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Machine Learning-Based Multi-Fault Diagnosis in Brushless DC Motors Using Electrical and Vibration Signal Features

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Abstract - Brushless DC (BLDC) motors play a key role in electric vehicles, robotics, unmanned aerial platforms, and industrial automation due to their compact construction, high efficiency, and minimal maintenance requirements. However, unexpected faults in these motors can cause downtime, reduced performance, and increased maintenance expenses. This work introduces a machine learning-based multi-fault diagnosis framework for BLDC motors that leverages both electrical and vibration signal features. The proposed system incorporates real-time acquisition of current, voltage, Hall sensor, and vibration data, followed by feature extraction in both the time and frequency domains. Statistical features such as RMS, kurtosis, spectral energy, and FFT components are used to train a Support Vector Machine (SVM) classifier for fault identification. The method is evaluated through MATLAB/Python simulation as well as hardware experiments. The results demonstrate strong classification performance across multiple fault types and operating conditions, highlighting the suitability of the proposed approach for low-cost and scalable predictive maintenance in BLDC motor-driven systems.

Keywords - Brushless DC motor (BLDC), fault diagnosis, machine learning, Support Vector Machine (SVM), predictive maintenance, vibration analysis, current signature analysis, feature extraction, FFT, condition monitoring.

I. INTRODUCTION

Brushless DC (BLDC) motors are increasingly utilized in modern electromechanical applications due to their high power-to-weight ratio, greater energy efficiency, precise speed control characteristics, and reduced maintenance requirements [1]. They serve as key actuators in electric vehicles (EVs), unmanned aerial vehicles (UAVs), robotic platforms, industrial automation systems, and medical devices, where reliable and continuous operation is essential. Despite the absence of brushes and commutators, BLDC motors are not immune to failures[2][3]. They can experience various electrical and mechanical faults such as phase open-circuit faults, Hall sensor malfunctions, bearing defects, and abnormal supply conditions, all of which can degrade performance or lead to unexpected shutdowns[4][5].

Traditional fault detection relies primarily on periodic inspection or threshold-based monitoring methods [6][7]. However, these approaches often struggle to identify early-stage or intermittent faults, resulting in unplanned downtime and increased operational costs[8]. With the growing availability of sensor data and advancements in artificial intelligence, machine learning-based diagnostic methods have gained significant attention for predictive maintenance. Such techniques analyze patterns within electrical and mechanical signals and are capable of automatically distinguishing between healthy and faulty motor states[9] [10].

In this context, the present work introduces a multi-fault diagnosis framework for BLDC motors using a Support Vector Machine (SVM) classifier [11][12]. The system integrates features extracted from both electrical measurements (current and voltage) and mechanical vibration signals to improve fault discrimination capability [13]. The proposed methodology is validated through simulation and real-time hardware experiments, demonstrating its potential as an efficient and scalable solution for intelligent fault monitoring in BLDC motor-driven systems.

II. LITERATURE REVIEW

Fault diagnosis of BLDC and other permanent magnet motors has attracted considerable research interest over the last decade, particularly due to the increasing adoption of electric drives in safety-critical applications. Various diagnostic approaches have been reported in the literature, ranging from analytical signal processing methods to modern data-driven machine learning techniques.

Signal-based strategies using current and vibration measurements have been widely explored because they are low-cost, non-invasive, and suitable for online monitoring. For instance, Zhang et al. investigated current signature analysis for detecting open-phase and inverter-related faults in BLDC motors using FFT-based features. Their study achieved reliable identification under steady-state scenarios but experienced degraded performance during rapid transients due to spectral smearing effects.

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Alternatively, vibration-based fault detection has been examined by Kumar and Singh, who extracted statistical time-domain features from accelerometer signals and used artificial neural networks for classification. While this approach demonstrated high accuracy for mechanical defects, it required a considerable amount of labeled data and computational resources, making real-time deployment more challenging.

Recent studies have highlighted the effectiveness of Support Vector Machines (SVMs) for motor fault classification due to their ability to handle high-dimensional feature spaces and relatively small training datasets. However, many existing SVM-based approaches focus on detecting a single fault type or rely solely on simulated data without hardware validation, thereby limiting their applicability in practical environments.

From the survey, it is evident that integrating multiple sensor modalities and validating diagnostic models under real operating conditions remain important research challenges. Motivated by these observations, the present work proposes a hybrid electrical and vibration feature-based BLDC motor fault diagnosis framework employing an SVM classifier, evaluated through both simulation and hardware experiments.

III. SYSTEM ARCHITECTURE

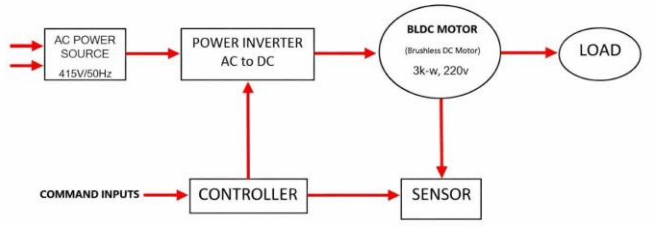

Fig. 1. Block Diagram

The overall framework of the proposed BLDC motor fault diagnosis system is illustrated in Fig. 1. The system comprises four major functional modules: data acquisition, signal preprocessing and feature extraction, machine learning-based fault classification, and fault visualization.

A. Data Acquisition

To capture both electrical and mechanical signatures of the BLDC motor, multiple sensors are interfaced with a microcontroller platform. The electrical quantities, including stator current and DC bus voltage, are monitored using an ACS712 current sensor and a voltage divider-based measurement circuit, respectively. Rotor position and commutation feedback are obtained from Hall-effect sensors, while mechanical vibrations associated with bearing and structural faults are recorded using an MPU6050 or SW-420 vibration sensor. The acquired signals are sampled in real time and transmitted to a host computer via serial communication for subsequent processing.

B. Feature Extraction

The raw sensor signals are filtered and normalized before feature computation. Both time-domain and frequency-domain descriptors are extracted to characterize the behavior of the motor under healthy and faulty conditions. The time-domain feature set includes statistical measures such as mean, RMS, standard deviation, skewness, and kurtosis, whereas FFT-based spectral components and spectral energy form the frequency-domain feature set. This hybrid feature representation enhances the classifier's ability to distinguish between different fault modes.

C. Fault Classification

The extracted feature vectors are fed into a Support Vector Machine (SVM) classifier trained with labeled datasets corresponding to healthy and various fault conditions. During operation, the trained model predicts the current state of the motor based on incoming feature patterns. The classification output is transmitted to a visualization interface, enabling real-time fault identification and monitoring.

D. Visualization and Monitoring

The final stage displays detected fault categories, operating status, and confidence levels through a graphical interface. This module supports real-time decision-making and enables predictive maintenance of BLDC motor-driven systems.

IV. BLDC MOTOR FAULT TYPES

The proposed system focuses on the following fault categories:

1. Open-Phase Fault: Disconnection in one of the stator phases causing unbalanced current and torque pulsations.
2. Hall Sensor Fault: Incorrect rotor position feedback resulting in improper commutation.
3. Bearing Fault: Mechanical wear leading to increased vibration and noise.
4. Overcurrent Fault: Excessive load or short circuit causing abnormal current rise.
5. Supply Voltage Fault: DC bus voltage fluctuations affecting speed and torque performance.

V. SIMULATION MODEL

The simulation environment is developed using MATLAB/Simulink and Python to model the dynamic behavior of the BLDC motor under various operating and fault conditions. The electrical subsystem incorporates the stator winding configuration, inverter switching model, and Hall sensor commutation logic, while the mechanical subsystem includes rotor inertia, load torque, and bearing friction components. The combined model enables the representation of realistic motor responses during steady-state and transient operations.

Fault scenarios are introduced by altering relevant motor parameters and control inputs. For example, open-phase faults are simulated by disconnecting stator phases, Hall sensor faults are emulated by modifying commutation signals, and mechanical anomalies such as bearing wear are represented by injecting vibration disturbances and varying load torque profiles. Both healthy and faulty datasets are generated through multiple simulation runs over different speeds and loading conditions.

The simulated current, voltage, speed, and vibration signals are exported for feature extraction and classifier training. This simulation-driven dataset enables controlled experimentation and supports the evaluation of machine learning models prior to hardware deployment, thereby reducing development time and cost.

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VI. HARDWARE IMPLEMENTATION

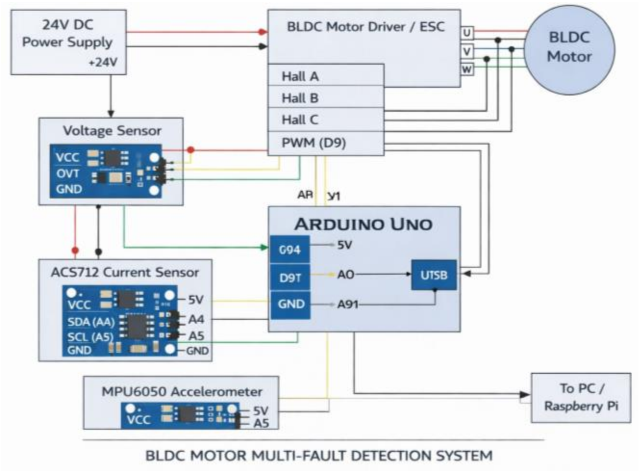

Fig. 2. System Architecture

The proposed multi-fault diagnosis framework is experimentally validated using a laboratory-scale BLDC motor test setup, as shown in Fig. 2. The hardware platform consists of a 24 V BLDC motor, electronic speed controller (ESC) or BLDC driver, sensor modules, and a data acquisition unit.

A. Motor Drive and Power Supply

The BLDC motor is driven through a commercially available ESC, which performs electronic commutation based on Hall sensor feedback. A regulated 24 V DC supply is used to power both the ESC and the sensing modules. The motor is operated under different speed and load conditions to emulate diverse real-world scenarios.

B. Sensor Integration

Multiple sensors are deployed to capture motor behavior during healthy and faulty operation. Stator current measurements are obtained using an ACS712 Hall-effect current sensor, while supply voltage variations are monitored through a voltage sensing interface. Mechanical vibration signals are recorded using an MPU6050 or SW-420 vibration sensor mounted on the motor casing. Hall-effect position sensors provide rotor feedback for commutation and fault emulation.

C. Data Acquisition and Communication

An Arduino Uno microcontroller serves as the data acquisition unit, sampling electrical and mechanical signals in real time. The sampled data is transmitted to a host PC through serial communication for further processing. Python-based scripts are employed to execute feature extraction and SVM-based classification during the validation stage.

D. Fault Emulation and Validation Procedure

Different fault types—including open-phase, Hall sensor malfunction, bearing-related vibration faults, and abnormal supply conditions—are manually introduced during the experiment. For each fault condition, corresponding sensor data is recorded and labeled to build the experimental dataset. The system's classification outputs are monitored to assess its real-time diagnostic performance and robustness under practical constraints.

The experimental results confirm that the proposed hardware platform can reliably detect multiple BLDC motor faults, validating the feasibility of deploying the methodology in industrial and vehicular applications.

VII. RESULT AND DISCUSSION

The proposed SVM-based fault diagnosis system was evaluated using both simulation and experimental datasets. Performance metrics were derived from the confusion matrices obtained for the test and validation phases, as shown in Figures 3 and 4.

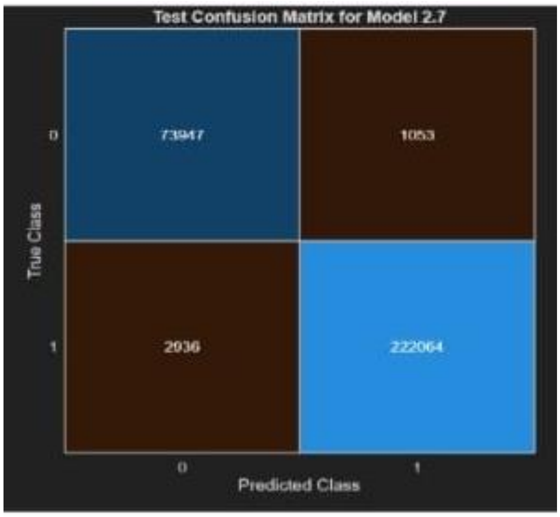

Fig. 3. Test Confusion Matrix

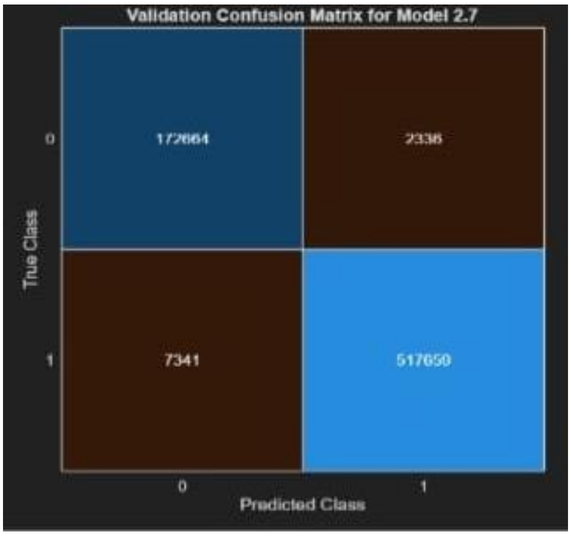

Fig. 4. Validation Confusion Matrix

A. Confusion Matrix Analysis

Figure 3 and Figure 4 shows the Test confusion matrix and Validation confusion matrix of the proposed SVM-based BLDC motor fault classifier (Model 2.7).

Test Dataset Confusion Matrix:

True Negative (TN) = 73,947

False Positive (FP) = 1,063

False Negative (FN) = 2,936

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True Positive (TP) = 222,064

Validation Dataset Confusion Matrix:

True Negative (TN) = 172,664

False Positive (FP) = 2,336

False Negative (FN) = 7,341

True Positive (TP) = 517,650

B. Performance Matrices

The following standard classification metrics were computed:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision = TP / (TP + FP)

Recall (Sensitivity) = TP / (TP + FN)

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

Metric	Test Dataset	Validation Dataset
Accuracy (%)	98.79	98.95
Precision (%)	99.52	99.55
Recall (%)	98.70	98.60
F1-Score (%)	99.11	99.07

C. Model Comparison

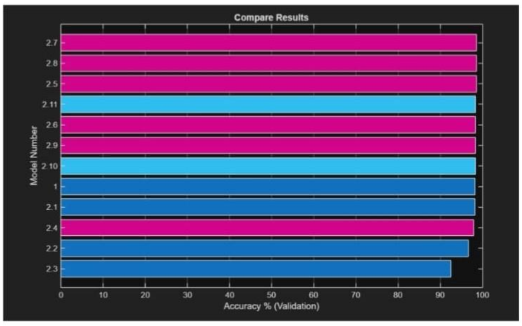

Fig. 5. Accuracy Comparison

Validation accuracy comparison of multiple trained models (2.1 to 2.11) showing superior performance of Models 2.7, 2.8, and 2.9.

Figure 4 illustrates the validation accuracy comparison of multiple trained models (2.1 to 2.11). Models 2.7, 2.8, and 2.9 achieved the highest validation accuracy, exceeding 98%, demonstrating strong generalization performance. Model 2.7 was selected as the final classifier due to its optimal trade-off between accuracy and computational complexity.

D. Discussion

The results indicate that combining electrical (current and voltage) and mechanical (vibration) features significantly improves fault classification performance compared to single-sensor-based methods. The low false positive and false negative rates highlight the robustness of the proposed framework for real-time predictive maintenance applications. Hardware validation further confirms the feasibility of deploying the system in industrial and EV-based BLDC motor environments.

VIII. CONCLUSION AND FUTURE SCOPE

This work presented a machine learning-based multi-fault diagnosis framework for BLDC motors using hybrid electrical and vibration signal features. The proposed approach integrates real-time data acquisition, feature extraction in both time and frequency domains, and SVM-based classification to identify multiple electrical and mechanical fault conditions. Experimental validation alongside simulation-based evaluation demonstrated high accuracy and reliable generalization capability across different datasets. The results confirm that combining electrical and mechanical sensing enhances diagnostic performance compared to single-sensor techniques, making the framework suitable for predictive maintenance applications in BLDC motor-driven systems.

Future research may focus on extending the system to deep learning architectures for automated feature extraction, incorporating larger datasets collected under diverse environmental and loading conditions, and deploying the diagnostic model on embedded edge platforms for real-time industrial and vehicular applications. Integration with IoT-enabled monitoring and cloud analytics also represents a promising direction for scalable fault diagnostics in smart manufacturing and electric mobility domains.

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