

Development and Evaluation of a Multi-Sensor IoT System for Real-Time Condition Monitoring and Fault Classification of an Industrial Electric Motor

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ABSTRACT

Industrial electric motors require continuous condition monitoring because developing electrical, thermal, and mechanical abnormalities can lead to unplanned shutdowns and equipment damage. This study developed and evaluated a multi-sensor Internet of Things system for real-time condition monitoring and fault classification of an industrial electric motor driving a fire-hydrant pump under field operating conditions. An ESP32 edge device was integrated with an MLX90614 infrared temperature sensor, an MPU6050 three-axis accelerometer, PZEM-004T electrical measurement modules, and an optical rotational-speed sensor. The system acquired temperature, vibration, phase voltage, current, frequency, power, power factor, and rotational-speed measurements. The acquired data were transmitted through authenticated Message Queuing Telemetry Transport communication to Node-RED for processing and routing, stored in InfluxDB Cloud, and presented through Grafana dashboards for real-time monitoring, trend analysis, and alert generation. Field measurements were combined with systematically labelled electrical, thermal, and mechanical fault-condition records to develop the classification dataset. Four recurrent deep-learning architectures—Long Short-Term Memory, Gated Recurrent Unit, Bidirectional Gated Recurrent Unit, and attention-enhanced Gated Recurrent Unit—were trained and comparatively evaluated using multimodal time-series sequences. The LSTM model achieved a test accuracy of 99.95%, while the GRU, Bi-GRU, and GRU-Attention models each achieved 99.97%. A hybrid decision mechanism further compared model predictions with predefined operational thresholds to identify inconsistent classifications and provide an independent condition check. The findings demonstrated that the developed system supported continuous field monitoring, reliable cloud-based data handling, and accurate classification of motor operating conditions. The system provides a practical basis for data-driven fault detection and predictive maintenance decision support for industrial electric motors.

Keywords: Industrial Electric Motor, Condition Monitoring, Internet Of Things, Fault Classification, ESP32, Recurrent Neural Network, Predictive Maintenance.

INTRODUCTION

Industrial electric motors drive critical equipment such as pumps, compressors, fans, and conveyors across manufacturing, energy, water-processing, and oil and gas facilities. Their reliability directly affects production continuity, safety, energy use, and maintenance planning [1], [2], [3], [4]. Motor faults often develop progressively through electrical, thermal, and mechanical abnormalities, including voltage imbalance, excessive current, overheating, bearing deterioration, rotor imbalance, shaft misalignment, looseness, and abnormal vibration [5], [6], [7], [8]. Detecting these conditions before functional failure therefore requires continuous observation of relevant operating variables.

Maintenance practice has consequently shifted from reactive and fixed-interval preventive strategies toward condition-based and predictive approaches. Reactive maintenance can cause unplanned downtime and secondary damage, while scheduled maintenance may result in unnecessary intervention or fail to detect defects that arise

between inspections [9], [10], [11], [12], [13], [14]. Condition-based and predictive maintenance instead use measured equipment behaviour and analytical models to support timely intervention [11], [15], [16], [17]. Their effectiveness, however, depends on the availability of reliable and representative operating data.

Motor condition cannot always be characterised adequately by a single sensing domain. Vibration measurements are useful for identifying bearing degradation, rotor imbalance, misalignment, structural looseness, and related mechanical defects [18], [19], [20], [21], [22], whereas temperature, electrical quantities, and rotational speed reveal complementary evidence of overheating, supply and load variations, and changes in motor-load performance. Integrating these measurements can therefore provide a more complete representation of operating condition and assist in distinguishing abnormalities with similar manifestations. Continuous acquisition is also preferable to periodic handheld inspection because transient events and gradual changes may occur between inspection intervals [18], [19], [20], [21].

The Industrial Internet of Things (IIoT) provides an enabling framework for this integration. Edge devices can acquire and organise multi-sensor measurements, transmit them to remote platforms, and create historical records for trend analysis and machine-learning development [23], [24]. Lightweight Message Queuing Telemetry Transport (MQTT) communication, middleware such as Node-RED, time-series storage such as InfluxDB, and Grafana dashboards can jointly support authenticated transmission, message processing, storage, visualisation, and alerting [25], [26], [27]. Nevertheless, a monitoring system must still demonstrate that its sensing and communication components operate reliably under actual industrial loading and environmental conditions.

This requirement exposes an important limitation in the literature. Many motor-monitoring and fault-classification studies have relied on laboratory rigs, simulations, public datasets, deliberately introduced faults, or restricted sensing configurations [28]. Although these approaches support controlled and repeatable experiments, they provide less evidence about the complete process of acquiring, transmitting, storing, visualising, and classifying multimodal data from a motor that remains connected to its operational load. Field implementation is therefore necessary to evaluate the integrated system under realistic operating and communication conditions.

Machine-learning methods can identify relationships within multidimensional condition data that may not be apparent from individual measurements. Conventional algorithms often depend on manually selected features, whereas deep-learning models can learn representations directly from structured or sequential inputs; however, their performance remains dependent on data preparation, class labelling, training design, and evaluation on unseen observations [29], [30], [31]. Because motor measurements are time-dependent, recurrent models are particularly relevant. Long Short-Term Memory (LSTM) networks use gated memory cells to retain temporal information, while Gated Recurrent Unit (GRU) networks provide related sequence-learning capability with a simpler gating structure [32], [33]. Bidirectional processing and attention can further exploit contextual information and emphasise informative portions of an input sequence. Comparing these architectures under the same field-derived multimodal dataset can clarify their relative suitability without claiming a new neural-network architecture.

Model predictions alone may still be affected by sensor noise, uncertainty, or operating conditions not represented during training. Where established limits exist for temperature, current, voltage, vibration, and speed, deterministic threshold rules can provide an independent check on individual measurements. Combining recurrent-model predictions with threshold-based assessment therefore allows relationships across variables to be evaluated while retaining transparent checks against known operating boundaries. Disagreement between the two outputs can be flagged for further assessment rather than accepting an uncertain classification without verification.

Accordingly, this study developed and evaluated a multi-sensor IoT system for real-time condition monitoring and fault classification of a 5.5-kW industrial electric motor that remained mechanically coupled to a fire-hydrant pump. The system acquired three-phase electrical quantities, motor and ambient temperatures, triaxial vibration, and rotational speed through an ESP32-based sensing unit and transmitted the data through an authenticated

MQTT pipeline for processing, time-series storage, dashboard visualisation, and alerts. The resulting multimodal sequential data were used to compare LSTM, GRU, bidirectional GRU, and attention-enhanced GRU classifiers under a common dataset and training configuration. Their outputs were integrated with predefined operational thresholds as a consistency check. The contribution is therefore the field-level integration and evaluation of multi-parameter sensing, IoT data management, recurrent-model comparison, and deterministic verification within one industrial motor-monitoring pipeline.

LITERATURE REVIEW

IoT-Based Condition Monitoring of Induction Motors

The growing application of the Internet of Things (IoT) in industrial maintenance has enabled motor operating variables to be collected, transmitted, stored, and visualised continuously. Unlike conventional inspection practices, which depend on periodic measurements, IoT-based systems allow changes in motor behaviour to be observed remotely and in near real time. Electrical quantities, temperature, vibration, and rotational speed are among the parameters commonly used because they reflect different aspects of motor condition. Electrical abnormalities may indicate supply imbalance, overload, undervoltage, overvoltage, or phase-related problems, whereas excessive temperature can reflect sustained overloading, inadequate ventilation, insulation deterioration, or increased internal losses. Similarly, vibration and speed variations may reveal developing mechanical or load-related abnormalities.

Yousuf et al. developed an IoT-based system for monitoring the health of an industrial AC induction motor using sensors, wireless communication, and cloud-based data services. The study demonstrated that motor parameters could be acquired remotely and used to support early abnormality detection and predictive-maintenance decisions [34]. Its principal contribution was the integration of sensing and remote communication into an operational monitoring structure. However, the investigation did not provide a comparative evaluation of recurrent deep-learning architectures for multimodal sequential fault classification. Consequently, it offers useful evidence for the feasibility of IoT-based motor monitoring but provides limited information about the relative performance and computational requirements of alternative sequence-learning models.

Many reported IoT monitoring systems concentrate primarily on whether sensed values can be transmitted successfully to a remote interface. Although this confirms communication and visualisation functionality, it does not necessarily establish whether the system can distinguish among multiple categories of motor abnormality. Systems based only on threshold alarms may also produce ambiguous results when several variables change simultaneously or when operating conditions approach the boundary between normal and abnormal states. A more complete condition-monitoring system should therefore combine the visibility provided by IoT infrastructure with a classification method capable of analysing temporal relationships among multiple measured variables.

Multi-Sensor Approaches to Motor Fault Diagnosis

Single-signal motor diagnosis has been investigated extensively, particularly through motor-current signature analysis and vibration analysis. These methods can perform effectively when the selected signal contains a strong signature of the fault being investigated. Their diagnostic coverage may nevertheless be restricted because motor faults do not always produce equally observable changes in every sensing domain. An electrical disturbance, for example, may first appear in voltage, current, frequency, or power-factor measurements, while a mechanical condition may be more evident in vibration or rotational-speed behaviour. Temperature may provide additional information about the cumulative effect of electrical loading and mechanical resistance. Combining these parameters can therefore provide a more comprehensive representation of motor condition than relying on one signal alone.

Long et al. proposed a multi-sensor motor fault-diagnosis method using current, magnetic-flux, and vibration measurements. Frequency-domain features were extracted through Hilbert and Fourier transformations and subsequently processed using an improved AdaBoost classifier with an attention-based weighting mechanism

[35]. Their results demonstrated the value of allocating different levels of importance to information obtained from different sensors. However, the method depended substantially on transformed frequency-domain features and controlled experimental data. It did not investigate an end-to-end IoT implementation involving continuous field acquisition, secure message transmission, time-series storage, dashboard visualisation, and recurrent classification of raw operational sequences.

Kullu and Cinar presented a multimodal sensor-fusion approach for equipment-fault detection using convolutional neural networks. Their method combined two sensor modalities and incorporated information from both the time and frequency domains [36]. The study showed that multimodal fusion can improve fault representation because complementary features are obtained from different signals. Nevertheless, the work focused principally on convolutional feature extraction and laboratory datasets. Continuous monitoring of a mechanically coupled industrial motor through an IoT telemetry pipeline was not the central subject of the investigation.

Abdelmaksoud et al. evaluated convolutional neural networks using single- and multi-channel induction-motor datasets. Voltage and current signals were obtained under conditions such as locked rotor, overload, voltage unbalance, overvoltage, and undervoltage, with different load levels represented in the dataset [37]. The multi-channel arrangement demonstrated the benefit of combining electrical signals when classifying motor operating conditions. However, the measurements were concentrated on electrical behaviour, including the motor starting period, rather than the sustained integration of electrical, thermal, vibration, and speed measurements during field operation.

These studies establish that sensor fusion can strengthen fault diagnosis. They also indicate that the term “multi-sensor” has been applied differently across the literature. In some cases, it refers to multiple sensors measuring the same physical phenomenon; in others, it refers to combining two sensing domains or transforming a small number of signals into multiple feature representations. Comparatively fewer studies have considered the simultaneous use of three-phase electrical measurements, motor and ambient temperatures, triaxial vibration, and rotational speed in one field-installed acquisition and classification system.

Machine-Learning and Deep-Learning Classification

Machine-learning techniques have been used to move motor monitoring beyond fixed threshold assessment. Conventional classifiers, including decision trees, random forests, support-vector machines, artificial neural networks, and boosting algorithms, can identify nonlinear relationships among measured motor variables. However, models that classify individual observations independently may fail to represent the temporal progression of a fault. Motor conditions generally develop over successive measurements, making sequence-learning architectures relevant to continuous condition monitoring.

Sobhi et al. investigated condition monitoring and fault detection in small induction motors using machine-learning algorithms. Their experimental arrangement used voltage and current measurements collected from multiple motors, including motors containing deliberately introduced defects. A convolutional neural network was used to represent normal motor behaviour, while a random-forest model was employed for anomaly detection. The reported true-positive rate was 0.948, with a false-positive rate of 0.033 [38]. An important methodological strength of the work was its use of a chronological training-and-testing arrangement, which reduced the possibility that closely related observations would be distributed randomly across the modelling subsets. Nevertheless, the study addressed anomaly detection more directly than multiclass electrical, thermal, and mechanical fault classification and did not incorporate temperature, triaxial vibration, and rotational speed into an IoT-based field system.

Recurrent neural networks are particularly relevant when the order of observations contains diagnostic information. Long short-term memory (LSTM) and gated recurrent unit (GRU) networks use gating mechanisms to retain useful temporal information while reducing the vanishing-gradient problem associated with conventional recurrent networks. Bidirectional recurrent architectures can process a completed sequence in both

temporal directions, while attention mechanisms allow a model to assign greater importance to the most informative parts of the sequence.

Vanga et al. applied a bidirectional LSTM network to the classification of six induction-motor operating conditions: normal operation, overload, overvoltage, undervoltage, voltage unbalance, and single phasing. Three line voltages and three line currents were supplied to the classifier, and the Bi-LSTM results were compared with those of a conventional LSTM model [39]. The study demonstrated that bidirectional temporal processing could improve the classification of external motor faults. However, it was based on the electrical measurements of a single machine and used data obtained from an existing source. Its authors also identified extension to different machine ratings and additional internal faults as areas for further investigation. The study did not evaluate GRU or attention-enhanced GRU models and did not include an IoT-based field-monitoring architecture.

Vo et al. combined convolutional and recurrent processing with attention mechanisms for induction-motor fault diagnosis using raw electrical signals [40]. The use of raw signals reduced dependence on manually engineered diagnostic features, while attention helped the model emphasise informative portions of the input. This represents an important development in end-to-end fault classification. Nevertheless, the investigation remained focused on algorithmic diagnosis using electrical signals. It did not evaluate whether attention-enhanced recurrent learning could operate with multimodal data obtained from a continuously monitored motor in its installed industrial environment.

Collectively, these studies show that high classification performance can be achieved using CNNs, LSTMs, bidirectional networks, attention mechanisms, and multimodal fusion. Direct comparison among reported accuracy values must nevertheless be undertaken cautiously. The studies use different motors, fault types, sampling frequencies, observation windows, class distributions, validation procedures, and fault-generation methods. A high result obtained from controlled or artificially separated fault classes does not necessarily demonstrate generalization to an independently operated motor. The experimental setting and data-partitioning strategy must therefore be considered together with the reported classification accuracy.

Comparative Synthesis of Previous Studies

The principal characteristics of the most relevant empirical investigations are summarised in Table 1.

Table 1. Comparative summary of related empirical studies.

Study	Measurements or data	Method	Experimental emphasis	Limitation relative to the present study
Long et al.	Current, magnetic flux and vibration	Improved AdaBoost with attention weighting	Multi-sensor fault diagnosis	Relied on transformed features and controlled experiments; no complete field IoT pipeline
Kullu and Cinar	Two sensor modalities with time- and frequency-domain representations	Multimodal CNN	Sensor-fusion-based equipment diagnosis	Laboratory and convolutional focus; no recurrent field-monitoring comparison
Sobhi et al.	Voltage and current from multiple small motors	CNN and random forest	Normality modelling and anomaly detection	Did not perform multimodal electrical, thermal, mechanical and speed-based multiclass diagnosis
Vanga et al.	Three-phase voltages and currents	LSTM and Bi-LSTM	Classification of six external motor conditions	Electrical data from one machine; no GRU, attention model or IoT field implementation
Abdelmaksoud et al.	Multi-channel electrical signals	CNN	Fault classification under different load levels	Predominantly electrical and start-up data; no continuous multisensor field monitoring

Vo et al.	Raw electrical signals	CNN, recurrent processing and attention	End-to-end deep fault diagnosis	Did not combine electrical, temperature, vibration and speed measurements in a deployed IoT system
Yousuf et al.	Motor-condition sensor measurements	IoT monitoring and abnormality detection	Remote industrial-motor health monitoring	Limited comparison of alternative recurrent fault-classification architectures

Identified Research Gap

The reviewed studies demonstrate substantial progress in IoT-based motor monitoring, multisensor fault diagnosis, and deep-learning classification. However, these research areas have often been investigated separately. Some studies have concentrated on transmitting motor measurements to remote platforms without performing multiclass sequential fault classification, while others have evaluated advanced classification models using laboratory, simulated, or secondary datasets without incorporating them into a complete field-installed monitoring pipeline. Furthermore, many reported methods have relied on a single sensing domain or a limited combination of electrical and vibration signals. Comparatively fewer studies have integrated three-phase electrical quantities, motor and ambient temperatures, triaxial vibration, and rotational speed within one IoT system and then evaluated multiple recurrent neural-network architectures under the same data and training conditions.

To address this gap, the present study developed and evaluated a multi-sensor IoT condition-monitoring system installed on a 5.5-kW three-phase induction motor mechanically coupled to a fire-hydrant pump. The system integrated sensor acquisition, authenticated MQTT transmission, middleware processing, time-series storage, dashboard visualisation, and fault classification. Multimodal sequential data were used to compare LSTM, GRU, Bi-GRU, and GRU-Attention models under a common experimental configuration. The study therefore contributes an integrated field-monitoring implementation and a controlled comparison of recurrent classification architectures. It does not claim universal model generalization because the evaluation was based on one motor installation and included synthetic fault-labelled observations.

MATERIALS AND METHODS

Research Design and System Architecture

This study adopted a system-development and quantitative evaluation approach for field-based motor-condition monitoring and fault classification. The monitoring system was implemented on a three-phase squirrel-cage induction motor driving a fire-hydrant pump. The motor remained mechanically coupled to the pump during data collection, allowing the acquired measurements to reflect its actual loading, electrical supply, mounting, and surrounding environmental conditions rather than the behaviour of an unloaded laboratory motor.

The developed system comprised multi-sensor data acquisition, ESP32-based edge processing, wireless MQTT communication, Node-RED data validation and routing, InfluxDB Cloud storage, Grafana visualisation, recurrent deep-learning classification, and deterministic threshold verification. Electrical, thermal, vibration, and rotational-speed measurements were acquired at the motor and transmitted as structured sensor records. Four recurrent models—LSTM, GRU, Bi-GRU, and GRU-Attention—were subsequently trained and evaluated to classify the motor condition as Normal, Electrical Fault, Thermal Fault, or Mechanical Fault.

Monitored Motor and Field Installation

The monitored equipment was a 5.5 kW, 415 V, three-phase squirrel-cage induction motor operating at a supply frequency of 50 Hz. Its rated rotational speed was 1,450 rpm, enclosure-protection rating was IP55, and insulation classification was Class F. The motor drove a fire-hydrant pump that maintained the hydrant-line pressure at approximately 10 bar. It operated automatically in response to changes in the system pressure.

Table 2. Specifications of the monitored motor and driven pump.

Parameter	Specification
Motor type	Three-phase squirrel-cage induction motor
Application	Fire-hydrant pump
Rated power	5.5 kW
Rated voltage	415 V line-to-line
Supply frequency	50 Hz
Rated speed	1,450 rpm
Enclosure protection	IP55
Insulation class	Class F
Approximate pump discharge pressure	10 bar

The sensor circuit and ESP32 were installed close to the motor. Temperature and vibration sensors were positioned on or near the motor casing, electrical measurements were obtained from the three-phase supply, and rotational speed was measured from the motor shaft.

Hardware and Circuit Configuration

The ESP32 served as the central data-acquisition and communication device. An MLX90614ESF-BAA infrared sensor measured the motor surface and ambient temperatures, while an MPU6050 accelerometer measured vibration along the x-, y-, and z-axes. Three PZEM-004T modules measured the voltage, current, frequency, active power, and power factor of the red, yellow, and blue phases. An optical slot sensor and a 20-slot encoder disc measured the motor-shaft rotational speed.

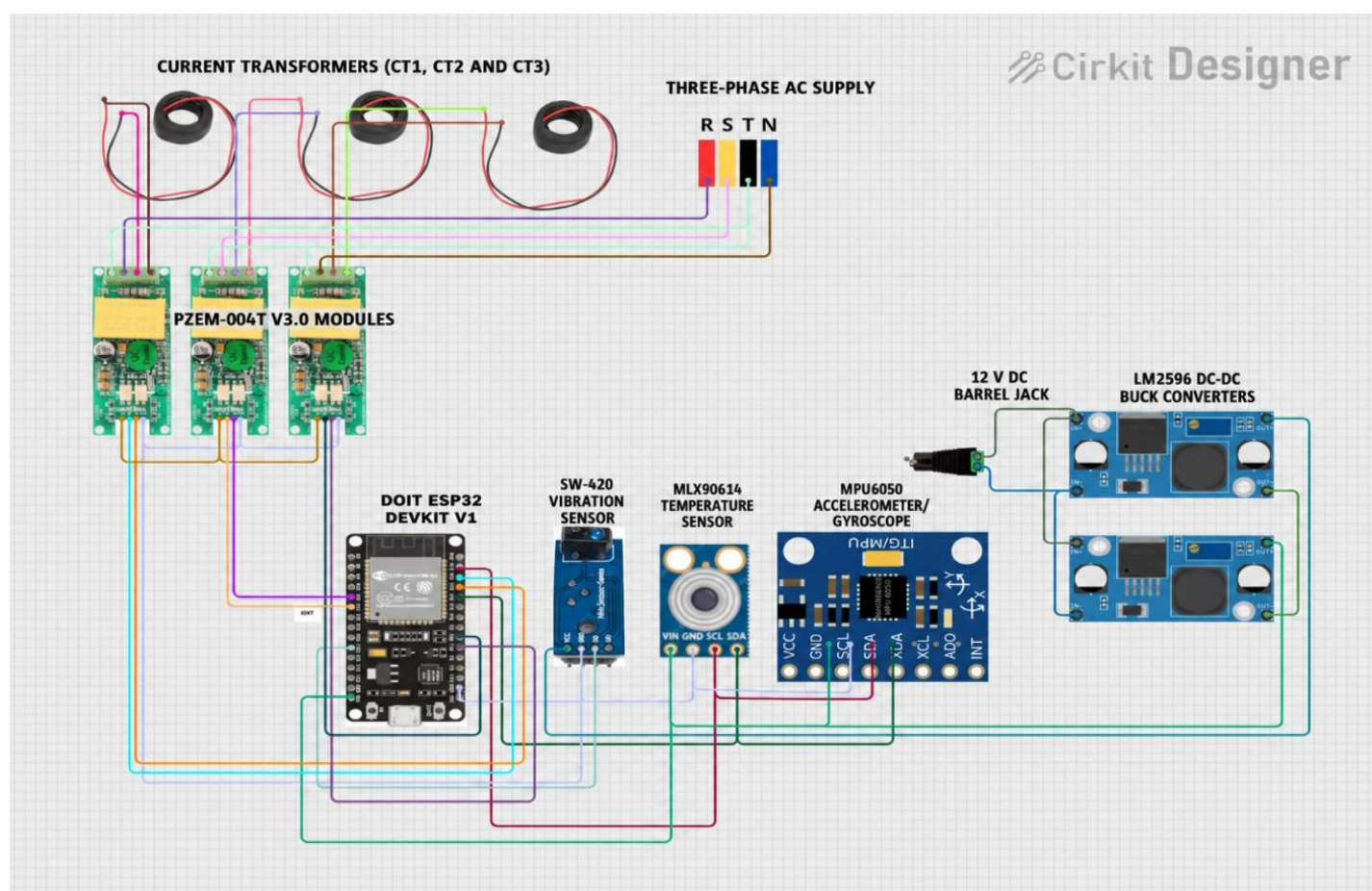


Figure 1. Circuit diagram of the developed multi-sensor IoT motor-monitoring unit

Figure 1 presents the circuit configuration of the developed multi-sensor monitoring unit. The ESP32 served as the central controller and interfaced with the temperature, vibration, three-phase electrical, and rotational-speed sensing components. The diagram also identifies the communication buses, assigned GPIO pins, current-transformer connections, and regulated power-supply path used in the field-installed unit.

The MLX90614 and MPU6050 shared the ESP32 I²C bus. GPIO 21 was configured as the serial-data line, while GPIO 22 was used as the serial-clock line. The MLX90614 retained its address of 0x5A, while the MPU6050 used 0x68. Because the devices had different addresses, they operated on the same I²C bus without an address conflict.

The three PZEM-004T modules were queried through UART2 at 9,600 bits per second using eight data bits, no parity, and one stop bit. GPIO 16 and GPIO 17 were configured as the receive and transmit pins, respectively, and the firmware associated each returned measurement with the corresponding red, yellow, or blue phase. Each module used an external current transformer around its assigned phase conductor and measured the associated phase-to-neutral voltage. Accordingly, the approximately 230 V measurements reported in this study are consistent with the motor's 415 V line-to-line rating.

The optical sensor output was connected to GPIO 4, which was configured as an interrupt-capable digital input. The sensor detected the slots passing through its optical gap, and the pulse count was converted into revolutions per minute. At a reference speed of 1,500 rpm, the 20-slot disc generated approximately 500 pulses per second.

The monitoring circuit was powered by a 100–240 V AC to 12 V DC, 2 A regulated adapter. An LM2596 step-down converter reduced and regulated the supply to the voltage required by the ESP32 and connected sensor circuit.

Sensor Installation and Verification

The MLX90614 was positioned perpendicular to a fixed point on the motor casing at an approximate distance of 10 cm. Its temperature readings were compared with those obtained using a handheld industrial infrared thermometer, with both instruments directed towards the same location under ambient and motor-operating conditions. The comparison verified that the MLX90614 accurately measured the motor-casing temperature.

The MPU6050 was secured to the motor housing in a fixed orientation. Stationary measurements were initially recorded to establish a baseline for the three acceleration axes. Measurements acquired during motor operation were subsequently compared with the stationary baseline, confirming that the sensor accurately detected changes in motor vibration along the three axes.

The three PZEM-004T modules were connected separately to the red, yellow, and blue phases. Their voltage readings were compared with measurements obtained using a Fluke 787 ProcessMeter, while their current readings were verified using a Fluke 325 clamp meter. The comparisons confirmed that the modules accurately measured the voltage and current of their respective phases before continuous monitoring commenced. All electrical connections were properly insulated before monitoring.

The optical slot sensor was aligned with the 20-slot encoder disc attached to the motor shaft. Its calculated rotational-speed readings were compared with measurements obtained using a Fluke 930 non-contact tachometer under steady operating conditions. The comparison verified that the optical sensor accurately measured the rotational speed of the motor shaft.

Data Acquisition and IoT Communication

The ESP32 acquired the electrical, thermal, vibration, and rotational-speed measurements and arranged them into a JSON payload. The system used a five-second acquisition and MQTT publishing interval. The transmitted payload contained 18 model input variables: three phase voltages, three phase currents, three phase frequencies,

three phase power factors, motor surface temperature, ambient temperature, three-axis vibration, and rotational speed.

Active power was acquired and stored for monitoring but was not included as an independent model input because it was derived from voltage, current, and power factor. Cumulative energy was also excluded because it represented the duration of operation more strongly than the immediate motor condition.

The ESP32 accessed the internet through an MTN MiFi operating on the 2.4 GHz Wi-Fi band. WPA2 pre-shared-key authentication protected the local wireless connection. The MQTT connection used broker authentication, Transport Layer Security, certificate validation, and port 8883.

The sensor payload was published under the topic esp32/sensors, while esp32/status was used for connection-status messages. MQTT Quality of Service level 0 was applied to reduce communication overhead. Consequently, individual messages were not acknowledged or guaranteed by the broker. The firmware monitored the Wi-Fi and MQTT connections and attempted reconnection following a communication interruption.

Node-RED version 3.1.7 subscribed to the sensor topic. It parsed each received JSON payload, verified the required parameter names and data types, and rejected missing or non-finite values. Because the ESP32 payload did not contain a timestamp, Node-RED added the reception timestamp before routing the record to InfluxDB Cloud, Grafana, and the machine-learning component.

Data Collection and Fault Labelling

Motor-condition data were collected over a 12-month period while the industrial motor remained connected to the fire-hydrant pump. Following data cleaning and quality screening, 200,000 valid timestamped records were retained for analysis and model development. The retained dataset represented the motor's monitored operating periods because the fire-hydrant pump operated intermittently in response to system-pressure conditions. Approximately 90% of the records represented normal operation, while the remaining records represented electrical, thermal, and mechanical abnormal conditions.

The dataset contained field-observed normal and abnormal operating records. Because abnormal conditions occurred less frequently than normal operation, synthetic fault-labelled records were also generated in Python from the measured operating patterns and class-specific data ranges. These additional records supplemented the underrepresented Electrical Fault, Thermal Fault, and Mechanical Fault categories.

A Python program assigned the records to Normal, Electrical Fault, Thermal Fault, or Mechanical Fault categories using the class-specific patterns applied during dataset construction. Electrical Fault records represented abnormal electrical behaviour, Thermal Fault records represented elevated motor surface temperature, and Mechanical Fault records represented increased acceleration or abnormal rotational-speed behaviour. These model-development labels were analytical condition categories and were not equivalent to the conservative critical limits used later by the hybrid verification mechanism. The operational limits in Table 6 were applied only as an independent post-classification safety check.

The complete class distribution was as follows:

Table 3. Distribution of the complete motor-condition dataset.

Motor-condition class	Records	Proportion
Normal	179,962	89.98%
Electrical Fault	6,579	3.29%
Thermal Fault	7,408	3.70%
Mechanical Fault	6,051	3.03%
Total	200,000	100.00%

Where more than one parameter exceeded its limit, the condition was assigned according to the dominant fault indicator. Electrical variables determined electrical faults, temperature determined thermal faults, and vibration or speed determined mechanical faults.

Data Preprocessing and Sequence Preparation

The complete dataset was examined for missing measurements, non-numerical values, invalid timestamps, unrecognised labels, and exact duplicate records. No invalid or duplicate records were identified, and all 200,000 records were retained for descriptive sensor-data analysis.

Because the complete dataset was dominated by the Normal class, a separate balanced subset was prepared for model development. This subset contained 5,000 records from each of the four condition classes, producing 20,000 records.

Min–max normalisation transformed the 18 input features to values between zero and one. The scaler was fitted using the training data and subsequently applied to the validation and test data. Timestamp, motor identification, and class-label fields were excluded from the feature matrix.

The normalised records were arranged into overlapping sequences of 10 consecutive observations. Each observation contained 18 features, giving a model input shape of 10×18 , and the label of the final observation was assigned as the target class. Although 19,991 windows are mathematically possible from 20,000 records with a window length of 10, the implemented loop stopped one position before the final possible window and produced the 19,990 sequences actually used in model development. The reported partition sizes and performance results correspond to those implemented sequences.

The sequences were initially divided into model-development and test portions using an 80:20 ratio with a random seed of 42. During training, 20% of the model-development portion was used for validation. The final allocation was:

Table 4. Allocation of sequences used for model development and evaluation.

Dataset portion	Sequences	Approximate proportion
Training	12,793	64%
Validation	3,199	16%
Test	3,998	20%
Total	19,990	100%

Machine-Learning Models

The models were developed using Python, TensorFlow 2.18, and Keras in a GPU-enabled Google Colab environment. All four models received sequences with an input shape of 10×18 and generated probabilities for the four motor-condition classes through a softmax output layer.

The LSTM model contained two recurrent layers with 128 and 64 units. A dropout layer with a rate of 0.30 followed the first recurrent layer. A dense layer containing 64 ReLU-activated neurons preceded the four-neuron output layer. The model contained 128,068 trainable parameters.

The GRU model used two GRU layers with 128 and 64 units, a dropout rate of 0.30, a 64-neuron ReLU dense layer, and a four-neuron softmax output layer. It contained 98,116 trainable parameters.

The Bi-GRU model contained bidirectional recurrent layers with 128 and 64 units in each processing direction. The concatenated output of the second bidirectional layer was passed through a 64-neuron dense layer and the four-neuron output layer. It contained 245,060 trainable parameters.

The GRU-Attention model used a 128-unit GRU layer that returned the hidden state for every observation. A temporal attention mechanism assigned a relative weight to each hidden state and combined them into a context vector. The context vector was supplied to a 64-neuron dense layer and the four-neuron output layer. The model contained 64,964 trainable parameters.

Table 5. Configurations and trainable parameters of the recurrent models.

Model	Main configuration	Dropout	Trainable parameters
LSTM	128-unit LSTM → 64-unit LSTM → Dense 64	0.30	128,068
GRU	128-unit GRU → 64-unit GRU → Dense 64	0.30	98,116
Bi-GRU	Bi-GRU 128 → Bi-GRU 64 → Dense 64	0.30	245,060
GRU-Attention	GRU 128 → Attention → Dense 64	0.30	64,964

Model Training and Evaluation

The Adam optimizer was applied with a learning rate of 0.001. Categorical cross-entropy was used as the loss function, and the models were trained with a batch size of 64 for a maximum of 20 epochs. A random seed of 42 was applied to improve reproducibility.

Early stopping monitored validation loss for the LSTM, GRU, and Bi-GRU models. Training stopped when validation loss failed to improve for three consecutive epochs, after which the weights associated with the minimum validation loss were restored. The uploaded GRU-Attention implementation did not apply early stopping and therefore completed all 20 epochs.

Performance was evaluated using test accuracy, weighted precision, weighted recall, weighted F1-score, number of classification errors, and confusion matrices. The same training, validation, and test partitions were used for the four models.

Hybrid Threshold Verification

A hybrid verification mechanism was implemented to combine the pattern-recognition capability of the recurrent neural-network models with predefined motor-operating limits. The machine-learning model provided the primary classification by analysing temporal relationships among the electrical, thermal, vibration, and rotational-speed measurements. After classification, the threshold mechanism examined the current measurements using the operational limits presented in Table 6. The threshold rules were not embedded in the recurrent-model architecture; they operated at the decision stage to provide an additional and transparent assessment of the motor condition.

Table 6. Operational limits used by the hybrid threshold-verification mechanism

Parameter	Normal range	Warning range	Critical condition
Phase voltage	218.5–241.5 V	207–218.4 V or 241.6–253 V	Below 207 V or above 253 V
Phase current	0–15 A	No separate warning range configured	Above 15 A
Frequency	49–51 Hz	47.5–48.9 Hz or 51.1–51.5 Hz	Below 47.5 Hz or above 51.5 Hz
Power factor	0.80–1.00	No separate warning range configured	Below 0.80
Motor surface temperature	Below 95 °C	No separate warning range configured	95 °C or above
Three-axis vibration	0–1.5 g	No separate warning range configured	Above 1.5 g on any axis
Rotational speed	0–1,500 rpm	No separate warning range configured	Above 1,500 rpm

When the threshold assessment agreed with the machine-learning prediction, the predicted class was retained as the final displayed condition. When a measured parameter exceeded a critical operational limit that was

inconsistent with the predicted class, the mechanism applied a rule-based override to the displayed condition and generated an alert. The affected parameter, measured value, applicable limit, model prediction, and reason for the override were displayed on the monitoring interface, stored for subsequent review, and communicated through an email notification. The override operated at the monitoring and decision-support level and did not directly stop or restart the physical motor.

RESULTS AND DISCUSSION

Field Monitoring and Dataset Characteristics

The developed monitoring system acquired electrical, thermal, vibration, and rotational-speed measurements from the 5.5 kW three-phase induction motor while it remained mechanically coupled to the fire-hydrant pump. The ESP32 organized the measurements into structured records at five-second intervals and transmitted them through the authenticated MQTT connection. Node-RED received the transmitted records, verified the required parameter names and data types, rejected invalid entries, and assigned a reception timestamp before routing the accepted measurements to InfluxDB Cloud and Grafana. The resulting dashboard displayed the current operating condition of the motor and provided access to historical trends and abnormal-condition alerts.

The implementation demonstrated the functional transfer of measurements from the field-installed sensing unit to the remote monitoring environment. The firmware also monitored the Wi-Fi and MQTT connections and attempted reconnection whenever communication was interrupted. However, end-to-end communication latency and message-delivery rate were not measured quantitatively. The results therefore establish the successful operation of data acquisition, transmission, validation, storage, and visualisation but do not demonstrate a guaranteed delivery percentage or a specific latency level.

Data acquisition was conducted over a 12-month observation period. Because the fire-hydrant pump operated intermittently in response to changes in system pressure, the recorded measurements represented accumulated monitored operating periods rather than 12 months of uninterrupted five-second sampling. A total of 200,000 timestamped records were obtained. Examination of the dataset identified no missing sensor measurements, non-numerical values, invalid timestamps, unrecognized condition labels, or exact duplicate records. Consequently, all the records were retained for descriptive analysis.

The dataset was dominated by Normal operation, which accounted for 179,962 records or 89.98% of the complete dataset. Electrical Fault, Thermal Fault, and Mechanical Fault conditions accounted for 6,579, 7,408, and 6,051 records, respectively. The distribution reflected the expected operating pattern of industrial equipment, in which normal conditions occur more frequently than abnormal conditions.

A balanced subset was prepared for model development to prevent the dominant Normal class from controlling the learning process. The subset contained 5,000 records from each of the four classes, resulting in 20,000 records. After min-max normalization, the records were transformed into overlapping sequences containing ten consecutive observations and 18 features per observation. The implemented program generated 19,990 sequences, which were divided into 12,793 training sequences, 3,199 validation sequences, and 3,998 test sequences.

The complete 200,000-record dataset was therefore used to characterize the monitored conditions, while the balanced subset was used for recurrent-model development and evaluation. This distinction is important because the reported machine-learning results were obtained from the balanced sequence dataset and not by testing every record in the complete dataset.

Sensor Behaviour Across Operating Conditions

The sensor measurements displayed identifiable differences among the four motor-condition classes. Under Normal operation, the mean red-, blue-, and yellow-phase voltages were 229.97 V, 230.01 V, and 229.96 V, respectively. Their standard deviations ranged from 1.92 V to 2.08 V, while the combined voltage range was

222.08–237.13 V. These results indicated relatively stable phase-to-neutral voltages around the nominal value of 230 V.

The Electrical Fault class exhibited substantially greater voltage variation. Red-phase voltage ranged from 209.23 V to 249.89 V, blue-phase voltage ranged from 205.07 V to 251.19 V, and yellow-phase voltage ranged from 209.59 V to 251.26 V. The corresponding standard deviations ranged from 11.47 V to 12.04 V. The mean voltage values remained relatively close to those observed during Normal operation, but the wider ranges and increased standard deviations revealed unstable phase-voltage behaviour. Electrical Fault conditions were therefore differentiated more strongly by voltage variability and extreme values than by differences in mean voltage.

The phase currents did not exhibit a similarly strong separation. During Normal operation, the mean red-, blue-, and yellow-phase currents were 10.02 A, 10.00 A, and 10.01 A, respectively. Under the Electrical Fault condition, the corresponding means were 10.06 A, 10.04 A, and 9.96 A. These small differences indicate that current alone would not have distinguished the two classes reliably within the developed dataset.

The recorded frequencies remained close to 50 Hz, while the power-factor values remained approximately 0.90 across the operating conditions. These variables did not independently distinguish the Electrical Fault class as clearly as voltage variation. Nevertheless, their inclusion allowed the recurrent models to assess the complete three-phase electrical pattern and determine whether changes in one electrical quantity were accompanied by corresponding changes in other measurements.

Motor surface temperature also varied between the Normal and Thermal Fault classes. During Normal operation, motor temperature ranged from 46.56°C to 83.20°C, with a mean of 64.93°C and a standard deviation of 4.94°C. Under the Thermal Fault condition, it ranged from 66.80°C to 89.63°C, with a mean of 78.81°C and a standard deviation of 5.74°C. The mean temperature of the Thermal Fault class was therefore 13.88°C higher than that of the Normal class.

Despite this difference, the temperature ranges overlapped between 66.80°C and 83.20°C. A temperature measurement within this overlapping interval could belong to either class when considered independently. The result demonstrates why temperature should be interpreted together with preceding temperature values and other measurements instead of being treated as an isolated indicator. The recurrent models could assess whether an elevated temperature formed part of a developing temporal pattern and whether it occurred alongside changes in electrical loading, vibration, or rotational speed.

Ambient temperature remained comparatively stable, with class means ranging from 27.56°C to 28.01°C. The absence of a corresponding increase in ambient temperature indicated that the higher values associated with the Thermal Fault class occurred mainly at the motor surface. Including ambient temperature also provided environmental context for interpreting surface-temperature changes.

The clearest separation between Normal and Mechanical Fault conditions occurred in the three-axis acceleration measurements. Under Normal operation, the mean x-, y-, and z-axis measurements were 0.01995, 0.02016, and 0.01980, respectively. Under the Mechanical Fault condition, the corresponding means increased to 0.09232, 0.09169, and 0.09446.

The mean resultant acceleration magnitude increased from 0.03536 during Normal operation to 0.16203 during the Mechanical Fault condition, representing an increase of approximately 4.58 times. The highest magnitude recorded for the Normal class was 0.05202, while the lowest value in the Mechanical Fault class was 0.12713. The absence of overlap between these ranges produced strong class separation within the prepared dataset and was likely an important contributor to the high classification performance.

The MPU6050 measurements represented acceleration and were used to identify relative changes in motor movement. They were not treated as standardised vibration-velocity measurements in mm/s RMS and should not be interpreted as a replacement for measurements obtained using a calibrated industrial vibration analyser.

The acceleration ranges used to characterise the model-development classes were also distinct from the conservative 1.5 g critical limit used by the hybrid verification mechanism. Rotational-speed measurements complemented the acceleration data by providing information about the behaviour of the motor and connected pump. Collectively, the sensor results showed that the condition classes were represented by different combinations of electrical, thermal, mechanical, and operational characteristics rather than by a single universally dominant variable.

Comparative Performance of the Recurrent Models

The four recurrent models achieved high within-dataset classification performance on the designated test subset of 3,998 sequences, with test accuracies ranging from 99.95% to 99.97%. The LSTM model completed training after six epochs because the early-stopping condition was satisfied. Its best validation performance occurred at Epoch 3, where it achieved a training accuracy of 99.92%, validation accuracy of 99.91%, and validation loss of approximately 0.0050. The restored model correctly classified 3,996 test sequences, producing a test accuracy of 99.95%.

The LSTM correctly classified all 991 Normal sequences and all 979 Mechanical Fault sequences. Of the 1,025 Electrical Fault sequences, 1,024 were classified correctly, while one was classified as Normal. Of the 1,003 Thermal Fault sequences, 1,002 were classified correctly, while one was classified as an Electrical Fault. These results indicate that the limited classification errors occurred between conditions whose measured ranges showed some degree of similarity.

The GRU model completed training after 11 epochs. Its minimum validation loss of approximately 0.0016 occurred at Epoch 8, where training and validation accuracy reached 99.98% and 99.97%, respectively. On the test dataset, the model correctly classified 3,997 of the 3,998 sequences, resulting in an accuracy of 99.97%. The only error involved an Electrical Fault sequence classified as Normal.

The Bi-GRU model completed training after six epochs. Its minimum validation loss occurred at Epoch 3, when the training accuracy was 99.97% and validation accuracy reached 100%. The model correctly classified 3,997 test sequences and misclassified one Electrical Fault sequence as Normal, producing a test accuracy of 99.97%.

The GRU-Attention model completed all 20 configured epochs because early stopping was not applied to its implementation. Its training accuracy increased from 88.23% at Epoch 1 to 99.99% at Epoch 20. Validation accuracy reached 99.97% at Epoch 3 and remained at that level, while the lowest validation loss of 0.00068 was recorded at Epoch 14. The model correctly classified 3,997 test sequences and misclassified one Electrical Fault sequence as Normal, resulting in a test accuracy of 99.97%.

Table 7. Comparative test performance of the recurrent models.

	Accuracy	Weighted precision	Weighted recall	Weighted F1-score	Errors	Parameters
LSTM	99.95%	0.99950	0.99950	0.99950	2	128,068
GRU	99.97%	0.99975	0.99975	0.99975	1	98,116
Bi-GRU	99.97%	0.99975	0.99975	0.99975	1	245,060
GRU-Attention	99.97%	0.99975	0.99975	0.99975	1	64,964

Figure 2 presents the class-specific confusion matrices obtained from the test dataset. The matrices confirm that all Normal and Mechanical Fault sequences were classified correctly by the four models. The LSTM produced two errors, whereas the GRU, Bi-GRU, and GRU-Attention models each produced one error involving an Electrical Fault sequence classified as Normal.

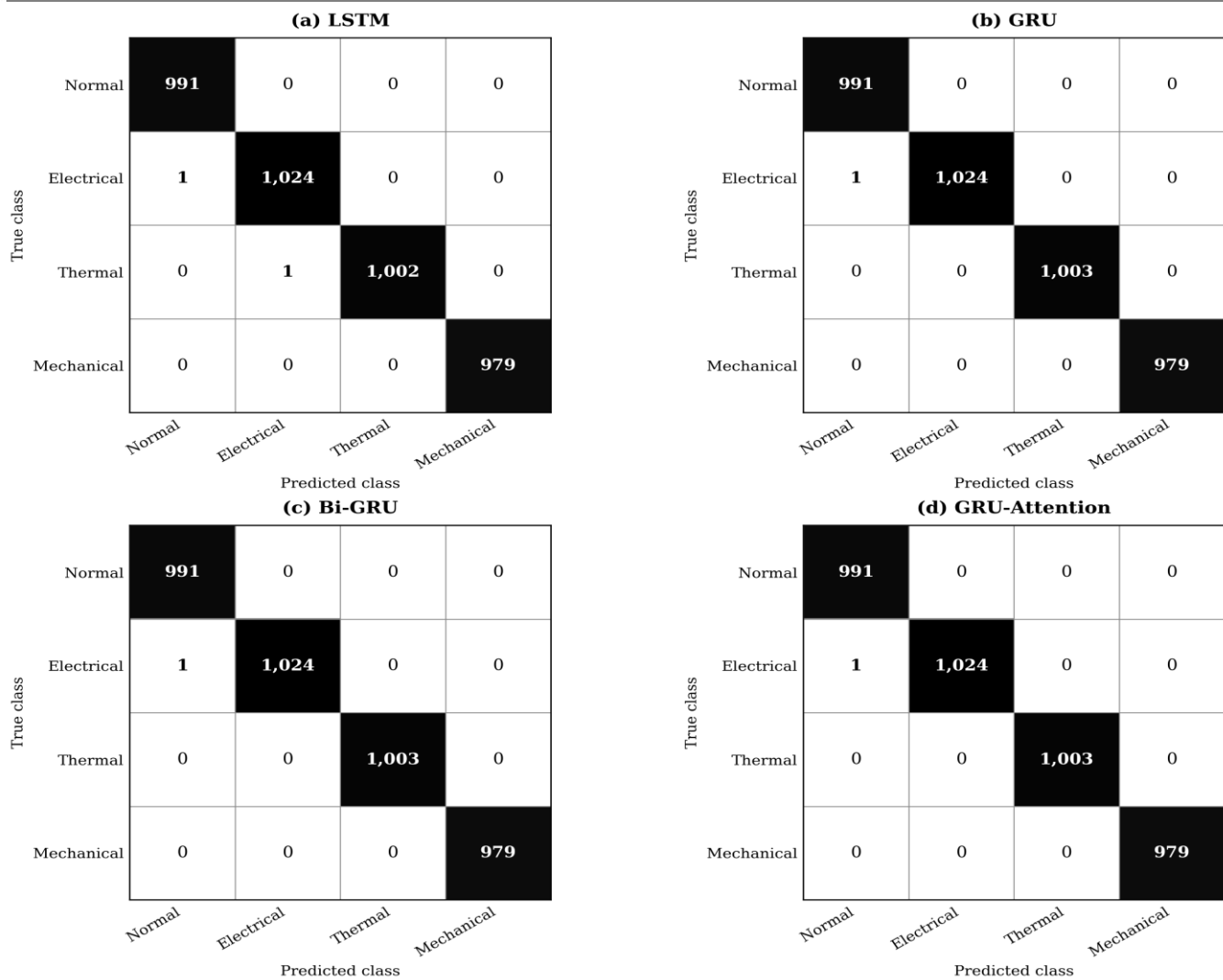


Figure 2. Confusion matrices of the LSTM, GRU, Bi-GRU, and GRU-Attention models on the test dataset

The GRU, Bi-GRU, and GRU-Attention models produced identical classification results on the test dataset. The inclusion of bidirectional processing or temporal attention therefore did not produce a measurable improvement in accuracy over the standard GRU. This finding indicates that the fault classes were already sufficiently distinguishable for a conventional GRU to learn the relevant temporal relationships.

Although GRU-Attention did not outperform the GRU and Bi-GRU in predictive accuracy, it achieved the joint-highest result with the lowest number of trainable parameters. Its 64,964 parameters represented approximately 33.8% fewer parameters than the GRU, 49.3% fewer than the LSTM, and 73.5% fewer than the Bi-GRU. The Bi-GRU had the largest architecture but produced no improvement in classification performance. GRU-Attention consequently provided the most favourable relationship between classification accuracy and model size among the evaluated architectures.

This result should not be interpreted as evidence that GRU-Attention was statistically superior to the other models. The models were not evaluated through multiple independent training runs, confidence intervals, or statistical significance tests. Inference time, memory consumption during deployment, and processor utilisation were also not measured. The conclusion is therefore limited to the observed accuracy and parameter count under the implemented training configuration.

Hybrid Threshold-Verification Results

The hybrid verification mechanism successfully compared the recurrent-model predictions with the configured operational limits. When the model prediction agreed with the threshold-based assessment, the predicted class

was retained and displayed. When a critical parameter violation conflicted with the predicted class, the system replaced the displayed prediction with a failsafe-override alert.

The override message identified the affected parameter, its measured value, the applicable operating limit, and the reason for overriding the original prediction. The resulting condition was displayed through the monitoring interface, stored with its timestamp, and communicated through email notification. This allowed maintenance personnel to determine whether the reported condition originated from model classification, direct threshold violation, or a disagreement between the two mechanisms.

The threshold mechanism served as an independent consistency check rather than another trained classifier. The recurrent model evaluated multidimensional relationships across consecutive observations, whereas the threshold component examined whether individual parameters exceeded configured operating boundaries. Their combination provided both pattern-based classification and an interpretable check against predefined operating limits.

The failsafe override affected only the condition reported through the software interface. It did not physically disconnect, stop, or restart the motor. Therefore, the term “override” refers to the replacement of the displayed classification and the generation of an alert rather than direct operation of an emergency shutdown or motor-protection circuit.

Testing confirmed the functional operation of threshold comparison, prediction verification, failsafe reporting, storage, dashboard display, and email notification. However, the number of model–threshold disagreements, override events, false-positive corrections, and false-negative corrections was not recorded as part of the quantitative evaluation. The results consequently demonstrate the functional implementation of an additional verification layer but do not establish a numerical improvement in classification accuracy or motor reliability.

DISCUSSION

The results demonstrated that electrical, thermal, vibration, and rotational-speed measurements could be integrated to provide a multidimensional representation of the motor’s operating condition. Voltage variability provided the strongest electrical-fault indicator, elevated surface temperature characterized the Thermal Fault class, and increased three-axis acceleration distinguished the Mechanical Fault class. Other measurements, including current, frequency, power factor, ambient temperature, and rotational speed, provided contextual information that allowed the models to evaluate relationships among different aspects of motor operation. This supports previous research indicating that multisensor information can provide broader fault representation than reliance on a single measurement [35], [36].

The field implementation also extended the monitoring process beyond standalone data acquisition. Sensor measurements were acquired from a motor that remained connected to its driven pump and were incorporated into an end-to-end pipeline involving ESP32-based acquisition, authenticated MQTT communication, Node-RED processing, InfluxDB Cloud storage, Grafana visualization, recurrent classification, and threshold verification. This integrated implementation distinguishes the study from investigations that concentrated primarily on either remote monitoring or offline fault classification.

All four recurrent architectures classified the prepared sequences with high accuracy. The results are consistent with earlier studies demonstrating the suitability of recurrent and attention-based models for motor fault diagnosis [39], [40]. However, increasing model complexity did not improve the test result. The GRU, Bi-GRU, and GRU-Attention models produced the same confusion matrix, while the LSTM recorded only one additional error. The selection of a model for this application should therefore consider computational complexity alongside classification accuracy.

GRU-Attention presented the most favourable performance-to-complexity relationship because it achieved the joint-highest accuracy with the lowest parameter count. Nevertheless, model size alone does not establish suitability for edge deployment. Measurements of inference time, runtime memory consumption, energy use,

and response time on the intended hardware would be required before concluding that the architecture is operationally more efficient.

The hybrid verification mechanism added interpretability by indicating when a model prediction conflicted with an established operating limit. This is relevant to industrial condition monitoring because maintenance personnel may require an identifiable measurement and threshold before acting on an automated classification. The designated test sequences were not used as labelled training instances. Nevertheless, because the sequences were generated using overlapping windows, neighbouring sequences in different data subsets may have shared some underlying observations.

The high model accuracies must be interpreted in relation to the dataset-development procedure. The model-development dataset included analytically labelled and synthetic fault-condition records. As a result, some classes may have contained strongly distinguishable parameter relationships. The reported performance therefore demonstrates the ability of the models to classify the prepared operating conditions but should not be interpreted as evidence that they will achieve the same accuracy for every naturally developing motor fault; hence the need for a hybrid verification mechanism.

A further limitation concerns the use of overlapping sequences. Consecutive ten-observation windows shared nine observations, and the sequences were randomly divided after generation. Neighbouring windows may consequently have appeared in different training, validation, and test subsets, introducing similarity between the data partitions and contributing to optimistic performance estimates. A stronger evaluation would divide the data chronologically or by independent operating sessions before generating the sequences.

Within these limitations, the findings establish the feasibility of integrating field-based multisensor acquisition, IoT-enabled data management, recurrent fault classification, and deterministic threshold verification within one motor-monitoring system. Validation using naturally occurring fault records, independent motor installations, and leakage-resistant data partitioning would be required to determine the generalizability of the reported classification performance.

CONCLUSION

This study established that multimodal field data can support reliable real-time condition monitoring and accurate fault classification of an industrial electric motor operating under its normal mechanical load. From the data collected over the 12-month monitoring period, 200,000 valid timestamped records were retained following data cleaning. These records captured the electrical, thermal, mechanical, and operational behaviour of the motor and provided the basis for distinguishing Normal, Electrical Fault, Thermal Fault, and Mechanical Fault conditions.

All four recurrent neural-network models demonstrated very high classification performance. The LSTM achieved an accuracy of 99.95%, while the GRU, Bi-GRU, and GRU-Attention models each achieved 99.97%. Although the attention mechanism did not increase classification accuracy beyond that of the GRU and Bi-GRU models, the GRU-Attention model achieved the joint-highest accuracy with substantially fewer trainable parameters than the other high-performing architectures. It therefore provided the most favourable balance between classification performance and model complexity among the evaluated models. These results also show that increasing architectural complexity does not necessarily produce a corresponding improvement in classification accuracy.

The hybrid verification mechanism strengthened the practical application of the classification system by combining data-driven predictions with transparent operational limits. The recurrent models assessed temporal relationships across multiple sensor measurements, while the threshold layer identified critical parameter excursions, applied a rule-based correction to an inconsistent displayed condition, and generated an alert for operator attention. This combination provided both intelligent condition classification and an interpretable operational check without requiring the mechanism to assume direct control of the physical motor.

The principal contribution of the study lies in demonstrating the integration of field-derived multimodal motor data, recurrent neural-network classification, and threshold-based decision support within a unified condition-monitoring system. The findings provide strong evidence of the system's capability to classify the operating conditions represented in the developed dataset and demonstrate its potential to support earlier fault identification and informed maintenance decisions. Further studies should extend the evaluation to additional motors, operating environments, load conditions, and independently collected fault events to determine the wider generalizability of the models. Such evaluations would complement the strong within-system performance established in this study and support broader industrial deployment.

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