



AI-Based Fault Detection in Electric Vehicle Motors Using FFT-Based Vibration Analysis and Edge AI

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Abstract. In order to ensure the safe and efficient working of electric vehicle motors, it is imperative to ensure the reliable and timely identification of defects. For this purpose, the Internet of Things, Fast Fourier Transform, and Edge Artificial Intelligence have been employed in the defect identification system proposed in this paper. A variety of sensors have been employed in the defect identification system, including an infrared sensor for speed measurement, DS18B20 for temperature measurement, INA219 for current measurement, and MPU6050 for vibration measurement. In order to detect mechanical defects like shaft misalignment, vibration is measured, and Fast Fourier transform (FFT) is applied for obtaining frequency domain values. A lightweight machine learning model is applied for defect classification using ESP32-S3. The proposed technique is applicable for electric vehicles as experimental results show that defects such as misalignment, overcurrent, and overheating can be identified.

Keywords: Electric vehicle motors, vibration analysis, Fast Fourier Transform (FFT), Edge AI, Internet of Things (IoT), machine learning.

1 Introduction

The electric motor is a critical component of both industrial and electric vehicles, which requires efficient and reliable operation. The electric motor performs well under regular conditions, but often, electric motors operate under harsh conditions, which can cause unexpected breakdowns. Winding problems, rotor and stator imbalances, broken rotors, air gap eccentricity, and bearings [1-4] are some common problems associated with electric motors. These problems can deteriorate motor performance, energy consumption, and can cause major system breakdowns. To avoid operational losses, it is important to diagnose the problems.

However, regular motor condition monitoring is crucial to ensure the continued and safe running of the motor. In the diagnosis of faults, different parameters, such as the stator's current [5-6], voltage, temperature [9], sound [10], and vibration [11], are often employed [5-11]. Vibration monitoring is regarded as the most successful method, given its ability to measure the mechanical, magnetic, and aerodynamic impacts within the motor. In fact, all abnormal situations have their 'own vibration signature, and thus, the precise identification of the situation is achieved. In fact, up to 90% of machine faults can be identified by vibration monitoring [12].

It is currently feasible to accumulate significant amounts of sensor data and transmit it in real time with the help of the rapid advancement of the Internet of Things (IoT). At the same time, data-driven techniques for detecting motor faults have been made feasible with the help of recent advancements in the field of artificial intelligence (AI). Data-driven techniques differ from traditional techniques in the sense that there is no need to understand the parameters of the system while using them for fault classification, and these techniques can detect patterns immediately from the data using deep learning and machine learning techniques [13].

Under this paradigm, the current research focuses on the detection and classification of conditions of motor malfunction through vibration analysis and edge AI [14-15]. Motor shaft misalignment is a common condition of motor malfunction caused by inappropriate installation, wear, or damage to some parts of the motor. This condition may result in problems with bearings, structures, and lifespan. To address this motor fault condition, a motor monitoring system was developed through experimentation, which includes multi-sensor data acquisition, signal analysis using a fast Fourier transform, and machine learning capabilities integrated into the ESP32-S3.

The proposed motor monitoring system can identify and classify motor fault conditions instantaneously, eliminating the delay associated with cloud computing. The experimental results proved the ability to differentiate between motor fault conditions and normal motor conditions through changes in vibration signal conditions, thereby confirming the validity of the proposed motor monitoring system.

The uniqueness of the proposed study is in combining real-time vibration-based fault detection with edge computing on the ESP32-S3 platform. In contrast to traditional methods that depend on cloud processing or high-computation models, the suggested system carries out Fast Fourier Transform (FFT)-based feature extraction and machine learning classification directly on an embedded device. Moreover, the integration of closed-loop pulse width modulation (PWM) regulation and IoT-enabled monitoring through Blynk offers a comprehensive real-time system for motor management, observation, and fault identification.

2 Development Of The Motor Failure Detection Model

2.1 Motor Model For Experimentation

Fig.1 depicts the experimental motor model designed in this research work for the real-time fault detection of electric vehicle motors. The proposed model for the electric vehicle motor fault detection includes the following components: DC Motor, Rotating Shaft, Supporting Bearings, Motor Driver Module BTS7960, Vibration Sensing Unit MPU6050 Sensor, Current Sensing Unit INA219 Sensor, Temperature Sensing Unit DS18B20 Sensor, Speed Sensing Unit Infrared Sensor, and Control and Processing Unit ESP32 and ESP32-S3.

The MPU6050 sensor is placed close to the body of the motor to detect vibration signals along three axes: X, Y, and Z. This shows the dynamic behaviour of the motor. The INA219 sensor is used to monitor the current consumption, and the DS18B20 is used to monitor the temperature changes. The IR sensor is used to measure the speed of the motor in terms of RPMs. All the data is collected using the ESP32 and processed locally.



Fig. 1. Experimental model

This information is sent using the Wi-Fi protocol via the TCP/IP protocol and is displayed using the Blynk platform. The ESP32-S3 microcontroller is used to execute the Edge AI-based fault classification using the extracted features.

2.2 Approaches And Procedures For Executing The Motor Fault Diagnosis Model

To simulate the issue of misaligned shafts with different speeds and the state of operation, the system configuration for the problem is depicted in the diagram as shown in Fig. 2. The system configuration comprises four components, namely: (i) a control unit that controls the motor's speed; (ii) a motor monitoring system using the Blynk system; (iii) a signal acquisition system for the vibration sensor, which includes

the processing of fault signals from the DC motor; and (iv) a system for monitoring electrical and thermal parameters.

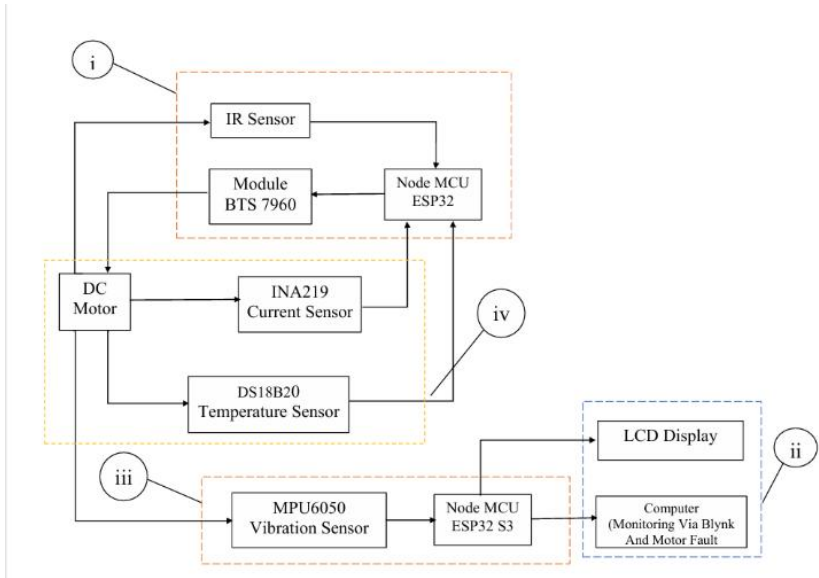


Fig. 2. Block diagram of the fault diagnosis system

Controller For Motor Speed Control

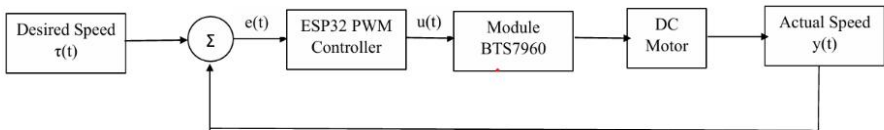


Fig. 3. Schematic representation of motor speed regulation system

This model for regulating the speed of the DC motor, which was employed in this research, is illustrated in Fig.3. As indicated, $\tau(t)$ represents the target motor speed, $u(t)$ represents the control signal applied to the motor driver, $y(t)$ represents the actual motor speed as detected by the IR sensor, and $e(t)$ represents the error signal, which is defined as the difference between the target and actual speeds. The error signal can be explained as:

$$e(t) = \tau(t) - y(t) \quad (1)$$

This error helps to control the speed of the motor and ensures its consistent performance.

This study uses a control system based on pulse width modulation (PWM) and the ESP32 microcontroller. The control system is based on a feedback-oriented control method, and the value of the pulse width modulation is variably changed depending on the difference between the desired and actual speeds. Rather than using the PID controller, the control system increases the value of the pulse width modulation depending on the value of the error, thus ensuring the efficiency of the control. In a generalized control system, the PID controller is defined by:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} \quad (2)$$

The constants K_p , K_i , and K_d stand for proportional, integral, and derivative constants, respectively. The transfer function of the PID controller is represented as:

$$G(s) = \frac{u(s)}{e(s)} = K_p + \frac{K_i}{s} + K_d s \quad (3)$$

In the proposed system, the ESP32 microcontroller sends a PWM signal for controlling the speed of the motor using the BTS7960 driver. This IR sensor measures the motor speed and transmits this information to the controller to make further modifications. The motor speed in revolutions per minute (RPM) can be calculated as:

$$RPM = \frac{N \times 60}{T} \quad (4)$$

where N is the number of pulses detected by the IR sensor, and T is the time interval. The control system utilizes feedback to ensure consistency in motor performance under varying load conditions, including situations where faults are simulated by introducing bent shafts. The control unit maintains a constant speed, facilitating vibration analysis and fault detection. The circuit for motor control is shown in Fig. 4.

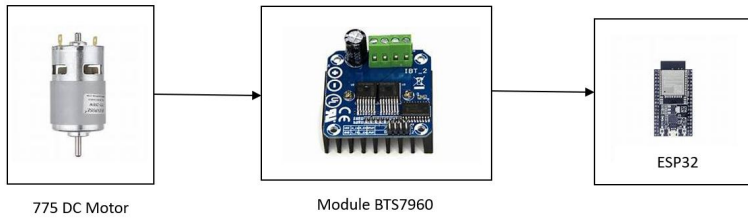


Fig. 4. Circuit for motor control

Vibration Signal Acquisition Unit

The unit for acquiring vibration signals is responsible for the acquisition of the vibration signals generated by the DC motor during its operation. This module comprises a vibration sensor, MPU6050, connected to the ESP32-S3 microcontroller unit, thereby allowing real-time acquisition of the signals.

The MPU6050 vibration sensor is an accelerometer-type sensor having three axes, which can measure acceleration along the X, Y, and Z axes. The signals of immediate acceleration are represented as:

$$a_x(t), a_y(t), a_z(t) \quad (5)$$

These signals are indicative of the motor's dynamic performance and vary according to the working conditions. The sensor is securely fixed on the casing of the motor for precise measurement of the generated vibration signals.

The obtained vibration signals are in the time domain, as the sampling of the sensor signals is performed at a fixed sampling frequency using the ESP32-S3 microcontroller's I2C communication protocol. The sampled values are stored for further analysis, as each value represents the motor's acceleration at a specific time instance.

In order to obtain a single value as a representation of the vibration signals, the obtained acceleration value is calculated as:

$$a(t) = \sqrt{a_x^2(t) + a_y^2(t) + a_z^2(t)} \quad (6)$$

The gathered vibration data includes information regarding the motor's mechanical state. Under typical operational situations, the gathered vibration signals are seen to have consistent patterns of low amplitude. However, during situations of problems such as shaft misalignment caused by bent shafts, significant changes are seen in the signals, as indicated by high amplitude irregular changes.

The data gathered from the vibration signals provides information about the mechanical condition of the motor. In normal conditions, the signals from the vibration exhibit patterns with low amplitude. However, when problems like the misalignment of the motor shaft occur due to a bent shaft, considerable changes in the signals from the vibration occur. The unit for collecting the vibration signals is shown in Fig. 5.

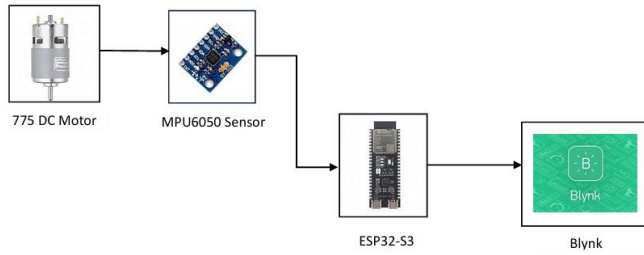


Fig. 5. Vibration signal collecting circuit

Electrical And Thermal Monitoring Unit

The unit for electrical and thermal monitoring monitors important motor parameters regarding the electric load and temperature changes. The INA219 current sensor and the DS18B20 temperature sensor, which connect to the ESP32 microcontroller, are included in this module.

The INA219 sensor measures the motor's consumed current. The operation of the INA219 is based on the principle that the voltage drop across a resistor measures the value of the current. The current is supplied by:

$$I = \frac{V_{shunt}}{R_{shunt}} \quad (7)$$

where V_{shunt} stands for voltage over the shunt resistor and R_{shunt} stands for the value of the resistor. Current observation is a fundamental aspect to identify electrical problems like overload conditions caused by an increase in mechanical resistance or motor failure.

The DS18B20 sensor monitors the motor temperature in real-time. This sensor offers precise digital temperature readings and uses a one-wire protocol to communicate with the ESP32 microcontroller. Current and temperature observation are essential to identify motor-related problems like overheating, which may impact motor reliability due to overheating of motor parts.

The ESP32 microcontroller processes current and temperature data in real-time while the motor is running. In a normal state, the current and temperature are within a specified range. However, in case of problems like motor shaft misalignment caused

by a bent motor shaft, the motor will be under more stress. This causes an increase in current consumption and temperature. The electrical and thermal collection circuit is shown in Fig. 6

The collected electrical and thermal values provide more information regarding motor condition, which can be used along with vibration analysis. These values can be employed to identify abnormal conditions and pinpoint exact fault causes.

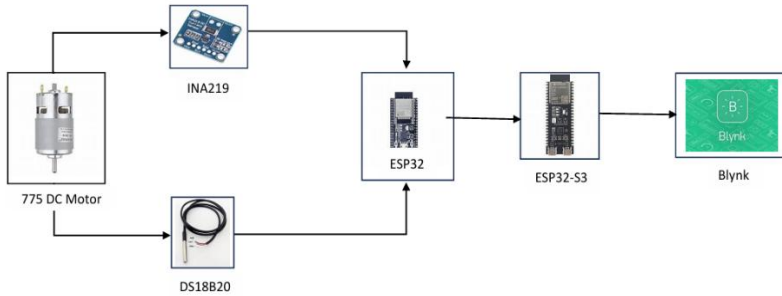


Fig. 6. Electrical and thermal collection circuit

Blynk-Based Motor Monitoring And Suggested Signal Processing Technique For Fault Detection In DC Motors

The motor monitoring and signal processing unit monitors the parameters of the motor and analyses the collected data to ensure effective fault detection. The proposed system uses a distributed approach for the acquisition and communication of the data by the ESP32 microcontroller and the signal processing and classification by the ESP32-S3 using edge AI.

The ESP32 microcontroller is responsible for collecting real-time data from different sensors integrated within the system. The INA219 sensor measures the current consumption of the motor by the INA219 sensor, providing an idea about the electrical load on the motor. The DS18B20 sensor detects the temperature changes and hence can be used to identify temperature-related faults such as increased temperature levels. The IR sensor detects the speed of the motor by generating pulses according to the rotation of the motor and hence can be used to find the speed of the motor in RPM. These parameters provide an extensive idea about the electrical, thermal, and mechanical condition of the motor.

The collected data is transmitted wirelessly to the Blynk IoT system via Wi-Fi using the TCP/IP protocol. Blynk provides a dynamic interface to monitor the motor parameters in real time, enabling users to monitor system performance from a distance. This monitoring ensures that any unusual system operation and potential failures are recognized in a timely manner.

The ESP32-S3 chip processes the collected vibration data from the MPU6050 sensor. To begin with, the vibration data is recorded in the time domain, showing

variations in acceleration from the motor. To obtain meaningful information from the data, the signal is converted from the time domain to the frequency domain by performing a Fast Fourier Transform (FFT), given by:

$$X(k) = \sum_{n=0}^{N-1} x(n)e^{-j2\pi kn/N} \quad (8)$$

Where $x(n)$ represents the sampled vibration signal, N represents the total number of samples, and $X(k)$ represents the signal in the frequency domain. The rate at which the signal components occur is given by:

$$f = \frac{k.F_s}{N} \quad (9)$$

where F_s represents the rate of sampling. The frequency spectrum provides a better understanding of the distribution of energy in the vibrations. The primary frequency element, which relates to the maximum amplitude in the frequency spectrum, acts as an important parameter in monitoring the condition of the motor. To accurately identify the characteristics of the vibration signal, the RMS value of the signal is calculated as:

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad (10)$$

The RMS value represents the amount of energy present in the vibration signal and assists in the identification of abnormal peaks in the vibration level.

The analysis in the frequency domain provides great insight into faults occurring in motors. When the motor is running normally, there will be a prominent frequency associated with the rotating speed with a relatively lower amplitude. The occurrence of shaft misalignment leads to the introduction of other frequencies in the spectrum due to mechanical imbalance, resulting in increased vibration amplitude. Dominant frequency and RMS changes become an important parameter for identifying the fault condition, thus making it possible to detect shaft misalignment in motors.

The characteristics of the vibration signal, such as dominant frequency, RMS vibration level, current level, temperature level, and speed level, create a multi-dimensional space that characterizes the state of the motor's operation and are fed into a compact machine learning model running on the ESP32-S3 microcontroller.

The characteristics extracted from the vibration signal, such as dominant frequency level, RMS level, current level, temperature level, and speed level, create a multi-dimensional space that illustrates the motor's operation level. The proposed system utilizes a multi-layer feedforward neural network (MLP) for classification. The MLP network has an input layer, two hidden layers formed by the dense layer, and an output layer.

- Input Layer: Receives extracted features (e.g., spectral features, RMS, and sensor data).
- Hidden Layer 1: 20 neurons with ReLU activation function.
- Hidden Layer 2: 10 neurons with ReLU activation function
- Output Layer: 4 neurons corresponding to motor conditions (Normal, Shaft Fault, Bearing Fault, Motor-Off), using SoftMax activation.

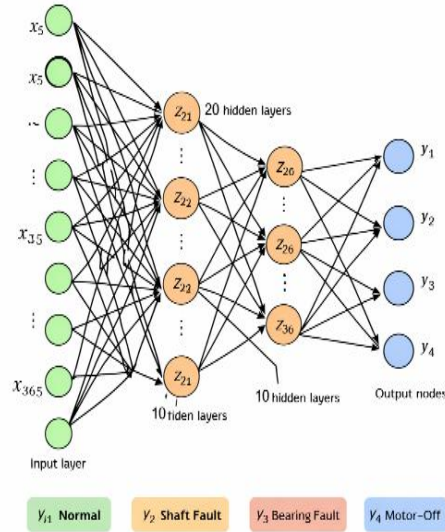


Fig. 7. Multi-layer feedforward neural network

This design is computationally efficient and suitable for immediate implementation on an embedded system such as ESP32-S3. Fault conditions are simulated by shafts having varying degrees of bending, which causes mechanical imbalance and misalignment. This results in distinct patterns of vibrations, which have varying degrees of amplitude and frequency. This model recognizes such patterns to classify normal and faulty conditions appropriately. The multi-layer feedforward neural network is shown in the Fig. 7.

This proposed system utilizes a simplified machine learning approach for real-time classification of motor states. In this case, a multi-layer perceptron (MLP) is used for classification after being trained using data collected under four different motor states: normal, shaft failure, bearing failure, and motor off. The data set comprises a number of instances for each class to ensure that the patterns of motor operation are learned efficiently. The optimized MLP model is then quantized for use in embedded systems with a compact size of approximately 20-30 KB. Moreover, the optimized MLP model operates within an inference time of less than 100ms using the ESP32-S3 microcontroller. The proposed MLP model is particularly useful for edge AI due to its ability to function with a small amount of memory, fast inference speed,

independence from cloud computing, and efficient operation on platforms with limited resources. Moreover, the MLP model operates directly on the ESP32-S3 microcontroller to minimize latency in fault detection.

The use of signal processing along with edge AI enables immediate fault detection without reliance on cloud computing. The classification results, along with sensor data, are sent to the Blynk platform for display. Alerts can be initiated in unusual cases.

The proposed system ensures minimum latency, computational efficiency, and fault detection, making it suitable for predictive maintenance in electric vehicle motor systems.

3 Outcomes And Assessment

3.1 Outcomes Of Speed Regulation

The motor speed control system using PWM is carried out using the ESP32 microcontroller and the BTS7960 motor driver. Unlike the traditional method of setting the duty cycle manually, the proposed method adjusts the duty cycle automatically. In the proposed method, the duty cycle is automatically adjusted using the feedback from the IR sensor, which measures the actual motor speed. The proposed method compares the actual motor speed with the desired motor speed. The difference between the two is used to increase or decrease the PWM value. This ensures that the motor runs at the desired speed. In addition, a gradual acceleration method is used to ensure smooth motor speed changes without any abrupt changes. From the experimental results, it is evident that the motor speed is stabilized using the proposed method. Even if disturbances like a bent shaft occur, the proposed method adjusts the duty cycle appropriately to ensure motor stability. The result of the motor speed is shown in the Fig. 8.

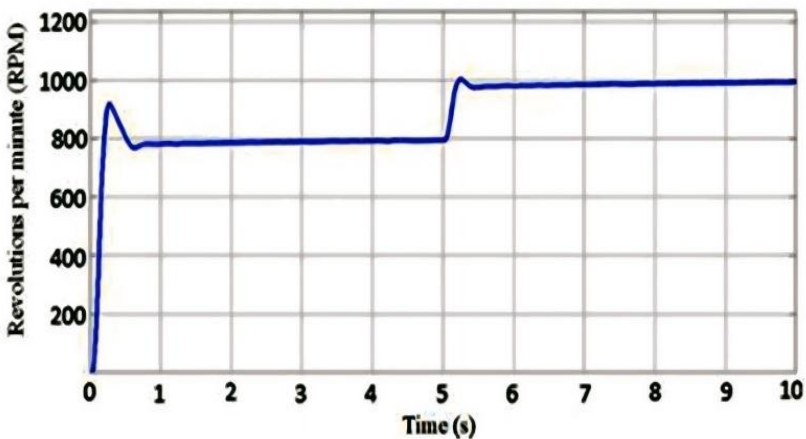


Fig. 8. Experimental results of speed regulations

3.2 Results From Data Collecting Kit

The efficiency of the vibration signal acquisition unit was evaluated using the MPU6050 sensor, which was connected to the motor for acquiring acceleration signals on the X, Y, and Z axes. The sensor was successful in acquiring the signals under different working conditions, providing reliable results. In the usual working conditions, the acquired vibration signals indicated low amplitude with steady and periodic changes, indicating stable motor performance. Additionally, the ESP32-S3 microcontroller was successful in acquiring signals from the sensor, ensuring precise acquisition of time-domain signals from the vibrating motor without loss of information. The acquired signal when the motor is operating at 12000 RPM under normal working conditions is shown in Fig. 9.



Fig. 9. Spectral plot of the normal motor shaft

The vibration signal acquisition unit's efficiency was evaluated with the MPU6050 sensor fixed to the motor to collect real-time acceleration measurements on the X-

axis, Y-axis, and Z-axis. The sensor was able to collect the vibration signals under different conditions, providing steady results. During normal operating conditions, the vibration signals indicated low amplitude with regular changes, indicating normal operation of the motor. The ESP32-S3 microcontroller was able to collect the sensor data at a steady rate, guaranteeing the exact acquisition of the vibration signals in the time domain without any loss of data. The acquired signal when the motor is working at 12000 RPM when at bent shaft is depicted in the Fig. 10.

DSP result

After filter



Fig. 10. Vibration plot of the bent motor shaft

3.3 Monitoring The Motor Through Blynk And Signal Analysis For Fault Detection

Motor Surveillance Through Blynk.

The data obtained from the system is sent to the server in order to facilitate motor control and supervision. All the data obtained is constantly sent via WIFI to the Blynk

app. The app's interface is designed in a manner that makes it easy to facilitate oversight and management of the system. The values of the motor speed and vibration parameters are viewed through the Blynk monitoring interface, as depicted in the Fig. 11.



Fig. 11. Dashboard of the Blynk webpage

Signal Processing For Fault Diagnosis.

These signals obtained from the MPU6050 sensor underwent pre-processing, and the data was made suitable for fault analysis. First, the signals were filtered using a high-pass filtering method to remove noise and other unwanted signals, like gravity effects. The signals were analyzed under two conditions: standard operation without any distortion in the shaft, and faulty operation with warped shafts. Different signals were obtained under different conditions to ensure proper analysis of the motor's behavior.

The signals were acquired at a constant rate in the time domain before being converted into the frequency domain. A suitable number of signals were acquired

when the motor was operating. The acquired signals were divided into small time intervals for observing the behaviour of the acquired signal within a small time period.

The major characteristics, like dominant frequency and vibration intensity (RMS), were derived from the frequency domain representation, which made it easier to assess the motor condition efficiently. To simulate faulty conditions, shafts with different amounts of bending were used, which resulted in different amounts of misalignment. This resulted in considerable changes in the patterns of vibration, which were recorded in the dataset and shown in the extracted features.

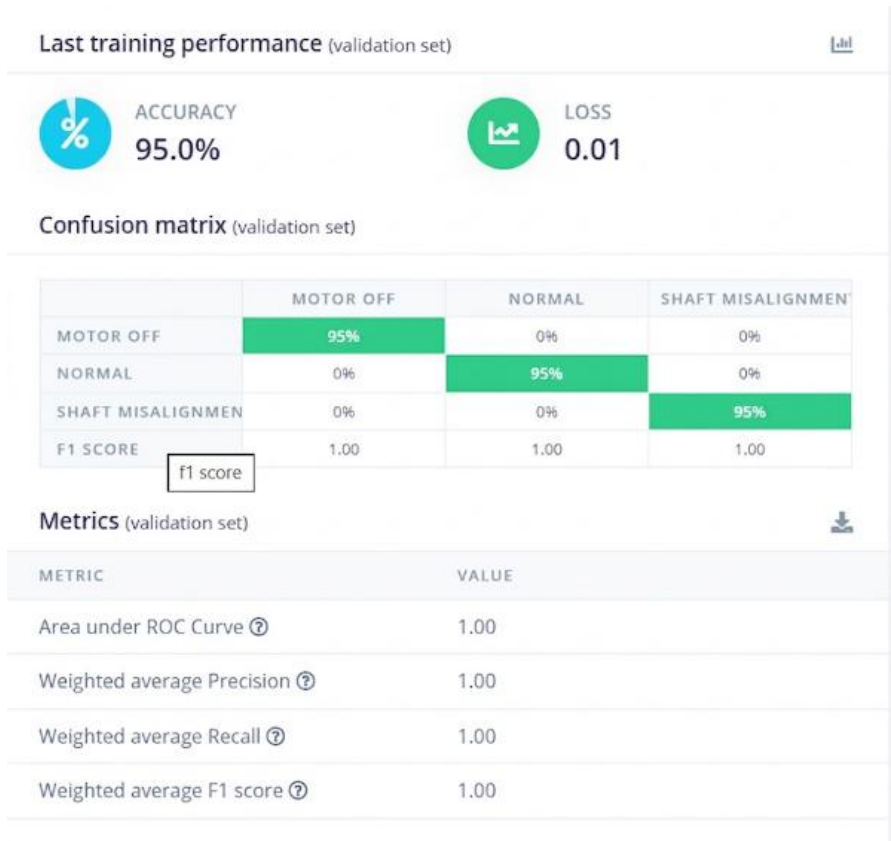


Fig. 12. Confusion matrix on the test set

The data obtained under standard and faulty conditions was used to perform further analysis and classification. Unlike image-based approaches, the proposed method uses numerical features, which reduces the complexity of computation and can be implemented in real-time using embedded systems like ESP32-S3. Data quality was

improved in the preprocessing and feature extraction stages, thus enhancing the data for fault diagnosis.

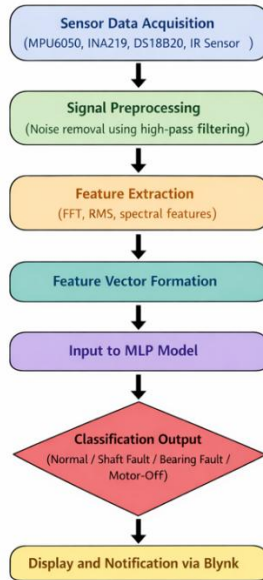


Fig. 13. Diagram of the proposed machine learning-based motor fault diagnosis system

Evaluation of the performance of the proposed model was done based on conventional metrics for assessing the effectiveness of a classifier model. The proposed model showed impressive results, as depicted in Fig. 12:

- Precision (Total precision): 95%
- Precision (Accuracy for positive classes): 100%
- Recall (Coverage for positive class predictions): 100%
- F1-score (Harmonic average of precision and recall): 1.0
- Validation dataset loss value: 0.00
- Precision on training dataset: 100%
- Precision on validation dataset: 95%

From this, it is evident that the proposed system is able to differentiate between various states of motor operation efficiently. However, further validation of this system is advisable to make it reliable in practical use.

Dataset Description and Evaluation Methodology.

The data set used for this study was developed by collecting vibration signals using the MPU6050 sensor fitted on the motor. Data collection took place under both faulty operation conditions and normal operation conditions by interchanging motor shafts. The fault conditions were established using shafts that were bent and displayed misalignment while the normal conditions were collected using an aligned shaft. This

ensured the development of a dataset that differed in terms of vibration signals with regard to various motor states.

Vibration signals were collected at a constant rate and saved as time series. The collected data were then segmented into smaller periods of time so as to make the analysis process easier. Features such as dominant frequency and RMS were calculated for every signal using the Fast Fourier Transform (FFT), hence enabling the characterization of the motor state in frequency domain. Approximately 10,000 samples were collected in the whole process.

The data was partitioned into three subsets, namely the training set (70%), the validation set (20%), and the test set (10%). The extracted features from the training set were used in training a small machine learning model on the ESP32-S3, allowing the model to detect patterns associated with the normal and abnormal performance of the motor. The model was tuned using the validation set in order to prevent overfitting, while the test set was used for evaluation purposes.

The performance of the machine learning model was tested using the test set, proving its ability to distinguish between normal and abnormal states of the motor based on the extracted features. The results indicate that the proposed approach to preparing the dataset and extracting features is an effective foundation for motor faults detection in DC motors.

4 Conclusions

In the course of carrying out this research, the concept of developing a system to monitor the speed of the motor and diagnose the faults occurring in DC motors through vibration analysis and the use of intelligence was introduced. The model proposed aims to recognize the misalignment problems occurring with the shaft through the collection of vibration signals from normal and faulty conditions with curved shafts. Along with the vibration signals, the electrical and thermal parameters such as current and temperature were also measured to obtain a complete idea of the working of the motor.

The vibration signals collected were analysed using the frequency domain analysis method through the application of the Fast Fourier Transform (FFT) to obtain the significant features such as dominant frequency and RMS value. These features helped to obtain a clear distinction between the normal and faulty conditions of the motor. A small machine learning model was applied to the ESP32-S3 to classify the faults occurring in real-time without the necessity to implement cloud processing. The application of the Blynk IoT platform helped to obtain better functionality of the system.

From the experimental results, the proposed system is effective in identifying motor faults in different conditions. However, it is worth noting that the performance of the proposed system may be affected by some mechanical components, like the alignment of the shaft and the stability of the bearings, especially at high speeds. In the future, the focus may be on how to make the proposed system robust and how to apply the model in detecting different faults in the electric vehicle motor.

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