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

Developing AI-based Preventive Maintenance Model for BGI Ethiopia: Washing Head.

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"Developing AI-based Preventive Maintenance Model for BGI Ethiopia: Washing Head."

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Declaration

I hereby declare that the work which is being presented in this thesis entitled "Developing AI-based Preventive Maintenance Model for BGI Ethiopia: Washing Head" 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.

____________________________ __________________________

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

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Abstract

This study addresses the significant operational challenge faced by BGI Ethiopia in its draft beer production linedue to the frequent rejection of kegs by the Slimline Monobloc 50 filler machine, particularly at the washingHead-4. These rejections, caused by steam supply inconsistencies, result in substantial downtime andeconomic losses. The objective of this research is to develop a predictive maintenance model to improveoperational efficiency and reduce these false rejections. By integrating real-time data from theComputerized Maintenance Management System (CMMS) and generating synthetic data to augment thedataset, the study trained several machine learning models, including AdaBoost, to predict the readinessstate of Head-4. The AdaBoost model exhibited superior performance, accurately forecasting potential kegrejections and enabling preemptive maintenance actions. This predictive approach not only minimizesdowntime by preventing the processing of faulty kegs but also enhances the reliability and efficiency of theproduction line. The findings demonstrate the value of AI-driven preventive maintenance in the breweryindustry, suggesting broader applications to improve production processes and reduce operational costs.The study concludes with recommendations for implementing real-time monitoring and continuous modelupdates to sustain and enhance the benefits of predictive maintenance.

Keywords: Preventive maintenance, Machine learning, Ensemble learning, Synthetic data generation, Brewery industry.

1. Introduction

Maintenance plays a crucial role in the manufacturing industry, as it directly impacts productivity, quality, and sustainability. Proper maintenance practices can enhance the performance and lifespan of manufacturing equipment, leading to increased production volumes, reduced operational costs, and improved product quality (Finch & Gilbert, 1986). Nigussie & Avvari, (2021) shows that, regardless of the scale of operation, or how modern the production equipment is, the most important thing is to keep the production lines functioning smoothly, which is preventative maintenance.

Particularly, preventive maintenance has emerged as a strategic approach to maintaining manufacturing assets. Preventive maintenance involves regularly scheduled inspections, adjustments, and replacements of components to prevent unexpected breakdowns and maximize equipment uptime (Holgado et al., 2020). This proactive approach contrasts with reactive, or corrective, maintenance, where equipment is repaired only after a failure has occurred. The benefits of preventive maintenance in the manufacturing industry are multifaceted. First, it can significantly reduce maintenance costs by preventing expensive and time-consuming emergency repairs. By keeping equipment in optimal working condition, preventive maintenance also improves energy efficiency and reduces the environmental impact of manufacturing operations.

Additionally, O'Donovan, (2015) and Holgado, (2020) says, preventive maintenance can enhance product quality and consistency, as well as worker safety, by ensuring that equipment is functioning as intended. Properly maintained machinery is less likely to produce defective products or expose workers to safety hazards. Recent research has highlighted the importance of data-driven approaches to maintenance in modern manufacturing (O'Donovan et al., 2015). The integration of industrial big data and analytics can enable predictive maintenance strategies, where equipment failures are anticipated and preemptively addressed.

Ayvaz & Alpay, (2021) developed a data-driven predictive maintenance system for manufacturing production lines using machine learning methods to detect signals before potential failures and take preventive measures. Similarly, (Theissler et al., 2021) proposed a maintenance strategy for automotive systems, which is based on machine learning methods aimed at ensuring product functional safety and controlling maintenance costs throughout the lifecycle.

In conclusion, the need for predictive maintenance in BGI Ethiopia's draft beer production line is critical to minimizing keg rejection and optimizing operational efficiency. The implementation of a machine learning model, leveraging both real-time sensor data and synthetic data, holds promise for accurately predicting the readiness state of washing head. By employing advanced ensemble learning techniques, this study seeks to provide a robust solution that can be integrated into the existing maintenance framework, ultimately leading to significant cost savings and improved operational reliability for BGI Ethiopia.

1.1. Background

In the world of breweries, maintenance is a crucial aspect to ensure smooth operations and high-quality beer production (Ardian et al., 2020). However, traditional maintenance practices can be time-consuming, inefficient, and prone to human error. Without proper maintenance, breweries face a range of issues that could ultimately impact their productivity, profitability, and even the quality of their products. Traditionally, breweries have relied on reactive maintenance, where equipment is repaired only after breakdowns occur. This approach is inefficient, leading to costly downtime, production delays, and reduced product quality (Sedghi, 2020). PM, however, offers a paradigm shift by predicting potential equipment failures before they happen, allowing for proactive maintenance interventions. This proactive approach minimizes downtime, optimizes resource allocation, and extends equipment lifespan (Abbasi, 2021).

To maintain traditional, experience-driven approaches edge and optimize production, breweries must embrace innovative technologies that enhance efficiency and reduce downtime. One such technology is Artificial Intelligence (AI)-driven Preventive Maintenance (PM), which offers a proactive approach to equipment maintenance, minimizing disruptions and maximizing productivity (Zhang et al., 2019). With the increasing adoption of artificial intelligence in various industries, the potential applications of AI in the industrial sector, particularly in preventive maintenance, have become a topic of interest (Emmert-Streib, 2021). AI algorithms have the capability to process large amounts of data and extract valuable insights. This makes them particularly suitable for enhancing the performance of preventive maintenance strategies.

BGI Ethiopia, a prominent player in the beverage industry, faces significant challenges related to the maintenance of its draft beer production line. One of the critical issues is the frequent rejection of kegs due to problems with the washing head (Head-4), which is integral to the internal sterilizing process of the kegs. The primary source of these issues is the inconsistent steam supply from the boiler, which often fluctuates in temperature and pressure, leading to condensation and inadequate operation. Consequently, a substantial number of kegs, which are otherwise in good condition, are incorrectly rejected as faulty. To address this challenge, leveraging machine learning for preventive maintenance emerges as a promising solution. By utilizing historical data from the Computerized Maintenance Management System (CMMS), operational parameters, and sensor readings, it is possible to develop a model that can predict the readiness state of the washing head.

This technology utilizes AI algorithms to analyze historical data and real-time sensor readings, allowing breweries to detect potential equipment malfunctions before they occur. By identifying patterns and anomalies in the data, AI-driven preventive maintenance can provide timely alerts and recommendations for maintenance activities, ensuring that maintenance is performed proactively rather than reactively. This helps breweries to prevent costly breakdowns and unplanned downtime, leading to uninterrupted production and higher overall efficiency.

1.1. Problem statement

Breweries operate complex machinery that requires regular maintenance to function properly. This includes pumps, valves, heat exchangers, filtration systems, and other critical components. If any of these components fail, it can result in major production stops that can cost the brewery significant losses in productivity, repairs, and product spoilage. One of the most common problems faced by beverage industries is the rejection of bottles or kegs during production due to different reasons.

BGI Ethiopia faces a significant challenge in its draft beer production line due to the frequent rejection of kegs caused by issues with the washing head (Head-4). Each of the 11 fillers in the production line is equipped with their own washing heads, responsible for the internal sterilizing of kegs by using steam supplied from a boiler. However, inconsistencies in the steam supply, such as fluctuations in pressure and temperature and condensation through the line leading to suboptimal sterilizing conditions, result in the incorrect rejection of a substantial number of kegs that are otherwise fit for use.

According to (CMMS Maintenance record, 2024, Maintenance Department), this operational inefficiency leads to an average false rejection of 50 kegs per day, totaling approximately 1,500 kegs per month for a filler. These false rejections not only incur considerable economic losses but also disrupt the production workflow, reducing the overall efficiency of the factory. The current maintenance practices are unable to adequately prevent these issues, highlighting the need for an advanced solution.

Currently, BGI Ethiopia's maintenance practices involve reactive maintenance, where actions are only taken after 13-18 kegs have been rejected. This approach leads to substantial operational inefficiencies, including increased downtime and production disruptions. The filler machines alarm the operators about Head-4 keg rejections after this threshold is reached. Traditional preventive maintenance (PM) practices at BGI Ethiopia are insufficient to handle the complex modern brewery equipment and maintain optimal production uptime. Key Performance Indicators such as downtime, production throughput, and rejection rates highlight these inefficiencies:

- **Downtime:** Frequent stoppages caused by the incorrect rejection of kegs due to issues with the washing heads increase downtime, which significantly lower overall production capacity.
- **Production Throughput:** The high rate of false rejections reduces the actual number of kegs processed, preventing the brewery from meeting its production targets and affecting operational efficiency.
- **Rejection Rates:** The large number of falsely rejected kegs raises the rejection rate, distorting quality metrics and leading to inefficient resource allocation for unnecessary maintenance.

Eyerusalem (2018) shows, maintenance management in Ethiopia’s food and beverage industries is an infant. Leveraging AI for preventive maintenance offers a promising solution, yet Ethiopian breweries exhibit a low adoption rate of AI-driven technologies. There is a limited awareness and understanding of AI-driven preventive maintenance benefits and many Ethiopian breweries lack knowledge about the potential of AI in optimizing maintenance processes.

Therefore, the primary objective is to develop a machine learning model that can predict the readiness state of the washing head (Head-4). This model aims to reduce false rejections by accurately identifying the conditions that lead to improper washing head operation. By implementing such a preventive maintenance system, BGI Ethiopia can enhance its operational efficiency, reduce economic losses, and improve the overall reliability of its draft beer production line.

1.2.1. Research Questions

I. How can machine learning be leveraged to predict the readiness state of the washing heads in BGI Ethiopia’s draft beer production line?

II. How can the implementation of AI-driven preventive maintenance reduce the downtime and improve the production throughput in BGI Ethiopia’s draft beer production line?

1.2. Objective of the Study

1.2.1. General objective

The general objective of this thesis is developing a reliable machine learning-based preventive maintenance model that leverages both real-time and synthetic data to accurately predict keg rejections in BGI Ethiopia's draft beer production line due to Head-4.

1.2.2. Specific objective

- Analyze the existing maintenance practices at BGI Ethiopia and identify key challenges related to the frequent rejection of kegs due to issues with the washing head (Head-4)
- Develop a machine learning model that accurately predicts the readiness state of the washing head (Head-4) using both real-time sensor data and synthetic data.
- Evaluate the predictive model’s performance using key performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC, ensuring its reliability in a real-world setting.
- Integrate the predictive maintenance model into BGI Ethiopia's maintenance strategy, thereby linking predictions to actionable maintenance decisions and reducing false rejections.

1.3. Scope of the Study

This thesis will focus on developing an AI-driven preventive maintenance model specifically for BGI Ethiopia's washing heads (Haed-4). It will not delve into broader applications for other equipment or industries. Identifying and collecting relevant data from BGI Ethiopia's existing sources, such as sensor readings, maintenance logs, and operational parameters. This data will be preprocessed and analyzed to extract key features and relationships related to washing head.

Evaluating the selected AI algorithms and techniques based on data characteristics and BGI Ethiopia's specific requirements. Training and optimizing the chosen model to achieve high accuracy and generalizability in reducing keg rejection due to washing head.

The thesis excludes venturing into areas like hardware modifications, sensor network design, or broader enterprise-wide maintenance system implementations. The focus remains solely on developing and evaluating an AI model for preventive maintenance of pressurized heads within BGI Ethiopia's current operational context.

1.4. Limitation

Data-related limitations:

Data quantity: Availability of sufficient historical and sensor data related to washing heads and other operational parameters are limited. This restricts the model's training effectiveness and generalizability.

Data access: Obtaining necessary data from various sources within BGI Ethiopia require overcoming access restrictions or data silos within the organization.

Feature Selection: The selection of relevant features is based on the available data, and there may be other influential factors affecting the operational states of the kegs that are not captured in the dataset.

Synthetic Data Generation: While Generative Adversarial Networks (GANs) can generate synthetic data to supplement the dataset, the synthetic data may not perfectly capture all nuances of real-world conditions, potentially impacting model accuracy.

Model-related limitations:

Model Generalization: The developed models are trained on historical and synthetic data specific to BGI Ethiopia’s operational context, which may limit their generalizability to other production lines or factories with different configurations and conditions. Continuous updates and retraining might be necessary.

Real-Time Implementation: Integrating the preventive maintenance model into the real-time operations of the factory involves technical and logistical challenges, such as ensuring timely data collection, processing, and response to predictions.

Computational limitations: Complex AI models might require significant computational resources for training and deployment, which could be an issue for BGI Ethiopia's IT infrastructure.

1.5. Significance

This research on AI-based preventive maintenance (PM) in BGI Ethiopia holds significant value not only for BGI itself, but also for the broader Ethiopian brewing industry and advancements in technology adoption. For BGI, the study offers a preventive maintenance model by using ML algorithms which helps to reduce keg rejection. This can inform strategic decision-making and technology investments for BGI to achieve its operational goals.

Moreover, the study contributes to wider knowledge about the benefits of AI in the Ethiopian brewing sector. By demonstrating BGI's potential journey with AI-based PM model, this research can encourage and guide other Ethiopian breweries to explore similar technological advancements, fostering industry-wide innovation and competitiveness.

Additionally, the research findings shed light on the broader application of AI in industrial contexts, offering valuable insights and best practices for effective technology implementation in diverse settings. This contributes to the ongoing dialogue about responsible AI development and adoption, potentially shaping future directions in technology for various industries beyond brewing. In conclusion, the significance of this research lies in its potential to improve BGI's operations, inspire technology adoption in the Ethiopian brewing industry, and inform broader discussions about responsible and impactful AI implementation across various sectors.

2. Literature review

2.1. Introduction to Preventive Maintenance and Importance in Manufacturing Industry

This literature review delves into the existing research and applications of AI-driven preventive maintenance. Various sources have been consulted to gain insights into the best practices and applications of AI in preventive maintenance. Studies highlight the use of novel innovative techniques in preventive maintenance, such as model-based approaches with the application of artificial intelligence and data-driven approaches. These techniques have been proven to achieve better performance than conventional preventive approaches. Another source discusses the integration of IoT technologies with artificial intelligence to fully leverage their benefits in maintenance (Pokorni, 2021).

Predictive maintenance (PdM) is a proactive approach that leverages data analysis techniques to predict equipment failures before they occur. This contrasts with traditional maintenance strategies, such as reactive and preventive maintenance, which either address issues after they arise or follow a set maintenance schedule regardless of the equipment's actual condition (Jardine et al., 2006; Lee et al., 2013).

In today's manufacturing industry, the need for efficient and cost-effective maintenance strategies has become increasingly important (Jin et al., 2016). Traditional reactive and preventive maintenance approaches are no longer sufficient to meet the demands of modern manufacturing systems (Wan et al., 2017). The transition towards preventive maintenance, enabled by artificial intelligence approaches, offers promising solutions to enhance the performance of maintenance activities and optimize the utilization of assets in manufacturing plants.

PM offers significant benefits, including reduced downtime, lower maintenance costs, and increased equipment lifespan. Studies have shown that implementing PM can lead to substantial improvements in operational efficiency and cost savings (Peng et al., 2010). For instance, (Lee et al., 2013), found that PM can reduce maintenance costs by up to 30% and decrease equipment downtime by 45%.

In the context of Ethiopian Breweries, preventive maintenance is crucial for ensuring smooth operations and maximizing production efficiency (Nigussie & Avvari, 2021). By implementing AI-driven preventive maintenance strategies, Ethiopian Breweries can significantly reduce costs associated with downtime, equipment failures, and reactive maintenance (McKone & Weiss, 2000). With advancements in AI technology, predictive maintenance has emerged as a more effective approach compared to traditional preventive methods (Chuang et al., 2019).

In recent years, there has been a growing interest in the application of AI-driven preventive maintenance in various industries, including the brewing industry (Hoffmann et al., 2021). With the advancement of AI algorithms and machine learning models, predictive maintenance has emerged as a valuable tool for enhancing operational efficiency, improving equipment reliability, and reducing downtime and maintenance costs (Hoffmann et al., 2021).

This shift towards preventive maintenance is made possible by the integration of machine learning and artificial intelligence, which can analyze large volumes of data from sensors and production lines to identify patterns and potential failures before they occur (Azari et al., 2023). Furthermore, the use of AI in predictive maintenance allows for real-time monitoring and analysis of equipment performance, enabling proactive decision-making and timely intervention (Zhu et al., 2023).

While research specifically focused on preventive maintenance (PM) practices in Ethiopian breweries remains scarce, examining studies from similar contexts in developing countries offers valuable insights. A study by Azouma and Giroux, (2010) in Africa shows a reliance on reactive maintenance in breweries, addressing equipment failures only after they occur. This approach, common in African breweries, leads to unplanned downtime, production losses, and higher maintenance costs. However, success stories also exist, Basri et al., (2017) showed significant improvements through implementing proactive PM, including scheduled maintenance and condition-based monitoring. Their approach resulted in reduced downtime by 20% and increased production efficiency by 15%.

The implementation of AI-driven preventive maintenance may face challenges related to the availability of sufficient data to train AI systems, as well as the limited ability of AI systems to recognize new types of potential equipment failures (Elan Maulani et al., 2023). This limitation underscores the importance of robust data collection and continuous updating of AI models to ensure their effectiveness in identifying and predicting maintenance needs.

Moreover, the application of AI in preventive maintenance requires significant technological investment and ongoing maintenance costs (Elan Maulani et al., 2023). This financial burden may pose challenges for breweries, particularly in resource-constrained settings such as Ethiopia.

Additionally, the explainability of AI models in the context of preventive maintenance is a critical limitation to consider. While AI systems can effectively identify potential maintenance issues, the lack of transparency in the decision-making process may hinder the understanding of maintenance recommendations by brewery maintenance personnel (Wickramasinghe et al., 2021). Ensuring the explainability of AI-driven maintenance recommendations is essential for gaining the trust and acceptance of brewery maintenance teams.

Furthermore, the integration of AI models into existing maintenance workflows may present organizational and cultural challenges within the brewery setting. Resistance to change, lack of technical expertise among maintenance staff, and the need for extensive training to effectively utilize AI-driven maintenance solutions are important considerations (Jones & Kerber, 2022).

In conclusion, while AI-driven preventive maintenance holds great promise for enhancing brewery operations, it is crucial to address the limitations related to data availability, financial investment, explainability, and organizational readiness. By acknowledging and mitigating these limitations, breweries like BGI Ethiopia can effectively harness the potential of AI-driven preventive maintenance to optimize their operations and minimize downtime.

2.2. Machine Learning Techniques in Preventive Maintenance

Machine learning (ML) plays a crucial role in PM by enabling the analysis of large datasets to identify patterns and predict failures. Techniques such as neural networks, decision trees, and ensemble methods like AdaBoost, Gradient Boosting, and XGBoost have been widely applied (Chen & Guestrin, 2016). These models have demonstrated high accuracy in predicting maintenance needs and have been successfully implemented in various industries (Ayvaz & Alpay, 2021; Theissler et al., 2021).

Machine learning algorithms analyze historical data, sensor readings, and equipment performance metrics to predict potential failures before they occur. By identifying patterns and anomalies in the data, these algorithms can forecast when maintenance is needed, allowing organizations to schedule maintenance activities at optimal times and prevent unexpected breakdowns (Pedro

Serrasqueiro Martins et al., 2020). Machine learning algorithms can be trained to recognize patterns associated with specific types of equipment failures. Martins et al., (2020) shows that, by learning from historical data and examples of past failures, these algorithms can classify and diagnose potential issues, helping maintenance teams to take corrective actions before failures occur.

A study (Li et al., 2022) utilizes ensemble learning to model AI algorithm, which combines multiple learning algorithms to enhance predictive performance beyond what individual algorithms can achieve alone. This approach helps in building a more robust and accurate predictive model. The study also uses RUS Boost, which is particularly effective at classifying imbalanced data, where some classes in the training data have significantly fewer instances than others. This capability is crucial in scenarios where certain maintenance decision categories may be underrepresented in the dataset. By utilizing ensemble learning and addressing imbalanced data issues, the RUS Boost algorithm can provide better predictive performance compared to standalone algorithms. But also uses a traditional approach like MIL-217, which often relies on generic assumptions and does not account for the specific operating environment and load conditions of the components, leading to inaccurate predictions. MIL-217 and similar methods may oversimplify the complexity of systems, leading to inaccurate reliability assessments, especially for components with non-linear degradation patterns.

A related study, Bampoula et al., (2021),develop and deploy deep learning models, particularly using LSTM Autoencoders, for predictive maintenance in industrial settings, leading to improved equipment reliability, reduced downtime, and cost savings. The study mentions the need for large amounts of high-quality data with maintenance records for training the deep learning model. However, the availability and accessibility of such data in real-world industrial settings can be a significant challenge.

Sang et al., (2021) also proposed PMMI 4.0 model which supports an optimized maintenance schedule plan for multiple machine components through the utilization of the Predictive Maintenance Schedule for Multiple Machines and Components (PMS4MMC). This model integrates predictive maintenance scheduling with a Long Short-Term Memory (LSTM) model for estimating the Remaining Useful Life (RUL) of individual machines and components.

As we can see, the above studies show that data is very significant to construct the AI/ML algorithm and to train the model. Masmoudi et al., (2021) revealed that changing the steps during data preparation can have a significant effect on the prediction accuracy of Machine Learning algorithms. The study emphasized the importance of systematic methodology for designing and selecting appropriate data preparation steps and techniques to achieve effective Condition-Based Maintenance (CBM) applications in industry. The experiments compared the effect of commonly used data cleaning, normalization, and reduction techniques on Machine Learning prediction accuracy.

Also, for data preparation there must be data to be prepared, data collection. The collected data must be compatible with the expected output. While developing a machine learning models for Predictive maintenance in industrial plants, Carlo, (n.d.) performs failure mode analysis to conduct a detailed analysis of plant failure modes to identify critical failure modes and their root causes. Failure Mode Analysis is a fundamental step in predictive maintenance as it provides valuable insights into critical failure modes, root causes of failures, selection of monitoring variables, and proactive planning for maintenance activities (Carlo, n.d.).

A study Mashghdoust, (2023) conducted on synthetic data states that, Synthetic data helps address data sensitivity issues by bypassing privacy concerns associated with real data, making it a secure option for training AI models and can be easily scaled up to generate large datasets for training complex ML models, providing flexibility in model development.

Synthetic data generation is often less expensive than collecting and labeling real-world data, making it a cost-effective solution for training ML models. It can introduce diverse scenarios and edge cases that may be rare or difficult to capture in real data, enhancing the robustness of ML models. Also, synthetic data can be used to augment real datasets, increasing the size and diversity of training data to improve model performance.

2.3. Preventive Maintenance Models in Different Contexts

There are many preventive maintenance models that have been developed in different industries. The following 5 studies have developed preventive maintenance models in 5 different industries. These papers were analyzed and summarized based on 5 key parameters for preventive maintenance model development and presented in the table.

Autor (Year)	Objective	Data type	Input variables	Output variables	AI/ML model Devt. technique
(Lin et al., 2021)	Develop a deep learning model for instance segmentation of nanowires in optical intensity-based images obtained from spectromicroscopy.	Synthetic datasets	Synthetic optical intensity-based images, Characteristics of the synthetic nanowire structures, Optical density compression and Pre-processed synthetic images.	Binary mask images, Segmentation masks, Statistical information and Evaluation metrics.	Mask R-CNN algorithm
Pedro Serrasqueiro Martins et al., (2020)	Implementing a predictive maintenance system based on machine learning approaches in the context of Industry 4.0.	Real-time and historical data	Sensor readings, equipment usage data, maintenance logs, environmental conditions, time series data, operational parameters, and equipment configuration.	Failure predictions, RUL estimates, maintenance recommendations, anomaly detection alerts, health scores, maintenance alerts, and diagnostic information.	ANN and SVR
Bampoula et al., (2021)	Developing a Deep Learning Model for Predictive Maintenance in Cyber-Physical Production Systems.	Historical data	Sensor Readings, Operational Parameters, Time-Series Data, Maintenance Records, and Anomaly Indicators	Estimating the RUL of the monitored equipment and classifying its health condition based on the input sensor data.	LSTM Autoencoders

Sang et al., (2021)	To develop and implement an advanced predictive maintenance model for Flexible Manufacturing in the Context of Industry 4.0.	Historical data	Sensor Data, Machine Condition Data, Historical Maintenance Records, Operational Parameters, Production Demand and Resource Availability	Predicted RUL value for each machine component	LSTM networks, RNN type
Li et al., (2022)	Develops a prognostic approach by considering actual load conditions and life limiting factors and utilizes machine learning algorithms to build the model.	Real-time and historical data	Measured values of the capacitor's part number, operating period, capacitance, and ESR	Risk category of the component, which is classified as red, yellow, or green based on the measured values of capacitance and ESR.	AdaBoostM1 Ensemble, MIL-217
(Carlo, n.d.)	Develop a diagnostic and prognostic ML model for industrial systems engineering, specifically focusing on the detection and prediction of failure modes in machinery.	Historical data	Physical quantities related to the pumping phenomenon, such as net active power, wet bulb temperature, gas flow rate, and various pressure readings.	Classification of the machinery's operating status, distinguishing between full capacity and anomaly classes.	Support Vector Machine (SVM)

Among the approaches used for PM, machine learning-based ones are the most suitable approaches because they can handle high-dimensional problems that consist of hundreds or thousands of variables (Wang et al., 2019). Of the three machine learning-based categories, there exist two main categories for PM. The first one is supervised approaches where the failure information exists in the dataset. The second one is unsupervised approaches, where there is only process information, and no failure-related information exists (Kang et al., 2021).

Machine learning methods have been increasingly applied in different areas to perform various tasks. Fault diagnosis is the most common application area of machine learning, which determines whether to send equipment to be fixed or to be replaced. This kind of task mainly uses binary classification or multi-category classification algorithms to predict failures or malfunctions (Kang et al., 2021).

This study has a labeled dataset from historical data such as previous maintenance logs and sensor readings which makes it select supervised approaches. Form various supervised machine learning algorithms, ensemble method is selected, because according to Li et al., (2022), it utilizes multiple learning algorithms to produce better predictive performance than could be obtained from any other constituent learning algorithm alone (such as SVM). Ensembles combine multiple hypotheses to form a better hypothesis. However, this method does entail significantly higher computation power during training as compared with other machine learning algorithms.

There are three ensemble methods, the first one is bagging, is mainly applied in classification and regression. It increases the accuracy of models through decision trees, which primarily reduces variance. The reduction of variance increases accuracy, eliminating overfitting, which is a challenge to many predictive models. The second and the selected one is boosting, learns from previous predictor mistakes to make better predictions in the future. The technique combines several weak base learners to form one strong learner, thus significantly improving the predictability of models. Boosting works by arranging weak learners in a sequence, such that weak learners learn from the next learner in the sequence to create better predictive models. The last one is Stacking, works by allowing a training algorithm to ensemble several other similar learning algorithm predictions. Stacking has been successfully implemented in regression, density estimations, distance learning, and classifications.

2.4. Gaps in the Literature

Despite the advancements in PM, there is a notable gap in its application within Ethiopian breweries. The limited adoption of AI-driven maintenance technologies in this sector underscores the need for research focused on developing and integrating effective PM strategies. This study aims to fill this gap by proposing a machine learning model tailored to the specific needs of BGI Ethiopia's draft beer production line.

Also, Nanavaty, n.d., stated that extreme Gradient Boosting (XGBoost) is a powerful ML algorithm noted for its efficiency and accuracy, particularly in predictive modeling and classification tasks. But the performance of ML models depends on that specific dataset. Cross-validation helps in estimating the generalization performance of different models and provides insights into their strengths and weaknesses. Rather than selecting a single "best" model, it's more practical to choose the model that suits the specific needs of the problem at hand. This often involves experimenting with multiple models, evaluating their performance, and selecting the one that provides the best balance of accuracy, interpretability, computational efficiency, and other relevant factors.

3. Research Methodology

This section details the methodology employed to develop a predictive maintenance model for a beverage factory using hybrid synthetic sensor data. The approach includes data generation, preprocessing, model development, evaluation and integration.

3.1. Research Design

This study utilizes a case study design, focusing on BGI Ethiopia as a case company, aimed at developing a predictive maintenance model for BGI Ethiopia's draft beer production line. The study leverages both real-time operational data and synthetic data to enhance the robustness and accuracy of the predictive model, while also offering insights relevant to the broader industry.

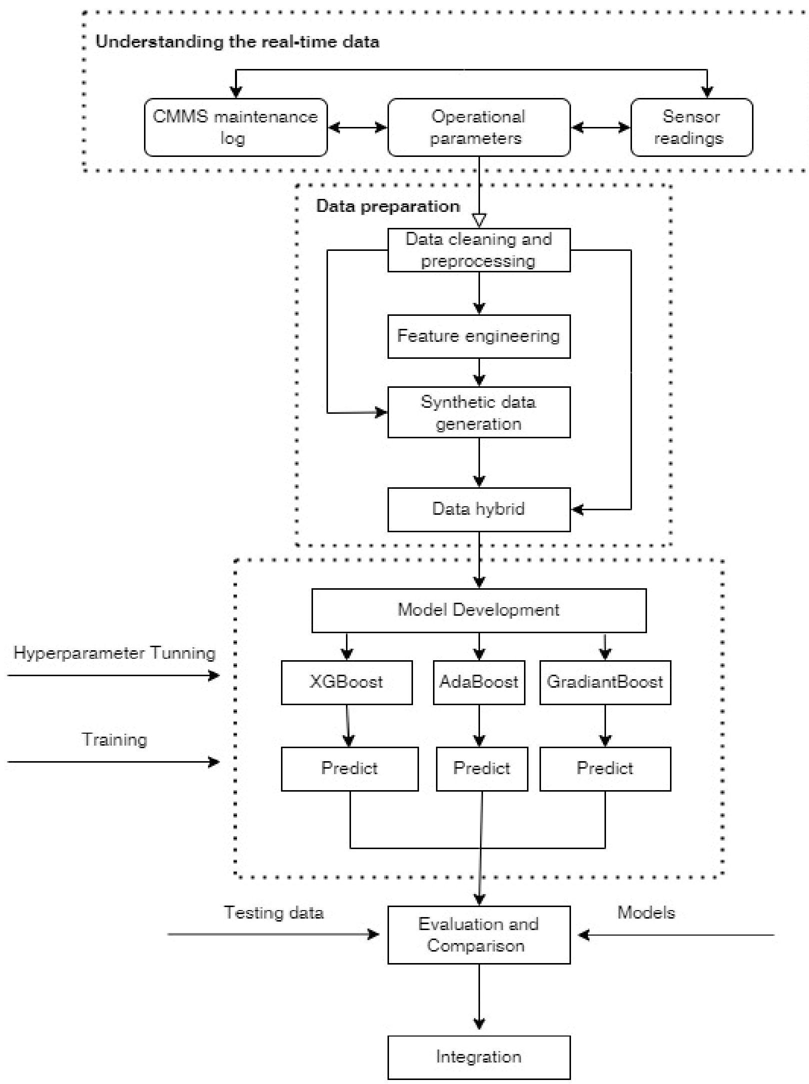


Figure 1: Project Framework

3.2. Data Collection

The data required for this research includes both historical operational data and real-time sensor data from BGI Ethiopia's draft beer production line. The specific types of data collected are historical maintenance, sensor Data and operational parameters.

Identify data sources: Collaborate with BGI Ethiopia to collect relevant data from keg rejection histories, sensor readings, historical maintenance logs, operational parameters, and any other available sources related to Head-4 (F1_H4_1St). Historical analysis of failures, to classify types of failures, their causes and maintenance activities were taken. Data from the CMMS (Computerized Maintenance Management Systems) system supporting the broadly understood Maintenance activities. The CMMS system records data, events related to all types of breakdowns, overhauls or inspections and other maintenance activities, as well as the management of maintenance personnel and service documentation. BGI has had CMMS system supporting maintenance management in place for the last few years.

Data Collection Process:

1. **Historical Data Extraction:** Extract historical maintenance and operational data from the CMMS. This includes details on past maintenance activities, equipment failure logs, and rejection rates. Collected 2,224 data points from 2/22/2019 to 1/4/2024.
2. **Real-time Data Collection:** Collect real-time sensor data over a specified period. The sensors record various parameters related to the washing heads' operation which is extracted from the collected maintenance history, such as steam FG entering pressure, steam waiting temperature, steam pressure, steam temperature, hot water temperature and hot water pressure. Gathered 500 data points for each feature from the sensors.
3. **Data Preprocessing:** Clean and preprocess the data to ensure it is suitable for analysis. This includes handling missing values and normalizing the data.

   Features Collected:

   - Maintenance Logs (Data points: 2,224)
   - Steam FG entering pressure (Data points: 500)
   - Steam waiting temperature (Data points: 500)

- Steam pressure (Data points: 500)
- Steam temperature (Data points: 500)
- Hot water temperature (Data points: 500)
- Hot water pressure (Data points: 500)

3.2.1. Understanding Real-World Data

The primary goal of this research is to predict the readiness state of washing head, specifically identifying whether Head-4 is ready for operation to minimize false rejections and improve maintenance decision-making.

Input Data: The input data for this study is derived from multiple sources, including historical maintenance logs from the Computerized Maintenance Management System (CMMS), operational parameters, and some sensor readings. The specific features used in the model include:

- Steam Waiting Temperature: The level of steam temperature before head-4 starts operation or before any keg arrived at head-4.
- Steam Entering FG (Filler group) Pressure: The pressure of steam as it enters the filler group. There are two filler groups, and each has 6 fillers.
- Steam Temperature: The temperature of steam as it starts operation or when a keg arrived from head-3 for sterilization.
- Steam Pressure: The pressure of steam as it starts operation or when a keg arrived from head-3 for sterilization.
- Hot Water Temperature: Temperature of the hot water used during operation.
- Hot Water Pressure: Pressure of the hot water used during operation.

These features are critical in determining the operational state of the washing head and its readiness to sterilize the kegs. Some simple preprocessing was made manually in excel, handle missing values and inconsistencies.

3.2.2. Data Augmentation

Given the limited availability of real-time sensor data, synthetic data generation was necessary to create a comprehensive dataset for training the machine learning models. Generative Adversarial Networks (GANs) were employed to generate realistic synthetic data based on the available real-world data.

Specifically, generated an additional 500 synthetic data points for each feature, bringing the total dataset to:

- Steam FG entering pressure (Data points: 1000)
- Steam waiting temperature (Data points: 1000)
- Steam pressure (Data points: 1000)
- Steam temperature (Data points: 1000)
- Hot water temperature (Data points: 1000)
- Hot water pressure (Data points: 1000)

The training data consists of a combined set of real and synthetic data, carefully curated to capture the variability and patterns necessary for effective model training. This dataset is used to train the machine learning models, enabling them to learn the relationships between the input features and the target variable. The target variable in this context is the readiness state of the Head-4, categorized into three classes:

- In Position and Ready
- Not in Position and Not Ready
- In Position and Not Ready

The training data is split into 80% of the total dataset, ensuring that the models have sufficient data to learn from. The testing data comprises the remaining 20% of the dataset, which is used to evaluate the performance of the trained models. This data is kept separate from the training data to provide an unbiased assessment of the models' generalization capabilities. The test data allows to measure the accuracy, precision, recall, F1-score, and other relevant metrics, ensuring that the models can accurately predict the readiness state of the kegs in real-world scenarios.

The primary predictive task of this study is to determine the readiness state of Head-4. By predicting whether Head-4 is "In Position and Ready," "Not in Position and Not Ready," or "In Position and Not Ready," the model aims to inform operators proactively. This prediction helps in minimizing false keg rejections and improving maintenance decision-making, ultimately enhancing operational efficiency and reducing economic losses for BGI Ethiopia.

3.3. Model Development

The model architecture is designed to incorporate the selected features and capture the temporal dependencies in the data. Ensemble machine learning methods are used, XGBoost, Adaboost and GradientBoost. Then these three models were combined with the boosting method to create an ensemble model.

1. **XGBoost**
   - Hyperparameter Tuning: Use Grid Search to optimize hyperparameters.
   - Model Training: Train the XGBoost model on the training data.
   - Evaluation: Evaluate the model on validation and test sets using metrics such as precision, recall, F1-score, and AUC-ROC.
2. **Adaboost**
   - Hyperparameter Tuning: Optimize hyperparameters by using GridSearchCV.
   - Model Training: Train the Adaboost model on the training data.
   - Evaluation: Evaluate the model using the same metrics as for XGBoost.
3. **GradientBoost**
   - Hyperparameter Tuning: Optimize hyperparameters by using GridSearchCV.
   - Model Training: Train the GradientBoost model on the training data.
   - Evaluation: Evaluate the model using the same metrics as for XGBoost.

3.4. Methods for Model Comparison

To evaluate and compare the performance of the predictive models AdaBoost, Gradient Boosting, and XGBoost various standard performance metrics were utilized, including accuracy, precision, recall, F1-score, and AUC-ROC. Additionally, confusion matrices were generated to provide a detailed breakdown of the models' predictions, illustrating the true positive, true negative, false positive, and false negative counts. This helped in assessing the models' ability to correctly classify the readiness state of Head-4. Feature importance analysis was also conducted to identify which features had the most significant impact on the models' predictions, providing insights into the key factors influencing the readiness state of the washing head. By combining these metrics, we were able to comprehensively evaluate each model's effectiveness and reliability in minimizing false keg rejections and improving maintenance decision-making.

3.5. Integrating the Model into the Maintenance Strategy

To attain the objective of developing a model that predicts the operational state of the washing head and measures its influence on maintenance activities, the following steps are undertaken:

1. **Predictive Model Development:** The model predicts whether the washing head is ready for operation based on real-time sensor data and synthetic data. The prediction helps to identify when the washing head might not be ready for operation, allowing for proactive maintenance.
2. **Impact Measurement:** The model's predictions are integrated into the maintenance schedule. The impact on key performance indicators (KPIs) such as keg rejection rate, rejection rate, and downtime is measured.
    - Rejection Rate**:** The model's accuracy in predicting the readiness state of the washing head reduces the number of false rejections, thereby lowering the rejection rate.
    - Production throughput: By reducing false rejections, the amount of lost product due to unnecessary rejections decreases, leading to cost savings.
    - Downtime: Proactive maintenance based on the model's predictions minimizes unexpected equipment failures, reducing downtime and improving production throughput.

4. Result and Discussion

4.1. Identifying the Problem Due to Washing Head 4

4.1.1. Background

BGI is a large-scale brewery and beverage production wing of Group Castel, operating in over 53 countries. Since 1998, BGI Ethiopia PLC has been operating in the production and distribution of beer, wine and other beverages. BGI owns five breweries including the iconic St. George Brewery in Addis Ababa, the Kombolcha Brewery, the Hawassa Brewery, Zebidar Brewery and Maychew Northern Brewery, producing 3.6 million Hectoliters of beer (bottles and draft) annually.

BGI Ethiopia P.L.C. also owns and manages the Castel winery and vineyard located in the town of Zeway. Established in 2012, the winery produces 12,000 Hectoliters of different wine varieties annually under the brand names Acacia and Rift Valley. BGI Ethiopia's products are distributed by partner agents in all corners of the country and exported internationally to North America, Europe, Middle East, Australia, Africa, and Asia.

This study works on St. George Brewery in Addis Ababa, which became a part of the BGI family in 1998 through privatization. Located in Mexico Square, Lideta sub-city at the heart of Addis Ababa; St. George Brewery currently has the production capacity of 550,000 HL per annum, providing jobs for 956 permanent and 58 seasonal employees. The company operates several production lines, each dedicated to different stages of the beer production process.

Draft beer is one of the most significant products in the beverage industry due to its freshness and taste, which are highly valued by consumers. The production and quality control of draft beer are critical to maintaining the brand’s reputation and market share. Any inefficiency or quality issue directly affects the bottom line. The draft beer production process involves multiple complex stages, each requiring precise control and monitoring. This complexity makes it a suitable candidate for exploring advanced predictive maintenance solutions, as there are many points where potential failures can occur. Issues in the draft beer production line, such as rejection of kegs, lead to substantial financial losses. By focusing on draft beer, the study targets a high-impact area where improvements can lead to considerable enhancement of efficiency and cost savings.

BGI Ethiopia operates a draft beer production line consisting of 11 fillers, each equipped with its own washing head for internal keg cleaning propose. One specific washing head, referred to as

Head-4, plays a critical role by receiving steam from the boiler. This steam is essential for the internal sterilization process of the kegs.

Head 4 is crucial in the draft beer filling process because it is responsible for the final sterilization of kegs using hot water and steam. Ensuring the proper operation of Head 4 is vital for maintaining the hygiene and quality of the beer. Empirical data from BGI Ethiopia showed that Head 4 frequently causes keg rejections due to issues with steam supply fluctuations and temperature variations. These problems result in false rejections of otherwise usable kegs, leading to significant operational inefficiencies. The issues related to Head 4 are well-documented, with ample data available from the CMMS logs, operational parameters, and sensor readings. This availability of data makes it feasible to develop and test a predictive maintenance model effectively.

4.1.2. Identifying Keg Rejection Issues

One of the significant challenges faced by BGI Ethiopia is the frequent rejection of kegs due to issues with the washing head (Head-4) in the draft beer production line. Each of the 11 fillers in the production line is equipped with washing heads responsible for the internal sterilization of kegs using steam supplied from a boiler. Inconsistencies in the steam supply due to condensation through the line leading to suboptimal sterilizing conditions, result in the incorrect rejection of a substantial number of kegs that are otherwise fit for use.

Current maintenance practices at BGI Ethiopia are reactive. Operators intervene only after 13-18 kegs have been rejected, at which point the machine notifies them of the issue. This necessitates stopping the machine, waiting for it to cool down, and performing maintenance tasks such as clearing condensation from the lines. In addition to false keg rejections, this process increases downtime, which leads to disruption of the production workflow, and economic losses due to wasted product and inefficient use of resources.

As (CMMS Maintenance record, 2024, Maintenance department), on average, 50 kegs per filler are wrongly rejected each day, amounting to approximately 1,500 rejections per month. Traditional preventive maintenance (PM) practices, based on scheduled maintenance regardless of actual equipment condition, are insufficient for managing the complex equipment and maintaining optimal production uptime. These practices often result in unnecessary maintenance or overlooked critical issues.

4.1.3. Analysis of Current Maintenance Practices

BGI Ethiopia follows a structured preventive maintenance (PM) schedule designed to ensure the reliability and efficiency of its draft beer production line. The maintenance schedule includes weekly, monthly, and yearly tasks, each with specific item descriptions, task descriptions, estimated times, periods and frequencies, as shown in Appendix Table A1.

The preventive maintenance schedule is only for one filler, this will be performed for the 11 fillers. Weekly maintenance tasks at BGI Ethiopia focus on routine inspections and minor cleanings that address immediate wear and tear on the machinery. These tasks are essential for maintaining daily operational efficiency and preventing small issues from escalating into significant problems. The weekly maintenances mostly take 5mins. All the 6 heads will be serviced with a service kit as per OEM procedure after every 80000 kegs which takes 120mins and their respective inlet and outlet of the media will be serviced after every 30000 kegs and takes 60mins.

The scheduled preventive maintenance (PM) is a systematic approach to ensuring the longevity and efficiency of machinery by performing regular inspections, cleaning, adjustments, and part replacements at predefined intervals. This practice is crucial in manufacturing environments where equipment reliability directly impacts productivity and product quality.

Despite the detailed preventive maintenance schedule, BGI Ethiopia still experiences significant daily keg rejections and downtimes. The current reactive maintenance approach, which only intervenes after multiple keg rejections, exacerbates the problem. This not only results in the rejection of good kegs but also leads to unnecessary production halts, extended downtimes, and increased operational costs. The below table shows the amount of daily filler rejections for 10 consecutive days.

Table 1: Keg Rejection record for 10 days

Fillers		Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
F1	Good	1460	1512	1465	1632	1463	1792	1800	1562	1916	1892
	Reject	172	103	112	73	117	63	59	102	69	61
F2	Good	1797	1467	1892	1563	2001	1832	1468	1789	1953	1498
	Reject	58	172	87	132	12	59	116	96	56	131
F3	Good	1800	1872	1567	1486	1932	1798	2002	1486	1846	1589

	Reject	43	56	132	134	93	68	15	143	81	119
F4	Good	1772	1694	1446	1885	2005	1661	1839	1451	2000	1536
	Reject	99	78	126	98	16	103	61	119	21	104
F5	Good	1418	1801	1494	1662	1834	1948	1478	2002	1439	2002
	Reject	147	43	153	79	113	59	136	14	127	19
F6	Good	1632	1424	1801	2000	1591	1890	1478	1645	1478	1951
	Reject	105	112	44	21	123	61	127	88	123	32
F7	Good	1898	1977	1912	1815	1552	1432	1531	1469	2003	1452
	Reject	133	19	32	99	91	126	87	119	20	131
F8	Good	1451	1891	1598	1443	1886	1584	1921	1501	1738	2000
	Reject	34	23	87	112	112	129	34	96	96	26
F9	Good	2003	1801	1882	1981	1561	1745	1441	1409	1679	1498
	Reject	19	132	64	52	89	49	133	138	83	111
F10	Good	1851	1784	2002	1772	1497	1839	1593	2001	1449	1776
	Reject	102	56	14	87	123	52	108	23	127	92
F11	Good	1880	2001	1984	1589	1501	1498	1912	2003	1439	1456
	Reject	46	12	23	116	99	128	52	15	149	126

These rejections are caused by a variety of factors, each impacting the production process in different ways. Common causes include mechanical issues such as bent pressing heads, which prevent a proper operation of spear. Sensor malfunctions, particularly with spear sensors, can lead to kegs not being properly opened for cleaning and filling process, resulting in rejections. Fluctuations in the pressurized head supply, especially for heads 1 through 5, often cause inconsistencies in cleaning and sterilization processes, leading to suboptimal keg preparation. Additionally, improper beer fill on head 6, either too high or too low, can result in kegs being deemed unsuitable. Finally, inherent defects in the kegs themselves, referred to as bad kegs, also contribute to the rejection rates. Understanding the specific causes behind these rejections is crucial for developing targeted solutions that can enhance the efficiency and reliability of the filling process. The below table categorizes the rejections with their respective cause, which helps to realize which cause is affecting the production more.

Table 2: Keg Rejection classification based on their Cause

Cause	Total rejection of 10 days	Percentage of Total rejection
Pressing head	745	8
Spear sensor	1,117	12
Pressurized head (Head1-Head5)	5,681	61
Beer fill	838	9
Bad kegs	931	10
Total	**9,312**	**100%**

As the above table shows the problem of pressurized head get the highest rejection rate. This cause related to the 5 heads, 4 washing head and 1 CO2 filling head. This is due to the fluctuation of media supply to the heads. Fluctuation in steam supply occurs higher than other media supply. Steam is used to sterilize the internal part of the keg, which is performed by head 4. The issues with Head-4 have a cumulative impact on the entire production line. Kegs pass through Heads 1-3 before reaching Head-4. If Head-4 fails to sterilize the keg, the effort and resources spent on the previous heads are wasted. This inefficiency underscores the importance of addressing Head-4's issues, therefore, this study will focus on head 4 due to higher impact on the production compared to other heads.

Current maintenance practices is corrective maintenance, operators intervene only after 13-18 kegs have been rejected by head 4, at which point the machine notifies them of the issue. The process of rejecting 13-18 kegs before operators are notified leads to unnecessary downtime. After the notification, operators need to stop the machine, wait for it to cool down, and perform maintenance tasks such as clearing condensation. This not only disrupts the production workflow but also results in economic losses due to wasted time and resources. As shown below (CMMS Maintenance record, 2024, Maintenance Department), 47 days of downtime due to head 4 is collected. Upon reaching the rejection threshold, the machine must be stopped to prevent further issues. This stoppage is not immediate so that it requires the machine to cool down to a safe temperature before any maintenance can be performed and takes more than a hour. This maintenance approach significantly increases downtime. Each maintenance intervention involves waiting for the machine to cool down, performing the necessary repairs, and then bringing the machine back up to operational temperature. This process results in frequent and extended production stoppages.

Table 3: CMMS, Maintenance Log

Equipment ID	Component_ Description	Remark	BT_ETAT _EQUIP	BT_ RUBRIQUE	Downtime (Hr)
FILLER, F2	WASHING HEAD_A	FILLER 2 AT HEAD 4 TOO MUCH REJECT	Breakdown	Corrective Maintenance	2.42
FILLER, F5	WASHING HEAD_A	F5 HEAD 4 DOES NOT WASH	Breakdown	Corrective Maintenance	0.17
FILLER, F11	WASHING HEAD_A	FILLER 11 HEAD 4 TEMPRETURE SENSOR HOLDER LEAKAGE	Breakdown	Corrective Maintenance	0.58
FILLER, F11	WASHING HEAD_A	F11 HEAD 4 DOES NOT WASH	Breakdown	Corrective Maintenance	0.12
FILLER, F2	WASHING HEAD_A	FILLER 2 HEAD 4 INSUFFICIENT WASH	Breakdown	Corrective Maintenance	0.63
FILLER, F6	WASHING HEAD_A	KEG SPEAR DOES NOT OPENED ON HEAD 4	Breakdown	Corrective Maintenance	0.5
FILLER, F6	WASHING HEAD_A	F6 HEAD 4 DOES NOT WASH	Breakdown	Corrective Maintenance	0.42
FILLER, F12	WASHING HEAD_A	F12 HEAD 4 INSUFFICIENT WASH	Breakdown	Corrective Maintenance	0.5
FILLER, F11	WASHING HEAD_A	REJECTS ON FILLER 11 HEAD 4	Breakdown	Corrective Maintenance	0.17
FILLER, F8	WASHING HEAD_A	FILLER 8 HEAD 4 HAS INSUFFICIENT WASH	Breakdown	Corrective Maintenance	1.17
FILLER, F10	WASHING HEAD_A	FILLER 10 HEAD 4 PRESSUR SENSOR DOES NOT START	Breakdown	Corrective Maintenance	0.92
FILLER, F11	WASHING HEAD_A	FILLER 11 HEAD 4 STERIL STEAM F11-H4-1ST MEDIA VALVE HAS HIGH PRESSURE	Breakdown	Corrective Maintenance	0.08
FILLER, F10	WASHING HEAD_A	FILLER 10 HEAD 4 F10-H4-1St STERILE STEAM MEDIA VALVE HAS INSUFFICIENT WASH	Breakdown	Corrective Maintenance	0.03
FILLER, F8	WASHING HEAD_A	FILLER 8 HEAD 4 MIXED WATER RETURN MEDIA VALVE F8-H4-2MwR HAS LEAKAGE	Breakdown	Corrective Maintenance	0.08
FILLER, F10	WASHING HEAD_A	FILLER 10 HEAD 4 STERILE STAM F10-H4-1ST MEDIA VALVE HAS INSUFFICIENT WASH	Breakdown	Corrective Maintenance	0.07
FILLER, F1	WASHING HEAD_A	LEAKGE ON FILLER 1 HEAD 4 THROUGH MEDIA VALVES AND DRAIN PIPE	Breakdown	Corrective Maintenance	0.62
FILLER, F5	WASHING HEAD_A	FILLER 5 HEAD 4 PRESSING CYLINDER HAS ABNORMAL PLAY	Breakdown	Corrective Maintenance	0.58
FILLER, F6	WASHING HEAD_A	FILLER 6 HEAD 4 PRESSURE SENSOR HAS WRONG READING	Breakdown	Corrective Maintenance	0.5
FILLER, F7	WASHING HEAD_A	FILER11 HEAD 4 HAS INSUFFICIENT WASH	Breakdown	Corrective Maintenance	0.25
FILLER, F11	WASHING HEAD_A	FILLER 11 HEAD 4 PRESSURE SENSOR HAS HIGH PRESSURE	Breakdown	Corrective Maintenance	0.1
FILLER, F6	WASHING HEAD_A	FILLER 6 HEAD 4 LIQUID SENSOR HAS WRONG READING	Breakdown	Corrective Maintenance	0.066666667
FILLER, F10	WASHING HEAD_A	FILLER 10 HEAD 4 PRESSURE SENSOR HAS WRONG READING	Breakdown	Corrective Maintenance	0.13
FILLER, F11	WASHING HEAD_A	FILLER 11 HEAD 4 HEAD HAS LEAKAGE	Breakdown	Corrective Maintenance	1.816666667
FILLER, F4	WASHING HEAD_A	FILLER 4 HEAD 4 PRESSURE SENSOR HAS WRONG READING	Breakdown	Corrective Maintenance	0.08

FILLER, F10	WASHING HEAD_A	FILLER 10 HEAD 4 HEAD HAS LEAKAGE	Breakdown	Corrective Maintenance	0.216666667
FILLER, F12	WASHING HEAD_A	FILER 12 HEAD 4 F12-H4-1St STEAM MEDIA VALVE HAS INSUFFICENT WASH	Breakdown	Corrective Maintenance	0.08
FILLER, F3	WASHING HEAD_A	FILLER 3 HEAD 4 LOW FLOW F3-H4-1LF MEDIA VALVE HAS LEAKAGE	Breakdown	Corrective Maintenance	0.17
FILLER, F6	WASHING HEAD_A	FILLER6 HEAD 4 PRESSURE SENSOR HAS WRONG READING	Breakdown	Corrective Maintenance	0.083333333
FILLER, F4	WASHING HEAD_A	F4 HEAD 4 PRESSURE TRANISMITER SENSOR HAS WRONG READING	Breakdown	Corrective Maintenance	0.12
FILLER, F11	WASHING HEAD_A	FILLER11 HEAD 4 PRESSURE SENSOR HAS WRONG READING	Breakdown	Corrective Maintenance	0.083333333
FILLER, F4	WASHING HEAD_A	FILLER 4 HEAD 4 MEDIA VALVE HAS INSUFFICENT WASH	Breakdown	Corrective Maintenance	0.5
FILLER, F4	WASHING HEAD_A	FILLER 4 HEAD 4 LIQUID SENSOR HAS WRONG READING	Breakdown	Corrective Maintenance	0.083333333
FILLER, F1	WASHING HEAD_A	FILLER 1 HEAD 4 HEAD HAS INSUFFICIENT WASH	Breakdown	Corrective Maintenance	0.216666667
FILLER, F10	WASHING HEAD_A	FILLER 10 HEAD 4 STERILIZE STEAM AND HOT WATER F10-H4-1ST AND F10-H4-1HW MEDIA VALVE HAS INSUFFICIENT WASH	Breakdown	Corrective Maintenance	0.033333333
FILLER, F11	WASHING HEAD_A	FILLER 11 HEAD 4 PRESSURE SENSOR HAS WRONG READING	Breakdown	Corrective Maintenance	0.033333333
FILLER, F10	WASHING HEAD_A	FILLER 10 HEAD 4 PURGE WASH PROBLEM	Breakdown	Corrective Maintenance	0.333333333
FILLER, F6	WASHING HEAD_A	FILLER F6 HEAD4 PRESSURE TRANSMITTER WRONG READING	Breakdown	Corrective Maintenance	0.85
FILLER, F11	WASHING HEAD_A	FILLER 11 HEAD4 F11-H4-1ST STERILE STEAM MEDIA VALVE HAS INSUFFICENT WASH	Breakdown	Corrective Maintenance	0.03
FILLER, F4	WASHING HEAD_A	FILLER 4 HEAD4 STERIL STEAM F4-H4-1St MEDIA VALVE HAS HIGH PRESSURE	Breakdown	Corrective Maintenance	0.08
FILLER, F11	WASHING HEAD_A	FILLER 12 HEAD4 STERILE STEAM F11-H4-1ST MEDIA VALVE HAS INSUFFICENT WASH	Breakdown	Corrective Maintenance	0.05
FILLER, F4	WASHING HEAD_A	REJECT KEG ON HEAD4 AND THERE WAS LEAKAGE ON PIPE FITTING	Breakdown	Corrective Maintenance	0.92
FILLER, F4	WASHING HEAD_A	FILLER 4 HEAD4 STERILE STEAM F4-H4-1ST MEDIA VALVE HAS INSUFFICENT WASHE	Breakdown	Corrective Maintenance	0.08
FILLER, F7	WASHING HEAD_A	FILLER 7 HEAD4 PRESSURE SENSOR HAS WRONG READING	Breakdown	Corrective Maintenance	0.05
FILLER, F4	WASHING HEAD_A	FILLER 4 HEAD4 HEAD HAS LEAKAGE	Breakdown	Corrective Maintenance	0.333333333
FILLER, F6	WASHING HEAD_A	FILLER 6 HEAD4 PRESSURE SENSOR HAS WRONG READING	Breakdown	Corrective Maintenance	0.033333333
FILLER, F11	WASHING HEAD_A	FILLER 11 HEAD4 STERILE STEAM MEDIA VALVE F11-H4-1ST HAS INSUFFICENT WASH	Breakdown	Corrective Maintenance	0.033333333
FILLER, F7	WASHING HEAD_A	FILLER 7 HEAD4 LIQUID SENSOR HAS WRONG READING	Breakdown	Corrective Maintenance	0.05

Given the limitations of current maintenance practices, there is a clear need for a more advanced solution. Leveraging Artificial Intelligence (AI) for preventive maintenance offers a promising solution. The proposed solution involves developing a predictive maintenance model to accurately predict the operational state of Washing Head 4 before keg rejections occur. By leveraging both real-time and synthetic data, the model aims to reduce false rejections and downtime, ensuring a more efficient and reliable production process. Implementing such a model will allow BGI Ethiopia to transition from reactive to proactive maintenance, enhancing overall operational efficiency and reducing economic losses.

4.1.4. Analysis of Head 4 Malfunctions

The rejection of kegs due to the issues with Head-4 can be attributed to several interrelated factors:

Steam Supply Fluctuations: The steam supplied to Head-4 from the boiler is subject to fluctuations in pressure. These fluctuations can be caused by varying demand for the boiler, maintenance issues, or inefficiencies in the steam distribution system. When the steam pressure is insufficient, it fails to adequately sterilize the kegs, leading to their rejection.

Temperature Variations Due to Condensation: Steam can lose heat and condense into water before reaching Head-4, especially if the steam lines are not adequately insulated or if there are leaks in the system. Condensed steam lowers the temperature, preventing the kegs from being sterilized at the required temperature. This inconsistency results in keg rejection even though they are otherwise in good condition.

System Lag and Response Time: The system's inability to quickly respond to fluctuations and temperature drops exacerbates the problem. There might be a lag in detecting and compensating for these variations, leading to prolonged periods where the steam quality is suboptimal for keg sterilizing and lead to increased downtime.

Operational Impact: The cumulative effect of these issues is a significant operational disruption. The rejection of 50 kegs per day means not only a loss in production output but also increased costs associated with reprocessing or disposing of these kegs. Over a month, the rejection of 1,500 kegs represents a substantial financial loss and resource wastage.

4.1.5. Impact of Head 4 Issues on Operations

The continuous rejection of kegs due to steam-related issues at Head-4 leads to several negative consequences for BGI Ethiopia:

Operational Inefficiency: Frequent keg rejections disrupt the production schedule, leading to delays and decreased overall productivity. The need to stop the production line after multiple rejections to address the issues with Head-4 interrupts the flow of operations, causing bottlenecks and reducing the efficiency of the production process. Each time the machine notifies operators after multiple keg rejections, the production line must be halted, cool down and maintenance tasks such as clearing condensation and adjusting steam parameters must be performed, which takes over 3 hours per filler. This downtime reduces the overall availability of the production line, leading to lower production capacity and potential delays in meeting customer demand. This inefficiency can lead to reduced output, further straining the brewery's resources.

Resource Wastage: Wasted materials and energy used in the production of rejected kegs represent an inefficient use of resources. The brewing process consumes significant amounts of water, energy, and raw materials, all of which are wasted when kegs are rejected. This wastage not only increases operational costs but also has environmental implications, as it leads to higher resource consumption and waste generation.

Financial Losses: The direct cost of rejected kegs, coupled with the lost opportunity to sell the beer, represents a significant financial burden. Each rejected keg not only incurs the cost of the raw materials and production but also the lost revenue from the inability to sell the finished product. Over time, these financial losses accumulate, impacting the overall profitability of the brewery.

4.1.6. AI-Based Predictive Maintenance Model and Justification

Given the identified issues with the current maintenance practices for Head-4 and the operational inefficiencies arising from steam pressure and temperature fluctuations, the proposed solution is to implement a predictive maintenance model using machine learning techniques. This model aims to predict the operational state of Head-4 before keg rejections start, thereby reducing rejection rates and associated downtime.

The data was collected from BGI Ethiopia's CMMS, which logs detailed operational parameters, maintenance activities, and real-time sensor readings. Initial observations revealed frequent keg rejections at Head-4, significant fluctuations in steam pressure and temperature, and substantial downtime associated with reactive maintenance tasks. The data shows that an average of 50 kegs per filler are rejected daily, totaling approximately 1,500 kegs per month. This high rejection rate directly impacts production efficiency and highlights a significant operational challenge.

Maintenance logs indicate that reactive maintenance is typically performed after 13-18 kegs are rejected. This involves stopping the production line, waiting for it to cool down, and clearing condensation from the lines, resulting in substantial downtime and inefficiency.

The data demonstrates a clear lag between the onset of steam supply issues and maintenance interventions, leading to prolonged inefficiencies. Predictive maintenance could provide early warnings based on the identified predictive indicators, allowing for proactive maintenance actions before rejections occur.

The analysis confirms that the absence of predictive maintenance is a significant contributor to the operational issues at Head-4. Implementing a predictive maintenance system could reduce keg rejections, minimize downtime, and improve overall operational efficiency, addressing the core issues identified in the data.

4.2. Understanding the current process of keg filler machine

The Lambrecht Slimline Monobloc 50 is an all-in-one keg Washing & Filling solution which was developed to fit in one 20-foot ocean container. This installation is equipped with its own built-in acid, caustic & mixed water detergent set. The built in external keg washer comes as an option. The setup consists of a straight ‘walking beam’ system with keg pull through, starting at one side and leaving the machine on the other side.

Figure 2: Lambrecht Slimline Monobloc 50 Draft beer filler machine

The Pre-washer (Chunnel 422) is designed and sized to automatically wash and sterilize kegs internally via installed process heads. The number of process heads is based on the requested capacity. The model number 422 indicates that the fillers are based on the following process steps:

- **4** washing / cleaning heads
- **2** waiting platforms: **1** soaking waiting platform.

  1 sterilization waiting platform.

- **2** filling heads: **1** CO_2 filling head

  1 filling head

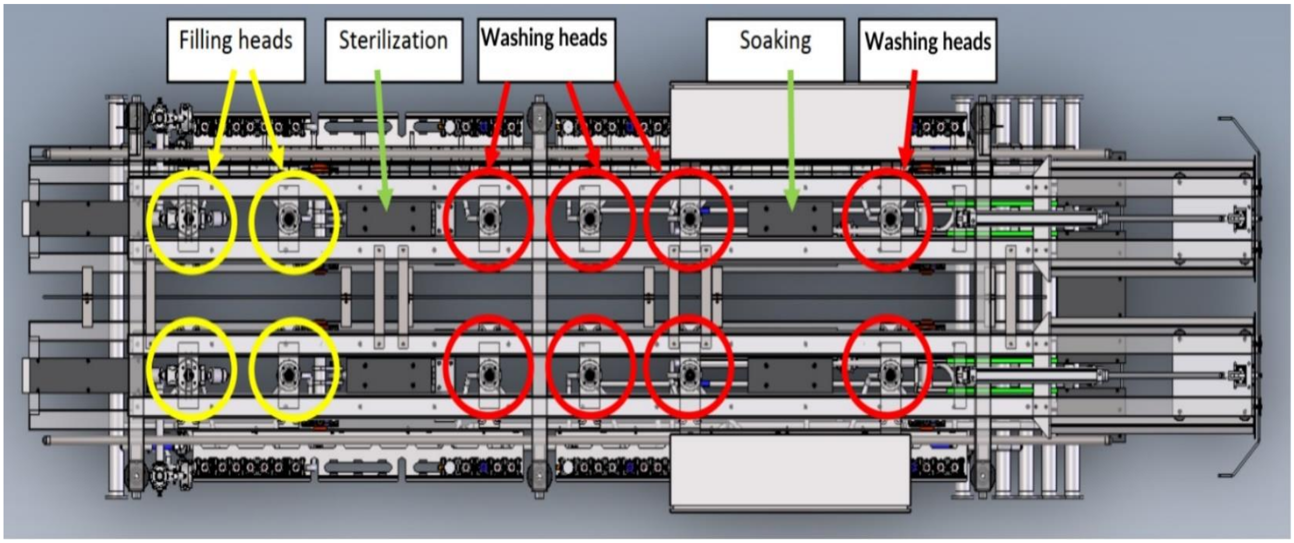


Figure 3: Heads Layout

The machine collects a keg from the entrance conveyor into the machine and is positioned on the entrance waiting platform. At the end of the process cycle, the walking beam transport system lifts all the kegs in the machine up, moves them forward and lowers the kegs onto the next process head. The last processed keg stands on a waiting platform at the end of the machine and is pushed out when the walking beam moves forward after having dropped the kegs.

The machine distinguishes 2 types of process heads, washing head, which are used for all internal cleaning, sanitizing and preparing the keg for filling and filling heads, which are solely used to fill product into the keg.

Step 1: Transfer and Positioning

Keg Conveyor: Once placed on the conveyor, the kegs are automatically transported towards the washing and filling lines.

Waiting Platform and Reference Position: The kegs are first pulled onto a waiting platform where they are held momentarily before being moved to a precise reference position. This ensures accurate alignment for subsequent processing stages.

Step 2: Washing Process

Head 1 Initial Washing: The keg is transferred from the reference position to Head 1, where the initial washing process begins. Here, the interior of the keg is thoroughly rinsed to remove any residual liquid or loose debris.

Head 2 Secondary Washing: Following the initial wash, the keg is moved to Head 2 for further cleaning. This stage typically involves the use of cleaning agents or detergents to ensure more thorough removal of contaminants.

Head 3 Final Rinse: The keg is then transferred to Head 3, where it undergoes a final rinse to wash away any remaining cleaning agents and contaminants from the previous stages.

Head 4 Sterilization: The last washing process is performed by Head 4, which is critical for sterilizing the internal part of the keg. This stage involves the use of high-temperature steam and hot water to ensure all microbial life is eradicated, making the keg hygienically safe for beer filling. In this study, the focus is on optimizing the performance of Head 4 to minimize keg rejections caused by inconsistencies in the steam supply.

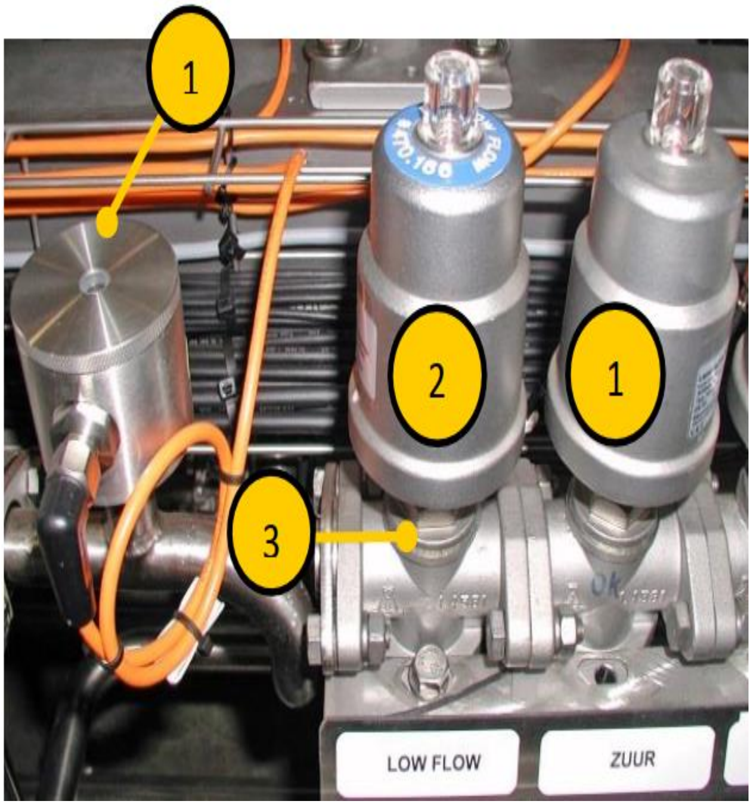
Step 3: Filling Process

Head 5 CO2 Filling: After the washing and sterilization processes are completed, the keg is transferred to the first filler head, Head 5, where it is filled with carbon dioxide (CO_2). This step is crucial for creating an inert environment inside the keg, which helps in preserving the beer's quality.

Head 6 Beer Filling: Finally, the keg is moved to Head 6, where it is filled with beer. This head ensures precise filling to avoid spillage and wastage, maintaining the high quality of the draft beer.

Both heads (washing and filling) have a common design and only differ on the media connection side. The process head is responsible for the connection with the keg through which it is possible to charge media in and out of the keg. Once the outer edge of the spear head is pressed onto the inner rubber seal, the central rising spear shaft in the process head is lifted by means of a pneumatic cylinder and the keg spear is opened. Here, a physical connection is made with the gas port and the beer port of the keg.

The media supplies to the process heads are controlled by one-way spring-loaded pneumatic valves ensuring correct fluid always flows in the right order and right time. A red indicator pops up if the valve is activated by compressed air. Pending the type of media needed for the process, the number and type of valves can differ from head-to-head. The valves are located on the side of the chunnel for easy access and maintenance.



1 - Media supply valve

2 - Low flow media valve: used together with a media supply valve, the pressure and flow to the head can be altered by switching on/off. A small center bore through the valve stem provides a leak path when the valve is closed.

3 - Valve collector: used to connect valves and create connections to heads.

4 - Capacitive level switch as used to check presence of fluid: to check if the intended processes using media have been applied correctly (time probe).

Figure 4: Media Valve

By understanding this detailed sequence of operations, particularly the critical role of the last washing head, Head 4 in the sterilization process, the study aims to develop a predictive maintenance model. This model will help anticipate and prevent issues with Head 4, thereby reducing keg rejections, minimizing downtime, and enhancing the overall efficiency of BGI Ethiopia's draft beer production line.

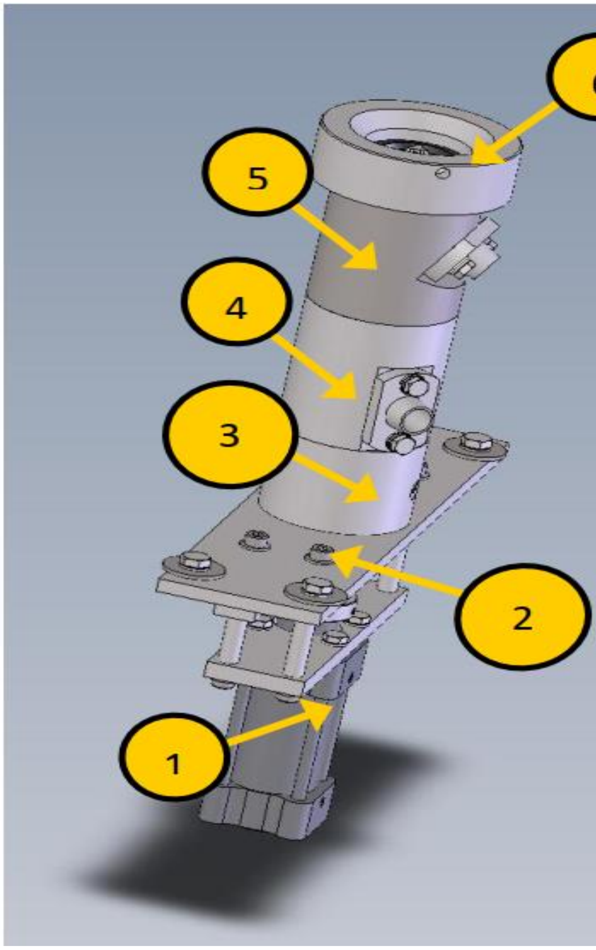


Figure 5: Washing process head.

1. Pneumatic cylinder which is connected to the internal shaft of the process head to open the kegs spear for processing.

2. Mounting plate to main frame.

3. Lower head section – locates internal shaft seals and allows for assembly to mounting plate.

4. Middle head section – locates internal shaft seals and provides media connection for the internal shaft bore.

5. Top head section – locates internal shaft seals and provides media connection around the internal shaft

6. Locator ring to facilitate keg positioning and incorporates keg to head seal.

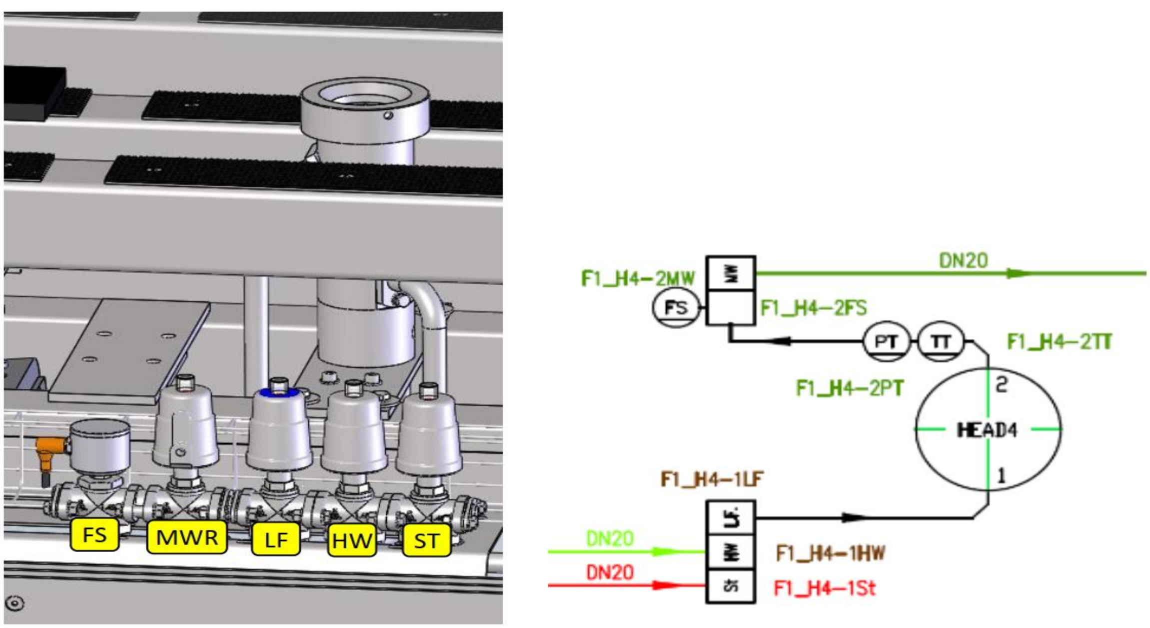


Figure 6: Head 4, Washing Heads and Connections

Table 4: Head 4 Process Steps

PROCESS STEPS		MEDIA VALVES				
FILLER HEAD 4	STEP	Steam Hot F1_H4_1St	Hot Water F1_H4_1HW	Low Flow F1_H4_1LF	Mixed water Return F1_H4_2MW_R	Spear F1_H4_YP_Spear
STEP 1	Head 4 (F1): Pressurise head	X		X		
STEP 2	Head 4 (F1): Head leak check delay					
STEP 3	Head 4 (F1): Depressurise head				X	
STEP 4	Head 4 (F1): Spear insertion				X	X
STEP 5	STEP 5 Head 4 (F1): Wash 7 Hot Water (on/off) + (wash guard)		X	1/0.	X	X
STEP 6	Head 4 (F1): Valves delay				X	X
STEP 7	Head 4 (F1): Purge wash 7 (probe off)\	X		X	X	X
STEP 8	Head 4 (F1): Steam Keg to Temperature	X		X	X	X
STEP 9	Head 4 (F1): Pressurise 1 Keg + check	X		X		X
STEP 10	Head 4 (F1): Steam Waiting Time			X		X
STEP 11	Head 4 (F1): Purge Keg X	X		X	X	X
STEP 12	Head 4 (F1): Pressurise 2 Keg + check	X		X		X
STEP 13	Head 4 (F1): Spear out				X	
STEP 14	Head 4 (F1): Depressurise head				X	
STEP 15	Head 4 (F1): END					

4.3. Understanding real-time data and synthetic data generation

For developing an effective predictive maintenance model, it is crucial to gather and understand real-time data from the production environment. In the context of BGI Ethiopia's draft beer production line, the key data sources include:

Maintenance Logs from CMMS: Historical data from the Computerized Maintenance Management System (CMMS) provides insights into past maintenance activities, equipment failures, and repair actions. This data is invaluable for understanding failure patterns and maintenance needs.

Operational Parameters: Real-time measurements of operational parameters such as steam pressure and temperature are critical for monitoring the conditions of the pressurized heads and fillers. These parameters help in identifying deviations that may indicate potential issues.

Sensor Readings: Sensors installed on the production line continuously capture data on various features relevant to the maintenance of washing heads. However, due to the limited availability of sensor readings, additional synthetic data generation was necessary.

4.3.1. Data Analysis and Correlation

To generate realistic synthetic data, a rigorous analysis and correlation of the available real-time data are essential. This process ensures that the synthetic data mirrors the complex patterns and relationships found in the actual operational environment. The key steps involved in this process are:

Feature Extraction

Identifying and extracting relevant features from the CMMS maintenance record is critical for accurate predictive modeling. This involves:

Variable Identification: Determining which variables are most relevant to the predictive maintenance task. This includes operational parameters such as steam pressure and temperature.

Correlation Analysis: Performing statistical analyses to identify significant correlations between variables. This helps in understanding how different factors influence the operational state of Head-4.

Dimensionality Reduction: Applying techniques like Principal Component Analysis (PCA) to reduce the number of variables while retaining essential information. This step helps in simplifying the model without sacrificing accuracy.

Time-Series Analysis: Analyzing time-series data to capture trends, seasonality, and cyclic patterns. This is particularly important for capturing the temporal dynamics of the steam supply and its impact on the washing head's performance.

Anomaly Detection: Identifying outliers and anomalies in the data that may indicate underlying issues. This helps in refining the dataset by removing or correcting these anomalies to improve model accuracy.

The six key features identified for this study are:

- Steam Waiting Temperature: The temperature of steam waiting for the process to start.
- Steam Entering Pressure: The pressure of steam as it enters the filler group (FG), there are 2 FG with 6 fillers each.
- Steam Temperature: The temperature of steam during head 4 operation.
- Steam Pressure: General steam pressure in the system.
- Hot Water Temperature: Temperature of the hot water used in the system.
- Hot Water Pressure: Pressure of the hot water used in the system.

Sensor Data Integration

Once the features are extracted from the CMMS data, recording the real-time sensor readings for the extracted features is crucial to train and test the predictive model. This involves:

Sensor Data Collection: Gathering real-time sensor readings to steam waiting temperature, steam entering pressure, steam temperature, steam pressure, hot water temperature and hot water pressure. Analyzing the relationship between sensor data and extracted features to understand their impact on the washing head's performance.

Data Fusion and Target classes: Combining sensor data with the CMMS-extracted features to create a holistic dataset that captures both historical and real-time operational parameters. Based on the analysis, three target classes were defined to represent the operational states of the kegs:

- In Position and Ready
- Not in Position and Not Ready
- In Position and Not Ready

Correlation Analysis: Examining the relationships between the extracted features and the target classes to understand how different operational parameters influence the readiness state of the kegs.

After collection and detail analysis the final extracted original data points is:

- Steam FG entering pressure (Data points: 500)
- Steam waiting temperature (Data points: 500)
- Steam pressure (Data points: 500)
- Steam temperature (Data points: 500)
- Hot water temperature (Data points: 500)
- Hot water pressure (Data points: 500)

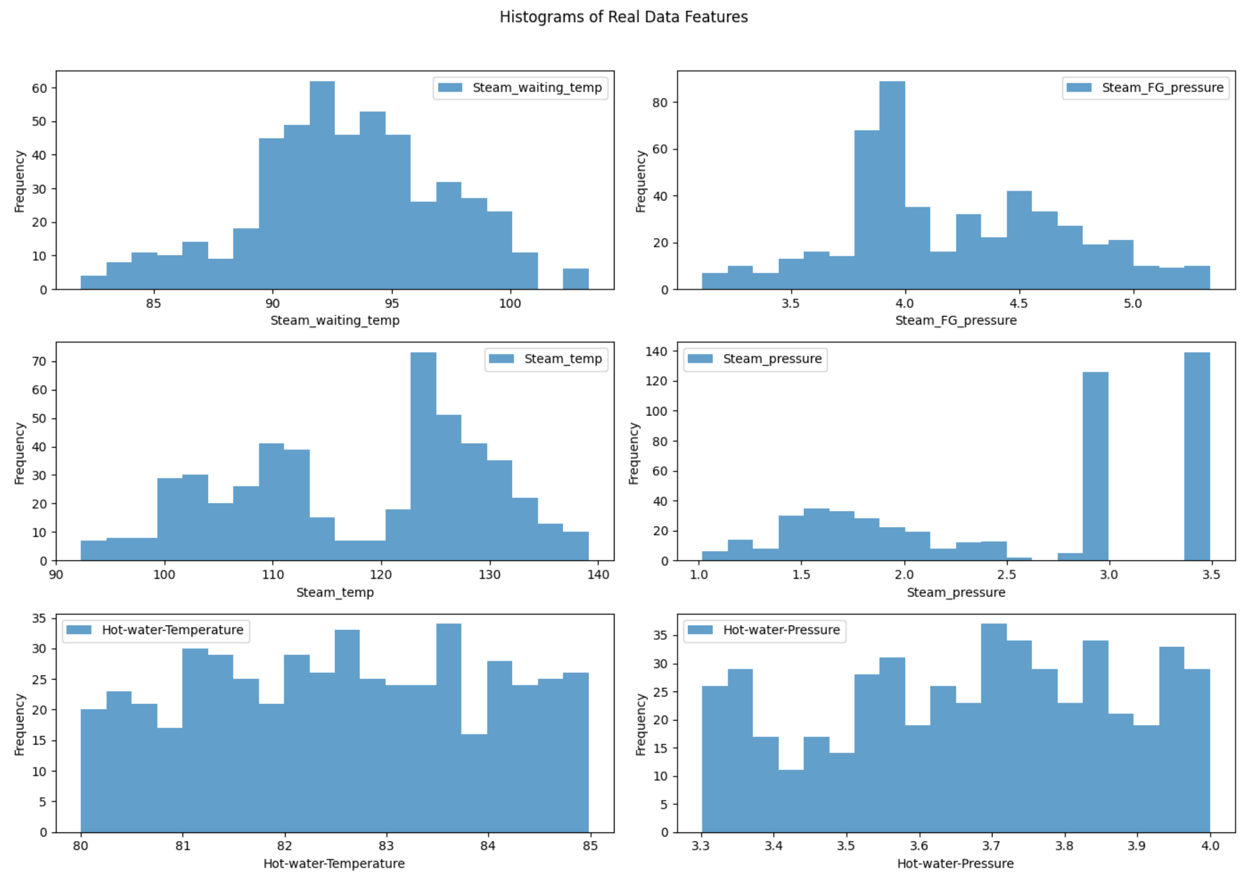


Figure 7: Histograms of Original Data Features

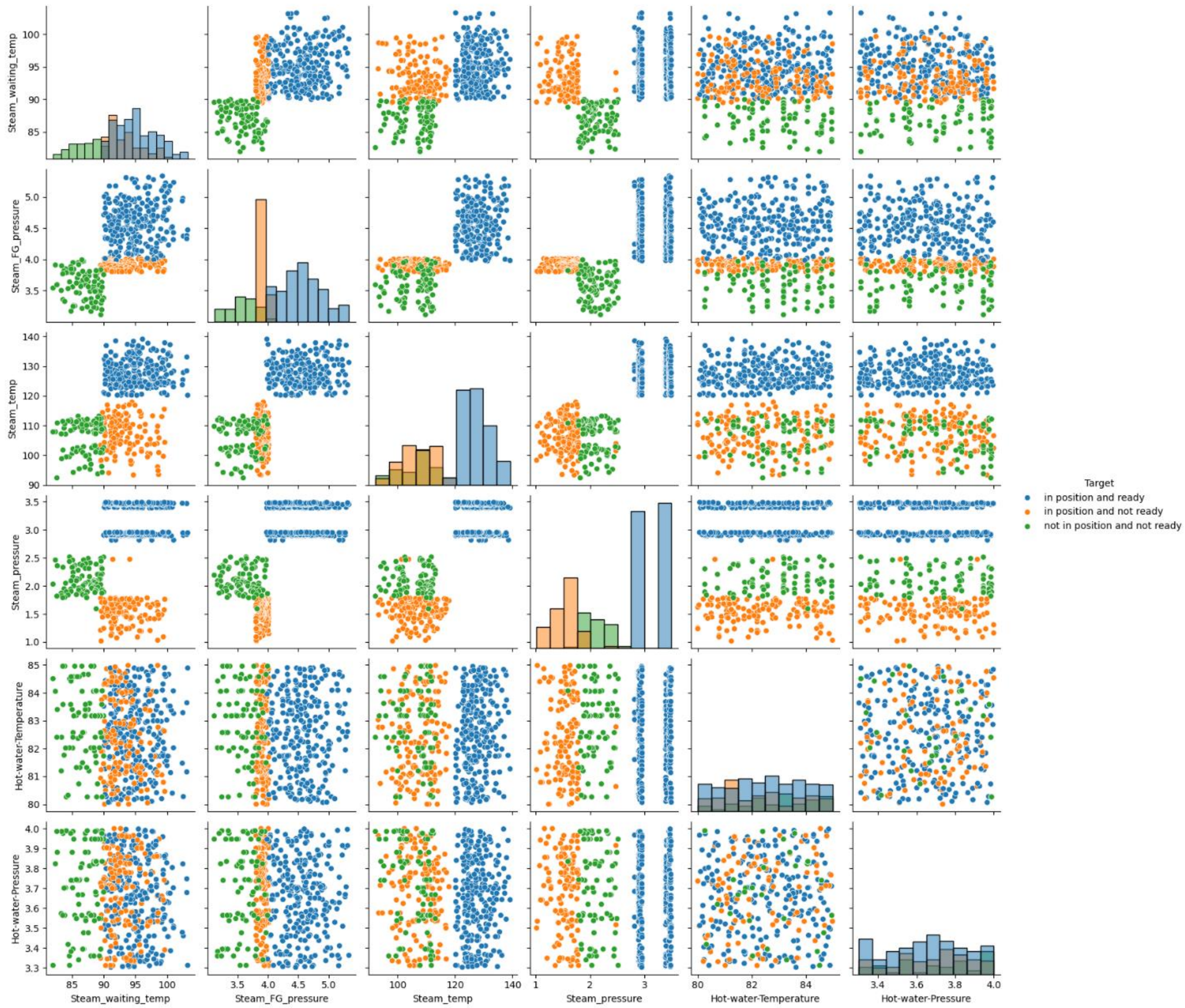


Figure 8: Pairplot of Original Data

4.3.2. Synthetic Data Generation Using GANs

Data Preparation for GAN

1. Loading Libraries: The first step involves importing the necessary libraries for data manipulation, model building, and training.
2. Loading and Preprocessing Real Data: The real sensor data is loaded into the environment and preprocessed. This involves handling missing values and normalizing the data.

GAN Architecture

1. Generator Network: The generator is designed to take random noise as input and generate synthetic data that mimics the real sensor data. The architecture includes multiple layers of dense (fully connected) layers with activation functions LeakyReLU.
2. Discriminator Network: The discriminator is a binary classifier that distinguishes between real and synthetic data. It also uses dense layers with LeakyReLU activations and a sigmoid activation in the output layer.
3. Compiling the GAN: The GAN model is compiled by combining the generator and discriminator. The discriminator is first trained separately on real and synthetic data. Then, the combined model is trained where the generator tries to fool the discriminator.

Training the GAN

1. Training Loop: The training loop involves alternating between training the discriminator and the generator. This process is repeated for a specified number of epochs. For each epoch, real data samples are selected, and the discriminator is trained to classify them as real, synthetic data samples are generated by the generator, and the discriminator is trained to classify them as fake, and the generator is trained to produce synthetic data that can fool the discriminator into classifying it as real.

Generating and Saving Synthetic Data

1. Post-Training Generation: Once the GAN is trained, it is used to generate a large volume of synthetic sensor data. This synthetic data is expected to have similar statistical properties to the real data.
2. Combining Real and Synthetic Data: The generated synthetic data is combined with the real data to form a comprehensive dataset. This augmented dataset is used for training machine learning models to predict the readiness state of Head-4.

Given the limited availability of sensor data, generating synthetic data was necessary to ensure a robust training dataset for the machine learning model. Generative Adversarial Networks (GANs) were employed for this purpose due to their ability to produce high-quality synthetic data that closely mimics real-world data. The process involves:

Data Preparation: Preparing the real-time data by normalizing the features and splitting it into training and validation sets.

Training the GAN: Utilizing real-time data to train the GAN. A GAN consists of two neural networks, a generator and a discriminator, which are trained simultaneously through an adversarial process. The generator aims to produce synthetic data that the discriminator cannot distinguish from real data, while the discriminator aims to correctly identify real versus synthetic data.

Generating Synthetic Data: Once the GAN is trained, it generates synthetic sensor readings that replicate the statistical properties and correlations observed in the real data. This synthetic data includes the six identified features and adheres to the patterns seen in the operational states of the kegs.

Validation and Refinement: Validating synthetic data against real data to ensure its accuracy and realism. Adjustments to the GAN may be made based on validation results to improve the quality of the generated data.

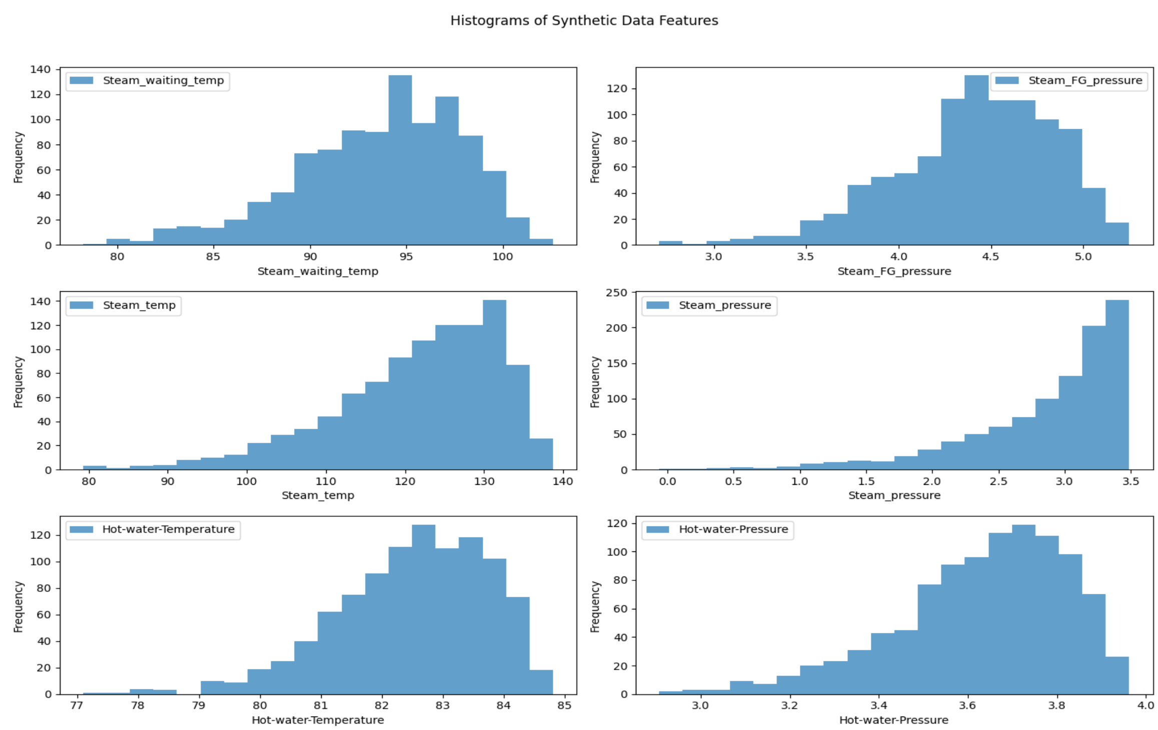


Figure 9: Histograms of Synthetic Data Features

- Steam FG entering pressure (Data points: 1000)
- Steam waiting temperature (Data points: 1000)
- Steam pressure (Data points: 1000)
- Steam temperature (Data points: 1000)
- Hot water temperature (Data points: 1000)
- Hot water pressure (Data points: 1000)

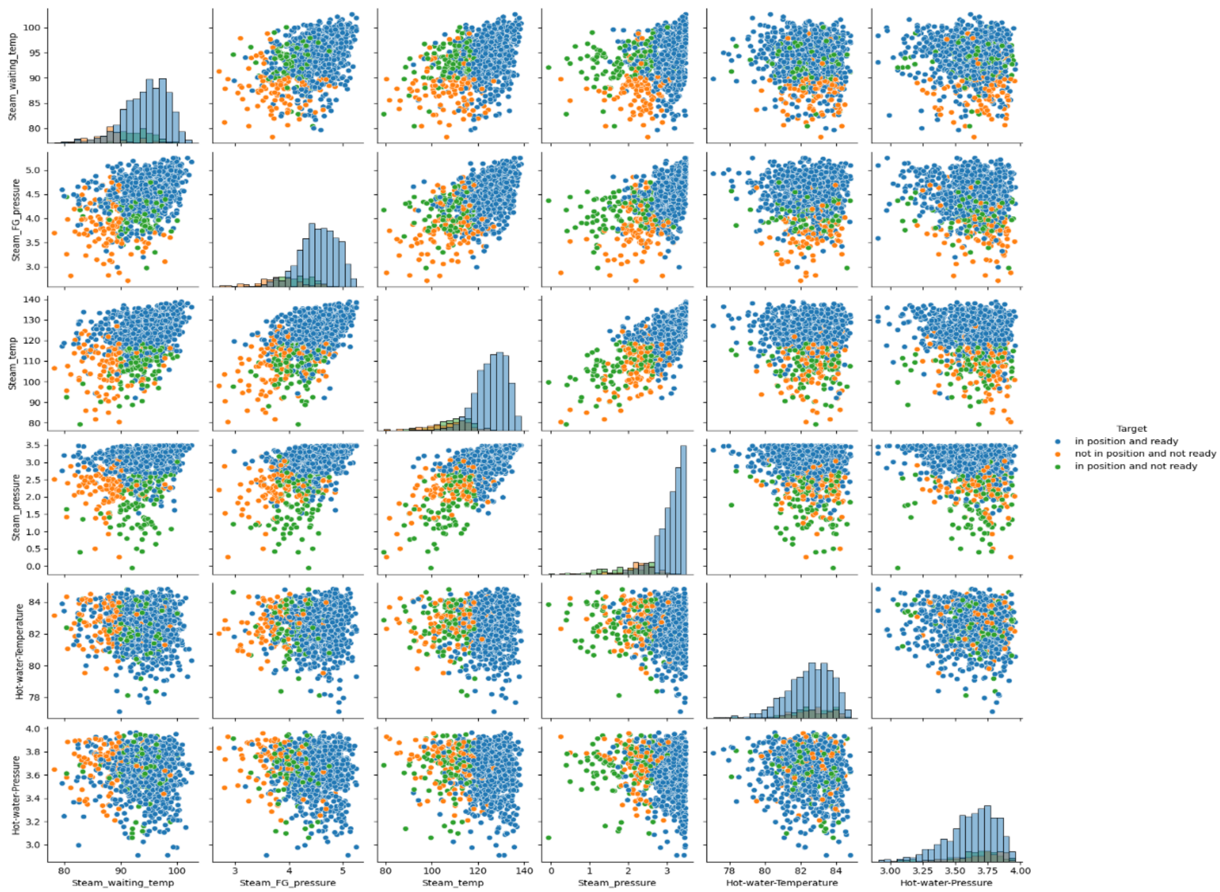


Figure 10: Pairplot of Synthetic Data

Hybrid Approach

To leverage the strengths of both real-time and synthetic data, a hybrid approach was adopted. Merging the 500 data points of each feature of real-time data with 500 data points of each feature of synthetic data to create a comprehensive training dataset. This combined dataset enhances the diversity and volume of data available for training the machine learning model, improving its ability to generalize to unseen data.

The combination of real-time data acquisition, synthetic data generation using GANs, and a hybrid approach ensures a robust and comprehensive dataset for training the predictive maintenance model. By integrating maintenance logs, operational parameters, and sensor readings, and augmenting them with high-quality synthetic data, BGI Ethiopia can effectively address the issue of keg rejections due to pressurized head failures, leading to improved operational efficiency and reduced wastage.

4.4. Model Development

The model development and evaluation section focus on the process of building, training, and assessing the performance of machine learning models for predicting the operational states of washing head in BGI Ethiopia's draft beer production line. This section includes the selection of models, data preparation, training, hyperparameter tuning, and performance evaluation. A supervised machine learning approach is implemented, with classification models, which represent the readiness state of the washing head, and are given as categorical values. The detection was made using six categories of input features: steam waiting temperature, steam entering pressure, steam temperature, steam pressure, hot water temperature, and hot water pressure.

The study employed advanced multiple tree models utilizing three ensemble learning methods, XGBoost (Extreme Gradient Boosting), AdaBoost (Adaptive Boosting), and Gradient Boosting. The main Python libraries used to run the three ensemble learning methods include xgboost for XGBoost, sklearn.ensemble for AdaBoost and Gradient Boosting. The dataset was split into 80% (training set) and 20% (testing set), ensuring that the models had sufficient data to learn from while also reserving a portion for evaluating their performance.

Feature Engineering: Identify and extract the relevant features for the model:

- Steam Waiting Temperature
- Steam Entering Pressure
- Steam Temperature
- Steam Pressure
- Hot Water Temperature
- Hot Water Pressure

Target Classes:

- In Position and Ready
- Not in Position and Not Ready
- In Position and Not Ready

Loading Libraries: The first step involves importing the necessary libraries for data manipulation, model building, and evaluation.

Loading and Preprocessing Data: The real sensor data is loaded and preprocessed. This involves handling missing values, encoding categorical features if any, normalizing the data, and splitting it into training and testing sets.

Hyperparameter Tuning with Grid Search: Hyperparameter Tuning with Grid Search involves conducting an exhaustive search over a predefined grid of hyperparameters to identify the optimal set that enhances model performance. Grid Search systematically evaluates every possible combination of hyperparameters, such as the number of estimators, learning rate, and maximum depth for a model. By performing cross-validation during this process, it ensures that the selected hyperparameters not only fit the training data well but also generalize effectively to unseen data. This rigorous tuning process is essential for maximizing the accuracy, precision, and overall performance of the model, ensuring it is well-equipped to predict the readiness state of the washing head in BGI Ethiopia's draft beer production line.

Training the Optimized Model: The best model identified by Grid Search, having undergone exhaustive hyperparameter tuning, is then utilized to train on the entire training dataset. This step ensures that the model benefits from the optimal hyperparameters found during the cross-validation process, thereby enhancing its learning capacity and generalization ability. By using the full training dataset, the model can capture a comprehensive understanding of the underlying patterns and relationships within the data, leading to improved performance when applied to new, unseen data. This thorough training process is crucial for maximizing the model's predictive accuracy and reliability in real-world applications, such as determining the readiness state of the washing head in BGI Ethiopia's draft beer production line.

Model Architectures

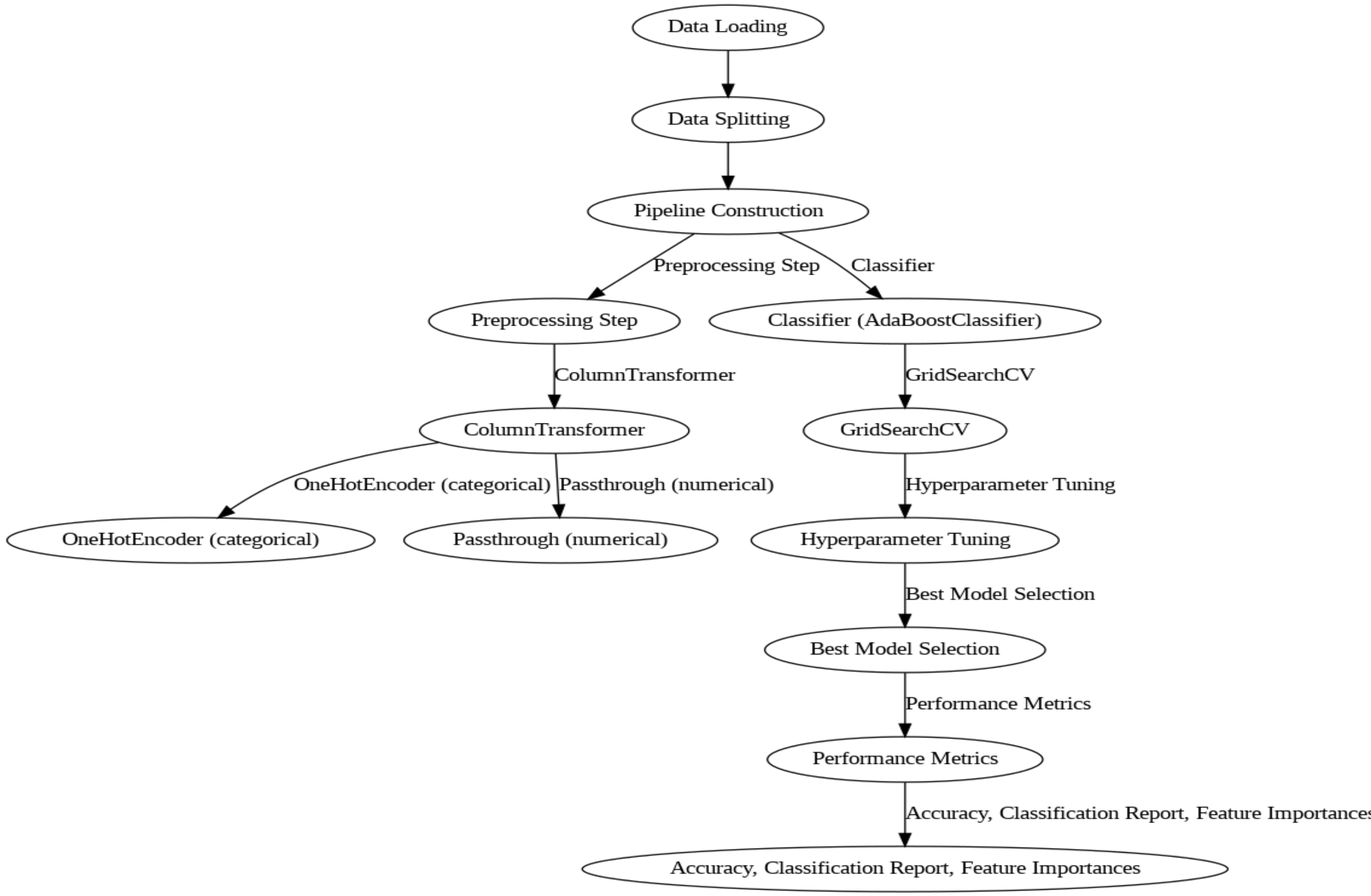


Figure 11: AdaBoost model architecture.

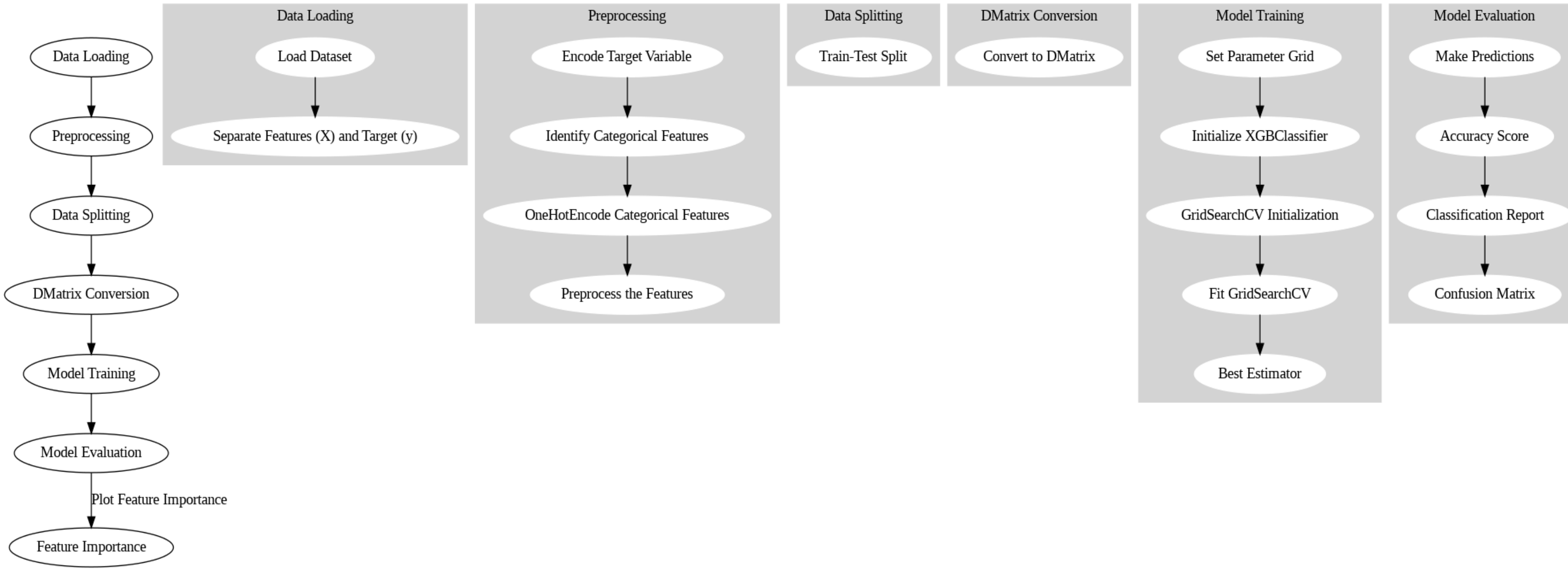


Figure 12: XGBoost model architecture.

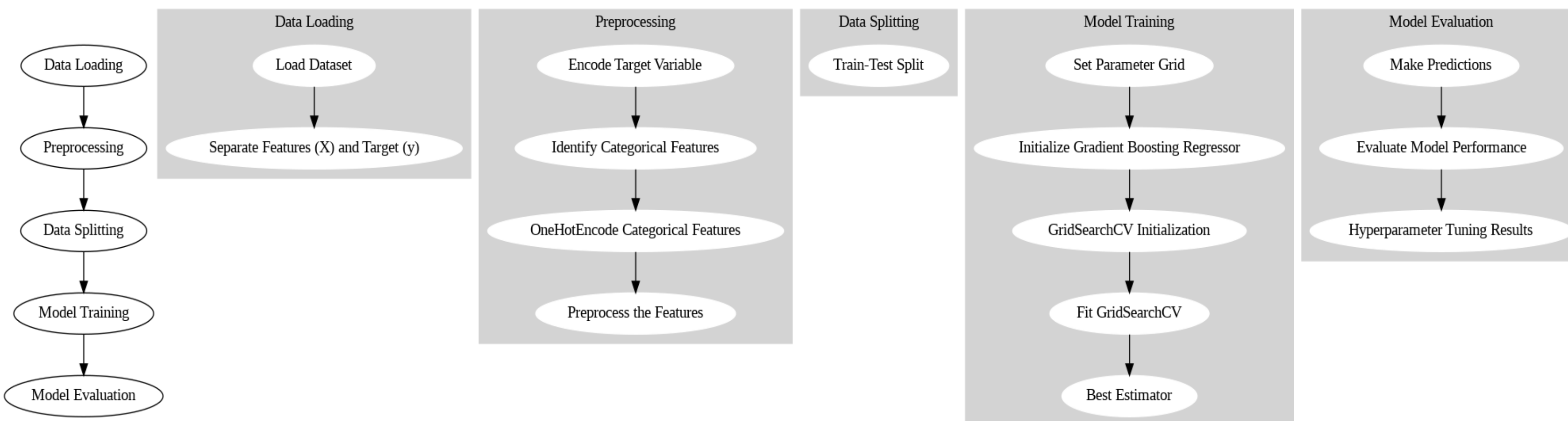


Figure 13:GradiantBoost model architecture.

4.5. Model Evaluation

The evaluation of the machine learning models employed a comprehensive set of metrics to assess their performance in predicting the operational states of washing heads within BGI Ethiopia's draft beer production line. The evaluation process aimed to provide insights into the models' effectiveness, generalization capabilities, and potential areas for improvement.

Accuracy: One key indicator of a model's general correctness in classifying instances is its accuracy. Out of all the instances in the testing dataset, it indicates the percentage of correctly classified instances. Better predictive performance is indicated by higher accuracy values.

Precision, Recall, and F1-Score: Out of all instances predicted as positive, precision quantifies the percentage of correctly predicted positive instances. It evaluates the model's resistance to false positives. The percentage of accurately predicted positive instances among all actual positive instances is determined by recall, which is also referred to as sensitivity. It assesses how well the model can locate every relevant instances.

The F1-Score offers a fair evaluation of a model's performance by combining recall and precision into a single statistic. It provides a thorough assessment of the model's efficacy and is expressed as the harmonic mean of recall and precision.

Confusion Matrix: The confusion matrix shows the number of true positive, true negative, false positive, and false negative occurrences, offering a thorough analysis of the model's predictions. It helps pinpoint possible areas for improvement and provides insights into the kinds of errors the model makes.

The area under the curve (AUC) and receiver operating characteristic curve (ROC): The trade-off between the true positive rate (sensitivity) and the false positive rate (1 - specificity) at various threshold values is depicted by the ROC curve. It shows how well the model can distinguish between positive and negative examples. The Area Under the Curve (AUC) quantifies the overall performance of the model by calculating the area under the ROC curve. A higher AUC value indicates better discrimination capability, with an AUC of 0.5 representing random chance and an AUC of 1.0 indicating perfect classification.

By evaluating the machine learning models using a combination of these metrics, a comprehensive understanding of their performance in predicting the operational states of washing head can be gain. These insights enable to assess the models' effectiveness, identify potential areas for improvement, and make informed decisions regarding their deployment in real-world applications.

4.6. Result

The results of this study demonstrate the effectiveness of using a hybrid approach, combining real-time sensor data and synthetic data, to develop a robust machine learning model for preventive maintenance in BGI Ethiopia's draft beer production line. The analysis of these results provides valuable insights into the performance of the models and their practical implications.

The implementation of machine learning models to predict the operational states of Head-4 in BGI Ethiopia's draft beer production line yielded promising results. By combining real-time sensor data with synthetic data generated through GANs, this study developed and evaluated three ensemble learning models: XGBoost, AdaBoost, and Gradient Boosting.

4.6.1. Model Performance Metrics

The performance of the three ensemble learning models XGBoost, AdaBoost, and Gradient Boosting was evaluated using several metrics, including accuracy, precision, recall, F1-score, confusion matrices, and ROC-AUC scores. The AdaBoost model emerged as the most accurate, achieving test accuracy of 83%, followed by Gradient Boosting with 82.5%, and XGBoost with 81.5%. This indicates that AdaBoost is highly effective in predicting the operational states of the kegs, reducing the incidence of false rejections significantly.

The models were evaluated using training accuracy, test accuracy, and cross-validation accuracy to assess their effectiveness and generalization capabilities, as shown in Figure A1, 2, and 3 (Appendix).

Table 5: Accuracy Matrix of Machine Learning Models

Model	Training Accuracy	Test Accuracy	Cross-Validation Accuracy
AdaBoost	84.25%	83%	82.25%
Gradient Boosting	94.6%	82%	82.7%
XGBoost	87.75%	81.5%	82.5%

The AdaBoost model shows consistent performance across all metrics, with training, test, and cross-validation accuracies closely aligned. The slight difference between training and test accuracies suggests that the model generalizes well to unseen data.

The Gradient Boosting model achieves perfect accuracy on the training data, indicating potential overfitting. However, the test and cross-validation accuracies are relatively high and consistent with each other, suggesting stable performance across different subsets of the data.

The XGBoost model demonstrates solid performance with training, test, and cross-validation accuracies that are relatively close. The test accuracy is slightly lower than that of the AdaBoost model, but the cross-validation accuracy indicates stable generalization.

Overall, all three models Adaboost, Gradient Boosting, and XGBoost show promising results in predicting the operational states of Head-4 in BGI Ethiopia's draft beer production line. The Adaboost model demonstrates consistent and reliable performance, while the Gradient Boosting model exhibits potential overfitting despite its high training accuracy. The XGBoost model strikes a balance between performance and generalization, with stable accuracy across different evaluation metrics.

The models were also evaluated using a variety of performance metrics, including precision, recall, F1-score, and ROC-AUC scores. The results are summarized in the blow table.

Table 6: Performance Metrics of Machine Learning Models

Models	Targets	Precision	Recall	F1-score	ROC-AUC
AdaBoost	In position and not ready	0.80	0.95	0.86	0.801
	In position and ready	0.88	0.84	0.86	
	Not in position and not ready	0.60	0.32	0.41	
Gradient Boosting	In position and not ready	0.83	0.94	0.88	0.801
	In position and ready	0.85	0.81	0.83	
	Not in position and not ready	0.54	0.37	0.44	
XGBoost	In position and not ready	0.81	0.94	0.87	0.783
	In position and ready	0.84	0.82	0.83	
	Not in position and not ready	0.56	0.26	0.36	

Precision, recall, and F1-score were used to further evaluate the models' performance in distinguishing between the three target classes: 'in position and ready', 'not in position and not ready', and 'in position and not ready'. The AdaBoost model demonstrated superior precision and recall across most classes, resulting in high F1-scores, particularly for the critical class 'In position and ready'. This high level of performance underscores the model's ability to correctly indicate Head-4 that are in position and ready for use, thus minimizing unnecessary rejections.

The ROC curves and corresponding AUC scores were used to assess the models' ability to discriminate between the positive and negative instances for each class. The AdaBoost and Gradient Boosting model achieved an AUC score of 0.801, indicating excellent discriminatory power, while the XGBoost models achieved AUC scores of 0.783. These results reinforce the conclusion that AdaBoost and Gradient Boosting provides the most reliable predictions.

4.6.2. Confusion Matrices

The confusion matrices provided a detailed breakdown of the models' predictions, highlighting areas where misclassifications occurred. For instance, the AdaBoost model shows fewer misclassifications compared to the other models, indicating its superior performance in accurately predicting the operational states of the washing head. The model showed minimal confusion between the 'Not in position and not ready' and 'in position and ready' classes, indicating its robustness in differentiating these states. In contrast, the XGBoost and GradiantBoost model exhibited more misclassifications between these classes, suggesting a lower reliability in predicting the readiness state of the kegs.

Table 7: AdaBoost Confusion Matrix

Actual \ Predicted	In position and not ready	In position and ready	Not in position and not ready
In position and not ready	70	4	0
In position and ready	13	90	4
Not in position and not ready	5	8	6

Table 8: Gradient Boosting Confusion Matrix

Actual \ Predicted	In position and not ready	In position and ready	Not in position and not ready
In position and not ready	74	4	1
In position and ready	14	83	5
Not in position and not ready	1	11	7

Table 9: XGBoost Confusion Matrix

Actual \ Predicted	In position and not ready	In position and ready	Not in position and not ready
In position and not ready	74	5	0
In position and ready	14	84	4
Not in position and not ready	3	11	5

These matrices provide a clear view of the models' ability to correctly classify each state and highlight where misclassifications occur.

4.6.3. Feature Importance

An analysis of feature importance of all models revealed that steam temperature and steam pressure were the most significant predictors of head 4 readiness. These features had the highest impact on the models' predictions, indicating that fluctuations in these parameters are critical in determining the operational state of the washing head. This insight is valuable for targeted maintenance strategies, emphasizing the need to monitor and control these parameters closely. The importance scores for each feature as determined by the models are illustrated in below.

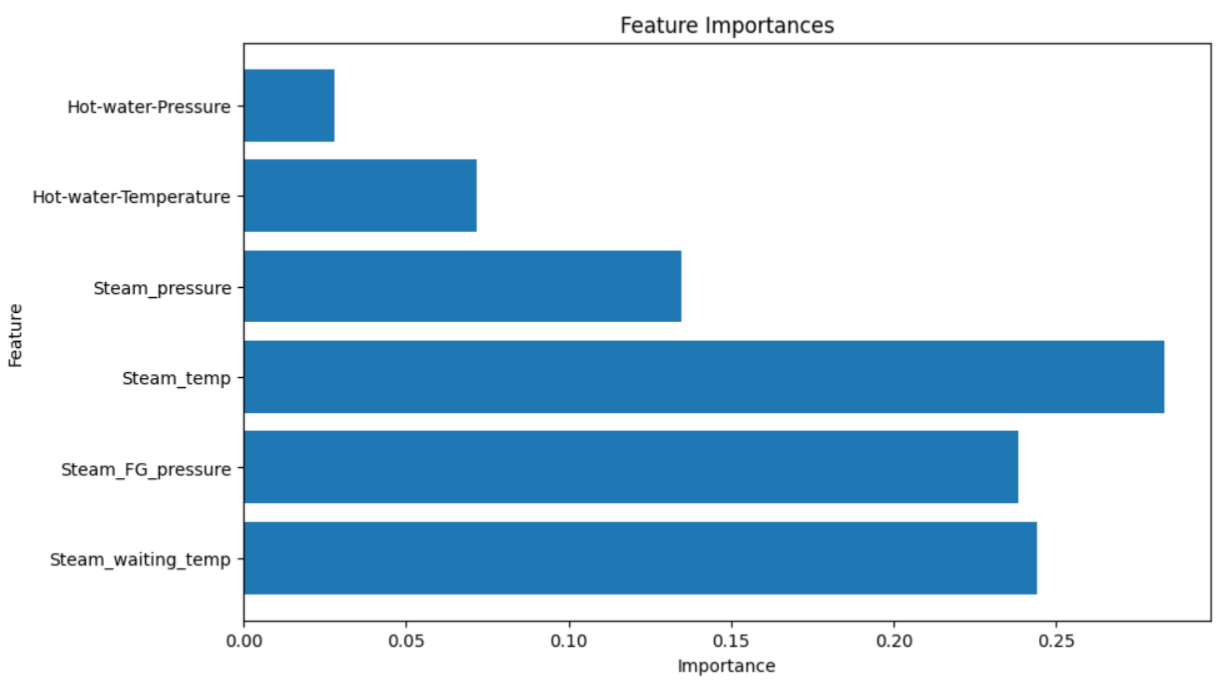


Figure 14: Feature Importance for AdaBoost model

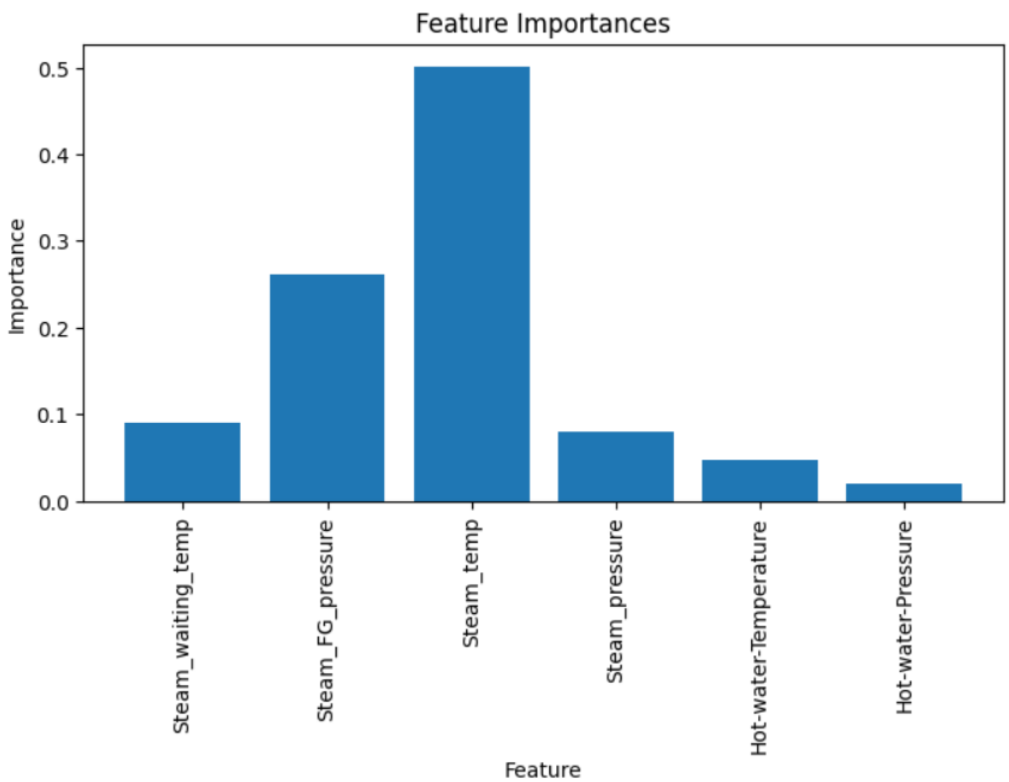


Figure 15: Feature Importance for GradientBoost model

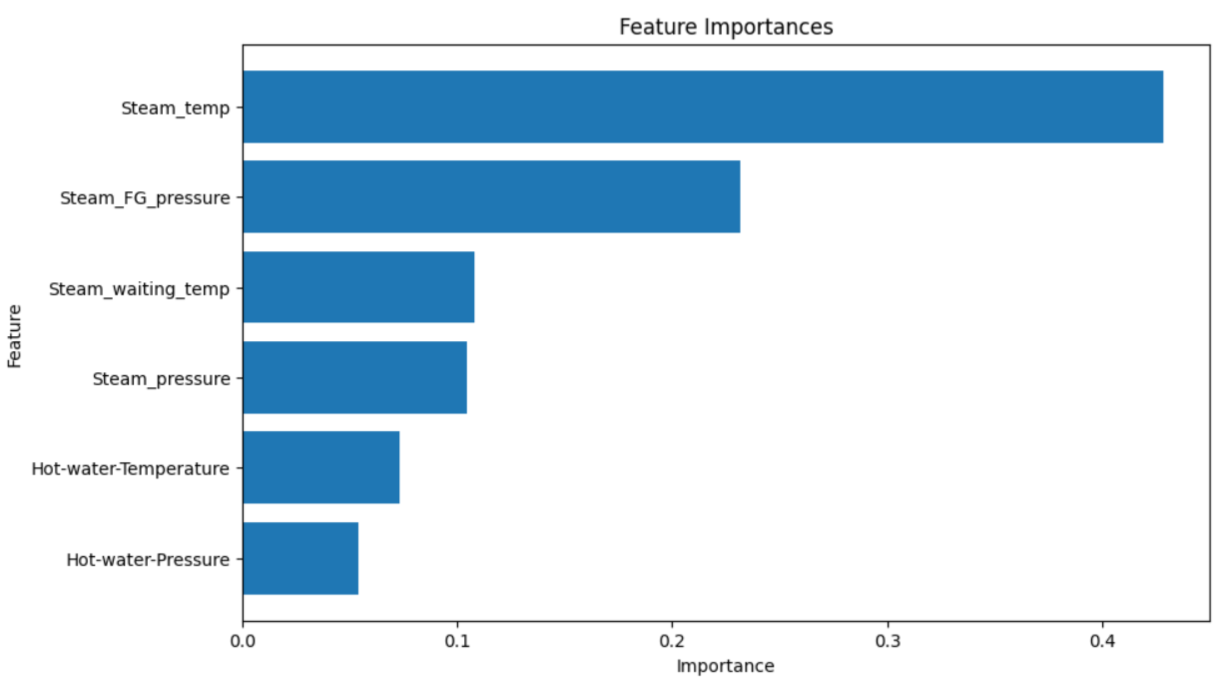


Figure 16: Feature Importance for XGBoost model

4.7. Discussion

The integration of the predictive maintenance model using the AdaBoost algorithm into BGI Ethiopia's maintenance framework represents a significant advancement in addressing the operational challenges related to Head-4. This section discusses the practical integration of the model into the existing maintenance framework and highlights its implications for maintenance decision-making and key performance indicators (KPIs).

BGI Ethiopia currently follows a scheduled preventive maintenance (PM) plan for the draft beer filler machine, Lambrecht Slimline monobloc 50. The PM schedule includes routine tasks such as inspections, cleaning, and maintenance of various components at weekly, monthly, and yearly intervals. Despite this systematic approach, the brewery still experiences significant operational disruptions due to keg rejections, particularly at Head 4. These rejections are primarily caused by fluctuations in steam pressure and temperature, condensation issues, and system lag.

4.7.1. Enhancing the Current Scheduled PM with Predictive Model

To address these issues, the integration of a predictive maintenance model can complement and enhance the existing PM schedule. The predictive model, using machine learning algorithms like AdaBoost, will forecast potential failures and alert the maintenance team before keg rejections occur. This proactive approach allows for timely interventions, reducing downtime and improving overall efficiency.

The current scheduled preventive maintenance (PM) at BGI Ethiopia is structured to include weekly, monthly, and yearly tasks, meticulously planned to cover all aspects of the draft beer filler machine’s operation. These tasks range from routine inspections and cleaning to more comprehensive checks and component replacements. Despite this well-structured schedule, the maintenance logs reveal a persistent issue, as Table 3 shows daily maintenance tasks are often performed reactively, triggered by machine breakdowns and keg rejections rather than planned interventions. This reactive maintenance approach results in significant production disruptions, increased downtime, and economic losses due to wasted materials and labor.

The introduction of a predictive maintenance model offers a transformative solution to these challenges. Unlike the traditional PM schedule, which operates on fixed intervals, the predictive model leverages real-time data to forecast potential failures and maintenance needs. Specifically for Head 4, which is crucial for the sterilization process but prone to issues due to steam supply fluctuations and condensation, the predictive model will provide timely alerts before keg rejections occur. By predicting the operational state of Head 4, the model enables maintenance teams to perform necessary interventions proactively, thus preventing unnecessary rejections and avoiding the need for unplanned daily maintenance.

Integrating the predictive maintenance model into the existing PM framework will bridge the gap between scheduled and reactive maintenance. The predictive insights will allow maintenance teams to optimize their efforts, ensuring that interventions are made precisely when needed to maintain optimal machine performance. This proactive approach will significantly reduce unplanned downtime, enhance production efficiency, and minimize the rejection of good kegs. In essence, the predictive maintenance model will transform the maintenance process at BGI Ethiopia, providing a data-driven approach that complements and enhances the traditional PM schedule, ultimately leading to more reliable and efficient operations.

How to Integrate the AdaBoost Model with the Current System

After developing the AdaBoost predictive maintenance model, it is essential to seamlessly integrate it into the existing maintenance system at BGI Ethiopia. This integration involves the following steps:

Data Flow and Integration: The predictive model requires continuous data inputs from various sensors and the CMMS. The integration process includes setting up a real-time data acquisition system that feeds the AdaBoost model with up-to-date operational data from Head 4 and other relevant components or selected features.

Model Deployment: Deploy the AdaBoost model on a server or cloud platform that can handle computational requirements and provide real-time predictions. The system should be robust enough to process incoming data and produce timely predictions about potential failures or maintenance needs.

Alert System Integration: An alert system needs to be set up to notify maintenance personnel of the predictions. This system can be integrated with existing communication tools used by the maintenance team, ensuring they receive timely alerts to perform necessary actions.

Maintenance Scheduling Adjustments: Based on the predictions generated by the AdaBoost model, the maintenance schedule can be dynamically adjusted. Instead of relying solely on the fixed weekly, monthly, and yearly schedules, the system can prompt maintenance actions when the model predicts an impending issue, thus transitioning from a purely scheduled maintenance approach to a predictive maintenance approach.

Training and Adaptation: Train the maintenance team on how to interpret and act on the predictions provided by the AdaBoost model. This includes understanding the model's output, the significance of predicted issues, and the required maintenance actions.

4.7.2. Implications for Predictive Maintenance

The AdaBoost model demonstrated superior performance in predicting the operational state of Head-4 compared to other models. The model's accuracy, reflected in the low misclassification rate in the confusion matrices, directly translates to fewer false positives and negatives. Its high predictive accuracy ensures potential issues are identified with greater precision, allowing to stop the false keg rejection. And this capability based on reliable predictions minimizes false alarms, reducing unnecessary maintenance tasks and resource wastage. The model's robust performance underscores its reliability in maintaining the sterilization process, which is critical for reducing keg rejections.

The feature importance analysis underscores the critical role of steam temperature and steam pressure in determining the readiness state of the Head-4. This insight can guide maintenance efforts to focus on these parameters, ensuring that they are maintained within optimal ranges to reduce the likelihood of keg rejections.

I. Downtime Reduction

The downtime due to Head-4 highlighted a significant reduction in unplanned maintenance events. With the AdaBoost model predicting failures before they occur, scheduled maintenance can be performed during non-peak hours, reducing the impact on production. Currently the maintenance task after 13-18 keg rejection takes almost 2 Hrs. including the cooling process because the task is performed after the filler machine runs for 0.33 Hr. This 0.33Hr. also consider as wasted because of the rejection the filler machine is not performing the filling process.

The proposed AdBoost model will alarm the operators before head 4 started rejection, which means when the filler machine starts running. Therefore, BGI can reduce the time for cooling the machine to perform the maintenance task and the 0.33Hr. of false keg rejection. This result is a smoother production process and higher overall equipment availability. By predicting issues before they escalate, the model helps avoid sudden breakdowns, ensuring continuous operation and reducing downtime.

The current system experiences an average of 1 hour of downtime per day due to Head 4 issues, and the model can predict and prevent 50% of these issues, the estimated downtime reduction would be:

Downtime reduction per day = 1 hour × 0.50 = 0.5 hours (For cooling the machine)

Over a year, this results in a substantial reduction per filler machine:

Annual downtime reduction = 0.5 hours/day × 365 days = 182.5 hours/year

Annual wasted time to process rejected kegs = 0.33 hour/day × 365 days = 120.45 hours/year

Therefore, the total annual estimated saved time per filler machine is **302.95 hours.**

II. Avoiding Good Keg Rejection

The AdaBoost model accurately predicts when Head-4 is likely to reject kegs due to steam supply issues, allowing operators to intervene before the rejection occurs. This proactive approach prevents the rejection of kegs that are otherwise in good condition, saving valuable resources and reducing waste. The analysis shows a significant reduction in the number of good kegs being rejected. By predicting the operational state of Head-4 accurately, the model ensures that only kegs that genuinely require rejection are discarded. Therefore, the factory avoids 50 false keg rejection per day from one filler machine.

III. Improved Production Throughput

Accurate predictions and timely interventions ensure the consistent operation of Head-4, reducing the number of rejected kegs and enhancing overall production throughput. This consistency allows the brewery to meet its production targets more effectively, optimizing the production process and increasing output. The consistent operation of Head-4, as predicted by the model, has led to a noticeable increase in production throughput. The reduction in false rejections ensures more kegs are processed correctly, improving the overall efficiency of the production line.

Lower Rejection Rates

The AdaBoost model's ability to accurately predict when Head-4 will fail ensures kegs are only rejected for legitimate reasons, significantly lowering the rejection rate. This reduction in false rejections leads to better resource utilization and cost efficiency, as fewer materials and less energy are wasted. This leads to a significant reduction in the number of false rejections, improving the rejection rate KPI.

Financial Benefits

The reduction in downtime, increased production throughput, and lower rejection rates all contribute to substantial cost savings. The predictive maintenance model helps optimize maintenance budgets by focusing efforts on preventing critical issues rather than reacting to failures. The initial investment in developing and implementing the predictive maintenance model is offset by the long-term financial benefits, including higher production efficiency.

The integration of the AdaBoost-based predictive maintenance model into BGI Ethiopia's maintenance framework offers significant improvements in maintenance decision-making and operational performance. By enhancing predictive accuracy, reducing downtime, improving production throughput, and lowering rejection rates, the model provides tangible benefits that directly impact the brewery's key performance indicators and overall financial health.

Model Implementation

Implementing the AdaBoost model in a real-time setting would involve integrating it with the existing data collection and processing systems at BGI Ethiopia. The model can provide real-time predictions of head-4 readiness, allowing for timely interventions and proactive maintenance actions. This could significantly enhance operational efficiency, reduce wastage, and improve overall productivity.

5. Conclusion and Recommendation

5.1. Conclusion

This study developed machine learning models to predict the operational states of kegs in BGI Ethiopia's draft beer production line, aiming to minimize false rejections and enhance maintenance processes. By leveraging both real-time sensor data and synthetic data generated through Generative Adversarial Networks (GANs), three ensemble learning models AdaBoost, Gradient Boosting, and XGBoost were tested for their effectiveness.

The results showed that the AdaBoost model achieved the highest and most consistent performance, with a test accuracy of 83% and closely aligned cross-validation accuracy of 82.25%. This indicates that AdaBoost generalizes well and is effective in predicting Head-4 readiness. The Gradient Boosting model, while achieving a perfect training accuracy of 100%, exhibited signs of overfitting, with a test accuracy of 82.5% and cross-validation accuracy of 82.6%. This suggests that while powerful, the model may require further regularization. The XGBoost model demonstrated a balanced performance, with training, test, and cross-validation accuracies of 87.75%, 81.5%, and 82.5%, respectively, indicating good generalization but slightly lower effectiveness compared to AdaBoost.

The current maintenance practices at BGI Ethiopia, although systematically planned with weekly, monthly, and yearly schedules, fail to address the daily operational challenges faced by the draft beer filler machines, particularly with Head 4. The reactive maintenance approach leads to frequent downtime and inefficiencies due to keg rejections and machine breakdowns. This study has identified the critical need for a predictive maintenance model to enhance the existing preventive maintenance framework.

The implementation of a predictive maintenance model using real-time data to forecast potential failures and maintenance needs for Head 4 can significantly reduce the occurrence of unnecessary keg rejections and minimize unplanned downtime. By accurately predicting the operational state of Head 4, the model enables timely interventions that prevent disruptions, optimize resource usage, and improve overall production efficiency. The integration of predictive maintenance into the existing PM schedule will not only address the immediate issues but also provide a sustainable solution for maintaining optimal machine performance and operational reliability.

5.2. Recommendation

Based on the findings and the successful implementation of the predictive maintenance model for Head-4 in BGI Ethiopia's draft beer production line, several key recommendations are proposed to further enhance maintenance practices and operational efficiency.

Firstly, it is crucial for BGI Ethiopia to continue leveraging AI-driven predictive maintenance across other critical components of the production line. The success with Head-4 demonstrates the potential benefits of predictive maintenance models, suggesting that similar approaches could be applied to other machinery and processes. By expanding the use of predictive maintenance, BGI can further reduce downtime, optimize resource allocation, and improve overall production throughput.

Additionally, the integration of real-time monitoring systems should be prioritized. Real-time data acquisition and analysis are essential for the continuous improvement of the predictive maintenance model. Investing in advanced sensor technologies and data infrastructure will provide the necessary foundation for real-time monitoring, enabling more accurate and timely predictions. This will enhance the responsiveness of the maintenance team and ensure that potential issues are addressed before they escalate.

Future Work

Future research should focus on expanding the dataset with more extensive real-time sensor data and exploring additional features that may influence washing head readiness. While the hybrid approach of combining real and synthetic data has proven effective, it is important to acknowledge the limitations associated with synthetic data generation. Future work could focus on enhancing the realism of synthetic data and exploring additional features that may influence not only washing heads but also filling heads readiness. Furthermore, expanding the dataset with more extensive real-time sensor data could further improve model accuracy and reliability.

Furthermore, collaboration with AI and machine learning experts should be encouraged. Continuous engagement with technology specialists will facilitate the refinement and optimization of the predictive maintenance models. This collaboration can lead to the development of more sophisticated algorithms, improved accuracy in predictions, and the ability to address complex maintenance challenges more effectively.

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Appendix

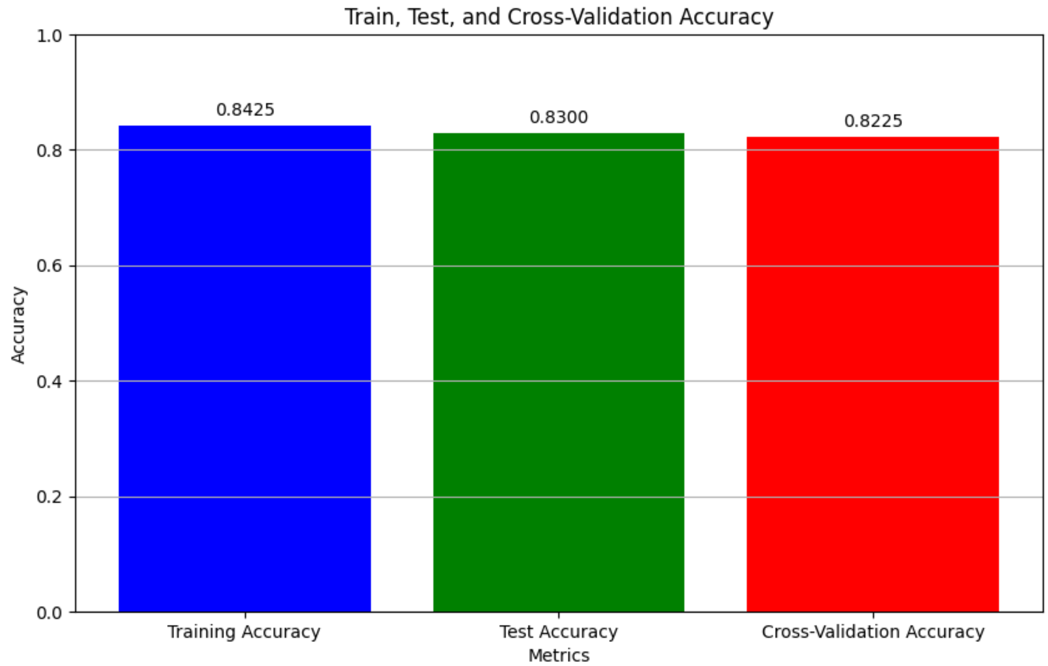

Figure A 1: Accuracy of AdaBoost Model

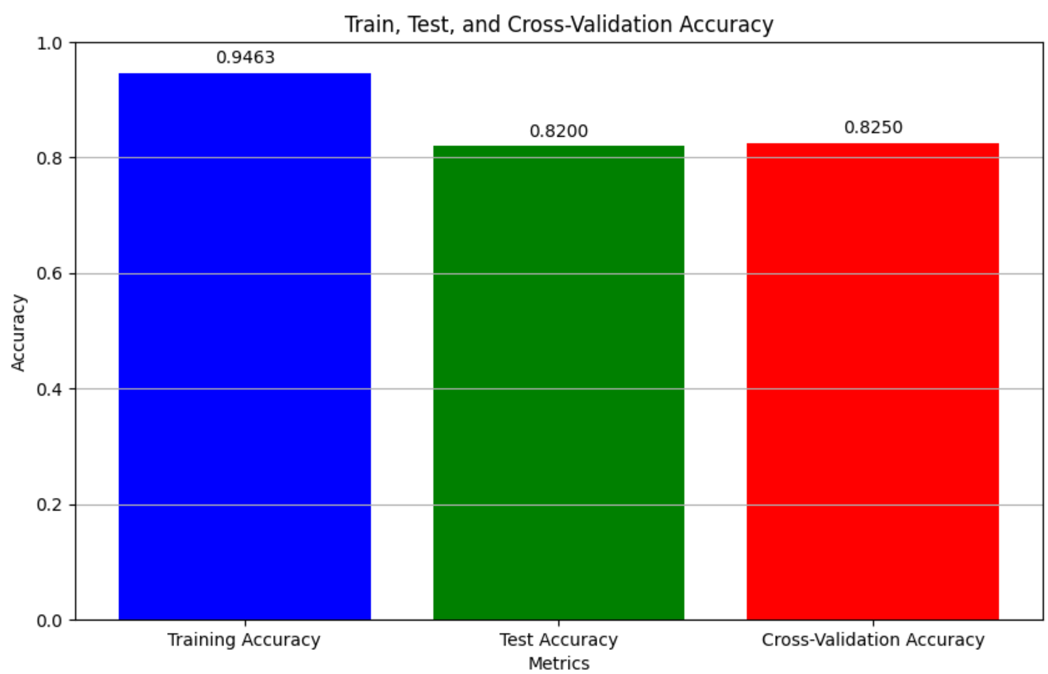

Figure A 2: Accuracy of GradiantBoost Model

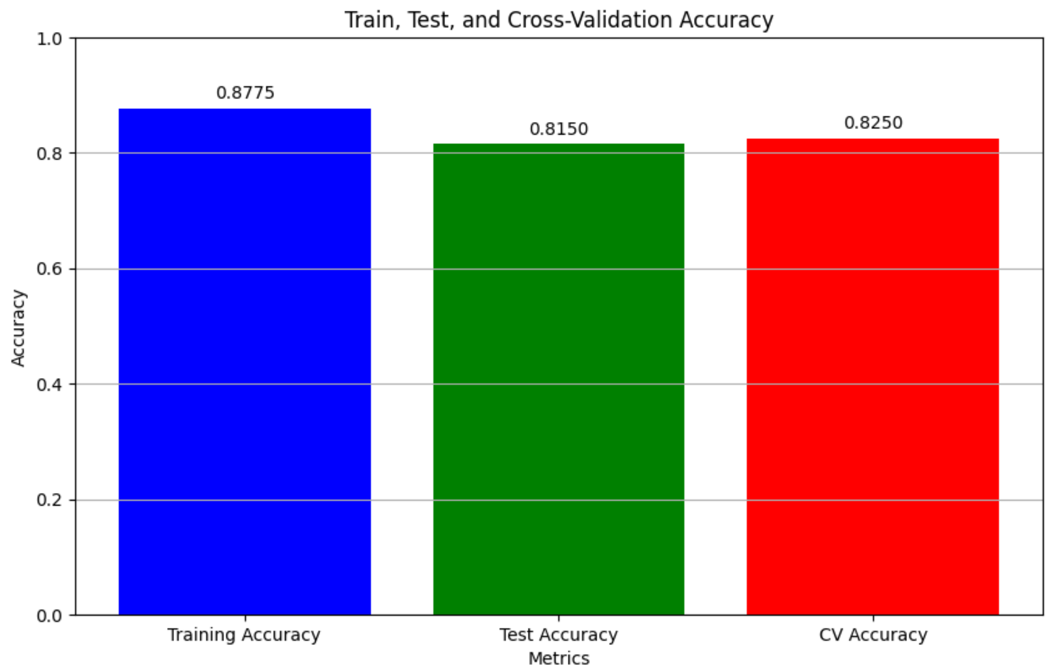

Figure A 3: Accuracy of XGBoost Model

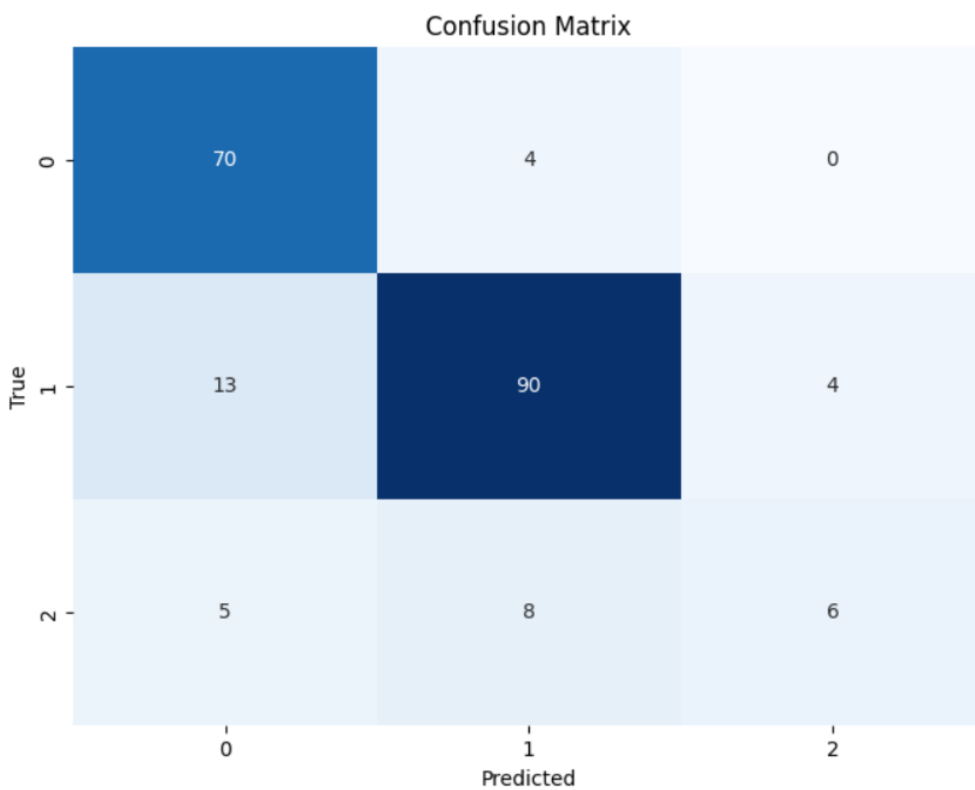

Figure A 4: Confusion Matrices Heatmap for AdaBoost

Table A 1: Preventive Maintenance Schedule of BGI Ethiopia for the Draft beer filler machine

BGI Ethiopia	**Preventive Maintenance Checklist**			**Equipment Manufacturer**	LAMBRECHTS	
				Equipment Model		
Site	Addis Ababa			**Analytic Center**	Bottling	
Equipment code	0096-00020			**Equipment Description**	Filler	
Item description	**Routine family**	**Task description**	**Estimated time**	**Period**	**Freq.**	
Keg Pusher Cylinder	Inspection	check the keg pusher cylinder for leakage. Tighten the mounting bolts.	8	WEEK	1	
Keg Pusher cylinder Reed switches	Inspection	check the keg pusher cylinder reed switches, connectors distributors, ground system.	8	WEEK	1	
Keg pusher Damper	Inspection	check the condition of keg pusher dampers for wear	5	WEEK	1	
Head1 Pressing Cylinder	Inspection	check the Head 1 pressing cylinder for leakage. Tighten the mounting bolts.	5	WEEK	1	
Head1 Pressing Cylinder Reed Switches	Inspection	check the Head 1 pressing cylinder reed switches, connectors distributors, ground system.	5	WEEK	1	
Head1 Pressing Cylinder top damper	Inspection	check the condition of Head1 Pressing Cylinder top damper for wear	5	WEEK	1	
Head1 Pressing Cylinder bottom dampers	Inspection	check the condition of Head1 Pressing Cylinder bottom dampers 3no's for wear	5	WEEK	1	
Head1 Bottom Cylinder	Inspection	check the Head 1 bottom cylinder for leakage. Tighten the mounting bolts.	5	WEEK	1	
Head1 Bottom Cylinder proximity sensor	Inspection	Inspect Head1 Bottom Cylinder proximity sensor, connectors distributors, ground system. Clean if found dirty	5	WEEK	1	
Head 1	Inspection	Inspect the head1 for leakage and the seal for wear	5	WEEK	1	
Head 1	Inspection	service the head1 with service kit as per OEM procedure	120	80000 Kegs	1	
Head 1 Leftover drain points	Inspection	Inspect the head1 leftover drain points 3no's for leakage	5	WEEK	1	
Head1 Inlet Sterile Air media valve	Inspection	Inspect the Head1 inlet Sterile air media valve for leakage	5	WEEK	1	
Head1 Inlet Sterile Air media valve	Inspection	Service the Head1 inlet Sterile air media valve as per OEM procedure	60	30000 Kegs	1	
Head1 Inlet Caustic A media valve	Inspection	Inspect the head1 inlet Caustic A media valve for leakage	5	WEEK	1	
Head1 Inlet Caustic A media valve	Inspection	Service the head1 inlet Caustic A media valve as per OEM procedure	60	30000 Kegs	1	
Head1 Inlet Mixed Water media valve	Inspection	Inspect the head1 inlet Mixed water media valve for leakage	5	WEEK	1	
Head1 Inlet Mixed Water media valve	Inspection	Service the head1 inlet mixed water media valve as per OEM procedure	60	30000 Kegs	1	
Head1 Inlet Low Flow media valve	Inspection	Inspect the head1 inlet low flow media valve for leakage	5	WEEK	1	
Head1 Inlet Low Flow media valve	Inspection	Service the head1 inlet low flow media valve as per OEM procedure	60	30000 Kegs	1	
Head1 Inlet Pressure sensor	Inspection	Inspect head1 inlet pressure sensor, connectors distributors, ground system. Clean if found dirty	5	WEEK	1	
Head1 Outlet Beer Recuperation media valve	Inspection	Inspect the head1 outlet Beer Recuperation media valve for leakage	5	WEEK	1	

Head1 Outlet Beer Recuperation media valve	Inspection	Service the head1 outlet Beer Recuperation media valve as per OEM procedure	60	30000 Kegs	1
Head1 Outlet Drain media valve	Inspection	Inspect the head1 outlet Drain media valve for leakage	5	WEEK	1
Head1 Outlet Drain media valve	Inspection	Service the head1 outlet Drain media valve as per OEM procedure	60	30000 Kegs	1
Head1 Outlet Caustic A media valve	Inspection	Inspect the head1 outlet Caustic A media valve for leakage	5	WEEK	1
Head1 Outlet Caustic A media valve	Inspection	Service the head1 outlet Caustic A media valve as per OEM procedure	60	30000 Kegs	1
Head1 Outlet Caustic A return media valve	Inspection	Inspect the head1 outlet Caustic A return media valve for leakage	5	WEEK	1
Head1 Outlet Caustic A return media valve	Inspection	Service the head1 outlet Caustic A return media valve as per OEM procedure	60	30000 Kegs	1
Head1 Outlet Flow Switch	Inspection	Inspect head1 Outlet Flow switch , connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Head2 Pressing Cylinder	Inspection	check the Head2 pressing cylinder for leakage. Tighten the mounting bolts.	5	WEEK	1
Head2 Pressing Cylinder Reed Switches	Inspection	check the Head2 pressing cylinder reed switches, connectors distributors, ground system.	5	WEEK	1
Head2 Pressing Cylinder top damper	Inspection	check the condition of Head2 Pressing Cylinder top damper for wear	5	WEEK	1
Head2 Pressing Cylinder bottom dampers	Inspection	check the condition of Head2 Pressing Cylinder bottom dampers 3no's for wear	5	WEEK	1
Head2 Bottom Cylinder	Inspection	check the Head2 bottom cylinder for leakage. Tighten the mounting bolts.	5	WEEK	1
Head2 Bottom Cylinder proximity sensor	Inspection	Inspect Head2 Bottom Cylinder proximity sensor, connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Head 2	Inspection	Inspect the head2 for leakage and the seal for wear	5	WEEK	1
Head 2	Inspection	service the head2 with service kit as per OEM procedure	120	80000 Kegs	1
Head 2 Leftover drain points	Inspection	Inspect the head2 leftover drain points 3no's for leakage	5	WEEK	1
Head2 Inlet Sterile Air media valve	Inspection	Inspect the Head2 inlet Sterile air media valve for leakage	5	WEEK	1
Head2 Inlet Sterile Air media valve	Inspection	Service the Head2 inlet Sterile air media valve as per OEM procedure	60	30000 Kegs	1
Head2 Inlet Caustic B media valve	Inspection	Inspect the head2 inlet Caustic B media valve for leakage	5	WEEK	1
Head2 Inlet Caustic B media valve	Inspection	Service the head2 inlet Caustic B media valve as per OEM procedure	60	30000 Kegs	1
Head2 Inlet Low Flow media valve	Inspection	Inspect the head2 inlet low flow media valve for leakage	5	WEEK	1
Head2 Inlet Low Flow media valve	Inspection	Service the head2 inlet low flow media valve as per OEM procedure	60	30000 Kegs	1
Head2 Outlet Drain media valve	Inspection	Inspect the head2 outlet Drain media valve for leakage	5	WEEK	1
Head2 Outlet Drain media valve	Inspection	Service the head2 outlet Drain media valve as per OEM procedure	60	30000 Kegs	1
Head2 Outlet Caustic B media valve	Inspection	Inspect the head2 outlet Caustic B media valve for leakage	5	WEEK	1
Head2 Outlet Caustic B media valve	Inspection	Service the head2 outlet Caustic B media valve as per OEM procedure	60	30000 Kegs	1
Head2 Outlet Caustic A return media valve	Inspection	Inspect the head2 outlet Caustic A return media valve for leakage	5	WEEK	1
Head2 Outlet Caustic A return media valve	Inspection	Service the head2 outlet Caustic A return media valve as per OEM procedure	60	30000 Kegs	1
Head2 Outlet Caustic B return media valve	Inspection	Inspect the head2 outlet Caustic B return media valve for leakage	5	WEEK	1
Head2 Outlet Caustic B return media valve	Inspection	Service the head2 outlet Caustic B return media valve as per OEM procedure	60	30000 Kegs	1

Head2 Outlet Flow Switch	Inspection	Inspect head2 Outlet Flow switch , connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Head2 Outlet Pressure sensor	Inspection	Inspect head2 outlet pressure sensor, connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Head3 Pressing Cylinder	Inspection	check the Head3 pressing cylinder for leakage. Tighten the mounting bolts.	5	WEEK	1
Head3 Pressing Cylinder Reed Switches	Inspection	check the Head3 pressing cylinder reed switches, connectors distributors, ground system.	5	WEEK	1
Head3 Pressing Cylinder top damper	Inspection	check the condition of Head3 Pressing Cylinder top damper for wear	5	WEEK	1
Head3 Pressing Cylinder bottom dampers	Inspection	check the condition of Head3 Pressing Cylinder bottom dampers 3no's for wear	5	WEEK	1
Head3 Bottom Cylinder	Inspection	check the Head3 bottom cylinder for leakage. Tighten the mounting bolts.	5	WEEK	1
Head3 Bottom Cylinder proximity sensor	Inspection	Inspect Head3 Bottom Cylinder proximity sensor, connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Head3	Inspection	Inspect the head3 for leakage and the seal for wear	5	WEEK	1
Head 3	Inspection	service the head3 with service kit as per OEM procedure	120	80000 Kegs	1
Head3 Leftover drain points	Inspection	Inspect the head3 leftover drain points 3no's for leakage	5	WEEK	1
Head3 Inlet Sterile Air media valve	Inspection	Inspect the Head3 inlet Sterile air media valve for leakage	5	WEEK	1
Head3 Inlet Sterile Air media valve	Inspection	Service the Head3 inlet Sterile air media valve as per OEM procedure	60	30000 Kegs	1
Head3 Inlet Acid media valve	Inspection	Inspect the Head3 inlet Acid media valve for leakage	5	WEEK	1
Head3 Inlet Acid media valve	Inspection	Service the Head3 inlet Acid media valve as per OEM procedure	60	30000 Kegs	1
Head3 Inlet Mixed Water media valve	Inspection	Inspect the head3 inlet Mixed water media valve for leakage	5	WEEK	1
Head3 Inlet Mixed Water media valve	Inspection	Service the head3 inlet mixed water media valve as per OEM procedure	60	30000 Kegs	1
Head3 Inlet Low Flow media valve	Inspection	Inspect the head3 inlet low flow media valve for leakage	5	WEEK	1
Head3 Inlet Low Flow media valve	Inspection	Service the head3 inlet low flow media valve as per OEM procedure	60	30000 Kegs	1
Head3 Outlet Drain media valve	Inspection	Inspect the head3 outlet Drain media valve for leakage	5	WEEK	1
Head3 Outlet Drain media valve	Inspection	Service the head3 outlet Drain media valve as per OEM procedure	60	30000 Kegs	1
Head3 Outlet Acid media valve	Inspection	Inspect the head3 outlet Acid media valve for leakage	5	WEEK	1
Head3 Outlet Acid media valve	Inspection	Service the head3 outlet Acid media valve as per OEM procedure	60	30000 Kegs	1
Head3 Outlet Acid return media valve	Inspection	Inspect the head3 outlet Acid return media valve for leakage	5	WEEK	1
Head3 Outlet Acid return media valve	Inspection	Service the head3 outlet Acid return media valve as per OEM procedure	60	30000 Kegs	1
Head3 Outlet Flow Switch	Inspection	Inspect head3 Outlet Flow switch , connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Head3 Outlet Pressure sensor	Inspection	Inspect head3 outlet pressure sensor, connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Head4 Pressing Cylinder	Inspection	check the Head4 pressing cylinder for leakage. Tighten the mounting bolts.	5	WEEK	1
Head4 Pressing Cylinder Reed Switches	Inspection	check the Head4 pressing cylinder reed switches, connectors distributors, ground system.	5	WEEK	1
Head4 Pressing Cylinder top damper	Inspection	check the condition of Head4 Pressing Cylinder top damper for wear	5	WEEK	1

Head4 Pressing Cylinder bottom dampers	Inspection	check the condition of Head4 Pressing Cylinder bottom dampers 3no's for wear	5	WEEK	1
Head4 Bottom Cylinder	Inspection	check the Head4 bottom cylinder for leakage. Tighten the mounting bolts.	5	WEEK	1
Head4 Bottom Cylinder proximity sensor	Inspection	Inspect Head4 Bottom Cylinder proximity sensor, connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Head4	Inspection	Inspect the head4 for leakage and the seal for wear	5	WEEK	1
Head4	Inspection	service the head4 with service kit as per OEM procedure	120	80000 Kegs	1
Head4 Leftover drain points	Inspection	Inspect the head4 leftover drain points 3no's for leakage	5	WEEK	1
Head4 Inlet Sterile Steam media valve	Inspection	Inspect the Head4 inlet Sterile Steam media valve for leakage	5	WEEK	1
Head4 Inlet Sterile Steam media valve	Inspection	Service the Head4 inlet Sterile Steam media valve as per OEM procedure	60	30000 Kegs	1
Head4 Inlet Hot Water media valve	Inspection	Inspect the head4 Hot water media valve for leakage	5	WEEK	1
Head4 Inlet Hot Water media valve	Inspection	Service the head4 Hot water media valve as per OEM procedure	60	30000 Kegs	1
Head4 Inlet Low Flow media valve	Inspection	Inspect the head4 inlet low flow media valve for leakage	5	WEEK	1
Head4 Inlet Low Flow media valve	Inspection	Service the head4 inlet low flow media valve as per OEM procedure	60	30000 Kegs	1
Head4 Outlet Mixed water return media valve	Inspection	Inspect the head4 outlet Mixed water return media valve for leakage	5	WEEK	1
Head4 Outlet Mixed water return media valve	Inspection	Service the head4 outlet Mixed water return media valve as per OEM procedure	60	30000 Kegs	1
Head4 Outlet Flow Switch	Inspection	Inspect head4 Outlet Flow switch , connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Head4 Outlet Pressure sensor	Inspection	Inspect head4 outlet pressure sensor, connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Head4 Outlet Temperature sensor	Inspection	Inspect head4 outlet Temperature sensor, connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Head5 Pressing Cylinder	Inspection	check the Head5 pressing cylinder for leakage. Tighten the mounting bolts.	5	WEEK	1
Head5 Pressing Cylinder Reed Switches	Inspection	check the Head5 pressing cylinder reed switches, connectors distributors, ground system.	5	WEEK	1
Head5 Pressing Cylinder top damper	Inspection	check the condition of Head5 Pressing Cylinder top damper for wear	5	WEEK	1
Head5 Pressing Cylinder bottom dampers	Inspection	check the condition of Head5 Pressing Cylinder bottom dampers 3no's for wear	5	WEEK	1
Head5 Bottom Cylinder	Inspection	check the Head5 bottom cylinder for leakage. Tighten the mounting bolts.	5	WEEK	1
Head5 Bottom Cylinder proximity sensor	Inspection	Inspect Head5 Bottom Cylinder proximity sensor, connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Head5	Inspection	Inspect the head5 for leakage and the seal for wear	5	WEEK	1
Head5	Inspection	service the head5 with service kit as per OEM procedure	120	80000 Kegs	1
Head5 Leftover drain points	Inspection	Inspect the head5 leftover drain points 3no's for leakage	5	WEEK	1
Head5 Outlet Drain media valve	Inspection	Inspect the head5 outlet Drain media valve for leakage	5	WEEK	1
Head5 Outlet Drain media valve	Inspection	Service the head5 outlet Drain media valve as per OEM procedure	60	30000 Kegs	1
Head5 Outlet Pressure sensor	Inspection	Inspect head5 outlet pressure sensor, connectors distributors, ground system. Clean if found dirty	5	WEEK	1

Head5 Inlet Collector media valve	Inspection	Inspect the head5 inlet Collector media valve for leakage	5	WEEK	1
Head5 Inlet Collector media valve	Inspection	Service the head5 inlet Collector media valve as per OEM procedure	60	30000 Kegs	1
Head5&6 Inlet Sterile Steam media valve	Inspection	Inspect the Head5&6 inlet Sterile Steam media valve for leakage	5	WEEK	1
Head5&6 Inlet Sterile Steam media valve	Inspection	Service the Head5&6 inlet Sterile Steam media valve as per OEM procedure	60	30000 Kegs	1
Head5&6 Inlet Hot Water media valve	Inspection	Inspect the head5&6 Hot water media valve for leakage	5	WEEK	1
Head5&6 Inlet Hot Water media valve	Inspection	Service the head5&6 Hot water media valve as per OEM procedure	60	30000 Kegs	1
Head5&6 Inlet CO2 media valve	Inspection	Inspect the head5&6 CO2 media valve for leakage	5	WEEK	1
Head5&6 Inlet CO2 media valve	Inspection	Service the head5&6 CO2 media valve as per OEM procedure	60	30000 Kegs	1
Head6 Inlet Collector media valve	Inspection	Inspect the head6 inlet Collector media valve for leakage	5	WEEK	1
Head6 Inlet Collector media valve	Inspection	Service the head6 inlet Collector media valve as per OEM procedure	60	30000 Kegs	1
Head6 Outlet Fob media valve	Inspection	Inspect the head6 outlet Fob media valve for leakage	5	WEEK	1
Head6 Outlet Fob media valve	Inspection	Service the head6 outlet Fob media valve as per OEM procedure	60	30000 Kegs	1
Head6 Outlet Pressure sensor	Inspection	Inspect head6 outlet pressure sensor, connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Head6 outlet sight glass	Inspection	Inspect the head6 outlet sight glass for leakage. Clean if found dirty	5	WEEK	1
Head6 Beer valve	Inspection	Inspect the head6 beer valve for leakage	5	WEEK	1
Head6 Beer valve	Inspection	Service the head6 beer valve as per OEM procedure	60	30000 Kegs	1
Head6 CO2 valve	Inspection	Inspect the head6 CO2 valve for leakage	5	WEEK	1
Head6 CO2 valve	Inspection	Service the head6 CO2 valve as per OEM procedure	60	30000 Kegs	1
Head6	Inspection	Inspect the head5 for leakage and the seal for wear	5	WEEK	1
Head6	Inspection	service the head5 with service kit as per OEM procedure	120	80000 Kegs	1
Head6 Pressing Cylinder	Inspection	check the Head6 pressing cylinder for leakage. Tighten the mounting bolts.	5	WEEK	1
Head6 Pressing Cylinder Reed Switches	Inspection	check the Head6 pressing cylinder reed switches, connectors distributors, ground system.	5	WEEK	1
Head6 Pressing Cylinder top damper	Inspection	check the condition of Head6 Pressing Cylinder top damper for wear	5	WEEK	1
Head6 Pressing Cylinder bottom dampers	Inspection	check the condition of Head6 Pressing Cylinder bottom dampers 3no's for wear	5	WEEK	1
Head6 Bottom Cylinder	Inspection	check the Head6 bottom cylinder for leakage. Tighten the mounting bolts.	5	WEEK	1
Head6 Bottom Cylinder proximity sensor	Inspection	Inspect Head6 Bottom Cylinder proximity sensor, connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Head6 Conductivity meter	Inspection	Inspect Head6 Conductivity meter, connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Head6 Flow meter	Inspection	Inspect Head6 Flow meter, connectors distributors, ground system. Tighten the ground cable.	5	WEEK	1
Head6 Beer line sight glass	Inspection	Inspect the head6 Beer line sight glass for leakage. Clean if found dirty	5	WEEK	1
Head6 Beer regulating valve	Cleaning	Clean the head6 beer regulating valve silencer.	5	WEEK	1

Head 6 back pressure relief valve	Inspection	Inspect the condition of diaphgrams of back pressure relief valve	15	MONTHLY	1
Walking Beam up/down Cylinder	Inspection	check the walking beam up/down cylinder for leakage. Tighten the mounting bolts.	5	WEEK	1
Walking Beam up/down Cylinder Reed switches	Inspection	check the walking beam up/down cylinder reed switches, connectors distributors, ground system.	5	WEEK	1
Walking beam rollers	Inspection	Inspect the condition of walking beam rollers. Replace if found worn out	120	YEARLY	1
Walking beam keg pusher	Inspection	Inspect the walking beam keg pusher for wear. Tighten the nuts and bolts	5	WEEK	1
Walking beam keg centering piece	Inspection	Inspect the walking beam keg centering piece for wear. Tighten the nuts and bolts	5	WEEK	1
Walking beam Rubber pads	Inspection	Inspect the walking beam rubber pads 20 no's for wear.	5	WEEK	1
Walking Beam Forward/backward Cylinder	Inspection	check the walking beam forward/backward cylinder for leakage. Tighten the mounting bolts.	5	WEEK	1
Walking Beam Forward/backward Cylinder Reed switches	Inspection	check the walking beam forward/backward cylinder reed switches, connectors distributors, ground system.	5	WEEK	1
Pneumatical control panel	Cleaning	Clean the Pneumatic control panel with a blower. Clean the silencers. Check for any leakage.	15	WEEK	1
Main Air regulator	Inspection	Inspect main air regulator for any leakage. Drain the moisture from separator. Clean the filter	8	WEEK	1
Main Air regulator pressure switch	Inspection	Inspect main air regulator pressure switch, connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Main Air regulator solenoid valve	Inspection	Inspect main air regulator solenoid valve, connectors distributors, ground system. Clean if found dirty	5	WEEK	1
Piping	Inspection	Check for any leakage at the flange joints on all the media pipings	5	WEEK	1