Department of Industrial Engineering & Maintenance

Machine Learning Driven Predictive Maintenance for Industrial IoT Electrical Systems

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Academic year:
2024-2025

Abstract: This study introduces a predictive maintenance framework that combines Internet of Things (IoT) sensor data with advanced machine learning (ML) techniques to improve the reliability and efficiency of industrial electrical systems. The proposed system analyzes real-time measurements such as temperature, vibration, current, and voltage to detect anomalies and predict equipment failures before they occur. It integrates essential processes including data cleaning, normalization, feature extraction, and model optimization to ensure accurate and timely predictions.Several ML models, including Random Forest, Support Vector Machines (SVM), and Artificial Neural Networks (ANNs), were evaluated for their performance. A real-world case study involving three industrial motors was conducted using over 10,000 time-series sensor records, 500 maintenance logs, and 100 documented failure cases.The results demonstrate a 35% reduction in unplanned downtime, a 25% increase in resource efficiency, and a 20% extension of equipment lifespan. These findings validate the effectiveness of the proposed approach in supporting proactive maintenance decisions in industrial environments.

Key-Words: IoT, predictive mainte- nance, machine learning, industrial electrical systems, detect anomalies, Neural Networks, Random Forests, Support Vector Machines.

Contents

1. Introduction

The rapid advancement of Industry 4.0 technologies has significantly transformed industrial maintenance strategies, particularly through the integration of Machine Learning (ML) and Internet of Things (IoT)-based predictive analytics. Traditional approaches such as Reactive Maintenance (RM) and Preventive Maintenance (PM) often lead to unexpected equipment failures, high maintenance costs, and inefficient downtime management. In contrast, Predictive Maintenance (PdM) uses real-time data from IoT sensors and AI-driven algorithms to anticipate failures before they occur, thereby improving system reliability and operational efficiency [1].

IoT-enabled industrial systems continuously generate large volumes of sensor data—such as vibration, temperature, current, and pressure—which offer valuable insights into equipment health. ML algorithms like Random Forest, Support Vector Machines (SVM), and Artificial Neural Networks (ANNs) are used to analyze these data, detect failure patterns, classify anomalies, and estimate Remaining Useful Life (RUL). The synergy between IoT-based data acquisition and ML-based analytics provides a scalable, real-time, and proactive maintenance solution.

Despite its clear benefits, integrating ML and IoT in predictive maintenance presents several technical challenges, including data heterogeneity, real-time processing constraints, cybersecurity concerns, and model interpretability. Selecting the most appropriate ML approach requires careful consideration of data complexity, computational resources, and reliability in industrial contexts [2].

This paper proposes a complete predictive maintenance framework tailored to industrial electrical systems. It explores key components such as data preprocessing, feature engineering, and model training strategies to enhance prediction accuracy. A real-world case study is presented to validate the proposed system, demonstrating significant improvements in equipment uptime and maintenance cost reduction.

2. Objectives of the Study

The primary goal of this study is to explore and validate the integration of machine learning techniques with Industrial Internet of Things (IIoT) systems to enhance predictive maintenance strategies for industrial electrical equipment. Specifically, the study aims to:

1. Design and implement a predictive maintenance architecture that combines real-time data acquisition from IoT sensors with advanced machine learning models.
2. Identify and apply suitable ML algorithms (Random Forest, SVM, Neural Networks) for anomaly detection and Remaining Useful Life (RUL) prediction in electrical industrial systems.
3. Evaluate the performance of the predictive system using key metrics such as accuracy, precision, recall, and F1-score across various experimental configurations.
4. Demonstrate the effectiveness of the system through a case study on electric motor monitoring, highlighting improvements in equipment reliability, downtime reduction, and resource optimization.
5. Assess operational challenges and scalability, including data quality, model interpretability, and deployment in real-world industrial environments.
6. Provide strategic recommendations for industrial adoption of ML-based predictive maintenance, incorporating future perspectives such as Edge AI, explainable models, and adaptive retraining.

3. Structure of the paper

This research article is organized into eight sections. It begins with an introduction to predictive maintenance in industrial IoT-based electrical systems, explaining the motivation and objectives. The second section presents a review of maintenance strategies and the role of IoT and machine learning. Section three focuses on data collection and preprocessing. Section four describes the development of machine learning models. The fifth section introduces the real-time monitoring system architecture. Section six explains testing and validation procedures. The seventh section covers full-scale deployment strategies. Finally, section eight presents continuous monitoring and optimization techniques, followed by a conclusion that highlights key findings and future directions.

4. Litterature review

4.1. Evolution of Maintenance Strategies in Industrial Systems

Modern industry relies on increasingly sophisticated equipment, making maintenance a strategic concern to ensure machine availability, reduce operational costs, and optimize productivity. Traditionally, industrial maintenance has been based on three main approaches:

- **Corrective Maintenance (Reactive Maintenance - RM)**: Interventions are performed after a failure occurs, often leading to high costs and unplanned downtime [3].
- **Preventive Maintenance (PM):** Maintenance tasks are scheduled at regular intervals to avoid failures. However, this approach can result in over-maintenance and unnecessary expenses [4].
- **Predictive Maintenance (PdM):** This strategy relies on real-time monitoring of machines using IoT sensors and data analysis to anticipate failures before they occur. With the rise of Industry 4.0, predictive maintenance has emerged as the most effective solution for reducing unexpected downtime and optimizing

maintenance operations. Its success relies on artificial intelligence (AI) and machine learning (ML), which are capable of processing large volumes of data to detect failure patterns and estimate the Remaining Useful Life (RUL) of equipment [5].

Maintenance	Description
Reactive Maintenance	▪ Allows components/assembly to run to failure ▪ Catastrophic failure which may lead to collateral damage ▪ High risk due to higher downtime ▪ High maintenance cost ▪ May lead to damage other sub-assemblies
Preventive Maintenance	▪ Prevents failure before they occur ▪ Chances of catastrophic failure is less ▪ Lower risk and lower downtime ▪ Less chances of damaging other sub-assemblies
Predictive Maintenance	▪ Full asset visibility ▪ Initial cost to benefit is high ▪ Early detection of wear and tear in components/assembly ▪ Increases asset life cycle ▪ Lowest downtime ▪ Significant reduction/complete elimination of unscheduled breakdowns.

Figure 1: Features of different types of maintenance

4.2. IIoT in Predictive Maintenance

The Industrial Internet of Things (IIoT) is a foundational element of Industry 4.0, representing the transition from traditional manufacturing systems to intelligent, connected industrial environments. IIoT enables the integration of machines, sensors, and control systems into a unified network that supports real-time data collection, monitoring, and analysis.[6] This connectivity allows companies to improve operational efficiency, reduce equipment downtime, and make faster, data-driven decisions.[7]Through continuous communication between devices, IIoT supports automation and enhances the ability to anticipate problems before they occur, making it a valuable asset in modern industrial operations. With the help of IIoT, industries have been able to shift from reactive and preventive maintenance strategies toward more advanced methods like predictive maintenance (PdM). PdM uses the large volumes of data generated by IIoT systems to detect early signs of equipment failure. This makes it possible to plan maintenance ahead of time, avoid unexpected breakdowns, and optimize resource allocation. [8]

4.3. The Importance of Machine Learning in Predictive Maintenance

Machine learning (ML) has emerged as a key driver in the evolution of predictive maintenance strategies. Unlike conventional methods such as reactive maintenance, which only intervenes after a failure, or preventive maintenance, which may involve unnecessary routine checks ML provides a more efficient, data-driven alternative[9]. By analyzing the continuous flow of data from IIoT-enabled systems, ML algorithms can uncover hidden patterns and detect early signs of equipment degradation [10]. This enables organizations to anticipate failures before they occur, schedule maintenance more effectively, reduce downtime, and increase the operational lifespan of industrial assets.

5. METHODOLOGY

5.1. Data Preparation and Preprocessing

Data preparation and preprocessing are foundational steps in the development of accurate and robust predictive maintenance systems. The process begins with the systematic collection of sensor data from industrial equipment using strategically deployed IoT devices. These sensors continuously record key operational parameters such as vibration, temperature, pressure, and current. Once acquired, the data is transmitted to centralized cloud-based infrastructures, where it undergoes a series of quality assurance procedures[11]. The preprocessing phase starts with data cleaning, which involves identifying and addressing missing values, outliers, and inconsistencies through interpolation, imputation, or filtering techniques. Given that sensor data is often contaminated with noise, noise reduction becomes essential. This is typically addressed using:

- **Frequency-domain methods** such as Fourier and wavelet transforms, which decompose signals into frequency components to isolate noise.
- **Time-domain methods** like moving average smoothing, which filters each data point based on neighboring values to reduce random fluctuations[12].

Following denoising, data normalization is applied to ensure that all features are on a consistent scale. Two primary techniques are used:

- **Min-Max normalization**, which rescales values within a defined range, usually [0,1].
- **Z-score normalization**, which standardizes data by centering it around the mean and scaling it by the standard deviation. This technique is particularly effective in dynamic environments but may struggle with non-stationary time series [13].

In parallel, feature engineering is employed to enhance the dataset's informational richness. This includes deriving new variables such as moving averages, rate of change, or frequency-domain features that capture subtle patterns related to potential equipment faults. Additionally, sensor data from multiple sources is synchronized and integrated using machine IDs and timestamps, and stored in data lakes to handle heterogeneous formats [14].

Together, these preprocessing steps result in a high-quality, noise-reduced, normalized, and enriched dataset that serves as a solid foundation for the training and deployment of machine learning models in predictive maintenance systems.

5.2. Development of Machine Learning Models

Machine learning algorithms play a key role in converting raw IoT data into valuable maintenance insights.

- **Supervised learning approaches** especially classification and regression models are commonly used to predict equipment failures and estimate the remaining useful life (RUL) of machines. Among the most widely used algorithms for these tasks are random forests, support vector machines, and neural networks, have shown strong capabilities in extracting features and handling time-series data effectively.

- **Random Forest:** This ensemble learning technique combines multiple decision trees to improve prediction accuracy and reduce overfitting. It is particularly effective for handling large datasets with many features [15].

Figure 2: Random forest regression algorithm for machine learning

- **Support Vector Machines (SVM):** SVMs work by constructing hyperplanes that separate data into distinct classes. They are especially useful in cases where the data is not linearly separable, leveraging kernel functions to map input data into higher-dimensional spaces [16].

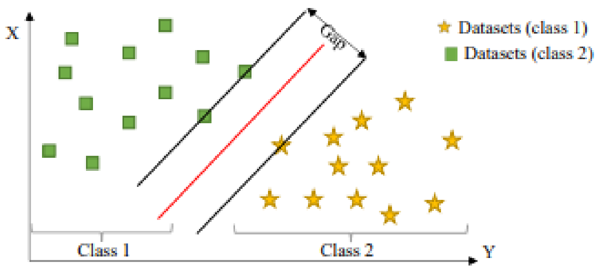

Figure 3: Support vector machine algorithm

- **Neural Networks:** Inspired by the structure of the human brain, neural networks consist of layers of interconnected nodes (neurons)[17], arranged in layers: an input layer, one or more hidden layers, and an output layer. Each neuron processes incoming signals using an activation function and passes the result to the next layer. ANN models are capable of learning from data by adjusting the connection weights through a training process [18].

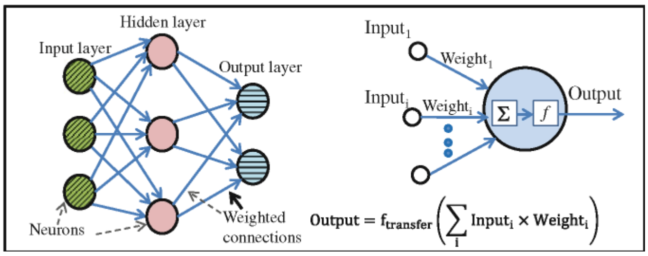

Figure 4: Architecture of artificial neural network

- **Gradient Boosting:** This sequential ensemble method builds models step-by-step, where each new model attempts to correct the errors of the previous one. It is known for its strong predictive performance, especially on imbalanced datasets [19].

In unsupervised learning, the model learns from data without any guidance or predefined labels. It is trained solely on input features, without access to corresponding outputs. The system analyzes the dataset to discover hidden patterns, groupings, or relationships within the data. While it can organize data into logical structures, it does not assign predefined labels to these groupings. There are two main types of unsupervised learning techniques:

- **Clustering:** This method divides data into distinct groups or clusters based on similarities or patterns, without requiring prior information. It is commonly used to uncover natural groupings in complex datasets.
- **Association:** A rule-based method that identifies frequent patterns or correlations between variables in large datasets. It is often applied in fields such as market basket analysis to reveal meaningful associations between items[20].
- **K-means Clustering** is applied to group similar data points, allowing for the identification of different operational states of industrial equipment. This clustering technique is particularly useful for segmenting large volumes of unlabeled data.
- **Principal Component Analysis (PCA)** serves as an effective method for reducing the dimensionality of complex sensor datasets. By transforming the data into a smaller set of uncorrelated variables, PCA helps isolate the most relevant features for predicting potential equipment failures.

Semi-supervised learning lies between supervised and unsupervised learning. In real-world applications, datasets often contain a mix of labeled and unlabeled data. In this approach, unsupervised techniques are first used to estimate or assign labels to the unlabeled data. These newly labeled samples are then used alongside the original labeled data to train a supervised learning model, improving overall prediction accuracy [21].

Each of these algorithms has its own advantages and limitations. Therefore, selecting the most appropriate model depends on the specific industrial context, the nature of the equipment, and the characteristics of the available data.

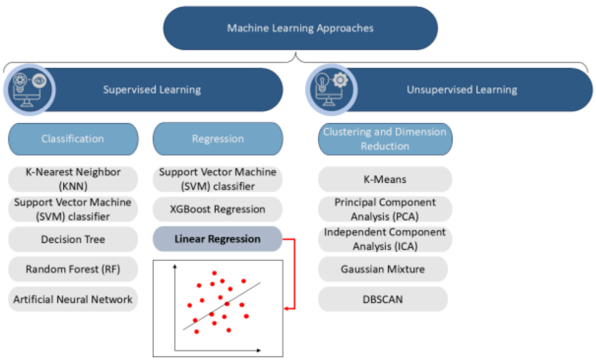

Figure 5: Machine learning algorithms

5.3. Real time monitoring system development :

The real-time monitoring system is developed through a structured approach that combines IoT-based sensor networks, secure data transmission, and automated data validation mechanisms. First, sensors are strategically deployed on key components of industrial electrical systems, selected based on failure criticality and operational stress zones. These sensors continuously capture parameters such as vibration, temperature, current, and pressure. Each device undergoes a calibration phase to ensure measurement accuracy under varying load and environmental conditions.
Once configured, the system initiates real-time data acquisition, where sensor outputs are collected at predefined intervals and transmitted using standard protocols like MQTT or HTTP. The data is streamed into a centralized cloud or edge platform that ensures low-latency access and high availability. Throughout the process, data quality is continuously monitored: anomalies, missing values, and outliers are detected and corrected through automatic cleansing routines[11].
To guarantee reliability and compliance, security measures including encryption, access control, and anonymization are applied. This real-time infrastructure enables predictive models to detect degradation trends early and trigger timely maintenance interventions minimizing unplanned downtime and ensuring optimal equipment performance.

5.4. System Testing and Validation

Model Training:
The chosen machine learning algorithms are trained using the designated training set from each dataset. To enhance their performance, hyperparameter tuning is conducted through cross-validation techniques, ensuring that the models are well-optimized and not overfitted to the training data.
Model Testing:
After training, the models are evaluated on the test set, which consists of previously unseen data. This step is crucial to assess how well the models generalize to new inputs. The predictions generated by the models are then compared with the actual outcomes to measure their accuracy and reliability.
Evaluation Metrics
To provide a well-rounded evaluation of each algorithm's performance, several key metrics are used:
1. Accuracy
This metric reflects the proportion of correct predictions made by the model. It is calculated as the number of true positives and true negatives divided by the total number of instances. Accuracy offers a general overview of how well the model performs across all classes.
2. Precision and Recall
o **Precision** indicates how many of the predicted positive cases are actually true positives.
o **Recall** (also known as sensitivity) measures how many of the actual positive cases are correctly identified by the model.
These two metrics are especially important when working with imbalanced datasets, where failure events are rare compared to normal operation.
3. F1 Score
The F1 Score is the harmonic mean of precision and recall, providing a single metric that balances both. It is particularly useful when there is a trade-off between minimizing false positives and false negatives.
4. Area Under the ROC Curve (AUC-ROC)
This metric evaluates the model's ability to distinguish between different classes such as faulty versus healthy equipment. A higher AUC value indicates better performance in correctly classifying states, even under varying threshold settings [9].
5. Computational Time:
The time taken to train and test the model, providing insights into the computational efficiency of each algorithm.
6. Scalability:
The ability of the algorithm to handle large datasets, assessed by analyzing the performance of the models as the dataset size increases.
7. Robustness to Noise:
The ability of the algorithm to maintain performance in the presence of noisy or incomplete data, crucial for real-world industrial applications.
By using these metrics, the study provides a thorough comparison of the machine learning algorithms, offering valuable insights into their applicability for predictive maintenance in IIoT environments [22].

5.5. Full-Scale Deployment

5.5.1 Deployment Strategy and Objectives

The full-scale deployment phase marks the transition from a successfully validated prototype to an operational predictive maintenance system integrated into the industrial environment. The primary objective is to implement the machine learning models in a way that supports real-time fault detection, minimizes downtime, and enhances decision-making. A progressive deployment strategy is often adopted, starting with limited pilot testing before rolling out the system to the entire production infrastructure. This approach reduces risks and ensures adaptability to site-specific constraints.[1]

5.5.2 System Integration with Industrial Platforms

For the system to be operational, the trained ML models must be embedded into the existing industrial infrastructure. This involves integration with tools such as:

- **CMMS (Computerized Maintenance Management Systems)** for maintenance scheduling and asset tracking.
- **SCADA (Supervisory Control and Data Acquisition)** for real-time supervision of equipment.
- **ERP systems** for higher-level business process synchronization.

Communication between components is ensured using standard industrial protocols like MQTT, Modbus, OPC-UA, or RESTful APIs, enabling seamless transmission of sensor data and predictions between devices, cloud platforms, and user dashboards.[23]

5.5.3 Visualization and Alert Management Interface

A key element of successful deployment is the user interface. A real-time monitoring dashboard is developed using web technologies (HTML5, JavaScript, D3.js or Plotly) to visualize the health status of equipment. Users can monitor variables such as vibration, temperature, or current through dynamic graphs and heatmaps.

In addition, a **notification system** is implemented using services like Twilio (for SMS) or email APIs, which immediately alert maintenance teams when an anomaly or predicted fault is detected. Alerts are configured with thresholds and priorities to avoid false alarms and alert fatigue.

5.5.4 Pilot Testing and User Acceptance

Before full-scale rollout, a pilot deployment is carried out in a controlled section of the plant. This test bed enables the system to be evaluated in real-world conditions on selected equipment. During this phase:

- **Environmental variables** (temperature, humidity) are standardized.
- **Sensor accuracy** is verified using calibration tools (oscilloscopes, multimeters. . .).
- **Operators** interact with the system to evaluate usability, response time, and alert relevance.

A User Acceptance Test (UAT) is conducted to collect feedback from technicians and engineers. Their insights are essential to adjust the dashboard design, model thresholds, or the frequency of alerts.

5.5.5 Scalability and Replication

Once the system has been validated at a local scale, the next step is to replicate the solution across multiple machines, production lines, or facilities. This requires: • Modular architecture that supports new sensor nodes or equipment types. • Cloud-based infrastructure (or Edge AI) that can handle increased data volume. • Automatic deployment tools (e.g., containerization via Docker) to facilitate model replication and updates. This ensures that the predictive maintenance approach is scalable, cost-effective, and sustainable across the enterprise.

5.5.6 Deployment Challenges and Mitigation

Common challenges during full-scale deployment include:

- **Data incompatibility** between new and legacy systems.
- **Resistance to change** from operators unfamiliar with automated predictions.
- **Network or latency issues** affecting real-time performance.

To overcome these, training sessions are provided to maintenance staff, dashboards are simplified for clarity, and fallback mechanisms are built into the system to ensure fault tolerance [24].

5.6. Monitoring and Optimization

5.6.1 Continuous System Monitoring

After deployment, predictive maintenance systems require ongoing monitoring and refinement to remain effective in dynamic industrial environments. The continuous tracking of key performance indicators (KPIs), such as Mean Time Between Failures (MTBF), false alarm rates, and equipment availability, helps ensure the system maintains high accuracy and reliability [23].

5.6.2 Model Retraining and Data Updates

To adapt to changing operational conditions, machine learning models are periodically retrained using updated sensor data and newly labeled failure cases. This retraining may follow a fixed schedule or be triggered automatically by performance degradation.

5.6.3 Technician Feedback Integration

Feedback from maintenance technicians also plays a vital role in system improvement. Their observations help refine alert thresholds, validate model predictions, and enhance the relevance of system outputs.[11]

5.6.4 Advanced Analytics Integration

Advanced techniques such as anomaly detection and Remaining Useful Life (RUL) prediction are integrated to anticipate failures more accurately. These methods provide early warnings and support maintenance scheduling, contributing to a shift from reactive to fully proactive maintenance strategies.

5.6.5 Long-Term System Optimization

Together, these optimization processes ensure the long-term adaptability, efficiency, and scalability of the predictive maintenance solution [25].

6. Challenges of Integrating ML and IoT in Predictive Maintenance

In conducting research focused on enhancing predictive maintenance in manufacturing through the application of machine learning algorithms and IoT-driven data analytics, several limitations were encountered that may affect the generalizability and applicability of the findings.

- **Data Quality and Availability:**

The research heavily relies on historical and real-time data collected through IoT devices. However, the quality and consistency of data can be a limiting factor. Any existing gaps, noise, or inaccuracies in the data can adversely affect the performance of the machine learning models. Furthermore, access to comprehensive datasets across diverse manufacturing environments was limited, which might restrict the scope of the conclusions drawn.

- **Cost of Implementation:**

The initial cost associated with IoT infrastructure deployment, data storage, and processing can be substantial, which may limit the adoption of these technologies, particularly in small to medium-sized enterprises. The cost-benefit analysis of predictive maintenance solutions needs careful consideration to justify the investment.

- **Ethical and Privacy Concerns:**

The extensive collection of data through IoT devices raises ethical and privacy concerns, especially regarding the ownership and use of data. Ensuring compliance with data protection regulations such as GDPR is essential but can complicate data collection and analysis processes [1].

- **Selection of right algorithm**

There are tens of widely popular algorithms available for ML implementation. Though algorithms can work in any generic conditions, there are specific guidelines available about which algorithm would work best under which circumstances. Improper selection of algorithm can produce garbage output after months of effort – leading to massive loss of the entire effort and pushing the target timelines further.

- **Selection of the right set of data**

As they say Garbage in will produce Garbage out, which is very well suited for the range of data set for machine learning. The quality, amount, preparation, and selection of data are critical to the success of a machine deep learning solution. Data selection may be impacted by Bias. It is important to avoid selection bias and select the data which is entirely representative of the cases [26].

- **Scalability :**

PDM implementation through large industrial activities requires evolution solutions that can manage a large amount of data in real time. Ensuring the ability to expand without programs to compromise the performance or increase the cost of is an important challenge [9].

- **Initial Investment:**

The implementation of PdM requires a significant initial investment in sensors, IIoT infrastructure, and machine learning systems. This can be a barrier, particularly for small and medium-sized enterprises [9].

7. A Case Study on Industrial Motor Systems : Integration of IoT and Machine Learning for Predictive Maintenance

7.1. Study Context

As part of improving industrial maintenance practices, this case study presents an integrated predictive maintenance system using Internet of Things (IoT) technologies and Machine Learning (ML) algorithms. The application focuses on industrial motors within a power plant, where unexpected failures can result in costly production downtime and compromise system safety. The objective is to transition from reactive or scheduled strategies to a proactive approach, enabling early fault detection through an intelligent model trained on sensor data and historical records.

7.2. IoT-Based Data Collection

Connected sensors were deployed on three industrial motors to monitor key parameters in real time, including:

- Temperature
- Vibration
- Current
- Voltage

These data are transmitted to a centralized platform for processing and visualization. Figure 6 illustrates the complete IoT integration process from monitoring objective definition to dashboard visualization while ensuring data security and regulatory compliance.

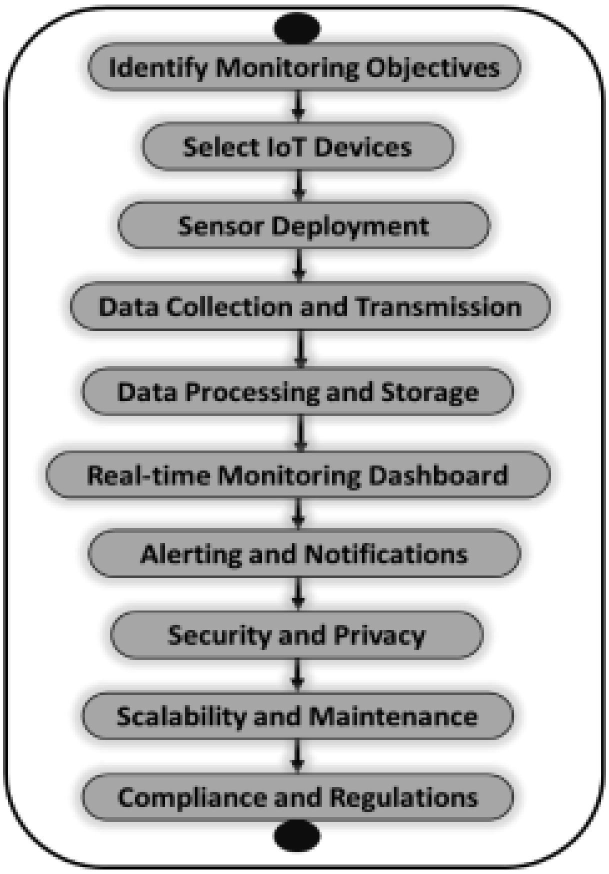

Figure 6: Integrating IoT devices for real-time monitoring

7.3. Historical Data

The predictive model integrates three types of data:

- 10,000 time-series sensor records
- 500 historical maintenance logs
- 100 documented motor failure cases

This multi-source database provides robust model training and ensures generalization to real industrial scenarios.

7.4. Model Development Process

Figure 7 outlines the model development pipeline, which includes:

- Data preprocessing (cleaning, missing value handling, normalization)
- Feature engineering: extraction of physical and statistical features (RMS, means, frequency)
- Machine Learning algorithm selection: supervised models for classification and time-series analysis
- Advanced training techniques:

o Self-attention mechanisms to focus on relevant time-series data

o Adaptive optimization (Adam, SGD)

o Loss function: Mean Squared Logarithmic Error (MSLE)

- Validation using classical metrics (accuracy, precision, recall, F1-score)
- Continuous deployment and monitoring.

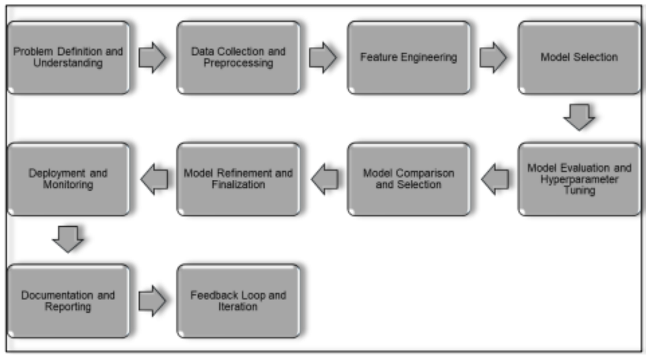

Figure 7: Selecting and implementing Process machine learning algorithms

7.5. Experimental Results and Interpretation

The model's performance was assessed through 10 experimental scenarios, with results summarized in Figures 8 to 13. The metrics evaluated were:

- Accuracy: Overall rate of correct predictions
- Precision: Ability to avoid false positives
- Recall: Ability to detect actual failures
- F1-score: Balance between precision and recall

7.5.1 Impact of Self-Attention Mechanism

The results illustrated in Figures 8 and 9 highlight the positive impact of incorporating the self-attention mechanism into the predictive maintenance model. Across the ten trials, the framework consistently achieved high accuracy, precision, recall, and F1-score, demonstrating its ability to capture long-range dependencies and select relevant features from sensor data. The stable performance across all scenarios confirms the model's robustness and reliability, enabling it to deliver accurate and consistent failure predictions for industrial motors.

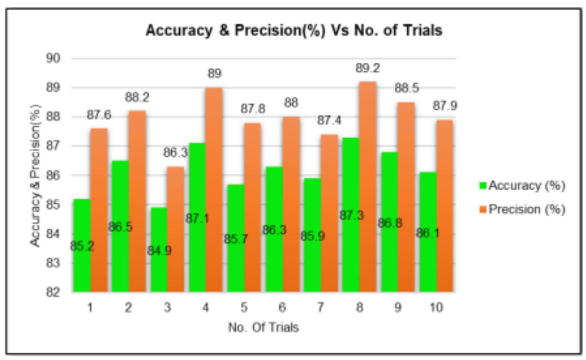

Figure 8: Self-Attention Mechanism Integration (Accuracy & Precision)

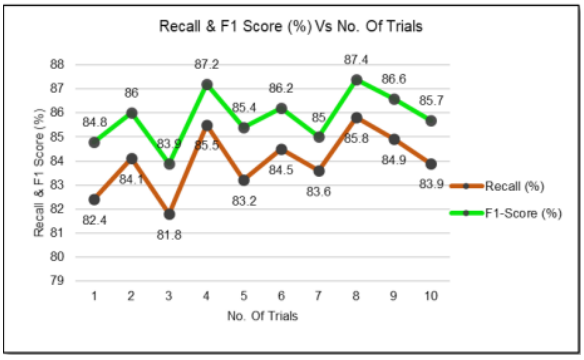

Figure 9: Self-Attention Mechanism (Recall & F1 Score)

7.5.2 Effect of Optimization Techniques

The results presented in Figures 10 and 11 highlight the significant role of optimization techniques such as Gradient Descent, Stochastic Gradient Descent, and Adam in enhancing the performance of the predictive maintenance model. Across the ten experimental trials, the model consistently achieved strong accuracy, precision, recall, and F1-score, indicating that these algorithms contribute to better parameter tuning, faster convergence, and improved generalization. As a result, they help ensure greater stability, accuracy, and overall efficiency of the predictive framework in industrial settings.

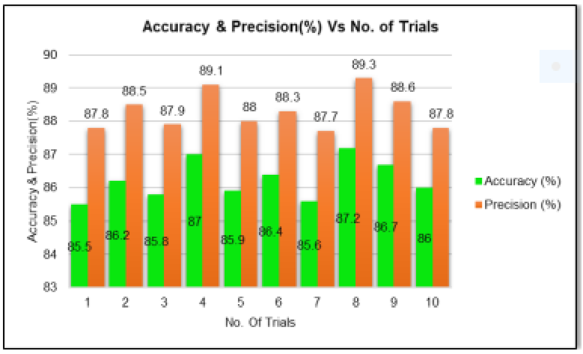

Figure 10: Optimization Techniques (Accuracy & Precision)

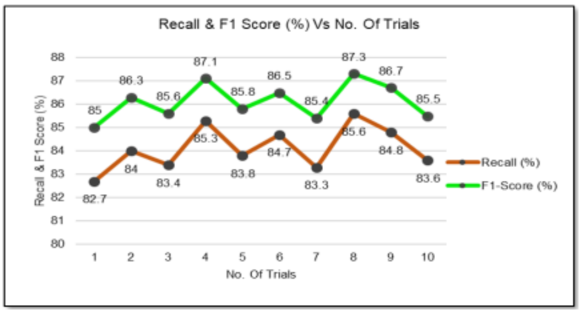

Figure 11: Optimization Techniques (Recall & F1 Score)

7.5.3 Role of MSLE Loss Function

The results related to the choice of loss function also provide key insights into its critical role in the performance of predictive maintenance models. As shown in Figures 12 and 13, which demonstrate consistently high levels of accuracy, precision, recall, and F1-score across the ten trials, selecting a loss function that aligns with the characteristics of the data and predictive maintenance goals is essential. The loss function directly influences the learning process by guiding the model to minimize prediction errors and produce reliable assessments of the condition of industrial motors. An inappropriate choice at this stage can significantly limit the model's effectiveness.

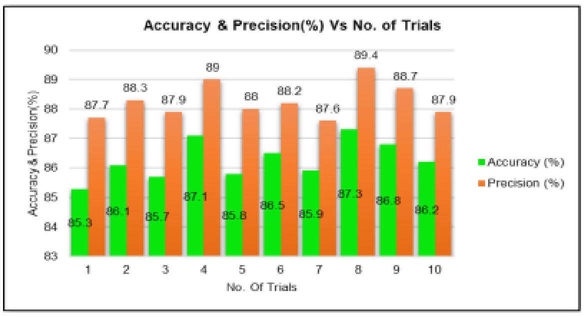

Figure 12: Loss Function Selection (Accuracy & Precision)

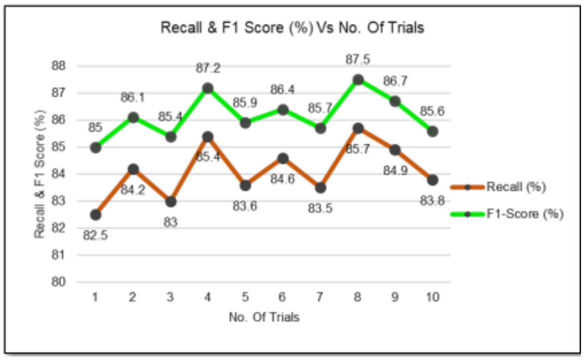

Figure 13: Loss Function Selection (Recall & F1 Score)

7.6. Operational Impact of the System

This figure highlights the practical benefits obtained from the implemented predictive maintenance system:

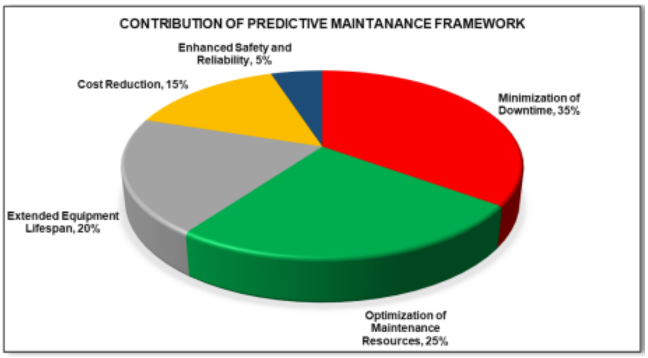

Figure 14: Contributions of predictive maintenance frameworks

Figure 14 highlights the key benefits of predictive maintenance. It shows that 35% of the improvements are linked to the reduction of unplanned downtime, followed by 25% for optimization of maintenance resources. Other benefits include extended equipment lifespan (20%) and cost reduction (25%). Lastly, 15% of the contributions relate to enhanced safety and reliability, emphasizing the effectiveness of predictive maintenance in preventing critical equipment failures.[27]

7.7. Case Study Conclusion

This case study demonstrates that combining IoT sensors, advanced ML models, self-attention mechanisms, adaptive optimizations, and the MSLE loss function results in a fully operational and scalable predictive maintenance system. The system ensures real-time monitoring, early fault detection, cost reduction, resource optimization, and asset life extension highlighting its potential for large-scale deployment in critical industrial environments.

8. Conclusion

This research demonstrates the effectiveness of an integrated approach combining IoT sensors, advanced data preprocessing techniques, and machine learning models for the implementation of a predictive maintenance system in industrial electrical environments. By leveraging methods such as neural networks, SVM, and Random Forest along with the integration of attention mechanisms and optimization techniques (Adam, MSLE) ,the proposed system achieves high performance in early anomaly detection and reduction of unplanned downtime. The case study applied to industrial motors highlights concrete benefits: a 35% reduction in failures, a 25% improvement in resource utilization, and an overall enhancement in equipment reliability. These results validate the robustness and relevance of the developed architecture for larger-scale deployments. However, several challenges remain to be addressed: the quality of the collected data, the security of information flows, the interpretability of models, and infrastructure costs. These limitations open up promising avenues for future research, particularly through the integration of Edge AI, federated learning, and explainable AI, in order to foster broader industrial adoption of intelligent maintenance technologies.

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