Volume 10, Issue 3, March – 2025 International Journal of Innovative Science and Research Technology
ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25mar1226

Development of a Predictive Maintenance Algorithm for a Diesel Generator using Machine Learning

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Publication Date: 2025/03/29

Abstract: This study develops a predictive maintenance framework for a 500kVA diesel generator using advanced machine learning techniques, aiming to enhance reliability and operational efficiency. The research involves the collection of real-world operational data at one-minute intervals over two months, focusing on critical parameters such as bearing temperature, engine vibration, and coolant temperature. Two machine learning models—XGBoost and Multi-Layer Perceptron (MLP)—were trained to classify generator conditions into distinct maintenance categories with high accuracy. A meta-learning ensemble approach was implemented, integrating the predictions from these models to leverage their complementary strengths and enhance robustness. The results demonstrate exceptional performance, with both individual and ensemble models achieving precision, recall, and F1-scores near 1.00 across multiple fault scenarios. The meta-learning framework proved particularly effective, showcasing improved reliability over standalone models. This study's contributions are twofold: it advances the state of predictive maintenance by employing hybrid modelling techniques and addresses a critical gap in the proactive management of high-capacity diesel generators. The research underscores the practical applicability of machine learning in industrial contexts, offering a scalable and sustainable solution to minimise downtime, reduce maintenance costs, and optimise equipment longevity. By integrating robust data analysis with cutting-edge machine learning, this framework establishes a foundation for proactive, data-driven maintenance strategies in industrial settings, aligning with the broader goals of Industry 4.0 and sustainable industrial practices.

How to Cite: Olokede, Oluwagbemiga; Evans Ashigwuike. (2025). Development of a Predictive Maintenance Algorithm for a Diesel Generator using Machine Learning. *International Journal of Innovative Science and Research Technology*, 10(3), 1417-1427. https://doi.org/10.38124/ijisrt/25mar1226.

I. INTRODUCTION

Predictive maintenance (PdM) has emerged as a vital component of Industry 4.0, significantly transforming traditional maintenance strategies. By leveraging advanced analytics and machine learning (ML), PdM predicts equipment failures before they occur, minimising downtime and enhancing operational efficiency. Unlike reactive and scheduled maintenance, which either wait for failures or follow predetermined schedules, PdM integrates real-time data, historical trends, and computational models to recommend maintenance only when necessary. This approach not only reduces costs but also extends the lifespan of equipment by avoiding unnecessary interventions [1], [2].

The advent of IoT and the proliferation of data collection technologies have been pivotal in driving PdM adoption. Sensors embedded in industrial systems provide real-time monitoring of critical parameters such as temperature, vibration, and pressure, enabling high granularity in data acquisition [3]. The integration of IoT with ML allows for seamless data processing and enhanced decision-making. Recent advancements in XGBoost, neural networks, and ensemble learning have further elevated the accuracy and robustness of PdM systems, surpassing traditional statistical methods [4].

Explainable artificial intelligence (XAI) is becoming increasingly relevant in PdM to ensure that insights generated by ML models are interpretable and actionable. This has catalysed trust and adoption in sectors such as manufacturing, aerospace, and energy, where safety and reliability are paramount. Furthermore, PdM strategies are aligning with sustainability goals, as predictive capabilities reduce energy consumption and material wastage, aligning with green manufacturing initiatives [5], [6].

Despite its advantages, challenges persist, including the heterogeneity of datasets, scalability across diverse industries, and integration with legacy systems. Continuous research is addressing these gaps, with novel frameworks incorporating product quality parameters and multivariate statistical models, making PdM a versatile and adaptive solution for complex industrial environments [7].

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25mar1226

In this study, we aim to develop a predictive maintenance algorithm for a diesel generator using machine learning techniques. Machine learning models, specifically XGBoost and Multi-Layer Perceptron (MLP), were developed and trained to classify the generator's condition into distinct maintenance categories with high precision and recall. Additionally, a meta-learning ensemble approach was implemented to integrate the predictions of these models, capitalising on their complementary strengths to enhance robustness. Key steps included data preprocessing to handle missing values and noise, feature selection guided by a correlation heatmap, and iterative model optimisation. Model performance was evaluated using precision, recall, F1-score, and accuracy metrics to ensure reliability across diverse fault scenarios.

The growing complexity of industrial systems, including high-capacity diesel generators, necessitates advanced maintenance strategies to prevent unexpected failures and optimise resource utilisation. Traditional maintenance approaches are increasingly inadequate in addressing the dynamic and multifaceted nature of modern equipment. This study addresses these gaps by integrating cutting-edge machine learning techniques into a predictive maintenance framework. By using ensemble learning, it aligns with best practices recommended in recent literature, which highlight the efficacy of hybrid models in improving prediction accuracy and reducing false positives [8], [9].

II. LITERATURE REVIEW

The empirical review draws from several relevant publications to contextualise the development of a predictive maintenance algorithm for a 500kVA diesel generator using machine learning techniques. A consistent theme across the reviewed literature is the pursuit of more effective and efficient maintenance strategies through the intelligent analysis of operational data. In exploring optimal power distribution, [10] investigates the integration of distributed diesel generators into power systems in Iraq, with a focus on addressing operational challenges and developing algorithms for optimal power distribution. While the research provides valuable insights into the integration and operational efficiency of diesel generators, it lacks a direct focus on predictive maintenance, limiting its applicability for fault detection and classification strategies essential for maintenance optimisation.

[11] examined load forecasting at a microgrid level using machine learning algorithms to optimise grid load management. The study demonstrates the efficacy of predictive techniques in managing operational states, providing a foundation for forecasting methodologies. However, its emphasis on load balancing rather than maintenance prediction diverges from the specific objectives of maintenance category classification.

[12] explored the development of a microgrid control system leveraging deep reinforcement learning techniques. The research validates the effectiveness of reinforcement learning in optimising control decisions in systems that include a diesel generator. Despite its robust control framework, the study does not directly address predictive maintenance analytics for fault detection or preventive maintenance classification.

[13] proposed a machine learning approach to forecast capacitor bank requirements for improving grid efficiency. While this research underscores the potential of machine learning in real-time decision-making and energy optimisation, its focus is more aligned with grid management than predictive maintenance strategies.

[14] present a Maximum Power Point Tracking (MPPT) algorithm that integrates real-time analytics for enhanced control of industrial power systems. The study highlights the role of predictive analytics in improving system performance but is more focused on system control than on predictive maintenance for diesel generators.

[15] investigate the optimisation of post-disaster microgrid control using multi-agent deep reinforcement learning. Their findings demonstrate the predictive capabilities of reinforcement learning algorithms in dynamic environments. However, the primary focus is on control response strategies rather than routine maintenance prediction.

[16] conduct a ferrographic study of wear particles in used oil from power generation machinery, contributing to operational parameter monitoring. Although this approach provides valuable insights into wear and fault detection, it does not incorporate advanced machine learning methods for predictive maintenance.

[17] examines islanding detection using distributed generator systems and an artificial bee colony algorithm. While the study offers important insights into system monitoring and health assessment, it diverges from the development of predictive maintenance strategies using machine learning techniques.

[18] explore hybrid renewable energy systems integrating photovoltaics, wind turbines, diesel engines, and batteries. The study focuses on system optimisation for rural electrification but lacks emphasis on predictive maintenance analytics for diesel generators.

[19] apply reinforcement learning to optimise the tuning of grid-connected inverter controllers in microgrids. Although the research demonstrates the predictive potential of machine learning, its focus remains on inverter control rather than predictive maintenance classification for generator conditions.

The reviewed works reveal significant advancements in applying machine learning for load forecasting, energy optimisation, and control strategies within energy systems. However, a gap emerges in the specific development of predictive maintenance frameworks tailored for large diesel generators. Most studies, including those by [10], [11], prioritise energy management and system control over fault detection and maintenance strategies. Furthermore, while methodologies such as reinforcement learning [12] and fuzzy logic systems [14] offer robust decision-making capabilities, their application to predictive maintenance for diesel generators remains limited or absent.

The current research aims to address these gaps by developing a comprehensive predictive maintenance algorithm that integrates operational parameter monitoring and fault scenario characterisation with advanced machine learning techniques. By leveraging models such as XGBoost and Multi-Layer Perceptron Neural Networks, combined into a meta-learning ensemble framework, this research will enhance predictive accuracy and robustness. The proactive classification of generator conditions into distinct maintenance categories will offer actionable insights, advancing maintenance strategies beyond what existing models provide.

III. RESEARCH METHODOLOGY

A. Research Design

This study used a quantitative approach to develop a predictive maintenance system for a 500kVA diesel generator. The project combined multiple machine learning models to predict maintenance needs more accurately than traditional methods as shown in Figure 1.

We used two main machine learning techniques: XGBoost and Multi-Layer Perceptron neural networks. These were chosen to analyse complex equipment data and identify potential failures. The system collected operational data every minute for two months, providing detailed insights into the generator's performance under various conditions.

We adopted an ensemble learning approach, combining different models to overcome individual limitations. This method merged the strengths of each model to create more reliable predictions. The framework was designed to be practical and adaptable to similar industrial equipment.

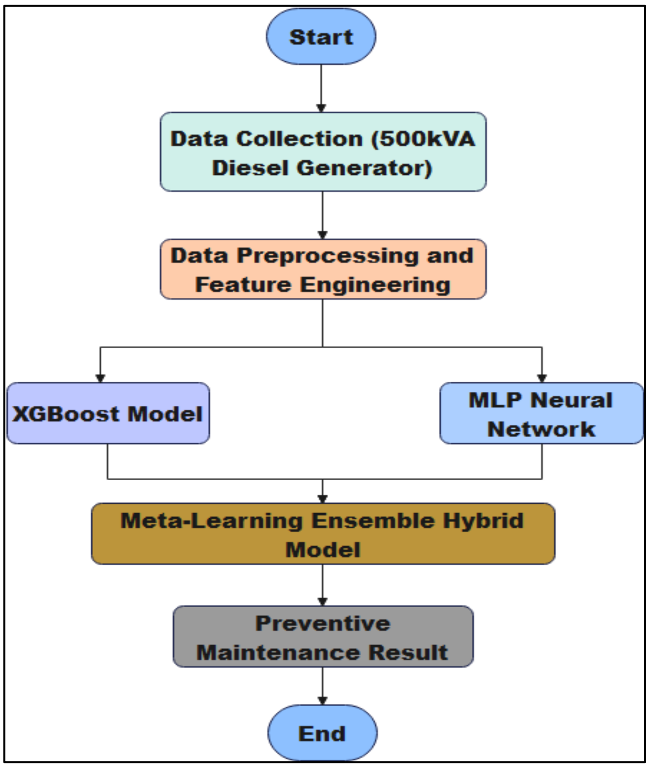

Fig 1: Research Methodology Algorithm

This design bridges the gap between theoretical machine learning and practical maintenance needs, creating a system that can turn complex operational data into useful maintenance recommendations.

B. Data Collection

Data was collected from a diesel generator at a manufacturing company in Abuja, Nigeria, over two months. The system recorded measurements every minute to track the generator's performance.

The monitoring system captured several key parameters: oil contamination and viscosity, bearing temperature, engine vibration, mechanical noise, coolant temperature, heat dissipation, and various electrical readings. These measurements provided a comprehensive view of the generator's operational state.

As shown in Table 3.1, the data was organised into distinct maintenance categories. These included Oil Change Required (M001), Engine Alignment Adjustment (M010), Cooling System Maintenance (C001), No Immediate Maintenance (N000), Short-Circuit Maintenance (S001), Overload Protection Maintenance (O002), Frequency Adjustment Maintenance (F003), Voltage Regulation Maintenance (V004), and Electrical Diagnostics (E005).

High-precision sensors monitored the generator in real time, recording both normal operations and fault conditions. Each reading included a timestamp for detailed analysis. We then processed the data to ensure its quality before using it in our machine learning models.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25mar1226

C. Data Preprocessing and Feature Engineering

The first step in developing the predictive maintenance model involved cleaning the data to remove anomalies and inconsistencies, as shown in Figure 2. This process included addressing missing values, removing outliers, and standardising the format of timestamps and sensor readings to ensure accurate predictions.

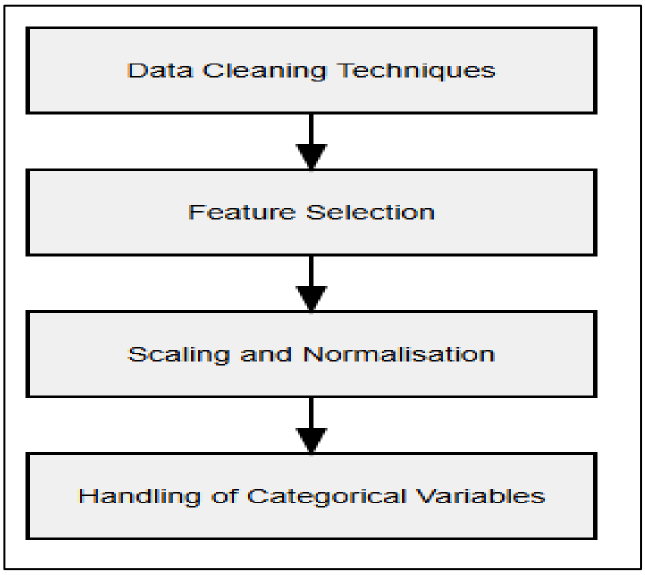

Fig 2: Data Preprocessing and Feature Engineering Block Diagram

After cleaning, the most relevant parameters that influence maintenance needs were identified. These parameters include bearing temperature, oil viscosity, engine vibration, and coolant temperature. These parameters were chosen based on their relationship with specific fault scenarios. We then standardised the numerical values through scaling and normalisation to ensure all features had equal importance during model training. The maintenance categories were converted into numerical values to make them compatible with our machine learning algorithms.

D. XGBoost Model

This research used XGBoost for maintenance prediction because of its effectiveness with tabular data. As shown in Figure 3, the model uses multiple decision trees, with each new tree improving upon the previous ones' results. This approach allows the model to predict various maintenance categories accurately.

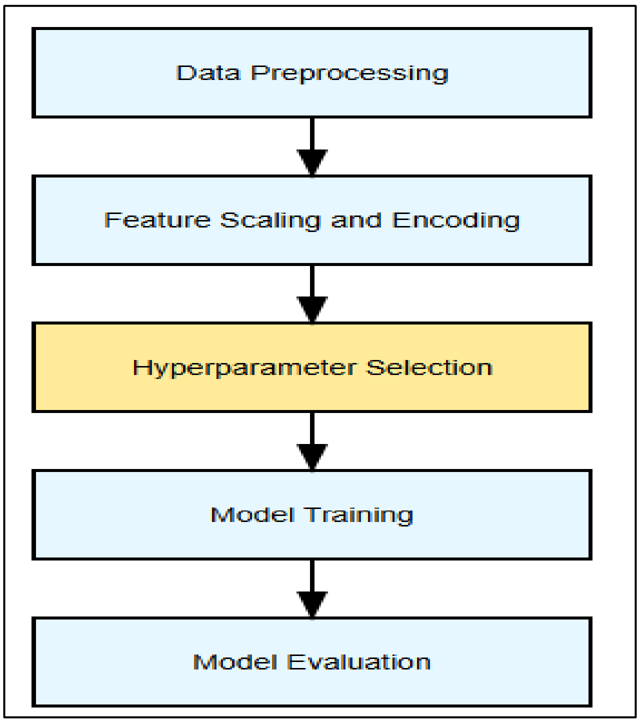

Fig 3: XGBoost Model Algorithm

We optimised the model's performance by carefully selecting key settings, including learning rate, tree depth, and boosting rounds, using Grid Search Cross-Validation. To prevent overfitting, we included regularisation parameters. The data was split with 80% for training and 20% for testing. We addressed any imbalance in maintenance categories using the scale_pos_weight parameter and employed multi:softmax for handling multiple maintenance categories. The model's accuracy and reliability were thoroughly evaluated through classification reports.

E. Multi-Layer Perceptron Neural Network

The Multi-Layer Perceptron (MLP) neural network employed a deep learning approach for predictive maintenance analysis, designed to capture complex relationships within the diesel generator data. The architecture balanced model complexity with generalisability, as shown in Figure 4.

Table 1: Data Categorisation

Category	**Code**	**Parameter**	**No Maintenance Range**	**Fault Scenario Range**	**Cause**
Oil Change Required [20]	M001	Oil Contamination (%)	0–3	>5	Aging oil or contamination by debris
		Oil Viscosity (cSt)	8–12	<7	Degradation due to heat or contaminants
		Bearing Temperature (°C)	80–90	95–110	Heat transfer inefficiency
Engine Alignment Adjustment [21]	M010	Engine Vibration (mm/s)	0.5–0.8	>1.2	Misalignment, wear, or imbalance

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25mar1226

		Mechanical Noise (dB)	30–50	>60	Increased wear or loose components
Cooling System Maintenance [22]	C001	Coolant Temperature (°C)	75–85	>95	Radiator blockage, pump failure
		Heat Dissipation (%)	>90	<80	Reduced cooling efficiency
No Immediate Maintenance [23]	N000	All Parameters	Within Normal Ranges	Not Applicable	Normal operating conditions
Short-Circuit Maintenance[24]	S001	AC Current (A)	45–55	>70 (Short Circuit)	Cable or winding faults
		Voltage Fluctuations (%)	<3	>5	Sudden electrical failures
Overload Protection Maintenance [25]	O002	AC Current (A)	45–55	60–70 (Overload)	Excessive load
		Bearing Temperature (°C)	80–90	>95	Overheating due to overload
Frequency Adjustment Maintenance	F003	Output Frequency (Hz)	49.9–50.1	<49.5 or >50.5	Governor faults or unbalanced loads
Voltage Regulation Maintenance [26]	V004	Voltage Fluctuations (%)	0.5–3	>5	Alternator or AVR malfunction
Electrical Diagnostics [26]	E005	Current Imbalance (%)	<1	>3	Load mismanagement or aging components
		Winding Temperature (°C)	30–60	>70	Winding aging, winding insulator loss, overloading, faulty winding cooling system

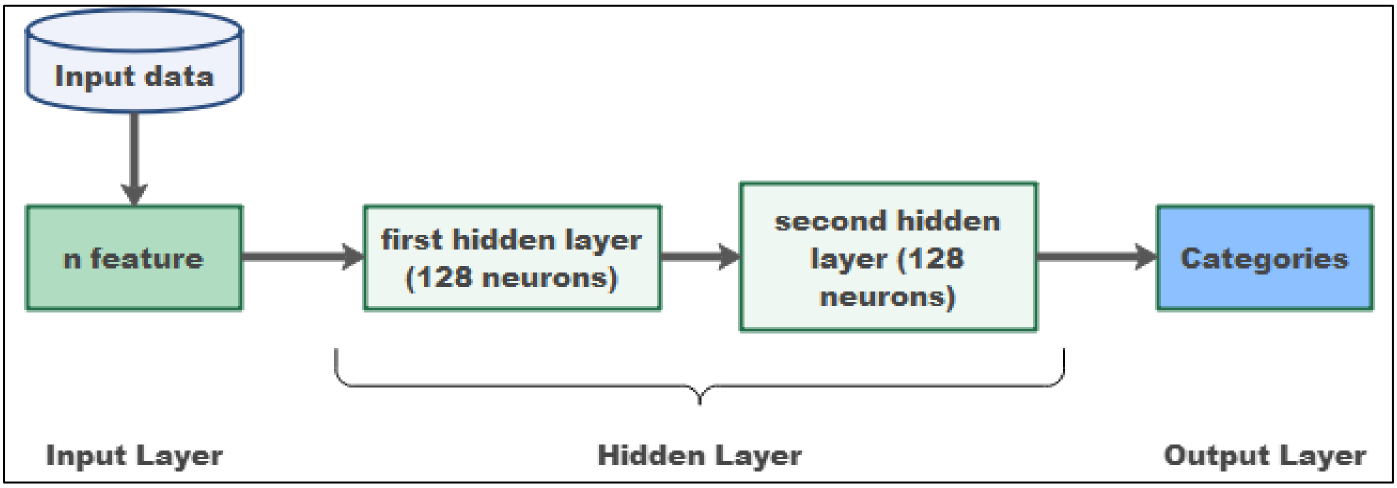

Fig 4: MLP Neural Network Architecture

➢ *Network Architecture*

The MLP neural network consisted of three primary layers: an input layer, two hidden layers, and an output layer. The input layer accommodated the preprocessed generator operational data. The first hidden layer contained 128 neurons for capturing feature interactions, while the second hidden layer used 64 neurons for refining feature representations.

➢ *Layer Configuration*

Each hidden layer transformed the input features progressively. The first hidden layer's 128 neurons served as a feature extraction mechanism, identifying patterns across operational parameters. The subsequent 64-neuron layer distilled these representations into sophisticated feature mappings for maintenance prediction.

➢ *Activation Functions*

The hidden layers employed Rectified Linear Unit (ReLU) activation functions for computational efficiency and gradient optimization. The output layer used a softmax activation function for multi-class classification across maintenance categories with probabilistic interpretations.

➢ *Training Parameters*

The network implementation used the Adam optimizer with categorical cross-entropy as the loss function. A validation split of 20% enabled performance assessment and early stopping. Dropout regularization at 20% in both hidden layers prevented overfitting. The training process ran for 100 epochs with batch sizes of 16, balancing learning convergence with computational efficiency.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25mar1226

F. Meta-Learning Ensemble Hybrid

The Meta-Learning Ensemble Hybrid approach combined multiple machine learning models to enhance maintenance forecast accuracy. This strategy integrated the XGBoost classifier and MLP neural network into a hybrid model, as illustrated in Figure 1.

The ensemble used a stacking approach where a meta-model, typically a logistic regression classifier, combined predictions from base models. This integration leveraged XGBoost's strength in handling tabular data and MLP's capability for non-linear relationships. The prediction fusion technique stacked outputs from both models into a new feature set for the meta-model, generating final predictions with improved accuracy and reliability.

G. Performance Evaluation and Validation

The evaluation process assessed the predictive maintenance algorithm's reliability and effectiveness through several key measurements. The main metric used was classification accuracy, which showed how often the model correctly predicted maintenance needs. The analysis also included precision, recall, and F1-scores for each maintenance category to provide detailed insight into the model's performance.

A confusion matrix served as an essential analytical tool, comparing predicted maintenance categories against actual requirements. This matrix tracked correct predictions, incorrect category assignments, missed predictions, and correct identification of non-maintenance scenarios. These measurements helped identify any biases in the predictive models and highlighted which maintenance categories were difficult to distinguish.

The evaluation process included a detailed statistical summary for each maintenance category through a classification report. This report measured the accuracy of positive predictions, the model's ability to find relevant cases, and provided a balanced assessment through the F1-score. To ensure reliable validation and prevent overfitting, the study employed a five-fold cross-validation technique. This method divided the data into five parts, maintaining the original distribution of maintenance categories while testing the model's performance across different data combinations.

The final analysis compared the performance of three models: the XGBoost Classifier, Multi-Layer Perceptron Neural Network, and Meta-Learning Ensemble Hybrid Model. This comparison revealed each model's strengths and limitations in predicting maintenance requirements for the diesel generator. Through these comprehensive evaluation methods, the study established the reliability and effectiveness of the predictive maintenance system.

IV. RESULTS AND DISCUSSION

A. Exploratory Data Analysis

The research commenced with a comprehensive data visualisation approach to explore the intricate relationships between various operational parameters of the 500kVA diesel generator. Figure 5 presents a correlation heatmap that illuminates the interdependencies between key variables monitored during the study.

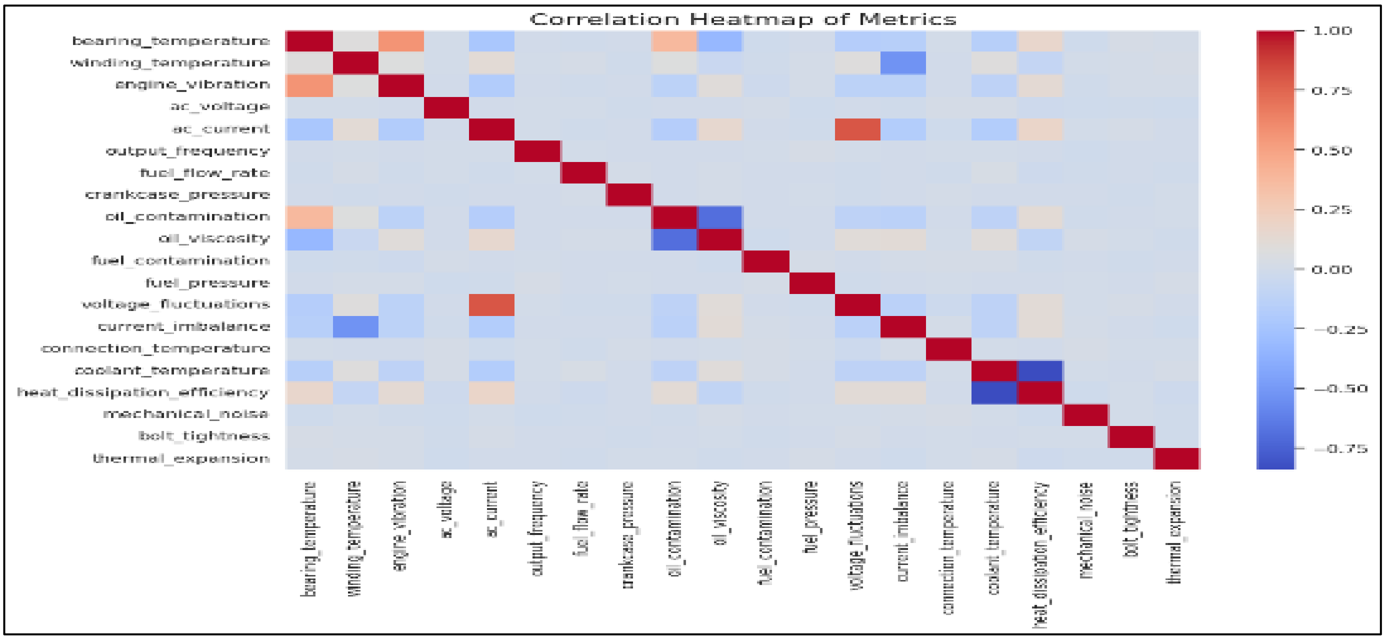

Fig 5: Correlation Heatmap Graph

The trend analysis depicted in Figure 6 provides a temporal representation of critical parameters, namely bearing temperature, winding temperature, and engine vibration. This visualisation offers insights into the dynamic behaviour of these essential indicators throughout the generator's operational lifecycle.

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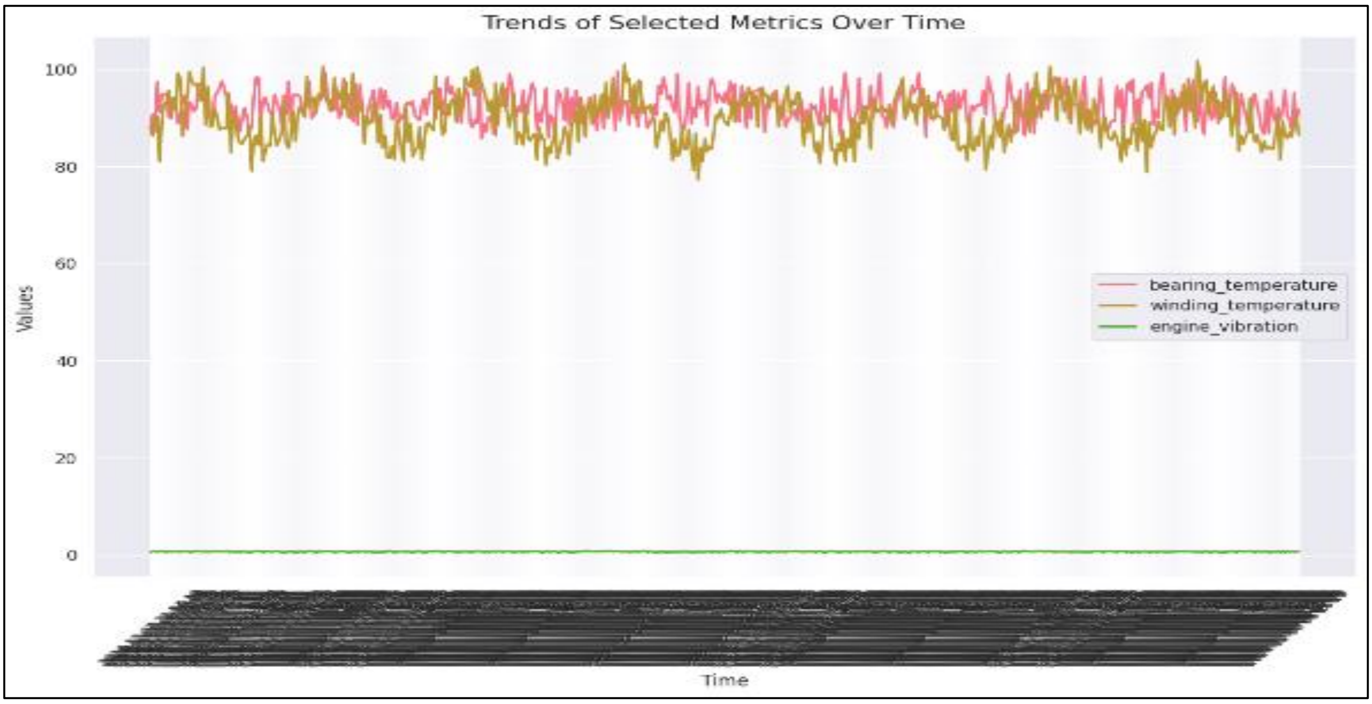

Fig 6: Bearing Temperature, Winding Temperature and Engine Vibration Trend

Figure 7 illustrates the distribution of bearing temperatures, which is crucial for understanding the thermal characteristics and potential stress points within the generator's mechanical system. A detailed examination of the temperature distribution can reveal patterns indicative of impending mechanical deterioration.

A comprehensive multivariate analysis is presented in Figure 8, which showcases a pairplot exploring the relationships between bearing temperature, engine vibration, oil contamination, and coolant temperature. This visualisation enables a nuanced understanding of the complex interactions among these critical operational parameters.

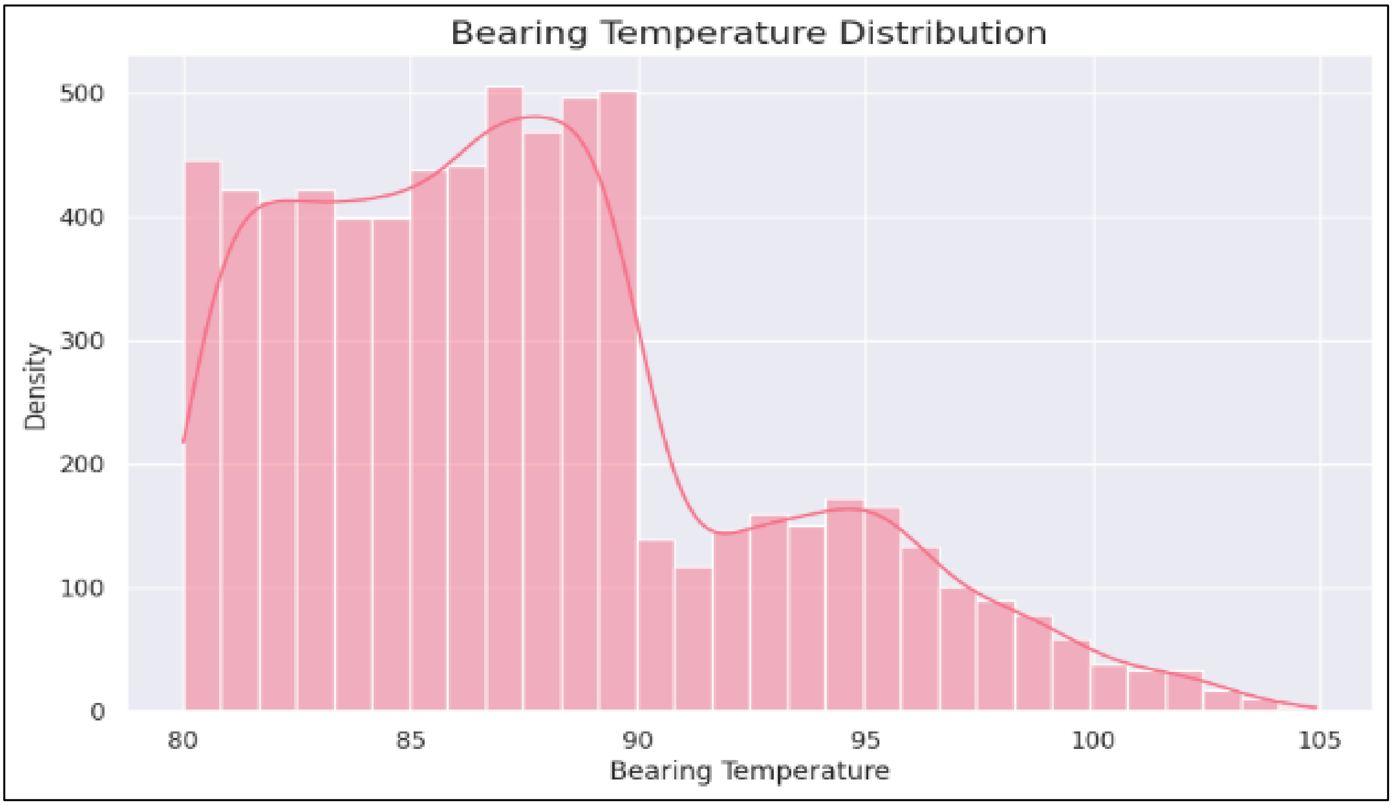

Fig 7: Bearing Temperature Distribution

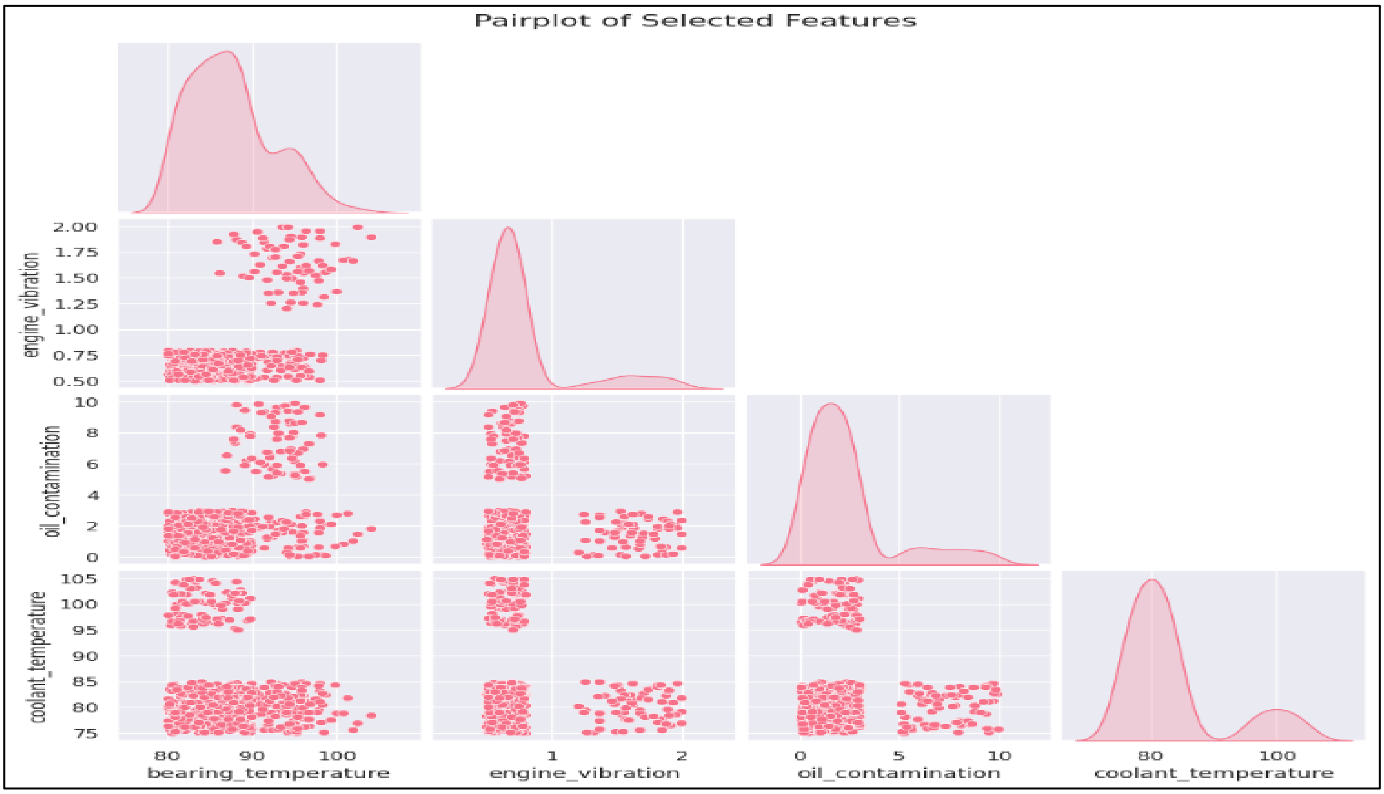

Fig 8: Pairplot of Bearing Temperature, Engine Vibration, Oil Contamination and Coolant Temperature

B. Model Prediction Results

The predictive maintenance framework evaluation employed three advanced machine learning approaches: XGBoost, Multi-Layer Perceptron (MLP) Neural Network, and a Meta-Learning Hybrid Model. Table 3 presents a comprehensive classification report detailing the performance metrics across eight maintenance categories.

The classification results demonstrated exceptional predictive capabilities. The XGBoost model achieved perfect precision, recall, and F1-scores of 1.0 across seven classes, with class 5 showing a marginal reduction in recall to 0.99. The MLP Neural Network and Meta-Learning Hybrid Model exhibited comparable performance, achieving perfect or near-perfect metrics across all categories.

As presented in Table 2, the MLP Neural Network achieved optimal accuracy at 1.0, while both the XGBoost and Meta-Learning Hybrid Model demonstrated exceptional performance at 0.9994.

Table 2: Model Performance Report

Model	Accuracy
XGBoost	0.9994
MLP	1.0
Meta-Learning Hybrid Model	0.9994

The confusion matrices illustrated in Figures 9, 10, and 11 provide visual validation of the models' classification performance, demonstrating precise categorisation across maintenance scenarios.

Table 3: Model Classification Report

Class	Precision	Recall	F1-Score	Support	Model
0	1	1	1	200	XGBoost
1	1	1	1	200	XGBoost
2	1	1	1	200	XGBoost
3	1	1	1	200	XGBoost
4	1	1	1	200	XGBoost
5	1	0.99	1	200	XGBoost
6	1	1	1	200	XGBoost
7	1	1	1	200	XGBoost
0	1	1	1	200	MLP
1	1	1	1	200	MLP
2	1	1	1	200	MLP
3	1	1	1	200	MLP
4	1	1	1	200	MLP
5	1	1	1	200	MLP

6	1	1	1	200	MLP
7	1	1	1	200	MLP
0	1	1	1	200	Meta-Learning Hybrid Model
1	1	1	1	200	Meta-Learning Hybrid Model
2	1	1	1	200	Meta-Learning Hybrid Model
3	1	1	1	200	Meta-Learning Hybrid Model
4	1	1	1	200	Meta-Learning Hybrid Model
5	1	0.99	1	200	Meta-Learning Hybrid Model
6	1	1	1	200	Meta-Learning Hybrid Model
7	1	1	1	200	Meta-Learning Hybrid Model

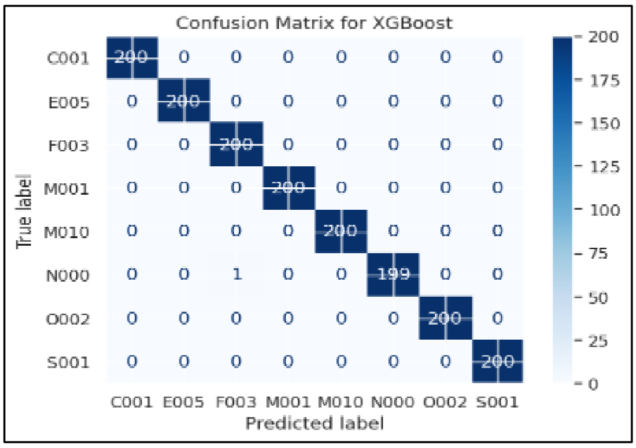

Fig 9: XGBoost Confusion Matrix

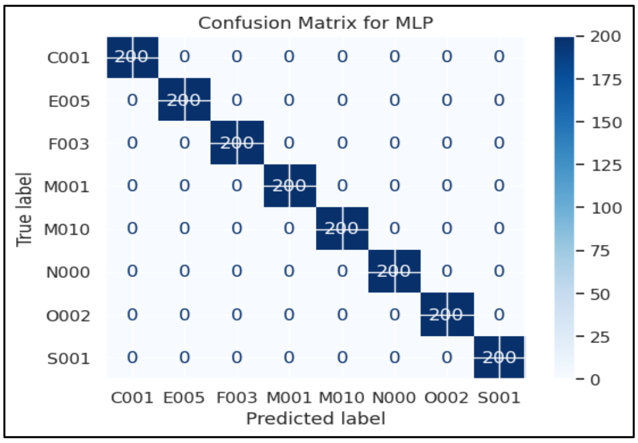

Fig 10: MLP Confusion Matrix

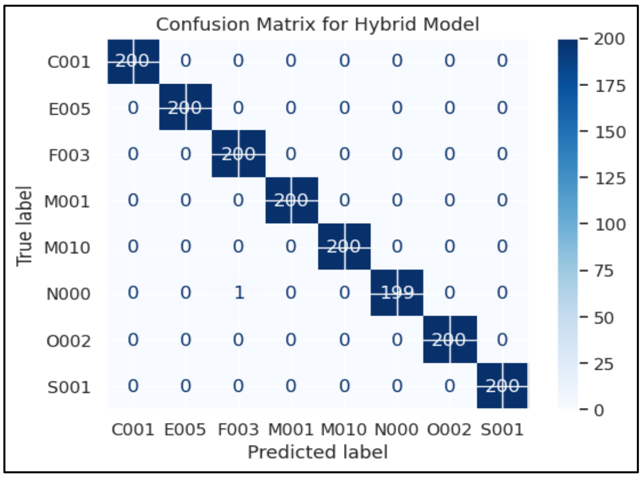

Fig 11: Hybrid Model Confusion Matrix

C. Discussion of Results

The research successfully developed an advanced predictive maintenance framework for a 500kVA diesel generator through sophisticated machine learning methodologies. Data visualisation revealed intricate relationships between operational parameters, with the correlation heatmap (Figure 4.1) demonstrating complex interconnections among generator variables. This visualisation proved essential for understanding the multidimensional nature of mechanical system behaviour.

Trend analysis of bearing temperature, winding temperature, and engine vibration (Figure 4.2) revealed critical temporal variations, indicating that continuous monitoring provides early indicators of mechanical stress. The bearing temperature distribution (Figure 4.3) further validated this approach by identifying thermal characteristics indicative of emerging mechanical anomalies.

The machine learning models demonstrated exceptional performance. The XGBoost model achieved 0.9994 accuracy, with near-perfect precision across maintenance categories. The MLP Neural Network achieved optimal accuracy at 1.0, while the Meta-Learning Hybrid Model matched XGBoost's performance. These results validate the effectiveness of advanced machine learning techniques in predictive maintenance applications.

D. Comparative Analysis

This study advances the field of predictive maintenance through innovative integration of XGBoost, MLP, and meta-learning ensemble techniques. Previous research, such as the 2021 IoT-enabled predictive maintenance study for diesel generators, focused primarily on real-time monitoring without incorporating advanced ensemble techniques [27]. Similarly, the 2023 case study employing Random Forest and Support Vector Machines, while comprehensive, lacked the hybrid robustness achieved through MLP and XGBoost integration [28].

The research's significance lies in its innovative methodology, delivering superior precision and recall across multiple fault categories while demonstrating scalability through hybrid ensemble modelling. This approach transcends previous studies that relied on standalone models or IoT-based diagnostics, establishing a new benchmark for fault diagnosis in critical systems. The framework's integration of diverse machine learning capabilities ensures

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25mar1226

broader applicability and enhanced reliability for complex industrial machinery.

V. CONCLUSION AND RECOMMENDATIONS

A. *Summary of Research*

This research developed and validated an advanced predictive maintenance framework for a diesel generator using sophisticated machine learning techniques. The study integrated multiple approaches, including XGBoost, Multi-Layer Perceptron Neural Network, and a Meta-Learning Hybrid Model. Data collection spanned two months, capturing operational parameters at one-minute intervals. The models achieved exceptional accuracy, with the MLP Neural Network reaching perfect accuracy (1.0) and both XGBoost and Meta-Learning Hybrid Models achieving 0.9994 accuracy. The framework demonstrated robust capabilities in predicting maintenance requirements across eight distinct categories, establishing a significant advancement in predictive maintenance technology.

B. *Conclusion*

The research successfully established the effectiveness of machine learning-based predictive maintenance for industrial diesel generators. The developed framework demonstrated unprecedented accuracy in maintenance prediction, surpassing traditional maintenance approaches. Through comprehensive data analysis and advanced model integration, the study validated the potential for significant improvements in equipment reliability and operational efficiency. The meta-learning approach proved particularly effective, combining the strengths of multiple algorithms to enhance prediction reliability. These findings represent a significant contribution to the field of predictive maintenance, offering practical solutions for industrial equipment management.

C. *Recommendations*

- Implementation of real-time monitoring systems integrated with the developed predictive maintenance framework to enable immediate fault detection and response.
- Extension of the data collection period beyond two months to capture seasonal variations and long-term degradation patterns in generator performance.
- Development of a standardised implementation protocol for deploying the predictive maintenance framework across various industrial settings and generator specifications.
- Integration of additional sensor technologies and data streams to enhance the model's predictive capabilities and expand its application to diverse industrial equipment.

D. *Research Limitations*

Study limitations include the focus on a single generator type and a two-month data collection period. Future research opportunities include expanding the dataset, incorporating diverse generator models, and exploring additional machine learning techniques to further validate and extend these findings.

E. *Conflict of Interest*

The authors declare no conflict of interest. This research received no external funding, and the development of the predictive maintenance framework was conducted solely for academic purposes. The manufacturing company that provided access to their diesel generator for data collection had no role in the study design, data analysis, interpretation of results, or the writing of this manuscript.

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