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Integrating Industrial Sensors for Predictive Maintenance of Squirrel Cage Induction Motors and Three-Phase Synchronous Motors Using ESP8266 and Message Queuing Telemetry Transport Protocol

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ABSTRACT

This study presents a comprehensive framework for integrating industrial sensors to enable predictive maintenance on three-phase synchronous motors and squirrel cage induction motors. ESP8266 and the Message Queuing Telemetry Transport (MQTT) protocol are used in this method to provide a wireless connection and data sharing, which enables real-time monitoring of vital factors, including vibration, temperature, and current. For advanced fault classification, the system uses a Convolutional Neural Network-Gated Recurrent Unit (CNN-GRU) architecture. This reduces the need for human feature selection and improves the accuracy of finding and classifying motor defects. The procedure starts with the use of industrial sensors to identify and analyze defects. Acquired data is then wirelessly sent to a central processing unit. Python is used to accomplish the suggested technique. By automatically identifying hierarchical characteristics from unprocessed sensor data, the CNN-GRU model maximizes the effectiveness of defect identification. A graphical user interface is designed for real-time monitoring and maintenance decision-making in order to guarantee user participation. The article addresses A/C drive system malfunctions, with a particular emphasis on motor terminal issues along with the way they affect the operation of induction motors. Min-max normalization is used to preprocess the data obtained from IoT devices, namely ESP8266, in order to rescale numerical characteristics for input into machine learning models. The CNN-GRU architecture combines the advantages of GRUs for temporal interdependence in sequential sensor data with CNNs for spatial feature extraction. The CNN-GRU model outperformed the K-Nearest Neighbor (KNN), Naive Bayes (NB), Support Vector Machine (SVM), Convolution Neural Network (CNN), Long Short Term Memory (LSTM), and CNN-LSTM techniques in terms of accuracy, precision, recall, and F1 score of 98.94%, 98.65%, 99.1%, and 99.45%. The results demonstrate the superiority of the suggested method over conventional approaches.

1. INTRODUCTION

Electrical machines play a crucial role in modern industrial automation because they provide reliable electromechanical energy conversion for various industrial processes. Among these machines, squirrel cage induction motors and three-phase synchronous motors are widely used due to their robustness, efficiency, and low maintenance requirements [1, 2]. These motors are widely applied in industrial systems such as conveyor belts, pumps, compressors, and manufacturing equipment, where continuous operation is essential.

However, unexpected motor failures can lead to significant production downtime, increased maintenance costs, and potential damage to associated equipment [3, 4]. Traditional maintenance strategies, such as corrective maintenance and scheduled preventive maintenance are often inefficient because they either react after failures occur or require unnecessary periodic inspections. To overcome these limitations, predictive maintenance has emerged as an effective approach that monitors machine health conditions and predicts potential failures before they occur [5].

With the advancement of Industrial Internet of Things (IIoT) technologies, industrial monitoring systems can collect real-time sensor data from machines and transmit it to centralized platforms for analysis. Wireless communication technologies such as ESP8266 modules and Message Queuing Telemetry Transport (MQTT) protocols enable reliable and low-cost data transmission in industrial environments. These technologies allow continuous monitoring of important motor parameters such as vibration, temperature, current, voltage, and acoustic signals [6].

In recent years, machine learning and deep learning techniques have been widely adopted for fault diagnosis and predictive maintenance of electrical machines [7]. Traditional machine learning approaches often require manual feature extraction and domain expertise, which limits their scalability when handling large industrial datasets [8]. Deep learning architectures such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) can automatically learn hierarchical features from raw sensor data, making them suitable for complex industrial fault detection tasks [9].

Despite these developments, several challenges remain in predictive maintenance systems, including integration of multiple industrial sensors, reliable wireless communication for real-time monitoring, and accurate fault classification models. Many existing studies focus either on communication frameworks or machine learning algorithms individually, without integrating both components into a unified predictive maintenance system [10].

Therefore, this study proposes a predictive maintenance framework for squirrel cage induction motors and three-phase synchronous motors by integrating industrial sensors with an ESP8266-MQTT communication architecture and a hybrid Convolutional Neural Network-Gated Recurrent Unit (NN-GRU) deep learning model. The proposed system enables real-time monitoring and accurate fault detection by combining spatial feature extraction through CNN layers with temporal sequence learning using GRU networks.

The main contributions of this research are summarized as follows [11-14]:

(1) Development of a multi-sensor predictive maintenance framework integrating vibration, temperature, sound, current, and voltage signals.
(2) Implementation of a wireless IIoT communication architecture using ESP8266 and MQTT protocol for real-time industrial monitoring.
(3) Design of a CNN-GRU hybrid deep learning model for automatic feature extraction and fault classification.
(4) Performance evaluation of the proposed model and comparison with traditional machine learning approaches.

The paper's summary is given in Section 1. In Section 2, a review of previous research is conducted with an emphasis on the gaps in the field of motor defect detection. The main study issue is outlined in Section 3. Data collection, preprocessing, and CNN and GRU integration are described in Section 4. Section 5 compares classifier performance and gives empirical data and Section 6 examines implications and potential avenues for further study.

2. LITERATURE REVIEW

Predictive maintenance has become an essential strategy for improving the reliability and operational efficiency of industrial motors. Traditional condition monitoring methods relied mainly on signal processing techniques applied to electrical and vibration signals. Daviu presented a transient-based monitoring approach that analyzes motor start-up signals to assess machine health under dynamic operating conditions. This method demonstrated improved accuracy in fault detection compared to conventional steady-state monitoring techniques.

Recent studies have also explored advanced predictive maintenance frameworks for industrial motors. Singh et al. [15] proposed a digital twin–based predictive maintenance system for squirrel cage induction motors, enabling early fault detection and estimation of remaining useful life. By integrating data modeling with sensor measurements, the digital twin architecture provided improved monitoring capability and enhanced maintenance decision-making.

Machine learning and deep learning techniques have further improved motor fault diagnosis performance. Ponce et al. [16] introduced an IoT-enabled deep learning approach for robust fault recognition in induction motors using sensor data. Similarly, Martinez-Roman et al. [17] developed a deep neural network architecture to detect stator winding faults under varying load conditions. These approaches demonstrated improved fault detection accuracy; however, many of these models rely on single-sensor data or require complex feature engineering [18]. Industrial Internet of Things (IIoT) technologies have also enabled real-time monitoring of industrial equipment through distributed sensor networks. Kazmi et al. [19] developed an IIoT-based smart sensor node capable of collecting vibration signals from induction motors and transmitting the data to cloud platforms for predictive maintenance analysis. Such IIoT architectures provide efficient data acquisition and communication mechanisms for large-scale industrial monitoring systems. Although previous studies have explored predictive maintenance using signal processing, machine learning, and IIoT-based monitoring frameworks, several limitations remain. Many studies focus only on single-sensor analysis, which may not capture the complete operating condition of industrial motors. Other works rely on traditional machine learning techniques requiring manual feature extraction, which limits their scalability. Furthermore, existing IIoT monitoring systems often lack advanced deep learning models capable of capturing both spatial and temporal dependencies in sensor signals. To address these limitations, this research proposes a multi-sensor IIoT-enabled predictive maintenance framework using a CNN-GRU hybrid deep learning architecture, enabling automatic feature learning and improved fault classification performance.

Table 1. Comparison of existing predictive maintenance methods

Ref.	Method	Sensors Used	Key Contribution	Limitation
[20]	SVM	Vibration	Machine learning approach for machine condition monitoring	Requires manual feature extraction
[21]	CNN	Vibration	Real-time motor fault detection using 1-D CNN	Limited temporal feature learning
[22]	LSTM	Time-series signals	Captures temporal dependencies in sequential data	High computational complexity
[23]	CNN-LSTM	Multi-sensor	Hybrid deep learning architecture for induction motor fault diagnosis	—
Proposed Method	CNN-GRU	Multi-sensor (temperature, vibration, sound, current, voltage)	Combines spatial feature extraction and temporal learning for predictive maintenance	—

Note: SVM = Support Vector Machine; CNN = Convolutional Neural Network; LSTM = Long Short Term Memory; CNN-GRU = Convolutional Neural Network-Gated Recurrent Unit

Table 1 presents a comparison of commonly used machine learning and deep learning approaches for motor fault diagnosis. The comparison highlights the advantages and limitations of existing techniques and demonstrates the motivation for adopting the proposed CNN-GRU architecture. The comparison in Table 1 shows that traditional machine learning techniques, such as Support Vector Machines rely heavily on manual feature extraction and domain expertise. Deep learning approaches such as Convolutional Neural Networks can automatically extract spatial features from sensor data, while recurrent architectures such as Long Short-Term Memory networks capture temporal dependencies in sequential signals. However, these methods often focus on either spatial or temporal characteristics individually. The proposed CNN-GRU architecture integrates convolutional layers for spatial feature extraction with GRU units for temporal sequence modeling. This hybrid structure improves fault classification accuracy while maintaining computational efficiency for real-time predictive maintenance applications.

3. PROBLEM STATEMENT

Predictive maintenance systems for industrial motors have gained significant attention in Industry 4.0 environments. However, several challenges still limit their effectiveness. Existing monitoring systems often suffer from high deployment cost, limited real-time communication capabilities, and insufficient fault classification accuracy when dealing with multi-sensor industrial data. Traditional approaches also require the extraction of manual features, which reduces scalability and adaptability in complex industrial environments.

Another limitation is the lack of integrated frameworks combining wireless industrial sensor networks with deep learning-based fault detection models. Although IIoT technologies such as ESP8266 and MQTT provide efficient communication mechanisms, their integration with advanced deep learning architectures for motor fault prediction remains limited.

Therefore, this study proposes a sensor-integrated predictive maintenance framework for squirrel cage induction motors and three-phase synchronous motors, combining IIoT communication (ESP8266-MQTT) with a CNN-GRU deep learning model to improve fault detection accuracy and enable real-time monitoring.

4. PROPOSED METHODOLOGY

In the methodology for integrating industrial sensors for predictive maintenance of squirrel cage induction motors and three-phase synchronous motors using ESP8266 and MQTT protocol, the process initiates with the detection and analysis of faults in the motors. Fault occurrences are monitored through a set of industrial sensors. The acquired data is then wirelessly transmitted to a central processing unit, powered by an alternative current supply in a three-phase configuration. A pivotal component of the methodology involves leveraging deep learning techniques for more advanced fault classification. Convolutional Neural Network-Gated Recurrent Unit architecture is utilized for feature extraction and classification. This approach allows for the automatic learning of hierarchical features directly from the raw sensor data, eliminating the need for manual feature selection. The classification process is executed using the CNN-GRU model, enhancing the system's ability to accurately identify and categorize motor faults. This streamlined approach optimizes the system's efficiency and performance in fault detection. To facilitate user interaction and visualization of results, a user-friendly graphical user interface has been developed. This interface provides a comprehensive platform for real-time monitoring and maintenance decision-making. The ESP8266 module and MQTT protocol continue to serve as the backbone for interconnecting the entire system, enabling seamless communication and data exchange between sensors, processing units, and the user interface. Figure 1 illustrates the overall predictive maintenance framework.

4.1 Air Conditioning drive systems failures

The construction of an induction motor operated by a voltage source inverter is depicted in Figure 1. It is made up of a three-phase Alternating Current (AC) supply, a Direct Current (DC) connection, a regulated or uncontrolled rectifier, and an inverter that may use Pulse-Width Modulation (PWM) pulses to provide variable voltage and frequency. The modulation coefficient and various PWM approaches will affect the stator currents and inverter line output voltages. To generate a DC voltage at the front end, a diode bridge rectifier is linked to the three-phase supply. The rectified voltage is received over a DC connection by the power inverter system, which is made up of sophisticated power electronic switching components like Metal-Oxide-Semiconductor Field-Effect Transistors (MOSFETs) or IGBTs (Insulated-Gate Bipolar Transistors) which are driven by gate drive circuits to supply changeable voltage and frequency to the changing loads for control of speed. Many different kinds of electrical failures, including those in the rectifier, inverter, motor terminals, and mechanical load, might affect the power electronic circuitry used in AC drives.

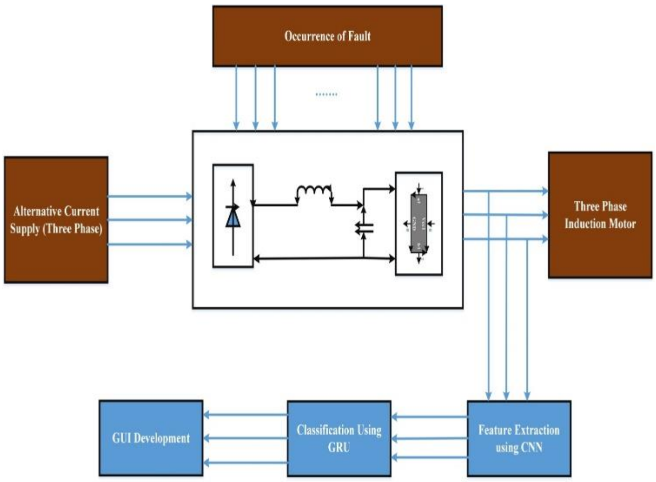

Figure 1. Proposed Industrial Internet of Things (IIoT)-based predictive maintenance framework for industrial motors

The three-phase motor input terminal receives the three-phase variable frequency and variable voltage output from the VSI. Problems at the motor terminal can occur from faults such as SLG, L-L, and lines open at the AC power line. If there is a line short, the induction generator will shut down, and ery high power will flow across the shorted terminals, damaging the diodes and IGBTs in the process. Induction motor malfunctions can also be caused by broken bars in the squirrel cage rotor, insulating failure, damage to the stator windings, and bearings. Unlike short-circuit faults, incipient errors do not result in the motor stopping. Even when there are minor defects, the induction motors continue to function. Over time, the machines' dependability tends to decrease and become damaged. They are therefore risky, as they might go unnoticed for long time and damage the engine without being noticed. In industrial procedures that entail failure identification and categorization based on position and severity, fault identification is essential. In order to prevent failure and machine damage, the operator must also be notified of the defect via an interface and be able to take prompt corrective action or precautions. We refer to the complete procedure as reliability-centered management. Of all the methods used for reliability-centered regular consumption, machine learning seems to be a promising one.

4.2 Data collection

The Resistance Temperature Detector, piezoelectric accelerometer, ultrasonic sensors, Hall effect current sensor, Voltage transducer were used to collect temperature, vibration, acoustic, current and voltage data for the research. The dataset contains sensor measurements collected under different motor operating conditions, including normal operation and fault conditions.

The dataset includes 10,000 samples with five sensor features:

- Temperature
- Vibration
- Sound
- Current
- Voltage

Each sample is labeled as either normal or faulty motor operation. The dataset was divided into:

- 70% training data
- 20% validation data
- 10% testing data

This split ensures that the model is trained effectively while maintaining independent data for evaluating generalization performance. The dataset used for this study was obtained from the publicly available Induction Motor Fault Dataset available on Kaggle [24].

The induction machine specifications include 4 poles, 1 HP mechanical power, a delta configuration, 220V supply voltage, and 3A rated current.

Table 2. Data description

	Temperature	Vibration	Sound	Current	Voltage
count	10000.000	10000.000	10000.000	10000.000	10000.000
mean	55.078	3.472	52.830	12.848	222.763
std	16.720	5.398	18.035	6.060	12.755
min	25.001	0.000	20.003	5.000	200.001
25%	41.308	0.343	37.818	8.286	212.501
50%	54.933	0.678	52.818	11.564	222.639
75%	68.879	5.338	67.617	14.691	232.731
max	99.282	20.790	98.066	34.668	259.750

In Table 2, the comprehensive dataset captures various levels of short-circuit emulations and operational parameters such as vibration, temperature, sound, current, and voltage, crucial for the proposed predictive maintenance system utilizing ESP8266 and MQTT protocol [24].

4.3 Data preprocessing

Before training the machine learning model, the raw sensor data undergoes several preprocessing steps to improve data quality and model performance.

The preprocessing process includes the following stages:

Noise filtering: Sensor signals may contain noise due to mechanical disturbances and environmental interference. A filtering process is applied to remove high-frequency noise components.

Outlier detection: Extreme values caused by sensor errors or abnormal measurements are identified and removed using statistical thresholds.

Data normalization: The sensor values are normalized using min-max normalization, which scales all features to the range [0,1]. This ensures that all features contribute equally during model training.

The preprocessing of data acquired from IoT devices, such as the ESP8266, for various applications, including predictive maintenance in industrial settings. When dealing with sensor data from devices like ESP8266, it's essential to preprocess the raw data before feeding it into machine learning models. This normalization method is applied to ensure that all features contribute equally to the analysis and prevent features with larger magnitudes from dominating the model. The formulation for min-max normalization is as described in Eq. (1):

$$Y_{norm} = \frac{Y - min(Y)}{max(Y) - min(Y)} \tag{1}$$

Here, Y represents the original feature values, $min(Y)$ is the minimum value in the dataset for that feature, and $max(Y)$ is the maximum value.

4.4 Classification of fault occurrence using Convolutional Neural Network-Gated Recurrent Unit

The CNN component consists of a one-dimensional convolution layer with 64 filters and a kernel size of 3 followed by batch normalization. The extracted spatial features are then passed to a GRU layer with 50 hidden units to capture temporal dependencies in the sequential sensor data. The output is flattened and processed by a dense layer with 128 neurons before the final sigmoid classification layer.This approach uses Scaled Exponential Linear Units (SELU) as the activation function to fire the neurons within our CNN. This selection offers significant benefits over traditional activation functions such as Rectified Linear Units (ReLU). Eq. (2), which represents the SELU activation function, has better convergence qualities, which improves the model's training process. It successfully addresses the problem of gradient vanishing, which is an important factor to take into account for predicting squirrel cage faults, since precise predictions depend on the capture and analysis of small spatiotemporal patterns [25].

$$SELU = \lambda\{T \text{ if } t > 0, \alpha e^{\wedge}t - \alpha \text{ Otherwise}\} \tag{2}$$

$$ReLU = max\,(0, t) \tag{3}$$

$$BN(t) = \gamma * \frac{(X - \mu)}{\sigma + \beta} \tag{4}$$

where, $BN(t)$ represents batch-normalized output, 'γ' Scaling factor, 't' Input data, 'μ' Mean of the batch, 'σ' Standard deviation of the batch, 'β' Shifting factor.

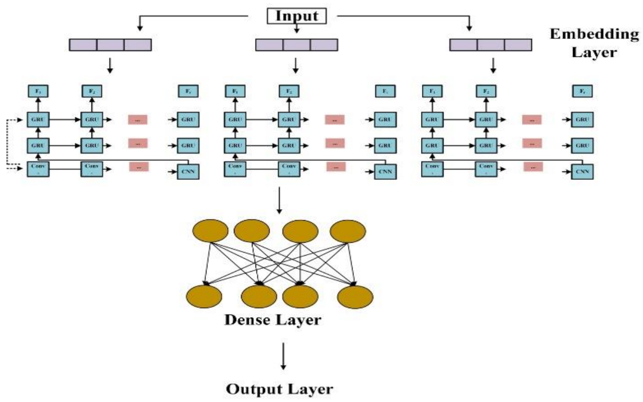

Figure 2. Proposed Convolutional Neural Network-Gated Recurrent Unit (CNN-GRU) architecture

The predictive maintenance for squirrel cage induction motors and three-phase synchronous motors, the classification of fault occurrences is achieved through an innovative approach leveraging Convolutional Neural Network-Gated Recurrent Unit architecture is presented in Figure 2. The methodology integrates industrial sensors for monitoring crucial parameters such as vibration, temperature, and current. These sensors capture real-time data on motor conditions, providing a comprehensive dataset for analysis. The acquired data is wirelessly transmitted to a central processing unit powered by an alternating current supply in a three-phase configuration. Unlike traditional methods, the CNN-GRU model is employed for classification, combining the strengths of Convolutional Neural Networks for spatial feature extraction and Gated Recurrent Units for capturing temporal dependencies in the sequential sensor data. The CNN component operates by applying convolutional layers to extract spatial patterns and pooling layers for spatial dimension reduction. This feature-rich output is then fed into the GRU component, which effectively captures the temporal dynamics of the motor data. The GRU utilizes update and reset gates along with a candidate hidden state to process sequential information, enhancing the model's ability to discern patterns indicative of motor faults. Eqs. (5)-(8) represent the derivation of the two fundamental gates that comprise the GRU: the gate for the update (A) and the gate for the reset (r).

$$At = \sigma(W_a.[h_{s-1}, x_t] + b_a) \tag{5}$$

$$rt = \sigma(W_r.[h_{t-1}, x_t] + b_r) \tag{6}$$

$$\tilde{h}t = tanh(W_a.[rt * h_{t-1}, x_s] + b_a) \tag{7}$$

$$ht = (1 - At) * h_{n-1} + At * \tilde{h}t \tag{8}$$

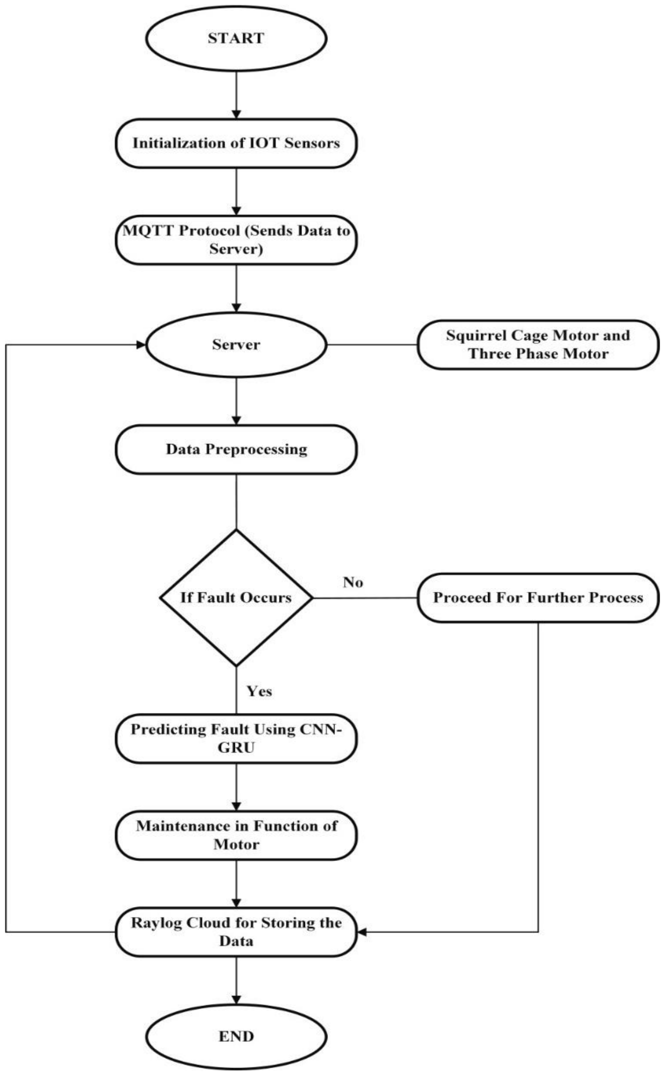

Figure 3. Flowchart for proposed predictive maintenance of squirrel cage induction motors and three-phase synchronous motors

Figure 3 illustrates the comprehensive flowchart of the proposed predictive maintenance system for Squirrel Cage Induction Motors and Three-Phase Synchronous Motors. The flowchart delineates the systematic steps involved in the process, beginning with the deployment of industrial sensors to monitor critical parameters such as vibration, temperature, and current in real-time. The acquired data is then wirelessly transmitted to a central processing unit via ESP8266 and MQTT protocol [26]. Notably, the flowchart incorporates the innovative integration of Convolutional Neural Network-Gated Recurrent Unit architecture for fault classification. The CNN-GRU model optimally captures spatial and temporal features from the raw sensor data, enhancing the system's accuracy in identifying and categorizing motor faults. The flowchart further illustrates the user interface for visualization, facilitating real-time monitoring and maintenance decision-making. The depicted flowchart provides a clear roadmap of the proposed methodology, emphasizing the synergy of advanced sensor technology, wireless communication, and deep learning for effective predictive maintenance in industrial motor systems. The CNN layers extract spatial features from sensor signals, while the GRU layer captures temporal dependencies in the sequential data as mentioned in Table 3.

Table 3. Proposed model configuration

Parameter	Value
Conv1D filters	64
Kernel size	3
Activation	SELU
Batch Normalization	Yes
Gated Recurrent Unit (GRU) units	50
Dense layer neurons	128
Learning rate	0.002
Optimizer	Adam
Epochs	50
Batch size	32

4.5 Experimental setup

The proposed CNN-GRU model was implemented using Python programming language with TensorFlow and Keras libraries. The training experiments were performed on a workstation with the following hardware configuration:

- Ubuntu operating system
- Intel Core i7 processor
- 16 GB RAM
- NVIDIA GPU acceleration

The model training process used the Adam optimizer, which is widely used for deep learning optimization due to its fast convergence and adaptive learning capability [27]. The batch size was set to 32, the learning rate of 0.002, and the model was trained for 50 epochs. To prevent overfitting and improve training stability, early stopping was implemented by monitoring validation loss with a patience of five epochs. Additionally, a learning-rate reduction strategy (ReduceLROnPlateau) was used to dynamically decrease the learning rate when the validation loss plateaued.

5. RESULTS AND DISCUSSION

The results section of this study serves the crucial purpose of presenting a comprehensive evaluation and analysis of the proposed methodology for predictive maintenance in the context of Squirrel Cage Induction Motors and Three-Phase Synchronous Motors. The series of visualizations, including box plots with swarm plots, confusion matrix, correlation heatmap, distribution graph, and histograms with Kernel Density Estimation (KDE), collectively aim to provide an in-depth understanding of the sensor data characteristics, model performance, and interrelationships between variables. These visualizations aid in uncovering patterns, anomalies, and correlations within the dataset, facilitating informed decision-making for predictive maintenance strategies. Additionally, the inclusion of the training and validation graphs for accuracy and loss provides insights into the learning dynamics of the machine learning model. The comparative table of performance metrics further offers a benchmarking perspective, demonstrating the superior effectiveness of the proposed CNN-GRU method compared to alternative approaches. The results section serves as a critical component in validating the efficacy of the proposed methodology and informing practitioners and researchers about the key insights derived from the study, ultimately contributing to advancements in the field of industrial predictive maintenance.

Figure 4 presents a comprehensive visualization of temperature distribution across different categories, utilizing a combination of box plots and swarm plots. Each box plot represents the central tendency and spread of temperatures within a specific category, with the box delineating the interquartile range (IQR) and the median, while the whiskers extend to the data range. Meanwhile, the swarm plot overlays individual data points, providing a detailed depiction of the data distribution. The juxtaposition of these two plot types allows for a nuanced understanding of temperature variations within each label, highlighting potential outliers and the overall pattern of the data. This integrated approach enhances the interpretability of the figure, enabling viewers to discern both the general trends and the granularity of temperature data within different categories.

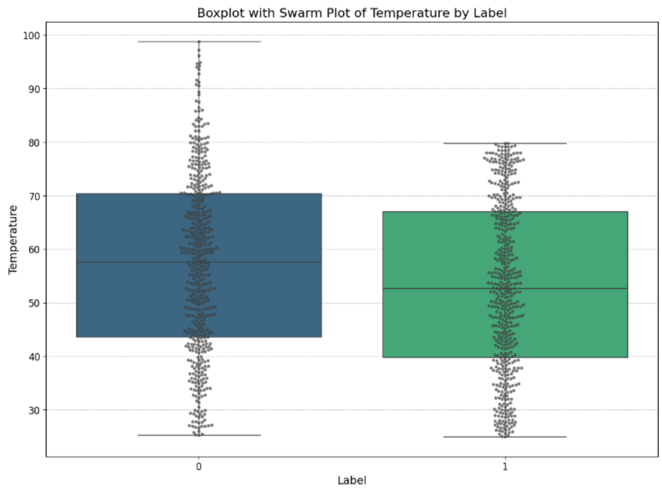

Figure 4. Boxplot with swarm plot of temperature by label

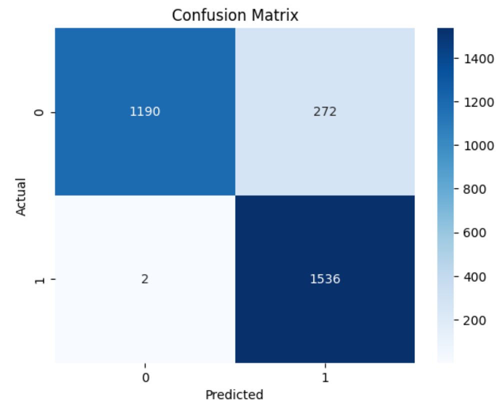

Figure 5. Confusion matrix

In Figure 5, the values 1190 and 272 represent the counts of true negatives (TN) and true positives (TP), respectively, indicating the instances where the model correctly predicted class 0 and class 1. The values 2 and 1536 represent the false positives (FP) and false negatives (FN), respectively, signifying instances where the model misclassified class 0 as class 1 and class 1 as class 0. This information is crucial for evaluating the model's precision, recall, accuracy, and other performance metrics, offering insights into its strengths and weaknesses in making predictions within the binary classification framework.

The correlation heatmap Figure 6 reveals a strong relationship between vibration and current parameters, indicating that abnormal vibration levels are often associated with increased motor current. This relationship is useful for predictive maintenance because it enables early detection of mechanical faults before catastrophic motor failure occurs.

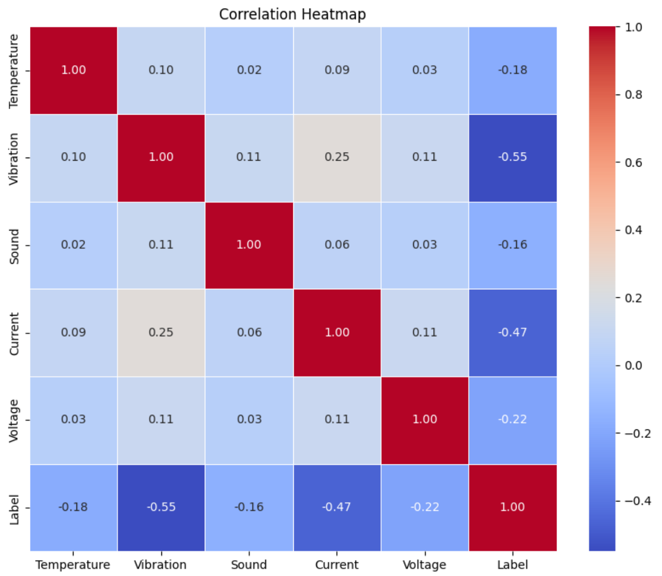

Figure 6. Correlation heatmap

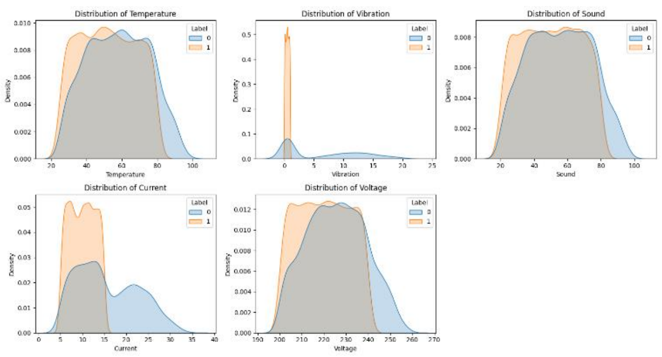

Figure 7. Distribution graph

The distribution graph in Figure 7 provides a comprehensive overview of the variability in the key sensor metrics, namely Temperature, Vibration, Sound, Current, and Voltage, crucial for predictive maintenance in the context of Squirrel Cage Induction Motors and Three-Phase Synchronous Motors. The graph incorporates density plots, offering a nuanced depiction of the data distribution for each sensor variable. This integration of density information allows for a detailed examination of the probability distribution of values, emphasizing regions of higher concentration and revealing potential outliers. The visualization serves as a fundamental component in understanding the sensor data landscape, enabling practitioners to discern patterns, anomalies, or trends that may inform predictive maintenance strategies. As industrial processes increasingly rely on the Internet of Things (IoT) technologies, with the usage of ESP8266, MQTT protocol further enhances the efficiency of data acquisition and transmission, laying the groundwork for proactive and timely interventions in motor health based on the observed sensor readings.

Figure 8 presents a detailed exploration of the distribution of key features, including Temperature, Vibration, Sound, Current, and Voltage, through a combination of histograms and KDE. The histograms provide a granular breakdown of the frequency of values within specific ranges for each sensor variable, offering insights into the central tendencies and dispersion of the data. Concurrently, the overlaid KDE curves provide a smooth, continuous representation of the probability density function, offering a more refined understanding of the underlying data distribution. This dual visualization approach allows for a comprehensive examination of the shape and characteristics of the feature distributions, aiding in the identification of potential patterns or anomalies. The integration of histograms and KDE in Figure 8 facilitates a holistic interpretation of the sensor data, providing valuable information for predictive maintenance strategies in the context of Squirrel Cage Induction Motors and Three-Phase Synchronous Motors.

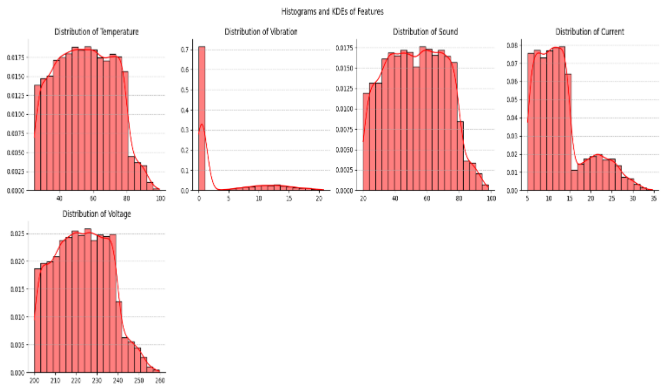

Figure 8. Histograms and Kernel Density Estimation (KDE) of features

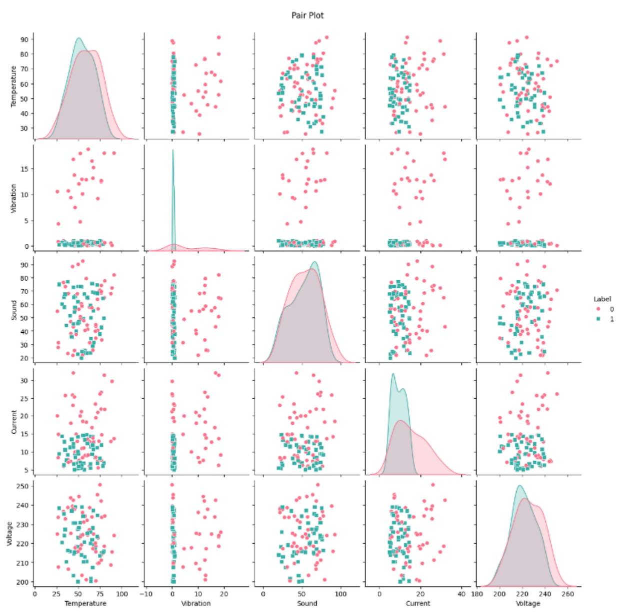

Figure 9. Pair plot

Figure 9 offers a comprehensive visual exploration of the pairwise relationships among Temperature, Vibration, Sound, Current, and Voltage, providing valuable insights into potential correlations and patterns in the sensor data. The subplot in the matrix represents a scatter plot of one feature against another, while the diagonal showcases the univariate distribution of each individual variable through histograms or kernel density estimates. By examining the scatter plots, viewers can discern trends, clusters, or outliers in the relationships between different sensor readings. This visualization is particularly powerful for identifying potential dependencies and understanding how variations in one variable may be associated with changes in another. The pair plot serves as a critical tool for gaining a holistic perspective on the interplay of sensor features, facilitating informed decision-making for predictive maintenance strategies in the realm of Squirrel Cage Induction Motors and Three-Phase Synchronous Motors.

In Figure 10, the training and validation accuracy and loss metrics provide a comprehensive evaluation of a machine learning model's performance during the training process. These metrics, often visualized over epochs, depict the model's ability to learn from the training data and generalize to unseen validation data. Training accuracy and loss measure the model's performance on the training set, indicating how well it fits the provided data. Validation accuracy and loss, on the other hand, assess the model's performance on a separate dataset that it has not seen during training, gauging its ability to generalize to new, unseen examples. A consistent increase in training accuracy and decrease in training loss are indicative of the model learning the training data, while validation accuracy and loss trends help identify potential overfitting or underfitting. These metrics collectively guide the fine-tuning of model parameters to achieve a balance among learning from the training data and generalizing effectively to new, unseen data, finally contributing to the model's reliability and overall performance.

Table 4. Comparison of performance metrics

	Accuracy	Precision	Recall	F1-Score
KNN	96.56	97.65	98.67	95.93
NB	94.67	95.38	97.6	97.54
SVM	82.3	80.1	81.4	80.7
CNN	88.4	86.9	87.6	87.2
LSTM	87.9	86.3	88.1	87.2
CNN-LSTM	90.6	88.3	91.4	89.8
Proposed CNN-GRU	98.94	98.65	99.1	99.45

Note: KNN = K-Nearest Neighbor; NB = Naive Bayes; SVM = Support Vector Machine; CNN = Convolution Neural Network, LSTM = Long Short Term Memory

Table 4 presents a comparative evaluation of multiple machine learning and deep learning models, including KNN, Naïve Bayes, SVM, CNN, LSTM, CNN-LSTM, and the proposed model. Notably, the method outperforms the other two approaches across multiple evaluation metrics. CNN-GRU achieves the highest accuracy at 98.94%, indicating its effectiveness in correctly classifying fault occurrences in the context of the study. Moreover, CNN-GRU demonstrates superior precision (98.65%), recall (99.1%), and F1-score (99.45%) compared to both KNN and NB.

Figure 11 highlights the robustness of CNN-GRU in providing accurate and well-balanced predictions, essential for the reliable identification of faults in the examined system. The findings suggest that CNN-GRU exhibits a notable advantage in fault classification performance, making it a promising method for enhancing the predictive maintenance system's effectiveness in industrial motor applications.

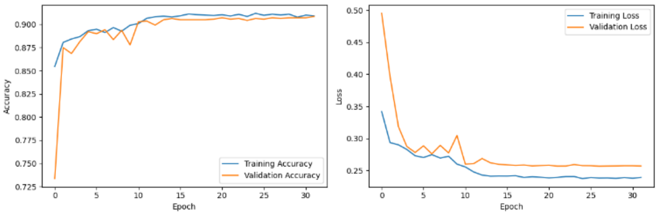

Figure 10. Validation and training graph for accuracy and loss

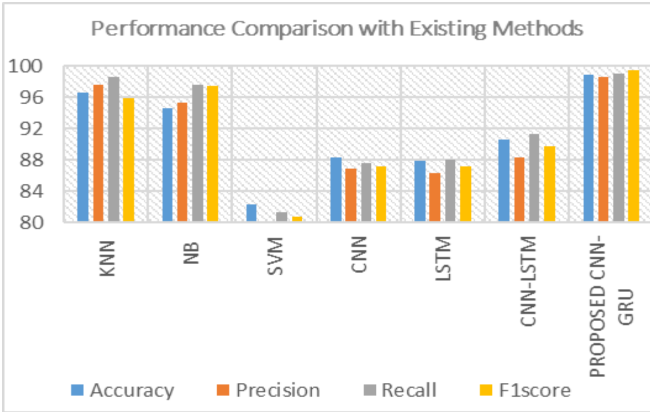

Figure 11. Performance comparison with existing methods

5.1 Discussion

The results underscore the effectiveness of the proposed methodology for predictive maintenance in Squirrel Cage Induction Motors and Three-Phase Synchronous Motors. The visualizations, ranging from box plots and swarm plots to correlation heatmaps and distribution graphs, offer a comprehensive exploration of sensor data characteristics and model performance [27]. These visual insights aid in uncovering nuanced patterns, potential anomalies, and correlations within the dataset, crucial for informed decision-making in predictive maintenance strategies. Notably, the proposed model demonstrates better performance on comparison with alternative methods, as indicated by higher accuracy, precision, recall, and F1-score. The inclusion of training and validation graphs further provides a dynamic view of the model's learning process, revealing its capacity to effectively generalize to new data. The study's comprehensive evaluation contributes valuable knowledge to the field of industrial predictive maintenance, demonstrating the potential of the proposed methodology, particularly the CNN-GRU model, in enhancing the reliability and efficiency of monitoring and managing motor health.

6. CONCLUSION AND FUTURE WORK

This study presented an IIoT-enabled predictive maintenance framework for squirrel cage induction motors and three-phase synchronous motors. The system integrates industrial sensors with an ESP8266-MQTT communication architecture and a CNN-GRU deep learning model for fault classification. Experimental results demonstrate that the proposed model achieves 98.94% accuracy, outperforming conventional machine learning methods. The framework enables reliable real-time monitoring and early fault detection in industrial environments. Future work will focus on validating the system in real industrial settings and exploring advanced deep learning architectures for improved predictive accuracy.

Declaration

- The authors have no financial or proprietary interests in any material discussed in this article.
- The authors have no relevant financial or non-financial interests to disclose.
- The authors have no competing interests to declare that are relevant to the content of this article.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization, methodology, writing original draft.

Author 2: Reviewing the content, editing and supervision.

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