizing environmental waste and reducing energy consumption through integration of data and machine learning techniques.

1.2 Statement of the Problem

Akaki Basic Metals Industry faces significant challenges due to casting defects in sand-cast components made of cast iron, bronze, and steel. Defects such as porosities, inclusions, metal penetration, cracks, misruns, shrinkages, and blowholes compromise structural integrity, leading to customer dissatisfaction, increased manufacturing costs, high rework and scrap rates, loss of competitiveness, and reduced profitability [1]. The complex nature of these defects is influenced by factors such as mold and core quality, grain size, binder content, gas permeability, and casting conditions. Reducing defects is critical as they impact structural integrity and performance and have significant environmental and energy implications [12], [13]. The energy-intensive processes of remelting and remanufacturing scrapped components contribute to higher energy consumption and environmental waste.

Foundries in developing countries frequently encounter defects due to numerous process parameters, resulting in poor quality and productivity [14].

Traditional defect detection methods in metal casting are either slow and costly (destructive testing) or risk missing defects (non-destructive methods) [15]–[17]. Akaki Basic Metals Industry high defect frequencies and accumulation of undesirable cast products indicate ineffective quality control measures and faces the challenge of insufficient computerized historical data, hindering comprehensive analysis and reducing of these defect frequencies. This data shortage limits the effectiveness of traditional and modern quality control measures, hindering to timely and precise identification or modification of casting defects. To overcome these challenges, machine learning models trained on historical datasets offer early defect detection, reducing reliance on human judgment and providing real-time feedback. Integrating these models is vital for improving defect detection and enhancing environmental sustainability in metal casting industries.

1.3 Research Questions

The study attempts to give solutions to the following questions:

- What are the determinant factors for sand casting defect?
- What are the machine learning algorithms used to predict whether there are sand casting defects?
- What criteria should be considered when selecting the optimal machine learning model for predicting sand casting defects?
- To what extent is the developed model effective in predicting defects and its severity?
- How to enhance model interpretability in predictive modeling for casting defects?

1.4 Objectives of the Study

1.4.1 General Objective

The main objective of this research is to predict sand casting defects using a supervised data-driven machine learning approach.

1.4.2 Specific Objective

The specific objectives of the study are as follows:

- ✓ To gather and preprocess a comprehensive dataset of historical sand casting records from Akaki Basic Metals Industry,
- ✓ To design and develop machine learning algorithms,
- ✓ To train and select a machine learning predictive model using different performance measure metrics,

- ✓ To compare the predictive capability of the proposed model,
- ✓ To improve model interpretability, create effective web-based application.

1.5 Scope of the Research

The scope of this research involves collecting and preprocessing historical sand casting product datasets from bronze, cast iron, and steel with their casting process parameters analyzing data from sand casting process, identifying key parameters influencing defect occurrence, and developing predictive models from Akaki Basic Metals Industry, training supervised learning models using different algorithms, developing the models, comparing their predictive performance to select the best, and finally, enhancing model interpretability by deploying a web-based application to predict casting defect types and severity.

1.6 Significance of the Research

The significance of this research is reflective, given its potential to revolutionize quality control practices in the foundry industry. Conventional methods for sand casting defect purpose, depend on numerical, analytical, and mechanical models, often struggle with accuracy due to characteristic assumptions and uncertainties. Especially, these approaches often supervise critical factor interactions and variations. In contrast, machine learning (ML) models present a revolutionary alternative, capable of extracting complex relationships from data without prior assumptions. Leveraging the power of ML techniques, this study aims to develop an accurate and reliable sand casting defect prediction model, by encompassing all essential parameters. By collecting a comprehensive database of sand-casting experiments, covering material properties and process parameters for metals cast iron, steel, and bronze, provides a robust foundation for model development. Through careful tuning of hyperparameters and comparative analysis of model performance, the study identifies the most effective ML model, showcasing superior predictive capabilities in terms of accuracy, safety, and economic aspects.

Beyond its direct implications for quality control enhancement, this research carries broader significance for sustainability and industry innovation. The organized dataset serves as a valuable resource for further exploration into defect prediction models, process optimization, and material efficiency. For the Akaki Basic Metals Industry, the establishment of a structured database ensures easy access to historical defect records, supporting ongoing research efforts and facilitating continuous improvement initiatives. Moreover, the database's alignment with environmental responsibility underscores its role in promoting industry competitiveness and contributing to broader sustainability goals.

1.7 Limitations of the Research

The limitation of this research is the difficulty in accessing essential data from the ABMI foundry due to the absence of documented information for each process parameter and the lack of a digital database within the company. The unavailability of comprehensive data records hinders the depth and accuracy of the analysis, while the absence of a digital database complicates data retrieval and organization, requiring manual efforts and potentially introducing errors. Additionally, the scarcity of previously studied research in the specific domain of sand casting defects prediction at ABMI limits benchmarking and guidance for the study's methodologies. However, utilizing manual efforts to record required parameters by collaborating with foundry experts and staff members can mitigate these challenges.

1.8 Thesis Organization

The six chapters that make up this study's paper are arranged in the following manner.

Chapter one: As mentioned above, chapter one contains the study's introduction, problem statement, research questions, study objective that would be addressed by the suggested solutions, scope and limitations, and study application outcomes.

Chapter two*:* This chapter covers literature review and related works describes theory and development of research related to sand casting surface defects and provides an overview of machine learning algorithms that are suitable for defect prediction purpose and research gaps.

Chapter three: In this chapter covers research design for the study, the data collection methods and procedures, the dataset preparation methods, the methods for developing the sand casting defect prediction models, the ML classification algorithms, the evaluation methods, and finally the implementation and experimentation process.

Chapter four: In this chapter, the data preparation steps, cleaning processes, essential for accurate and meaningful analysis are discussed.

Chapter five: In this chapter, the experimentation, primary findings from a comparison of all models based on the research's performance metrics utilizing various ML algorithms are also discussed, along with the results and discussions of proposed ML methodologies.

Chapter six: In this chapter, the research issue is concluded, a recommendation is made, and future works are listed.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Introduction

In this chapter discuss key aspects of metal casting, focusing on sand casting covers the process and types of molding sands, discusses common defects and their causes, and examines contributing parameters. Traditional and modern defect assessment and prediction techniques, including machine learning, are reviewed together with data pre-processing, model design, and evaluation methods. Additionally, the chapter addresses model interpretation techniques, applications of machine learning in manufacturing, and identifies gaps in previous research, summarizing the existing literature.

2.2 Metal Casting

Casting in foundry stands as one of the ancient manufacturing methods, well-known for its metallurgical process. Essentially, casting involves pouring melted metal into a mold space, enabling it to take on the intended form. This versatile method accommodates the creation of both straightforward and intricate designs using any melt-able metal. Regarded as a skilled and artistic process, casting integrates various elements to ensure high quality outcomes. Casting is a primary method widely employed for crafting metal components, particularly those used outside the mouth [10]. This ancient and intricate metallurgical practice relies on the fundamental principle that molten material adapts to the shape of its container. The procedure includes encasing a wax model in a mold capable of withstanding high temperatures, eliminating the wax through heat, and pouring liquid metal into the mold through a designated passage called the sprue. While minor defects can typically be controlled during casting, the emergence of significant defects may lead to heightened expenses in the production process [18].

2.3 Sand Casting Process

Sand casting finds frequent application in different industries for example automotive, aerospace, and design, among others, for producing components made from materials both ferrous and non-ferrous. The required metal melted in a range of furnace at specified temperatures poured in the mold cavity crafted from sand. This method is favored due to its cost-effectiveness and relatively low expense. Nevertheless, defects are prevalent in sand-cast parts, impacting the properties of the castings [19].

Sand casting, a cost-effective method, is a global economic force in metal component production, supporting various industries. Its scalability, efficiency, and adaptability contribute to job creation, resilient supply chains, and infrastructure development. Technological advancements enhance its relevance and sustainability, impacting local economies and aligning with global manufacturing standards [20]. Sand casting's affordability and accessibility make it essential for both small and large-scale operations, fostering economic interdependence and supporting innovation for environmentally conscious practices [21]. Critical factors influencing casting quality include sand quality, procedure of mixing, binder composition mix, and the compactness of sand mixtures [22]. Key defects associated with sand casting include porosity, skin defects, defects related to silica thermal expansion, and inclusion-related defects. The possibility of defects being influenced by mechanisms showed associated with the mold linked to the metal [23].

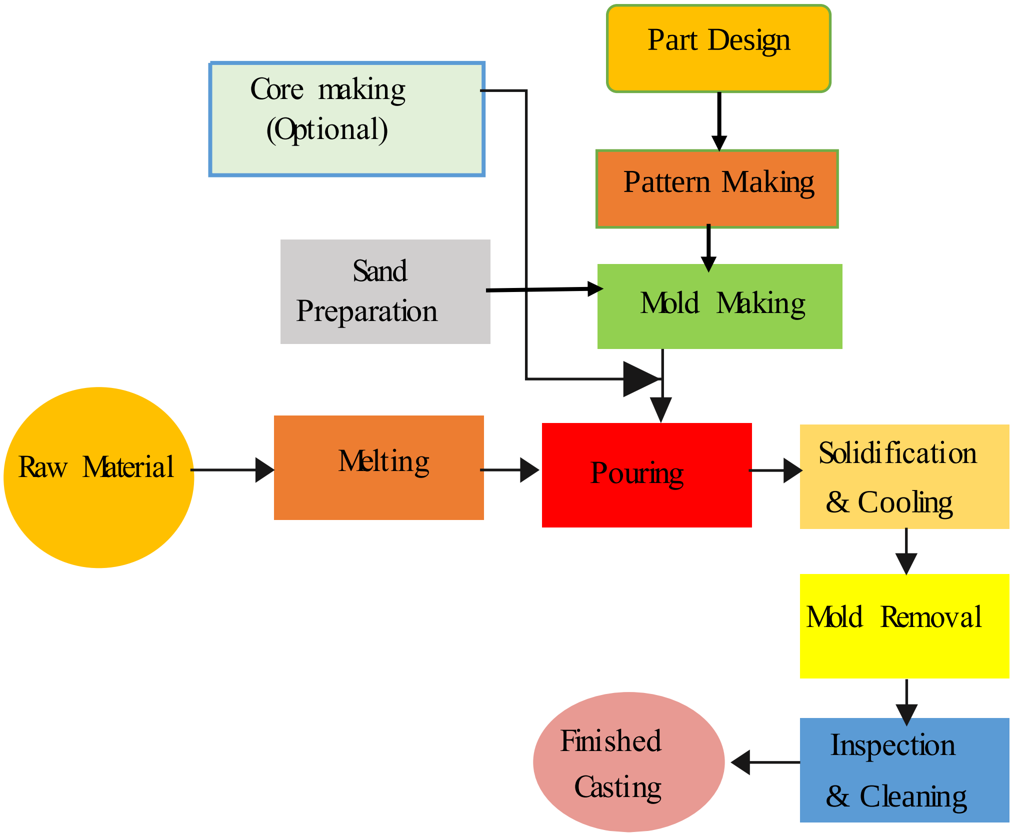


Figure 2.1 Sand casting process

2.4 Types of Molding Sand

Various types of molding sands play crucial roles in the casting process, Greensand, crucial component for both ferrous and non-ferrous materials, comprises sand, bentonite clay, pulverized coal, and water, offering good porosity and a soft, fine texture with a clay content of 30% and water content of 8%. However, its presence doesn't guarantee defect-free castings, as issues improper mixing or inadequate compaction can lead to casting defects such as surface roughness or incomplete mold filling [20].

Dry sand, achieved by baking the sand mold to eliminate moisture, offers considerable strength suitable for large-scale molding, preventing defects linked to gas pockets. Loam sand, comprising a blend of sand, clay, and water with proportions of 50% sand and 18% clay, is preferred for larger castings; however, improper preparation and compaction may lead to casting flaws such as sand inclusions or uneven surfaces. Facing sand, situated directly against the pattern's surface, forms the mold face in direct contact with molten metal, boasting high strength and refractoriness; nonetheless, inadequate compaction or uneven application can result in defects like misruns or cold shuts. Backing sand, also recognized as flour sand, provides support to facing sand but may contribute to defects like porosity or metal penetration if not adequately recycled or if the concentration of coal dust is excessive. Core sand, crucial for core formation and alternatively known as oil sand, consists of silica sand and core oil, with defects often arising from insufficient venting, leading to issues such as blowholes or core shift [24].

The casting process, an ancient and complex metallurgical technique, involves pouring melted metal into a mold to create various metal components. Sand casting, a widely used method across industries like automotive and aerospace, involves creating molds from sand. This cost-effective method is chosen for its scalability and adaptability despite common defects in the resulting parts. Two main types of sand, green sand, and chemically bound sand, are used in the process, each with its advantages and considerations. Various molding sands, including greensand, dry sand, loam sand, facing sand, backing sand, and core sand, play crucial roles in achieving quality castings but require proper handling to avoid defects.

2.5 Defects in Sand Casting

Casting defects are any irregularities that undermine the mechanical strength, integrity, or appearance of components. Consequently, any variation from the desired shape or structural stability of a part, which may affect its functionality, is considered a defect. A particular defect type may manifest varied attributes influenced by factors such as casting geometry, process timing, or foundry discrepancies.

While these variations can pose diagnostic hurdles, providing precise descriptions facilitates understanding the underlying causes and mechanisms of each defect [25].

In real-world scenarios, castings, like other metallurgical items, can contain voids, inclusions, and similar imperfections that are commonly accepted and do not necessarily affect their overall quality. These defects are only labeled as genuine defects when they pose concerns about the product's functionality or appearance. In such cases, decisions regarding salvage, rejection, or replacement should be based not only on the defect itself but also on its impact on the casting's intended function and the relevant quality and inspection standards applied [26].

2.5.1 Surface Defects

Surface defects in casting refer to irregularities or imperfections that appear on the external surfaces of the cast metal components. These defects can compromise the integrity, functionality, and appearance of the final product. In the foundry industry, where components are manufactured using sand molds, the quality of the mold material significantly impacts the rate of post-production scrap, Various factors, including the grain size of the mold material, binder content, gas permeability, mold compactability, casting temperature, and metallo-static pressure, contribute to these defects. Mineralization, a chemically induced penetration, leads to a pockmarked surface due to fused sand adherence. The complex origins of these defects are intertwined, involving intricate relationships among multiple parameters, which pose challenges for analysis [1], [10], [27].

2.5.2 Gas Defects

Gas defects in sand casting refer to flaws or irregularities that arise due to the presence of gases within the casting material or mold. Blowholes present a notable challenge in casting, originating from the buildup and complexity of gases during the casting process. Larger gas cavities that form on the casting's surface, typically caused by gases escaping from the mold during pouring. Sand casting, numerous defects can emerge, with a significant portion linked to gas emissions. Among the primary defects attributed to gases are holes, including pinholes and blowholes. Blowholes appear as smooth, spherical cavities within the casting, typically not extending to its external surface [24], [28]–[32]. Pinholes small gas cavities within the casting material, often formed by gases evolving from the molten metal during solidification [33].

2.5.3 Crack, Metal Penetration and Inclusion Defects

Cracks undermine the structural integrity and have the potential to expand over time and mineralization, distinct from actual mechanical or physical penetration, involves chemically induced penetration, while burnt sand occurs when a thin sand crust strongly adheres to the casting. Mineralization creates a pockmarked appearance across the entire surface due to a fused sand layer. [34]. Inclusions, caused by foreign materials oxides or sand, compromise the casting's mechanical properties. Cold shut defects occur when molten metal flows at different times, leading to incomplete fusion and weakened joints [35]. Metal penetration in castings arises when liquid metal infiltrates voids between sand grains without displacing them, influenced by factors like metallostatic and dynamic pressure. This defect encompasses various forms, including common penetration, chemical reaction-induced penetration, and explosive penetration in low-permeability regions, being more prevalent in grey iron alloys due to their lower surface tension. Strategies to minimize this issue involve addressing surface finish concerns during the molding process [13], [18], [36].

Misruns result from inadequate fluidity, causing the metal to fail in filling the mold completely. Scabs, formed by overheating or turbulent pouring, compromise structural integrity. Rat tails, narrow projections, stem from inadequate venting or improper gating [36].

Figure 2. 2 Major casting defects on different products in Akaki Basic Metals Industry

2.5.4 Shrinkage Defects

Shrinkage defects in sand casting result from the contraction of the casting material during solidification, leading to localized voids, cracks, or distortions in the final product [31]. These defects may appear as shrinkage cavities, internal voids or porosity formed as the material cools and contracts, or hot tears, which are cracks occurring at high-stress areas within the mold. Preventing such defects necessitates careful consideration of factors like proper gating and riser design, control of cooling rates, and the implementation of feeding systems to ensure uniform solidification [37].

2.5.5 Shaping Faults during Pouring

Shaping faults during pouring arise when irregularities in the cast's shape occur due to improper pouring techniques. Cold shut/lap defect manifests as a surface anomaly, typically appearing as a line or crack with a rounded edge on the surface of the casting. Cold shuts occur when molten metal flows into the mold from two separate gates, causing streams to converge at a junction. Prevention strategies involve enhancing the fluidity of the molten metal through various methods, such as optimizing gating systems, elevating pouring temperatures, and enhancing the gas permeability of the mold [10], [32].

Cold shots occur when the temperature of the liquid metal is insufficient to reach the farthest points of the mold cavity before solidifying, resulting in incomplete filling. Similar to cold shuts, the causes and preventive measures for cold shots revolve around factors such as mold and gating system design, as well as the fluidity of the molten metal [18]. Meanwhile, splashing during pouring can lead to the formation of solid globules known as cold shots, which freeze and become trapped in the casting. Typically spherical or droplet-shaped, these cold shots are loosely attached to the metal [22]**.** Preventive actions involve adjusting pouring procedures to minimize turbulence and modifying gating system designs to decrease gate speed. Preventing slag inclusion entails removing slag particles from the molten metal prior to pouring using techniques such as fluxes, ingredient additions for slag floatation, or the incorporation of ceramic filters in the gating system [38]**.**

2.5.6 Contraction and Dimensional Defects

Contraction and dimensional defects in sand casting arise from shifts in the dimensions of the casting material during the solidification and cooling phases, resulting in deviations from the intended size, shape, or dimensions of the final product. Defects include various issues, including shrinkage, warping, and misalignment [39]. Shrinkage defects occur when the casting material contracts during cooling, leading to the formation of voids, cracks, or distortions. Warping defects manifest as uneven or distorted shapes due to differential cooling rates or internal stress. Misalignment defects arise from improper assembly, resulting in dimensional inaccuracies [25]. Preventing these defects entails careful considerations such as optimizing gating and riser design, controlling cooling rates, and implementing appropriate feeding systems to ensure uniform solidification. Thorough inspection and quality control are imperative for identifying and rectifying these defects before they compromise the final product's quality and integrity [40]**.**

2.5.7 Compositional Errors and Segregation Defects

Compositional inaccuracies and segregation defects in sand casting arise from inconsistencies or uneven dispersion of alloying components within the casting material. These result in deviations in material composition, leading to unfavorable properties or performance attributes in the end product [41]. Compositional inaccuracies occur when the alloy makeup strays from the intended specifications, potentially undermining the mechanical or chemical traits of the casting. Segregation defects entail the unequal distribution of alloying elements during solidification, resulting in localized regions with distinct compositions or characteristics within the casting [35]. Modifying compositional inaccuracies and segregation defects necessitates precise control over alloy composition, melting techniques, and solidification processes. Comprehensive quality control measures, such as chemical analysis and microstructural assessment, are crucial for identifying and remedying these defects before they compromise the functionality or integrity of the final casting [42].

Casting defects in sand casting encompass a range of issues that can compromise the integrity, functionality, and appearance of metal components. Surface defects, such as scorched sand and blowholes, arise from factors like mold material quality and gas buildup during casting. Gas defects, including blowholes and pinholes, result from gas entrapment in the molten metal or mold. Crack, metal penetration, and inclusion defects are influenced by factors like nitrogen content and mold preparation, leading to surface cracks, metal infiltration, and foreign material incorporation. Shrinkage defects occur due to material contraction during solidification, while shaping faults during pouring, like cold shuts and cold shots, stem from improper pouring techniques. Contraction and dimensional defects result from shifts during cooling, while compositional errors and segregation defects arise from inconsistent alloy distribution. Preventing these defects requires particular control over casting parameters and thorough quality control measures throughout the production process.

2.6 Parameters Contributing to Sand Casting Defects

2.6.1 Mold Material Characteristics

Mold material characteristics pivotal role in shaping the quality of cast metal components. Properties like permeability, strength, and collapsibility have crucial factors impacting mold performance. Permeability, affects to the mold's capacity to allow gases to escape during casting, effectively preventing defects such as porosity. Optimal permeability ensures proper ventilation, facilitating the expulsion of gases generated during metal solidification and ultimately yielding defect-free castings.

The strength of the mold material assumes significant importance in upholding the structural integrity of the mold cavity during metal pouring and solidification stages. A mold possessing sufficient strength can endure the mechanical stresses encountered during casting, thereby avoiding deformations or fractures that might compromise the quality of the final product. Collapsibility emerges as another vital characteristic, denoting the mold's ability to deform or collapse after the casting has solidified. This feature facilitates the seamless removal of the casting without causing damage. Mold materials able with appropriate collapsibility ensure smooth demolding processes, thereby reducing the likelihood of casting defects such as surface irregularities or dimensional deviations [43]–[45].

2.6.2 Molding Process Parameters

Parameters encompass a range of factors, including ramming pressure, moisture content, sand compactability, and temperature regulation during mold preparation. Each of these elements influences the density, resilience, and overall excellence of the mold, thereby impacting the final casting outcome. Effective adjustment of ramming pressure ensures thorough compaction of the sand around the pattern, resulting in a solid and uniform mold structure [46]. Monitoring moisture content and fine-tuning sand compactability ensure high-quality mold formation, while temperature regulation optimizes mold hardness and strength for superior casting production [47], [48].

2.6.3 Pouring Temperature and Rate

Pouring temperature and rate are critical factors influencing sand casting defects, affecting volumetric changes, material flow, and air entrapment during mold filling. Lower pouring temperatures have been linked to decreased defects like porosity, with studies indicating finer microstructure and reduced defects in alloy castings within the range of temperature. Higher pouring temperatures may result in issues such as deformation and cracking in molding sand, compromising casting quality [48], [49].

Accurate testing at high temperatures is vital for risk reduction. In some applications, such as natural gas power cylinder bodies, controlled pouring temperatures improve feeding properties and reduce defects. Precise control of pouring temperature and metal velocity is crucial to optimize solidification kinetics and minimize shrinkage defects in sand casting processes [47], [50].

2.6.4 Metal Composition

Variations in alloying elements and impurities influence metal flow characteristics and defect susceptibility during casting. Alloying elements can alter viscosity and flow properties, impacting mold cavity filling and leading to defects like misruns. Impurities may cause gas porosity or inclusion defects. Changes in metal composition affect solidification behavior, potentially causing shrinkage or cracks. Thus, careful consideration of metal composition is crucial in sand casting to minimize defects and ensure high-quality casting [44], [51].

2.6.5 Core Design and Placement

Design and positioning of cores are critical aspects of the sand casting process, exerting direct influence on the quality and structural integrity of the resultant casting. Cores, responsible for creating internal features in the casting, require precise engineering to facilitate proper filling and solidification of the molten metal. Various factors including core geometry, size, and material composition impact the overall strength and dimensional accuracy of the casting. Moreover, the strategic placement of cores within the mold cavity is indispensable for achieving the desired shape and internal configuration of the casting [52]. Incorrect core placement may lead to defects like shifts, misruns, or incomplete fillings, which can compromise the final product's quality. Hence, meticulous attention to core design and placement is imperative to mitigate defects and ensure the production of top-notch castings [53].

2.6.6 Pattern Design and Quality

Pattern design and quality are critical aspects of the sand casting process, significantly impacting the final product's characteristics and integrity. The pattern serves as a template for creating the mold cavity and directly influences the casting's dimensions, surface finish, and overall quality. Proper pattern design ensures accurate reproduction of the desired part geometry and features, minimizing dimensional inaccuracies and surface imperfections in the final casting. Additionally, quality of the pattern, including its durability and dimensional stability, affects the mold's longevity and the consistency of castings produced over time. Issues such as pattern wear or deformation can result in defects like shifts, misruns, or surface irregularities in the castings [50], [54].

Figure 2. 3 Rejected and unwanted products in foundry Workshops

Sand casting defects can arise from various parameters across mold material characteristics, molding process parameters, pouring temperature and rate, metal composition, core design and placement, and pattern design and quality. Mold material characteristics such as permeability, strength, and collapsibility significantly impact mold performance and the quality of castings. Molding process parameters including ramming pressure, moisture content, sand compactability, and temperature regulation during mold preparation influence the density overall excellence of the mold. Pouring temperature and rate affect volumetric changes, material flow, and air entrapment during mold filling, thereby influencing defect formation. Metal composition variations impact flow characteristics and susceptibility to defects during casting. Proper core design and placement are crucial for achieving the desired shape and internal configuration of the casting. Similarly, pattern design and quality directly influence the final product's characteristics and integrity. Therefore, careful attention to these parameters is essential to mitigate defects and ensure the production of high-quality cast metal components.

2.7 Techniques to Asses and Predict Casting Defects

Sand casting defects can result from various factors including mold design, material properties, process parameters, and environmental conditions. Understanding and predicting these defects necessitates a thorough comprehension of how these factors interact and influence the casting process. Several techniques and methodologies have been devised to assess and predict sand casting defects, enabling manufacturers to effectively anticipate and address potential issues [55]–[57].

2.7.1 Traditional Method

2.7.1.1 Visual Inspection

Visual inspection is the most widely employed method among all non-destructive testing approaches. In sand casting, visual inspection is vital for ensuring component quality. It's quick, affordable, and serves as a pre-check before other tests. Using light, defects are visually assessed, aided by tools if needed. Clear illumination and clean surfaces are crucial for accurate evaluation [58], [59].

2.7.1.2 Mold Design and Process Controls

In sand casting, experience-based mold design is crucial for crafting molds that meet specific requirements. Mold designers rely on accumulated knowledge and past successes to anticipate and overcome potential challenges effectively. Key control parameters, such as pouring temperature, sand composition, and mold density, are carefully managed to ensure optimal casting quality and minimize defects. This approach enables manufacturers to consistently produce high-quality castings [60], [61].

2.7.2 Modern Method

2.7.2.1 Computer Simulation

Computer-aided engineering (CAE) software facilitates simulating the entire casting process, encompassing mold filling, solidification, and cooling. These simulations offer insights into potential defects like shrinkage, porosity, and hot tearing, empowering engineers to optimize process parameters and mold designs to minimize defects. Utilizing casting simulation, often referred to as 'virtual casting,' enables the optimization of process parameters and the anticipation of defects. This approach is extensively employed in foundries to replicate authentic casting processes and refine designs. Although highly valuable, it necessitates experienced users and cannot rectify pre-existing processes. Nonetheless, it contributes to enhanced reliability and efficiency in casting operations [62]–[64].

The combination of CAD software with simulations like Finite Element Analysis (FEA) and Computational Fluid Dynamics (CFD) presents a potent toolkit for refining mold designs and anticipating defects in manufacturing. Employing these tools allows manufacturers to optimize mold designs, mitigating issues like shrinkage, gas porosity, and hot spots. This strategy boosts product quality, slashes production expenses, and expedites time-to-market by preemptively tackling potential issues [65]–[69].

2.7.2.2 Design of Experiments (DOE)

DOE involves systematically varying process parameters such as pouring temperature, mold temperature, and cooling rate to discern their impacts on casting quality. In sand casting, both ANOVA and Taguchi methods are valuable for optimizing process parameters and enhancing casting quality. ANOVA systematically varies factors like pouring temperature and sand composition to identify key parameters affecting quality through statistical analysis. Taguchi methods focus on defining quality characteristics, selecting critical parameters, and efficiently designing experiments to cover all combinations. By analyzing signal-to-noise ratios, Taguchi methods determine optimal parameter settings to maximize desired quality. These approaches enable manufacturers to systematically improve process parameters, reduce defects, and boost casting quality [70]–[72].

2.7.2.3 Finite Element Analysis (FEA)

FEA is a numerical method for analyzing the structural behavior of complex systems, including casting molds and components. By modeling the casting process and its interactions with the mold, FEA predicts potential defects like distortion, stress concentrations, and mold deformation, enabling engineers to optimize mold designs and process parameters [73]–[75].

2.7.2.4 Non-Destructive Testing (NDT)

NDT methods like X-ray radiography and ultrasonic testing identify internal defects in castings without damaging them. Conducting NDT inspections on finished castings helps detect issues such as porosity and cracks, enabling corrective actions to prevent future problems. advanced techniques prioritizes product integrity while minimizing disruption to manufacturing operations [76]–[79].

2.7.2.5 Machine Learning, Neural Networks Predictive Analytics

Neural networks and machine learning algorithms leverage historical casting data to predict defect occurrence based on input parameters like material composition, mold geometry, and process conditions. These predictive models aid manufacturers in identifying potential defects early and implementing preventive measures to enhance casting quality.

By integrating these techniques into the analysis of sand casting defects, manufacturers gain valuable insights into defect origins and can proactively enhance casting quality, reduce scrap rates, and improve overall process efficiency. Using Artificial Intelligence (AI) to analyze defects in casting involves employing advanced algorithms and data-driven techniques to detect, classify, and address various types of defects [80]–[82].

Analyzing defects in sand casting using Artificial Intelligence (AI) involves deploying sophisticated algorithms to detect patterns in historical data and forecast defect occurrences. Parameters like material composition, pouring temperature, and mold design are considered in crafting predictive models. AI techniques is employed for defect analysis, mimicking human intelligence to refine casting processes, minimize defects, and elevate product quality. Furthermore, computer-based software aids in mold design, employing methods such as modulus-based reasoning, case-based reasoning, rule-based approaches, and simulation software. These AI-driven methodologies facilitate efficient defect analysis and mold design in sand casting, ultimately enhancing manufacturing outcomes [83]–[85].

Method involves using AI and X-ray for examining defects in aluminum castings, emphasizing the importance of maintaining quality standards in manufacturing. It combines image analysis, geometrical metrics, and neural networks to improve defect recognition, offering benefits to industries reliant on aluminum components. Another approach utilizes neural networks to analyze factors affecting steel casting, validated using plant data. Machine learning and deep learning techniques are employed to predict manufacturing quality, categorized based on processes, data sources, and models. Monitoring manufacturing environments is crucial for preventing downtime and identifying defects, with an AI-driven visual inspection automation proposed. This includes a custom Convolutional Neural Network achieving high accuracy, promising enhanced quality inspection in manufacturing [86]–[88].

Deep transfer learning, focuses on predicting product quality in aluminum gravity die casting, emphasizing the importance of high-quality output and reduced rejection rates in manufacturing. It addresses challenges in data-driven approaches for metal casting, aiming to develop robust models that efficiently predict product quality while leveraging digitalization for quality prediction and control. Through transfer learning, the research seeks to overcome issues like sparse and imbalanced data, human interaction, and frequent mounting events, facilitating accurate and resource-efficient quality prediction in aluminum gravity die casting [89].

A deep learning framework is utilized for detecting defects in casting products, enhancing efficiency and quality control in mass production. It employs Convolutional Neural Networks (CNNs) and machine learning algorithms for classification, addressing uncertainty through ensemble methods [90].

Deep learning techniques, particularly convolutional neural networks, to tackle issues associated with artifact-prone CT scans a novel method of training models solely on realistically simulated CT data, demonstrating encouraging outcomes in defect detection [91].

2.8 Traditional Methods vs. Machine Learning Predictive Analytics

Traditional sand casting relies on established processes and manual adjustments, while predictive analytics for sand casting, utilizing machine learning algorithms, forecast outcomes with advanced precision and parameters are determined based on experience and manual adjustments. In contrast, machine learning algorithms such as artificial neural networks, and extreme gradient boosting predict properties unconfined compressive strength and decoding behavior. Furthermore, machine learning techniques analyze complex relationships between input variables and casting properties, providing a data-driven approach to optimize processes and enhance product quality [92]–[94].

2.9 Machine Learning

Machine learning (ML) stands as a pivotal branch where computers harness datasets to discern concealed patterns. ML algorithms facilitate self-training, crafting models attuned to the data and making predictions based on the assimilated knowledge. The efficacy of ML models in prediction tasks flourishes with ample data, emphasizing the significance of both quantity and quality for accurate predictions. The selection of algorithms hinges upon the data type and the targeted activities for automation. ML's profound impact extends across diverse industries grappling with the manual extraction of information from data, including manufacturing [95].

Educational domains benefit from ML for language learning, while security sectors leverage it for surveillance and recognition tasks. ML's influence also extends to transportation for traffic monitoring and telecommunication networks for optimization. Presently, machine learning serves as a critical tool enabling systems to acquire knowledge and refine performance through prior training, obviating the need for explicit coding or programming [96].

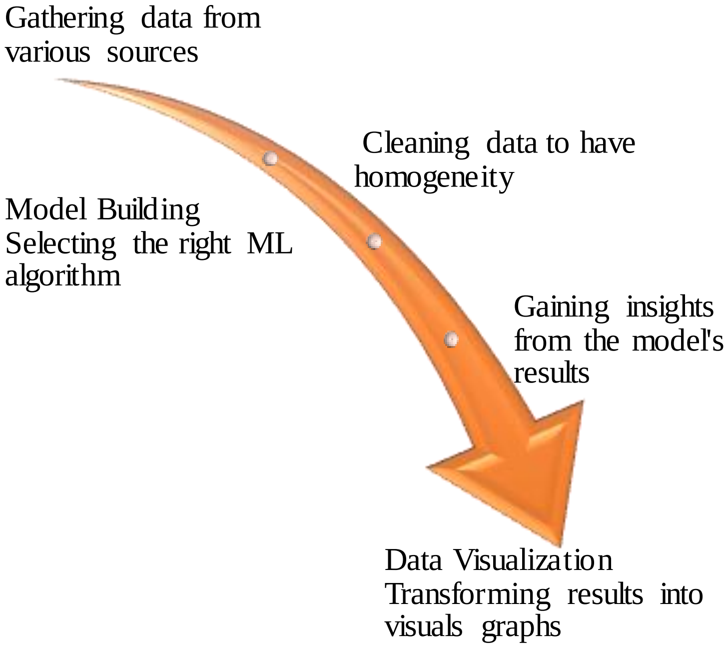


Figure 2. 4 Process of machine learning

Machine learning, with its ability to leverage datasets and past experiences for prediction and optimization, presents a potent tool for simplifying complex problems and constructing accurate systems. Through the fusion of computer vision, automation, and manufacturing, ML enhances system capabilities, underscoring its pivotal role in modern technological advancement and classified in to three types as shown below [97].

2.9.1 Supervised Learning

An approach in ML leverages input data, consist of numerical or string values, to predict various features based on past inputs. It is divided into regression and classification subcategories, where regression predicts continuous numerical values, and classification categorizes new data points based on historical patterns. This implementation follows a four-phase workflow. Initially, relevant data is collected from diverse sources and structured into prescribed datasets.

Data preprocessing ensues, involving tasks such as managing missing values, standardizing datasets, and converting non-numeric features. Techniques such as feature scaling, averaging, and encoding are applied to enhance model accuracy. Strategies for handling missing data include using values like zero, average, or mode settings, while string or text values are transformed through categorized encoding [98], [99].

In a manufacturing data-focused machine learning project, data is sourced from sources such as ERP databases and IoT devices. Data preprocessing remains crucial, encompassing tasks such as addressing missing values, standardizing datasets, and converting non-numeric features. Techniques such as imputation, scaling, and encoding are employed to optimize model performance. Feature engineering assumes a pivotal role, generating new features from existing ones to provide additional insights to the model [82], [96], [100].

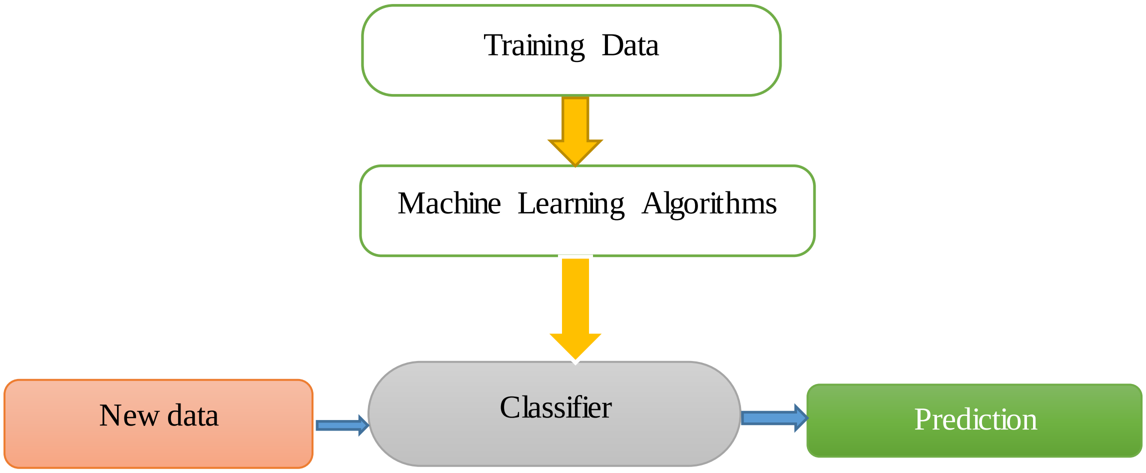


Figure 2. 5 Supervised Algorithms workflow

2.9.2 Unsupervised learning

Unsupervised learning, a distinct ML approach, leverages historical data to predict outputs without labeled examples, uncovering intrinsic patterns autonomously. Unlike supervised learning, it operates independently, analyzing unlabeled data to unveil hidden insights, useful for tasks like clustering and reducing dimensionality. This method finds applications in various fields, including text mining and face recognition, especially beneficial for datasets lacking predetermined outcomes [101], [102].

2.9.3 Reinforcement learning

Reinforcement Learning algorithms offer a dynamic learning approach, distinct from supervised and unsupervised methods, by making sequential decisions to maximize cumulative rewards through interactions with an environment. Particularly valuable in real-time decision-making scenarios such as robotics, gaming, and navigation, it finds applications in autonomous systems like self-driving cars and industrial robotics. Combining reinforcement learning with methods like unsupervised learning showcases the adaptability of machine learning techniques, enabling intelligent decision-making based on environmental feedback [103].

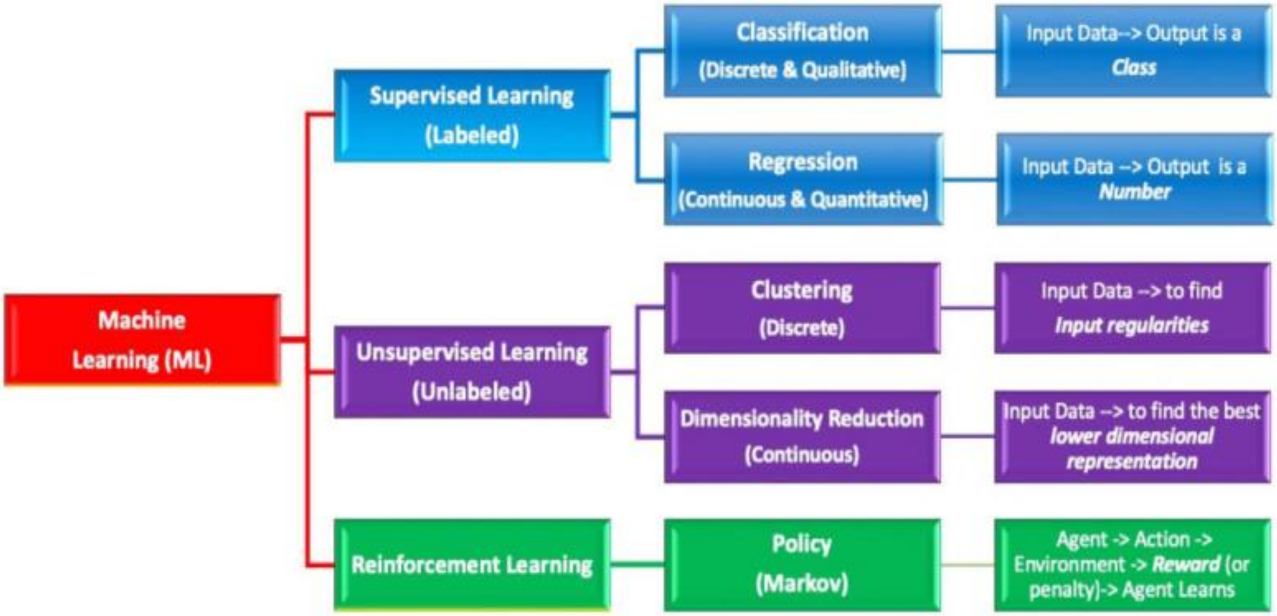


Figure 2. 6 Machine learning algorithms classification [104]

ML offers powerful tools for predicting and optimizing processes in various industries, including sand casting. ML algorithms, particularly supervised learning, are effective in harnessing large datasets to discern patterns and make accurate predictions, which includes regression and classification, views out for its ability to predict outcomes based on historical data, making it particularly suitable for applications of defect prediction in sand casting.

In comparison, unsupervised learning identifies hidden patterns in data without labeled responses, useful for clustering and dimensionality reduction, while reinforcement learning focuses on optimizing decision-making through feedback and rewards, relevant for dynamic environments like robotics.

For this study, supervised classification is the preferred method due to its ability to categorize defects and assess their severity based on past data, ensuring precise and reliable predictions and also this approach not only enhances defect detection but also optimizes process parameters, leading to improved casting quality and reduced scrap rates.

2.10 Supervised Machine Learning Algorithm

2.10.1 Artificial Neural Network

The human brain comprises billions of interconnected neurons, allowing for complex decision-making and parallel processing. Similarly, artificial neural networks have been designed to mimic this biological structure. At the core of neural networks are nodes or units that receive inputs from external sources, in each assigned weight. These units compute the weighted sum of their inputs. NN typically comprise three (input, hidden and output) layers, interconnected with a feed-forward manner [105].

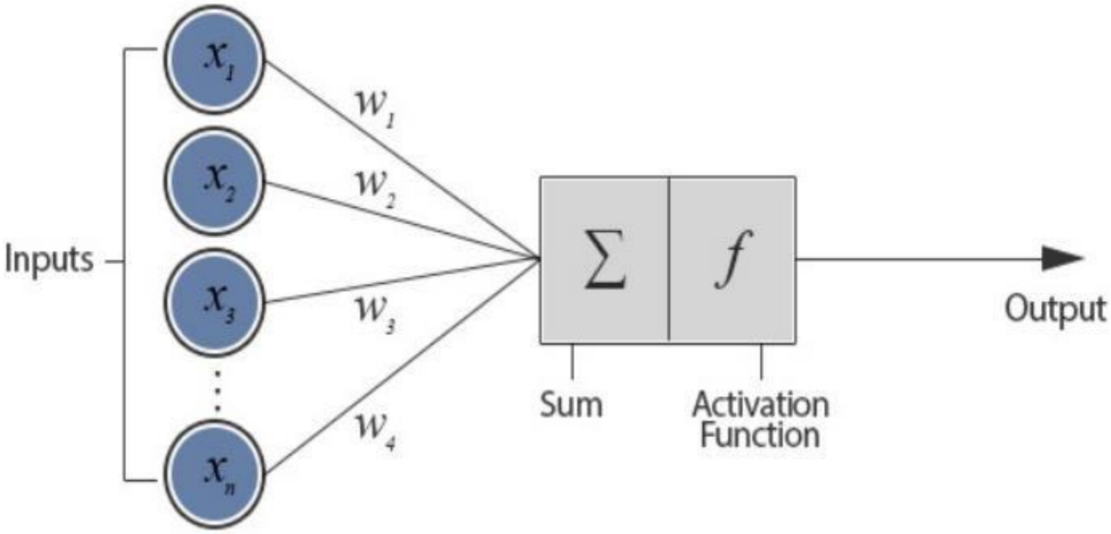


Figure 2. 7 Artificial neurons modeling [106]

As illustrated in figure 2.7, a typical perceptron features numerous inputs, each of which is individually assigned a weight. These weights serve to either enhance or diminish the original input signal. When the input is 1 and its weight is 0.2, the input signal is reduced to 0.2. Subsequently, these weighted signals are aggregated and fed into the activation function. The activation function serves the purpose of converting the input into a more meaningful output. Various types of activation functions exist, with one of the simplest being the step function. A step function typically yields a 1 if the input surpasses a certain threshold; otherwise, its output remains 0 [107].

2.10.2 Support Vector Machine

One of the most widely used and sophisticated machine learning techniques is the Support Vector Machine (SVM). These models, accompanied by specialized learning algorithms, are prominent in classification and regression tasks within the field of machine learning. In addition to their effectiveness in linear classification, SVMs excel in nonlinear classification through the kernel trick, which maps inputs into high-dimensional feature spaces. Essentially, SVMs establish margins between classes, ensuring maximal distance from the classes to minimize classification errors [108].
These advanced ML techniques include Support Vector Machine (SVM) models, which share similarities with classical multilayer perceptron NNs and designed around the concept of margin regions surrounding a hyperplane that separates two data classes. Maximizing this margin, which creates the maximum distance between the dividing hyperplane and the instances on each side, has been shown to minimize the expected generalization error

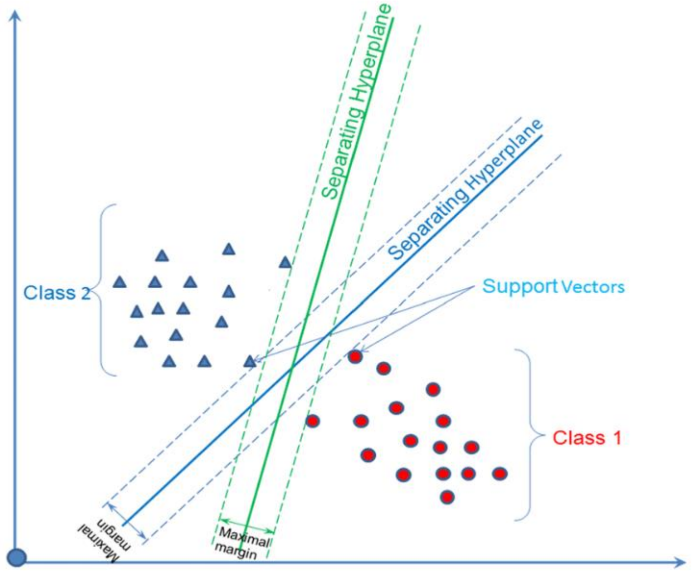


Figure 2. 8 SVM model [109]

SVM, Shown in Figure 2.8, is a parametric technique widely utilized in machine learning research. It has gained considerable traction in tackling classification tasks and has shown successful applications across diverse real-world domains. [110], [111].

2.10.3 Logistic Regression

LR is a predictive analysis method used for discrete binary values based on a specified set of independent variables. LR characterizes the data and clarifies the relationship between a binary dependent variable and independent variables.

$$P = \frac{e^{(b0+b1*x)}}{1+e^{(b0+b1*x)}} \tag{2. 1}$$

It predicts likelihood of event occurrence by fitting the data to a logit function, known as LR. Input values (x) are combined linearly using coefficient values (b) to calculate an output value (p), which falls between 0 and 1, rendering the outputs predictable. The input data corresponds to coefficients (b), constant values acquired from training data. 'p' denotes the output, 'b0' signifies an intercept term, and 'b1' represents the coefficient of input value (x), as depicted in the model [112].

2.10.4 Decision Tree

Decision Tree (DT) is a graphical decision support model commonly used in research and classification tasks, dividing data into subsets based on key attributes to aid decision-making. It's also known as "decision trees" or Classification and Regression Tree (CART) and assumes feature independence for fruit identification probability [110], [113], [114].

2.10.5 Naive Bayes classifier

Supervised learning is employed in NB classifiers to improve the efficiency of learning classification tasks. This increased efficiency stems from NBC's ability to learn parameters by extracting basic per-class statistics from features through individual observations. The NB model uses parameter estimation via the maximum likelihood method across various applications. NBC fundamental tool for probabilistic classification, grounded in Bayes' theorem. This model operates under the assumption that each feature in the training set is statistically independent and unrelated to the others [7].

2.10.6 K-Nearest Neighbors

KNN is used in both regression and classification tasks, with a primary focus on classification. The KNN classifier stores all known instances and classifies new instances based on the majority vote of its nearby neighbors. A new instance is assigned to the class most common among its k closest neighbors, determined by a distance function. [116], [117].

Figure 2. 9 K-NN algorithm during classification [118]

2.10.7 Random Forests (RF)

RF are ensemble learning techniques used for regression, classification, and other tasks. They generate multiple decision trees during training and produce the average prediction for regression or the most common class for classification. RFs reduce overfitting by aggregating several decision trees, each contributing its classification based on the new case's attributes. The final classification is determined by majority vote from all trees. The process includes randomly selecting a sample with replacement from the training set for each tree, choosing a random subset of variables at each node, and splitting the node using the best criteria among these variables [119], [120].

2.10.8 Ridge Regression

Linear least squares with regularization challenges issues encountered with Ordinary Least Squares by imposing a penalty on the magnitudes of coefficients. The ridge coefficients aim to minimize a penalized residual sum of squares Regression, XX represents the matrix of input features, and ww is the vector of weights (regression coefficients) that need to be determined. The vector yy contains the observed values. The Euclidean norm ($\ell 2$ norm) is denoted by $\|\cdot\|2$. The regularization parameter is represented by α (alpha) [121].

$$\boldsymbol{min_w \|X_w - y\|_2^2 + \alpha \parallel \mathbf{w} \parallel_2^2} \tag{2. 2}$$

2.10.9 Random Forest Regression

The algorithm consists of multiple decision trees that work together to make predictions based on their collective results. Training the forest can be done using bagging or bootstrap aggregating. Bagging uses different data samples to add randomness, reducing the variance of the base estimator, while bootstrap trains weaker learners on altered versions of the data. The predictions from these trees are combined through a weighted majority vote to form the final prediction. Random Forests address the limitations of individual decision tree algorithms by reducing overfitting, enhancing accuracy, and averaging the outputs of multiple trees to make predictions [122], [123].

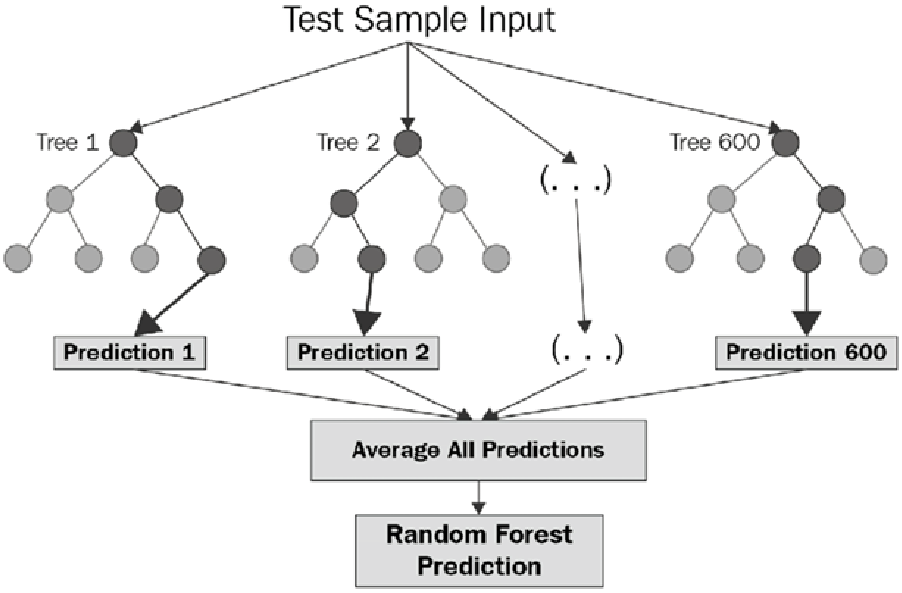


Figure 2. 10 Random forest structure [124]

2.10.10 Extremely Randomized Trees

Unlike random forests, Extremely Randomized Trees (ET) introduce additional randomness in split computation without sampling observations during tree construction. Instead, it randomly selects split-points for each chosen predictor and identifies the best split from this restricted set of options. Although this approach slightly increases bias, it decreases the model's variance. ET outperforms the other five models across all scoring metrics, indicating its superior performance during testing [125], [126].

2.10.11 Extreme Gradient Boosting (XGBoost)

Extreme Gradient Boosting, a method combining decision trees, incorporates boosting, where subsequent trees assign more weight to incorrectly predicted samples by previous trees. Predictions are derived from a weighted agreement of all trees. XGBoost employs gradient descent to minimize loss when introducing new models, blending the strengths of tree-based and boosting algorithms for robust supervised learning [113], [127].

2.10.12 CatBoost and AdaBoost

CatBoost algorithm, leveraging boosting, gives in its capacity to successfully grip diverse categories of data and handle missing numerical values. In contrast to XGBoost, CatBoost utilizes symmetric trees, employing identical splits in nodes at every level, resulting in accelerated processing. It iteratively trains the overall model by calculating residuals for each data point, generating distinct residual data for subsequent iterations and evaluating them as targets for further refinement AdaBoost is an ensemble learning technique that combines weak learners to create a strong classifier by iteratively adjusting weights of misclassified instances [112], [122].

2.10.13 Gradient Boosting Regression

Gradient Boosting Regression is an ensemble learning algorithm that combines weak predictive models, typically decision trees, into a stronger predictive model starts with a constant prediction, like the mean of target values, and iteratively fits decision trees to predict the negative gradients of the samples. These gradients are updated iteratively, contributing to the improvement of the overall model [128], [129].

ML algorithms, including NN, SVM, LR, DT, KNN, RF, Ridge Regression, Extremely Randomized Trees (ET) Regression, CatBoost, Extreme Gradient Boosting (XGBoost), and Gradient Boosting Regression, offer versatile approaches for classifying and predicting the severity of defects in sand casting processes. These algorithms utilize various methodologies, such as mimicking neural structures (NN), maximizing class margins (SVM), valuing event probabilities (LR), and graphically representing DT, to analyze complex datasets and predict outcomes. Ensemble methods like RF, ET, XGBoost, and CatBoost further enhance prediction accuracy by combining different models and reducing overfitting.

2.11 Data Pre-Processing and Feature Engineering

Machine learning provides substantial advantages in automating diverse data pre-processing tasks such as cleaning data, engineering features, and selecting relevant characteristics. It helps in detecting and eliminating outliers, correcting errors, and generating synthetic data to enhance existing datasets, thereby reducing manual effort for data scientists effectively classify various fruits based on attributes like size, shape, color, and texture, showcasing its utility in real-world applications. [130].

ML exhibits efficiency in detecting and classifying fruit diseases or defects such as spots or discoloration. Computer vision techniques can be applied proactively for fruit preservation. Classification, Segmentation, and regression are among the different machine learning methods and approaches utilized. By analyzing and processing data, trends and patterns related to cleanness, shelf life, and other factors crucial for fruit preservation can be identified [131]–[133].

2.11.1 Exploratory Data Analysis

Conducting EDA is essential for uncovering patterns, detecting outliers, and testing hypotheses through statistical methods and visualizations, aiding in better data comprehension and preparation for machine learning. EDA lays the groundwork for developing accurate algorithms by extracting patterns from the data, offering crucial insights before algorithm implementation [134]. Aim of using EDA to understand data characteristics before algorithm development, involving steps like loading the dataset, analyzing variable types, and assessing data quality through summary statistics [135]. Following data preprocessing, feature engineering was carried out using Python toolkits, while statistical analysis in the time domain was employed to extract nine classical condition parameters from all intrinsic mode functions [110], [111].

2.11.2 Data Augmentation Techniques

Data augmentation is pivotal in mitigating data imbalance in ML models [138]. By broadening feature amplitudes, it aids in associating data changes with labels, enhancing model generalization. This impacts model weights and feature selection, bolstering accuracy for minority classes. A meta-classifier combining original and augmented data enhances prediction accuracy, correlation coefficient values, leveraging improved metrics and augmentation may introduce noise, potentially hindering performance[139]. SMOTE, known as Synthetic Minority Over-sampling Technique, stands out as a frequently employed method for tackling class imbalance in machine learning datasets [140] .

Machine learning's role in automating data pre-processing tasks like cleaning and feature selection, easing the workload for data scientists and the importance of Exploratory Data Analysis (EDA) for understanding data patterns and anomalies before implementing machine learning algorithms. Feature engineering is conducted post-preprocessing using tools to derive essential parameters. Additionally, data augmentation techniques SMOTE are crucial for addressing data imbalance, although they may introduce noise impacting model performance.

2.12 Train and Test Model Design

The Learning model involves the initial division of datasets into two essential parts for effective processing. Learning dataset component focuses on understanding how to effectively utilize the dataset in the algorithmic process. Evaluation (Testing) set part aims to execute the algorithm while assessing its accuracy and performance. Before proceeding with the model, it is crucial to inspect the dataset's readiness [139], [140].

Initially, Python is explored as a programming language, predominantly implemented as Python, Learning model design involves defining the problem, acquiring and preprocessing data, engineering relevant features, selecting appropriate algorithms, training and evaluating the model, tuning its parameters, ensuring interpretability, deploying it into production, and monitoring its performance over time [143].Throughout this process, documentation and knowledge sharing are essential for collaboration and decision-making. The goal is to create a robust and effective model that addresses the problem statement and provides actionable insights or predictions in real-world scenarios [144], [145].

2.12.1 Bayesian Probability Theorem

The Bayesian Probability Theorem is a fundamental concept in Bayesian analysis, providing a framework for understanding the conditional probabilities of events. For any two events, X and Y the probability condition can be mathematically expressed as:

$$\mathbf{P}\ (\mathbf{X}|\mathbf{Y})\ =\ \mathbf{P}\ (\mathbf{Y}|\mathbf{X})\ *\ \mathbf{P}(\mathbf{X})\ /\ \mathbf{P}(\mathbf{Y}) \qquad (2.\ 3)$$

This theorem provides a graphical method to represent the realistic probability of a given problem, facilitating the creation of expert systems by iteratively adjusting rules. Bayesian optimization, this theorem plays a crucial role. By maintaining a probabilistic surrogate model of the objective function, Bayesian optimization adapts its understanding of the function's behavior based on observed data. This adaptive process efficiently explores and exploits the input space to identify the optimal solution with minimal evaluations. The strength of the Bayesian Probability Theorem lies in its ability to handle uncertainty and make informed decisions [146]–[148].

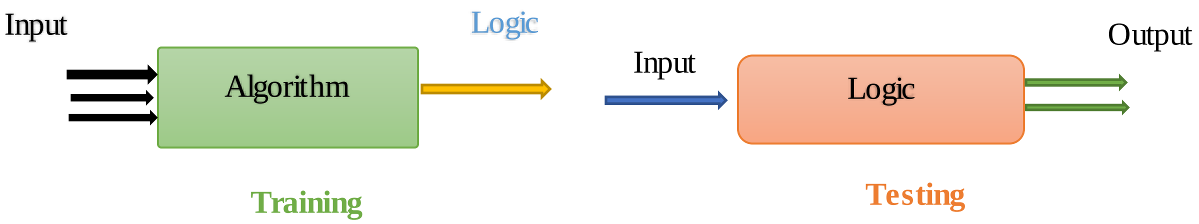


Figure 2. 11 Mapping of labels algorithms in train and test data

2.13 Models Evaluation

2.13.1 Regression Models Evaluation

For regression models, assessment typically involves metrics MSE, MAE, and R-squared. MSE and MAE measure the average difference between actual and predicted values, R-squared gauges the proportion of variance explained by the model. Additionally, RMSE and Adjusted R-squared provide nuanced evaluation, with the former indicating error in the target variable's units and the latter penalizing complexity. Residual analysis scrutinizes error distribution and patterns, offering insights into biases and model performance.

If errors, flaws, or chances for enhancement are spotted in the datasets, adjustments can be made to improve the model's effectiveness and applicability. After defining an acceptable set of hyperparameters and optimizing the model's performance, testing will be conducted on the test dataset to validate feature utilization[149], [150]. Several metrics are introduced to assess the performance of a regression model, including Mean Absolute Error, which measures the absolute error loss of the expected value.

$$\mathbf{MAE(y,y^{\circ}) = \frac{1}{n}\sum_{i=0}^{n-1}|yi - y^{\circ}i|} \qquad (2.\ 4)$$

$$\mathbf{MSE(y,y^{\circ}) = \frac{1}{n}\sum_{i=0}^{n-1}(yi - y^{\circ}i)^{2}} \qquad (2.\ 5)$$

$$\mathbf{RMSE(y,y^{\circ}) = \sqrt{MSE}} \qquad (2.\ 6)$$

$$\mathrm{R}^2\,(\mathbf{y},\mathbf{y}^\circ) = \mathbf{1} - \frac{\sum_{\mathbf{i=1}}^{\mathbf{n-1}}(\mathbf{yi}-\mathbf{y}^\circ\mathbf{i})^{\mathbf{2}}}{\sum_{\mathbf{i=0}}^{\mathbf{n-1}}(\mathbf{yi}-\mathbf{y})^{\mathbf{2}}} \qquad (2.\ 7)$$

$$\mathbf{RMSLE}(\mathbf{y},\mathbf{y}^\circ) = \sqrt{\frac{\mathbf{1}}{\mathbf{n}}\sum_{\mathbf{i=0}}^{\mathbf{n-1}}(\mathbf{log}_{\mathbf{e}}(\mathbf{1}+\mathbf{yi}) - \mathbf{log}_{\mathbf{e}}(\mathbf{1}+\mathbf{y}^\circ\mathbf{i}))^{\mathbf{2}}} \qquad (2.\ 8)$$

2.13.2 Classification Models Evaluation

In classification, evaluation centers metrics such as precision, recall, accuracy and F1 score. Accuracy indicates correct classification proportion, while precision measures positive instance identification accuracy. Recall assesses positive instance capture, and F1 score balances precision and recall. ROC curve and AUC gauge discrimination ability, while the confusion matrix offers detailed performance breakdown. Log Loss is useful for probabilistic predictions, and precision-recall curve complements ROC curve in imbalanced datasets. Cross-validation, like k-fold cross-validation, enhances evaluation reliability for both regression and classification models. In training machine learning models, numerous hyperparameters settings are involved [119], [148], [151].

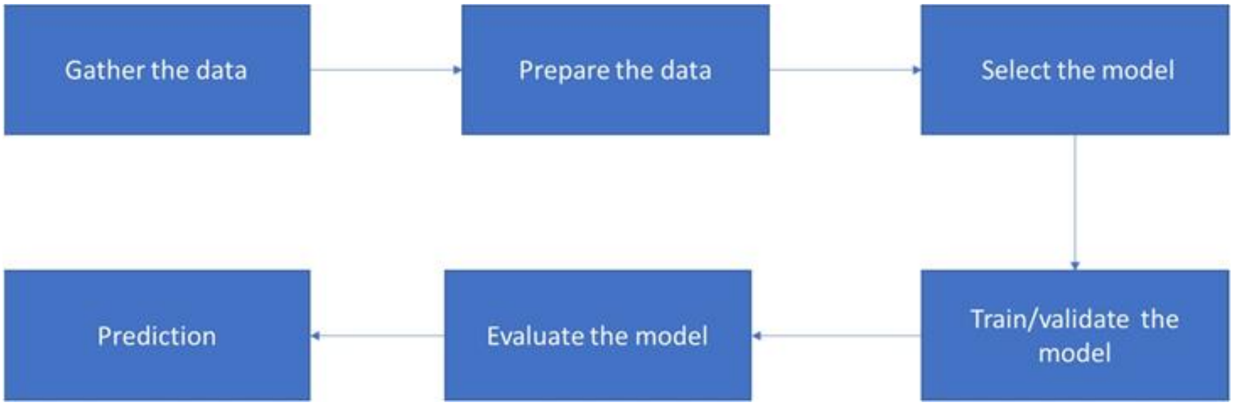


Figure 2. 12 Flowchart to solve problem by using supervised method

2.14 Model interpretation and Explanation Techniques

Interpreting machine learning models has become increasingly imperative with the widespread adoption of ML. The demand for explainable ML stems from the necessity for users to comprehend and trust model decisions, especially ML systems are deployed extensively. Transparent explanations into model operations are vital for ensuring fairness, identifying biases in training data, addressing regulatory concerns, and optimizing models for optimal performance [152]–[155].

2.14.1 Local Interpretable Model-agnostic Explanations

Algorithm capable of accurately explaining the predictions of any ML either regression or classified by locally approximating them with an interpretable model. A modular and adaptable approach aimed at accurately explaining predictions made by machine learning models in a comprehensible manner. SP-LIME, a technique for selecting representative and non-redundant predictions to offer users a global perspective of the model's behavior. Through experiments conducted in text and image domains, involving both expert and non-expert users, the study showcases the utility of explanations in various trust-related tasks such as model selection, trust assessment, model refinement, and gaining insights into predictions [156].

2.14.2 SHapley Additive exPlanations

According to Lundberg and Lee, SHAP exhibits several advantages over other ML interpretation methods. Firstly, it provides global interpretability by revealing how each predictor contributes to the target variable, whether positively or negatively. SHAP proposes a model-agnostic approximation, applicable to any machine learning model, unlike other methods that often rely on specific types of surrogate models [157], [158] .

The skill to accurately understand the output of a predictive model holds great significance. It fosters confidence among users, offers valuable clues for enhancing the model, and aids in grasping the underlying processes being modeled. In certain scenarios, straightforward models like linear models are favored due to their simplicity in interpretation, despite potentially lower accuracy compared to more intricate ones. Nevertheless, with the rise of big data, a growing advantage in utilizing complex models, which brings into focus the balance between a model's accuracy and its interpretability [157]–[159].

LIME and SHAP are methods for explaining machine learning model predictions. LIME provides local explanations by approximating complex model behavior with simpler models for individual predictions, while SHAP offers global insights by attributing feature importance across all predictions [160], [161].

2.14.3 Permutation Feature Importance (PFI)

It tells key features impacting predictions, aiding in understanding relationships with the target variable. By measuring performance changes with shuffled features, PFI ranks feature importance, aiding in feature selection and model enhancement. Understanding the most important features in machine learning models is vital for interpretability. Two common methods for this are Feature Importance (FI) and Permutation Importance (PI). FI assesses the significance of features, mainly in tree ensembles like Random Forests (RF) and Gradient Boosting (GB). PI, measures the impact of shuffling a single feature's values on the model's score.FI is model-specific and favors numerical features, PI is model-agnostic and offers a more balanced view, especially for categorical variables [162]–[164].

From these interpretation techniques, Random Forest feature importance, because Random Forests are suitable for identifying significant features in the predictive modeling tasks. Random Forests excel in taking complex relationships between features and target variable by handling nonlinearities and interactions effectively.

2.15 Machine Learning Applications in Manufacturing

Machine learning (ML) has transformed manufacturing operations by providing sophisticated analytical tools to optimize processes, enhance quality control, and prevent equipment failures through predictive maintenance. In the realm of defect detection, ML algorithms examine vast datasets of product images or sensor data to quickly identify abnormalities and defects. For instance, in the automotive sector, ML algorithms are adept at examining car body panels for surface imperfections like scratches or dents, facilitating prompt detection and corrective measures [133], [165].

ML also revolutionizes quality control in manufacturing by streamlining inspection tasks and enhancing precision. ML models, trained on historical data, forecast product quality using diverse parameters, empowering manufacturers to dynamically adjust production processes to uphold stringent standards. In semiconductor manufacturing, for example, ML algorithms meticulously analyze sensor data to pinpoint irregularities in chip fabrication processes, ensuring the production of flawless products [166].

Predictive maintenance stands out as another critical ML application in manufacturing. By analyzing sensor data from equipment, ML models predict potential machinery failures and schedule maintenance preemptively, minimizing downtime and cutting maintenance expenses. For instance, within the aviation sector, ML algorithms analyze aircraft engine performance data to anticipate component failures before they manifest, thereby ensuring the safety and efficiency of operations [9].

Successful applications of ML in analogous domains encompass the utilization of computer vision algorithms in food processing to detect contaminants or foreign substances in food items, thereby bolstering food safety. Moreover, ML finds application in predictive maintenance within the energy sector, where it monitors the condition of power generation equipment to avert costly unscheduled shutdowns [167].

2.16 Previously Performed Research

Scholars have conducted different research on various aspects of machine learning applications in casting processes. Summarizing the literature reveals significant findings and identifies gaps for potential research. The following are the ones listed:

Shikun Chen et al. [1] illustrate the use of ML to predict casting defects on external surfaces by collecting production data from steel and cast iron foundries. In this approach, six machine learning algorithms are trained, and the SHAP framework is employed for model interpretation. This demonstrates the potential of data-driven methods to enhance casting quality control and reduce defects. Machine learning's surge in popularity enables the development of smarter systems capable of tasks like image recognition, natural language understanding, autonomous driving, manufacturing, and optimizing metal casting processes.

Zou et al. [3] developed a predictive model for internal cracks in continuous casting billets utilizing principal component analysis and a deep neural network. The DNN model demonstrated notable accuracy and stability compared to alternative methods, rendering it valuable for real-world production scenarios.

Thakare et al. [4] reviewed the challenges in casting production, emphasizing the importance of a disciplined approach to identify and address defects. They propose a novel approach to help foundries effectively control and reduce defects.

Muhammad Zain et al. [5] conducted an assessment of different ML models for software defect prediction utilizing NASA Metrics Data Program (MDP) datasets. The evaluated models encompassed k-NN, decision trees, logistic regression, LDA, SHL-MLP, and SVM. The researchers optimized the models' hyperparameters through random search and employed principal component analysis (PCA) to diminish feature dimensionality. Additionally, to tackle class imbalance, they utilized the Synthetic Minority Oversampling Technique (SMOTE). The primary outcome of the study indicated that k-NN exhibited robust performance for defect software prediction across multiple datasets. SHL-MLP and

SVM also demonstrated effectiveness on specific datasets, while logistic regression and LDA showed inferior performance.

Bramah Hazela et al. [7] discussed various aspects of machine learning, including supervised algorithms, and their application in identifying defects in high-precision foundry operations. It highlighted the significance of high-quality manufacturing in industries like automobiles and aeronautics and delved into the prevention of shrinkage defects and the mechanical properties of forged parts. The study introduced machine learning, particularly supervised algorithms, and explored methods like the Bayesian Probability Theorem, K-NN, and ANN for defect prediction and optimization. The authors provided a comprehensive methodology, validation system, and testing methods for their research. In their findings, they revealed the effectiveness of Bayesian networks in addressing microleakage, with an accuracy rate of 82%, while ANN excelled in predicting ultimate tensile strength. The article concluded by recommending the use of Bayesian networks for microleakage issues and K-NN for sensitive cases.

Domingo Mery et al. [8] investigated the exploration of deep learning-based object detection techniques for examining aluminum castings within the automotive sector. The study underscored the significance of detecting defects imperceptible to the human eye. The results revealed notable performance, with a precision average of 0.90 and an F1 score of 0.91 on real defect testing datasets. Moreover, the model exhibited real-time inspection capabilities, processing 90 X-ray images per second. Mery's work provided code and openly accessible datasets for prospective investigations while discussing limitations, including data scarcity and the reliance on costly X-ray equipment. It underscored the potential of deep learning in the aluminum casting industry, laying the groundwork for effective defect detection methodologies in forthcoming endeavors.

Igor Santos et al. [168] conducted research into the utilization of machine learning for predicting microshrinkages, a particularly challenging defect in high-precision foundry processes. These methods are put to the test using real data from a foundry process, with results compared against a prior approach. The authors employ various machine learning algorithms, including Bayesian networks, artificial neural networks, support vector machines, k-nearest neighbors, and decision trees. The outcomes are presented in terms of accuracy and the area under the ROC curve, a confusion matrix providing insights into the effectiveness of LSA in noise reduction.

Iker Pastor-Lopez et al. [81] aim to introduce an innovative approach for accurately detecting and categorizing surface defects in foundry castings using ML techniques and utilizing machine vision. An advanced machine-vision system comprising a laser camera, a high-speed processing unit, and a robotic arm. This system employs a segmentation method to identify potential defects and utilizes various machine-learning algorithms for defect classification. The research demonstrates that their machine-learning models achieve high accuracy in defect categorization, emphasizing the importance of improving the segmentation process to enhance defect detection coverage in real-world foundry settings. In summary, this study underscores the promising integration of machine-learning techniques in the foundry industry for efficient defect detection and quality control, while also highlighting the need for refining the segmentation method to ensure practical applicability in this domain.

David Blondheim Jr. et al. [11] conducted a study investigating the operation of ML in the manufacturing sector. Crucial role of precise defect classification and examined four key factors influencing classification accuracy. Results underscored the significance of data quality, particularly in high-pressure die casting (HPDC) processes. The study introduced the critical error threshold (CET) as a pivotal factor for justifying the adoption of machine learning. It also addressed inherent and bias errors, offering recommendations to enhance classification accuracy. Topics discussed included supervised machine learning, the bias-variance tradeoff, and the utilization of confusion matrices for assessing model performance.

Dorota Wilk-Kołodziejczyk et al. [12] developed an intelligent IT system to support casting production, incorporating a cost function and heuristic optimization techniques. They employed a weighted secularization method for criteria optimization. The primary approach involved combining machine learning and computer simulation in the MAGMA Soft environment to forecast mechanical properties and microstructure based on chemical composition. Results were validated through physical experiments, highlighting the potential of integrating these methods to optimize production parameters.

Sika et al. [13] applied the k-nearest neighbors algorithm to predict ductile cast iron casting defects using historical data encompassing parameters like green sand properties and pouring parameters, revealing that tailored weight sets enhanced prediction quality and held potential for optimizing foundry processes; however, the study lacked an in-depth exploration of weight optimization challenges and real-world implementation considerations, and the objectives were to demonstrate the feasibility of using the k-NN algorithm for predictive purposes in foundry processes.

Igor Santos et al. [169] employed Bayesian networks, K-nearest neighbors, and ANN to predict ultimate tensile strength in foundry castings, revealing that Multilayer Perceptron (MLP) excels among classifiers; however, the study highlighted the potential issue of reduced accuracy with the full training dataset and aimed to integrate machine-learning classifiers into a meta-classifier for enhanced UTS prediction, indicating the need for further research to address this accuracy reduction and optimize the prediction process.

Suthar et al. [52] illustrate foundries worldwide that produce cast metal components critical for various industries. Quality assurance in these components is paramount to product excellence. Foundry operations' complexity grows with intricate designs, patterns, and geometries, necessitating stringent monitoring of casting process quality parameters. This study focuses on improving the quality of the foundry industry. A primary dataset from sand and investment casting experts was analyzed using machine learning and cluster analysis methods. The findings identify key process variables influencing quality parameters with high accuracy levels, aiding practitioners in effective quality control.

Table 2. 1 Tabular summary of literature

Author (year)	Methodology	Main findings	Gaps Identified
Shikun Chen et.al.(2021)	Data collection, Machine Learning, SHAP framework	Machine learning, ET, effectively predicts casting surface defects in foundries. Key influencing variables related to mold quality are identified.	Lack of comprehensive and high-quality data in the foundry industry, which hinders the full potential of machine learning for addressing casting defects and optimizing production processes.
Zou et al.(2021)	Data collection, DNN, PCA modeling	A PCA-DNN model is effective for real-time prediction of internal cracks in steel billets during continuous casting.	Limited data, implementation insights, diverse setting model effectiveness exploration needed

Muhammad Zain et.al,(2023)	Used NASA MDP data, k-NN, decision trees, LR, SVM; tuned hyperparameters, applied PCA, SMOTE.	K-NN excelled, SHL-MLP, SVM effective, logistic regression, LDA underperformed. Model optimization crucial.	Incomplete exploration of classification ensembles' potential for enhancing model performance.
Hazela, B., et al. (2022)	Collects precision foundry data, classification and regression methods	Bayesian networks excel in micro shrinkage (82% accuracy), ANN in tensile strength, K-NN in sensitive cases.	Lack of exploration on handling class imbalance in machine learning models.
Mery, D. (2021)	Evaluated YOLO, RetinaNet, and best simulated defects. Real-time inspection	YOLOv5s trained in 2.5 hrs., achieved 90% precision, 91% F1 on real defects, inspected 90 images/sec.	The study lacks diversity in defect types, focusing on simulated ellipsoidal defects.
Igor Santos et al.(2010)	LSA, SVD for data preprocessing; Found LSA significantly enhanced accuracy in microshrinkage prediction.	LSA significantly enhanced the accuracy of different ML algorithms in predicting microshrinkage in high-precision foundry processes	Limited exploration of contemporary noise reduction methods; potential for broader defect prediction and algorithm comparison
Iker Pastor et.al (2012)	Used machine vision, segmentation, and machine learning for automated foundry casting defect detection	Random Forest achieved 96.12% accuracy in defect categorization	Need to enhance segmentation coverage for practical deployment in real foundry applications.
David Blenheim Jr,(2021)	investigated ML in manufacturing, analyzed defect classification impact, proposed solutions, and emphasized data collection strategies for improvement	critical role of accurate defect classification and critical error threshold	Identified challenges in defect classification, suggested a systems approach, and recommended future studies for data optimization.

Dorota Wilk (2023)	Applied AI for casting production modification, integrated cost function, validated results through computer simulation and experiment	Combined ML, simulation, and heuristic optimization to derive new production parameters effectively	Unspecified challenges or areas for improvement in the application of AI in casting production.
Sika et al (2009)	K-NN for ductile cast iron defect prediction using green sand and pouring parameters.	Optimal weight sets influence prediction quality; tailored k-NN approach for foundry processes.	Limited discussion on algorithm limitations and scalability in real-world foundry applications
Uyan et al (2022)	Employed industry 4.0 and supervised ML classification models to predict defectives in LPDC processes.	Successfully predicted porosity defect occurrence rates in LPDC processes	Difficulty in root cause analysis due to low defect occurrence rates and numerous potential process measurement variables.
Upadhye,et.al.(2023)	Literature Review, Analysis of AI methods	Metal casting industry employs AI methods like decision trees, rough set theory, case-based reasoning, fuzzy logic, and ANN to improve casting quality and minimize rejection rates.	Incorporating AI technologies in foundries revolutionizes sand mold design and defect analysis, offering significant enhancements in operational efficiency and global competitiveness.
Chinnadit Baitiang et al. (2023)	Statistical Analysis, Regression Modeling	Proposes a data-driven approach for real-time process control in cast iron foundries to enhance casting quality and productivity.	Incomplete casting traceability complicates data collection, while unstable parameters hinder precise synchronization between inline and part quality data, impacting defect analysis

Bang Guan et al. (2024)	Data collection, Random Forest Classification Algorithm	Proposes a data-driven method for reducing casting defects in sand casting, utilizing RF classification, feature importance analysis, and Monte Carlo simulation.	Identified key process parameters affecting casting defects and demonstrated the potential of data-driven methods in reducing scrap rates through quality prediction and process optimization.
Selvaraj et al. (2022)	Machine learning, deep learning	Injection molding benefits from machine learning techniques for quality enhancement. Neural networks are extensively applied for optimization, prediction, and monitoring in manufacturing.	Challenges include data management and model validation in practical implementation, such as data division, preprocessing steps, and algorithm selection.

2.17 Gaps Identified and Review Summary

Existing literature highlights the growing interest in leveraging machine learning for defect prediction in casting processes, emphasizing quality control improvements. Commendable developments have been made, yet challenges persist, urging further research on prediction accuracy optimization, unique casting process challenges, and practical applicability in real-world foundry settings. The literature emphasizes aligning machine learning models with specific dataset characteristics and the understated nature of casting-related data. The journey involves deeper exploration of hyperparameter tuning, model-dataset alignment, and advanced techniques to address challenges like class imbalance and noisy data. Beyond refining predictive models, exploring real-world machine learning implementation in foundry environments is crucial, addressing scalability, adaptability, and integration challenges. The ongoing journey extends beyond quality improvement and defect prediction to impact sustainability, energy efficiency, economics, and worker safety. Machine learning holds potential for optimizing production, contributing to sustainability, and indirectly promoting worker safety by minimizing casting faults. Continued exploration aligns with broader objectives of fostering sustainable, safe, and economically viable foundry operations.

Research gaps in sand casting processes include limited research, particularly within Ethiopian industries, and a lack of comprehensive understanding of the full potential of machine learning due to data scarcity and implementation challenges in real-world foundry settings. There has also been limited investigation into the use of supervised ensemble methods in casting defect prediction. Additional gaps include the need for integrating various models for defect prediction, addressing practical challenges in applying machine learning to foundry settings, and optimizing hyperparameters for better model performance. Further research is needed to explore explanation methods beyond SHAP for model interpretability and to understand the impact of machine learning applications on sustainability, energy efficiency, economics, and worker safety. Encouraging collaborative efforts between academia and industry is crucial for bridging theoretical advancements and practical implementation.

CHAPTER THREE

3. RESEARCH METHODOLOGY

In this chapter examines the research methodologies employed to construct the datasets and achieve the research objectives, outlining the strategies used in predicting sand casting defects and justifying their application. Design science research technique has been selected as a technique for coming across and identifying possibilities and problems of sand casting defects in a manufacturing foundry.

3.1 Research Design Method

The experimental design method and quantitative research approach are used in this study to predict the defects of sand casting using parameters. The quantitative research method is used to examine foundry data sets. A literature survey will be conducted, summarizing published works on machine learning models for predicting sand casting defects, including features associated to specific types of defects such as porosities, inclusions, metal penetration, shrinkages, blowholes, and misruns.

3.1.1 Experimental Research Design

The methods of the research were experimental. A literature review is conducted to understand the issue and formulate the research questions. Data gathering follows the creation of the study question. The problem's solution is outlined and designed. The solution is next evaluated, and the evaluation's findings are examined.

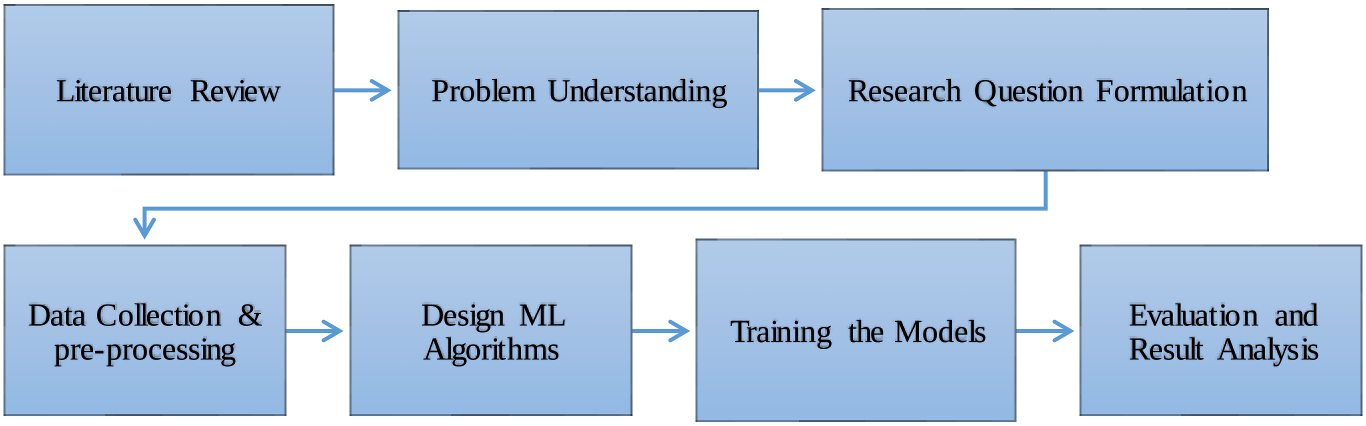


Figure 3. 1 Design of the research methodology

3.1.2 Quantitative Research Approach

The research approach for this study was quantitative. The data gathered from the Akaki Basic Metal Industry is the numerical data required. The overall goal of quantitative research to explore a specific activity through the measurement of variables in quantifiable terms. It was dependent on the collection and analysis of numerical data.

3.2 Case Study Area: Akaki Basic Metals Industry

Akaki Basic Metals Industry (ABMI), formerly Akaki Spare Parts and Hand Tools Share Company (ASPSC), has been a cornerstone of Ethiopia's industrial growth, particularly in casting processes. Situated approximately 22 kilometers southeast of Addis Ababa, near Akaki town, ABMI was established in 1989. It has supplied spare parts, machinery components, and advanced the metal industry since its inception.

The genesis of ABMI stemmed from Ethiopia's urgent need for spare parts in industries, with preliminary studies conducted by the German Democratic Republic (GDR) and the United Nations Industrial Development Organization (UNIDO) importance the necessity for a spare parts factory. A comprehensive feasibility study funded by the Swedish International Development Agency (SIDA) paved the way for establishing the factory, with project implementation beginning in April 1985.

SWECO conducted a thorough research that included four important businesses (the metalworking, cement, textile, and sugar industries), even though it had been suggested that a factory for spare parts be established that could produce nearly 3600 different things. Between Nations Metal Works Corporation and an Italian engineering company, "FATA," The construction of "a spare parts factory" and the factory, which had a capital of Birr 142,298,000.00 and a total area of 155.000 m2, were both opened. Currently ABMI is under Ethio Engineering Group and now in the reformation stage to develop it competitiveness in the local and regional market.

The AKAKI basic metals sector uses a variety of technologies and production techniques to create completed and semi-finished goods from ferrous and non-ferrous materials. There are five factories functioning within the sector, namely: foundry and heat treatment shop, machine shop, fabrication shop, forging and surface treatment, and steel processing factory. ABMI addressed the limitations faced by Ethiopia's metal processing plants by providing dedicated foundry workshops for ferrous and nonferrous and, thus supporting emerging factories and propelling the country's metal sector forward. With a state-of-the-art foundry workshop equipped with various casting processes, ABMI has become integral to Ethiopia's metal industry, contributing significantly to its development.

3.2.1 Sand Casting Defects at Akaki Basic Metal Industry

At Akaki Basic Metals Industry (ABMI), typical casting defects and their potential consequences are noted. However, the observed defects and their impacts at ABMI may differ based on the particular casting techniques, materials used, and the effectiveness of quality control measures in place.

Table 3. 1 Sand casting defects and their impact

Defect	Description	Impact
Metal penetration	Molten metal seeping into the sand mold	Surface irregularities, compromised structural integrity, aesthetic issues.
Inclusions	Presence of foreign particles	Aesthetic concerns, potential material weakness, diminished overall quality.
Blowholes(porosity)	Formation of voids due to gas entrapment during solidification.	Reduced mechanical properties, aesthetics, and potential material failure.
Incomplete fusion	Insufficient bonding between molten metal and existing surfaces.	Weak joints, susceptibility to stress, compromised structural integrity.
Casting surface cracks	Appearing on the surface of cast metal.	Weakened structural integrity, potential for catastrophic failure, durability.
Surface irregularities	Irregular surfaces on the cast metal.	Aesthetic concerns, potential functional issues, reduced product value.
Dimensional inaccuracies	Variations in size, shape, or dimensions	Compromised functionality, assembly difficulties, potential rejection by end-users.
Shrinkages	Forming during the cooling process.	Potential for material failure, compromised product lifespan.

3.2.2 Parameters and Data Collection Process

Collecting data from Akaki Basic Metals Industry (ABMI) for predicting sand casting defects involves gathering information directly from casting processes, encompassing both dependent variables (defect types and severity) and independent variables (such as temperature, sand type, and material composition). Close collaboration with domain experts like metallurgists ensures insights into critical features of the casting process, while data from Quality Control (QC) and Production Planning and Control (PPC) records provide ground truth for model training, with accepted components denoting defect-free castings and rejected components indicating defects. Thorough documentation ensures the reliability of the collected data, forming foundation for developing an effective machine learning model.

The primary objectives of data collection are to gain detailed insights into ABMI's casting processes and gather information necessary for developing a predictive model for casting defects. Collaboration with QC and PPC departments facilitates access to detailed records, including job order details, defect types, and critical casting parameters. Validation checks and collaboration with QC and PPC teams ensure data accuracy and consistency, with clearly defined criteria for component acceptance and rejection based on QC standards. The systematic collection of diverse casting scenarios enriches the dataset, prioritizing the identification of dependent variables (defect type and severity) and independent variables (casting process parameters) critical for defining predictive features in the model.

3.3 Design Models for Prediction of Casting Defects and Severity

3.3.1 Machine Learning Algorithms

To identify predictors and build ML models for sand casting processes, various machine learning algorithms are applied to datasets with the objective of accurately predicting and mitigating defects in the casting industry of ABMI. The chosen classifiers KNN, SVM, XGBoost, Gradient Boosting, DT, LR, Ensembles of Random Forest (AdaBoost, Gradient Boosting, XGBoost), and NN algorithms are selected due to their successful classification performance and popularity in addressing issues identified in earlier research, which has informed related work in other nations.

Prediction models are developed using these machine learning methods. For comparison and assessment of prediction accuracy, performance measures such as, recall, precision ,F1 score, and ROC curve are utilized [170].

3.3.2 Train and Test of Machine Learning Classifiers

The focus is on training supervised machine learning classifiers using labeled datasets specific to sand casting defects found in the industry. Input features and corresponding labels are analyzed to develop classifiers capable of accurately predicting defect presence and severity, aiding decision-making in foundries. During the data training phase, the algorithm constructs classification models using provided training data, with evaluations performed to quantify model performance and assess generalization error. This study assesses machine learning classifiers' performance using various evaluation criteria tailored to finite dataset training [171], [172].

3.3.3 Performance Evaluation Metrics and Confusion matrix

Due to the bias of classification algorithms, prediction model evaluation is necessary to quantify the performance of the model. Evaluated and tested machine learning models that were developed using the sand casting product dataset for learning capabilities. Finding an appropriate generalization error estimate for models that have been trained on finite datasets is the fundamental goal of machine learning models.

Confusion Matrix constructs an A x A matrix, with A representing the number of predicted sand casting defect classes. This metric evaluates model accuracy and correctness, especially useful in scenarios with imbalanced datasets. Comprising Actual and Predicted dimensions, each with multiple sets of classes, the confusion matrix aids in calculating diverse performance metrics [173].

In classification problems, four key components. True positive (TP) instances signify the model correctly identifying sand casting defects, aligning predictions with actual positive outcomes. False positive (FP) cases occur when non-defective items are incorrectly identified as defective, resulting in inaccurate positive predictions. True negative (TN) instances represent the model accurately identifying non-defective items, with predictions matching actual negative outcomes. Conversely, false negative (FN) occurrences entail the model erroneously classifying defective items as non-defective, leading to incorrect negative predictions.

Table 3. 2 Confusion matrix

	Predictive Positive	**Predictive Negative**
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

To ensure accurate evaluation of the machine learning classifiers, crucial metrics were derived from the confusion matrix. These metrics include true positive rate (TPR), false positive rate (FPR), precision, recall, and F1 score, in addition to accuracy [174], [175].

Accuracy, Precision, and Recall assess the prediction accuracy of severity and defect types. Accuracy gauges the percentage of accurately predicted defects, Precision measures the true positives among all predicted positives, and Recall indicates the ratio of correctly predicted positives to all actual positives, indicating the model's defect identification capability [176].

Table 3. 3 Performance Evaluation Metrics of Machine Learning classifiers [177]

Name of Measurements	**Formula**
Correct Classification Rate/Accuracy	$\frac{\mathrm{TP} + \mathrm{TN}}{TP + FB + FN + TN}$
TPR, Sensitivity or Recall	$\frac{\mathrm{TP}}{TP + FN}$
FPR(1-Specificity)	$\frac{\mathrm{FP}}{FN + TN}$
Specificity or True Negative Rate (TNR)	$\frac{\mathrm{TN}}{FP + TN}$
Precision	$\frac{\mathrm{TP}}{TP + FP}$
F1- Score	$\frac{2 \text{ x Precision x Recall}}{\text{Precision} + \text{Recall}}$

Correlation coefficients gauge the strength and direction of the association between two variables, with values ranging from -1.0 to 1.0. A coefficient of 1.0 denotes a perfect positive correlation, -1.0 indicates a perfect negative correlation, and 0.0 suggests no correlation between the variables [178].

Table 3. 4 Correlation coefficients description

Correlation size	**Interpretation**
0.90 to 1.00 (-0.90 to -1.00)	Very high positive (negative) correlation
0.70 to 0.90 (-0.70 to -0.90)	High positive (negative) correlation
0.50 to 0.70 (-0.50 to -0.70)	Moderate positive (negative) correlation
0.30 to 0.50 (-0.30 to -0.50)	Low positive (negative) correlation
0.00 to 0.30 (-0.00 to -0.30)	Little if any correlation

3.4 Model Building for Defect and Severity Prediction

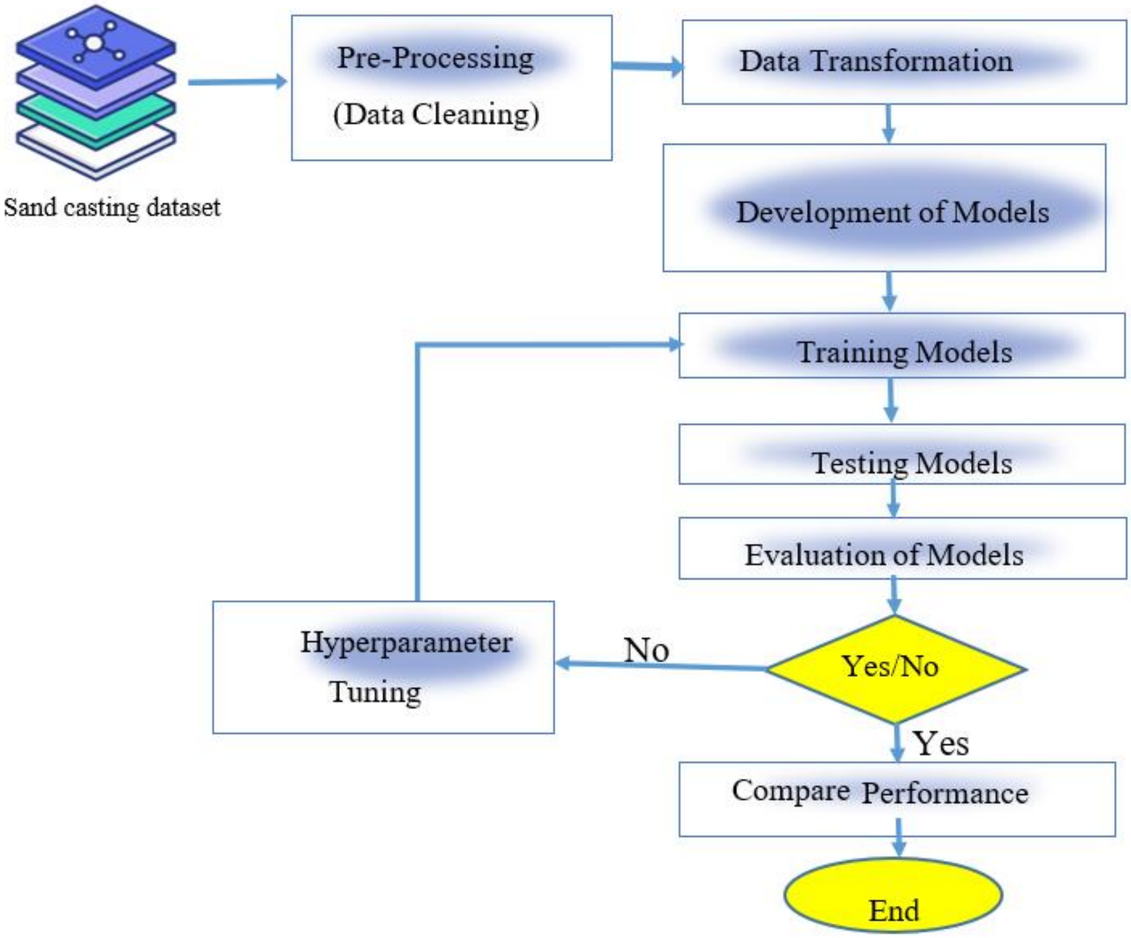


Figure 3. 2 Research Method Framework

Predicting sand casting defects involves collecting a dataset of accepted and rejected sand casting products. Various classifiers algorithms are selected based on their successful classification performance. These classifiers undergo training on the dataset and are subsequently evaluated using metrics Recall, Precision, F1-Score, to identify the best prediction model. This model is then utilized to develop a prediction model, encompassing both defect type and severity. A machine learning classification model, incorporating techniques such as SVM, NB, DT, RF, KNN, LR, Ensembles of Random Forest (such as AdaBoost, Gradient Boosting, and XGBoost), and Neural Networks, is employed. The performance of these models is compared to select the most effective one. Finally, chosen model is deployed as a web-based application to facilitate real-time defect prediction in sand casting processes.

3.5 Implementation and Experimentation

This study works an experimental approach to determine effective ML algorithm for predicting sand casting defects. Furthermore, separate models are applied to each dataset within the experiment.

3.5.1 Implementations

Various development tools and Python packages for predicting sand casting defects and its severity, covering data loading, model construction, and assessment. The table below lists the tools and Python packages used, along with their version numbers and descriptions.

Table 3. 5 Description of the Python tools used

Tools	Description	Version
Anaconda Navigator	Without using commands, enables us to run development applications and simply manage conda packages and environments.	-
Jupyter notebooks	The system integrates web app and notebook features for creating and sharing live documents with code, visuals, and text, serving purposes like data processing, machine learning, and visualization.	1.0.0

Python	An application for machine learning can be created using this sophisticated, yet simple-to-learn programming language.	3.7.13 (default, December,21,2023,01:04:09) [GCC 7.5.0]
Microsoft Excel	Used to clean, filter, and sort the data that has been obtained for data preparation operations.	Microsoft Excel professional , 2016

Table 3. 6 Description of the Python packages used

Packages	**Description**	**Version**
Packages	A collection of easy-to-use and effective Python modules	1.0.2
Scikit-learn	For data mining and machine learning. Used to test and train models. Sklearn is the name of the package.	-
Pandas	Tools for data analysis that are high-performance and simple to use. Used for handling the data frame for reading, manipulating, and writing data.	1.3.5
NumPy	Processing of arrays for objects, strings, and integers. Used to handle numerical data when testing and training a model.	1.21.6
matplotlib	Python publishing of high-quality figures. It is used to visualize the data and findings.	3.2.2
Statsmodels	Provides classes and functions for estimating statistical models, investigating statistical data, and running statistical tests.	0.10.2
Seaborn	Built on top of matplotlib, offers a user-friendly interface for creating visually appealing and insightful statistical plots in Python.	0.11.2
SciPy	Computational library built on NumPy, offering additional utility functions for tasks such as optimization, statistics, and signal processing.	1.7.3

3.5.2 Deployment

The tools mentioned in the table were installed on a personal computer with the following configuration: Windows 10 Pro operating system, 64-bit, Intel® Core™ i7-75000U processor clocked at 2.90GHz with 2 cores, 8GB of RAM, and a 250GB hard disk drive.

CHAPTER FOUR

4. DATA PREPARATION AND PREPROCESS

4.1 Data Collection Method Procedure

Collection of data process involved obtaining secondary data on sand casting from physical documents maintained at the Akaki Basic Metal Industry. These documents, including records from Production Planning and Control and quality control, were accessed through formal procedures, with authorization secured from the Akaki Basic Metal Industry administrator to ensure compliance with industry regulations. The acquisition of data was formalized through official communication between AAiT and the industry.

Defect information crucial for the study was sourced from the Akaki Basic Metal Industry's Foundry workshop, which consolidates data from various sand casting processes during production. Collaboration with industry authorities facilitated access to comprehensive defect records for analysis. The dataset was organized and stored using MS Excel, providing a standardized format conducive to data management and analysis. Throughout the process, adherence to established protocols and regulations was paramount to maintaining the dataset's integrity and reliability for subsequent research and analysis actions.

4.2 Ethical Clearance

The study was conducted following approval from the ethical clearance committee of Addis Ababa Institute of Technology (AAiT). Prior to data collection related to sand casting, explicit permission was obtained from the Akaki Basic Metal Industry. To reinforce confidentiality measures, steps were taken to anonymize the collected data, safeguarding the privacy and confidentiality of individuals involved in the sand casting processes.

4.3 Ethical Considerations

During the research, ethical considerations included protecting the privacy and confidentiality of collected data, obtaining informed consent from participants, maintaining transparency in research methods, avoiding bias, ensuring fairness and equity in the research process, mitigating risks associated with model implementation, considering societal impacts, and responsibly disseminating research findings.

4.4 Validity and Reliability

The study obtained its data by gathering sand casting records from Akaki Basic Metal Industry, ensuring adherence to industry protocols and standards. This was facilitated through formal communication between our university and the industry, guaranteeing the legitimacy of the data collection process. Focusing exclusively on the sand casting data from Akaki Basic Metal Industry provided a comprehensive dataset for analysis, allowing for robust conclusions and generalizations to be drawn. The study employed conventional machine learning methods to analyze the data, utilizing multiple algorithms to derive its findings and make informed decisions.

4.5 Population and Sampling

The population being investigated includes sand casting found in both defective and non-defective casted components documented at the Akaki Basic Metal Industry from 2012 to April 2024. A total of 2881 sand-casting datasets constitute the population. After undergoing data cleaning, a subset of 1001 records with 45 variables were chosen for subsequent processing and analysis.

4.6 Data Type and Data Source

The research relies on secondary data, obtained from the databases of the Akaki Basic Metal Industry under the Ethio Engineering Group. This secondary dataset comprises records of sand casting products, which were originally collected by the industry as part of their quality control and production monitoring procedures. Utilizing these pre-existing databases enables the analysis of historical data spanning a considerable timeframe, thereby enabling the identification of trends and patterns associated with sand casting defects and its severity within the industry.

4.7 Cleaning for Dataset Preparation

The research methodologies involving MS Excel and machine learning emphasize the importance of preparing and ensuring the quality of the dataset through processes such as data cleaning, integration, and transformation. After collecting the data, a preparation phase is conducted to screen for null values and extraneous characters. MS Excel is employed for this purpose to gather and organize the datasets before constructing the training model for predicting sand casting defects and its severity. The dataset within the database consists of thirty three variables (features), encompassing various factors such as Material Form on casting, Material Type, Part Name, Order Quantity, Non-defective, Defective, Defect

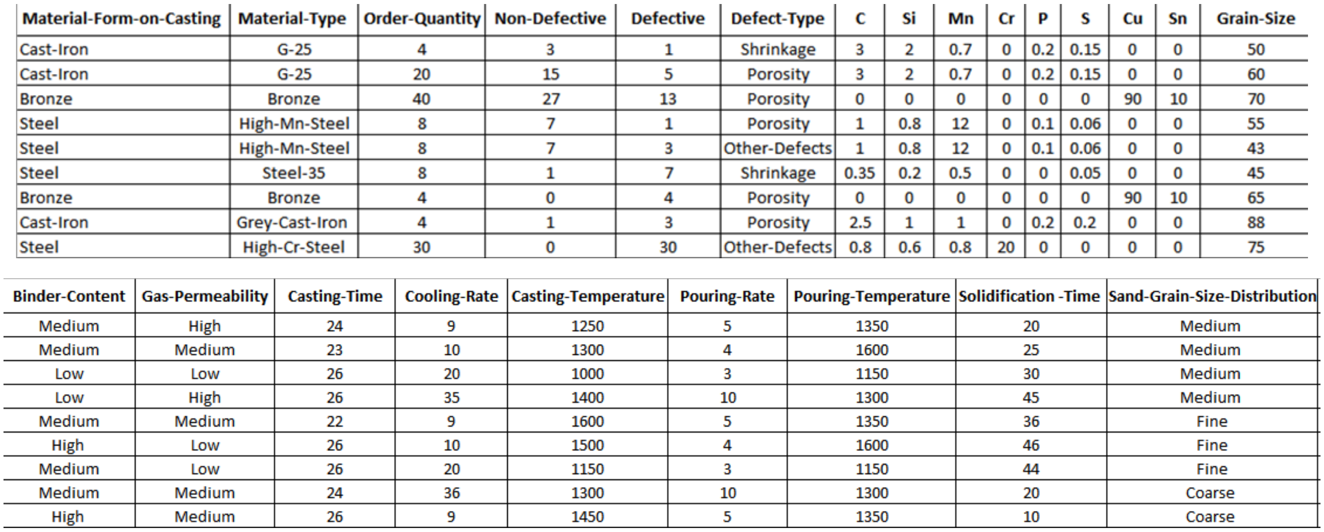
Type, C (%), alloy composition, Grain Size (p), Binder Content, Gas Permeability, Casting Time (hrs.), Cooling Rate (°C/min), Casting Temperature (°C), Pouring Rate (kg/s), Pouring Temperature (°C), Core quality, Mold quality, Moisture Content (%), Alloy Melting Point (°C), Shakeout Time (min), Silica Sand, Severity of Defect etc. According to expert perspectives and insights gleaned from diverse literature sources, a precisely chosen set of thirty-seven variables (features) has been incorporated into this study. These variables have been recognized as pivotal factors impacting sand casting defects and are considered essential for the predictive modeling attempt.

Table 4. 1 Description of input parameters from sand casting data

S.N.	**Parameter**	**Description/Units**
1	Material-Form-on-Casting	Description of the material used for casting
2	Material-Type	Categorical: cast iron, steel, bronze
3	Order –Quantity	Quantity of parts ordered for casting
4	Sand-Flowability	Ability of sand to flow
5	Non-defective	Number of castings that are non-defective
6	Defective	Number of castings that are defective
7	Defect –Type	Type of casting defects (porosity, shrinkage, misrun, blowhole)
8	C (%)	Percentage of carbon content in the alloy
9	Si (%)	Percentage of silicon content in the alloy
10	Mn (%)	Percentage of manganese content in the alloy
11	Cr (%)	Percentage of chromium content in the alloy
12	P (%)	Percentage of phosphorus content in the alloy
13	S (%)	Percentage of sulfur content in the alloy
14	Cu (%)	Percentage of copper content in the alloy
15	Sn (%)	Percentage of tin content in the alloy
16	Mold-Strength	Ability of the molding material
17	Grain- Size	Grain size of the sand used in casting (micrometers)
18	Binder –Content	Categorical: binder content used in mold (low, medium, high)
19	Gas –Permeability	Categorical: gas permeability of the mold (low, medium, high)

20	Casting -Time	Time taken of casting process (hours)
21	Cooling -Rate	Rate of casting cools down (degrees Celsius per minute)
22	Casting -Temperature	Temperature casting is poured (degrees Celsius)
23	Pouring -Rate	Molten metal is poured into the mold (kg per second)
24	Pouring -Temperature	Molten metal temperature during pouring (in degrees Celsius)
25	Core- Quality	Categorical: quality of the core used in casting (low, medium, high)
26	Mold- Quality	Categorical: quality of the mold (low, medium, high)
27	Moisture -Content	Percentage of moisture content in the sand mold (%)
28	Alloy- Melting -Point	Melting point of the alloy (degrees Celsius)
29	Shakeout -Time	Time taken for shakeout process (in minutes)
30	Silica –Sand	Type of sand used in casting (first, second, third claimed)
31	Solidification –Time	Time taken to solidify (in seconds)
32	Grain- Size –Distribution	Sand grain sizes used in casting (fine, medium, coarse)
33	Sand –Temperature	Temperature of the sand (degrees Celsius)
34	Sand –Reuse- Rate	Rate at which sand can be reused (percentage)
35	Sand –Flowability	Measure of how easily sand flows into molds (low, medium, high)
36	Pattern –Quality	Categorical: quality of the pattern used (low, medium, high)
37	Severity -of –Defect	Categorical: severity of casting defects (minor, moderate, severe)

Following data collection, eliminate non-significant parameters or those with excessive null values, then address null values and outliers to enhance the data's significance.



Material-Form-on-Casting	Material-Type	Order-Quantity	Non-Defective	Defective	Defect-Type	C	Si	Mn	Cr	P	S	Cu	Sn	Grain-Size
Cast-Iron	G-25	4	3	1	Shrinkage	3	2	0.7	0	0.2	0.15	0	0	50
Cast-Iron	G-25	20	15	5	Porosity	3	2	0.7	0	0.2	0.15	0	0	60
Bronze	Bronze	40	27	13	Porosity	0	0	0	0	0	0	90	10	70
Steel	High-Mn-Steel	8	7	1	Porosity	1	0.8	12	0	0.1	0.06	0	0	55
Steel	High-Mn-Steel	8	7	3	Other-Defects	1	0.8	12	0	0.1	0.06	0	0	43
Steel	Steel-35	8	1	7	Shrinkage	0.35	0.2	0.5	0	0	0.05	0	0	45
Bronze	Bronze	4	0	4	Porosity	0	0	0	0	0	0	90	10	65
Cast-Iron	Grey-Cast-Iron	4	1	3	Porosity	2.5	1	1	0	0.2	0.2	0	0	88
Steel	High-Cr-Steel	30	0	30	Other-Defects	0.8	0.6	0.8	20	0	0	0	0	75

Binder-Content	Gas-Permeability	Casting-Time	Cooling-Rate	Casting-Temperature	Pouring-Rate	Pouring-Temperature	Solidification -Time	Sand-Grain-Size-Distribution
Medium	High	24	9	1250	5	1350	20	Medium
Medium	Medium	23	10	1300	4	1600	25	Medium
Low	Low	26	20	1000	3	1150	30	Medium
Low	High	26	35	1400	10	1300	45	Medium
Medium	Medium	22	9	1600	5	1350	36	Fine
High	Low	26	10	1500	4	1600	46	Fine
Medium	Low	26	20	1150	3	1150	44	Fine
Medium	Medium	24	36	1300	10	1300	20	Coarse
High	Medium	26	9	1450	5	1350	10	Coarse

Figure 4. 1 Selected features/input variables

The available data organizes parameters related to the material form in casting products into three main categories: steel, bronze, and cast iron. Within these groups, various attributes are considered, such as material type, order quantity, defect type, chemical composition (C, Si, S, P, Cr, Mn, Sn, Tn), grain size, casting conditions (time, cooling rate, temperature), pouring conditions (rate, temperature), mold quality, moisture content, alloy melting point, shakeout time, silica sand usage, and defect severity. Each category presents unique characteristics specific to its material form, allowing for thorough analysis and assessment.

Before creating models for sand casting defects, data processing and cleaning are essential. The data may exhibit imbalance issues, with some defect types never observed, as noted by subject matter specialists. The casted products are classified into four defect-type groups: porosity, shrinkage, other defects (misrun, blowhole, inclusion, crack, metal penetration), and non-defects. Additionally, defect severity is categorized into three levels: severe, minor, and moderate.

Porosity refers to small voids or holes within the material, while shrinkage defects occur due to material contraction during cooling. Other defects include issues like misrun, blowholes, inclusions, cracks, and metal penetration, arising from incomplete mold filling, gas pockets, foreign particles, or material fractures. Non-defects indicate castings that meet required standards, ensuring the final product's integrity and performance. Defect severity ranges from minor to severe, indicating the extent to which a defect compromises the casting's integrity, functionality, or appearance. Minor defects have minimal impact, while severe defects may render the casting unusable or compromise its structural integrity.

4.8 Method of Data Analysis

In order to meet the research objectives, it was imperative to conduct numerical data collection and analysis, sourced from both the quality control and production processes of the Akaki Basic Metal Industry. Following this data gathering phase, a diverse array of machine learning techniques and algorithms were employed. Specifically, the study utilized classification machine learning methods for data analysis. This choice was driven by the effectiveness of classification algorithms in categorizing data into distinct classes based on specific features or attributes. Through the application of classification methods, the research aimed to distinguish patterns, predict future occurrences of defects, offer decision support for quality control personnel, optimize production processes, and foster continuous improvement within the metal industry.

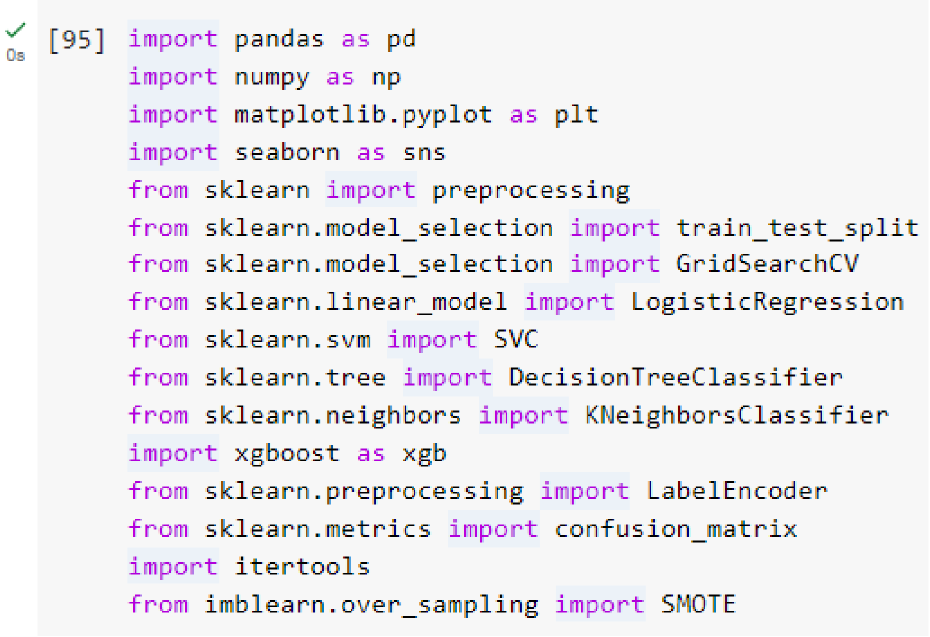
CHAPTER FIVE

5. EXPERIMENTAL RESULT AND DISCUSSION

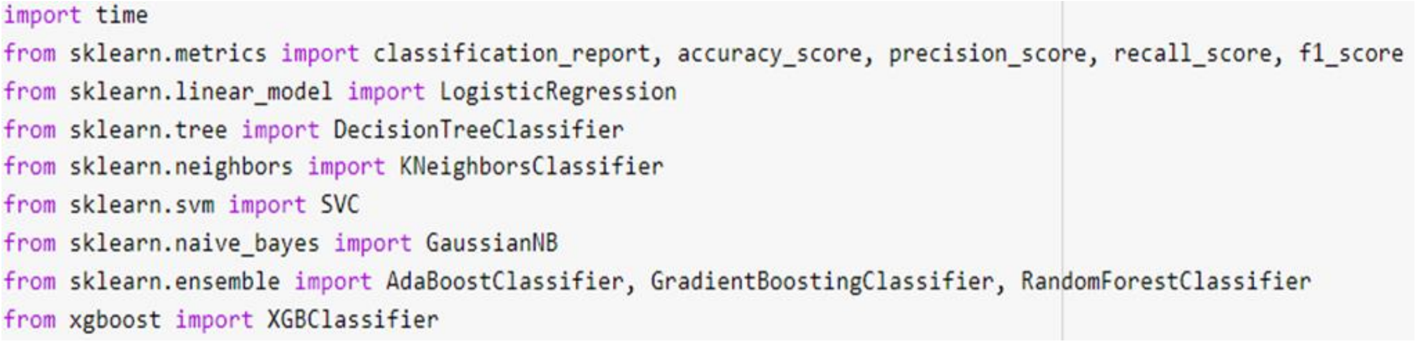
In this chapter covers result discussion of an experiment to verify the proposed machine learning method for predicting sand casting defects. The results of each model for each dataset are discussed in this section. The study also discusses measuring the accuracy of models that have been applied in cases of sand-casting defects.

5.1 Machine Learning Library and Module

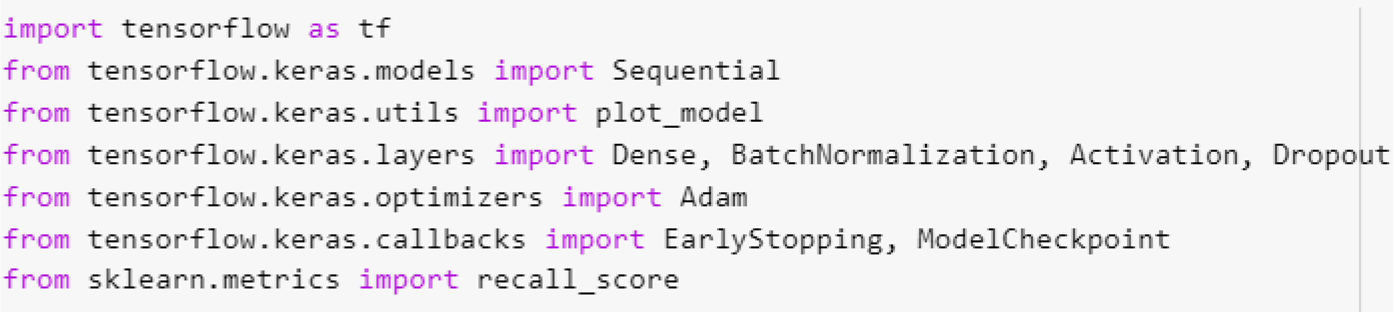
Study utilized the Python panda's library for data handling and followed conventional practices by importing essential packages for modeling and evaluation. This involved constructing a machine learning model using the proposed methodology and importing libraries for data preprocessing and training phases as shown in figure 5.1.



```
[95] import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
     from sklearn import preprocessing
     from sklearn.model_selection import train_test_split
     from sklearn.model_selection import GridSearchCV
     from sklearn.linear_model import LogisticRegression
     from sklearn.svm import SVC
     from sklearn.tree import DecisionTreeClassifier
     from sklearn.neighbors import KNeighborsClassifier
     import xgboost as xgb
     from sklearn.preprocessing import LabelEncoder
     from sklearn.metrics import confusion_matrix
     import itertools
     from imblearn.over_sampling import SMOTE
```



```
import time
from sklearn.metrics import classification_report, accuracy_score, precision_score, recall_score, f1_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier, RandomForestClassifier
from xgboost import XGBClassifier
```

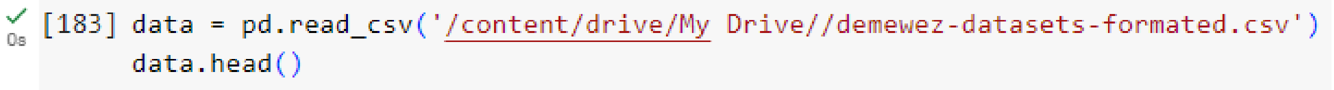


```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.utils import plot_model
from tensorflow.keras.layers import Dense, BatchNormalization, Activation, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from sklearn.metrics import recall_score
```

Figure 5. 1 Import Library and Define Auxiliary Functions

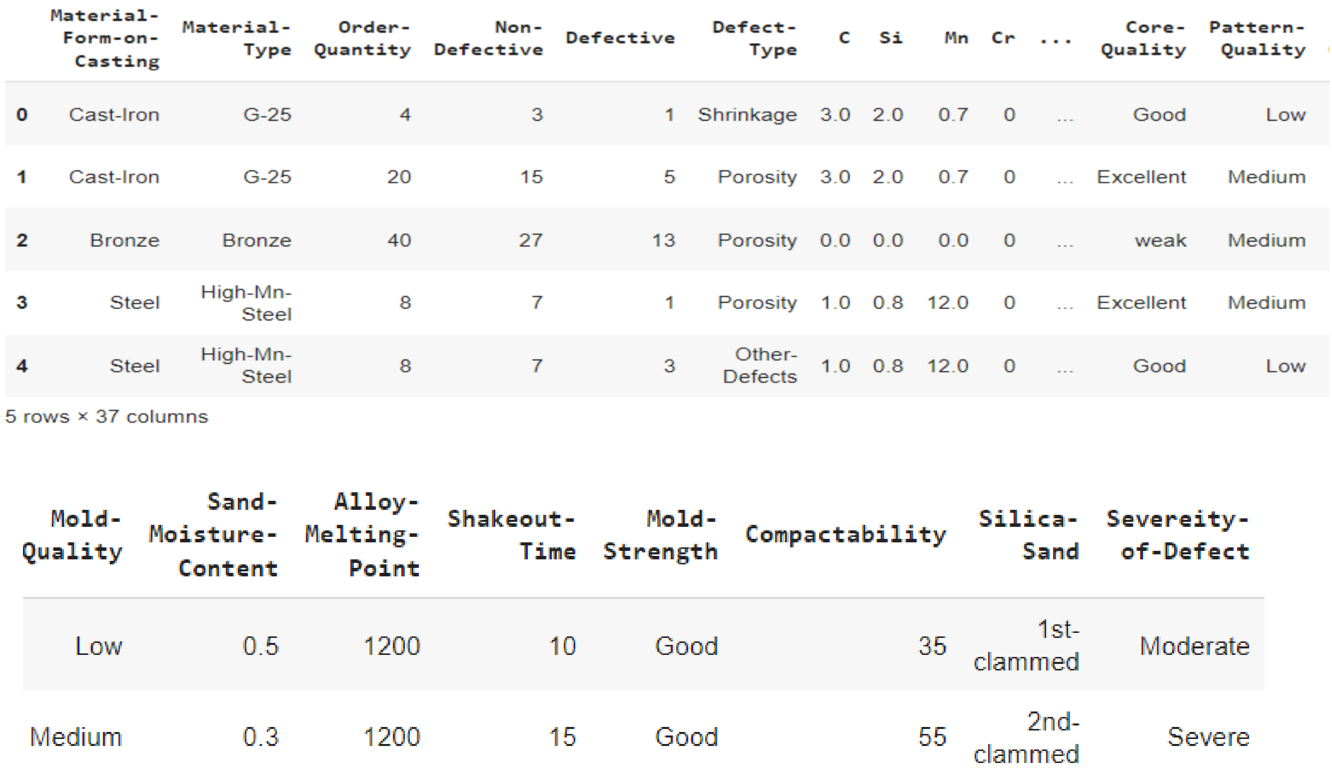
5.2 Loading and Reading the Data Preprocessing Implementation

The study utilized Jupyter Notebook to load and read sand casting datasets, employing codes to import necessary library packages and upload dataset files to the disk to fully apply the methodologies. The execution of this study utilized the loaded dataset, prepared in Excel CSV format, created with pandas.



```
[183] data = pd.read_csv('/content/drive/My Drive//demewez-datasets-formated.csv')
      data.head()
```

Here is the full information of the loaded data in figure 5.2.

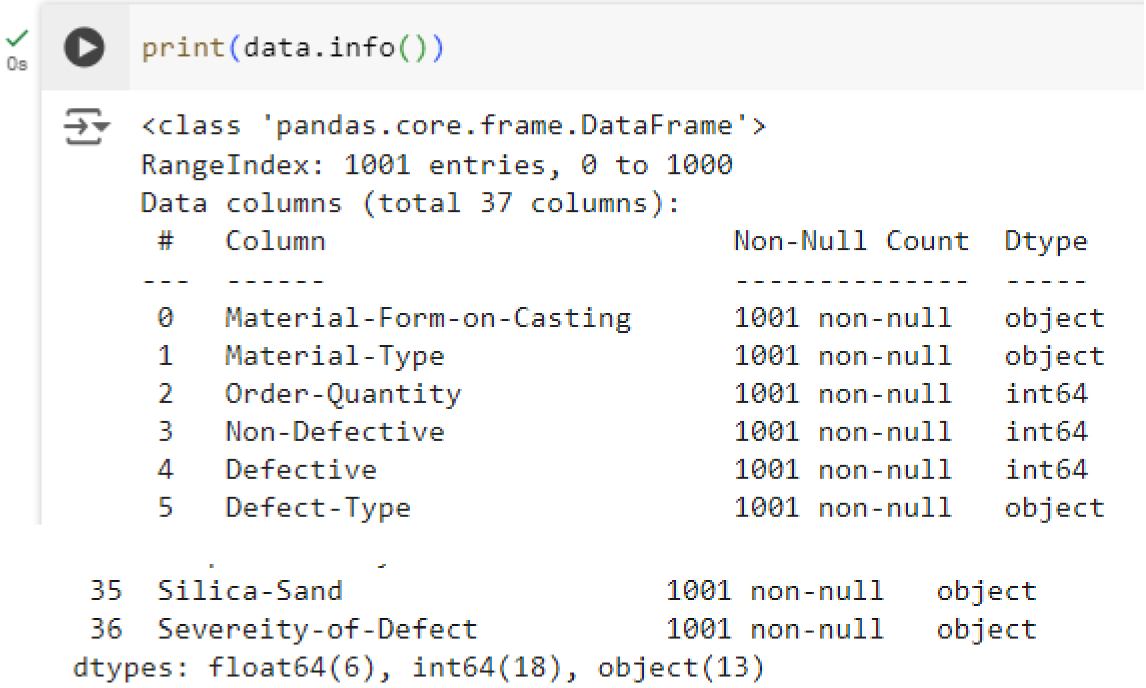


	Material-Form-on-Casting	Material-Type	Order-Quantity	Non-Defective	Defective	Defect-Type	C	Si	Mn	Cr	...	Core-Quality	Pattern-Quality
0	Cast-Iron	G-25	4	3	1	Shrinkage	3.0	2.0	0.7	0	...	Good	Low
1	Cast-Iron	G-25	20	15	5	Porosity	3.0	2.0	0.7	0	...	Excellent	Medium
2	Bronze	Bronze	40	27	13	Porosity	0.0	0.0	0.0	0	...	weak	Medium
3	Steel	High-Mn-Steel	8	7	1	Porosity	1.0	0.8	12.0	0	...	Excellent	Medium
4	Steel	High-Mn-Steel	8	7	3	Other-Defects	1.0	0.8	12.0	0	...	Good	Low

5 rows × 37 columns

Mold-Quality	Sand-Moisture-Content	Alloy-Melting-Point	Shakeout-Time	Mold-Strength	Compactability	Silica-Sand	Severeity-of-Defect
Low	0.5	1200	10	Good	35	1st-clammed	Moderate
Medium	0.3	1200	15	Good	55	2nd-clammed	Severe

Figure 5. 2 Information of the loaded data

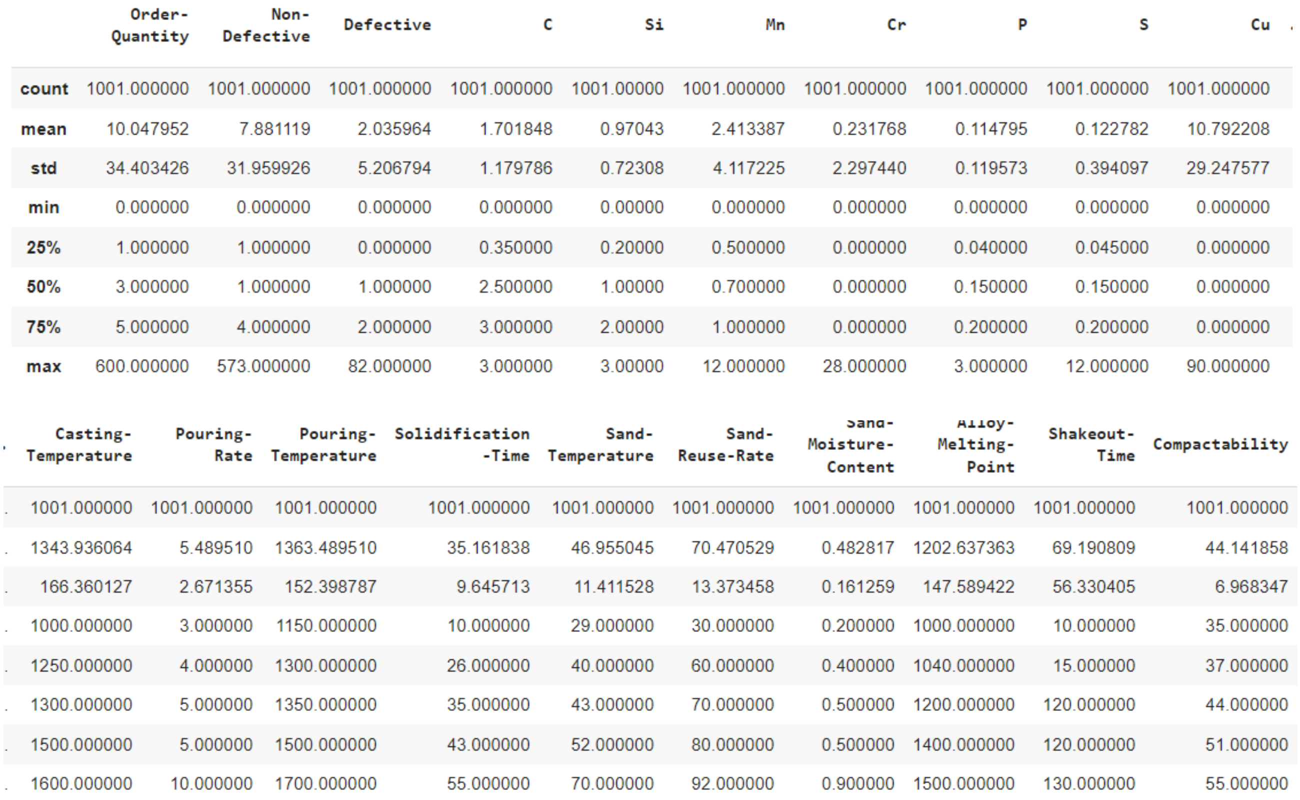


```
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1001 entries, 0 to 1000
Data columns (total 37 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   Material-Form-on-Casting       1001 non-null   object
 1   Material-Type                  1001 non-null   object
 2   Order-Quantity                 1001 non-null   int64
 3   Non-Defective                  1001 non-null   int64
 4   Defective                      1001 non-null   int64
 5   Defect-Type                    1001 non-null   object

 35  Silica-Sand                    1001 non-null   object
 36  Severeity-of-Defect            1001 non-null   object
dtypes: float64(6), int64(18), object(13)
```

Figure 5. 3 Information of the cleaned data

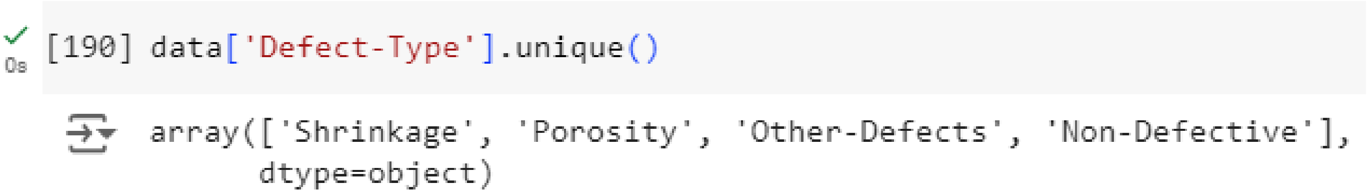


	Order-Quantity	Non-Defective	Defective	C	Si	Mn	Cr	P	S	Cu
count	1001.000000	1001.000000	1001.000000	1001.000000	1001.00000	1001.000000	1001.000000	1001.000000	1001.000000	1001.000000
mean	10.047952	7.881119	2.035964	1.701848	0.97043	2.413387	0.231768	0.114795	0.122782	10.792208
std	34.403426	31.959926	5.206794	1.179786	0.72308	4.117225	2.297440	0.119573	0.394097	29.247577
min	0.000000	0.000000	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	1.000000	0.000000	0.350000	0.20000	0.500000	0.000000	0.040000	0.045000	0.000000
50%	3.000000	1.000000	1.000000	2.500000	1.00000	0.700000	0.000000	0.150000	0.150000	0.000000
75%	5.000000	4.000000	2.000000	3.000000	2.00000	1.000000	0.000000	0.200000	0.200000	0.000000
max	600.000000	573.000000	82.000000	3.000000	3.00000	12.000000	28.000000	3.000000	12.000000	90.000000

	Casting-Temperature	Pouring-Rate	Pouring-Temperature	Solidification-Time	Sand-Temperature	Sand-Reuse-Rate	Sand-Moisture-Content	Alloy-Melting-Point	Shakeout-Time	Compactability
	1001.000000	1001.000000	1001.000000	1001.000000	1001.000000	1001.000000	1001.000000	1001.000000	1001.000000	1001.000000
	1343.936064	5.489510	1363.489510	35.161838	46.955045	70.470529	0.482817	1202.637363	69.190809	44.141858
	166.360127	2.671355	152.398787	9.645713	11.411528	13.373458	0.161259	147.589422	56.330405	6.968347
	1000.000000	3.000000	1150.000000	10.000000	29.000000	30.000000	0.200000	1000.000000	10.000000	35.000000
	1250.000000	4.000000	1300.000000	26.000000	40.000000	60.000000	0.400000	1040.000000	15.000000	37.000000
	1300.000000	5.000000	1350.000000	35.000000	43.000000	70.000000	0.500000	1200.000000	120.000000	44.000000
	1500.000000	5.000000	1500.000000	43.000000	52.000000	80.000000	0.500000	1400.000000	120.000000	51.000000
	1600.000000	10.000000	1700.000000	55.000000	70.000000	92.000000	0.900000	1500.000000	130.000000	55.000000

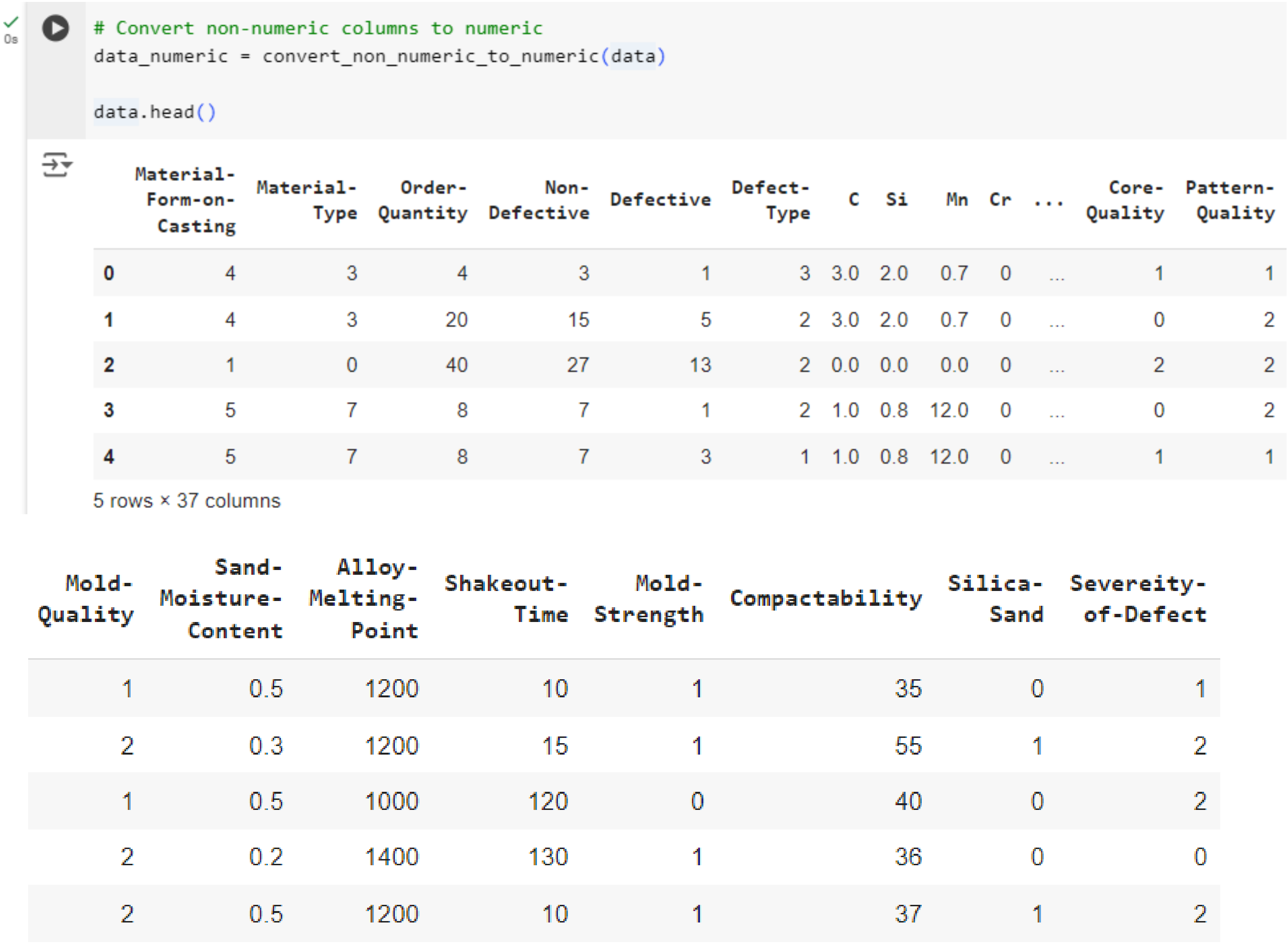
Figure 5. 4 Statistical summary of the data frame after cleaned

View the statistical description of the data frame. The statistical description shows in figure 5.4 count (non-null values in the column), mean, standard deviation, minimum value, maximum values, and finally percentiles of the values in that column.



```
[190] data['Defect-Type'].unique()
```

```
array(['Shrinkage', 'Porosity', 'Other-Defects', 'Non-Defective'],
      dtype=object)
```



```
# Convert non-numeric columns to numeric
data_numeric = convert_non_numeric_to_numeric(data)

data.head()
```

	Material-Form-on-Casting	Material-Type	Order-Quantity	Non-Defective	Defective	Defect-Type	C	Si	Mn	Cr	...	Core-Quality	Pattern-Quality	Mold-Quality	Sand-Moisture-Content	Alloy-Melting-Point	Shakeout-Time	Mold-Strength	Compactability	Silica-Sand	Severeity-of-Defect
0	4	3	4	3	1	3	3.0	2.0	0.7	0	...	1	1	1	0.5	1200	10	1	35	0	1
1	4	3	20	15	5	2	3.0	2.0	0.7	0	...	0	2	2	0.3	1200	15	1	55	1	2
2	1	0	40	27	13	2	0.0	0.0	0.0	0	...	2	2	1	0.5	1000	120	0	40	0	2
3	5	7	8	7	1	2	1.0	0.8	12.0	0	...	0	2	2	0.2	1400	130	1	36	0	0
4	5	7	8	7	3	1	1.0	0.8	12.0	0	...	1	1	2	0.5	1200	10	1	37	1	2

5 rows × 37 columns

Figure 5. 5 Conversion of Non-Numeric to Numeric Values in DataFrame

As shown in figure 5.5 function convert non numeric to numeric turn things that aren't numbers in a DataFrame into numbers. It uses a tool called Label Encoder to change categories into numbers. First, it goes through each column in the DataFrame, looking for things that aren't numbers. Then, it turns these non-number things into numbers using label encoding.

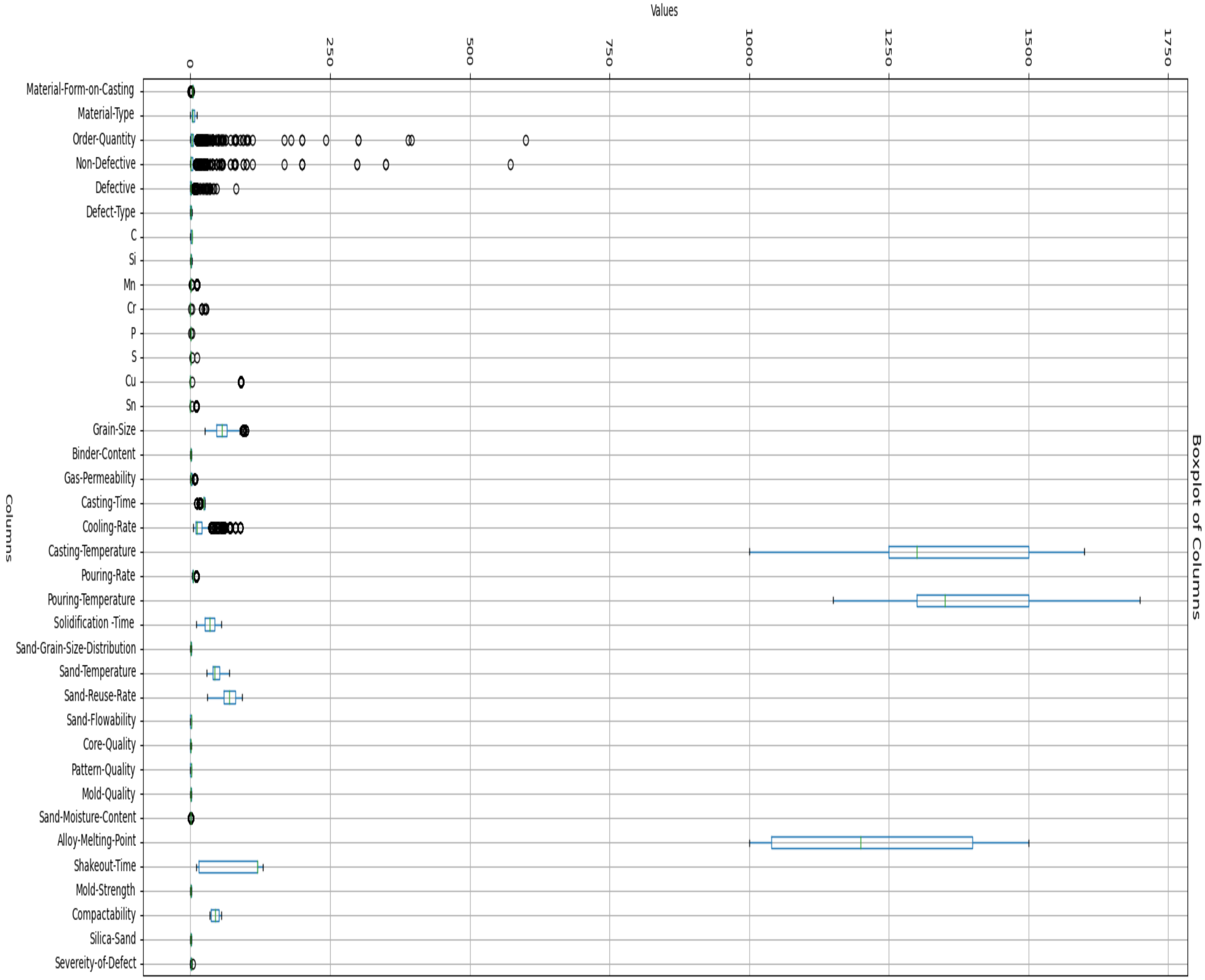
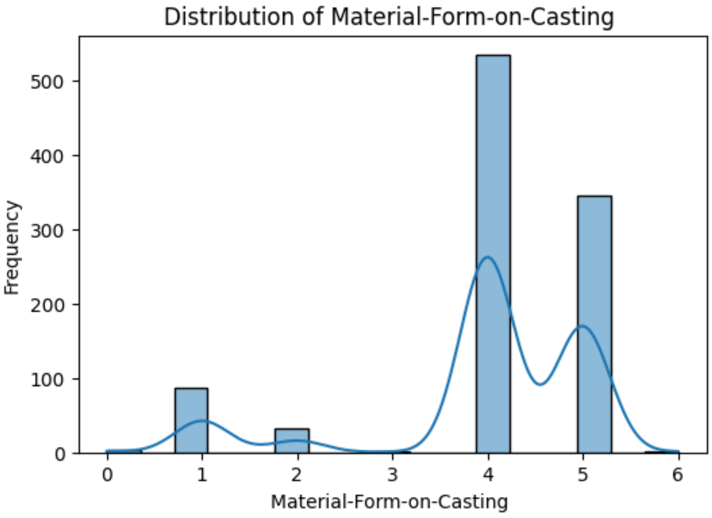
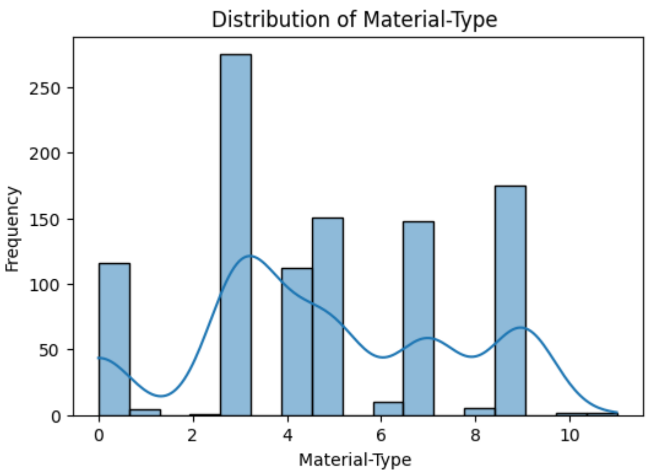
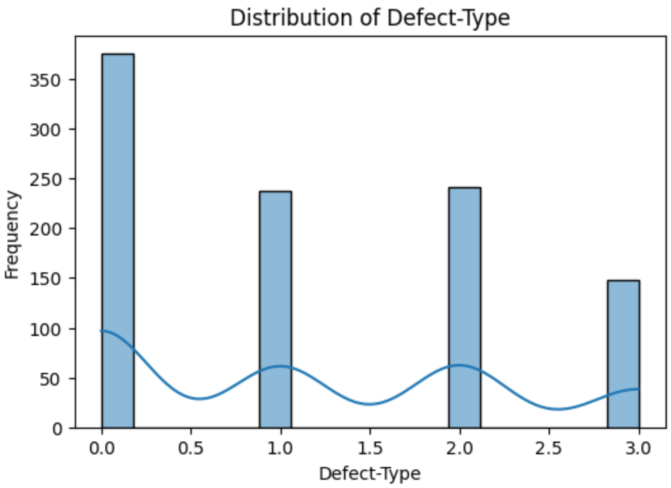


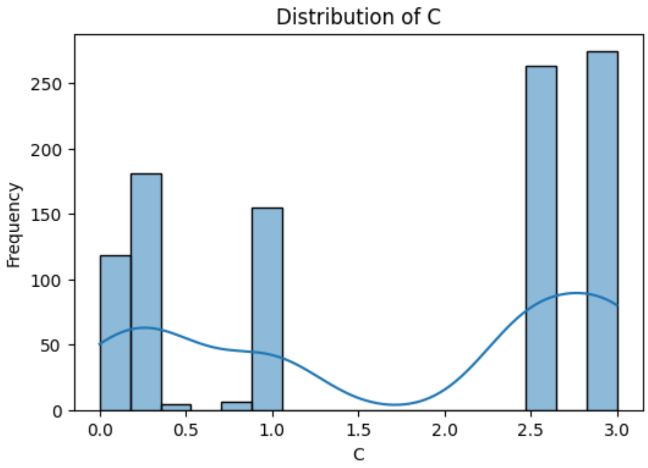
Figure 5. 6 Boxplot of Columns outlier

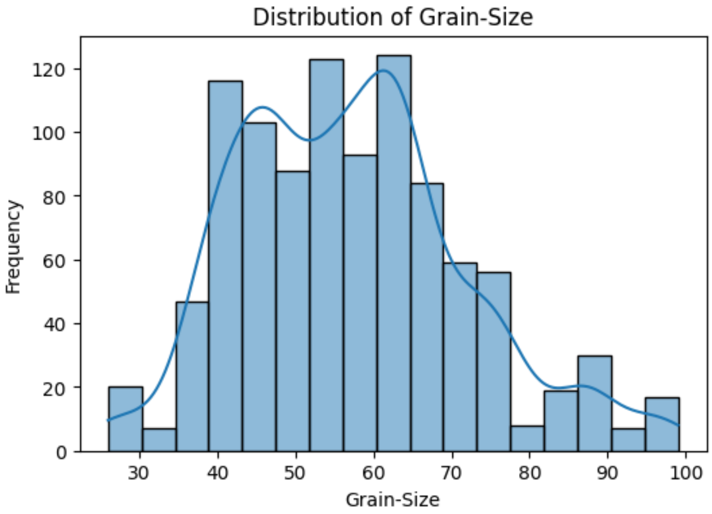
As shown in figure 5.6 outliers treatment important to find and remove unusual or extreme data points, also known as outliers. Outliers can affect the model's understanding of the data and lead to wrong predictions. By identifying and removing outliers, the model becomes more accurate and reliable, and can better capture the actual patterns in the data. There is no outlier present in any of the variable. Data types of all variables is fine.

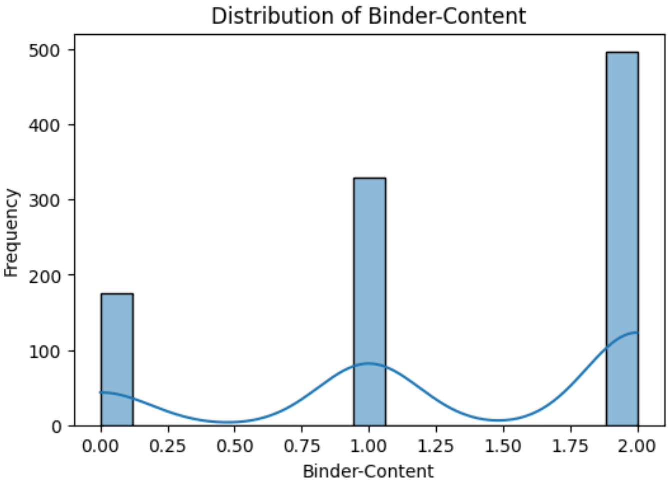

Distribution of Material-Form-on-Casting
Frequency
0
100
200
300
400
500
0
1
2
3
4
5
6
Material-Form-on-Casting

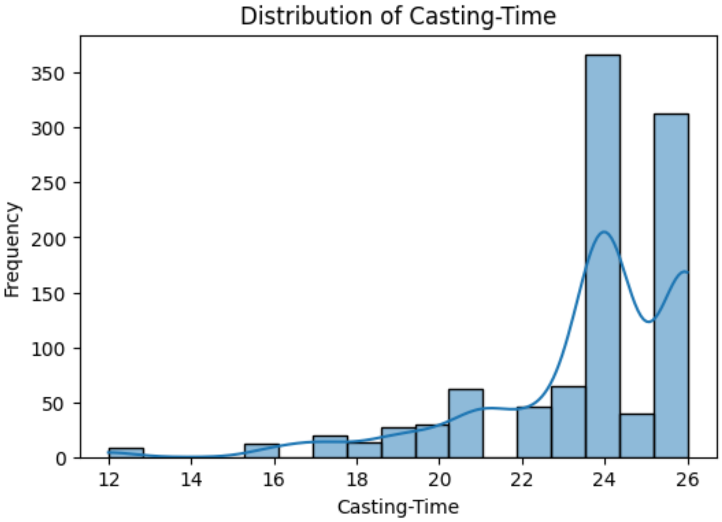

Distribution of Material-Type
Frequency
0
50
100
150
200
250
0
2
4
6
8
10
Material-Type

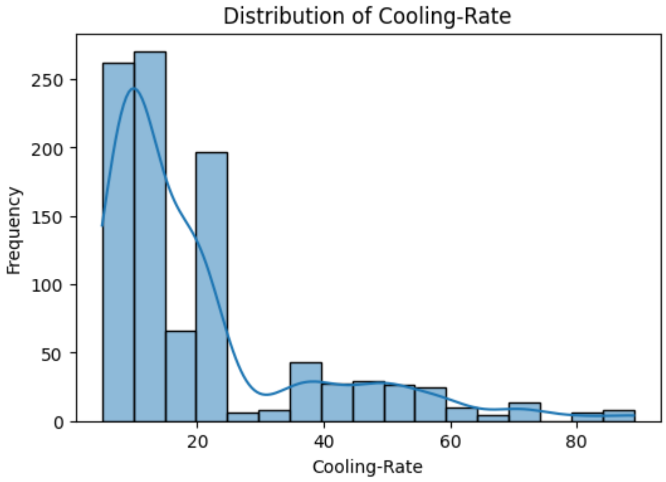

Distribution of Defect-Type
Frequency
0
50
100
150
200
250
300
350
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Defect-Type

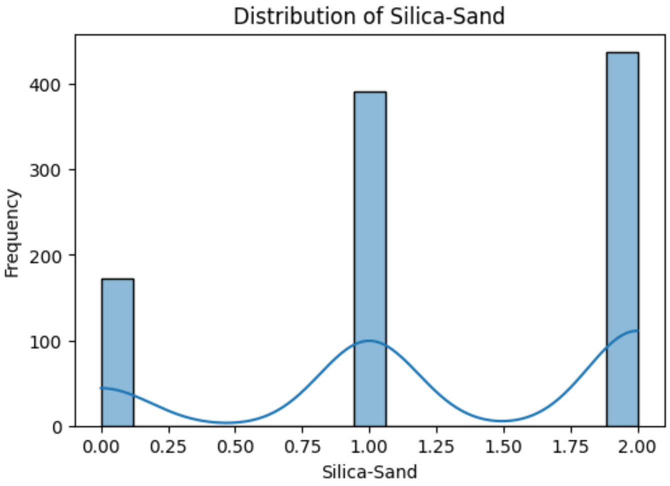

Distribution of C
Frequency
0
50
100
150
200
250
0.0
0.5
1.0
1.5
2.0
2.5
3.0
C

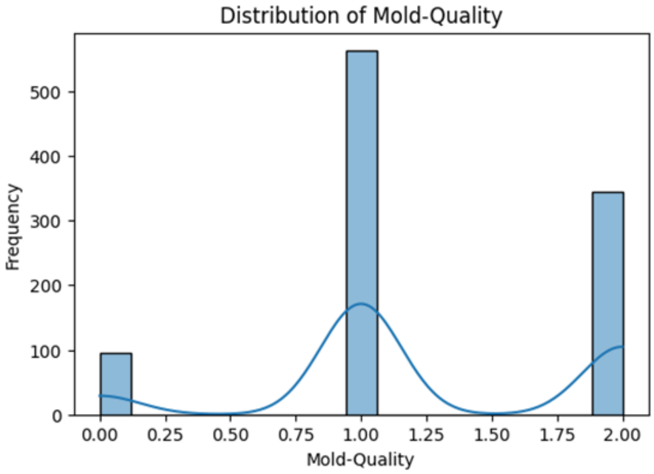

Distribution of Grain-Size
Frequency
0
20
40
60
80
100
120
30
40
50
60
70
80
90
100
Grain-Size

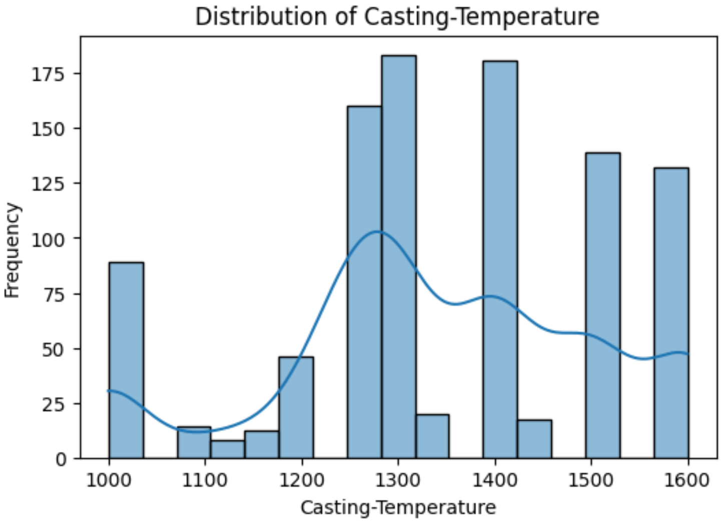

Distribution of Binder-Content
Frequency
0
100
200
300
400
500
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Binder-Content

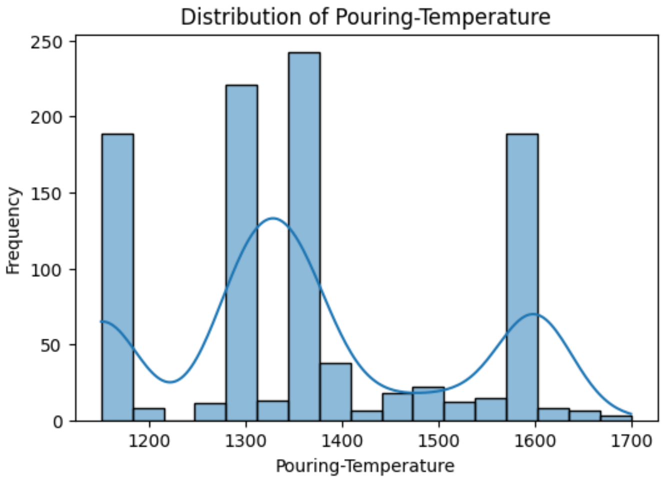

Distribution of Casting-Time


Distribution of Cooling-Rate


Distribution of Silica-Sand


Distribution of Mold-Quality


Distribution of Casting-Temperature


Distribution of Pouring-Temperature

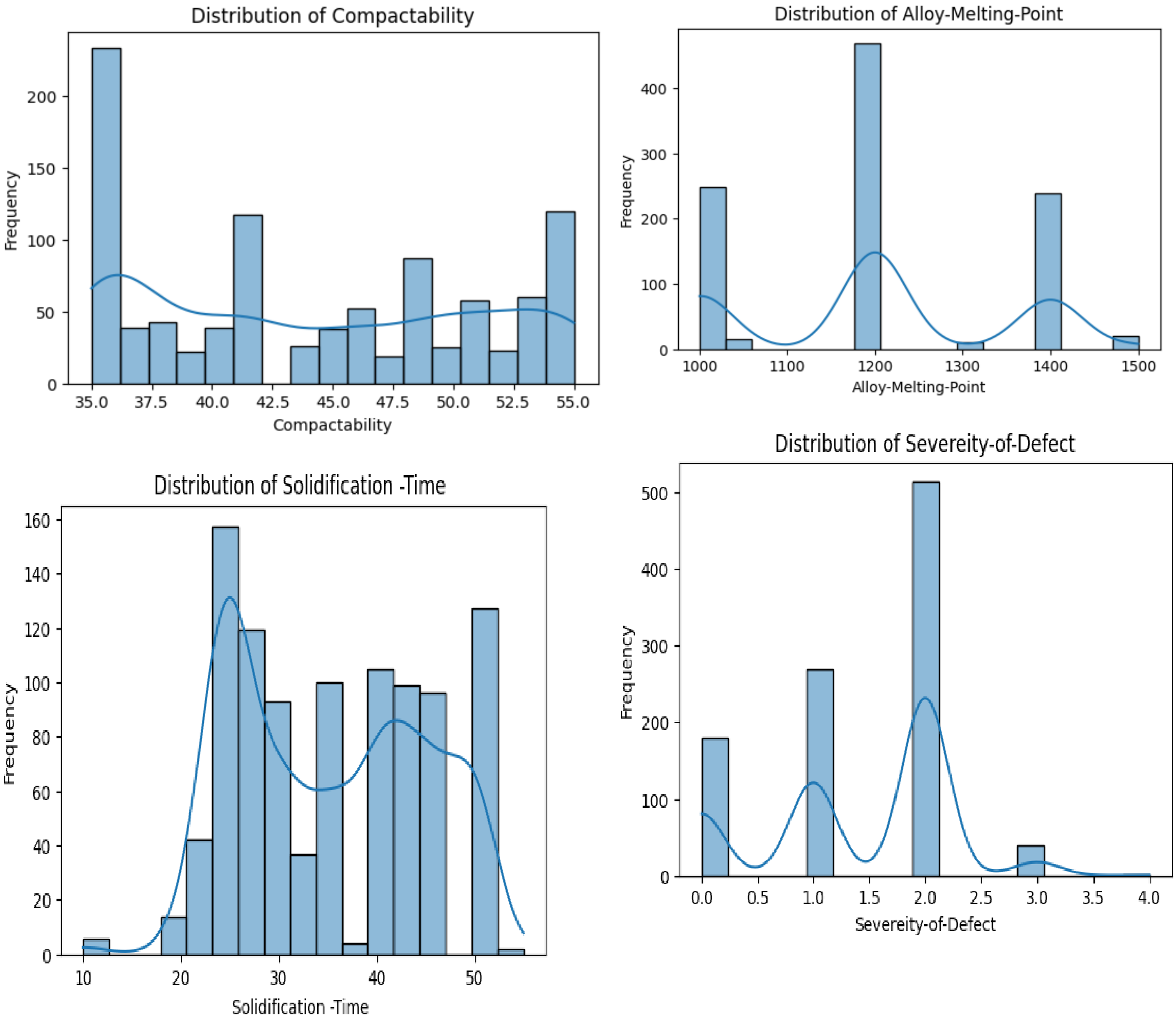


Figure 5. 7 Distribution of data features or input variables

In machine learning, assessing the spread of data across various values, known as data distribution, is crucial. Skewed data, with more points in one area than others, can impact model performance, especially if skewed towards the majority class, leading to potential issues in accurately predicting minority classes. As shown in figure 5.7 data distribution indicates to select effective strategies for address these imbalances.

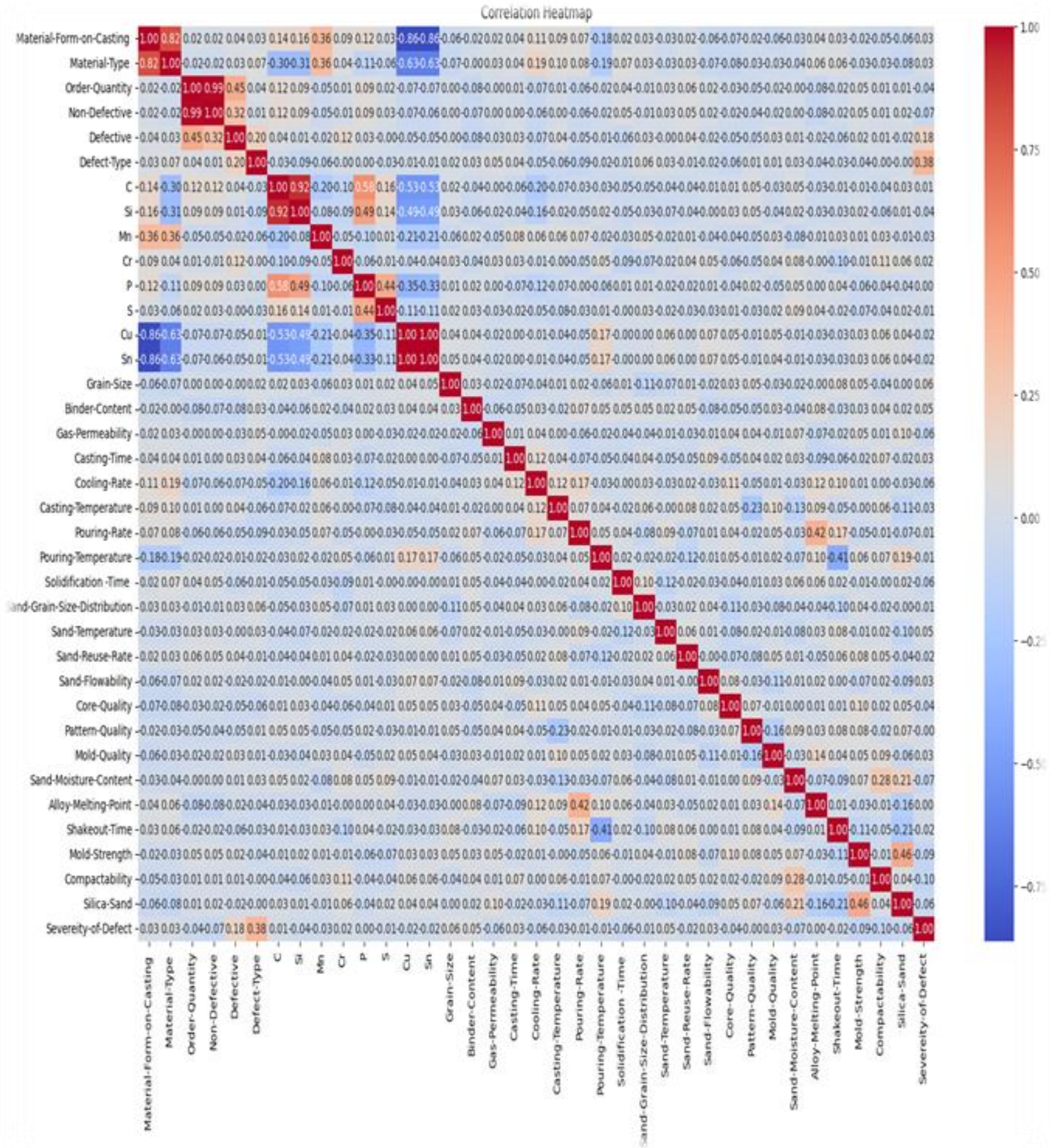


Figure 5. 8 Correlation matrix Heatmap of features

A heatmap of the correlation matrix in the figure 5.8 visually represents the relationships between different features, with darker colors (close to 1 or -1) indicating strong correlations and lighter colors (close to 0) indicating weak correlations. Analyzing the heatmap helps identify features with strong correlations to the target variable (defect type and severity) and those with weak correlations. Retain features with high absolute correlation values and remove those with low values. To enhance model performance, select the top 37 features with the highest correlations to the target variable and eliminate the 8 lowest, ensuring the model is trained on the most relevant features, improving accuracy and reducing complexity.

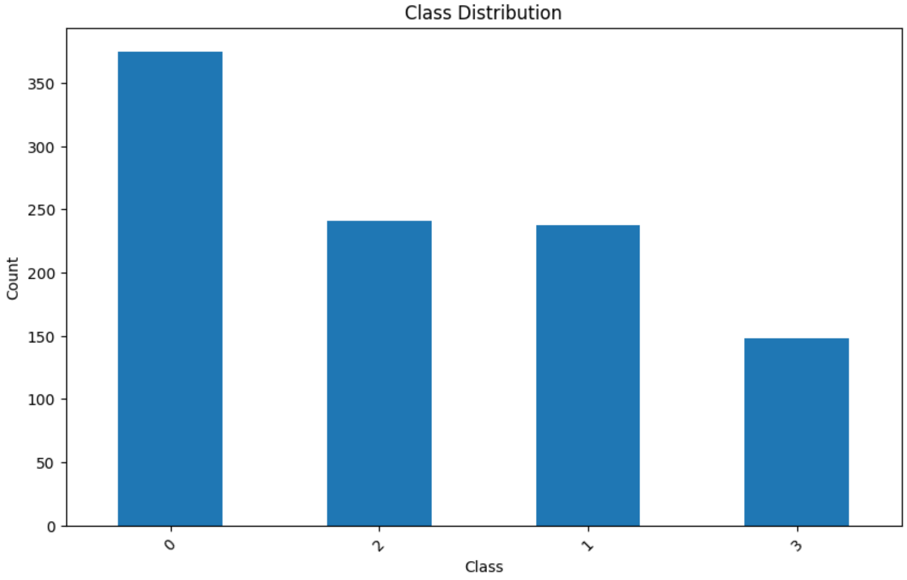
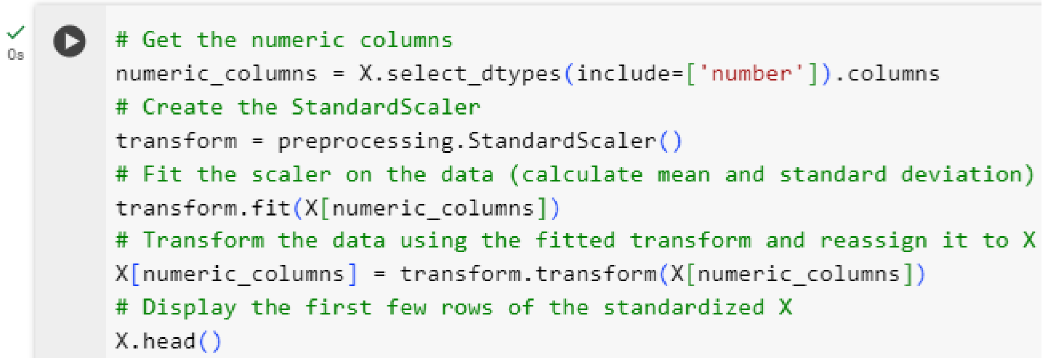


Figure 5. 9 Types of defect class distribution

As shown figure 5.9 there is uneven distribution of variables, with significantly more instances in the "Non-Defective" class (375) compared to "Porosity" (241), "Other-Defects" (237), and "Shrinkage" (148), signals a problem of class imbalance. To address this issue, let's employ the augmentation technique SMOTE to balance the classes. After applying SMOTE the unique defect value counts are: Non-Defective (375), Porosity (375), Other-Defects (375), and Shrinkage (375), resulting in a total of 375×4=1500 resampled data points, each with 37 features.

In the same way, for the "Severity-of-Defect" dataset, the initial class distribution is Severe (553), Moderate (269), and Minor (179), indicating an imbalance. After applying SMOTE, the balanced class distribution is Severe (553), Moderate (553), and Minor (553), resulting in a total of 553×3=1659 resampled data points, each with 37 features.



```
# Get the numeric columns
numeric_columns = X.select_dtypes(include=['number']).columns
# Create the StandardScaler
transform = preprocessing.StandardScaler()
# Fit the scaler on the data (calculate mean and standard deviation)
transform.fit(X[numeric_columns])
# Transform the data using the fitted transform and reassign it to X
X[numeric_columns] = transform.transform(X[numeric_columns])
# Display the first few rows of the standardized X
X.head()
```

Figure 5. 10 Standardize and normalization of Features

Standardizing features involves ensuring that all features are on the same scale, making them comparable and avoiding the dominance of certain features due to their larger magnitudes. As shown in figure 5.10 achieved by applying feature scaling using the Standard Scaler, which transforms the values to have a mean 0 and a standard deviation of 1. This normalization ensures uniformity across the dataset and prevents any bias that might arise from differences in feature magnitudes. By standardizing features, the dataset becomes more suitable for machine learning algorithms that are sensitive to feature scales, such as support vector machines and k-nearest neighbors.

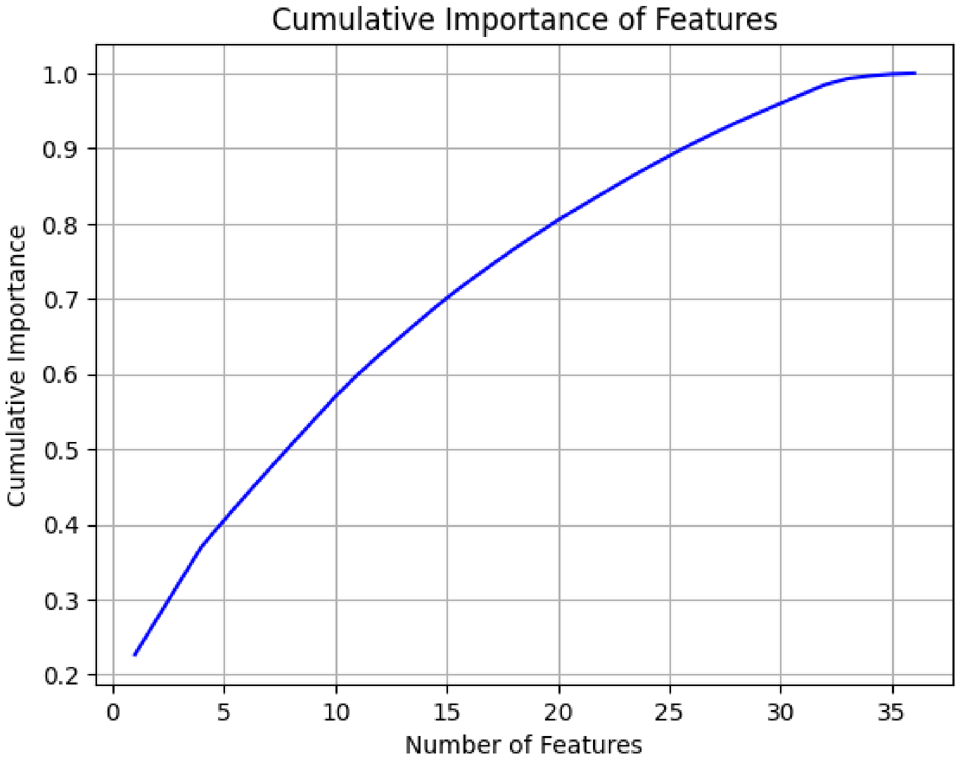


Figure 5. 11 Feature Selection using Random Forest Feature Importance Method

The graph in figure 5.11 displays feature importance scores from the Random Forest algorithm is an integral part of feature engineering helps to identify which features have the most significant impact on predicting the target variable. By analyzing the graph, one can determine the number of features that contribute significantly to the model's predictive power. The x-axis represents the cumulative features considered, while the y-axis shows the cumulative importance of these features. Higher scores indicate greater contribution to the model's performance, guiding decisions on which features to prioritize for optimization. Feature importance scores offer valuable insights into the relevance of each feature, helping in effective feature selection to improve model accuracy and robustness.

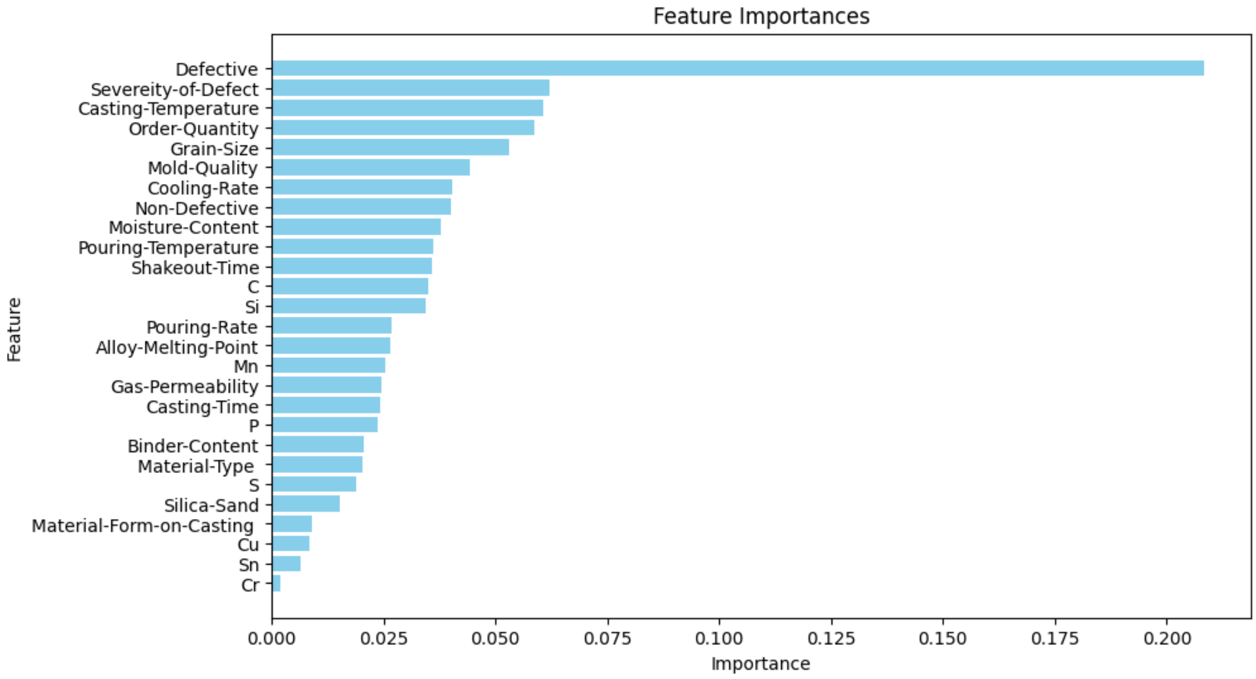


Figure 5. 12 Important features using a RF feature importance technique of defect types

In figure 5.12 displayed as feature importance plot tells that the most significant contributors to predicting defect types in the casting process are the 'Defective' status, 'Severity-of-Defect,' 'Casting-Temperature,' and 'Order-Quantity.' these top features suggest that both the presence defects, along with key process parameters like temperature and order size, are crucial for accurate predictions. Other moderately important features, such as 'Grain-Size,' 'Mold-Quality,' and 'Cooling-Rate,' also play a distinguished role, indicating that material properties and specific aspects of the casting process significantly impact the outcome. Less critical yet still relevant factors include chemical compositions and additional process parameters, which collectively influence the model's performance.

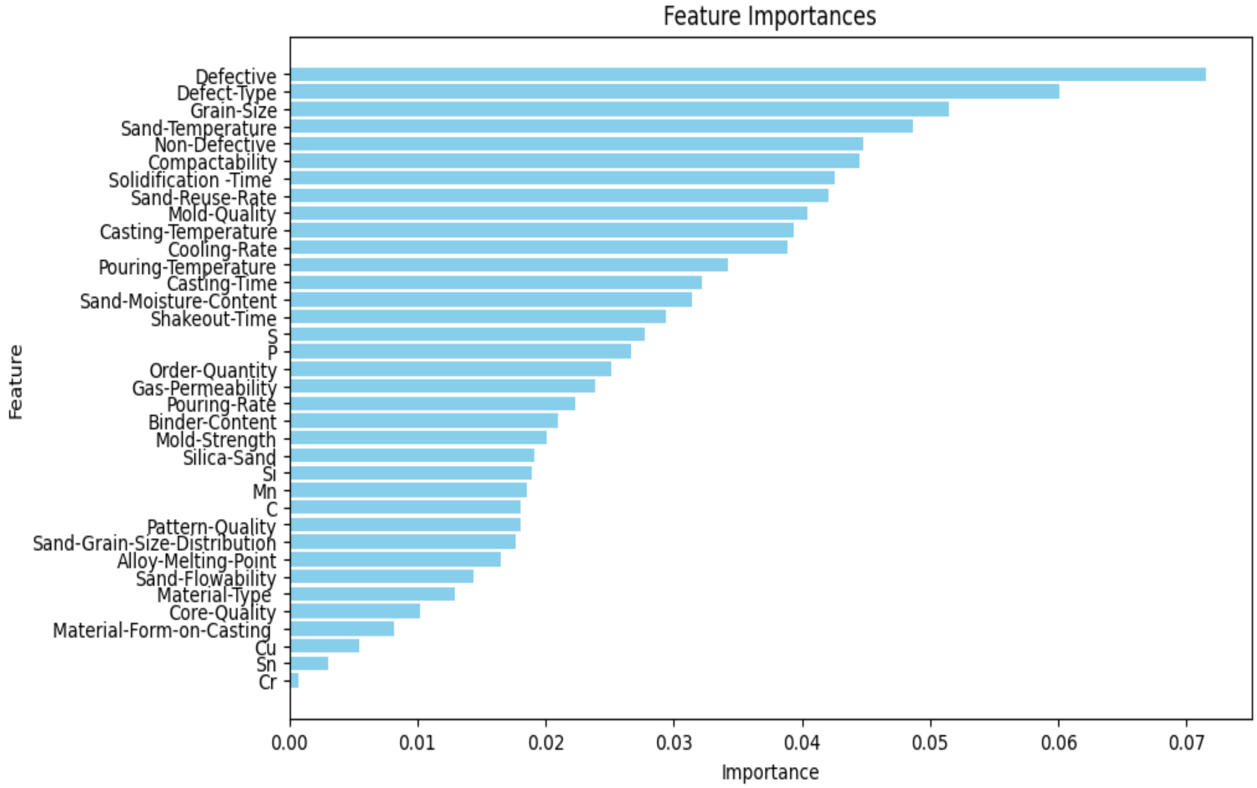
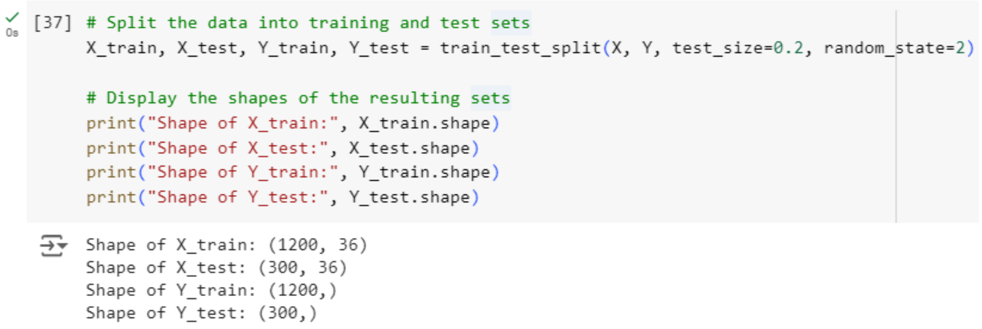


Figure 5. 13 Important features using a RF feature importance technique of defect severity

In the above figure 5.13 feature importance values reveal that Grain-Size (0.07), Sand-Temperature (0.06), Compactability (0.05), Solidification-Time (0.05), Sand-Reuse-Rate (0.04), and Mold-Quality (0.04) are the key factors impacting the target variable in your casting or manufacturing process. These factors should be the main focus for optimization to enhance quality. Additionally, moderately important features such as Casting-Temperature, Cooling-Rate, and Pouring-Temperature (each around 0.03) should be closely monitored. Features with very low or zero importance can potentially be deprioritized, simplifying the model and allowing efforts to be concentrated on the most significant variables.

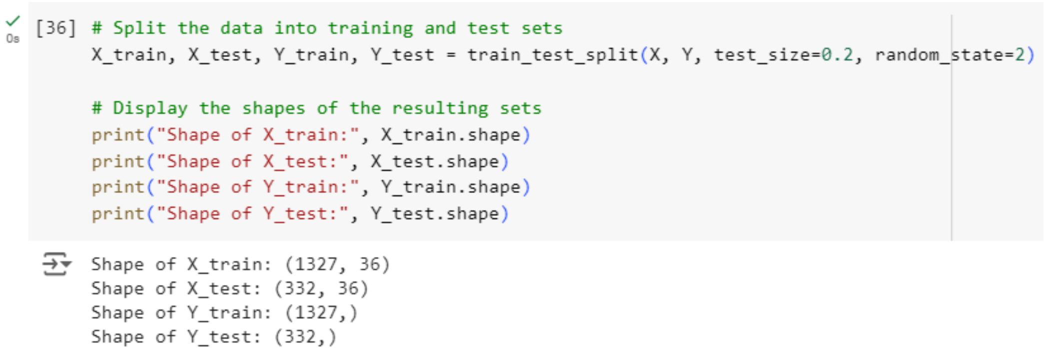


```
# Split the data into training and test sets
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=2)

# Display the shapes of the resulting sets
print("Shape of X_train:", X_train.shape)
print("Shape of X_test:", X_test.shape)
print("Shape of Y_train:", Y_train.shape)
print("Shape of Y_test:", Y_test.shape)
```

```
Shape of X_train: (1200, 36)
Shape of X_test: (300, 36)
Shape of Y_train: (1200,)
Shape of Y_test: (300,)
```

Figure 5. 14 Split the data into Train and Test Set for defect type



```
# Split the data into training and test sets
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=2)

# Display the shapes of the resulting sets
print("Shape of X_train:", X_train.shape)
print("Shape of X_test:", X_test.shape)
print("Shape of Y_train:", Y_train.shape)
print("Shape of Y_test:", Y_test.shape)
```

```
Shape of X_train: (1327, 36)
Shape of X_test: (332, 36)
Shape of Y_train: (1327,)
Shape of Y_test: (332,)
```

Figure 5. 15 Split the data into Train and Test Set for severity of defects

Figure 5.15 shows dataset was divided into a training set (80%) and a test set (20%) for machine learning. The training set was used to develop the model, while the test set evaluated its performance, enabling an assessment of the model's effectiveness on unseen data.

5.3 Machine Learning Models Building for Sand Casting Defect Types

The development of ML models for accurately identifying and classifying sand casting defect types including Defective, Non-Defective, Porosity, and Shrinkage through experimentation of six classifier algorithms, ensembles of Random Forest, and Neural Networks. Each model's performance and interpretability are thoroughly examined, allowing for a comparison of results. This comparison enables identification of the most effective model for identifying and justifying sand casting defect types.

5.3.1 Building Machine Learning Models with Six Classifier Algorithms

Table 5. 1 Performance Comparison of classifier Algorithms on Training Data

S.N	Classifier Algorithms	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Building Times(s)
0	Decision Tree	99.67	99.67	99.67	99.67	0.38955
1	K-Nearest Neighbors	77.41	77.89	77.41	76.96	0.186876
2	Gradient Boosting	95.12	95.16	95.16	95.16	2.564478
3	Random Forest	99.67	99.67	99.67	99.67	0.624217
4	XGBoost	99.67	99.67	99.67	99.67	1.529194
5	Support Vector (SVC)	84.08	84.16	84.08	84.02	0.213433

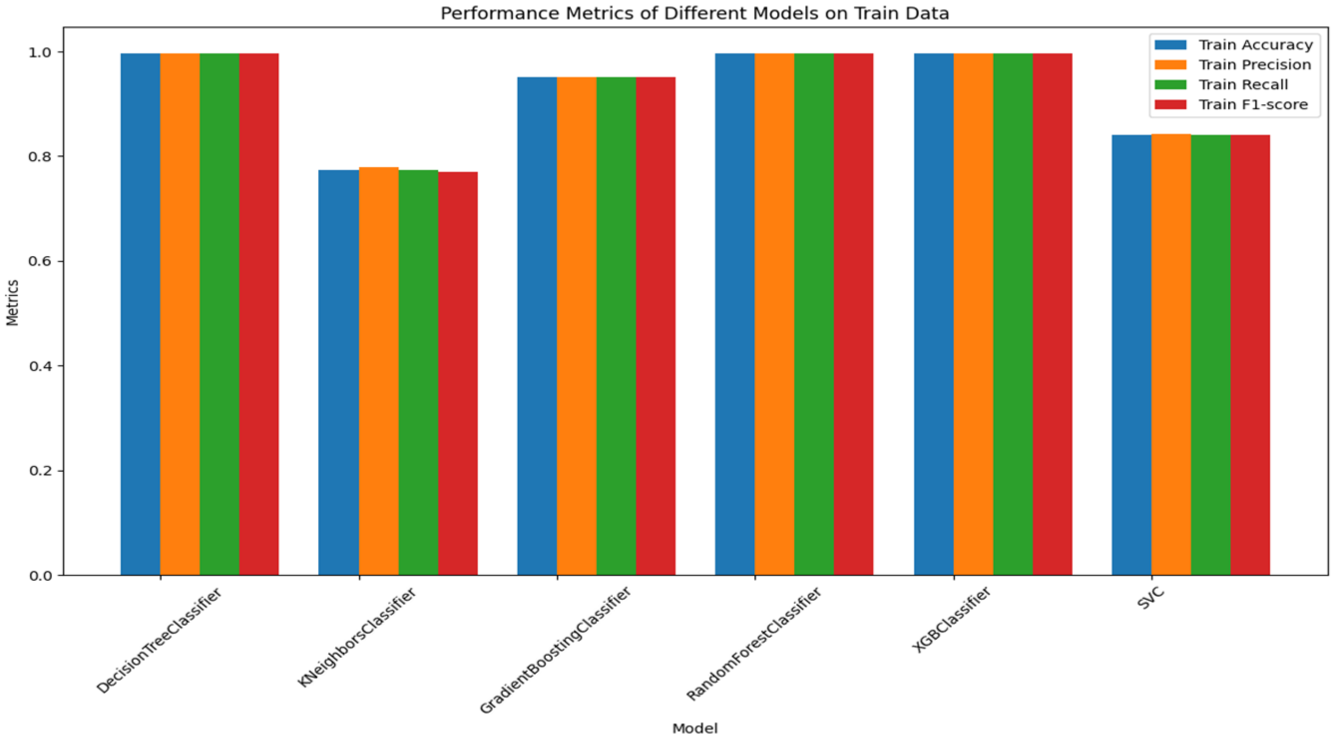


Figure 5. 16 Performance Comparison of ML Algorithms on Training Data

As in table 5.1 summarizes the performance metrics and building time for different ML algorithms trained on the dataset. The Decision Tree, Random Forest, and XGBoost classifiers achieved near-perfect accuracy scores of approximately 99.7%, indicating their ability to accurately classify instances in the training data. The Gradient Boosting Classifier also performed well with an accuracy of 95.2%. However, the K-Nearest Neighbors and Support Vector Classifier (SVC) exhibited lower accuracy scores of 77.4% and 84.1%, respectively. Additionally, while the Decision Tree and Random Forest classifiers demonstrated the fastest training times, the Gradient Boosting Classifier required significantly more time, likely due to its iterative nature. These results which is shown in figure 5.16 indicates that the XGBoost, Decision Tree and Random Forest, classifiers are best models for further evaluation on unseen test data due to their high accuracy and relatively fast training times.

Table 5. 2 Performance Comparison of classifier Algorithms on Testing Data

S.N	**Classifier Algorithms**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
0	Decision Tree	81.00	81.18	81.00	81.01
1	K-Nearest Neighbors	60.33	59.38	60.33	59.45
2	Gradient Boosting	79.67	79.87	79067	79.65
3	Random Forest	85.33	85.80	85.33	85.00
4	**XGBoost**	**87.0**	**87.4**	**87.0**	**86.99**
5	Support Vector (SVC)	64.0	63.64	64.0	63.57

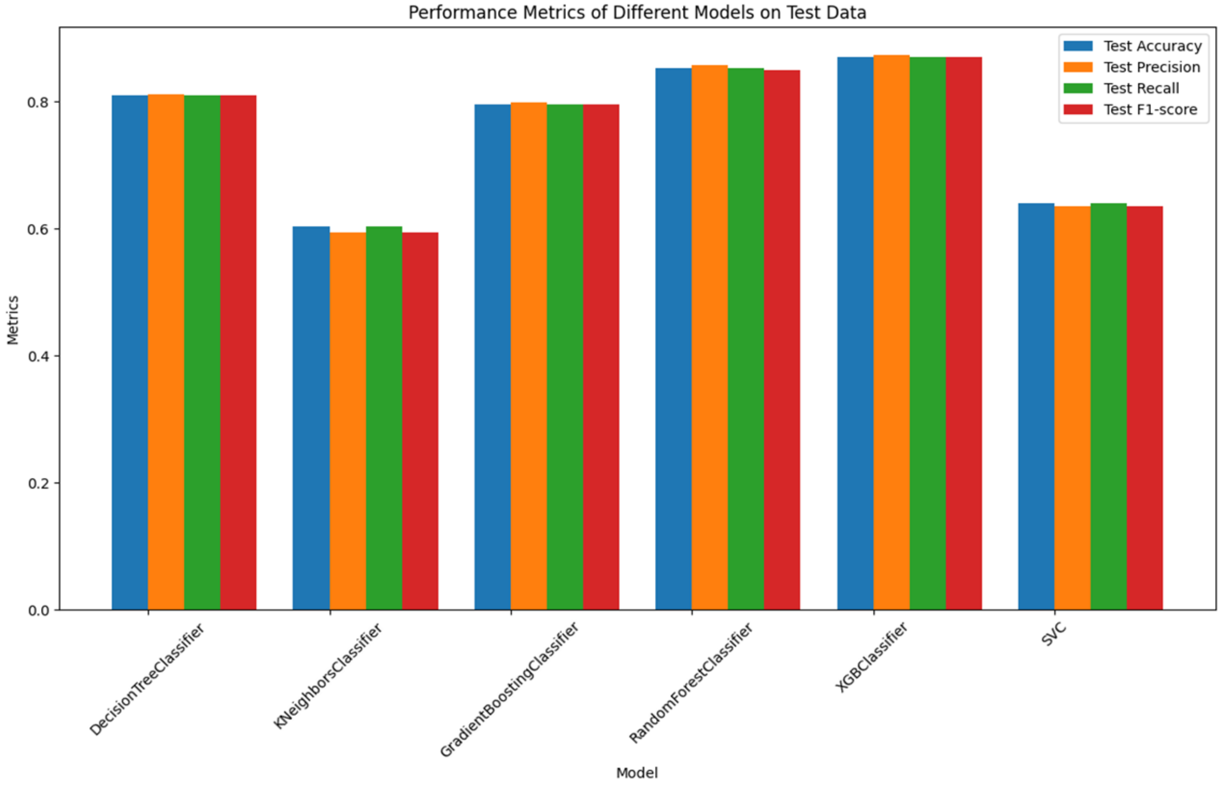


Figure 5. 17 Performance Comparison of ML Algorithms on Testing Data

Test results of the models shown in table 5.2 of different performance metrics in classifying sand casting defect types. XGBoost exhibited the highest accuracy (87%) and precision, indicating its effectiveness in accurately predicting defect types. Random Forest also performed well with an accuracy of 85.3%, closely followed by the Gradient Boosting Classifier at 79.7%. However, the K-Nearest Neighbors and Support Vector Classifier (SVC) demonstrated lower accuracy scores of 60.3% and 64%, respectively, suggesting limitations in their predictive capabilities. Despite achieving high accuracy during training, the DT Classifier's performance dropped to 81% on the test set, indicating potential issues with generalization graphically shown in figure 5.17.

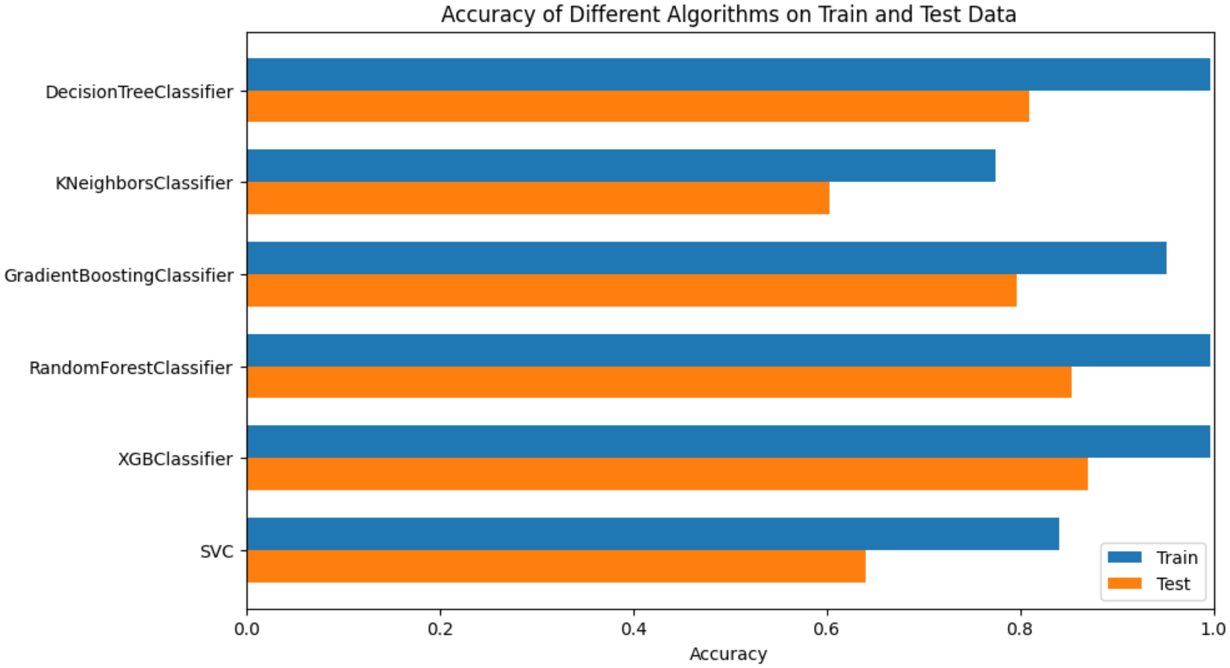


Figure 5. 18 Accuracy of Classifiers on Train and Test Data

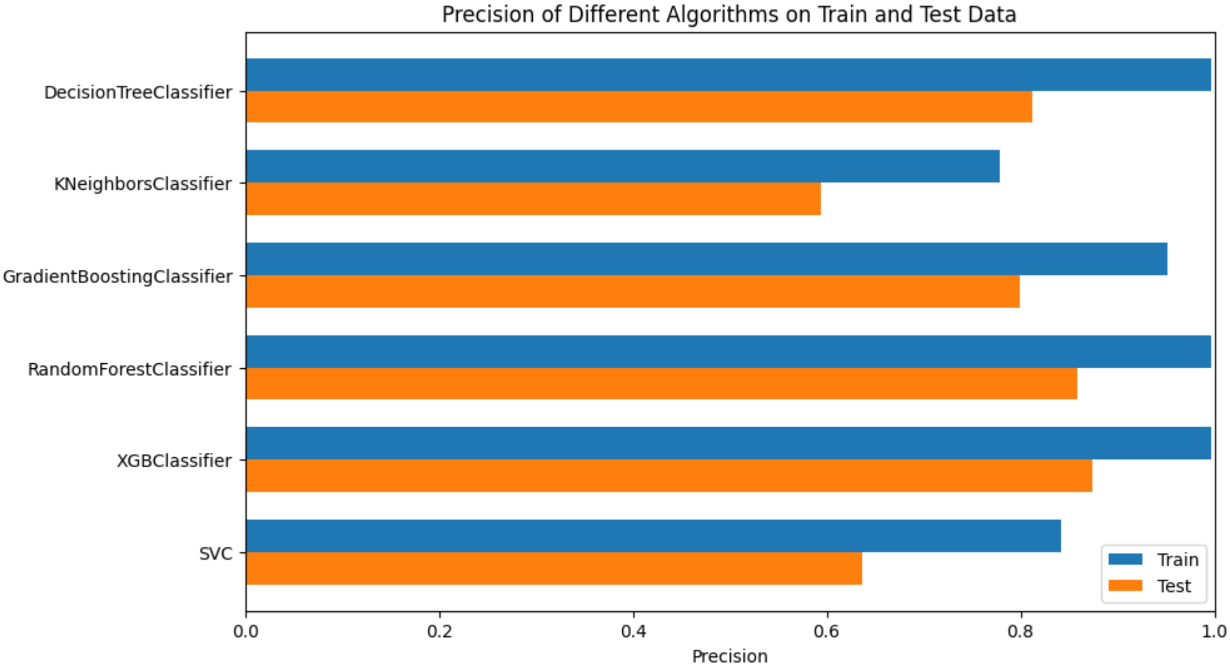


Figure 5. 19 Precision of Different Algorithms

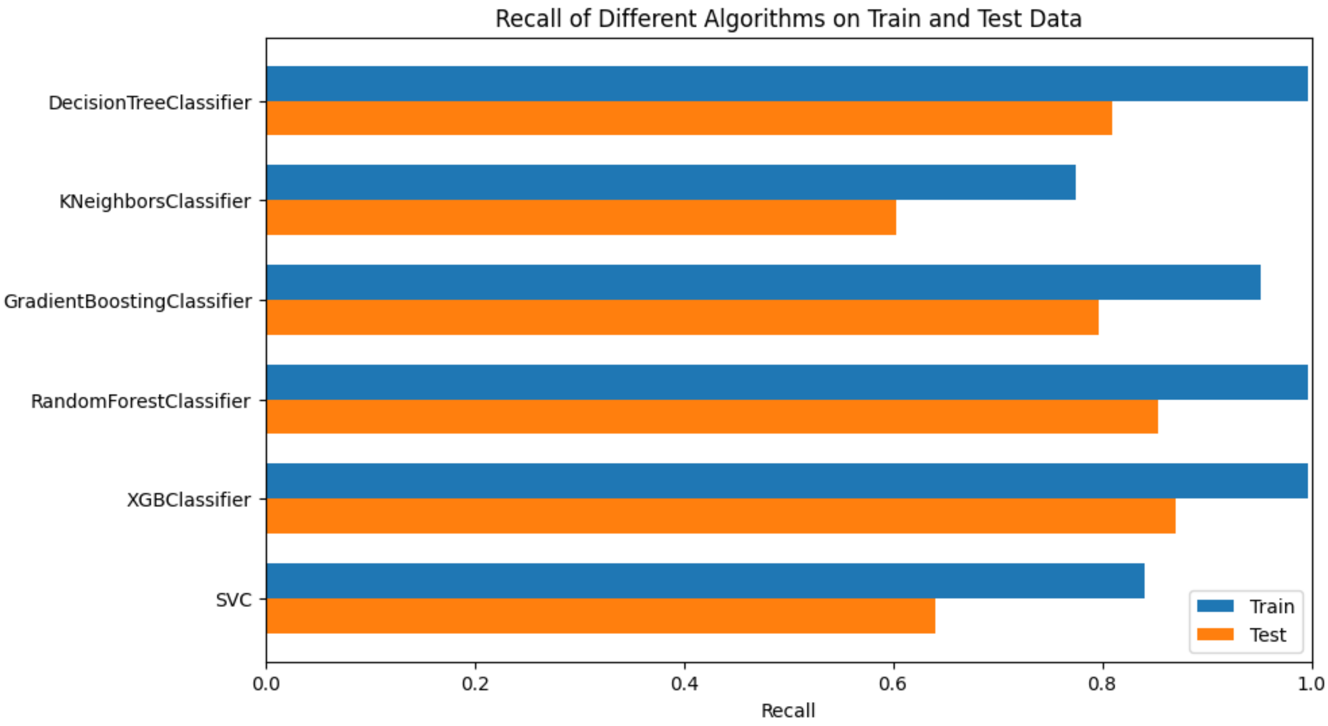


Figure 5. 20 Recall of Different Algorithms

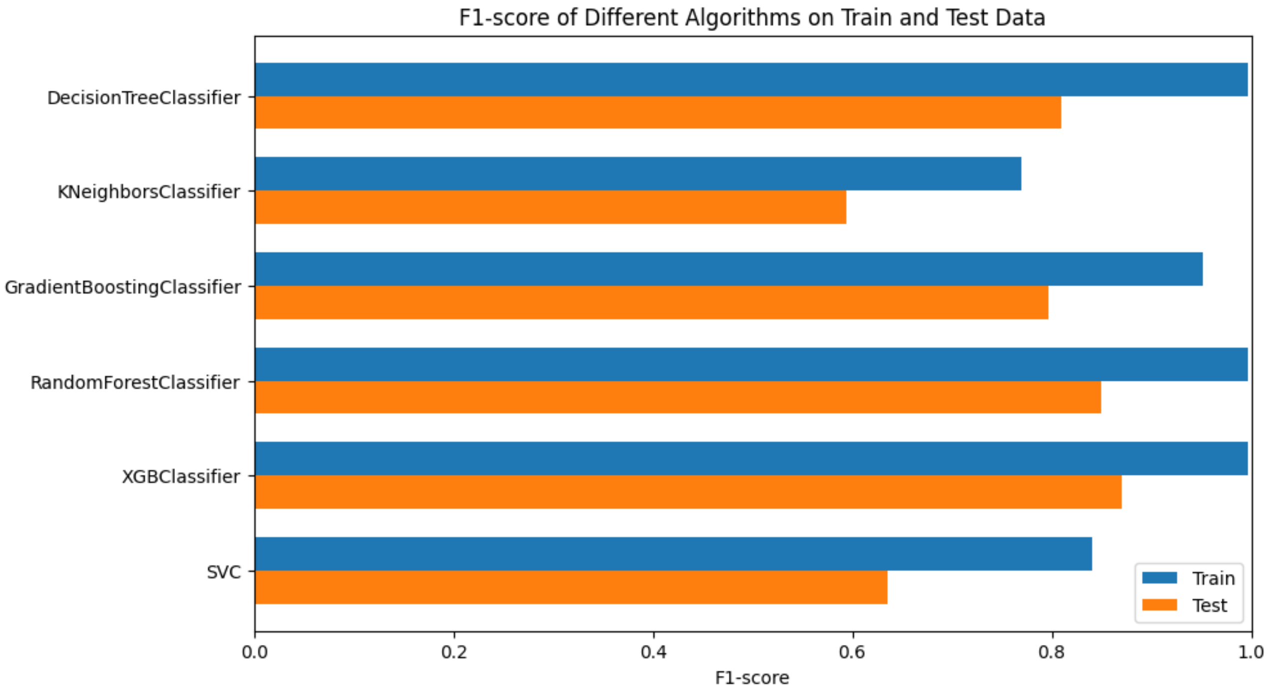


Figure 5. 21 F1-Score of Different Algorithms

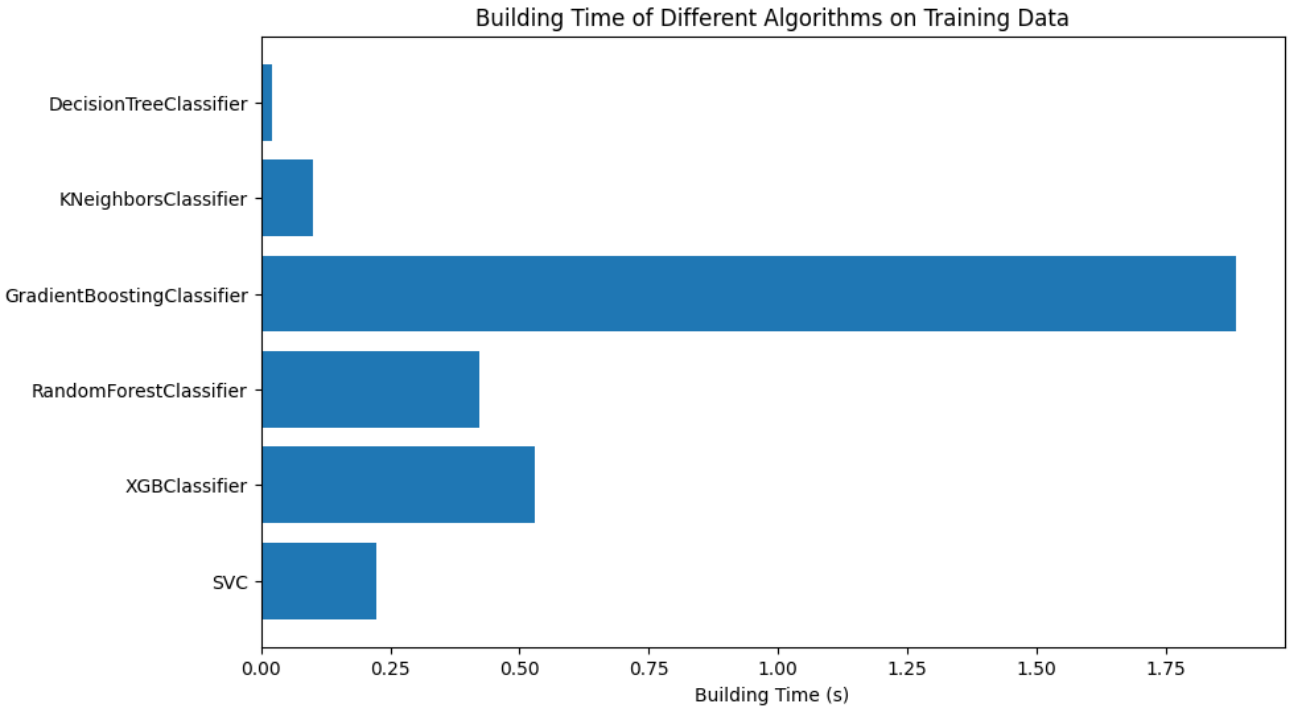
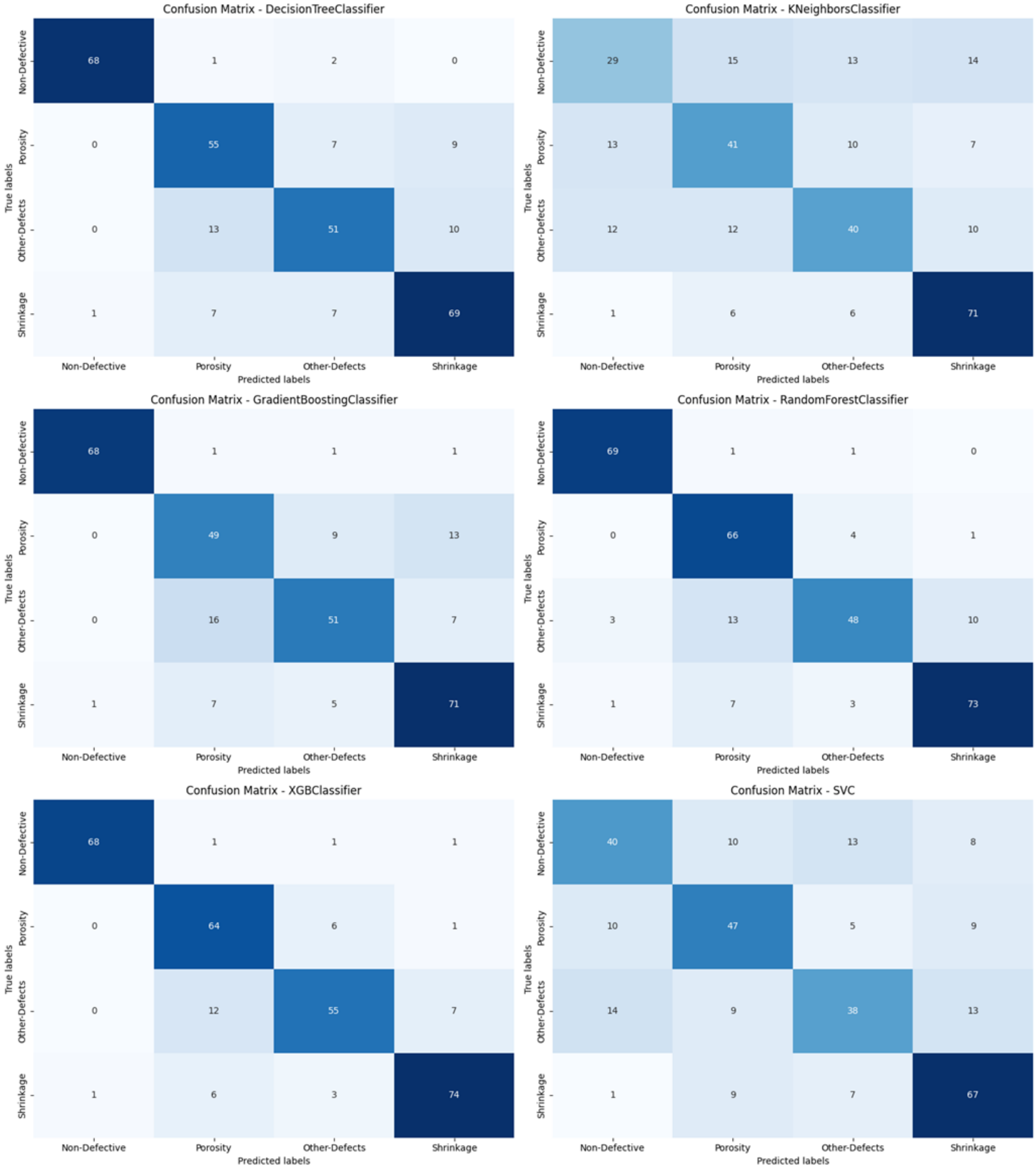


Figure 5. 22 Building Time of Different Algorithms

The evaluation of several machine learning algorithms on the training data highlighted three top-performing models such as Decision Tree Classifier, Random Forest Classifier, and XGBoost Classifier, each achieving 99.67% accuracy with high precision, recall, and F1-scores, demonstrating their effectiveness. The Decision Tree Classifier was particularly efficient due to its fast building time.

For the test data, the XGBoost Classifier proved to be the best, with an accuracy of 87%, the highest precision (87.41%), recall (87%), and F1-score (86.99%), indicating strong generalization capabilities. The Random Forest Classifier followed with 85.33% accuracy, while the Gradient Boosting Classifier achieved 79.67%. The Decision Tree Classifier, although excellent in training, had a lower test data score (81%), suggesting potential overfitting. XGBoost's superior performance on test data highlights its reliability in predicting casting defect types.



Confusion Matrix - DecisionTreeClassifier

	Non-Defective	Porosity	Other-Defects	Shrinkage
Non-Defective	68	1	2	0
Porosity	0	55	7	9
Other-Defects	0	13	51	10
Shrinkage	1	7	7	69

Confusion Matrix - KNeighborsClassifier

	Non-Defective	Porosity	Other-Defects	Shrinkage
Non-Defective	29	15	13	14
Porosity	13	41	10	7
Other-Defects	12	12	40	10
Shrinkage	1	6	6	71

Confusion Matrix - GradientBoostingClassifier

	Non-Defective	Porosity	Other-Defects	Shrinkage
Non-Defective	68	1	1	1
Porosity	0	49	9	13
Other-Defects	0	16	51	7
Shrinkage	1	7	5	71

Confusion Matrix - RandomForestClassifier

	Non-Defective	Porosity	Other-Defects	Shrinkage
Non-Defective	69	1	1	0
Porosity	0	66	4	1
Other-Defects	3	13	48	10
Shrinkage	1	7	3	73

Confusion Matrix - XGBClassifier

	Non-Defective	Porosity	Other-Defects	Shrinkage
Non-Defective	68	1	1	1
Porosity	0	64	6	1
Other-Defects	0	12	55	7
Shrinkage	1	6	3	74

Confusion Matrix - SVC

	Non-Defective	Porosity	Other-Defects	Shrinkage
Non-Defective	40	10	13	8
Porosity	10	47	5	9
Other-Defects	14	9	38	13
Shrinkage	1	9	7	67

Figure 5. 23 Confusion matrix comparison of test results of six models

Confusion matrix analysis shown in figure 5.23 for the six algorithms Decision Tree Classifier, K-Nearest Neighbors (KNN), Gradient Boosting Classifier, Random Forest Classifier, XGBoost Classifier, and SVC reveals the models' performance on test data by comparing actual versus predicted classifications of defect types: Non-Defective, Porosity, Other-Defects, and Shrinkage.

XGBoost showed the highest accuracy, with the major true positives and fewest misclassifications. Random Forest also performed well, with a high rate of correct predictions. Gradient Boosting was slightly less accurate but still competitive. The Decision Tree Classifier indicated overfitting, with more misclassifications in the test data. KNN and SVC had the lowest accuracy, with significant misclassifications, especially between Porosity and Other-Defects. Confusion matrix shows XGBoost and Random Forest as the most reliable models for predicting sand casting defects.

5.3.2 Building Machine Learning Models with Ensembles Model

Table 5. 3 Comparison of Ensemble model Training results

S.N	**Ensembles of Random Forest**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Building Time(sec)**
0	AdaBoost	99.67	99.66	99.67	99.67	24.068
1	Gradient Boosting	89.41	89.38	89.42	89.39	0.9280
2	XGBoost	99.67	99.67	98.66	99.67	0.322

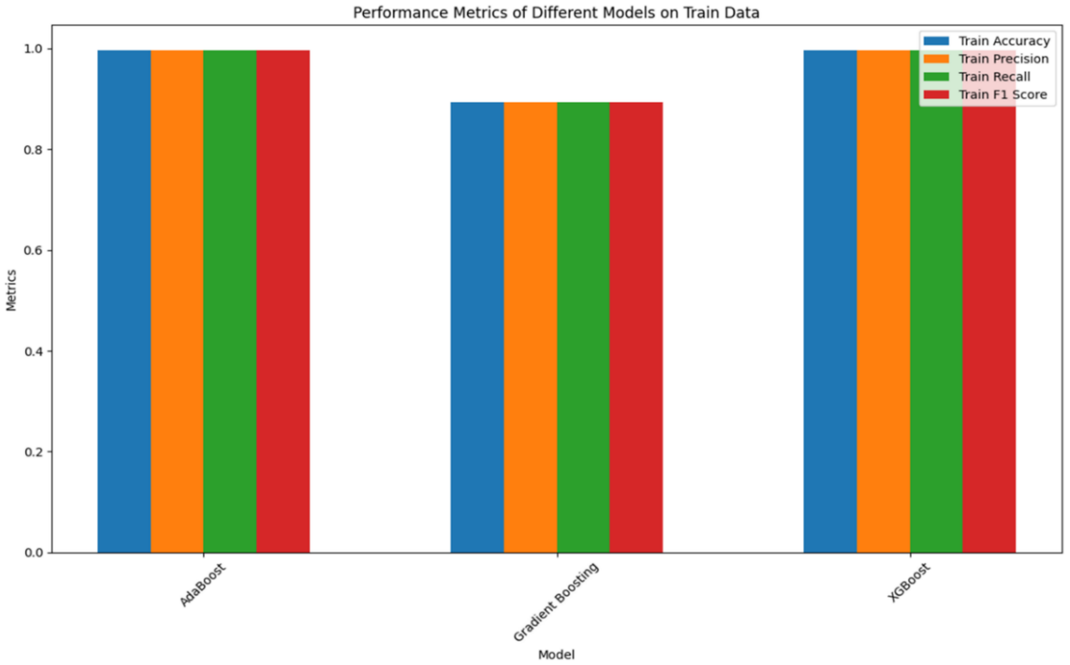


Figure 5. 24 Performance Comparison of Ensembles on Training Data

Table 5.3 compares the training results showcase the performance of three ensemble methods AdaBoost demonstrated superior performance with a precision, recall, accuracy, and F1 score all at 0.996667, indicating excellent classification accuracy and minimal errors. However, this method had the longest training time, taking approximately 22.92 seconds to build the model. Gradient Boosting had a lower accuracy of 0.894167, with comparable precision, recall, and F1 scores, suggesting a higher rate of misclassification compared to AdaBoost and XGBoost. Despite this, it was relatively quick to train, with a building time of just 0.93 seconds. XGBoost matched AdaBoost in all performance metrics, achieving an accuracy, precision, recall, and F1 score of 0.996667. Additionally, it was significantly faster, with a building time of only 0.30 seconds. From these results XGBoost efficiency and strong predictive capability, making it an effective choice for the classification task as shown in figure 5.24.

Table 5. 4 Comparison of Ensemble model testing results

S.N	Ensembles of Random Forest	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Building Time (s)
0	AdaBoost	76.67	76.54	76.67	76.55	21.259686
1	Gradient Boosting	75.66	75.67	75.39	75.39	1.269347
2	XGBoost	86.87	86.83	86.67	86.66	2.921892

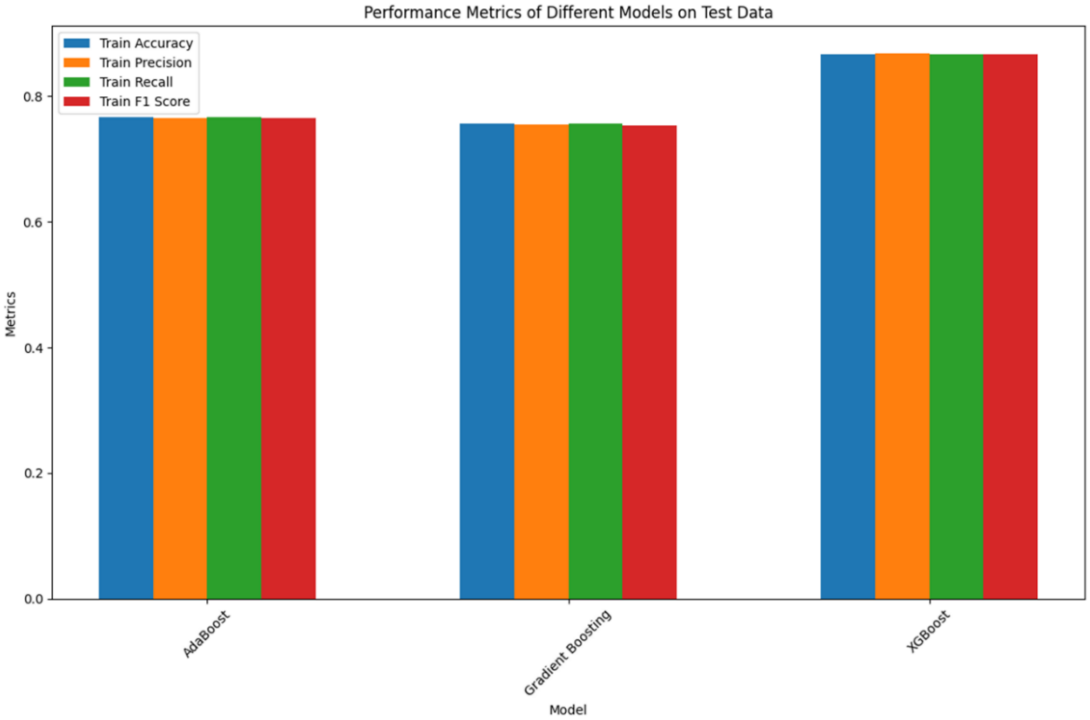


Figure 5. 25 Performance Comparison of Ensembles on Testing Data

Test data results compare in the table 5.4 the performance models AdaBoost had a decent performance with an accuracy of 0.766667 and similar precision, recall, and F1 scores around 0.765. However, it had the longest building time of about 22.92 seconds. Gradient Boosting showed slightly lower accuracy at 0.756667 and similar precision, recall, and F1 scores around 0.754. It was more efficient in terms of building time, taking only 0.93 seconds. XGBoost outperformed both AdaBoost and Gradient Boosting with an accuracy of 0.866667 and precision, recall, and F1 scores around 0.868. It was also much faster to build, requiring only 0.30 seconds. From these XGBoost demonstrated the best performance and efficiency, making it the top choice for this classification task and graphically displayed in figure 5.25.

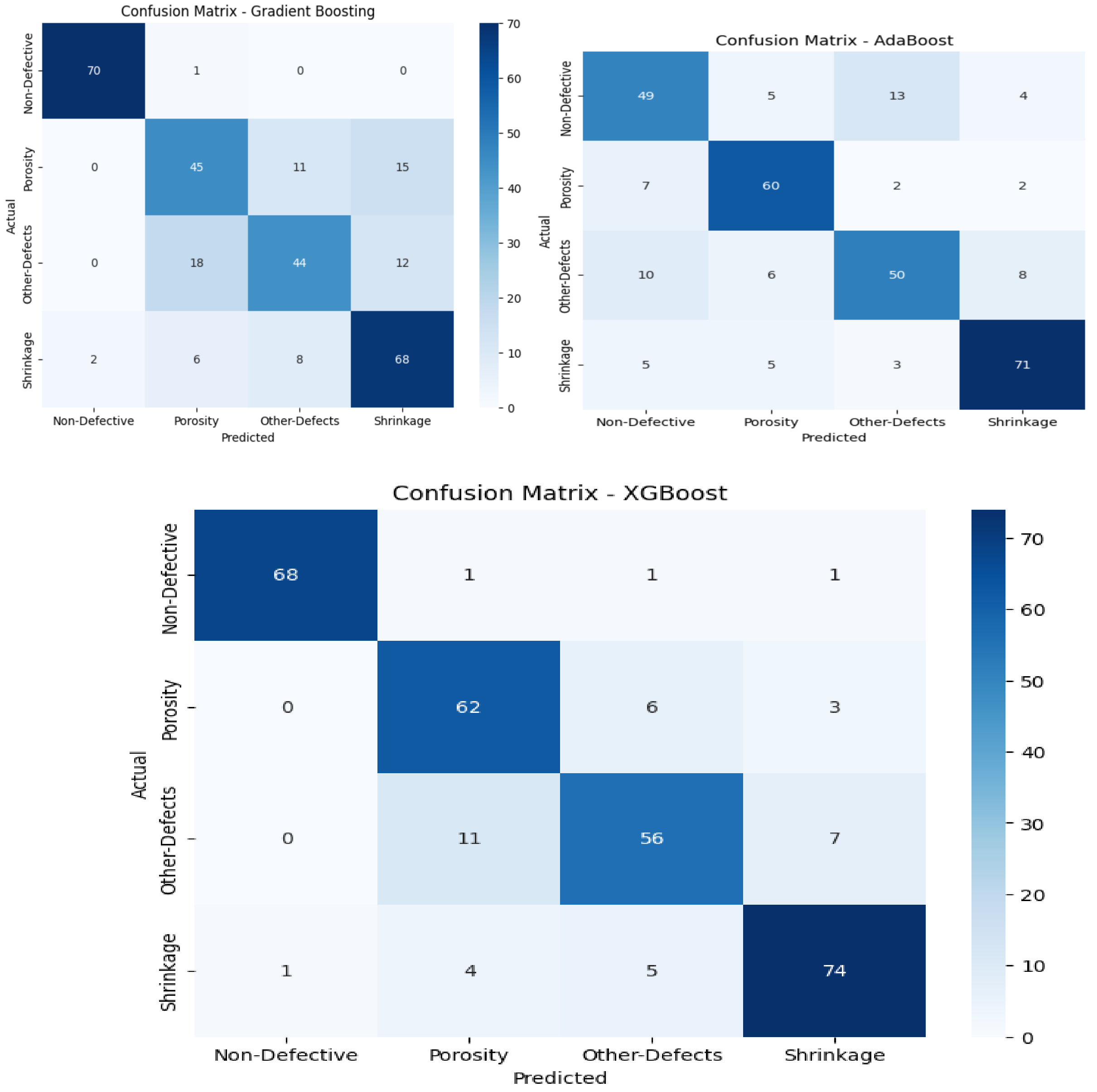
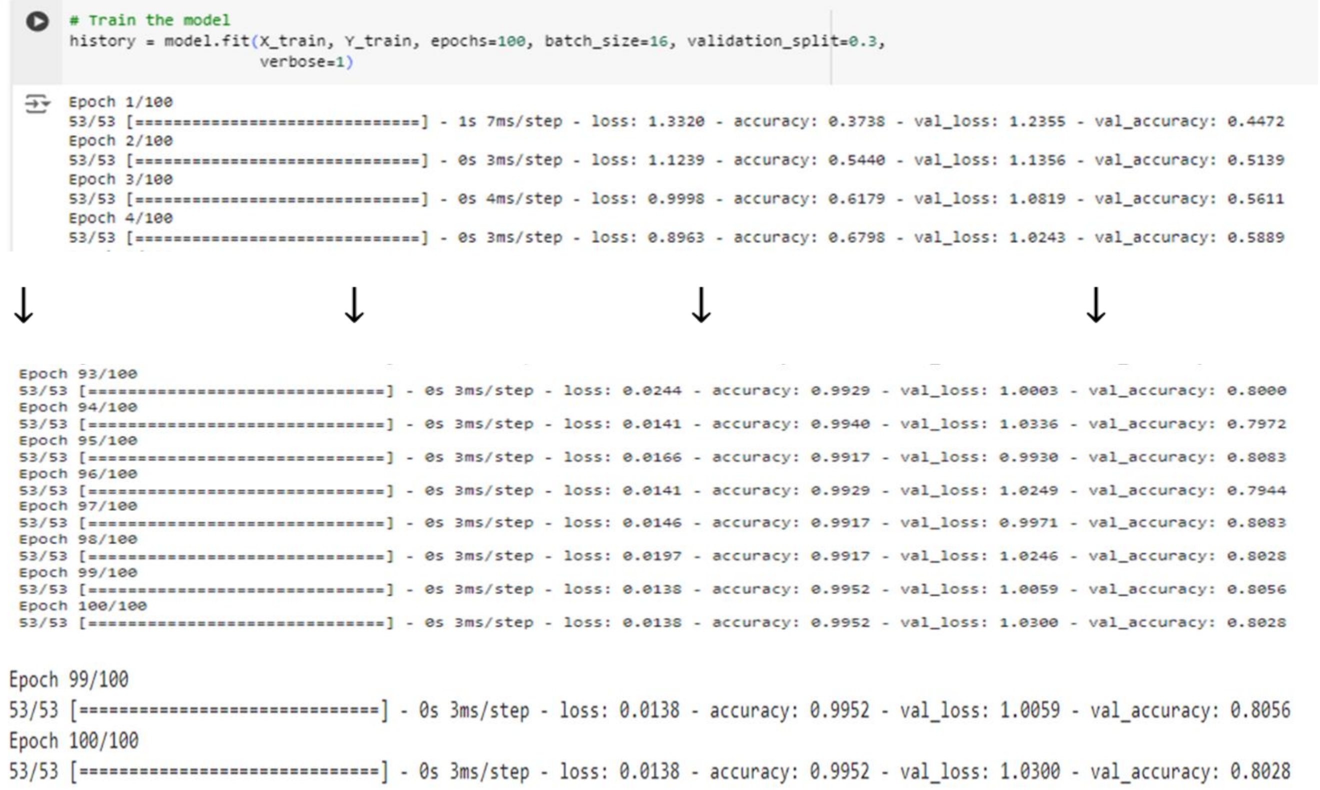


Figure 5. 26 Confusion matrix for test results of Ensembles model

As shown in figure 5.26 XGBoost model provides a rapid and straightforward comparison of its effectiveness in distinguishing between various defect types, including Non-Defective, Porosity, Other-Defects, and Shrinkage, from a dataset comprising 75 product instances. Among these instances, the XGBoost model correctly identified 68 as Non-Defective, 62 as Porosity, 56 as Other-Defects, and 74 as Shrinkage. This interpretation underscores the models to discern between different defect categories with a level of accuracy, its effectiveness in practical applications within the manufacturing domain.

5.3.3 Building Machine Learning Models with Neural Network



```
# Train the model
history = model.fit(X_train, Y_train, epochs=100, batch_size=16, validation_split=0.3,
                    verbose=1)
```

```
Epoch 1/100
53/53 [==============================] - 1s 7ms/step - loss: 1.3320 - accuracy: 0.3738 - val_loss: 1.2355 - val_accuracy: 0.4472
Epoch 2/100
53/53 [==============================] - 0s 3ms/step - loss: 1.1239 - accuracy: 0.5440 - val_loss: 1.1356 - val_accuracy: 0.5139
Epoch 3/100
53/53 [==============================] - 0s 4ms/step - loss: 0.9998 - accuracy: 0.6179 - val_loss: 1.0819 - val_accuracy: 0.5611
Epoch 4/100
53/53 [==============================] - 0s 3ms/step - loss: 0.8963 - accuracy: 0.6798 - val_loss: 1.0243 - val_accuracy: 0.5889
```

```
Epoch 93/100
53/53 [==============================] - 0s 3ms/step - loss: 0.0244 - accuracy: 0.9929 - val_loss: 1.0003 - val_accuracy: 0.8000
Epoch 94/100
53/53 [==============================] - 0s 3ms/step - loss: 0.0141 - accuracy: 0.9940 - val_loss: 1.0336 - val_accuracy: 0.7972
Epoch 95/100
53/53 [==============================] - 0s 3ms/step - loss: 0.0166 - accuracy: 0.9917 - val_loss: 0.9930 - val_accuracy: 0.8083
Epoch 96/100
53/53 [==============================] - 0s 3ms/step - loss: 0.0141 - accuracy: 0.9929 - val_loss: 1.0249 - val_accuracy: 0.7944
Epoch 97/100
53/53 [==============================] - 0s 3ms/step - loss: 0.0146 - accuracy: 0.9917 - val_loss: 0.9971 - val_accuracy: 0.8083
Epoch 98/100
53/53 [==============================] - 0s 3ms/step - loss: 0.0197 - accuracy: 0.9917 - val_loss: 1.0246 - val_accuracy: 0.8028
Epoch 99/100
53/53 [==============================] - 0s 3ms/step - loss: 0.0138 - accuracy: 0.9952 - val_loss: 1.0059 - val_accuracy: 0.8056
Epoch 100/100
53/53 [==============================] - 0s 3ms/step - loss: 0.0138 - accuracy: 0.9952 - val_loss: 1.0300 - val_accuracy: 0.8028
```

```
Epoch 99/100
53/53 [==============================] - 0s 3ms/step - loss: 0.0138 - accuracy: 0.9952 - val_loss: 1.0059 - val_accuracy: 0.8056
Epoch 100/100
53/53 [==============================] - 0s 3ms/step - loss: 0.0138 - accuracy: 0.9952 - val_loss: 1.0300 - val_accuracy: 0.8028
```

Figure 5. 27 Training and validation history graph

During the training process, shown in figure 5.27 the model achieved a training accuracy of 99.52% and a validation accuracy of 80.28%. Analyzing the training history graph revealed fluctuations in both validation loss and accuracy, as well as training loss and accuracy, across the training and validation phases. Initially, the validation loss decreased, but it started to rise after the 100th epoch, indicating potential overfitting to the training data. Overfitting might result in poorer performance on new, unseen data. Consequently, we consider the model trained up to the 100th epoch with the specified training and validation accuracies as the final model, as further training beyond this point could exacerbate overfitting issues.

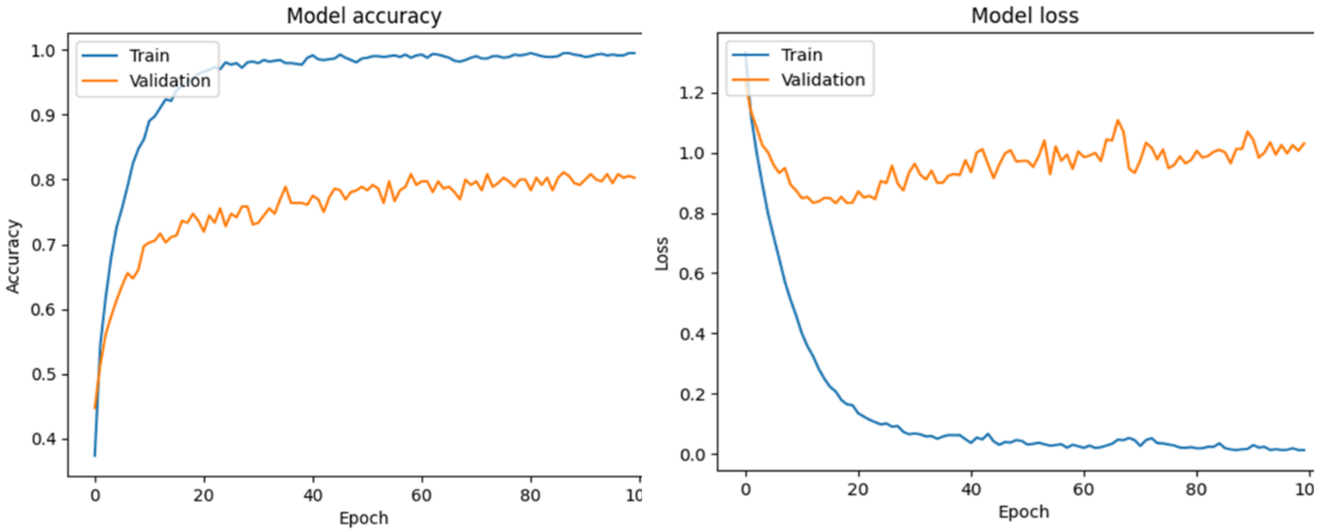
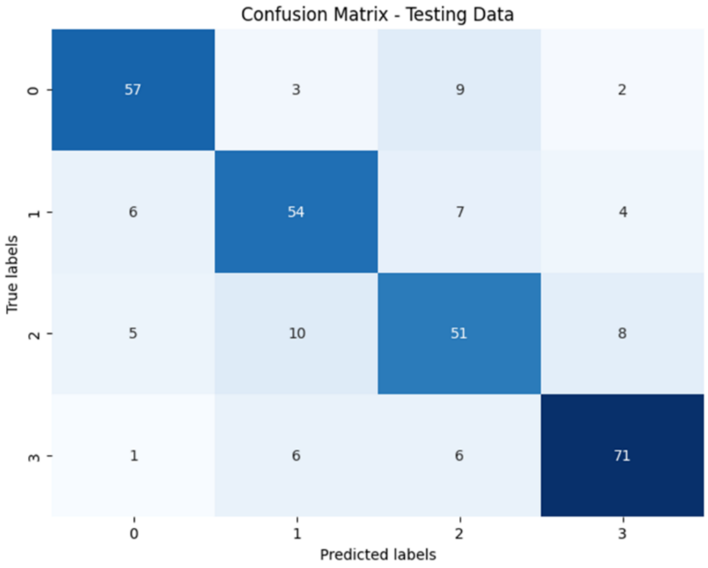
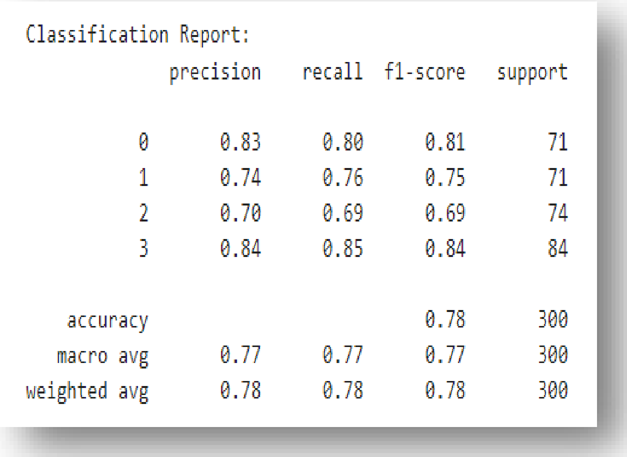


Figure 5. 28 Model Accuracy and Model Loss

The graph displayed in figure 5.28, the gap between the model accuracy and loss indicates overfitting, which is a concerning observation. When comparing the validation accuracy to the training accuracy, it becomes evident that the validation accuracy surpasses the training accuracy, suggesting overfitting. This discrepancy implies that the model may not generalize well to unseen data and may perform poorly on new instances. The occurrence of overfitting during the training phase is problematic as it compromises the model's ability to effectively learn from the data without memorizing it.



	0	1	2	3
0	57	3	9	2
1	6	54	7	4
2	5	10	51	8
3	1	6	6	71



```
Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.80      0.81        71
           1       0.74      0.76      0.75        71
           2       0.70      0.69      0.69        74
           3       0.84      0.85      0.84        84

    accuracy                           0.78       300
   macro avg       0.77      0.77      0.77       300
weighted avg       0.78      0.78      0.78       300
```

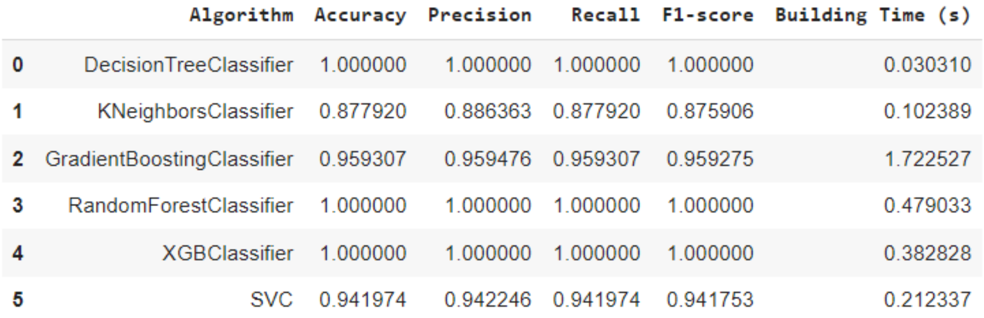
Figure 5. 29 Confusion Matrix and Precision, Recall, F1-score, Support

In figure 5.29 indicated as model demonstrates varying precision, recall, and F1-score across different classes, with Class 0 (None defect) and Class 3 (Shrinkage) showing superior performance compared to Class 1 (other defect) and Class 2 (porosity). Despite this, the overall accuracy remains at 75%, implying correct predictions for 75% of instances in the test dataset. The confusion matrix reveals insights into correct and incorrect predictions, aiding in identifying patterns in misclassifications and evaluating the model ability to distinguish in classes. While both the classification report and confusion matrix offer valuable performance insights, caution is advised when training neural networks on small datasets due to overfitting risks and resource constraints.

5.4 Machine Learning Models Building for Severity of Sand Casting Defects

ML models built for defect severity identification, using six classifier algorithms, Random Forest ensembles, and Neural Networks, are compared to determine the most effective model for categorizing defects as severe, moderate, or minor.

5.4.1 Building Machine Learning Models with Six Classifiers



	Algorithm	Accuracy	Precision	Recall	F1-score	Building Time (s)
0	DecisionTreeClassifier	1.000000	1.000000	1.000000	1.000000	0.030310
1	KNeighborsClassifier	0.877920	0.886363	0.877920	0.875906	0.102389
2	GradientBoostingClassifier	0.959307	0.959476	0.959307	0.959275	1.722527
3	RandomForestClassifier	1.000000	1.000000	1.000000	1.000000	0.479033
4	XGBClassifier	1.000000	1.000000	1.000000	1.000000	0.382828
5	SVC	0.941974	0.942246	0.941974	0.941753	0.212337

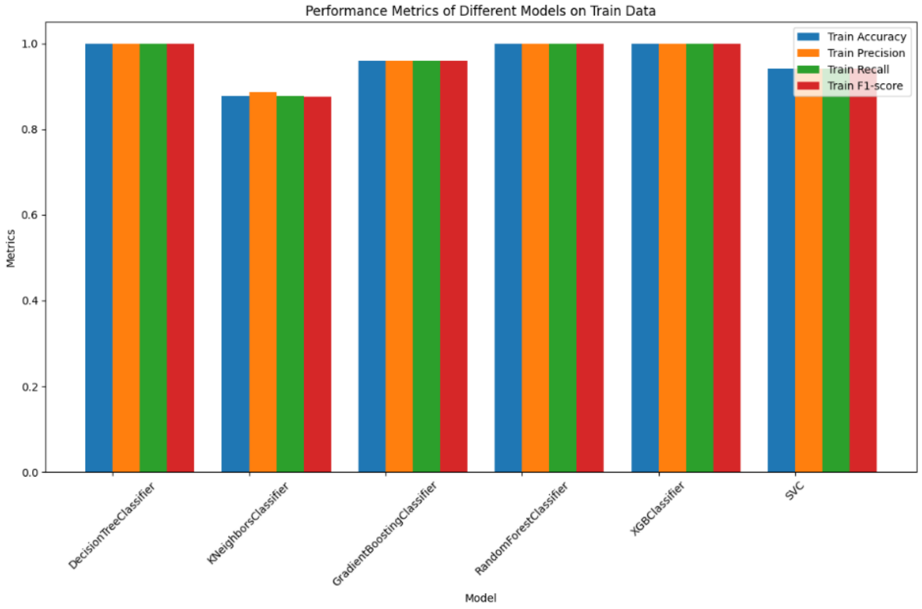


Figure 5. 30 Performance Comparison of ML Algorithms on Training Data

As shown in the above figure 5.30 summarizes the performance metrics attained by different classification algorithms in predicting the severity levels of defects, categorized as minor, moderate, and severe. Notably, the XGBoost, Decision Tree, and Random Forest models showcased impeccable accuracy, precision, recall, and F1-scores, achieving a flawless 100% across all metrics. This exceptional performance underscores their effectiveness in accurately discriminating between varying degrees of defect severity. KNN model, while slightly irregular the tree-based classifiers, still exhibited respectable performance metrics, recording an accuracy of approximately 87.79%. Similarly, the Gradient Boosting Classifier and Support Vector Classifier (SVC) demonstrated estimable accuracy rates of around 95.93% and 94.20%, respectively. Decision Tree, Random Forest, and XGBoost algorithms are highly recommended for defect severity classification due to their outstanding performance, while the KNN, Gradient Boosting, and SVC models offer viable alternatives with reasonably good accuracies ranging from about 87.79% to 95.93%.

Table 5. 5 Comparison of Six Classifier Algorithms on Testing Data

S.N	**Classifier Algorithms**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score %)**
0	Decision Tree	78.01	78.23	78.01	78.05
1	K-Nearest Neighbors	78.91	80.83	778.92	78.33
2	Gradient Boosting	84.94	85.00	84.92	84.85
3	Random Forest	91.86	91.99	91.86	91.86
4	XGBoost	93.97	93.97	93.97	93.97
5	Support Vector (SVC)	84.64	84.63	84.63	84.57

Table 5.5 indicates test results of the models show different performance metrics of different classification algorithms in forecasting a specific outcome. Notably, Random Forest and XGBoost classifiers showed the highest accuracy, precision, recall, and F1-score, achieving around 91.87% and 93.98% accuracy, respectively this indicates their effectiveness in accurately predicting the severity.

Gradient Boosting Classifier also performed well with an accuracy of about 84.94%. Decision Tree and K-Nearest Neighbors (KNN) classifiers produced similar results, with accuracies of roughly 78.01% and 78.92%, respectively.

Support Vector Classifier (SVC) achieved an accuracy of approximately 84.64%. These findings suggest that while all algorithms performed reasonably well, Random Forest and XGBoost classifiers outperformed others in accuracy and overall predictive capability. Hence, for severity prediction task, either Random Forest or XGBoost algorithm would be recommended, XGBoost used due to their superior performance graphically shown in figure 5.31.

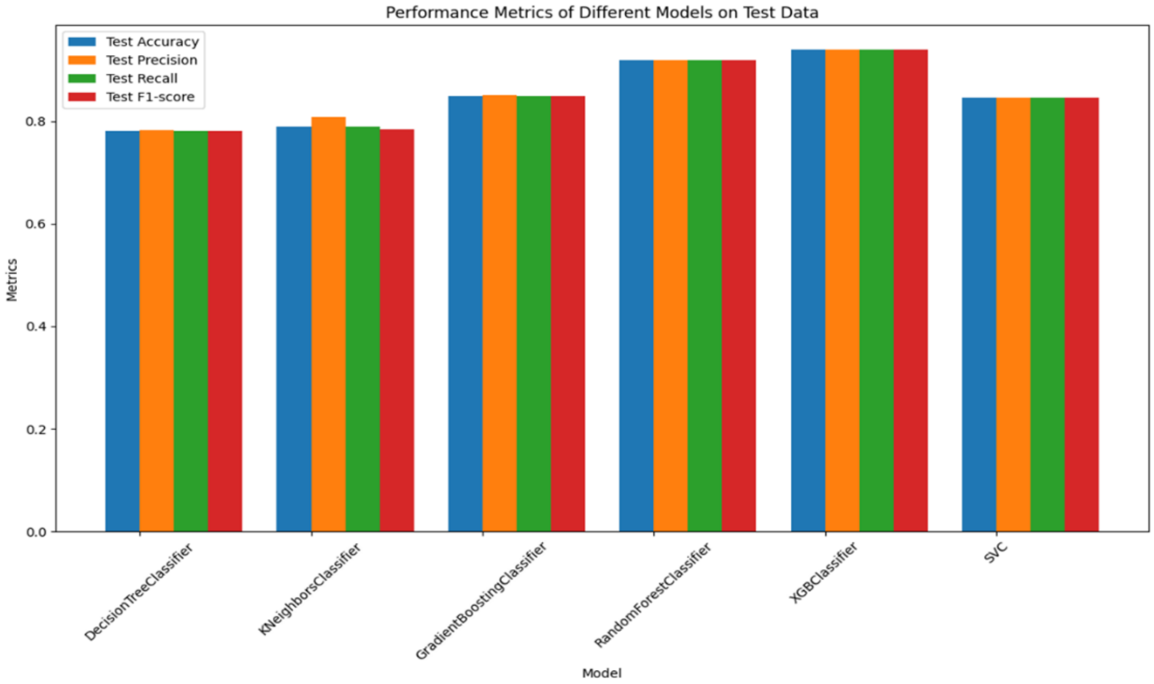


Figure 5. 31 Performance Comparison of ML Algorithms on Testing Data

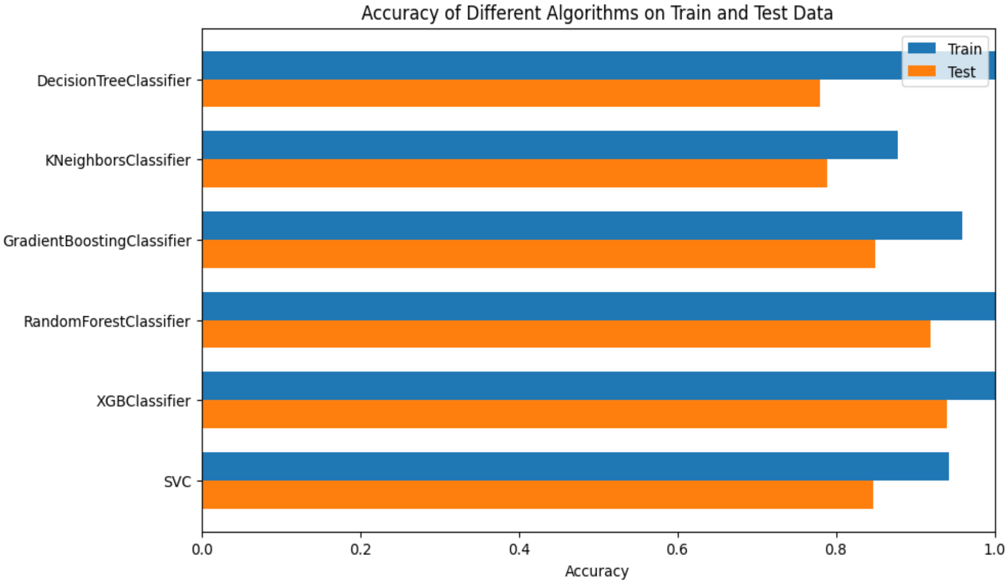


Figure 5. 32 Different Algorithms Accuracy

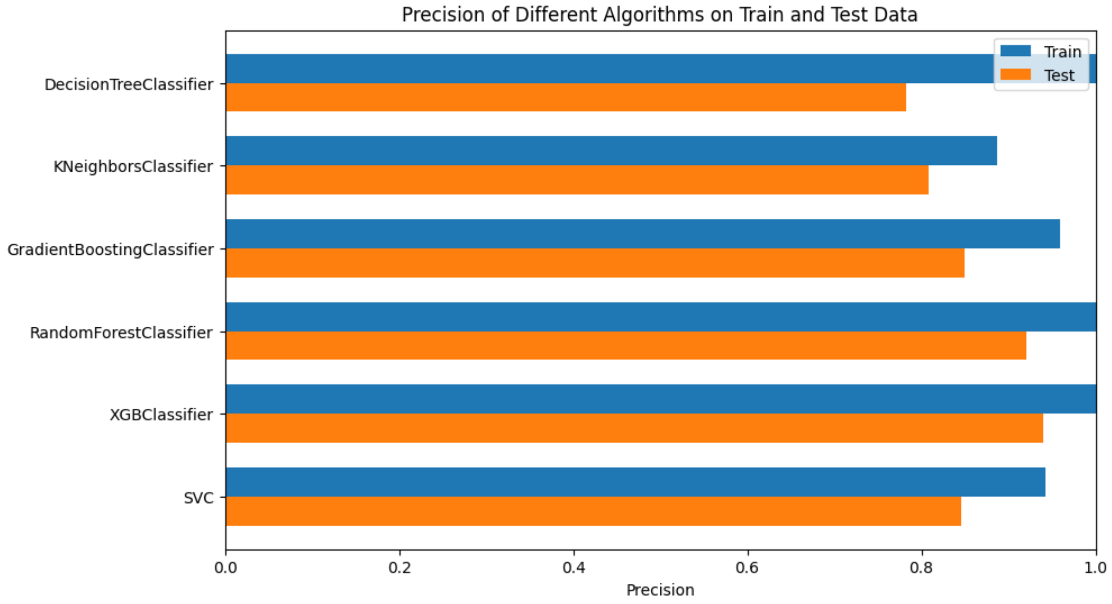


Figure 5. 33 Precision of Different Algorithms

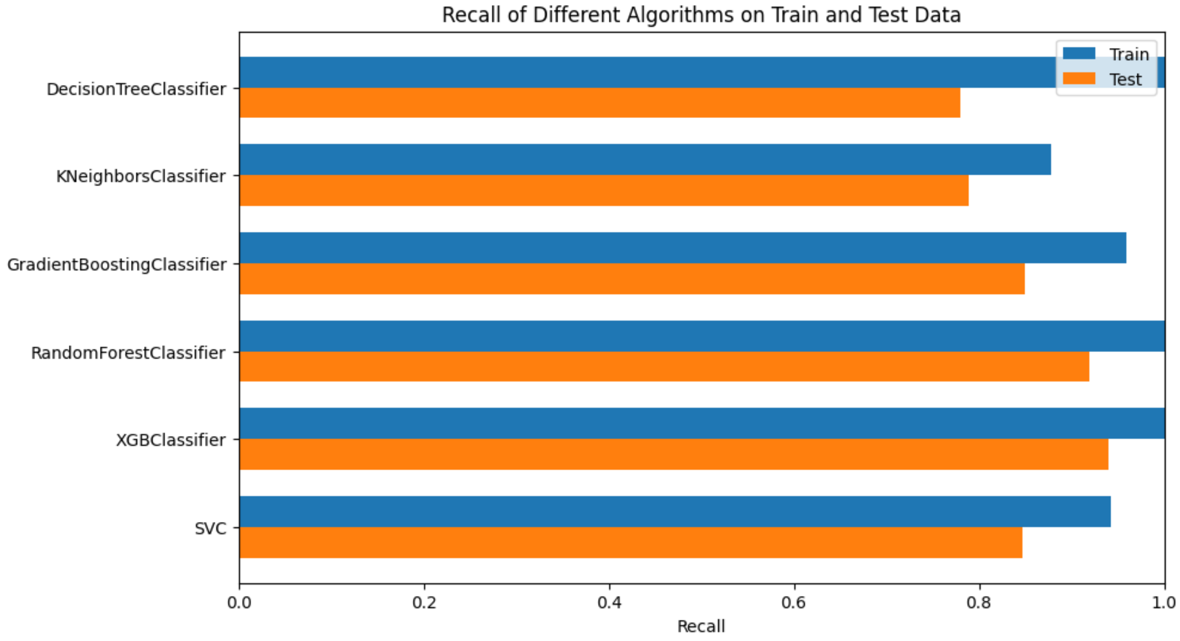


Figure 5. 34 Recall of Different Algorithms

All models shown in figure 5.32 up to figure 5.36 performed perfectly during training, with Decision Tree, XGBoost, and Random Forest, achieving 100% recall, accuracy, precision, and F1-score. However, in testing phase, only XGBoost maintained strong performance, scoring nearly 94% accuracy. This indicates that XGBoost is the most reliable model for both training and testing, making it the best choice overall.

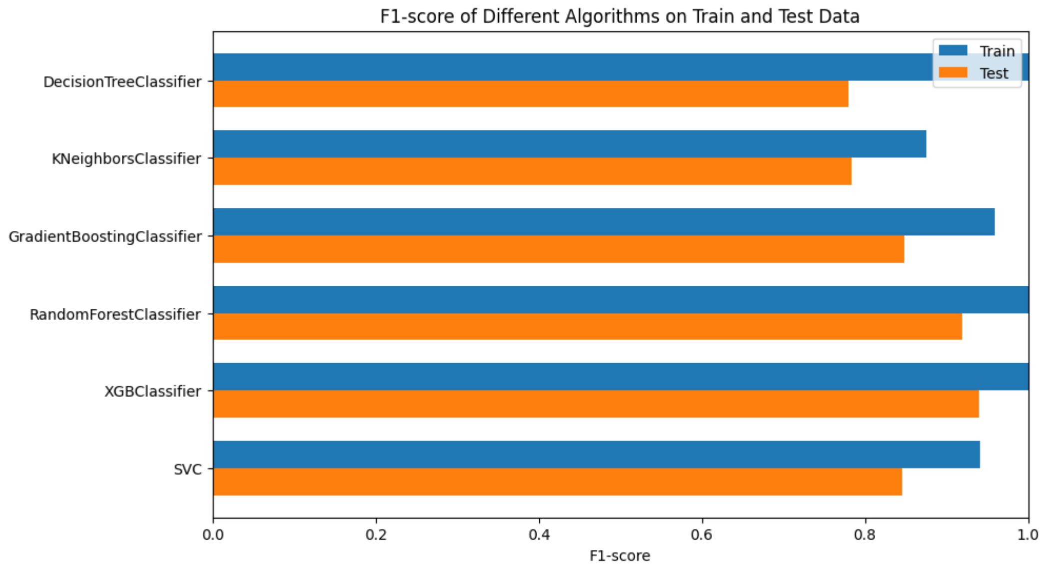


Figure 5. 35 F1-Score of Different Algorithms

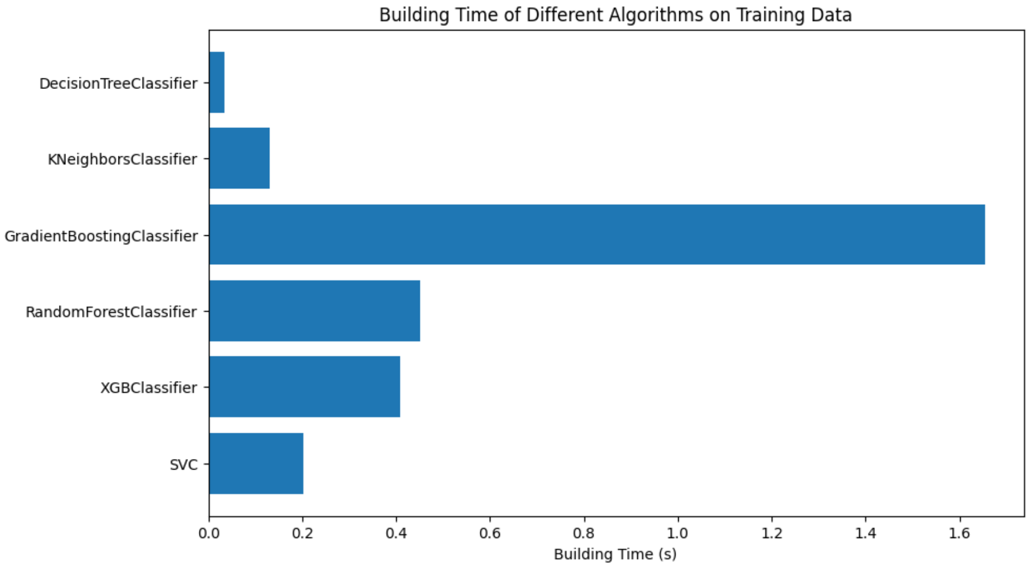


Figure 5. 36 Building Time of Different Algorithms

Visualizations of confusion matrices shown in figure 5.37 provide a clear view of how well different algorithms detect defects classified as Minor, Moderate, and Severe. Among these algorithms, XGBoost stands out as the top performer. It accurately identified 110 Minor, 106 Moderate, and 96 severe defects. While XGBoost excels overall, it's still essential to examine any misclassifications to understand its limitations. Despite this, XGBoost proves to be a reliable choice for effectively classifying defects of varying severity levels.

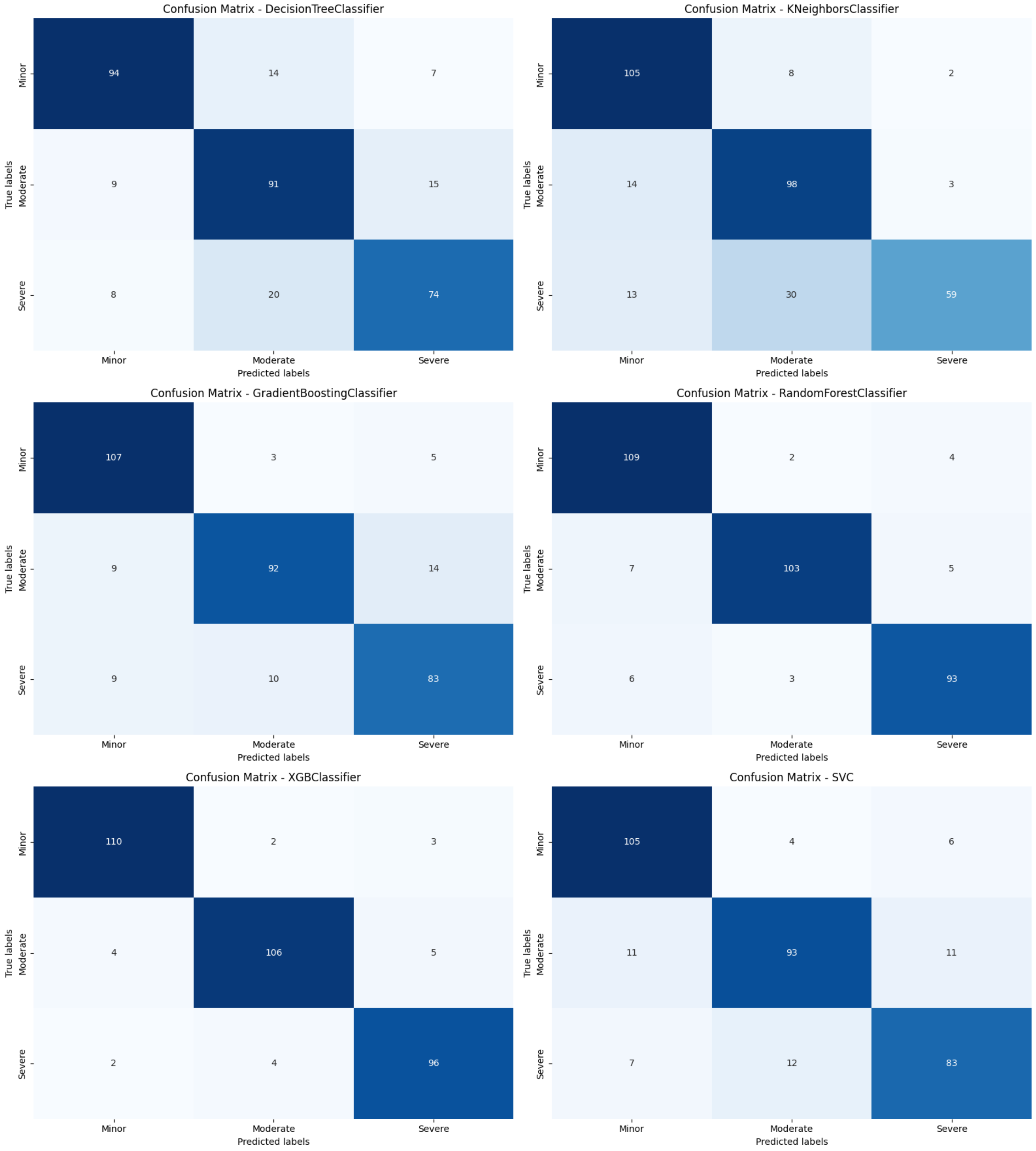


Figure 5. 37 Confusion matrix for test results of six models

5.4.2 Building Machine Learning Models with Ensembles models

Training results shown in figure 5.38 the performance of three ensemble methods AdaBoost demonstrated superior performance with an accuracy, precision, recall, and F1 score all at 01, indicating good classification accuracy and minimal errors. However, this method had the medium training time, taking approximately 0.41 seconds to build the model. Gradient Boosting had a lower accuracy of 0.897513, with comparable precision, recall, and F1 scores, suggesting a higher rate of misclassification compared to AdaBoost and XGBoost. Despite this, it was relatively quick to train, with a building time of just 0.81 seconds. XGBoost matched AdaBoost in the metrics, achieving an accuracy, precision, recall, and F1 score of 1. Additionally, it was significantly faster, with a building time of only 0.22 seconds. From these results XGBoost efficiency and strong predictive capability, making it an effective choice for the classification task.

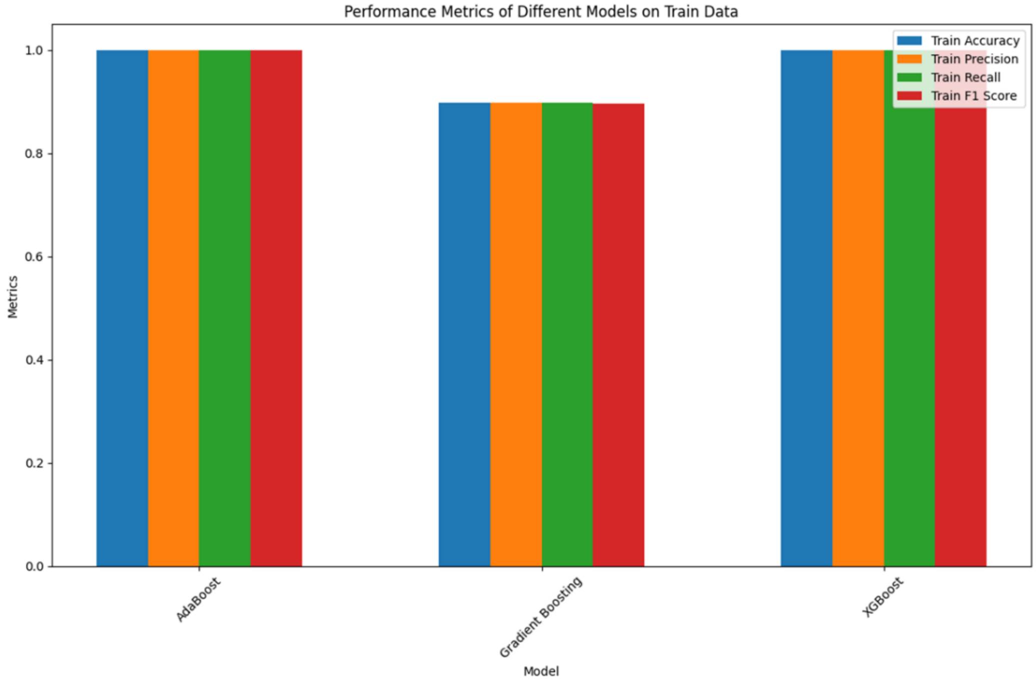


Figure 5. 38 Performance Comparison of Ensembles on Training Data

Test data results compare in the table 5.7 the performance models AdaBoost had a decent performance with an accuracy of 0.903614 and similar precision, recall, and F1 scores around 0.903539. However, it had the medium building time of about 0.41 seconds. Gradient Boosting showed slightly lower accuracy at 0.810241 and similar precision, recall, and F1 scores around 0.808784. It was more efficient in terms of building time, taking only 0.81 seconds. XGBoost outperformed both AdaBoost and Gradient Boosting with an accuracy of 0.930723 and precision, recall, and F1 scores around 0.930708. It was also much faster to build, requiring only 0.22 seconds. From these XGBoost demonstrated the best performance and efficiency, making it the top choice for this classification task graphically represent in figure 5.39.

Table 5. 6 Comparison of Ensemble model testing results

S.N	Ensembles Models	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Building Time (s)
0	AdaBoost	90.36	90.56	90.36	90.35	0.410958
1	Gradient Boosting	81.02	81.29	81.02	80.87	0.814504
2	XGBoost	93.07	93.07	93.07	93.07	0.223568

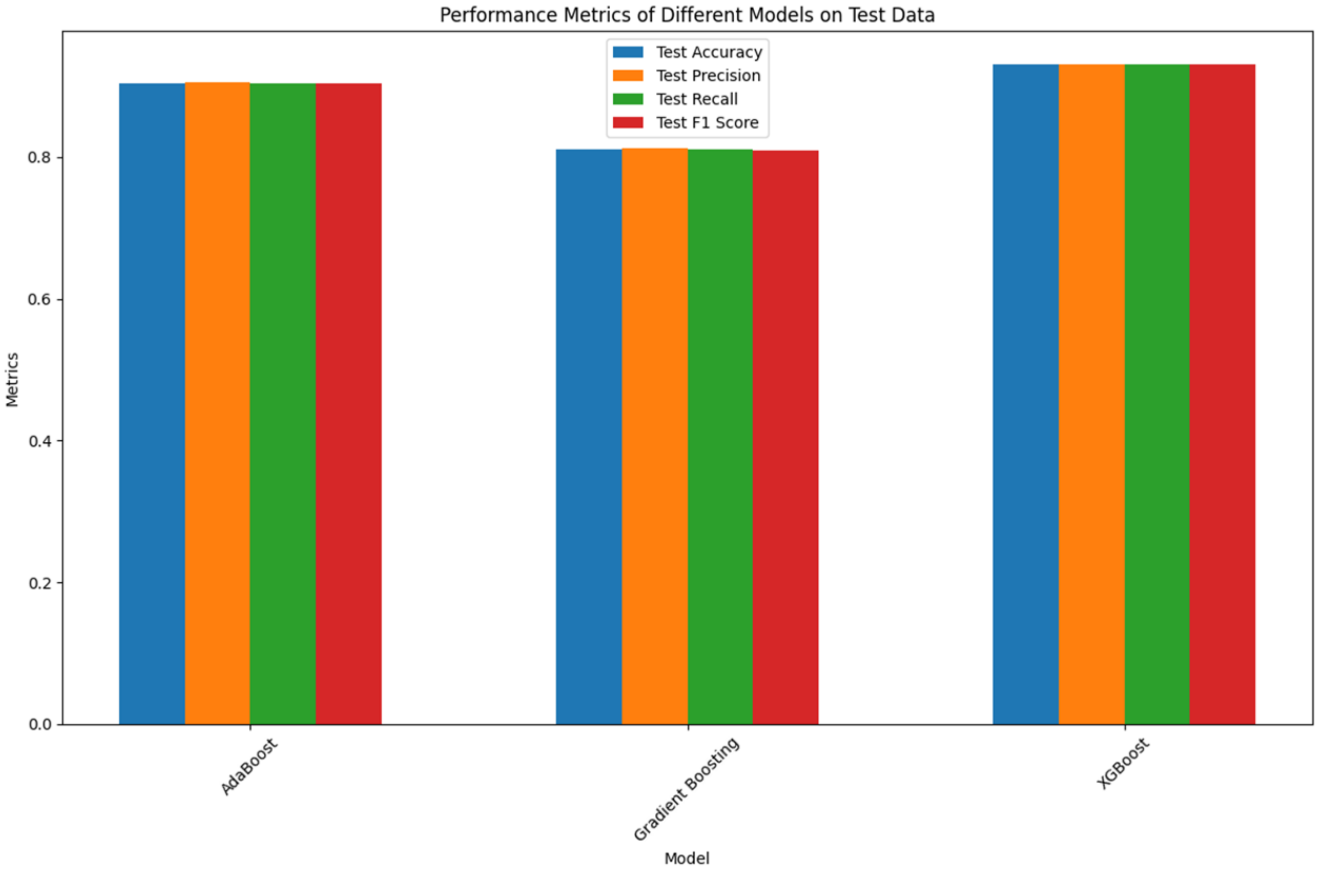
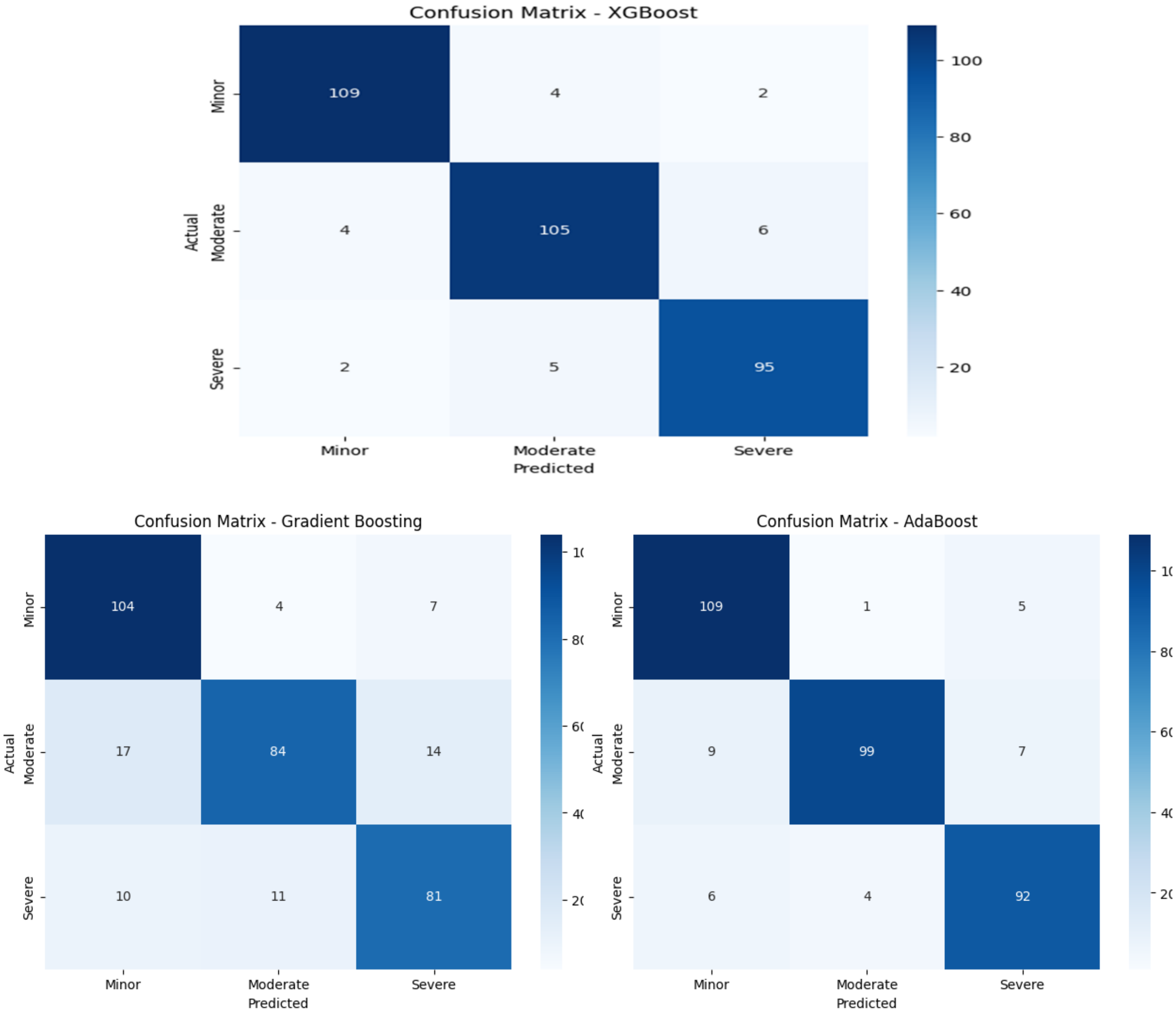


Figure 5. 39 Performance Comparison of Ensembles on Testing Data


Confusion Matrix - XGBoost

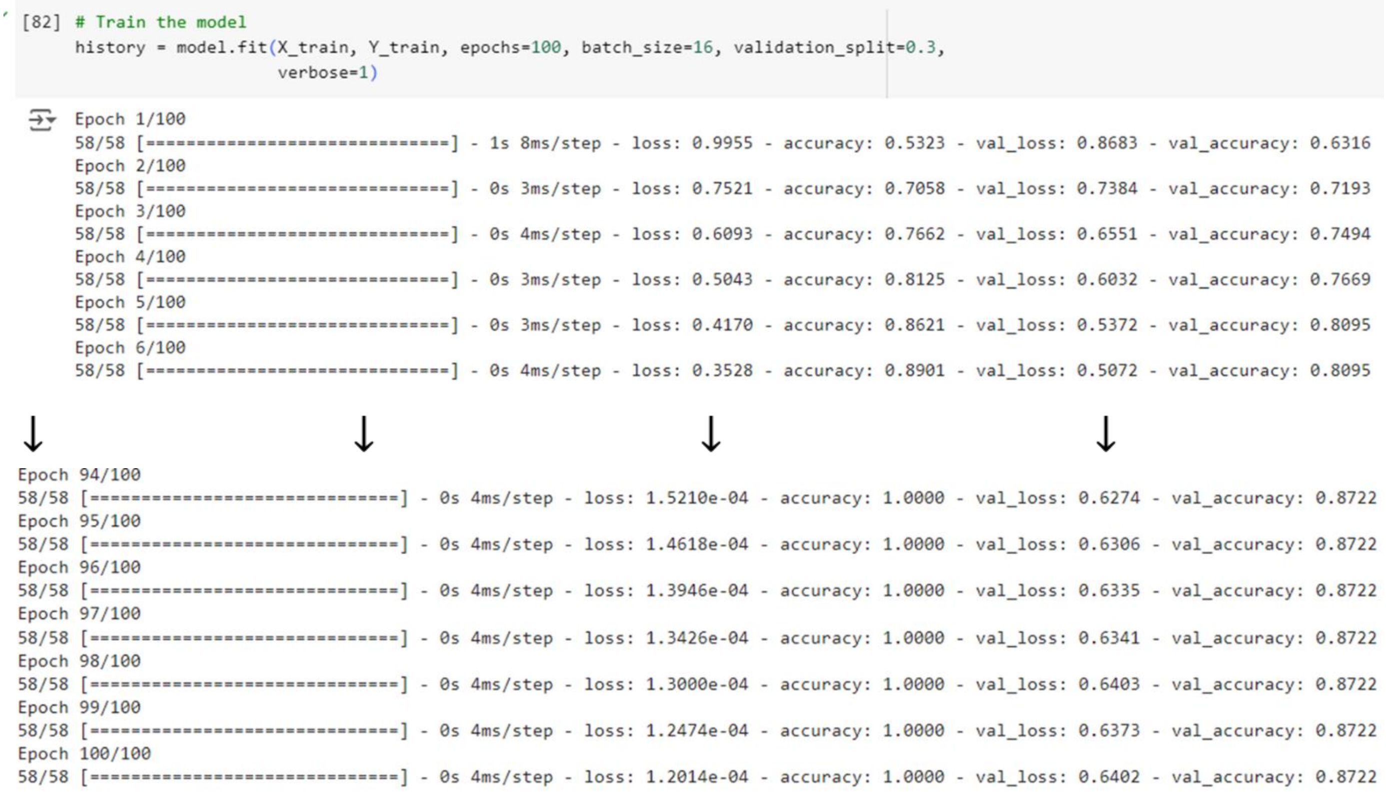
Confusion Matrix - Gradient Boosting

Confusion Matrix - AdaBoost

Figure 5. 40 Confusion matrix for test results of Ensembles model

As shown in figure 5.40 XGBoost model provides a rapid and straightforward comparison of its effectiveness in unique between various defect severities, including minor, moderate, and severe, from a dataset comprising 111 product occurrences. Among these instances, the XGBoost model correctly identified 109 as minor, 105 as moderate, and 95 as severe. This interpretation underscores the model's capability to distinguish between different defect severities categories with a notable level of accuracy, its effectiveness in practical applications within the manufacturing domain.

5.4.3 Building Machine Learning Models with Neural Network



```
[82] # Train the model
     history = model.fit(X_train, Y_train, epochs=100, batch_size=16, validation_split=0.3,
                         verbose=1)
```

```
Epoch 1/100
58/58 [==============================] - 1s 8ms/step - loss: 0.9955 - accuracy: 0.5323 - val_loss: 0.8683 - val_accuracy: 0.6316
Epoch 2/100
58/58 [==============================] - 0s 3ms/step - loss: 0.7521 - accuracy: 0.7058 - val_loss: 0.7384 - val_accuracy: 0.7193
Epoch 3/100
58/58 [==============================] - 0s 4ms/step - loss: 0.6093 - accuracy: 0.7662 - val_loss: 0.6551 - val_accuracy: 0.7494
Epoch 4/100
58/58 [==============================] - 0s 3ms/step - loss: 0.5043 - accuracy: 0.8125 - val_loss: 0.6032 - val_accuracy: 0.7669
Epoch 5/100
58/58 [==============================] - 0s 3ms/step - loss: 0.4170 - accuracy: 0.8621 - val_loss: 0.5372 - val_accuracy: 0.8095
Epoch 6/100
58/58 [==============================] - 0s 4ms/step - loss: 0.3528 - accuracy: 0.8901 - val_loss: 0.5072 - val_accuracy: 0.8095
```

```
Epoch 94/100
58/58 [==============================] - 0s 4ms/step - loss: 1.5210e-04 - accuracy: 1.0000 - val_loss: 0.6274 - val_accuracy: 0.8722
Epoch 95/100
58/58 [==============================] - 0s 4ms/step - loss: 1.4618e-04 - accuracy: 1.0000 - val_loss: 0.6306 - val_accuracy: 0.8722
Epoch 96/100
58/58 [==============================] - 0s 4ms/step - loss: 1.3946e-04 - accuracy: 1.0000 - val_loss: 0.6335 - val_accuracy: 0.8722
Epoch 97/100
58/58 [==============================] - 0s 4ms/step - loss: 1.3426e-04 - accuracy: 1.0000 - val_loss: 0.6341 - val_accuracy: 0.8722
Epoch 98/100
58/58 [==============================] - 0s 4ms/step - loss: 1.3000e-04 - accuracy: 1.0000 - val_loss: 0.6403 - val_accuracy: 0.8722
Epoch 99/100
58/58 [==============================] - 0s 4ms/step - loss: 1.2474e-04 - accuracy: 1.0000 - val_loss: 0.6373 - val_accuracy: 0.8722
Epoch 100/100
58/58 [==============================] - 0s 4ms/step - loss: 1.2014e-04 - accuracy: 1.0000 - val_loss: 0.6402 - val_accuracy: 0.8722
```

Figure 5. 41 Training and validation history graph

As indicated in figure 5.41 training, the model achieved a training accuracy of 100% and a validation accuracy of 87.22%. Analyzing the training history graph revealed fluctuations and overfitting in both validation loss and accuracy, as well as training accuracy and loss, across training and validation phases. Initially, the validation loss decreased, but it started to rise and down after some epoch, indicating potential overfitting to the training data. Overfitting leads in poorer performance on new, unseen data. Consequently, consider the model trained up to the 100th epoch with the specified training and validation accuracies as the final model, as further training beyond this point could exacerbate overfitting issues due to small dataset.

Training and validation phases of the model reveal distinct patterns as the epoch's progress. Initially, both training and validation accuracies show rapid improvement, with the model quickly learning to generalize to unseen data. However, as training continues, validation accuracy tables around 75%, while training accuracy steadily approaches 100%, indicating a significant difference between the model's performance on training data and test data. This discrepancy highlights the risk of overfitting, where the model becomes overly specialized to the training data, reducing its generalization capability. The tendency towards overfitting can be partly attributed to the relatively small dataset size, as neural networks generally need large amounts of data to learn complex patterns and generalize effectively. In this case, the limited dataset size leads to the model memorizing the training data rather than learning underlying patterns. Consequently, the performance on unseen data suffers, as evidenced by the hilling validation accuracy. To mitigate overfitting on small datasets, simpler models or alternative Traditional machine learning more suitable, as they are less prone to overfitting and can provide more reliable performance with limited data, while the neural network initially demonstrates promising learning capabilities, its performance is hindered by overfitting, exacerbated by the small dataset size.

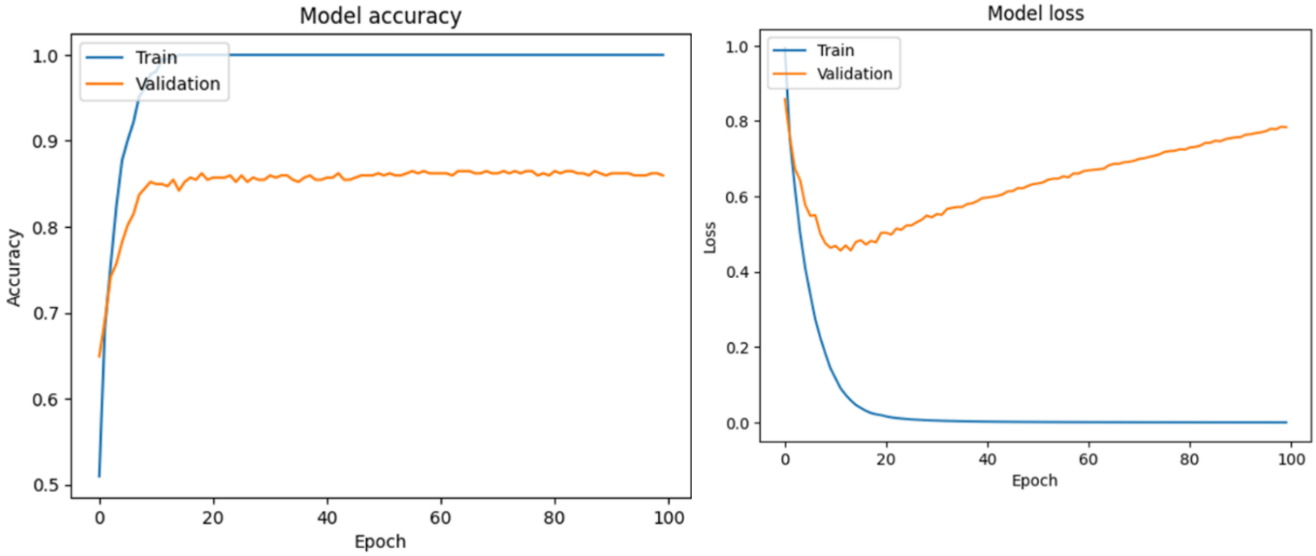
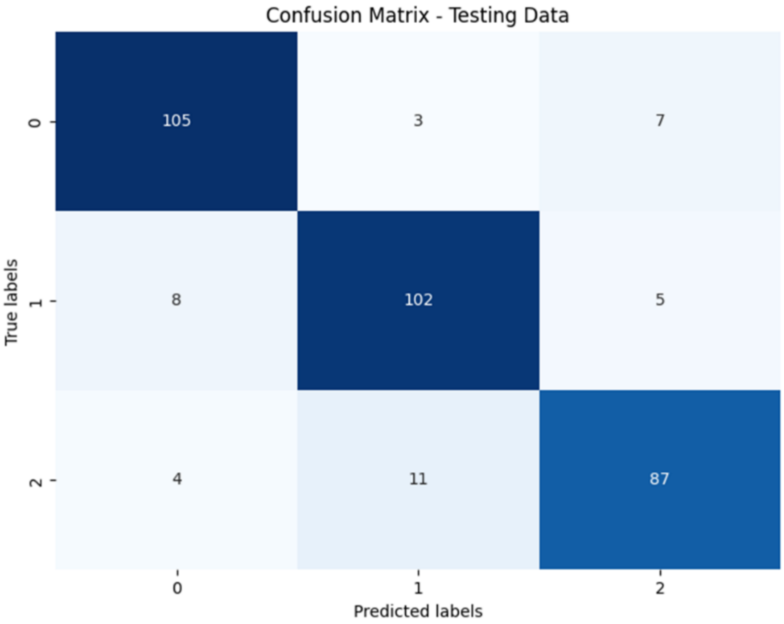
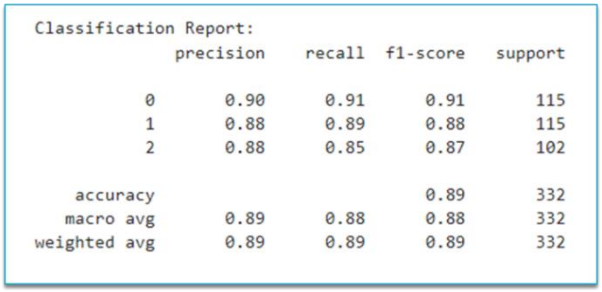


Figure 5. 42 Model Accuracy and Model Loss

In figure 5.42 the gap between the model accuracy and loss indicates overfitting, which is a concerning observation. When comparing the validation accuracy to the training accuracy, it becomes evident that the validation accuracy surpasses the training accuracy, suggesting overfitting. This difference implies that the model may not simplify well to unseen data and may perform poorly on new occurrences. The occurrence of overfitting during the training phase is problematic as it compromises the model's ability to effectively learn from the data without memorizing it.





```
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.91      0.91       115
           1       0.88      0.89      0.88       115
           2       0.88      0.85      0.87       102

    accuracy                           0.89       332
   macro avg       0.89      0.88      0.88       332
weighted avg       0.89      0.89      0.89       332
```

Figure 5. 43 Confusion Matrix and metrics result

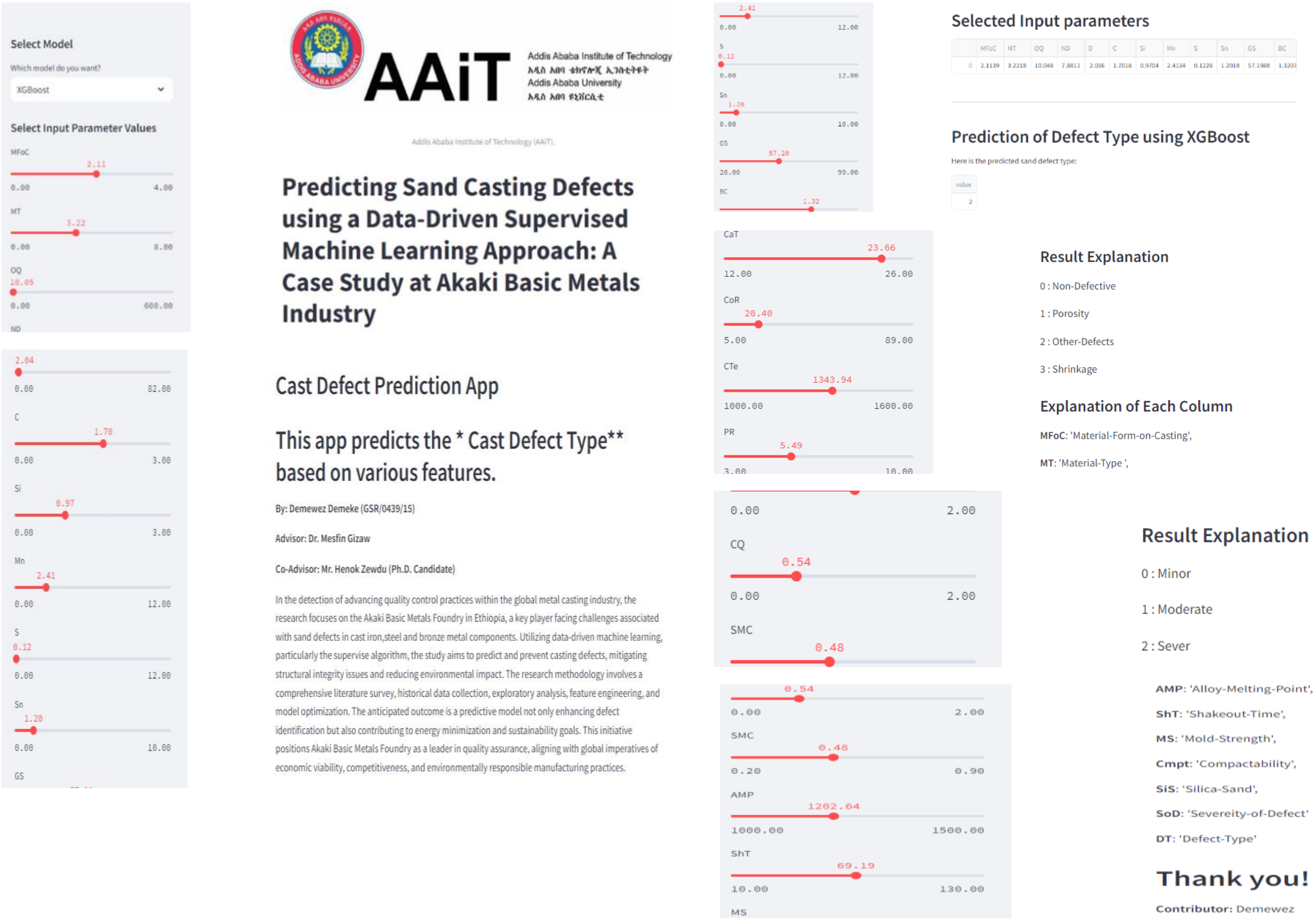
In figure 5.43 classification report reveals the performance of the neural network on a dataset of 332 samples, categorized into three classes: Minor (0), Medium (1), and Severe (2). The model achieved an overall accuracy of 85%, correctly predicting the class labels for 85% of the instances in the test dataset. For Minor defects, the model attained a precision of 87%, recall of 84%, and F1-score of 85%, indicating high accuracy in identifying true positive instances.

For Medium defects, it attained a precision of 85%, recall of 87%, and F1-score of 86%, reflecting effective capture of relevant instances. For Severe defects, all three metrics were at 84%, showing a better balance in between precision and recall. The confusion matrix offers a visual representation of the correct and incorrect predictions, helping identify patterns in the model's errors and assess its discrimination capabilities between classes.

Overall, the neural network shows strong performance, with high precision, recall, and F1-scores across all classes, despite some misclassifications. This indicates the model is effective in classifying defects into Minor, Medium, and Severe categories, making it a useful tool for defect severity identification.

5.5 Deployment of the Supervised ML Model to a Web-Based Application

The developed models, including XGBoost, Decision Tree (DT), Random Forest, and Gradient Boosting, are deployed to a user-friendly web-based application. These models predict types of sand casting defects and their severity deployed models can be accessed at the following URLs: https://scdp-dt.streamlit.app/ and https://scdp-severity.streamlit.app respectively. It can be used for reliable and accurate sand casting production. Particularly, it is of great interest to practitioners and designers as it is user-friendly and superior in terms of its prediction capability compared to other available models and code equations. The developed web-based application does not require knowledge of the machine learning algorithms, making it very attractive to practitioners and researchers in the field of manufacturing engineering. Additionally, it can be used for teaching purposes as it allows for quick and accurate determination of the defect types and the severity of sand castings. The screenshot of the deployed model is shown below:



Select Model

Which model do you want?

XGBoost

Select Input Parameter Values

MFoC
2.11
0.00 4.00

MT
3.22
0.00 8.00

OQ
10.05
0.00 600.00

ND
2.04
0.00 82.00

C
1.70
0.00 3.00

Si
0.97
0.00 3.00

Mn
2.41
0.00 12.00

S
0.12
0.00 12.00

Sn
1.20
0.00 10.00

GS
57.20
26.00 99.00

BC
1.32

Addis Ababa Institute of Technology (AAiT).

Predicting Sand Casting Defects using a Data-Driven Supervised Machine Learning Approach: A Case Study at Akaki Basic Metals Industry

Cast Defect Prediction App

This app predicts the * Cast Defect Type** based on various features.

By: Demewez Demeke (GSR/0439/15)

Advisor: Dr. Mesfin Gizaw

Co-Advisor: Mr. Henok Zewdu (Ph.D. Candidate)

In the detection of advancing quality control practices within the global metal casting industry, the research focuses on the Akaki Basic Metals Foundry in Ethiopia, a key player facing challenges associated with sand defects in cast iron,steel and bronze metal components. Utilizing data-driven machine learning, particularly the supervise algorithm, the study aims to predict and prevent casting defects, mitigating structural integrity issues and reducing environmental impact. The research methodology involves a comprehensive literature survey, historical data collection, exploratory analysis, feature engineering, and model optimization. The anticipated outcome is a predictive model not only enhancing defect identification but also contributing to energy minimization and sustainability goals. This initiative positions Akaki Basic Metals Foundry as a leader in quality assurance, aligning with global imperatives of economic viability, competitiveness, and environmentally responsible manufacturing practices.

CaT
23.66
12.00 26.00

CoR
20.40
5.00 89.00

CTe
1343.94
1000.00 1600.00

PR
5.49
3.00 10.00

CQ
0.54
0.00 2.00

SMC
0.48
0.20 0.90

AMP
1202.64
1000.00 1500.00

ShT
69.19
10.00 130.00

MS

Selected Input parameters

	MFoC	MT	OQ	ND	D	C	Si	Mn	S	Sn	GS	BC
0	2.1139	3.2218	10.048	7.8811	2.036	1.7018	0.9704	2.4134	0.1228	1.2018	57.1988	1.3207

Prediction of Defect Type using XGBoost

Here is the predicted sand defect type:

	value
0	2

Result Explanation

0 : Non-Defective
1 : Porosity
2 : Other-Defects
3 : Shrinkage

Explanation of Each Column

MFoC: 'Material-Form-on-Casting',
MT: 'Material-Type ',

Result Explanation

0 : Minor
1 : Moderate
2 : Sever

AMP: 'Alloy-Melting-Point',
ShT: 'Shakeout-Time',
MS: 'Mold-Strength',
Cmpt: 'Compactability',
SiS: 'Silica-Sand',
SoD: 'Severeity-of-Defect'
DT: 'Defect-Type'

Thank you!

Contributor: Demewez

Figure 5. 44 Deployed model of defect types and severity

In the screenshot figure 5.44 shows, users can select input parameter values from the options listed on the left-hand side. They can define the input variables by scrolling under each parameter. Once the input values are selected, a summary of these values is displayed on the right-hand side under "Selected Input Parameter Values". The predicted defect and its severity in sand casting based on the defined variables can then be observed on the same screen. This user-friendly application can be accessed and utilized on any device, including mobile phones, tablets, and computers, without requiring prior knowledge of machine learning algorithms or the theory behind casting mechanisms.

CHAPTER SIX

6. CONCLUSION, RECOMMENDATION AND FUTURE WORK

6.1 Conclusion

In conclusion, research underlines the effectiveness of employing a supervised machine learning approach to predict sand casting defects and their severity within the Akaki Basic Metals Industry. Leveraging a dataset comprising 1001 records with 37 features and employing an 80-20% training-testing data split, different machine learning algorithms were explored, including Decision Tree, K-Nearest Neighbors, Gradient Boosting, Random Forest, XGBoost, Support Vector Classifier (SVC), Ensemble, and Neural Network (NN). Among the models tested, XGBoost consistently emerged as the top performer, boasting high accuracy rates for defect prediction and severity classification tasks. Additionally, the ensemble XGBoost model showcased exceptional performance, particularly in predicting defect severity. While the NN model exhibited remarkable accuracy, it also hinted at potential overfitting, particularly noticeable in smaller datasets. To mitigate class imbalance issues, Synthetic Minority Over-sampling Technique analysis was applied, enhancing the robustness of predictive models. Confusion matrix analysis provided further insights into model performance and error patterns across different defect types. Additionally, the creation of a dashboard interface enhanced the accessibility and usability of the model's results, allowing stakeholders to interactively explore predictions, visualizations, and performance metrics in an easily interpretable manner and facilitated informed decision-making by providing stakeholders with a comprehensive kind of the model's behavior and performance.

Potential of machine learning and deep learning methods for enhancing the quality assurance of metal casting processes. The findings demonstrate how foundries can utilize algorithm predictions to make data-driven decisions, thereby gaining better control over the casting process and potentially saving time and resources through predictive maintenance. Moreover, the research emphasizes the significance of machine learning techniques in identifying crucial features within metal casting datasets, aligning with the expertise of domain specialists regarding the essential parameters governing the casting process.

Beyond defect prediction, this research underscores the significance of sustainability initiatives within the manufacturing sector. By leveraging machine learning models, manufacturers can minimize energy wastage, reduce rework costs, and optimize resource utilization. This study contributes to advancing manufacturing practices, fostering innovation, and aligning with global imperatives for environmental sustainability. Furthermore, the availability of comprehensive datasets serves as a valuable resource for further research and collaboration, enriching academic inquiry and providing practical understandings for industry practitioners.

6.2 Recommendation

To utilize the knowledge gained from this research, company should consider integrating top-performing predictive models, such as XGBoost, into their operational processes. Continued collaboration between researchers and industry stakeholders is essential to refine predictive models and explore new applications within the manufacturing sector. Investing in digital infrastructure to ensure the accessibility and availability of production process data is crucial for facilitating ongoing collaboration and improvement efforts. Furthermore, utilized a user-friendly dashboard for stakeholders to interact with predictive model outputs can enable informed decision-making and process optimization.

6.3 Future Work

In the future work will involve tasks directed at move forward quality assurance in metal casting processes. Firstly, efforts will focus on improving the accuracy of six classifiers, ensemble models and Neural Networks (NN) trained on a large dataset of production sand casting data. Secondly, developed predictive models will undergo experimental confirmation or validation using methods like Design of Experiments (DOE) to confirm their effectiveness. Thirdly, investigation of advanced technologies such as computer vision and sensor fusion will be followed to further enhance defect prediction capabilities. Additionally, a comparison will be made between large dataset-driven machine learning and deep learning methods, particularly Convolutional Neural Networks (CNNs), to optimize quality assurance processes. Incorporating real-time monitoring systems into predictive models will allow for proactive maintenance and optimization of processes. Ongoing collaboration with industry stakeholders will refine these predictive models and explore their potential in various manufacturing applications. Additionally, priority will be given to investing in digital infrastructure to ensure production data accessibility and availability, facilitating continuous improvement efforts.

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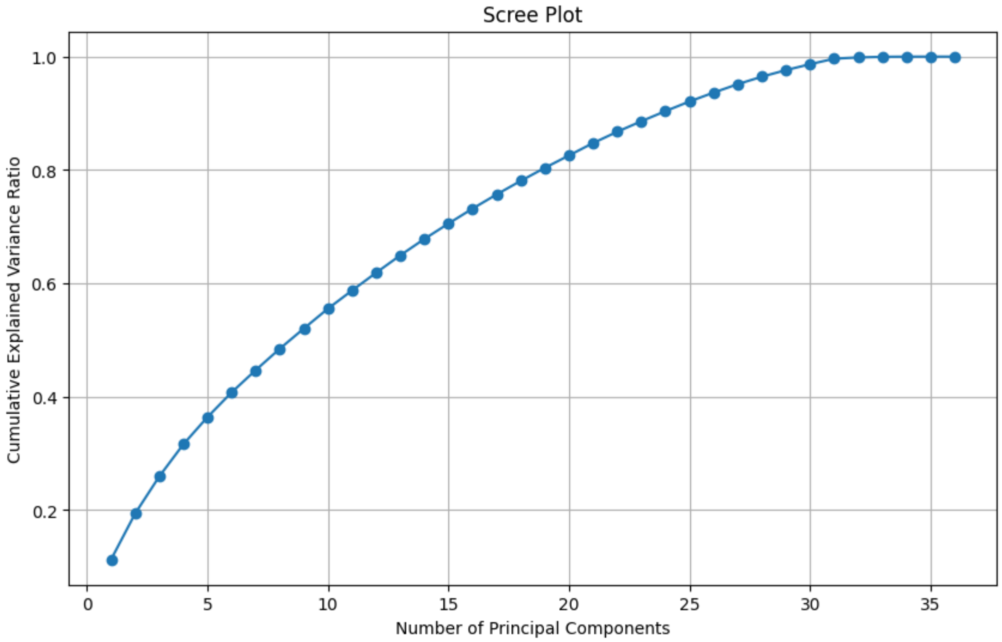
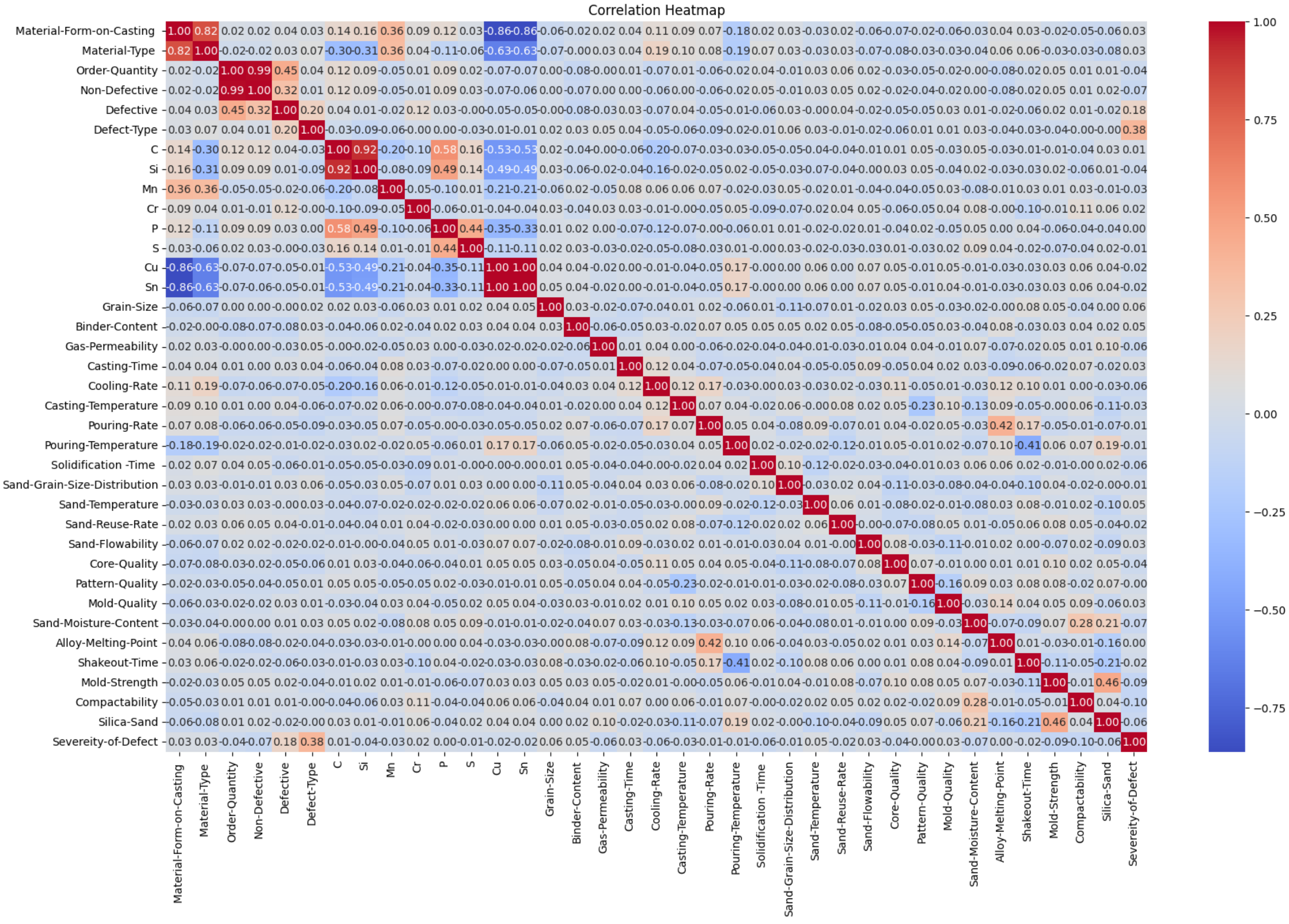
APPENDIX-I: Results in Plots from Experimentation





APPENDIX-II: Data Collection Request Form

AAiT
Addis Ababa Institute of Technology
Addis Ababa University

School of Mechanical and Industrial Engineering
Tel: +251 (0)111 232414
email: dean.smie@aait.edu.et

Date: - 15/12/2023

DATA COLLECTION REQUEST FORM

To:- Akaki Basic Metal Industry,

Mr./Mrs. Demewez Demere, is a BSc/MSc/PhD student in our School at, Addis Ababa Institute of Technology, Addis Ababa University at this Moment he/she is doing his/her thesis/ Project/ term paper entitled

- Development of Data Driven Machine Learning Predicti
model for - casting Surface defects

In order to successfully complete his/her paper, the student wants to obtain information from your factory/Industry /Organization.

The School strongly appreciates for any sort of assistance you provide to our student related to his/her thesis/ Project/ term paper. In addition, we would like to inform you that the data is required for educational purpose.

Thank you in advance for your cooperation.

Dr./Araya Abera
Dean, School of Mechanical and Industrial Engineering
Addis Ababa Institute of Technology
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