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A hybrid framework of IoT and machine learning for predictive analytics of a DC motor

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ABSTRACT

Many industrial applications utilize direct current (DC) motor as an essential element. It functions as the backbone of several industries and global pillar of manufacturing applications. The predictive analytics of motor is primary for preventing unpredicted downtime, reducing protection costs, and improving system effectiveness. This paper presents a hybrid framework integrating the internet of things (IoT) and machine learning (ML) for real-time predictive analytics of DC motors. The leveraging of machine learning algorithms in predictive maintenance of DC motors has shown significant potential in reducing downtime and increasing the lifespan of the motor. Therefore, a system for predictive analytics with machine learning strategy is proposed and message queuing telemetry transport (MQTT messaging) is included for effective information transmission between sensors and gateways. The data received from the sensors is utilized to make prediction about the remaining useful life of the motor and generate alerts for maintenance before failures occur. So, the integration of machine learning algorithms in predictive maintenance of DC motors is a promising approach to increase the reliability and efficiency of DC motors. The highest performance is achieved in random forest with accuracy of 93.4%.

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1. INTRODUCTION

Direct current (DC) motors are multifarious electro-mechanical devices which transform electrical energy into mechanical energy. Common DC motor applications include pumps, machineries in automobile industries, centrifugal machines, machine tools, conveyors, and elevators [1]. On the other hand, machinery in coal plants, grain elevators, and shredders use DC motors in dangerous settings, as do petrochemical and natural gas plants [2]. Normally, electrical and mechanical troubles can cause a motor to fail [3]. Mechanical loads caused by overloads and abrupt load shifts can result in bearing failure and rotor bar rupture. On the other hand, electrical strains are typically connected to the power source. When powered by alternating current (AC) drives, DC motors are more prone to failure.

DC motors are incredibly trustworthy devices, especially squirrel cage DC motors. Due to its nature, this motor may function in a range of challenging circumstances. It may have a number of defects or anomalies [4]. The most common defects are faults in the bearing, stator, and rotor. Many of these defects have negative effects of their own. These side effects turn dangerous for the engine if the fault is not fixed. Therefore, it's crucial to address a problem as quickly as possible. The greater voltage tension on the stator's windings, the higher frequency of the stator current elements, and the stimulated bearing currents caused by AC drives are the causes of this. Additionally, motor over voltages can happen because of the length of the cable connecting the motor to the alternating current (AC) drive. Temperature, current, and vibration sensors are used by electrical motors to collect data in real time. The data is then evaluated and failures are predicted using machine learning models [5], [6].

Industry 4.0 technology has the potential to create systems for condition-based monitoring and predictive maintenance by integrating artificial intelligence (AI), internet of things (IoT), big data analytics, and cyber physical systems [7], [8]. Predictive analytics is an efficient tool for condition monitoring [9]. To find flaws, the DC motor's current and vibration were monitored. Vibration spectrum analysis is used to identify mechanical problems like bearing damage, whereas the current analysis is used to identify electrical faults like single phase with unbalanced supply. The relation between electrical parameters (voltage, current, and temperature) and mechanical properties such as an air flow from the blower, and brush length exactly reveals about the operating conditions of DC motor [9]. Most of the manufacturing industries use predictive maintenance to improve their capacity and quality. Machines produce huge amount of data and all these data to be converted to valuable and actionable information. The challenge lies in interpreting the data for creating useful insight [10].

Data analysis and ML algorithms are used in predictive maintenance, a proactive maintenance strategy, to forecast and stop equipment faults before they happen. This approach records data on each component functioning and circumstances, allowing for a trend analysis of overall behaviour. The stored information and current data are used to make intelligent decision on maintenance activities. To find trends and anomalies that can point to a future failure, these algorithms can examine data from a variety of sources, including historical data, sensor data, and environmental data. For motor predictive maintenance, combining an embedded system with machine learning algorithms has a number of benefits. It first provides early failure detection, which can cut downtime and maintenance costs. Second, by identifying and fixing problems before they worsen, it can increase the motor's overall effectiveness and performance. This may lead to energy savings and less damage to the engine. Finally, by minimizing wear and tear brought on by unexpected failures, it can aid in extending the motor's lifespan. The objective is to design a model that predicts potential fault present in the DC motor.

Hashemian and Bean [10] described about the role of online maintenance and calibration techniques employed to determine the lifespan of industrial machines. Wu *et al.* [11] proposed a method to minimize cost involved in predictive maintenance by employing neural network-based prediction model. Lu *et al.* [12] developed a preventive maintenance technique based on continuous monitoring for induction motors. This approach fails in real time monitoring since it does consider past history of data [13]. Lu *et al.* [12] designed a condition-based monitoring to minimize economic losses. This method suggests a suitable technique called nonintrusive motor-efficiency estimation [14].

Industrial application of motor current signature analysis for fault estimation is done. The vibration sensor data obtained from sensors put on machines to monitor crucial components. The pre-processed signals were decomposed into many signals comprising one approximation and some details using wavelet packet decomposition, which were then transferred to the frequency domain using the fast Fourier transform [15]. The features retrieved from the frequency domain could be utilized to train an artificial neural network (ANN). Trained artificial neural networks can anticipate degradation (remaining useful life) and discover faults in components and equipment [16]. A non-invasive method measuring vibration data for prediction and diagnosis of fault in industrial machines is done [17].

Unal *et al.* [18] modelled a neural network that has been trained to predict preventive maintenance using sensor data. The variations in temperature, battery voltage, and brake wear are monitored by a group of IoT sensors to improve the efficiency of predictive maintenance [19]. Predictive maintenance of machine tool systems is done using artificial intelligence [20]. Edge computing and cybersecurity techniques are utilized in smart manufacturing for Industry 4.0 [21]-[23]. The efficiency and dependability of the motor can be increased by gathering sensor data, utilizing machine learning models to interpret the data, and predicting when maintenance is necessary. Monitoring a motor’s working condition and possible anomaly identification are required before they become serious with the help of predictive maintenance [24], [25]. This paper analyses some characteristics DC motor such as current, voltage, temperature, speed, and vibration in order to predict the working condition of DC motor. The DC motor offers some flexibility in measuring external blower current, speed measurement, and temperature measurement (control panel and ambient temperature). Errors indicated in above mentioned parameters indicate the presence of potential issues which have to be addressed immediately to continue the normal working condition. The main theme of the work with the specific goals of the design are given below: i) real-time acquisition of motor parameters (e.g., speed, voltage, current, temperature) through IoT-enabled sensors; ii) pre-processing and transmission of this data to a central or edge computing node; and iii) Application of supervised ML algorithms (such as decision trees, random forest, or ANN) to predict motor health, classify operational states, and forecast anomalies.

2. METHOD

This model employs both hardware unit and software algorithms to predict the condition of motor. The hardware arrangement necessary for the collection of the sensor data is shown in Figure 1. The motor's behaviour and data collection are implemented using a variety of sensors such as temperature sensor, vibration sensor, voltage sensor, and current sensor.

The mechanical and electrical parameters associated with the operation of the motor and overall condition of the motor was thoroughly analyzed using this multi-sensor approach. This proposed approach collects the data automatically from a variety of sensors and pre-processing them. Subsequently, it performs feature extraction, model building, training, validation, and deployment to create a predictive maintenance model. Data collection is the primary part of an automatic monitoring system that allows data collection from different sensors, such as vibration, temperature, current, and voltage.

The DS18B20 temperature sensor was employed to acquire temperature data. It simplifies the wiring complexity by enabling the connection of multiple sensors on a single data line through the one-wire interface. It is capable of measuring temperatures within the range of -55 °C to +125 °C with a resolution of up to 12 digits. The ACS712 current sensor is a sensor that operates on the Hall effect principle. It is equipped with a low-resistance current conductor and a 2.1 kV RMS voltage isolation capability. Using a microcontroller-based data collection system and a combination of sensors, this methodology facilitated an exhaustive and detailed analysis of the motor's performance and health. Various other types of sensors have been employed to gather vibration data from the system. These sensors include accelerometer sensor (X-NUCLEO-IKS02A1), microphone, and industrial motion MEMS sensor. It contains the IIS2MDC 3-axis magnetometer, the IIS2DLPC 3-axis accelerometer, and the ISM330DHCX 3-axis accelerometer and gyroscope motor for position and vibration measurement. The default I²C port of the X-NUCLEO-IKS02A1 can be modified, and it provides an interface with the Arduino microcontroller via I²C pin.

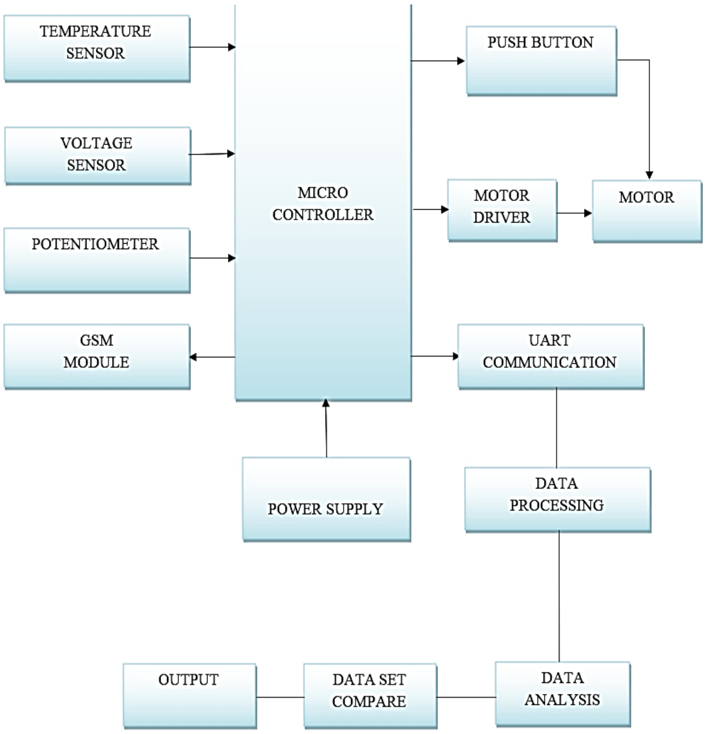

Figure 1. Hardware diagram of predictive analytics model

2.1. Development of a predictive analytics using machine learning model

AI systems transforms unprocessed input into useful knowledge. Electrical motors use vibration, current, and temperature sensors to collect data in real time. The data is then evaluated and failures are predicted using four machine learning models: k-nearest neighbour (KNN), support vector machines (SVM), random forest (RF), and linear regression (LR). Message queuing telemetry transport (MQTT) protocol enables effective communication between sensors, gateways, and cloud servers. When it comes to working motors, RF displays the highest precision and optimises maintenance schedules to reduce expenses and downtime.

The prediction process is done by AI algorithms that entails the learning of patterns from data, and the making of decisions with minimal oversight as represented in Figure 2. Conclusions are subsequently made based on the new data and past history using these models. Data collection is done during normal and fault conditions. The dataset is divided to three parts (70% for training, 15% for testing, and remaining 15% for validation) machine learning based predictive maintenance attempts to learn from collected data (both present and past experiences) to discover system failure possibilities.

The data is cleaned by pre-processing, which may include filtering, smoothing, or normalization, to get rid of any noise or undesired signals. The next stage is feature extraction, which extract essential features from the collected data. Frequency domain statistical metrics like mean, standard deviation, and kurtosis are extracted. The feature extraction enables the machine learning model to recognize data patterns that are an indicative of disorders of motor health. This can be accomplished using a variety of machine learning techniques, such as KNN, SVM, RF, and LR. The pre-processed data and the extracted features are used to train the constructed model. The training data has to have illustrations of both healthy and faulty motor conditions.

A different set of data that wasn't utilized for training is used to validate the model after it has been trained. This makes it more likely that the model will correctly categories brand-new data that it has never seen before. The validation of the model is a crucial stage since it guarantees its accuracy, dependability, and ability to accurately identify motor defects. The trained and verified model is then embedded into the microcontroller for real-time motor health monitoring.

Python and the pySerial library are utilized to establish a connection with the serial device and retrieve the data transmitted through the serial port interface. The pySerial library provides user-friendly function for the management of serial communication protocols. A Python script establishes a serial connection with the target device, specifying the necessary parameters, including the port and baud rate, in order to collect data. Upon establishing the connection, the script executes a loop that continuously retrieves data from the serial port. The data that is extracted from the serial interface is typically in binary or string format and is consistent with the device's protocol. Each data point, which denotes a measurement from the serial device, is recorded as a row in a CSV file, with each parameter designated to its corresponding column. The model continuously examines the motor data and notifies the operator of any anomalies or approaching failures by sending an alarm. The objective is to create a precise and trustworthy model that can identify motor flaws before they result in expensive downtime or repairs.

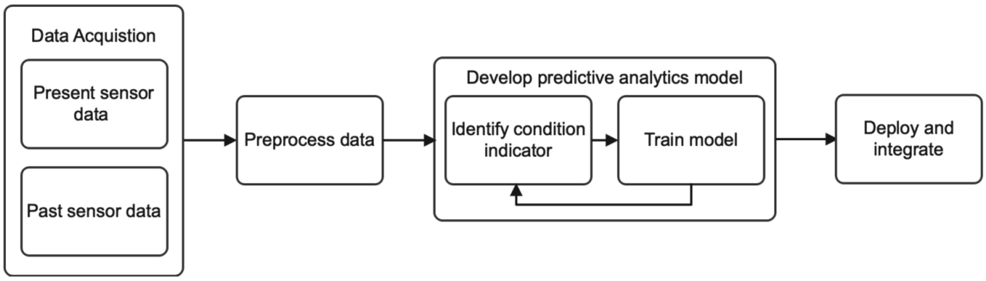

Figure 2. Block diagram of machine learning assisted predictive analytics model

3. RESULTS AND DISCUSSION

3.1. Analysis of vibration signal

The vibration of the motor is modest in amplitude, with a rhythmic increase in amplitude occurring once per cycle. On the other hand, the signal exhibits numerous rhythmic surges during the bubbling process. The accelerometer is fixed on the bearing in order to observe oscillation for every 10 seconds. Fast Fourier transform is used to calculate power spectral density from raw data samples. The sequence of raw data samples taken from DC motor in the form of fourier series, it could be break down into sine wave component using fourier analysis. In order to do fourier analysis, each frequency component is "tested" for presence.

The raw waveform is multiplied by sine waves of discrete frequencies using a discrete Fourier transform (DFT) to see if they match and to find the amplitude that correspond to each waveform. The FFT divides the process into cascading groups of two in order to take advantage of these symmetries, and therefore requires a signal length of some power of two for the transform. A DFT requires N2 operations if N is the signal length, whereas an FFT requires N*log2(N), which significantly increases processing speed. The number of samples in the original waveform directly correlates with the number of discrete frequencies that are evaluated as part of a Fourier transform. The number of frequency lines or bins is equal to N/2, where N is the signal length.

In this predictive analysis of DC motor, a vibration profile will usually have a variety of frequency components in addition to electrical and mechanical noise. This data was created using X-NUCLEO-IKS02A1 sensor module. Vibration analysis from Figure 3 provides complete vibration magnitudes at different instant of time.

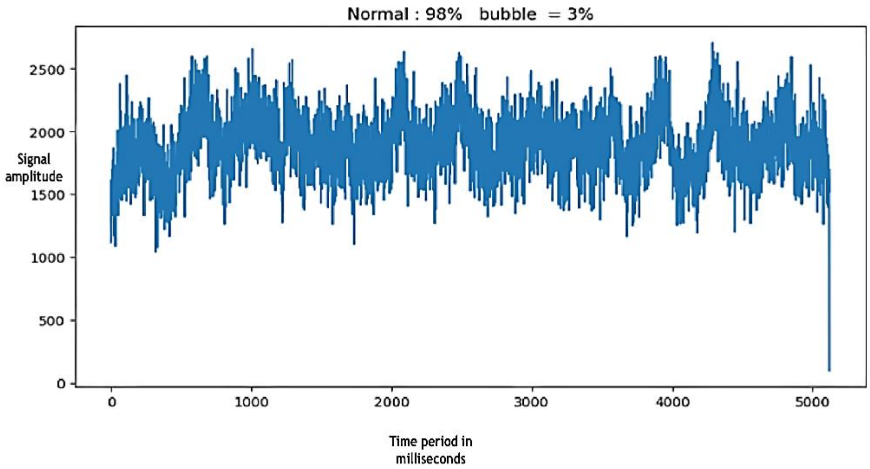

Figure 3. Vibration analysis for motor fault detection

3.2. Proposed machine learning approach for predictive analytics

Neural networks have a slow learning rate, though, and simple tasks require hundreds of thousands of training cycles, which can quickly lead to local minimums. In order to overcome this, the proposed approach uses machine learning model. When there is imbalance in linear regression with high-speed network training, random forests can more effectively balance the mistake than neural networks. Figure 4 illustrates a graph between actual and predicted current sample values using machine learning model.

Table 1 compares different machine learning algorithm performance in predictive analytics. The highest performance is achieved in random forest with accuracy of 93.4%. The runtime environment in Python environment is illustrated in Figure 5. This indicates the performance parameters measured during real time.

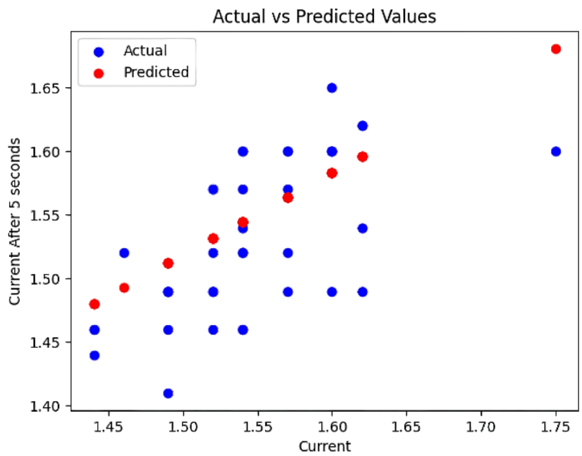

Figure 4. Actual and predicted current sample values

Table 1. Performance of different ML algorithms

Name of the regression algorithm	RF mean squared error	RF mean absolute error	Accuracy
k-nearest neighbour	17772.26	29.89	62%
Support vector machine	3774.31	48.79	89.4%
Decision tree	3460.48	44.28	91%
Random forest	3214.30	41.08	93.4%

Figure 6 describes MQTT protocol message output at receiver node. This provides a continual message to the user about whether or not the system was operating. The notice in the app is either "system works" or "system fails" and includes a time stamp. Using this app, users may remotely monitor the status of the system. The experimental verification is done by the circuit arrangement as illustrated in Figure 7. It gives the real time overview of present conditions of asset and improves reliability of asset. The confusion matrix is represented in Figure 8.

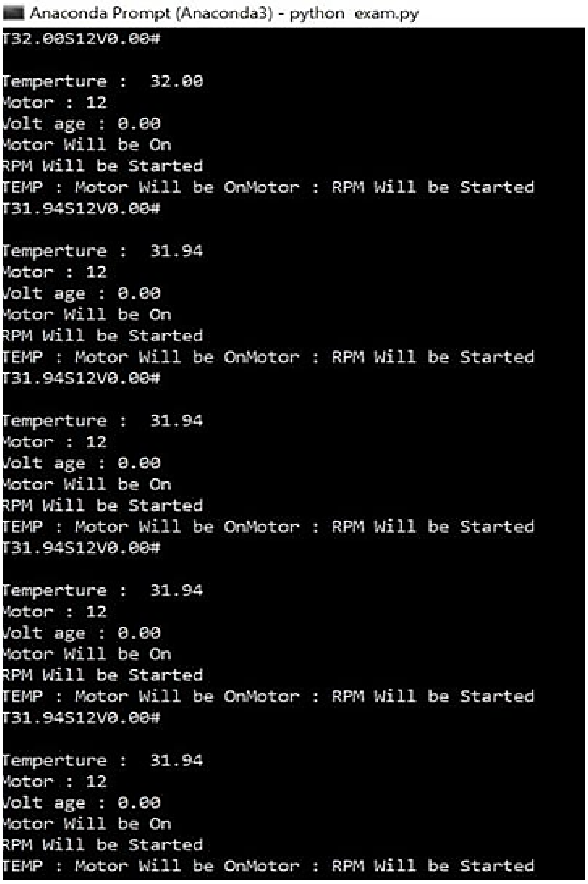

Figure 5. Runtime deloyment screen

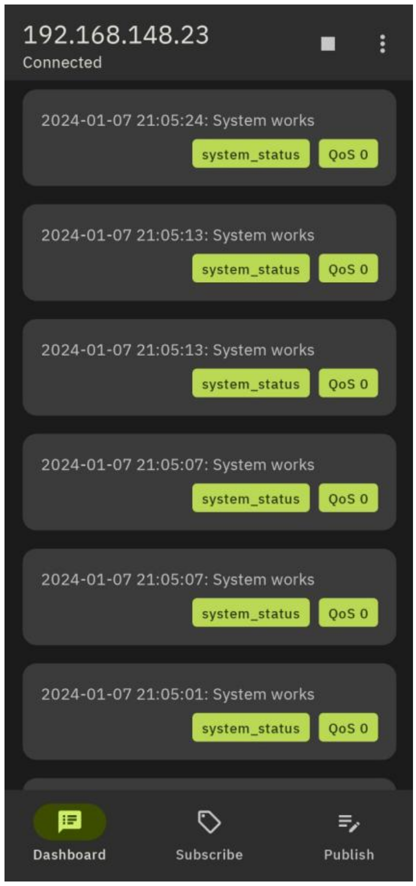

Figure 6. Message output from receiver node

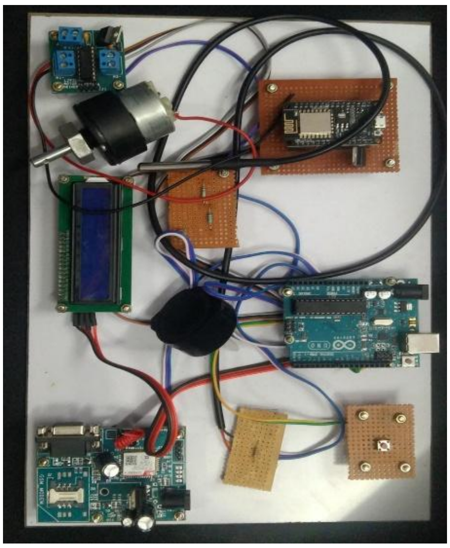

Figure 7. Experimental set up for predictive analytics

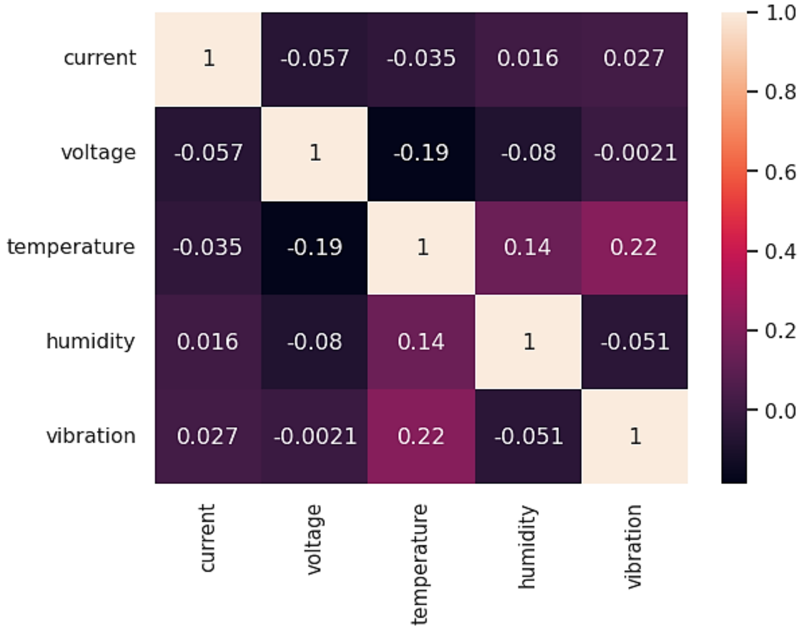

Figure 8. Confusion matrix

4. CONCLUSION

The reliability and effectiveness of DC motor is raised by doing predictive maintenance using machine learning. The technology can forecast when maintenance is necessary before a malfunction occurs by gathering real-time data from sensors put on the motor and using machine learning algorithms to analyse the data. This preventative maintenance strategy can reduce downtime, lower maintenance expenses, and increase the motor's lifespan. Also, by integrating microcontroller and a machine learning model, maintenance duties can be automated. in general, predictive maintenance of a DC motor employing an MCU with machine learning integration has the potential to dramatically increase the reliability and efficiency of motor systems, making it an appealing alternative for a variety of sectors. IoT sensors can also make it possible to remotely monitor and control the motor system, which offers more ease and flexibility. In future edge computing can be used to make the prediction model as a portable one.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Annapoorani Ganesan		✓				✓		✓	✓	✓	✓	✓		
M. Shunmugathammal	✓		✓	✓			✓			✓	✓		✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [MS], upon reasonable request.

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