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ADVANCED FAULT DETECTION AND IDENTIFICATION IN BRUSHLESS DC MOTORS USING ARTIFICIAL NEURAL NETWORKS AND LONG SHORT-TERM MEMORY

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ABSTRACT

In the realm of electric vehicles (EVs), ensuring the reliability and safety of critical components such as brushlessDC (BLDC) motors, inverters, and battery packs are paramountto prevent breakdowns and accidents. By closely monitoring operational conditions and identifying failures at an early stage, here our approach is mainly to enhance the safety and dependabilityof electric vehicles. The complexity of early failure recognition, exacerbated by intricate processes and unpredictability, presents a significant challenge that this study addresses through the application of ANNs, thereby facilitating effective online problem detection and fault-tolerant control. This research contributes to the knowledge by providing a detailed analysis of potential problems in electric vehicle motors and proposing a robust fault detection framework to mitigate these issues, ensuring continued safe operations of electric vehicles. This paper focuses on developing and implementing fault identification diagnosis techniques tailored to electric vehicle motors such as open circuit faults, short circuit faults, sensor faults, and temperature changes, leveraging the capabilities of Artificial Neural Networks (ANNs) models to offer a solution that is accurate and fast but also sensitive and cost-effective.

Index Terms: Brushless DC motor, Artificial Neural Networks,Electric vehicles, etc.

I. INTRODUCTION

Brushless motors are renowned for their high efficiency and lightweight nature, making them ideal for use in electric vehicles. Their main parts consist of windings, magnets, anda path for magnetic flux. Brushless Direct Current (BLDC) motors are composed of stator and rotor windings and find applications across various sectors such as space, automotive, and healthcare. These motors are compact, light, and capable of delivering significant torque, boosting rapid response times,enhanced efficiency, reliability, and longevity. When comparedto traditional DC motors, BLDC motors have the upper handin speed and torque capabilities. Currently, BLDC motors are categorized into trapezoidal (or square-wave) and sine-wave types. However, there's a viewpoint that trapezoidal or square-wave brushless motors alone should be considered BLDC motors, while sine-wave brushless motors fall under the category of permanent magnet synchronous motors. An artificial neuralnetwork monitors and compares the current, speed, and torqueof a BLDC motor against previously gathered benchmark values.

The evolution of electric vehicles (EVs) signifies a pivotal shift towards sustainable transportation, underscoring the critical role of Brushless DC (BLDC) motors in enhancing vehicle performance and efficiency. As environmental concerns and fuel costs rise, electric vehicles emerge as a viable alternative, offering a cleaner, more efficient mode of transport. The BLDC motor, with its high efficiency, reliability, and lower maintenance requirements, has become a cornerstone technology in the electric vehicle industry. This transformationnot only supports global sustainability goals but also presents new challenges promising the dependability and safety of these advanced electric drive trains.

Identification of faults and monitoring in electric vehiclesis paramount for ensuring the safety and reliability of these modern transport solutions. Given the complexity of electric vehicle systems, particularly the electric motor, and its associated components, identifying potential issues before they escalate is essential. An effective Fault Detection & Diagnosis(FDD) system can prevent minor issues from becoming major failures, reducing the risk of accidents and enhancing the overall vehicle performance. Moreover, timely fault detection can significantly extend the lifespan of electric vehicle components, leading to cost savings and increased user satisfaction.

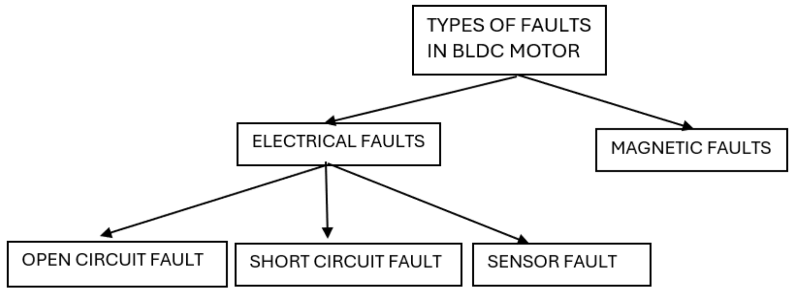

Fig. 1: Types of faults

Detecting faults in BLDC motors poses a special set of difficulties, owing to the motor's intricate design and the critical role it plays in electric vehicles (EVs). The nature of these motors demands sophisticated diagnostic [5] techniques that can accurately identify a wide range of potential faults, from winding issues to sensor failures. Traditional diagnostic methods often fall short of pinpointing the exact nature of the

problem, necessitating advanced approaches that can adapt to the complex operational dynamics of BLDC motors. This complexity underscores the need for innovative fault identification strategies that are both sensitive and accurate.

Artificial Neural Networks (ANN) have emerged as a powerful tool in the realm of fault detection for BLDC motors [6]. By mimicking the human brain's ability to learn from and adapt to new information, ANNs offer a dynamic approach to diagnosing motor faults. These networks can process vast amounts of data, learning to recognize patterns that may indicate a fault. This capability makes ANNs [7] particularly suited to the demands of modern electric vehicles (EVs), where the ability to quickly and accurately diagnose issues can significantly enhance vehicle safety and efficiency. Integrating ANNs into fault detection systems [8] represents a promising advancement in the ongoing effort to improve electric vehicle (EV) reliability.

II. METHODOLOGY

The efficiency and reliability of Brushless Direct Current (BLDC) motors are paramount, especially in applications demanding precise control and longevity. Identifying potential faults early is critical to maintaining optimal performance and preventing premature failures. This methodology introduces a sophisticated fault detection system utilizing a combination of hardware components and software algorithms to monitor and adjust the operational parameters of BLDC motors in real time.

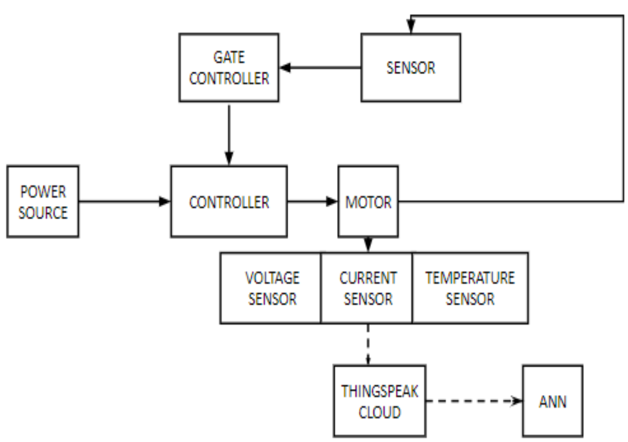

Fig. 2: Block diagram

This simulation represents a sophisticated control strategy for a Brushless DC (BLDC) motor that incorporates fault detection using Artificial Neural Networks (ANN). The goal is maintaining the desired motor performance while identifying and responding to potential faults. At the heart of the control system is a Proportional-Integral (PI) speed regulator that maintains the motor speed at a set reference value, in this case, 1500 RPM. The discrepancy between the reference speed and the actual speed is corrected by adjusting the voltage input V_{dc} to the motor, which is represented by a green block in the simulation.

The system monitors the BLDC motor through various feedback loops. Motor speed and electromagnetic torque are crucial parameters for performance analysis and fault detection. The simulation includes a block that represents the motoritself, with its associated parameters like stator currents (is_a, is_b, is_c) and back electromotive force (emf_{abc}), as well asa sensor for the rotor speed. These values are essential forthe ANN to determine the health status of the motor. Any anomalies in these readings could indicate a potential fault within the motor.

Fault detection is achieved using an Artificial Neural Network, as indicated by the blocks sending data to the Thingspeak output channel. This cloud-based IoT analytics platform collects real-time data from the system, which can be used for monitoring and analyzing the motor's condition over time. TheANN is trained to recognize patterns that deviate from normal operation, signaling possible faults. For instance, unexpected fluctuations in the stator currents or an abnormal torque outputcould be flagged by the ANN for further investigation.

Communication and data handling are vital for the fault detection process. The system is designed to communicate with an external platform, as shown by the multiple ThingSpeak output blocks. These allow the system to send data to a channel for remote monitoring. Parameters such as the rotor speed in radians per second (rad/s), the converted speed in RPM, electromagnetic torque (T_e), and system inputs like V_{dc} are transmitted continuously, providing a comprehensive overview of the system's health in real time. This connectivity ensures that operators can detect faults as they arise and respond promptly to maintain optimal motor function.

III. ANN ALGORITHM

Artificial neural networks (ANNs) are computational systems inspired by the structure of the human brain, consisting oflayers of interconnected nodes or artificial neurons. These networks are organized into input, hidden, and output layers, with the hidden layers being crucial for processing and transforming input data. Through a process of adjusting weights, which represent the influence of one node over another, ANNs are capable of making refined decisions or predictions based on the input they receive. This mechanism enables the networks to learn and improve their performance over time, mirroring the capability of the human brain to recognize patterns and adapt based on new information.

Among the various types of neural networks, Long Short- Term Memory networks (LSTMs) stand out for their ability to remember information for long periods, addressing challenges faced by traditional recurrent neural networks, such as the vanishing gradient problem. This makes LSTMs particularly effective for tasks that require understanding data sequences, such as language modeling and speech recognition, representing- in a significant advancement in the field of neural network research and application

Fig.3 shows the Python code for the training of data. The flowchart delineates an automated data retrieval and analysis procedure employing ThingSpeak, an Internet of Things platform, to monitor and classify the operational status ofa Brushless DC (BLDC) motor using an Artificial Neural

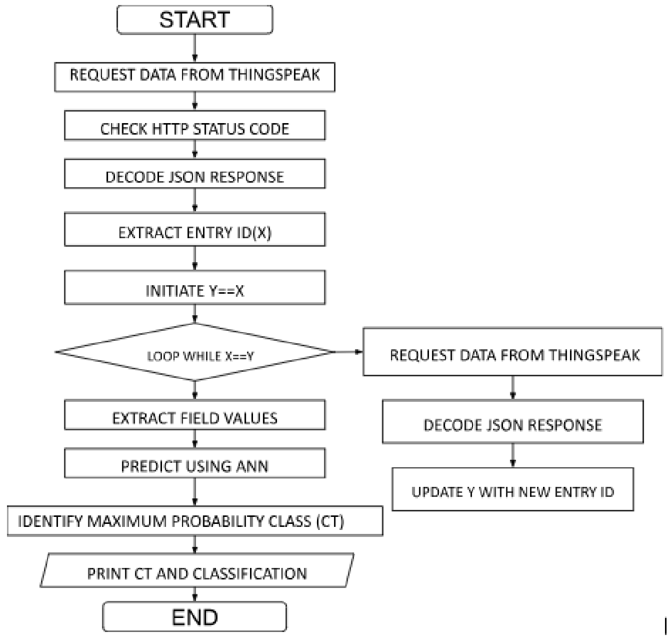

Fig. 3: Python code flow chart

Network (ANN). The process commences with the system sending a request to ThingSpeak to fetch the latest operational data from the motor. Upon receiving the data, the system verifies the HTTP response code to ensure the successful transmission of data. The received data, formatted in JSON, is then decoded to extract pertinent metrics, which include the unique Entry ID.

This Entry ID serves as an iterative checkpoint; the system sets an internal tracking variable, Y to this value. A loop is initiated, wherein the system continually queries ThingSpeak for new data entries. If a new Entry ID is detected, indicating fresh data, the system updates Y and proceeds to decode the JSON response again. Within this loop, the system extracts field values relevant to motor performance, such as speed, current, and torque, and inputs these values into the ANN.

The ANN, previously trained on historical data, now evaluates these real-time metrics to predict the motor's current operational state. It assigns probabilities to various predefined[13] classes representing different motor conditions, including potential fault states. The system then identifies the class with the highest probability as the most likely current state of the motor. This prediction, alongside its associated classification, is output for review or further action.

This process culminates in providing a dynamic and continuous assessment of the motor's performance, with the potential to facilitate preemptive maintenance actions based on the ANN's real-time analysis, thus enhancing the reliability and efficiency of the BLDC[14] motor's operation within various applications.

Furthermore, implementing LSTM models in programming languages such as Python has become common place, making these powerful tools accessible for a wide range of machine

learning applications. With libraries and frameworks designed for ease of use, setting up and training an LSTM [15] model can be straightforward for those familiar with Python coding. In essence, neural networks and their sophisticated variants like LSTMs embody a blend of biology-inspired structure and computer science that enables them to tackle complex computational tasks [16]. This has led to their widespread adoption in fields ranging from autonomous vehicles to financial forecasting, revolutionizing [17] the way we approach problem-solving with machines.

IV. WORKING

Artificial Neural Networks (ANNs) are leveraged to - enhance the reliability of Brushless DC (BLDC) motors through advanced fault detection. At the heart of the system lies the ANN, configured to process operational data from themotors in real time [18]. This network comprises multiple layers of interconnected artificial neurons that simulate the decision-making process of the human brain. Each neuronweighs incoming data such as motor speed, torque, and current against predefined parameters representing the motor's optimal operating conditions. These parameters are drawn from a comprehensive dataset, which includes both normaland faulted states as recorded in the IoT cloud platform, ThingSpeak. By continuously comparing the incoming data to these benchmarks, the ANN is trained to identify subtle patterns and anomalies [19] that may indicate the onset of a fault.

The ANN's training is a critical phase where it learns to discern between normal operational variances and those indicative of a potential malfunction. It involves feeding the network with historical data that encompasses a range of fault scenarios, including short circuits, open circuits, and sensor faults [20]. The neurons within the ANN adjust their weights through an iterative process, refining the model's predictive accuracy with each cycle. When the live operational data deviates from the expected range by a significant margin, the ANN flags this as an anomaly. This threshold for triggering alerts is carefully calibrated to minimize false positives[21], ensuring that only substantial and consistent discrepancies are reported. The flagged anomalies prompt immediate analysis, enabling maintenance teams to intervene before faults escalateinto failures. Once a potential fault is identified, the ANN's output initiates a set of protocols designed to mitigate risk andsafeguard the motor's function. This could involve automatic adjustments to the motor's operation or triggering an alert for human intervention, depending on the severity and nature of the detected anomaly. Over time, the ANN continues to evolve,harnessing every new piece of data to refine its diagnostic algorithms, thus improving its accuracy in fault detection. As a result, the system not only acts as an early warning mechanism but also contributes to a more comprehensive understanding of BLDC motor behavior under varying conditions. This project illustrates the power of machine learning in industrial applications, where predictive maintenance can lead to increased uptime, improved safety, and optimized performance, highlighting a significant step forward in smart manufacturing and automation.

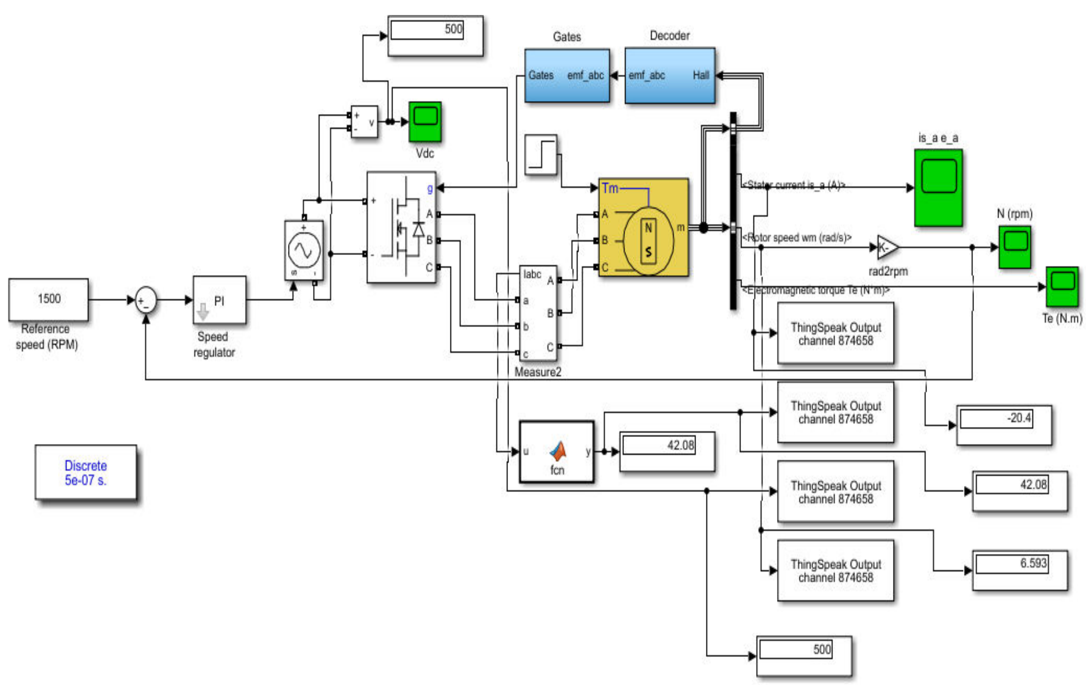

Fig. 4: Simulation

This system in real time uses a 24-volt lead acid battery as its supply. Both the Electronic Stability System (ESC), which is made up of the Buck and Boost Converters, and the NodeMCU receive the necessary 5-volt supply. Converters like the Buck and Boost assist in adjusting voltage as needed. A converter provides the processed voltage to the BLDC motor. Torque, speed, and current measurements in real-time are supplied to the NodeMCU, which then sends the data to Thingspeak, an IOT cloud platform. Thingspeak uses Python code to run on a Google Collab platform to continually gather data. Using both ANN models—ideally the LSTM—the data will be trained.

V. SIMULATION AND RESULT

In the simulation study, we observed the BLDC motor's response under various operational conditions. The response curves indicate the motor's performance in terms of speed, current, and torque over time. Initial spikes in the current and torque graphs suggest transient behaviors during startup, which quickly stabilize indicating successful attainment of the desired steady-state operation. Consistent readings in the speed graph corroborate the motor's ability to maintain set speeds despite potential load variations, reflecting the control system's robustness. The simulation results, therefore, substantiate the effectiveness of our control strategy in achieving and maintaining desired operational states.

Our classification model's performance, as illustrated by the confusion matrices, reveals a high level of accuracy in fault detection. The dominant figures along the diagonal of the matrices indicate a substantial number of correct predictions for each fault category. For instance, in Fig. 11, Class 2, presumptively representing a specific fault condition, shows a complete prediction accuracy with no misclassifications, as the model correctly identifies all instances without any false positives or negatives. This level of precision demonstrates the model's adeptness in distinguishing between the various states of the BLDC motor.

The LSTM model's accuracy and loss graphs show rapid convergence, with the accuracy plateauing at high values, suggesting the model's capability to generalize well from the training data to unseen data. The loss graph corroborates this, with a steep initial decline that tapers off, indicating the model's learning efficacy. Notably, the proximity of training and validation lines in both graphs suggests that our model is not overfitting and is likely to perform well on real-world data.

Mathematical Model of the Artificial Neural Network

Input Layer: The input layer directly receives the feature vectors from the dataset:

$$\mathbf{x} \in \mathrm{R}^{d}$$

where d is the number of features in your input dataset.

First Hidden Layer

This layer is a fully connected (dense) layer with 64 neurons, employing a ReLU (Rectified Linear Unit) activationfunction:

$$\mathbf{z}^{[1]} = \mathbf{W}^{[1]}\mathbf{x} + \mathbf{b}^{[1]}$$

$$\mathbf{a}^{[1]} = \mathrm{ReLU}(\mathbf{z}^{[1]})$$

where $\mathbf{W}^{[1]} \quad \mathrm{R}^{64\times d}$ and $\mathbf{b}^{[1]} \quad \mathrm{R}^{64}$ are the weight matrix and bias vector for the first layer, respectively.

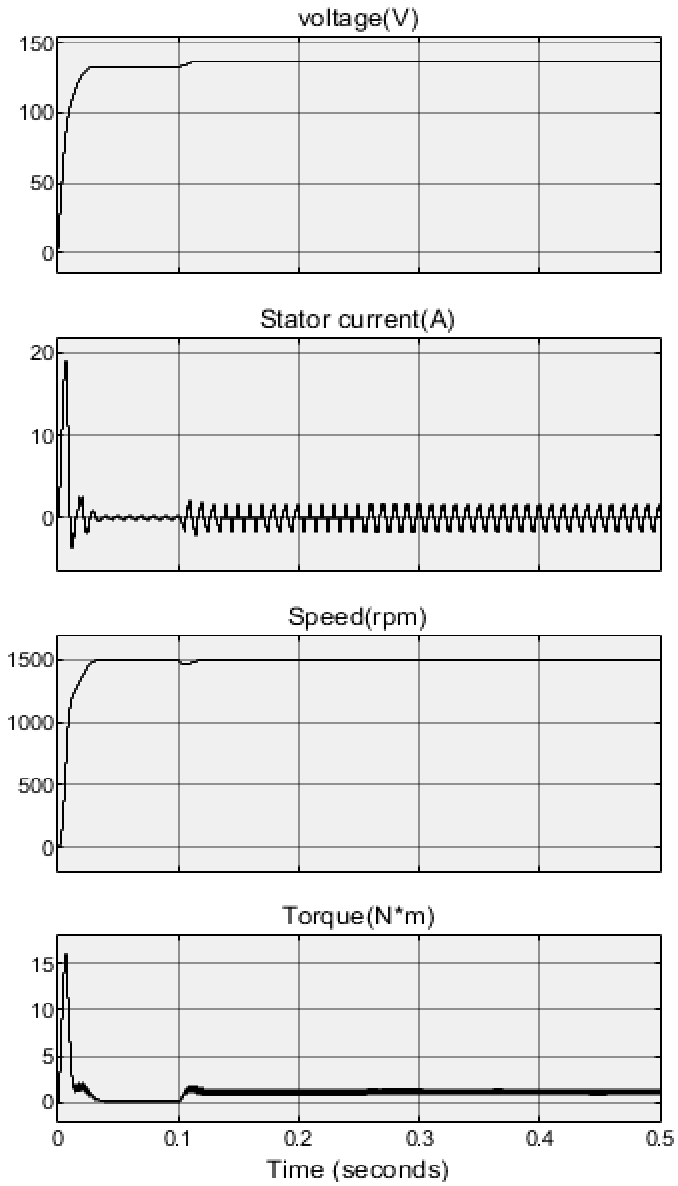

Fig. 5: Waveform of BLDC motor during normal conditions

First Dropout Layer

A dropout layer with a dropout rate of 0.5 follows, which randomly sets half of the input units to zero at each training step to prevent overfitting:

$$\mathbf{a}^{[1']} = \text{Dropout}(\mathbf{a}^{[1]})$$

Second Hidden Layer

Another fully connected layer with 32 neurons follows,using the ReLU activation function:

$$\mathbf{z}^{[2]} = \mathbf{W}^{[2]}\mathbf{a}^{[1']} + \mathbf{b}^{[2]}$$

$$\mathbf{a}^{[2]} = \text{ReLU}(\mathbf{z}^{[2]})$$

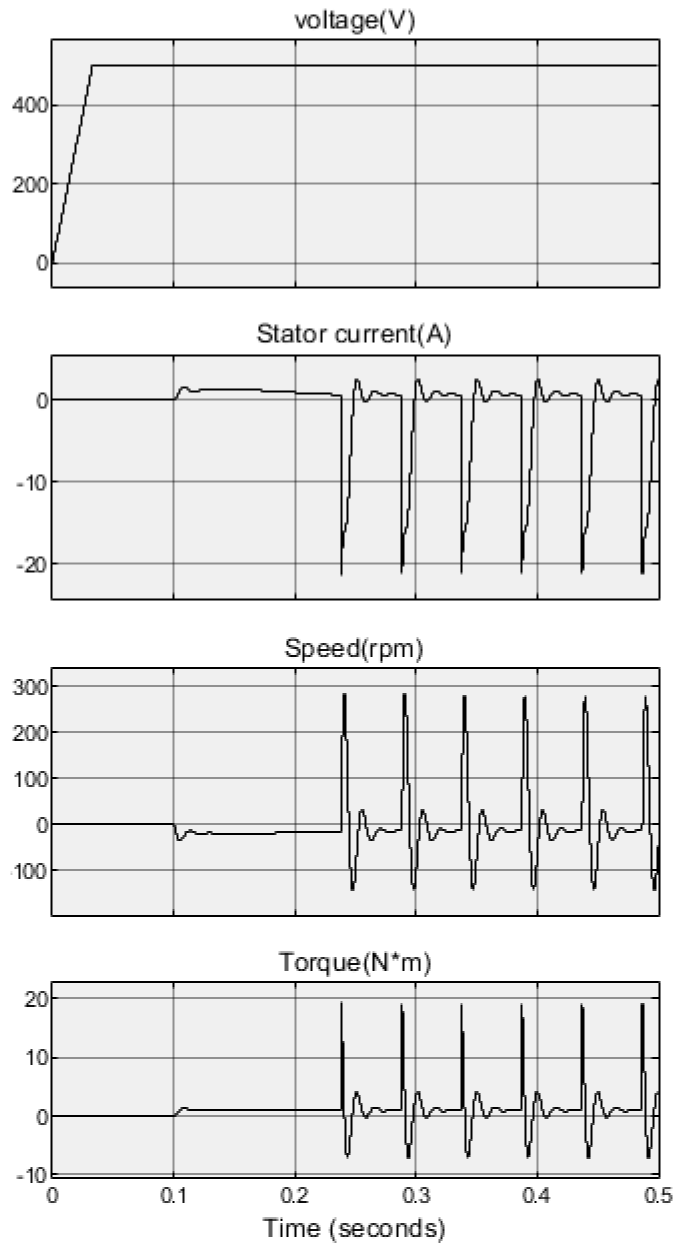

Fig. 6: Waveform of BLDC motor during Short circuit faults

where $\mathbf{W}^{[2]} \in \mathbb{R}^{32\times64}$ and $\mathbf{b}^{[2]} \in \mathbb{R}^{32}$.

Second Dropout Layer

A second dropout layer follows with the same dropout rate:

$$\mathbf{a}^{[2']} = \text{Dropout}(\mathbf{a}^{[2]})$$

Output Layer

The output layer of the network is a fully connected layer with a softmax activation function suited for multi-class classification:

$$\mathbf{z}^{[3]} = \mathbf{W}^{[3]}\mathbf{a}^{[2']} + \mathbf{b}^{[3]}$$

$$\mathbf{a}^{[3]} = \text{Softmax}(\mathbf{z}^{[3]})$$

where $\mathbf{W}^{[3]} \in \mathbb{R}^{num\_classes \times 32}$ and $\mathbf{b}^{[3]} \in \mathbb{R}^{num\_classes}$.

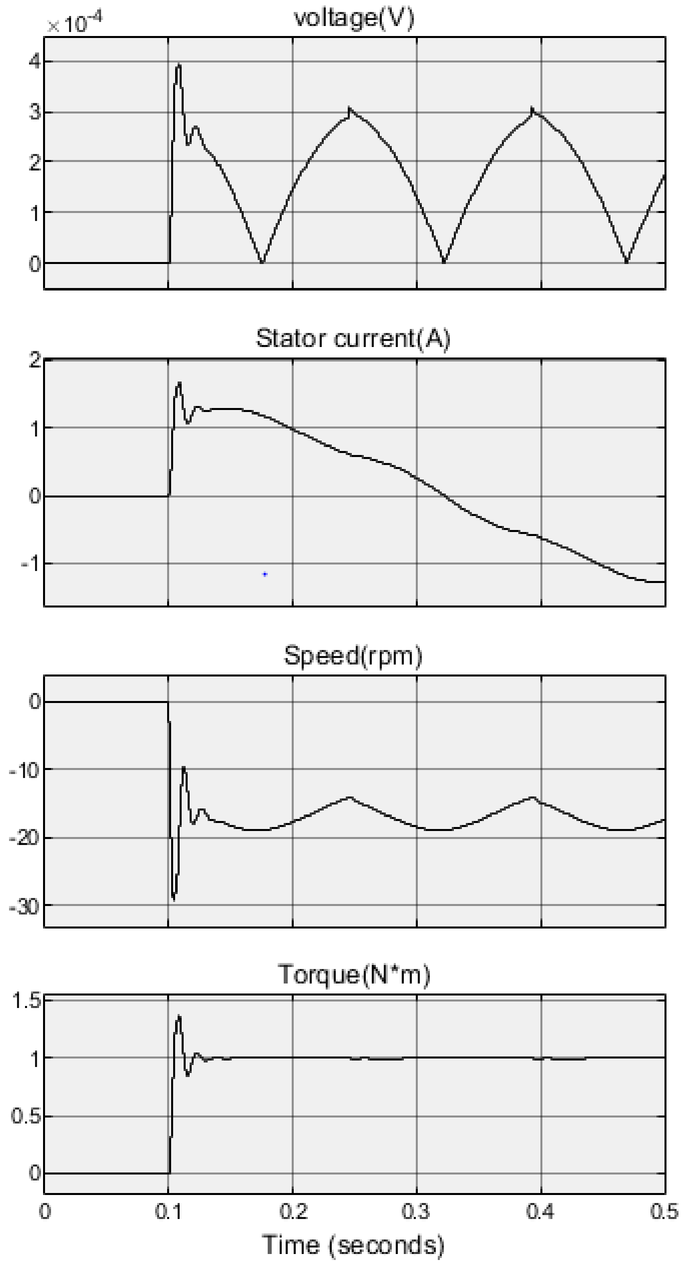

Fig. 7: Waveform of BLDC motor during open circuit faults

Softmax Activation Function

The softmax function is used in the output layer to realize the output to a probability distribution over predicted output class:

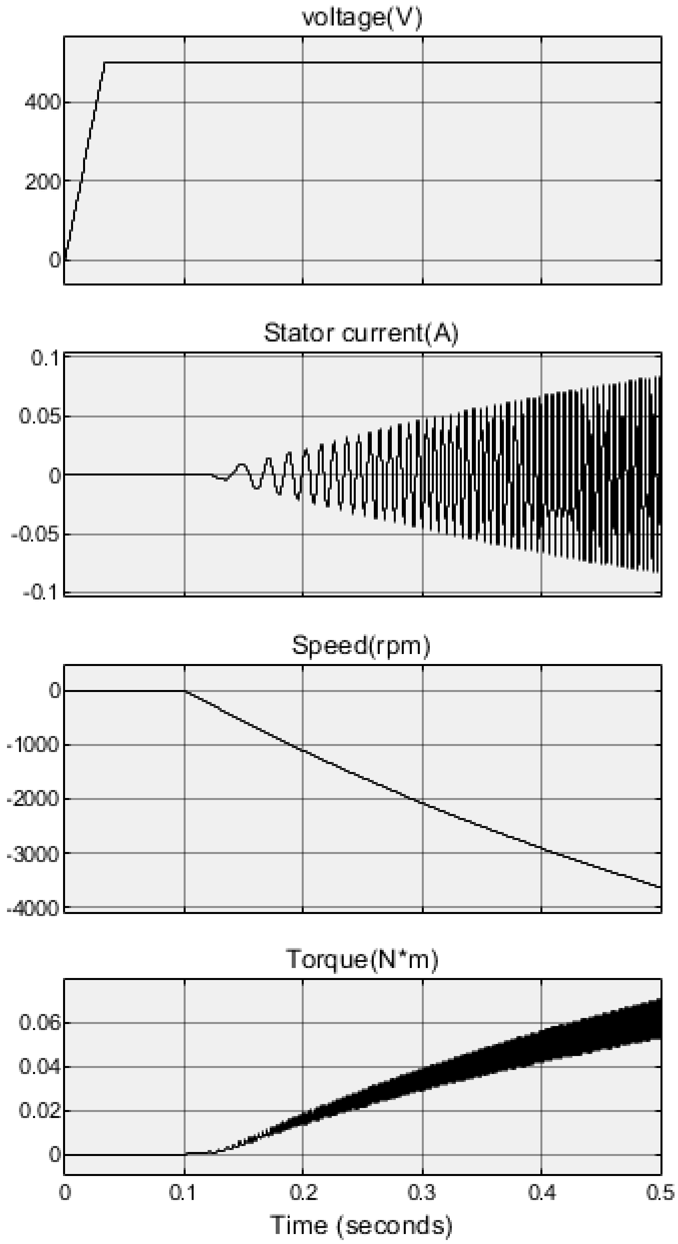

Fig. 8: Waveform of BLDC motor during sensor faults

where p_y is the predicted probability of the true classy.

$$\text{Softmax}(\mathbf{z})i = \frac{e^{z_i}}{\sum j e^{z_j}}$$

for each component i of the output vector $\mathbf{z}$.

Training

The model is trained using the Adam optimizer to minimizethe sparse categorical cross-entropy loss function:

$$L = -\log(p_y)$$

LSTM Model Description

An LSTM model is comprised of LSTM cells, each of which processes single-time steps of input sequences, maintaining an internal state and memory through time. The computations within an LSTM cell can be described by the following equations:

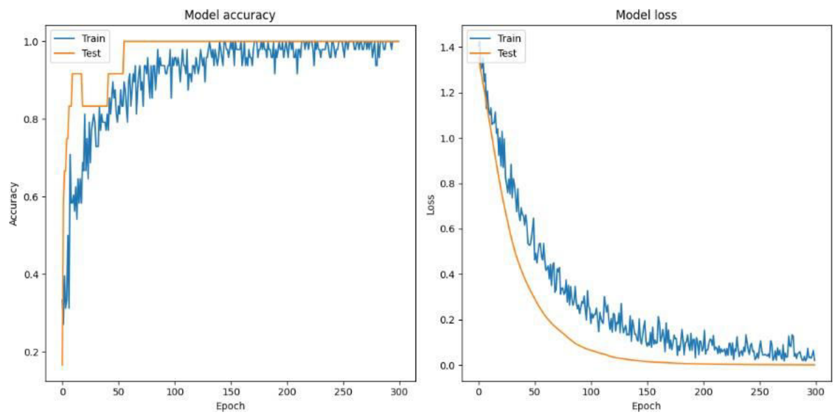

Fig. 9: Model accuracy and loss in ANN

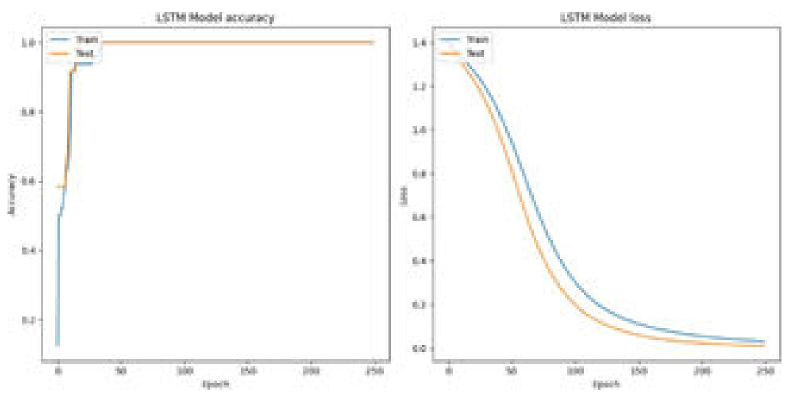

Fig. 10: Model accuracy and loss in LSTM

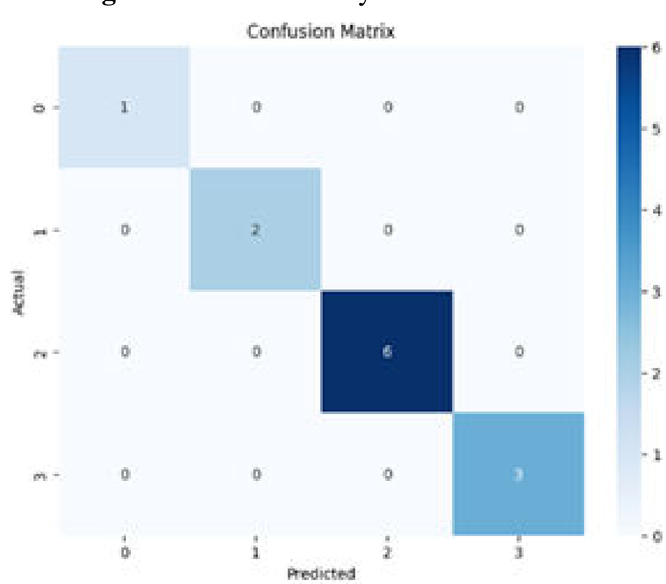

Fig. 11: Confusion matrix of ANN

Where:

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

$\tilde{C}t = \tanh(W_C \cdot [ht - 1, x_t] + b_C)$

$C_t = f_t * C_{t-1} + i_t * \tilde{C}t$

$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$

$h_t = o_t * \tanh(C_t)$

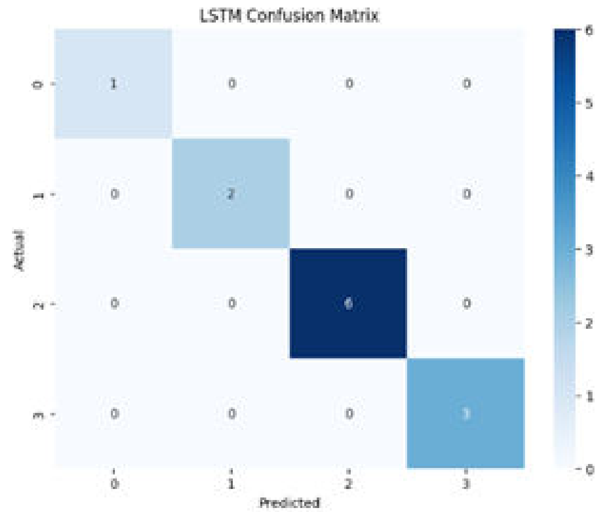

Fig. 12: Confusion matrix of LSTM

- x_t: Input vector at time step t.
- h_t: Output vector at time step t.
- C_t: Memory cell vector at time step t.
- f_t: Forget gate's activation vector at time step t.
- i_t: Input gate's activation vector at time step t.
- $\tilde{C}t$: Cell input activation vector at time step t.
- o_t: Output gate's activation vector at time step t.
- W, b: Weight matrices and bias vector parameters thatneed to be learned during training.
- σ: Sigmoid function.
- $*$: Element-wise multiplication.

The LSTM's final layer in the described model is a dense layer with softmax activation, used for classification.

The softmax function is given by:

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

where z_i are the logits (inputs to the softmax function) fromthe final dense layer.

The proposed approach utilizing an Artificial Neural Network (ANN) for fault detection in Brushless DC (BLDC) motors offers a distinct advantage over traditional diagnostic methods, such as rule-based diagnostics and signal analysis. While conventional techniques often rely on predefined thresholds and simplistic anomaly detection, the ANN method learns from data, allowing it to identify complex fault patterns that may not be apparent through manual inspection. This capability to recognize non-linear and interacting fault indicators significantly enhances fault detection accuracy and speed, essential for real-time applications.

Another significant enhancement of the proposed ANN-based method is its integration with cloud-based IoT analytics platforms like ThingSpeak. This integration facilitates real-time data monitoring and analysis, surpassing older methods that often involve delayed processing and local data handling. By continuously transmitting crucial motor parameters such as rotor speed, electromagnetic torque, and voltage inputs, the system allows for immediate identification of anomalies and proactive maintenance. This immediacy and dynamic monitoring capability is largely absent in traditional fault detection systems, which are typically reactive and less adaptable to varying operational conditions.

While the proposed ANN-based approach provides superiorfault detection capabilities, it does introduce increased system complexity and demands higher initial setup and training costs compared to simpler, conventional methods. The need for comprehensive data collection to train the ANN and the integration with sophisticated IoT platforms might pose challenges for implementation in smaller or less technologically advanced operations. However, the long-term benefits ofimproved fault detection accuracy and operational efficiency can justify these initial investments, making it a worthwhile approach for critical and high-value motor applications

VI. HARDWARE IMPLEMENTATION

The fault detection system for a BLDC motor employs a range of components, each chosen for its specific role in ensuring efficient and accurate monitoring. The core of the system is a 24V 350W BLDC Motor, valued for its high efficiency and robust performance, essential for dynamic fault analysis. Power is supplied by a 24V, 12Ah Lithium- Ion Battery, selected for its long-lasting charge capacity and reliability. Voltage regulation is managed by a Buck Converter, which steps down voltage from the battery to appropriate levels for other electronics, preventing over-voltage and en- suring stable operation. Current and voltage monitoring are handled by the ACS 712 and ZMPT101B sensors respectively; the former detects current flow anomalies indicating potential circuit faults, while the latter monitors voltage stability across the system. An MCP3000 ADC Converter is utilized to digitizethe analog signals from these sensors for further processing.

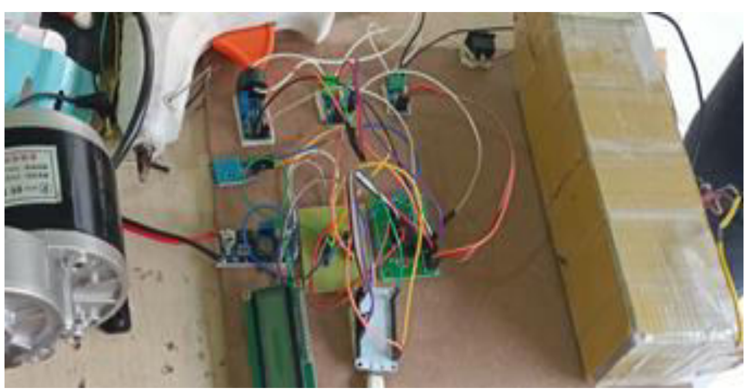

Fig. 13: Hardware

The environmental conditions around the motor are moni- tored using a DHT sensor, which measures temperature and humidity, crucial for identifying temperature-related faults that might impair motor functionality. All the collected data from the current, voltage, and temperature sensors are fed into an ESP8266 microcontroller, a compact module with built-in Wi-Fi capabilities. This setup not only simplifies the integration but also aids in real-time data processing and transmission.

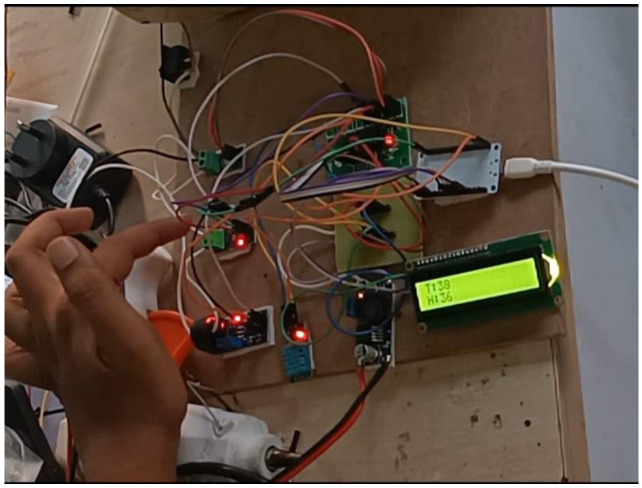

Fig. 14: Hardware Implementation

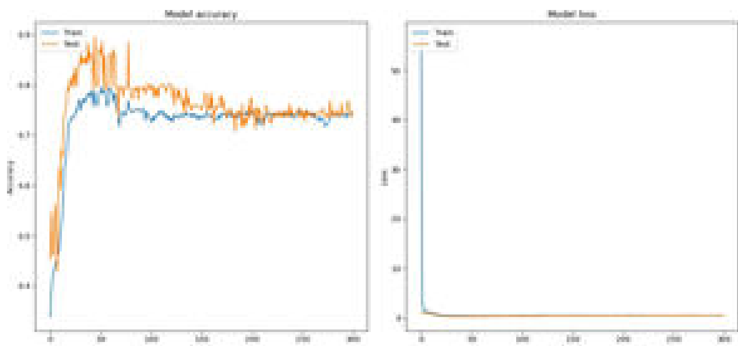

Fig. 15: Confusion matrix

The ESP8266 serves as the communication hub, interfacing directly with both the sensors and the ADC Converter, ensur- ing that sensor data is accurately converted from analog to digital form before processing.

Data transmission to the ThingSpeak API is orchestrated by the ESP8266, which packages the sensor data and sends it over Wi-Fi using HTTP POST requests. This method facilitates real-time data upload to the ThingSpeak cloud, where data visualization and further analysis are performed. The cloud platform plays a critical role in the ANN-based fault detection process, analyzing incoming data to identify patterns and anomalies that signify various faults such as open circuits, short circuits, sensor malfunctions, and overheating. This integrated approach not only enhances the system's ability to predict and diagnose faults effectively but also ensures continuous monitoring and immediate fault detection, crucial for maintaining the operational integrity of the BLDC motor. The confusion matrix of the hardware model is shown in Fig.

15. The accuracy of the model is 78 percent.

VII. CONCLUSION

In conclusion, the integration of a PI controller with a sophisticated monitoring and control system for BLDC motors, leveraging IoT analytics via ThingSpeak, has markedly enhanced operational efficiency and reliability. The application of advanced machine learning techniques, specifically ANN and LSTM models, has significantly improved fault detection and monitoring, ensuring smoother operation by promptly identifying and addressing various faults. The comparative analysis revealed that the LSTM model excels in reducing noise levels, underscoring its superiority over traditional ANN models for this application. This innovative approach not only paves the way for real-time diagnostics and condition monitoring but also establishes a robust framework for predictive maintenance in electric vehicles. Consequently, it mitigates the risk of unforeseen failures, optimizing the performance and extending the lifespan of BLDC motors. This study underscores the vital role of AI in enhancing the diagnostics and maintenance strategies of electric vehicles, promising a future of safer, more reliable, and more efficient transportation solutions.

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