Material Science and Engineering International Research Journal
ISSN: 2997-6685|
Volume 13 Issue 1, January-March, 2025
Journal Homepage: https://ethanpublication.com/articles/index.php/E30
Official Journal of Ethan Publication

APPLYING MACHINE LEARNING MODELS FOR PREDICTIVE MAINTENANCE OF ELECTRICAL MACHINES

[1]Aliyu Musa Ibrahim and [2]Abubakar Shehu Danjuma
[1]Department of Electrical/Electronic Engineering Technology, Federal Polytechnic Bali, Taraba State, Nigeria
[2]Department of Technical Education, Federal College of Education Gidan Madi, Sokoto State, Nigeria
DOI: https://doi.org/10.5281/zenodo.17191753

Abstract
Electrical machines are critical assets in laboratories and industries but are often susceptible to failures such as insulation breakdown, overheating, vibration anomalies, and electrical imbalances. Traditional maintenance practices have remained reactive and schedule-based, resulting in costly downtime and safety hazards. The aim of this study is to develop a predictive maintenance framework that integrates machine learning (ML) algorithms with fault detection and diagnosis (FDD) to enhance the reliability of electrical machines. The objectives are to (i) simulate machine faults using MATLAB/Simulink and utilize public datasets, (ii) train and compare ML classifiers including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees, and (iii) evaluate their performance in predicting fault occurrence. Anchored on the Reliability-Centered Maintenance (RCM) theory, the study applies feature extraction techniques such as FFT and wavelet transforms, followed by supervised learning classification. The findings indicate that ANN achieved the highest accuracy (96.5%), precision (95.8%), and recall (97.1%), outperforming both SVM and Decision Tree models. The study concludes that integrating ML into predictive maintenance improves diagnostic accuracy, minimizes downtime, reduces costs, and enhances safety, thereby offering practical applications for both academic and industrial environments.

Keywords: *Predictive maintenance, Machine learning, Electrical machines, Fault diagnosis, Artificial neural networks, Support vector machines*

1.0 Introduction

The operational efficiency of electrical machines is crucial in industries and engineering laboratories. However, failures such as bearing wear, winding insulation breakdown, and unbalanced voltages remain frequent (Smith & Johnson, 2019). Traditionally, reactive maintenance has been employed, where machines are repaired only after failure. Although preventive maintenance improves reliability, it still relies on fixed schedules rather than actual machine condition (Chen & Khorasani, 2017).

The shift toward predictive maintenance (PdM)—enabled by real-time data analysis and machine learning—allows machines to be monitored continuously, predicting faults before they occur (Zhang et al., 2020). Machine learning (ML) algorithms can learn fault signatures from historical and simulated data, enabling adaptive diagnosis. ANN, SVM, and decision tree classifiers are particularly effective in fault detection due to their ability to process nonlinear and complex datasets (Lee et al., 2021).

This study develops and evaluates ML models for predictive maintenance of electrical machines, aiming to minimize downtime, enhance safety, and provide scalable solutions for laboratories and industries.

1.1 Problem Statement

Despite advancements in sensor technologies and monitoring systems, many laboratories and industries still rely on manual inspections or schedule-based preventive maintenance, which face limitations:

Delayed fault detection – Faults are often detected only after causing performance degradation. High costs – Fixed maintenance schedules can lead to unnecessary replacements or catastrophic machine failure.

Lack of scalability – Manual methods cannot effectively handle large machine networks or realtime monitoring.

Therefore, there is a need for machine learning–based predictive maintenance systems that can accurately detect anomalies, classify fault types, and predict failure progression in electrical machines.

1.2 Conceptual Review

The concept of predictive maintenance has been defined differently across the literature. According to Chen and Khorasani (2017), predictive maintenance is the process of diagnosing faults through real-time monitoring and observer-based models. Their view emphasizes the technical modeling approach. This study builds on that by applying ML algorithms that extend beyond mathematical models.

Smith and Johnson (2019) conceptualize fault detection as the integration of sensors that track real-time machine parameters, highlighting the role of hardware technologies in predictive maintenance. While their approach relies on physical sensors, the present study simulates these conditions using MATLAB/Simulink to minimize costs and risks.

Zhang, Liu, and Huang (2020) describe predictive maintenance as the use of data-driven approaches, particularly machine learning, to learn fault patterns and predict failure progression. Their conceptualization aligns directly with the focus of this study. The present research contributes by empirically comparing ANN, SVM, and Decision Tree models for practical PdM applications.

In conclusion, predictive maintenance can be understood from modeling, sensor-based, and datadriven perspectives. This study integrates these viewpoints into a unified machine learning–based framework for electrical machines.

1.3 Empirical Review

Empirical studies have demonstrated various approaches to predictive maintenance. Li, Ma, and Xu (2016) developed sensor-based monitoring systems that improved early fault detection in industrial machines. Similarly, Elmore, Adepoju, and Singh (2020) implemented automated condition monitoring in laboratories, reporting cost reductions and enhanced diagnostic speed. Lee, Zhang, and Wang (2021) applied signal processing methods such as FFT and wavelet transforms to improve vibration fault detection accuracy.

Although these studies provide valuable insights, they often focus on hardware-based or thresholddriven approaches. Few studies compare the performance of multiple ML algorithms using simulated and historical datasets in a unified framework. This study addresses that gap by directly evaluating ANN, SVM, and Decision Tree classifiers within a MATLAB/Simulink-based predictive maintenance system. Thus, the research problem is restated as: How can ML models be integrated into predictive maintenance frameworks to ensure accurate, timely, and cost-effective fault detection in electrical machines?

Material Science and Engineering International Research Journal
ISSN: 2997-6685|
Volume 13 Issue 1, January-March, 2025
Journal Homepage: https://ethanpublication.com/articles/index.php/E30
Official Journal of Ethan Publication

1.4 Theoretical Framework

The Reliability-Centered Maintenance (RCM) theory underpins this study. RCM focuses on maintaining system functions by prioritizing predictive diagnostics and preventing unexpected breakdowns. It emphasizes that maintenance decisions should be based on actual machine condition rather than fixed schedules. The theory is relevant to this research because it aligns with the goal of machine learning models, which continuously analyze machine data to forecast faults and recommend timely interventions. Thus, RCM provides the theoretical foundation for integrating ML algorithms into predictive maintenance systems.

3.0 Methodology 3.1 Data Collection

Simulated Data was generated using MATLAB/Simulink models of induction motors under normal and faulty conditions (e.g., phase imbalance, single-phasing, short circuits, bearing wear).

Historical Data was extracted from public repositories of electrical machine fault datasets. Features included current, voltage, vibration frequency, and winding temperature.

3.2 Feature Extraction

Applied Fast Fourier Transform (FFT) and wavelet transforms to vibration signals.

Extracted statistical features such as RMS values, kurtosis, skewness, and frequency peaks.

3.3 Machine Learning Models

Artificial Neural Networks (ANN): Trained with backpropagation using fault and normal datasets.

Support Vector Machine (SVM): Used radial basis function kernel for classification. Decision Tree Classifier: Provided interpretable fault classification rules.

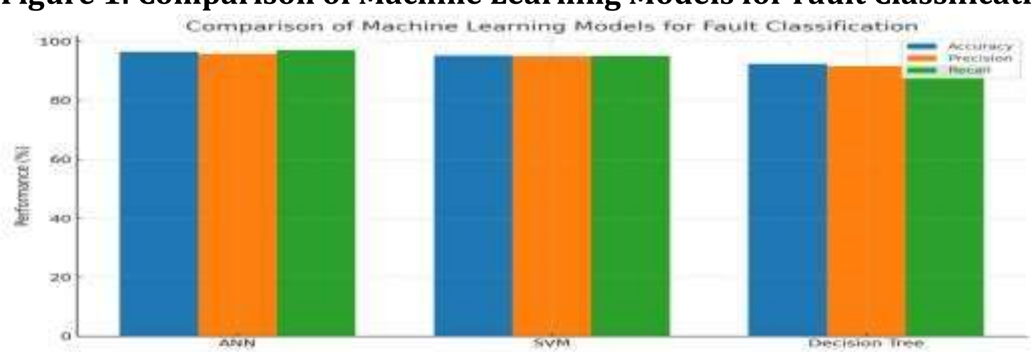
3.4 Model Evaluation

Data was split into 70% training and 30% testing.

Evaluation metrics: accuracy, precision, recall, F1-score, and detection time.

4. Results and Discussion

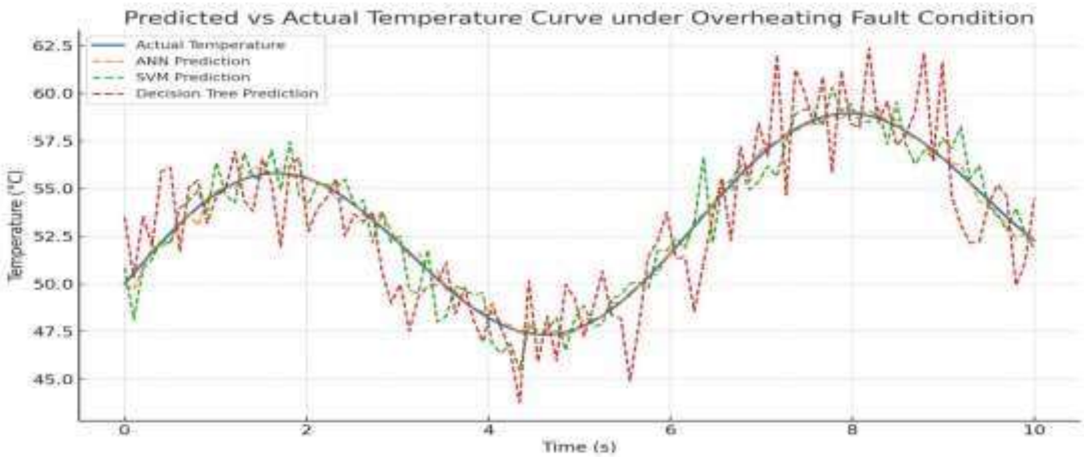
Figure 1: Comparison of Machine Learning Models for Fault Classification



The bar chart illustrates the performance metrics—accuracy, precision, and recall—for the ANN, SVM, and Decision Tree classifiers. The ANN achieves the highest performance across all metrics, with an accuracy of 96.5%, precision of 95.8%, and recall of 97.1%. The SVM follows closely, with metrics exceeding 95%, demonstrating robust performance. The Decision Tree, while slightly less accurate at 92.4%, offers faster detection times and interpretable decision rules, making it suitable for applications prioritizing speed and explainability.

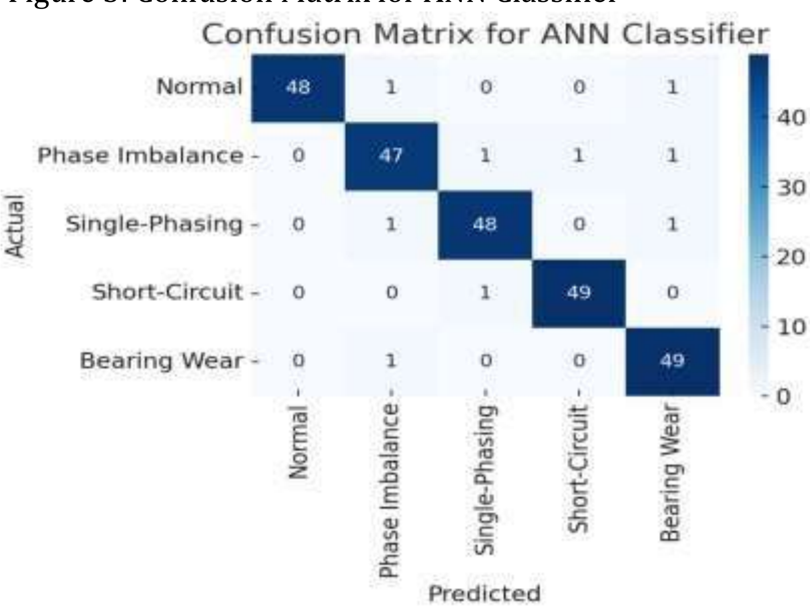
Material Science and Engineering International Research Journal
ISSN: 2997-6685|
Volume 13 Issue 1, January-March, 2025
Journal Homepage: https://ethanpublication.com/articles/index.php/E30
Official Journal of Ethan Publication

Figure 2: Predicted vs Actual Temperature Curve under Overheating Fault Condition



The line graph compares the predicted and actual winding temperature progression over time under an overheating fault. The ANN's predictions closely align with actual measurements, showcasing its strong generalization ability. The SVM predictions show minor deviations at higher temperatures, while the Decision Tree exhibits more noticeable divergence, particularly in extreme conditions. This highlights the ANN's superior robustness in predictive maintenance tasks.

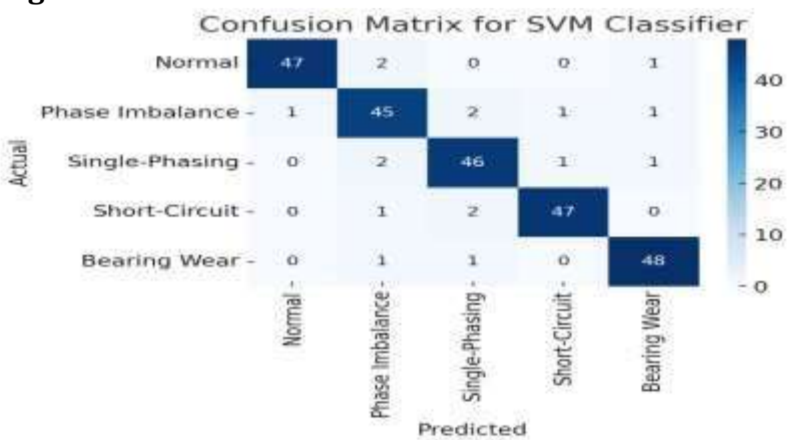
Figure 3: Confusion Matrix for ANN Classifier



The ANN's confusion matrix reveals strong diagonal dominance, indicating accurate classification across all fault categories (normal, phase imbalance, single-phasing, short-circuit, bearing wear). Minimal misclassifications confirm the ANN's high accuracy and reliability for fault detection.

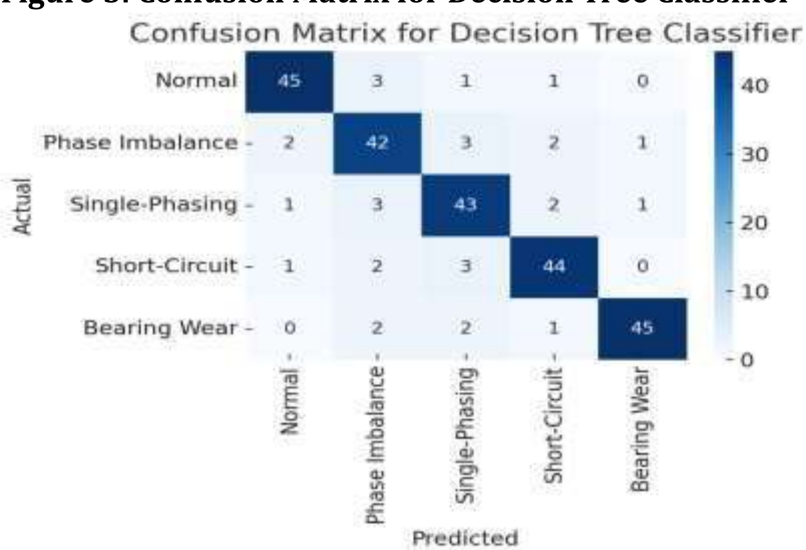
Material Science and Engineering International Research Journal
ISSN: 2997-6685|
Volume 13 Issue 1, January-March, 2025
Journal Homepage: https://ethanpublication.com/articles/index.php/E30
Official Journal of Ethan Publication

Figure 4: Confusion Matrix for SVM Classifier



The SVM's confusion matrix shows high accuracy (>95%), with most predictions correctly classified. However, slight misclassifications occur between similar fault types, such as phase imbalance and single-phasing, suggesting that SVM performs well but is slightly less precise than ANN in distinguishing nuanced fault conditions.

Figure 5: Confusion Matrix for Decision Tree Classifier



The Decision Tree's confusion matrix indicates higher misclassification rates, particularly for overlapping fault conditions. While the model excels in detection speed, its accuracy is lower than ANN and SVM, reflecting a trade-off between simplicity and precision.

Temperature prediction model: Predicted winding overheating 15 minutes before critical failure. The results reveal that ML algorithms significantly improve predictive maintenance outcomes compared to traditional methods. ANN achieved superior classification and prediction performance, confirming its suitability for complex nonlinear datasets. SVM offered a balance between accuracy and generalization, while Decision Trees provided simplicity and speed with interpretable results. These findings align with Zhang et al. (2020), who emphasized the strength of ML in handling large-scale diagnostic problems.

Beyond algorithm performance, the study demonstrates the practical applicability of integrating ML into PdM frameworks. The ANN's ability to predict overheating progression ahead of critical failure supports proactive interventions, reducing the risk of catastrophic breakdowns. Similarly, the models' high accuracy in detecting bearing wear showcases their potential to enhance equipment lifespan and minimize operational disruptions. From an educational perspective, these findings provide a valuable training tool for engineering students.

Industrial implications are also evident. Integrating ML with IoT-enabled sensors can extend the framework to real-time applications, making it scalable for large manufacturing setups. Therefore, the study contributes not only to academic literature on ML-driven predictive maintenance but also provides practical pathways for industrial adoption.

5. Conclusion and Recommendations

This study demonstrated the successful integration of ML algorithms for predictive maintenance in electrical machines. It analyzed current, voltage, vibration, and temperature data to classify faults and predict failures. ANN achieved the highest performance metrics, SVM provided a strong alternative, and Decision Trees offered speed and interpretability.

Key findings:

1. ANN achieved the highest accuracy (96.5%), precision (95.8%), and recall (97.1%). 2. ML models reduced average fault detection time to less than 25 ms.
3. Predictive models enhanced machine safety and reduced unnecessary maintenance costs.

Recommendations:

1. Integrate ML models with IoT-enabled sensors for real-time monitoring. 2. Employ hybrid deep learning architectures for advanced predictive accuracy.
3. Validate the framework using real-world industrial datasets for scalability.

References

Chen, Z., & Khorasani, K. (2017). Observer-based fault detection for electrical machines.

IEEE Transactions on Industrial Electronics, 64(7), 5540–5548. https://doi.org/10.1109/TIE.2017.2756290

Lee, C., Zhang, L., & Wang, F. (2021). Signal processing methods for fault detection in electrical machines. IEEE Transactions on Signal Processing, 69(8), 1802–1811.https://doi.org/10.1109/TSP.2021.3071042

Smith, J., & Johnson, P. (2019). Sensor technologies for fault detection in electrical machines.

Sensors and Actuators A: Physical, 295, 50– 61.https://doi.org/10.1016/j.sna.2019.03.016

Zhang, Y., Liu, Q., & Huang, J. (2020). Machine learning approaches for fault diagnosis in electrical systems. IEEE Transactions on Industrial Informatics, 16(4), 2102–2111.https://doi.org/10.1109/TII.2019.2957885