Department of Industrial Engineering & Maintenance

# Implementing Machine Learning for Industrial Electrical Systems Maintenance and Remote Monitoring

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Master's thesis in MIMI

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**Abstract:** Predictive maintenance and remote monitoring have become essential components in modern industrial environments, particularly for electrical systems, which are critical to ensuring operational continuity, safety, and productivity. Traditional maintenance strategies, based on reactive or time-based interventions, often lead to unexpected failures, increased costs, and inefficient use of resources. This research addresses these limitations by proposing an intelligent maintenance system that integrates Machine Learning (ML) and Internet of Things (IoT) technologies to predict failures and enable real-time monitoring of industrial electrical equipment. The methodology involves collecting real-time data from electrical systems using smart sensors, transmitting it through an IoT infrastructure, and applying ML algorithms to analyze equipment behavior, detect anomalies, and forecast potential failures. The system is tested under simulated industrial conditions to assess its accuracy, responsiveness, and usability. A case study on a DC motor equipped with sensors (temperature, humidity, current, and vibration) and connected to an ESP8266 microcontroller demonstrates the system's effectiveness, with data transmitted via MQTT to a cloud platform and processed using the Random Forest algorithm, achieving 90% accuracy in fault classification. The results show significant improvements in fault detection, maintenance scheduling, and system reliability, contributing to the development of intelligent maintenance frameworks and supporting the digital transformation of industrial practices in alignment with Industry 4.0 objectives.

**Key-Words:** Predictive Maintenance; Machine Learning; Internet of Things (IoT); Industrial Electrical Systems; Remote Monitoring; Anomaly Detection; Smart Sensors; Condition-Based Maintenance; Industry 4.0; Data-Driven Maintenance

## Contents

# 1. Introduction

In industrial environments, electrical systems represent the backbone of production processes, ensuring the functioning of machinery, lighting, automation systems, and safety mechanisms. The maintenance of these systems is therefore critical to avoid costly production downtimes and ensure the safety and reliability of operations. However, traditional maintenance strategies, often reactive intervening only after a failure has occurred or preventive based on fixed schedules regardless of actual equipment condition are proving increasingly inadequate in modern industrial contexts. These approaches can result in unexpected equipment breakdowns, excessive and unnecessary maintenance actions, inefficient use of resources, and an overall lack of responsiveness to real-time operating conditions. Such limitations are particularly problematic in complex and high-demand industrial environments, where electrical failures can cascade into serious operational disruptions. The emergence of new digital technologies has opened promising paths for overcoming these challenges. In particular, the convergence of Machine Learning (ML) and the Internet of Things (IoT) is redefining the field of industrial maintenance by enabling a shift toward predictive and condition-based maintenance models. ML algorithms are capable of processing and learning from vast volumes of sensor data collected from electrical equipment, identifying subtle patterns or anomalies that may indicate early signs of failure. At the same time, IoT provides the technological infrastructure for real-time data collection, remote monitoring, and system connectivity, allowing maintenance teams to have continuous visibility into equipment performance. Together, ML and IoT form the foundation of intelligent maintenance systems that not only predict failures before they occur, but also optimize the timing and scope of maintenance interventions. his research is particularly significant in the current industrial era, where operational efficiency, reliability, and safety are more critical than ever. By moving from reactive to predictive strategies, companies can reduce maintenance-related costs, extend equipment lifespan, minimize downtime, and prevent catastrophic failures that might compromise entire production lines. The integration of ML and IoT technologies into electrical system maintenance also promotes data-driven decision-making, enabling more accurate diagnostics, real-time alerts, and dynamic maintenance planning based on actual usage and condition rather than arbitrary schedules. The primary objective of this article is to propose a comprehensive framework for implementing Machine Learning and IoT in the predictive maintenance and remote monitoring of industrial electrical systems. This involves designing a system capable of collecting and transmitting real-time data through smart sensors, processing this data using advanced ML models to detect faults and predict failures, and providing remote access to this information via user-friendly platforms. The proposed solution aims to demonstrate how such an integrated system can enhance maintenance operations, increase electrical system reliability, and support the broader goals of Industry 4.0 and intelligent manufacturing. This study adopts a systematic methodology to develop and validate an intelligent predictive maintenance system for industrial electrical systems, integrating Machine Learning (ML) and Internet of Things (IoT) technologies. The process begins with requirements gathering, where industrial maintenance challenges and system specifications are analyzed to define functional needs ( real-time fault detection) and non-functional criteria ( scalability, data security). Next, data preparation involves collecting sensor data (current, voltage, temperature, vibration) via IoT devices, followed by cleaning, noise reduction, and feature engineering to enhance model accuracy. For ML model development, four algorithms Random Forest (RF), Long Short-Term Memory (LSTM), Support Vector Machine (SVM), and XGBoost are trained and evaluated using metrics like precision, recall, and computational efficiency. The IoT integration phase designs a layered architecture (perception, network, middleware, application) to enable real-time data transmission, cloud storage, and remote monitoring via protocols like MQTT. Implementation proceeds through a pilot deployment, where the system's performance is tested in real-world conditions, followed by full-scale rollout with integration into industrial platforms ( SCADA, CMMS). Finally, a case study on motor condition monitoring validates the framework, demonstrating 90This structured approach ensures a robust, scalable, and data-driven maintenance system that transitions industries from reactive to predictive strategies.

# 2. Initial Analysis and Requirements Gathering

The implementation of predictive maintenance and remote monitoring in industrial electrical systems requires a thorough understanding of the current maintenance landscape and the operational requirements of the target environment. Traditional maintenance strategies in many industrial settings are predominantly reactive or based on scheduled interventions, which often result in unexpected equipment failures, increased downtime, and higher maintenance costs [1]. These approaches fail to leverage real-time operational data, leading to inefficient decision-making and suboptimal asset utilization. The growing complexity of electrical systems and the need for higher reliability have highlighted the inadequacies of such conventional methods [2]. Consequently, the integration of intelligent technologies such as Machine Learning (ML) and the Internet of Things (IoT) has become increasingly essential. ML provides tools to analyze equipment behavior through historical and real-time data, enabling early fault detection and condition-based interventions [3]. At the same time, IoT ensures seamless data acquisition and communication from remote or distributed systems, thus enhancing visibility and responsiveness. To meet these challenges, the system must address several functional requirements, including the ability to collect real-time data from key electrical components, identify anomalies using ML models, and alert maintenance personnel before failure occurs. Additionally, non-functional requirements such as system reliability, data security, scalability, and low-latency performance are critical for industrial adoption. The proposed system will rely on sensors capable of measuring electrical parameters (voltage, current, temperature), which will be connected via IoT modules such as GSM or Wi-Fi for remote transmission. The collected data must be sufficient in volume and quality to train supervised ML algorithms capable of distinguishing normal from faulty behavior. Furthermore, the involvement of key stakeholders maintenance engineers, operators, and management is essential to ensure that the system aligns with operational workflows and addresses real-world maintenance challenges. This initial analysis and requirements gathering phase is crucial for the successful design and deployment of a predictive maintenance solution tailored to the specific needs of industrial electrical systems.

# 3. Data Preparation and Preprocessing

The world is currently undergoing a fast-paced fourth industrial revolution, driven by rapid technological advancements. Digital systems are now present across all sectors, including healthcare, education, manufacturing, entertainment, and telecommunications, all of which generate vast amounts of data. These systems have become major sources of big data, enabling the extraction and analysis of insights to uncover new patterns and knowledge. Such information is crucial for developing intelligent applications tailored to these domains.

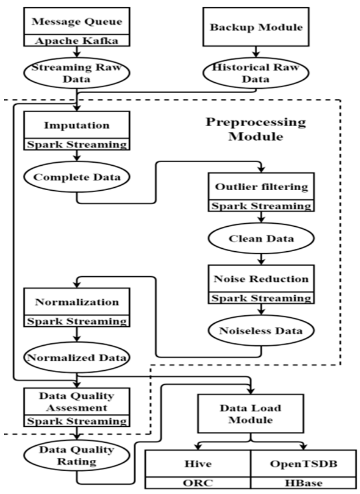


Figure 1: Components and data flow within the preprocessing module

## 3.1. Types of Sensors and Variables Measured

In the Industry 4.0 context, the adoption of diverse sensors has grown significantly due to advances in data handling technologies [4]. Industrial settings, given their machinery diversity and sector-specific needs, require a wide variety of sensors to monitor processes and components effectively. While many machines include built-in sensors, additional sensors are often used to complete data acquisition systems.

According to [5], machine condition monitoring involves tracking parameters like temperature, vibration, noise, acoustic emissions, and oil pressure, among others. Vibration analysis is notably widespread [6][7][8], since vibration patterns evolve with fault development. Techniques for vibration monitoring include proximity probes, velocity transducers, accelerometers (most common), dual probes, and laser vibrometers [9]. Acoustic analysis using microphones is also employed, though it can be limited in noisy environments [10].

Monitoring electrical current is a cost-effective method for motors and generators [6][11], often complemented by torque, speed, and especially temperature measurements crucial for diagnosing abnormal operation [12]. Thermography is frequently used to track surface temperature through infrared imaging [13], useful in tool wear detection [14], while thermocouples offer affordable point measurements.

Acoustic Emission (AE) techniques detect stress waves from localized faults like cracks or leaks [15][16][17], especially in large machinery. Similarly, ultrasound is used to inspect materials for surface and internal defects [18], while eddy current testing evaluates conductive material integrity [19]. Radiographic inspection identifies internal flaws in cast or welded components [20], whereas liquid penetrant testing detects surface anomalies.

Lubricant analysis assesses oil composition and contamination using ferrography, spectrometry, and chromatography. Ferrography detects wear via iron particles [21]; spectrometry identifies metal and non-metal particles for early fault detection [22]; chromatography evaluates oil property changes like viscosity and water content [9].

Beyond one-dimensional data, smart manufacturing also leverages multidimensional data, particularly through vision-based inspection systems [23], including 3D vision for assembly quality control [24]. Acoustic cameras, integrating microphones to localize noise, support diagnostics in systems like conveyors [25].

Additional sensor types cater to specific systems: pneumatic/hydraulic components benefit from pressure, flow, and position monitoring; cyclic load machines use load cells or strain gauges to measure stress and ensure structural integrity.

## 3.2. Data Preparation and Preprocessing

Data preparation and preprocessing are critical foundations for building accurate and reliable predictive maintenance systems. The process begins with the systematic acquisition of sensor data collected from industrial equipment via strategically placed IoT devices. These sensors continuously monitor key operational metrics such as vibration, temperature, pressure, and current. The collected data is then transmitted to centralized, cloud-based platforms, where it undergoes a series of quality control checks.

The preprocessing phase starts with data cleaning, aimed at detecting and correcting issues such as missing values, outliers, and inconsistencies. Techniques like interpolation, statistical imputation, and filtering are applied. Since raw sensor signals are often affected by noise, denoising is a crucial step, addressed using:

- Frequency-domain techniques (Fourier and wavelet transforms), which break down signals into their spectral components to isolate and suppress noise;
- Time-domain approaches (moving average filters), which smooth out short-term fluctuations based on surrounding values.

After denoising, normalization is performed to align feature scales across the dataset. The most common methods include:

- Min-Max normalization, which scales values to a fixed range (typically [0, 1]);
- Z-score normalization, which standardizes data by centering it around the mean and adjusting for standard deviation especially useful in dynamic environments, though less effective for non-stationary time series.

Simultaneously, feature engineering is applied to enrich the dataset. This involves generating new attributes such as moving averages, derivatives, or frequency-domain features that help reveal patterns associated with early signs of equipment failure. In addition, data from multiple sensors is synchronized and integrated using identifiers such as machine IDs and timestamps, and stored in data lakes to accommodate diverse formats and sources.

Through this comprehensive preprocessing pipeline covering data cleaning, noise reduction, normalization, feature engineering, and data integration a high-quality, consistent, and enriched dataset is produced. This refined dataset provides a robust foundation for training and deploying machine learning models in predictive maintenance applications.[26][27]

# 4. ML Model Development

The evolution of computational tools and frameworks has provided effective solutions to everyday problems. Among these advancements, machine learning has emerged as a prominent computational approach that uses algorithms and statistical models to perform tasks without explicit programming. Instead, it leverages data patterns to draw inferences and support automated decision-making processes.

Machine learning refers to the use of computer algorithms that enable systems to learn and improve from data automatically, allowing them to predict or classify the nature of this data through pattern recognition [28]. It is generally considered a subfield of artificial intelligence (AI) that enables systems to make autonomous decisions without external intervention, by uncovering meaningful hidden patterns within complex datasets.

The machine learning approach varies depending on the nature of the input and output data, as well as the specific problem being addressed. It operates through embedded instructions and minimal programmer supervision to carry out tasks based on data-driven decision-making [28]. Machine learning techniques are typically classified into supervised learning, semi-supervised learning, unsupervised learning, and reinforcement learning, although hybrid and alternative methods also exist [29].

## 4.1. Machine Learning Techniques

Machine learning techniques are primarily categorized into four main types: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning [28]. Each of these approaches is applied based on their suitability for addressing specific real-world problems, and their use varies depending on the nature of the task and the available data.

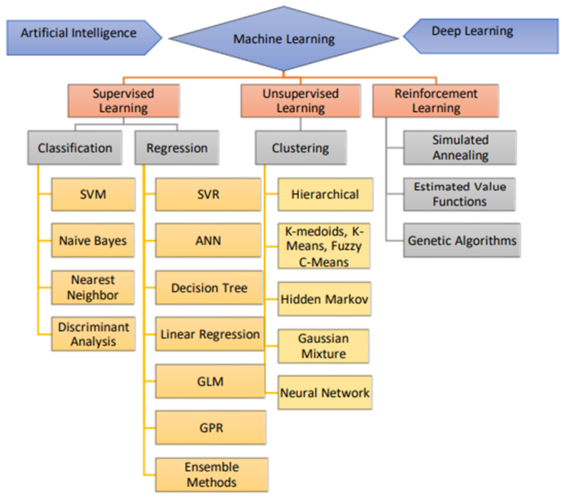


Figure 2: Classifications within Machine Learning Techniques

### 4.1.1 Supervised Learning

In supervised learning, a category of machine learning, algorithms operate by developing a mathematical model based on input-output data pairs [30]. This process involves translating the problem into a mathematical formulation where the input data (data fed

into the system) is associated with corresponding expected outputs (the resulting processed information). The dataset used is known as training data, consisting of multiple examples with one or more inputs.
Supervised learning typically employs feature vectors (array vectors used for feature extraction) and organizes the training data into a matrix structure. Through iterative learning, the algorithm adjusts to improve the accuracy of its predictions or classifications. Once the algorithm has effectively learned from the data, it can reliably produce accurate results [31].

### 4.1.2 Unsupervised Learning

Unsupervised learning algorithms function by analyzing datasets to detect patterns, primarily for grouping or clustering purposes. These algorithms identify similarities within the data and respond according to the presence or absence of these patterns in new, incoming data. Unlike supervised learning, unsupervised learning does not rely on labeled, classified, or categorized input; instead, it learns directly from unstructured data without human intervention, making it a purely data-driven approach [32].
Common tasks in unsupervised learning include anomaly detection, dimensionality reduction, clustering, density estimation, feature learning, and the discovery of association rules [33].

### 4.1.3 Semi-Supervised Learning

Semi-supervised learning lies between supervised learning (which uses labeled data) and unsupervised learning (which uses unlabeled data). It is considered a hybrid machine learning approach because it operates on both labeled and unlabeled datasets, often resulting in improved prediction accuracy. This technique leverages the strengths of both methods to enhance learning performance, especially when acquiring labeled data is costly or time-consuming. Semi-supervised learning is commonly applied in areas such as text classification, fraud detection, and machine translation [34].

### 4.1.4 Reinforcement Learning

Reinforcement learning refers to a machine learning approach in which software agents or machines make decisions autonomously within an environment to optimize performance. It is widely applied in fields such as operations research, game theory, information theory, swarm intelligence, and genetic algorithms. This learning technique is based on a reward-penalty system, where the agent learns to take actions that maximize rewards or minimize risks based on feedback from the environment.
Reinforcement learning is particularly effective for tasks that require continuous decision-making, such as autonomous vehicle navigation, playing games against human opponents, and robotics. It is increasingly used in automation, including manufacturing processes and supply chain logistics [28].

## 4.2. Algorithms for Predictive Maintenance

For this research, we evaluate four of the most frequently applied predictive maintenance algorithms:

1. Random Forest (RF)
2. Long Short-Term Memory (LSTM)
3. Support Vector Machine (SVM)
4. Extreme Gradient Boosting (XGBoost)

All algorithms are tested based on accuracy, precision, recall, and computational performance using artificial data created from IIoT sensors.

### 4.2.1 Random Forest (RF)

Random Forest is a supervised machine learning technique that constructs multiple decision trees during training and aggregates their predictions to improve accuracy. It is widely used in predictive maintenance for both classification and regression tasks due to its robustness and ability to model complex, nonlinear relationships often found in IIoT sensor data [35].
**Working Mechanism:**

- Random Forest randomly selects subsets of features and data instances to train a diverse ensemble of decision trees
- Each tree makes an independent prediction; the final result is obtained by majority voting (for classification) or averaging (for regression) [36]
- The model is inherently resistant to overfitting and performs well with noisy industrial datasets

**Advantages:**

- Efficient handling of high-dimensional data
- Reduced risk of overfitting compared to individual decision trees
- Tolerant of missing values and outliers

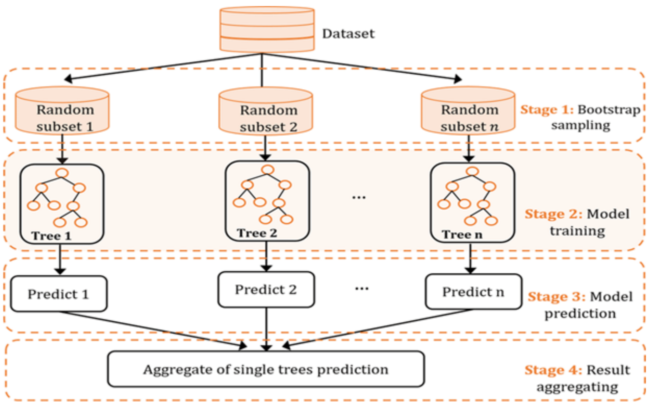


Figure 3: Random Forest (RF) Algorithm

### 4.2.2 Long Short-Term Memory (LSTM)

LSTM is a specialized type of Recurrent Neural Network (RNN) designed to handle sequential and time-series data. It is particularly effective in IIoT-based predictive maintenance, especially when sensor readings evolve continuously over time [37].
**Working Mechanism:**

- LSTM networks consist of memory cells that retain information over extended time intervals, effectively mitigating the vanishing gradient problem
- Each memory cell contains input, forget, and output gates that regulate the flow of information through the network
- The model is capable of learning long-term dependencies in time-series data, making it ideal for identifying progressive faults such as wear and tear in industrial equipment [38]

**Advantages:**

- Highly suitable for time-series forecasting in IIoT environments
- Capable of capturing long-term relationships in sequential sensor data
- Effectively detects complex patterns in machine behavior and performance

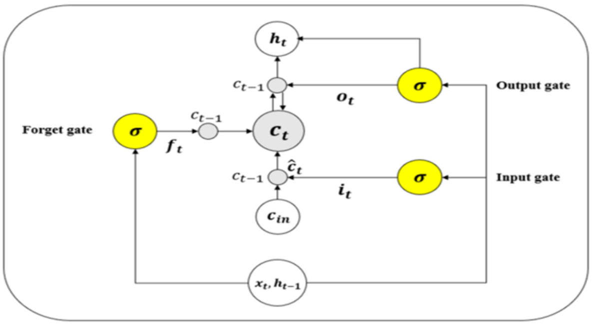


Figure 4: Long Short-Term Memory (LSTM) Algorithm

#### 4.2.3 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a powerful classification algorithm that identifies the optimal hyperplane that maximizes the margin between different classes in a high-dimensional feature space. In predictive maintenance, SVM is often used for binary classification tasks such as predicting whether a machine is likely to fail or not [39].

**Working Mechanism:**

- SVM constructs a decision boundary (hyperplane) that maximizes the margin between classes
- It can handle non-linearly separable data by applying kernel functions such as linear, polynomial, or radial basis function (RBF) kernels [40]
- The algorithm performs well when sensor data contains distinct failure signatures or patterns

**Advantages:**

- Delivers strong performance with relatively small datasets
- Effectively handles nonlinear relationships through the use of kernel methods
- Suitable for both binary and multi-class classification tasks

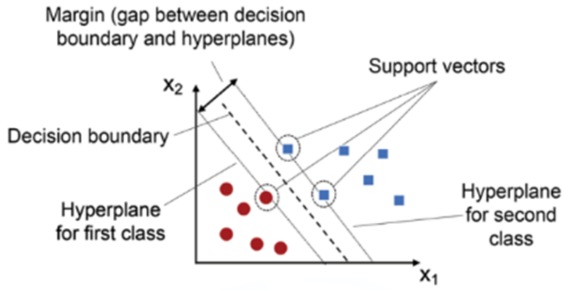


Figure 5: Support Vector Machine (SVM) Algorithm

#### 4.2.4 Extreme Gradient Boosting (XGBoost)

XGBoost is an ensemble learning technique that improves predictive performance by iteratively training decision trees in a manner that minimizes prediction errors. It is widely used in IIoT systems for tasks like fault detection and anomaly detection.

**Working Mechanism:**

- XGBoost constructs multiple weak learners (decision trees) and aggregates their outputs to form a strong, accurate predictor
- It uses gradient boosting to minimize the loss function, enhancing the model's accuracy [41]
- The algorithm is highly efficient in handling large-scale sensor data

**Advantages:**

- Exceptionally efficient and scalable, making it suitable for large IIoT datasets
- Delivers high prediction accuracy with minimal computational overhead
- Handles imbalanced data effectively, making it ideal for real-world IIoT applications

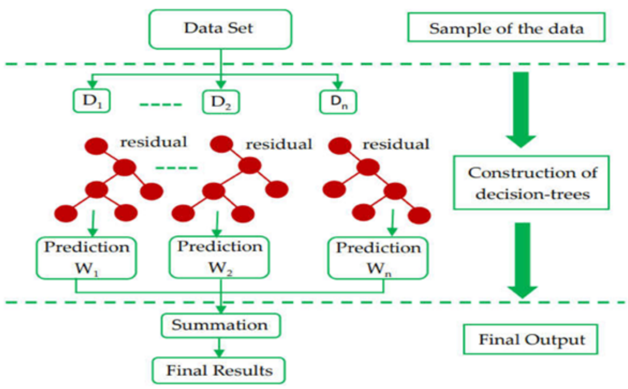


Figure 6: Extreme Gradient Boosting (XGBoost) Algorithm

### 4.3. Importance of Machine Learning in Predictive Maintenance

Machine Learning (ML) has become a foundational component of predictive maintenance, enabling the analysis of large-scale data produced by Industrial Internet of Things (IIoT) systems. Traditional mainte-

nance approaches such as reactive maintenance, which addresses failures after they occur, and preventive maintenance, which may involve unnecessary interventions often result in inefficiencies.
In contrast, ML algorithms can detect patterns and anomalies within operational data, enabling accurate predictions regarding the timing and location of potential failures [42]. This predictive capability facilitates proactive maintenance actions, optimizes maintenance schedules, and contributes to prolonging the service life of industrial equipment.

## 4.4. System Testing and Validation

### 4.4.1 Model Training

The selected machine learning algorithms are trained using the predefined training subsets from each dataset. To enhance model performance and prevent overfitting, hyperparameter tuning is performed using cross-validation techniques. This process ensures that the models are optimally configured and capable of generalizing beyond the training data.

### 4.4.2 Model Testing

Once trained, the models are evaluated on a separate test set comprising unseen data. This stage is critical to assess the model's generalization capabilities. Predictions generated during testing are compared with the actual outcomes to evaluate accuracy and reliability.

### 4.4.3 Evaluation Metrics

To ensure a comprehensive assessment of each algorithm's performance, several evaluation metrics are employed:

- **Accuracy**: Represents the proportion of correct predictions (true positives and true negatives) relative to the total number of instances. It provides a general measure of overall model performance.
- **Precision and Recall**:
  - Precision measures the proportion of true positives among all positive predictions
  - Recall measures the proportion of true positives that were correctly identified
- **F1 Score**: The harmonic mean of precision and recall. It serves as a balanced metric when there is a need to trade off between minimizing false positives and false negatives.
- **Area Under the ROC Curve (AUC-ROC)**: Evaluates the model's ability to distinguish between different classes ( faulty vs. healthy equipment). A higher AUC value indicates superior performance in classifying data across various threshold settings.
- **Computational Time**: Measures the time required for model training and testing, offering insights into the algorithm's computational efficiency.
- **Scalability**: Assesses how well the algorithm performs as the dataset size increases, which is essential for industrial scale applications.
- **Robustness to Noise**: Evaluates the model's ability to maintain accuracy in the presence of noisy or incomplete data an essential feature for real-world industrial environments.

By employing this diverse set of metrics, the study delivers a detailed comparison of the machine learning algorithms, highlighting their suitability for predictive maintenance in Industrial Internet of Things (IIoT) contexts [43].

# 5. IoT Integration for Remote Monitoring

## 5.1. IoT Architectures and Technologies

The Internet of Things (IoT) revolves around physical devices commonly referred to as "things" such as sensors and actuators that communicate with a central system, typically an IoT platform. For instance, an air quality sensor can report environmental data to a server, while a ventilation system (as an actuator) can be remotely activated by user commands. A key principle of IoT systems is the bidirectional interaction between users and physical devices: sensors gather and transmit environmental data, and users (or automated rules) can trigger actions based on that data. This architecture enables the development of smart applications that support tasks such as monitoring, control, prediction, and automated responses, automatically turning on a fan when air quality falls below a certain threshold [44].

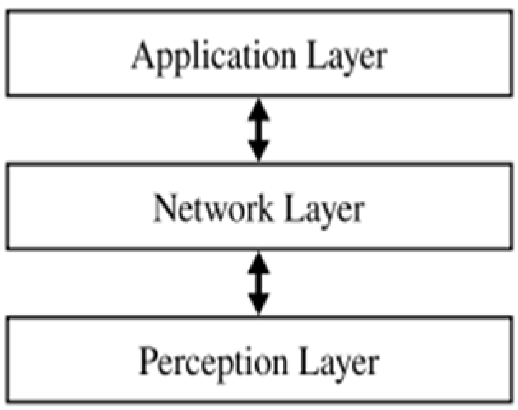


Figure 7: three-layer architecture

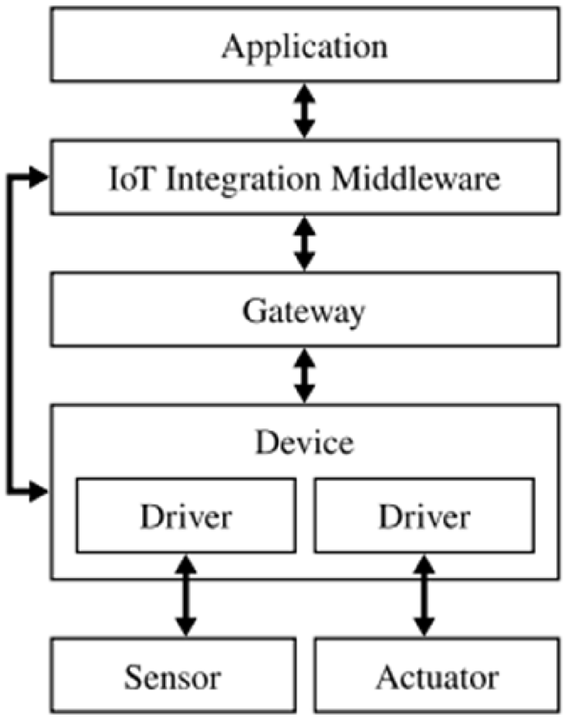


Figure 8: IoT architecture

#### 5.1.1 Perception Layer

The perception layer, also referred to as the sensing layer, is responsible for collecting data from the environment through various sensing devices. It processes the data to extract valuable information and then transmits it to the network layer via network access devices like WSN gateways. This layer is made up of integrated hardware that handles data acquisition and perception. Common sensing technologies include RFID, cameras, sensors, and barcodes.

RFID (Radio Frequency Identification) plays a crucial role in the development of microchips for wireless communication. RFID tags can be active or passive, and are embedded in objects for automatic identification. Active RFID tags are self-powered and initiate communication, while passive tags lack internal power. Passive tags are commonly used in applications such as transportation, retail, logistics, road tolls, and smart bank cards, whereas active RFID tags are used in automotive manufacturing and remote monitoring. These tags feature a small transceiver that enables both receiving queries from a reader and transmitting the tag ID.

Wireless sensors are electronic chips commonly used for remote sensing applications. They are known for their low cost, small size, high efficiency, and their ability to collect, process, and analyze data. When combined with RFID, wireless sensor networks (WSN) can more effectively track environmental changes and monitor the status of objects, including location, temperature, and movement.

Cameras are utilized to address logistical challenges and enhance home security. In addition to use in vehicles for navigation, intelligent cameras can detect and capture specific moments. For example, cameras installed along roads help optimize driving by notifying drivers of available space in a lane. Many smart cameras in IoT systems store only relevant data, which can be used later for analysis.[45]

#### 5.1.2 Communications Network

To facilitate data exchange between sensors, actuators, the IoT platform, and gateway components, one or more communication networks must be established. These networks are required to support the physical, data link, and network layers in accordance with the Open Systems Interconnection (OSI) model[46]. The network layer plays a crucial role in packet forwarding and routing. Among the most commonly used protocols at this layer are:

- **IPv4:** Internet Protocol version 4 (IPv4) remains the most widely used IP version. Introduced in 1983, it utilizes 32-bit addresses, allowing for $2^{32}$ unique addresses, of which $2^{24}$ are reserved for use in private local area networks (LANs). However, the limited number of addresses has led to near exhaustion of available IPv4 addresses, known as the IPv4 address exhaustion problem.
- **IPv6:** To address the limitations of IPv4, Internet Protocol version 6 (IPv6) was developed. It uses 128-bit addresses, offering a vastly larger address space compared to IPv4.
- **6LoWPAN:** Developed by the Internet Engineering Task Force (IETF), IPv6 over Low-Power Wireless Personal Area Networks (6LoWPAN) introduces an adaptation layer that enables IPv6 to function over the low-rate wireless personal area networks defined by the IEEE 802.15.4 standard[47].

#### 5.1.3 IoT Gateway

IoT devices often utilize a wide range of communication networks, data link protocols, and data formats, many of which may not be natively supported by the IoT platform. To address this interoperability challenge, a middleware component commonly referred to as a *gateway* or *edge gateway* is introduced between the IoT devices and the IoT platform. This gateway acts as an intermediary that standardizes communication by translating diverse protocols and formats into a unified network interface, data link layer, and data format compatible with the platform. In practical deployments, multiple gateways are typically used, with each one managing communication for a specific group of IoT devices.[44].

#### 5.1.4 Middleware Layer

This layer operates between the application layer and the network layer. Its primary role is to abstract hardware complexities, allowing developers to focus on building applications without needing to manage low-level device interactions. Additionally, it ensures interoperability, scalability, abstraction, and offers essential services to users. Key functions of this layer include user authentication and secure service delivery, creating a trusted environment for data processing and communication.[48].

#### 5.1.5 Application Layer

The application layer is responsible for developing a wide range of applications tailored to meet business needs. It serves as the interface between end users and the Internet of Things (IoT), providing customer-facing services and enabling interaction with IoT systems. Its primary objective is to deliver high-quality, intelligent services that fulfill user requirements. This layer supports key functions such as information storage, data mining, and decision-making across diverse applications. To enable intelligent IoT solutions, it integrates with industry standards and leverages advanced technologies including distributed computing, intelligent processing of large-scale data, and information discovery. The application layer underpins a variety of use cases such as intelligent transportation, smart logistics, smart cities, environmental monitoring, e-health, and precision agriculture[49]. Additionally, it offers global capabilities for managing and deploying IoT applications. An example of its application is in intelligent transportation systems, an emerging technology aimed at enhancing road safety, optimizing traffic flow, improving the driving experience, and minimizing travel time through advanced route optimization techniques.

### 5.2. Internet of Things for Remote Monitoring Services

Condition monitoring services are essential across a wide range of industries. This process involves the acquisition and analysis of data that reflects the operating condition of a machine over time, with the goal of delivering real-time, actionable insights to minimize risk and prevent failures[50].

A typical remote monitoring program is designed to support effective and efficient predictive maintenance and generally follows four key steps[51]:

- **Data Acquisition**: This involves collecting relevant data from physical assets and converting it into digital form suitable for analysis.
- **Data Processing**: In this step, the digitized data is transformed into meaningful information by quantifying the operational conditions of the equipment.
- **Decision-Making**: This phase goes beyond merely identifying machine faults it enables the detection, diagnosis, and classification of failures. Based on the analysis, appropriate corrective or preventive actions can be triggered automatically to manage machine operations.
- **Remote Communication**: This function allows the transmission of critical information, such as machine status and alarm conditions, over a network to support remote diagnostics and decision-making.

## 6. Full-Scale Implementation

The full-scale deployment of a predictive maintenance system represents the transition from a validated prototype to a fully operational solution integrated within the industrial environment. The primary objective is to enable real-time anomaly detection, reduce unplanned downtime, and enhance decision-making processes. This implementation follows a progressive strategy, starting with a limited pilot phase to mitigate risks and tailor the system to site-specific constraints. The trained machine learning models are integrated into existing industrial platforms such as CMMS for maintenance management, SCADA for real-time equipment monitoring, and ERP systems for aligning with broader business processes. Data exchange is facilitated through standard industrial protocols like MQTT, Modbus, OPC-UA, or RESTful APIs, ensuring seamless communication between sensors, cloud platforms, and user interfaces. A user-friendly web-based dashboard, developed using HTML5, JavaScript, D3.js, or Plotly, visualizes critical operational parameters (temperature, vibration, current), while a notification system via SMS (Twilio) or email APIs alerts maintenance teams immediately when a fault is predicted. Before large-scale rollout, a pilot deployment in real-world conditions validates sensor accuracy, system responsiveness, and alert relevance, followed by a User Acceptance Test (UAT) to refine thresholds, alert frequency, and interface design based on technician feedback. Once approved, the system is replicated across additional equipment or sites using a modular architecture, scalable cloud or Edge AI infrastructure, and automated deployment tools such as Docker. This approach ensures a scalable, cost-effective, and sustainable implementation. However, several challenges may arise, including data incompatibility, user resistance, and network latency issues. To address these, training sessions are provided, interfaces are simplified, and fallback mechanisms are built in to maintain system resilience. [52][53]

## 7. Monitoring and Optimization

After deployment, predictive maintenance systems require continuous monitoring and refinement to ensure their effectiveness in dynamic industrial settings. Key performance indicators (KPIs) such as Mean Time Between Failures (MTBF), false alarm rates, and equipment availability must be consistently tracked to maintain system accuracy and reliability. To keep up with changing operational conditions, machine learning models are periodically retrained with updated sensor data and newly labeled failure cases, either on a fixed schedule or in response to performance degradation.

Feedback from maintenance technicians is also essential, as their insights help refine alert thresholds, validate model predictions, and improve the relevance of system outputs. Additionally, advanced analytics such as anomaly detection and Remaining Useful Life (RUL) predictions are integrated to offer more precise failure forecasts, enabling a shift from reactive to proactive maintenance. Together, these ongoing optimization efforts ensure the long-term adaptability, efficiency, and scalability of the predictive maintenance system. [52]

## 8. Case Study: Remote Motor Condition Monitoring Using IoT and Machine Learning

### 8.1. Related Work

The reviewed literature emphasizes the growing role of advanced technologies such as the Internet of Things (IoT), machine learning (ML), and data fusion in enhancing predictive maintenance and industrial monitoring. Several studies demonstrate how monitoring motor parameters like temperature, vibration, and current can be used with analytical models to predict equipment failures effectively. Machine learning techniques, including supervised learning and ensemble classifiers, are widely adopted to improve the accuracy and robustness of failure predictions, especially when dealing with real-world, unstructured data. Multisensor data fusion, as applied through 2D convolutional neural networks (CNNs) and motor current signature analysis (MCSA), enables more comprehensive and accurate fault diagnosis in complex components like gearboxes. IoT plays a crucial role by enabling real-time data collection from various industrial assets, which supports timely maintenance decisions and reduces unexpected downtimes. Studies also highlight cost-effective systems for condition monitoring, such as those used in BLDC motors, where IoT and ML help detect and diagnose faults efficiently. Furthermore, secure and scalable frameworks are essential in remote monitoring scenarios, where methods like attribute-based encryption (ABE) and federated learning ensure data privacy and flexible access control. In addition, low-power communication protocols like LoRaWAN and MQTT are compared for optimal data transmission in resource-constrained environments. Finally, the research explores the use of prototyping tools like block-based programming for building IoT applications and demonstrates how IoT sensor data can be used for classification tasks in industrial contexts. Together, these studies highlight the effectiveness of combining IoT and machine learning to optimize maintenance strategies, enhance operational reliability, and ensure data security in smart industrial systems.[54].

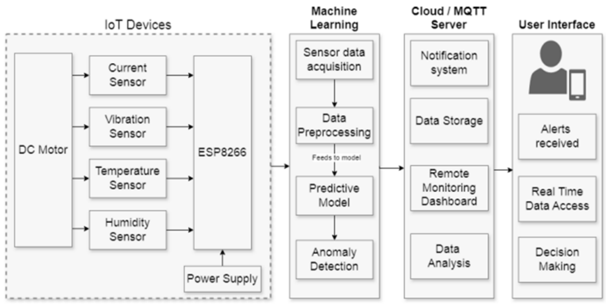


Figure 9: Proposed system for remote monitoring of the motor using IoT and machine learning

### 8.2. Methodology

This project develops a prototype for remote motor condition monitoring using IoT and machine learning. It uses sensor data and a prediction model for predictive maintenance. Key components include an ESP8266 microcontroller, ACS712 current sensor, DHT11 sensor, DC motor, and a vibration sensor.

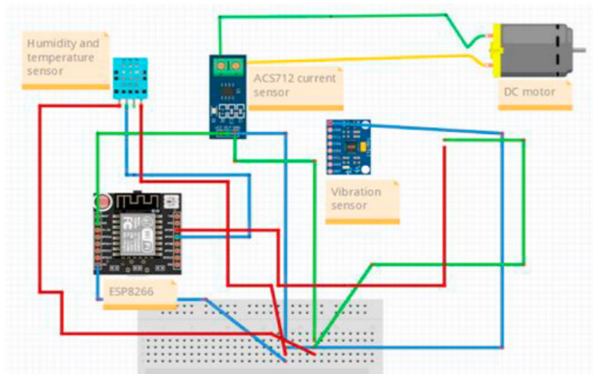


Figure 10: Circuit diagram for remote monitoring of the motor using IoT and machine learning

#### 8.2.1 IoT based data acquisition

The system employs a range of sensors including current, voltage, temperature, and humidity connected to an ESP8266 microcontroller, which transmits the collected data to a cloud platform using the MQTT protocol. This setup enables real-time monitoring of the motor's operating conditions. Figure **??** illustrates the circuit diagram for the IoT- and machine learning-based remote motor monitoring system.

#### 8.2.2 Data Transmission and Storage

Sensor data is wirelessly sent to a central server and stored in a time-series database via the MQTT server, allowing for efficient analysis and long-term monitoring.

#### 8.2.3 Machine Learning Model

**Data Collection and Storage** : Sensor data including temperature, humidity, current, and voltage is collected via the ESP8266 microcontroller. The DHT11 sensor records temperature and humidity, while the ACS712 sensor captures current and voltage readings.

**Data Preprocessing :** Collected data is cleaned to eliminate noise and improve prediction accuracy. Key features influencing motor performance are extracted:

- **Temperature**: High levels may cause overheating and efficiency loss.
- **Humidity**: Can lead to condensation or corrosion, impacting electrical performance.
- **Voltage:** Fluctuations may indicate supply issues or motor malfunctions.
- **Current:** Deviations often signal overloads, faults, or mechanical problems.

The target variable `motor_status` indicates the motor's operational condition:

- **0**: Normal operation
- **1**: Faulty or abnormal condition

The goal is to predict the motor's operational status using sensor features: temperature, humidity, voltage, and current. Each feature has a direct influence on motor health:

- **Temperature:** Elevated temperatures may increase the risk of motor failure due to overheating.
- **Humidity:** Excess moisture can lead to condensation or corrosion, potentially causing electrical issues.
- **Voltage:** Sudden voltage fluctuations can disrupt motor function and signal power-related problems.
- **Current:** Irregular current flow may indicate overloads, faults, or mechanical issues.

Understanding these relationships helps the machine learning model accurately predict motor status and detect early signs of failure.

**Model Training and Prediction :** A supervised machine learning approach is used. Historical, labeled data is split into training (80

**Model Deployment :** The trained model is deployed on a server or cloud platform to process incoming sensor data in real time. It continuously predicts the motor's status, helping to detect faults early and enable predictive maintenance.

## 8.3. Result Analysis

System Performance Evaluation The system's performance was evaluated using real-time IoT sensor data for motor condition monitoring. The analysis focused on parameter distribution, correlation, and machine learning model effectiveness.

### 8.3.1 Sensor Data Insights

- **Current**: Ranged from 1.39 A to 2.75 A, with stable operation mostly between 1.5–1.6 A. Spikes reflect transient load increases.
- **Voltage**: Varied from 298 V to 586 V, showing typical operating fluctuations.
- **Temperature**: Remained stable in a narrow range of 26.8°C–27.1°C, suggesting a consistent environment.
- **Humidity**: Maintained between 60%–62%, also indicating stable ambient conditions.

#### Statistical Analysis

- **Box Plots** (Fig. 11):
  Showed low variability in temperature and humidity (tight distribution, minimal outliers). Voltage and current had higher variability, consistent with electrical fluctuations.
- **Correlation Matrix** (Fig. 12):
  Current and voltage showed a strong positive correlation ($\rho \approx 1$), reflecting normal electrical behavior. Temperature and humidity had a strong negative correlation ($\rho \approx -0.88$), likely due to environmental factors.

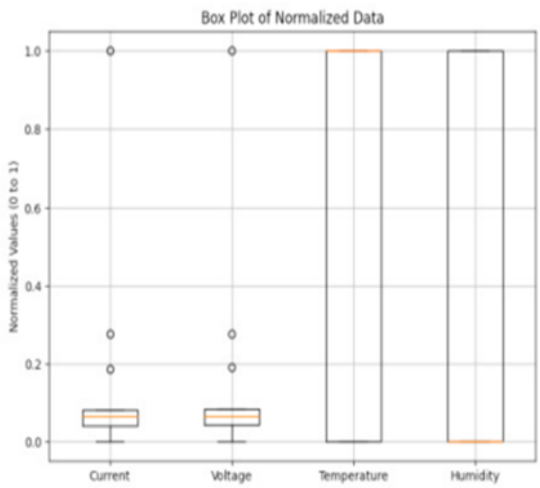


Figure 11: Box plot of the different feature variables

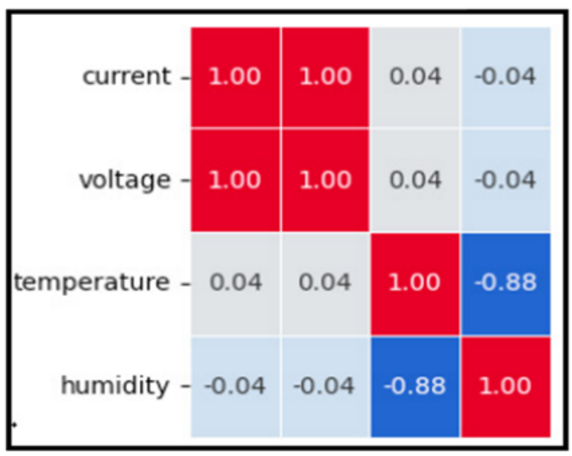


Figure 12: Correlation between the different feature variables

**Machine Learning Model Performance**

- **Confusion Matrix** (Fig. 13): Demonstrated the model's reliability in distinguishing between *Failure* and *No-Failure* conditions.
- **Classification Metrics** (Fig. 14):
  . Accuracy: 90%
  . Precision: 91.37%
  . Recall: 98.14%
  . F1-Score: 94.64%

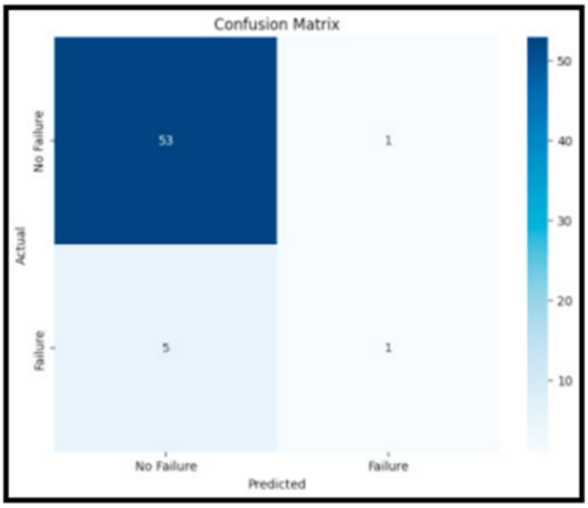


Figure 13: Correlation between the different feature variables

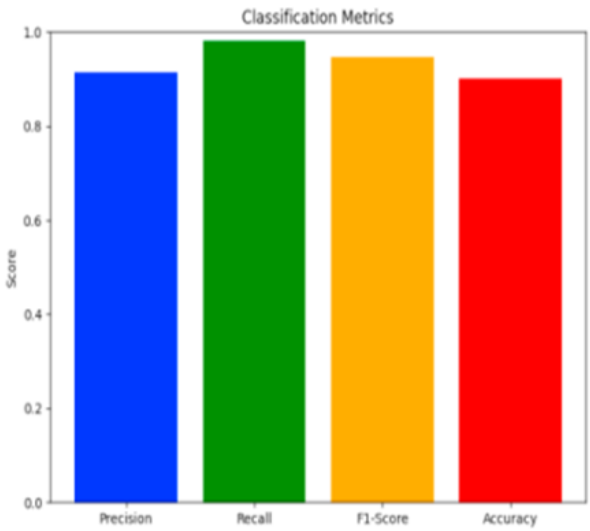


Figure 14: Correlation between the different feature variables

These results confirm that the Random Forest classifier successfully identifies motor anomalies based on real-time sensor data, enabling early fault detection and reducing unplanned downtimes.

## 8.4. Conclusion and future work

This study developed an IoT-based system for real-time monitoring and predictive maintenance of DC motors using machine learning. By collecting sensor data (temperature, humidity, voltage, and current) and transmitting it via MQTT to a cloud platform, the system ensures continuous and efficient performance tracking. A Random Forest classifier was implemented to accurately predict motor conditions and detect potential failures. Built around the ESP8266 microcontroller, the system demonstrates the practicality of IoT for industrial applications. Its cloud-based architecture supports scalability and real-time analytics, while the user-friendly interface enhances operational safety and ease of use. The findings highlight the potential of combining IoT and ML for smart maintenance strategies. Future research could expand this approach to other types of industrial equipment for broader applicability.

# 9. Conclusions

The maintenance and monitoring of industrial electrical systems have long relied on reactive or scheduled interventions, often resulting in inefficiencies, unexpected failures, and costly downtimes. This study demonstrated how the integration of Machine Learning and Internet of Things technologies can overcome these limitations by enabling predictive maintenance and real-time remote monitoring. By designing a system that collects operational data through IoT-enabled sensors and applies ML algorithms to analyze and forecast equipment conditions, we have shown the potential of this approach to transform industrial maintenance practices. The proposed framework improves fault detection accuracy, optimizes intervention timing, and enhances the overall reliability of electrical systems. The outcomes confirm that data-driven maintenance, supported by smart technologies, significantly reduces operational risks and contributes to more sustainable and cost-effective industrial operations. This work also aligns with the broader vision of Industry 4.0, where intelligent systems and automation drive efficiency and innovation. Future research may focus on expanding this framework to other types of industrial equipment, improving the scalability of the system, and incorporating explainable AI models to increase transparency and trust in decision-making processes. Overall, the integration of ML and IoT represents a promising direction for the future of industrial maintenance and opens the door to fully autonomous and intelligent maintenance ecosystems.

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