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# AI-Based Predictive Fault Detection for Smart Electrical Equipment Using IoT and Machine Learning

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***Abstract- Smart electrical equipment such as transformers, induction motors, generators, and industrial automation systems are critical components in modern industries. Unexpected failures in these systems can cause production interruptions, increased maintenance cost, equipment degradation, and safety hazards. Traditional maintenance strategies, including reactive and preventive maintenance, are often inefficient because they either respond only after failures occur or rely on fixed maintenance schedules without considering real-time equipment conditions. To address these limitations, this paper proposes an AI-driven self-learning failure prediction system for smart electrical equipment using IoT-enabled monitoring and machine learning techniques.The proposed system continuously acquires real-time operational parameters such as temperature and current using embedded sensors integrated with a microcontroller-based edge computing unit. The collected sensor data is processed using machine learning algorithms including Random Forest (RF), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) networks to identify abnormal operating conditions and predict potential equipment failures. The system incorporates a self-learning mechanism that updates the prediction model using newly acquired operational data, thereby improving fault detection accuracy over time. An IoT-based communication framework provides real-time monitoring and instant fault alerts through cloud-connected applications.***

***Index Terms: Predictive Maintenance, Artificial Intelligence, Internet of Things (IoT), Machine Learning, Smart Electrical Equipment, Failure Prediction, LSTM, Random Forest.***

## I. INTRODUCTION

Electrical equipment such as motors, transformers, and industrial drive systems are essential components in modern industries and power systems. Failure of these systems can result in production downtime, increased maintenance cost, equipment damage, and safety risks. Therefore, continuous monitoring and early fault detection are important for maintaining reliable industrial operation.

Traditional maintenance strategies mainly include reactive maintenance and preventive maintenance. Reactive maintenance repairs equipment only after failure occurs, often causing unexpected downtime and expensive repairs. Preventive maintenance schedules servicing activities at fixed intervals regardless of actual equipment condition, leading to unnecessary maintenance and inefficient resource utilization.

Recent advancements in Artificial Intelligence (AI), Internet of Things (IoT), and embedded systems have enabled predictive maintenance systems capable of monitoring equipment conditions in real time. Parameters such as temperature and current provide important information about equipment health. Excessive temperature rise may indicate insulation degradation, overload conditions, or internal electrical stress, while abnormal current variations may occur due to short circuits or unstable load conditions.

Machine learning algorithms such as Random Forest (RF), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) networks have significantly improved fault prediction accuracy by analyzing sensor data and identifying abnormal operating patterns. These algorithms enable intelligent classification of equipment conditions and early prediction of potential failures.

This paper proposes an AI-based predictive fault detection system for smart electrical equipment using IoT-enabled monitoring and hybrid machine learning techniques. The proposed system continuously acquires temperature and current data using LM35 and ACS712 sensors integrated with an Arduino Uno microcontroller. The collected data is analyzed using RF, SVM, and LSTM algorithms to predict abnormal operating conditions and generate real-time alerts through IoT communication.

The proposed framework provides a low-cost, scalable, and efficient predictive maintenance solution suitable for smart industrial environments.

## II. RELATED WORK

Traditional machine learning algorithms have been widely used for equipment fault classification and predictive maintenance. Cortes and Vapnik (1995) [1] introduced Support Vector Machines (SVM), which are highly effective in nonlinear classification and fault boundary detection. Breiman (2001) [2] proposed Random Forest (RF), an ensemble learning algorithm capable of improving classification accuracy and reducing overfitting through multiple decision trees. Widodo and Yang (2007) [3] demonstrated the effectiveness of machine learning techniques for intelligent fault diagnosis in rotating machinery systems.

Deep learning approaches have significantly improved predictive maintenance performance by enabling efficient analysis of large-scale sensor data. Hochreiter and Schmidhuber (1997) [4] introduced Long Short-Term Memory (LSTM) networks, which are capable of learning long-term dependencies in sequential data. Fischer and Krauss (2018) [5] applied LSTM networks for time-series forecasting and showed their superior capability in capturing temporal patterns. Zhao et al. (2019) [6] further demonstrated that deep learning models improve fault diagnosis accuracy in industrial monitoring systems.

Recent research has focused on integrating IoT technologies with AI-based monitoring systems. Lee et al. (2018) [7] proposed an Industrial AI framework for predictive analytics in smart manufacturing systems using real-time sensor monitoring. Tao et al. (2019) [8] developed a digital twin-driven predictive maintenance framework for industrial equipment using IoT-enabled data acquisition. Zhang et al. (2017) [9] introduced an intelligent fault diagnosis system using deep learning techniques and raw sensor signals for industrial applications.

Edge computing has also become an important component in predictive maintenance systems because it reduces latency and enables faster decision-making. Shi et al. (2016) [10] discussed the role of edge computing in industrial IoT applications and highlighted its advantages in real-time monitoring systems. Recent studies have also explored hybrid machine learning models combining Random Forest, SVM, and deep learning approaches for improving fault prediction accuracy and reducing false alarms.

## III. METHODOLOGY

The proposed methodology is designed to perform intelligent real-time monitoring and failure prediction for smart electrical equipment using IoT-enabled sensors, edge computing, and machine learning techniques. The system continuously acquires operational data from electrical equipment, processes the collected signals, analyzes abnormal behavior using machine learning models, and generates early fault alerts through cloud-based communication. The complete methodology consists of five major stages: data acquisition, signal preprocessing, feature extraction, machine learning-based fault prediction, and IoT-based alert generation.

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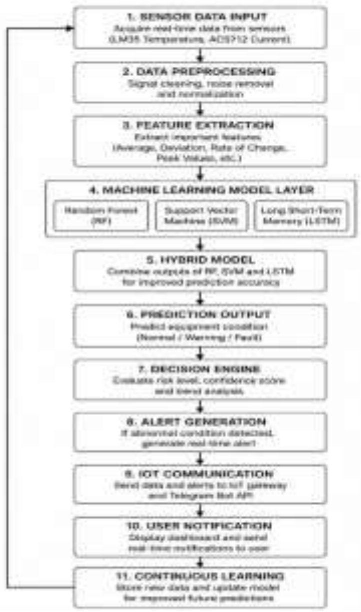


Fig. 1. Workflow of the Proposed AI-Driven Self-Learning Failure Prediction System

A. Data Acquisition

The first stage of the proposed system involves continuous acquisition of real-time operational data from electrical equipment. In industrial systems, abnormal variations in parameters such as temperature and current are strong indicators of equipment degradation and potential failure. Therefore, the system uses embedded sensors to continuously monitor these parameters.

1) Temperature Monitoring

Temperature monitoring is performed using the LM35 precision temperature sensor. The sensor is directly attached to the electrical equipment surface to measure thermal variations during operation. The LM35 generates an analog voltage output proportional to the measured temperature with a sensitivity of 10 mV/°C. Sudden temperature rise may indicate overload conditions, insulation degradation, poor ventilation, or internal electrical stress.

2) Current Monitoring

Current monitoring is carried out using the ACS712 Hall-effect current sensor. The sensor measures both AC and DC current flowing through the equipment and produces an analog voltage proportional to the measured current. Abnormal current fluctuations may occur due to short circuits, unstable loads, winding faults, or mechanical blockage. Continuous current monitoring helps in identifying electrical abnormalities at an early stage.

The sensor outputs are connected to the analog input pins of the Arduino Uno microcontroller for further processing and analysis.

B. Signal Preprocessing and Normalization

The raw analog signals collected from the sensors cannot be directly used for machine learning analysis because they contain noise and unscaled voltage values. Therefore, preprocessing and normalization are required to convert the sensor outputs into meaningful engineering units.

1) Temperature Signal Normalization

The Arduino Uno contains a 10-bit Analog-to-Digital Converter (ADC) that converts the analog sensor voltage into digital values ranging from 0 to 1023. The temperature value is calculated using the following equation:

$$Temperature\ (^{\circ}C) = \frac{Analog\ Value \times 5.0 \times 100}{1024}$$

where:

- Analog Value represents the ADC output value
- 5.0 V is the reference voltage of the Arduino
- 1024 represents the 10-bit ADC resolution

This equation converts the raw analog signal into temperature values measured in degrees Celsius.

2) Current Signal Normalization

The ACS712 current sensor produces an output voltage centered around 2.5 V under zero-current conditions. The actual current value is calculated using:

$$Current\ (A) = \frac{\left(\frac{Analog\ Value \times 5.0}{1024} - 2.5\right)}{0.185}$$

where:

- 2.5 V represents the sensor offset voltage
- 0.185 V/A represents the sensitivity of the ACS712 5A module

Normalization improves data consistency and removes scaling differences between sensor outputs, thereby improving machine learning model performance.

C. Feature Extraction

After preprocessing, important operational features are extracted from the normalized sensor data. Feature extraction is necessary because machine learning algorithms perform better when meaningful statistical and operational characteristics are used instead of raw sensor readings.

The extracted features include:

- Average operating temperature
- Current deviation from normal conditions
- Peak current values
- Rate of temperature increase
- Sudden current fluctuations

D. Machine Learning-Based Fault Prediction

The proposed system uses a hybrid machine learning framework consisting of Random Forest (RF), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) algorithms. The combination of multiple algorithms improves prediction accuracy and enables efficient handling of both static and sequential sensor data.

1) Random Forest (RF)

Random Forest is an ensemble-based supervised learning algorithm that combines multiple decision trees for classification. Each decision tree independently analyzes the sensor features, and the final prediction is determined through majority voting.

In the proposed system, Random Forest classifies equipment conditions into three categories:

- Normal Condition
- Warning Condition
- Fault Condition

The algorithm provides high classification stability and reduces overfitting caused by noisy industrial sensor data.

2) Support Vector Machine (SVM)

Support Vector Machine is used for identifying optimal boundaries between normal and abnormal operating conditions. SVM is effective in handling nonlinear fault patterns using kernel functions.

The SVM decision function is represented as:

$$f(x)=w^T x+b$$

where:

- $w$represents the weight vector
- $x$represents the feature vector
- $b$represents the bias term

SVM improves fault classification precision, particularly in conditions where operational parameters overlap.

3) Long Short-Term Memory (LSTM)

Electrical equipment degradation often occurs gradually over time through continuous overheating, repeated current spikes, or fluctuating operational behavior. LSTM captures these temporal degradation patterns and predicts failures before critical breakdown occurs.

The forget gate equation in LSTM is given by:

$$f_t=\sigma (W_f [h_{t-1}, x_t] +b_f)$$

where:

- $f_t$is the forget gate output
- $W_f$is the weight matrix
- $h_{t-1}$is the previous hidden state
- $x_t$is the current input
- $b_f$is the bias vector

The hybrid integration of RF, SVM, and LSTM enables accurate fault classification, nonlinear boundary detection, and time-series degradation analysis simultaneously.

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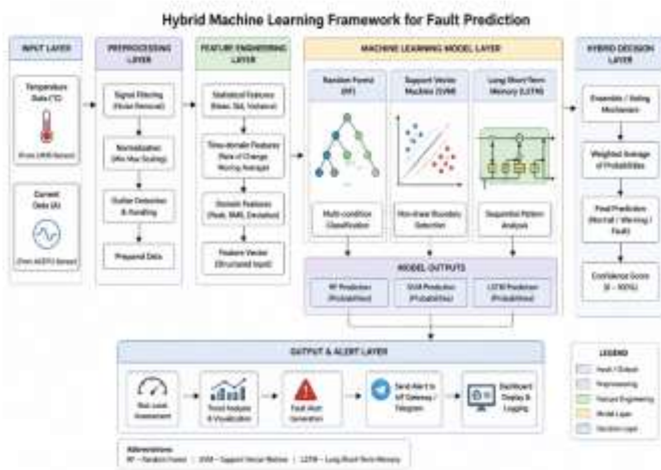


Fig. 2. Hybrid Machine Learning Framework for Fault Prediction

E. IoT-Based Alert and Communication System

The final stage of the methodology involves real-time communication and alert generation. Processed sensor data and prediction results are transmitted from the Arduino Uno to a laptop-based IoT gateway using UART serial communication.
A Python-based monitoring application continuously analyzes incoming data and sends instant fault notifications through the Telegram Bot API whenever abnormal operating conditions are detected. The alerts contain:

- Equipment status
- Temperature readings
- Current values
- Fault classification
- Timestamp information

This IoT-based communication framework enables maintenance personnel to take preventive action before equipment failure occurs, thereby reducing downtime, improving operational safety, and minimizing maintenance cost.

## IV. SYSTEM ARCHITECTURE

### A. ARCHITECTURE OVERVIEW

The proposed AI-driven failure prediction system is designed using a layered architecture that integrates sensor-based monitoring, edge computing, machine learning, and IoT communication for real-time equipment health analysis. The architecture enables continuous acquisition of operational data, local processing of sensor signals, intelligent fault prediction, and remote alert generation.

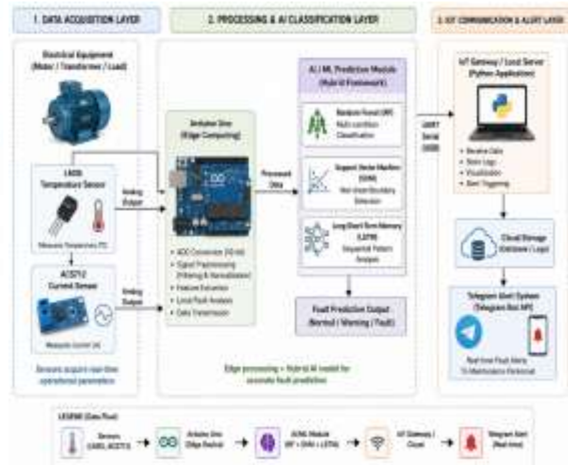

Fig. 3. Proposed System Architecture for AI-Driven Failure Prediction

A. Data Acquisition Layer

The Data Acquisition Layer is responsible for continuously collecting real-time operational parameters from electrical equipment. The system uses embedded sensors to monitor important electrical and thermal characteristics associated with equipment health.

1) Temperature Monitoring Module

The LM35 temperature sensor is used to monitor the operating temperature of the electrical equipment. The sensor is attached directly to the equipment surface to measure thermal variations during operation. Since overheating is one of the primary indicators of equipment degradation, continuous temperature monitoring helps identify abnormal operating conditions such as overloading, insulation failure, and poor cooling performance.

2) Current Monitoring Module

The ACS712 Hall-effect current sensor is used to measure the current flowing through the equipment. The sensor continuously monitors electrical load variations and detects abnormalities such as short circuits, unstable loads, and winding faults. The sensor output is provided as an analog voltage proportional to the measured current.

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3) Sensor Interface
Both sensors are connected to the analog input channels of the Arduino Uno microcontroller. The analog sensor outputs are converted into digital values using the built-in 10-bit Analog-to-Digital Converter (ADC) for further processing.

B. Processing and AI Classification Layer
The Processing Layer acts as the core computational unit of the proposed system. It performs real-time sensor data acquisition, preprocessing, feature analysis, and fault prediction.

1) Edge Computing Unit
The Arduino Uno microcontroller functions as the edge computing device responsible for collecting sensor data and performing initial processing operations. Edge-level processing reduces communication delay and minimizes dependency on cloud infrastructure. The major operations performed in this layer include:

- Real-time sensor data acquisition
- Signal normalization
- Feature extraction
- Local fault analysis
- Data transmission to IoT gateway

2) AI-Based Prediction Module
The processed sensor data is analyzed using a hybrid machine learning framework consisting of Random Forest (RF), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) algorithms. The AI module classifies equipment conditions into normal, warning, and fault states based on operational behavior. The integration of multiple machine learning models improves prediction accuracy and enables efficient analysis of both static and sequential sensor data.

C. IoT Communication Layer

1) Serial Communication Interface
The Arduino Uno transmits processed sensor data to a laptop-based gateway system using UART serial communication through a USB connection. The gateway acts as an intermediate communication interface between the edge device and cloud services.

2) Cloud Monitoring System
A Python-based monitoring application running on the gateway continuously receives sensor data and prediction results. The application analyzes equipment conditions and maintains operational logs for monitoring purposes.

3) Telegram Alert System
The system integrates the Telegram Bot API to provide instant fault notifications whenever abnormal operating conditions are detected. Alert messages include:

- Equipment status
- Temperature readings
- Current values
- Fault condition information
- Timestamp details

The real-time alert mechanism enables maintenance personnel to take preventive action before critical equipment failure occurs.

D. Self-Learning Framework
The proposed architecture incorporates a self-learning mechanism that continuously updates the prediction model using newly acquired operational data. As additional sensor readings are collected, the machine learning models adapt to changing operating conditions and improve fault prediction accuracy over time.

The self-learning capability provides:

- Improved prediction performance
- Reduced false alarm generation
- Better adaptability to industrial environments
- Continuous optimization of fault classification accuracy

The overall architecture provides a low-cost, scalable, and intelligent predictive maintenance framework suitable for smart industrial applications. The integration of IoT-enabled sensors, edge computing, and machine learning algorithms enables continuous real-time monitoring of equipment health with minimal computational overhead.

## V. RESULT AND DISCUSSION

The proposed system was tested using real-time temperature and current data collected under different operating conditions of smart electrical equipment. The hybrid machine learning framework successfully identified abnormal operating behavior such as overheating and sudden current fluctuations before critical equipment failure occurred. Fig. 4 illustrates the real-time temperature monitoring results obtained during system operation.

During normal operating conditions, the temperature remained within the safe range. As the equipment load increased, a gradual rise in temperature was observed. When the temperature exceeded the predefined warning threshold, the system classified the equipment condition as abnormal and generated an early warning notification. Further temperature increases beyond the critical threshold indicated a potential fault condition, triggering instant alerts through the Telegram Bot API. The graph demonstrates the capability of the proposed system to continuously monitor equipment health and identify overheating conditions before major failure occurs.

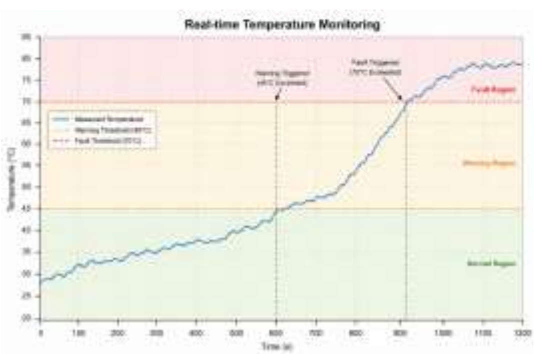


Fig. 4. Real-Time Temperature Monitoring Under Different Operating Conditions

The processed sensor data was analyzed using Random Forest (RF), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) algorithms for fault prediction and condition classification. Table I presents the performance comparison of the machine learning algorithms used in the proposed system.

Table I. Performance Evaluation of Machine Learning Models

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| Random Forest (RF) | 91.2 | 90.4 | 89.8 | 90.1 |
| Support Vector Machine (SVM) | 93.5 | 92.7 | 92.1 | 92.4 |
| Long Short-Term Memory (LSTM) | 95.1 | 94.6 | 94.2 | 94.4 |
| Proposed Hybrid Model | 97.3 | 96.8 | 96.5 | 96.6 |

The evaluation was performed using standard performance metrics including accuracy, precision, recall, and F1-score. Among the individual models, the LSTM algorithm achieved higher prediction performance due to its ability to analyze sequential sensor behavior and capture temporal degradation patterns. The proposed hybrid model achieved the highest overall performance with an accuracy of 97.3% by combining the advantages of Random Forest, SVM, and LSTM algorithms. The integration of multiple machine learning techniques improved fault classification accuracy, reduced false alarms, and enhanced real-time predictive maintenance capability.

The experimental results demonstrate that the proposed framework provides reliable fault prediction, reduced equipment downtime, improved operational safety, and cost-effective predictive maintenance for smart industrial environments.

## VI. CONCLUSION AND FUTURE SCOPE

This paper presented an AI-based predictive fault detection system for smart electrical equipment using IoT-enabled monitoring and hybrid machine learning techniques. The proposed system continuously monitors temperature and current parameters using LM35 and ACS712 sensors integrated with an Arduino Uno microcontroller. The collected sensor data is analyzed using RF, SVM, and LSTM algorithms to predict abnormal operating conditions and equipment failures.

The proposed framework enables real-time monitoring, intelligent fault prediction, and instant alert generation through IoT-based communication. Experimental results demonstrated improved prediction accuracy, reduced maintenance cost, minimized downtime, and enhanced operational safety.

Future work can focus on integrating additional sensors, implementing advanced deep learning models, and developing cloud-based analytics for large-scale industrial predictive maintenance applications.

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