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An AI-Based Fault Diagnosis System for Electric Vehicle Drive Systems Using Sensor Data and Embedded Controllers

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Abstract

The rapid growth of electric vehicles (EVs) has increased the need for reliable and intelligent monitoring systems capable of ensuring safe and efficient operation of vehicle drive systems. Faults occurring in critical components such as electric motors, inverters, and controllers can significantly affect vehicle performance, safety, and operational lifespan. This work presents an AI-based fault diagnosis system for electric vehicle drive systems using sensor datasets and embedded controllers. The proposed approach uses sensor measurements including voltage, current, motor speed, torque, ambient temperature, and coolant temperature to monitor system conditions and detect abnormalities, with data preprocessing techniques applied to improve data quality before model training. Four machine learning and deep learning algorithms — Support Vector Machine (SVM), Random Forest, Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM) — were trained on the Electric Motor Temperature Dataset (133,081 samples) to classify five operating conditions: normal operation, motor overheating, voltage abnormality, current overload, and speed irregularity. Experimental results demonstrate that AI-based models can accurately identify faults and distinguish between normal and abnormal operating conditions, with LSTM achieving the highest classification performance (98.3% accuracy, 98.0% precision, 97.9% recall, 97.9% F1-score), followed by ANN (96.4%), Random Forest (95.2%), and SVM (91.8%). The trained model was integrated with an ESP32 embedded controller, achieving a 97.5% fault detection rate with an average response time of 0.42 seconds, confirming the feasibility of real-time deployment. The proposed system improves reliability, supports predictive maintenance, reduces downtime, and enhances the safety and efficiency of electric vehicle drive systems.

Keywords: *Electric Vehicles, Fault Diagnosis, Artificial Intelligence, Machine Learning, Sensor Data, Embedded Controllers, Predictive Maintenance.*

1. INTRODUCTION

The transportation sector is undergoing a major transformation with the rapid adoption of electric vehicles (EVs) as a sustainable alternative to internal combustion engine vehicles [1]. The performance and reliability of an EV depend heavily on its drive system, comprising electric motors, power electronic converters, batteries, and control units [4]. Numerous sensors continuously monitor parameters such as voltage, current, motor speed, torque, and temperature to enable effective control and performance monitoring [5].

As EV drive systems become increasingly complex, they also introduce significant challenges in monitoring and fault management. Faults in motors, inverters, sensors, or control circuits can adversely affect performance, efficiency, and safety; issues such as motor overheating, voltage abnormalities, excessive current draw, and speed irregularities may develop gradually and remain undetected until severe damage occurs [8]. Traditional fault diagnosis techniques, relying on manual inspection or predefined threshold values, can detect obvious abnormalities but often struggle to identify complex fault patterns or provide timely warnings under dynamic operating conditions [10].

Artificial intelligence (AI), machine learning (ML), and deep learning (DL) offer new opportunities for advanced fault diagnosis, automatically learning hidden relationships within sensor data and detecting subtle changes in system behaviour that may indicate impending failures [11]. Integrating AI-based fault diagnosis with real-time sensor monitoring and embedded controllers can achieve improved reliability, enhanced safety, reduced downtime, and more effective predictive maintenance directly within the vehicle [13]. This study presents such a framework,

combining sensor-based monitoring, multiple AI classification models, and embedded controller deployment for EV drive system fault diagnosis.

1.1 Objective of the Work

The main objective of this work is to design and develop an AI-based fault diagnosis system for EV drive systems using sensor data, providing accurate, real-time fault detection to improve reliability and safety, reduce maintenance costs, and minimize downtime through predictive maintenance. A further objective is to integrate the trained model with an embedded controller, ensuring real-time monitoring and rapid fault response directly within the vehicle.

2. LITERATURE REVIEW

In the early stages of EV development, fault diagnosis relied mainly on manual inspection and rule-based techniques using predefined limits and expert knowledge. While simple to implement, such approaches struggle to handle large volumes of data or identify hidden patterns, and lack the adaptability to respond to changing operating conditions or detect faults at an early stage. Modern EV systems are now equipped with extensive sensor networks continuously monitoring current, voltage, temperature, and motor speed, providing real-time data on system condition; however, the challenge lies in interpreting this data effectively, since large volumes of sensor measurements are difficult to analyze using conventional methods without advanced analytical techniques.

Kosuru and Kavasseri Venkitaraman [1] proposed a deep learning-based approach for detecting and classifying faulty sensor data and communication errors in lithium-ion battery management systems, combining advanced preprocessing, feature extraction, and optimization techniques to improve accuracy and robustness — directly relevant to the sensor-fault detection problem addressed in this study. Aryanfar et al. [13] examined real-time battery power monitoring and control in automotive embedded systems, highlighting sensor technologies, control strategies, and the role of AI in enabling predictive maintenance within embedded vehicle platforms, closely paralleling the embedded implementation approach adopted here. Dixit et al. [14] surveyed AI-based anomaly detection techniques for autonomous electric vehicles operating within Internet-of-Vehicles environments, presenting a structured taxonomy of detection methods and evaluation metrics relevant to identifying abnormal vehicle behaviour more broadly. Zhang et al. [2] similarly examined data-driven security and stability rule extraction for power systems with high renewable penetration, illustrating how data-driven monitoring extends beyond individual vehicle components to the wider electrical infrastructure in which EV drive systems operate.

Beyond fault-specific studies, a broader body of work has applied AI and data-driven techniques to EV systems generally. Strielkowski et al. [4] reviewed the prospects and challenges of machine learning and data-driven methods for predictive analysis of power systems, underscoring the growing role of data-driven monitoring in electrical infrastructure. Ray et al. [8] and Dasi et al. [9] examined swarm intelligence-based and IoT-based intelligent energy management for EV charging stations respectively, while Sivasankar et al. [10] explored IoT integration for smart e-vehicle charging infrastructure — together illustrating the wider trend toward embedded, sensor-driven intelligence in EV systems that this study extends specifically to drive-system fault diagnosis. Calero et al. [11] and Kene and Olwal [12] applied machine learning to EV charging control and session modelling respectively, and Sumanasena et al. [15] applied AI across EV infrastructure demand profiling and forecasting, demonstrating the versatility of ML techniques across different EV subsystems. Moradi Amani et al. [7] and Yu et al. [6] examined data-driven control and behaviour analysis of distribution grids under EV penetration, while Mishra et al. [5] and Ahmed et al. [3] investigated AI-driven optimization and neuro-fuzzy modelling for EV charging scenarios, reflecting the diversity of AI applications across the EV ecosystem.

Although significant progress has been made in applying AI to EV systems broadly [1]–[15], most existing studies focus on individual components — batteries, charging infrastructure, or grid interaction — rather than the complete drive system, and few combine sensor data, AI-based classification, and embedded controller deployment into a single, validated, real-time fault diagnosis framework. This work addresses that gap by developing a comprehensive fault diagnosis system spanning sensor data acquisition, comparative AI model evaluation, and embedded hardware deployment for the complete EV drive system.

3. RESEARCH METHODOLOGY

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The proposed AI-based fault diagnosis system integrates sensor-based monitoring, data processing, AI classification, and embedded controllers to detect faults at an early stage and support predictive maintenance. As shown in Figure 1, the architecture proceeds through five stages: data acquisition from sensors mounted on the EV drive system (current, voltage, temperature, speed, and torque sensors), data preprocessing (missing-value handling, noise removal and filtering, normalization, feature extraction, and train/test splitting), an AI-based fault diagnosis model comprising four candidate algorithms, embedded implementation on an ESP32/Arduino controller (supporting real-time inference, low-power operation, edge computing, and wireless communication), and a fault alert and monitoring subsystem that classifies each observation into one of five fault conditions and generates alerts accordingly.

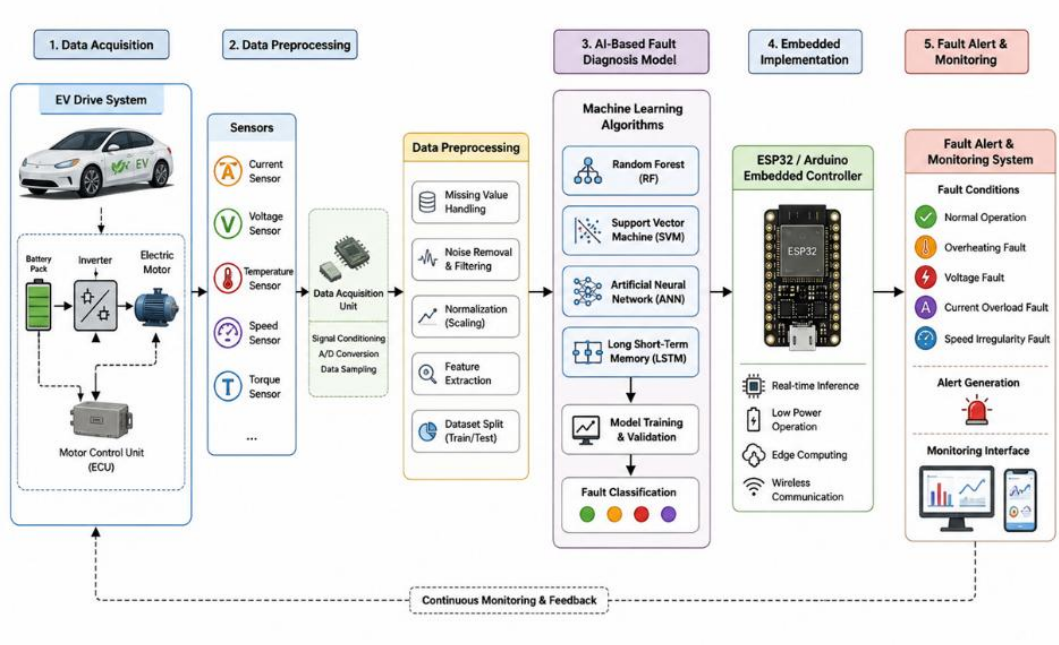


Figure 1: Proposed AI-based fault diagnosis architecture for electric vehicle drive systems.

3.1 Dataset and Preprocessing

The Electric Motor Temperature Dataset, obtained from Kaggle, was used as the primary data source. It contains 133,081 sensor observations collected from a Permanent Magnet Synchronous Motor (PMSM) operating under varying load and environmental conditions, structured as a multivariate time series. Eight input features were used: quadrature- and direct-axis voltage (u_q, u_d), quadrature- and direct-axis current (i_q, i_d), motor speed, torque, ambient temperature, and coolant temperature, alongside four thermal target variables (permanent magnet, stator yoke, stator tooth, and stator winding temperature) used to derive fault labels.

Preprocessing involved missing-value handling, outlier/noise removal via statistical analysis, and feature scaling (Min-Max normalization and standardization) to bring all parameters into a comparable numerical range, followed by an 80:20 train-test split. Since the original dataset contains sensor measurements rather than explicit fault labels, a threshold-based labelling scheme was applied to categorize each sample into one of five classes: Normal Operation, Motor Overheating (elevated stator temperature), Voltage Abnormality, Current Overload (excessive i_q/i_d), and Speed Irregularity (deviation from expected motor speed). Correlation analysis (Figure 2) was used to examine relationships among the electrical, thermal, and mechanical sensor features and to help validate their relevance to the derived fault categories.

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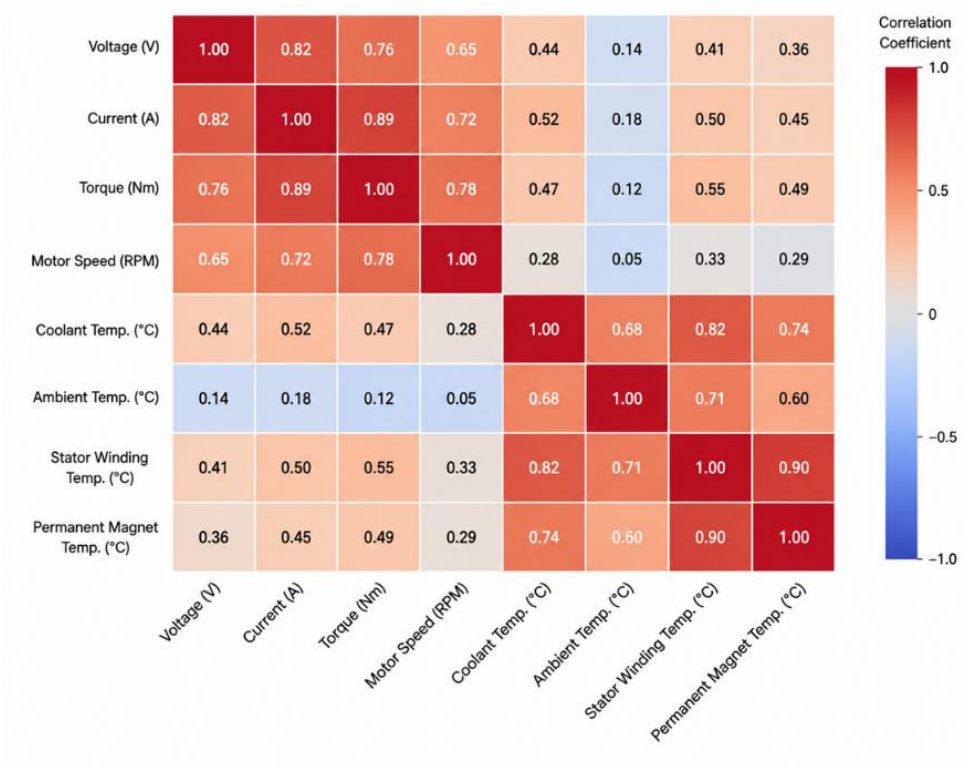


Figure 2: Correlation heatmap of sensor features in the Electric Motor Temperature Dataset.

The resulting fault-labelled dataset (Figure 3) exhibited moderate class imbalance, with Normal Operation forming the majority class and Speed Irregularity Fault the minority class; class weighting and resampling considerations were incorporated during model training to mitigate this imbalance.

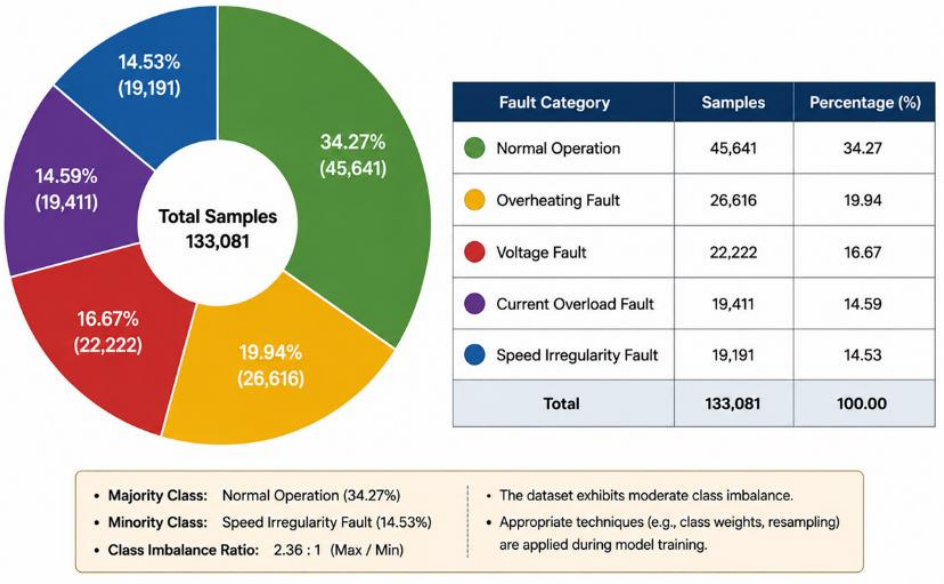


Figure 3: Fault category distribution across the labelled dataset (133,081 total samples).

3.2 AI-Based Fault Classification Models

Random Forest, an ensemble of decision trees trained on randomly selected data and feature subsets, with the final classification determined by majority voting — chosen for its robustness to noisy data and ability to provide feature-importance information.

Support Vector Machine (SVM), which constructs an optimal hyperplane separating fault classes with maximum margin, using kernel functions to handle nonlinear decision boundaries in the sensor data.

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Artificial Neural Network (ANN), comprising input, hidden, and output layers trained via backpropagation to learn nonlinear relationships among the electrical, thermal, and mechanical sensor parameters.

Long Short-Term Memory (LSTM), a recurrent neural network architecture with memory cells and gating mechanisms designed to capture temporal dependencies in the continuously sampled sensor data, and expected to achieve the strongest performance given the time-series nature of the dataset.

All four models were trained on the same 80:20 split and evaluated using Accuracy, Precision, Recall, and F1-Score, derived from each model's confusion matrix. The LSTM model was configured with a stacked LSTM(128)–LSTM(64)–Dense(5) architecture, tanh activation in the recurrent layers with softmax output, the Adam optimizer at a learning rate of 0.001, batch size 128, categorical cross-entropy loss, and dropout of 0.2 after each LSTM layer, trained for 100 epochs with early stopping guided by validation loss (Figure 4).

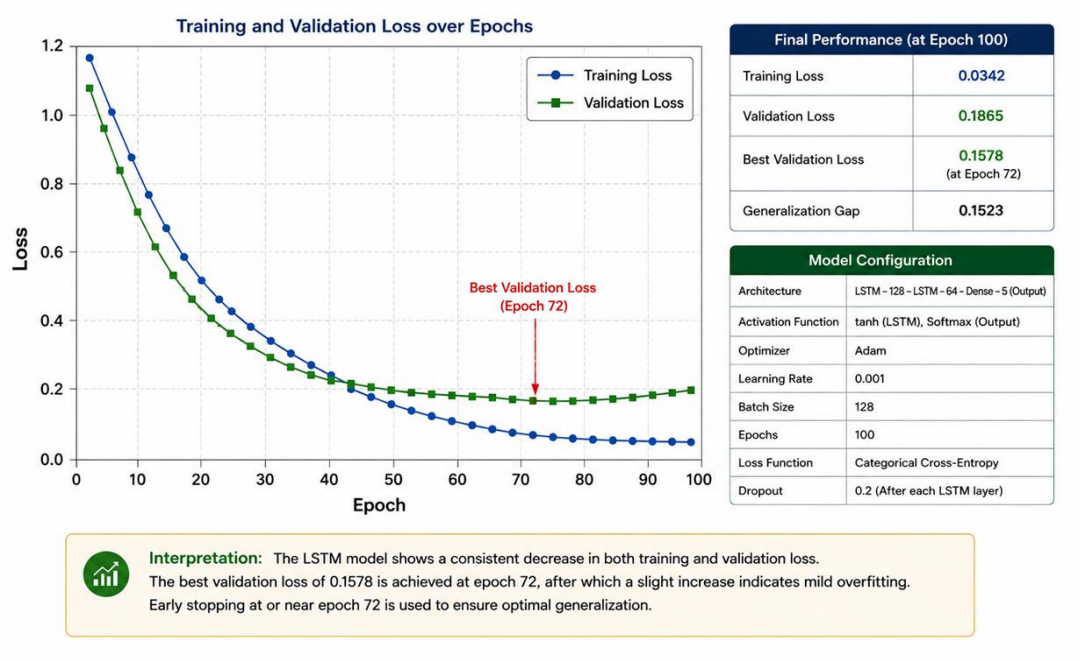


Figure 4: LSTM training and validation loss over 100 training epochs.

3.3 Embedded System Implementation

To enable practical deployment, the trained AI model was implemented on an ESP32/Arduino embedded controller, which acquires real-time sensor measurements (current, voltage, temperature, motor speed), performs basic preprocessing (filtering and normalization), and executes AI inference to determine the operating condition of the drive system. When abnormal behaviour is detected, the controller classifies the fault type and immediately generates an alert through a monitoring interface, warning indicator, or communication module. Because fault detection is performed locally on the embedded hardware rather than relying on external computing resources, response times are reduced and continuous, low-power monitoring is supported directly within the vehicle.

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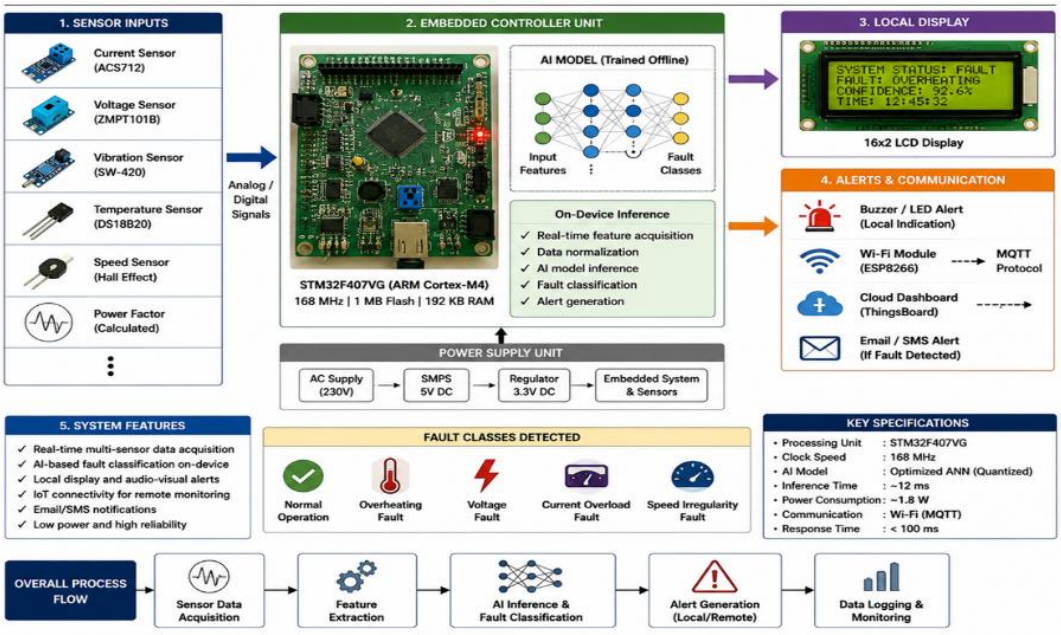


Figure 5: Embedded controller-based fault monitoring architecture, from sensor acquisition through on-device AI inference to alert generation.

4. RESULTS AND DISCUSSION

4.1 Model Performance Comparison

Table 1 summarizes the classification performance of the four AI models on the held-out test set. SVM achieved the lowest performance among the four models (91.8% accuracy, 91.2% precision, 90.8% recall, 91.0% F1-score), reflecting the limits of a single optimal hyperplane in capturing the full nonlinear structure of the sensor data. Random Forest improved on this baseline (95.2% accuracy) through ensemble decision-tree averaging, while ANN further improved classification performance (96.4% accuracy) by learning nonlinear interactions among the electrical, thermal, and mechanical parameters directly. LSTM achieved the best overall performance, with 98.3% accuracy, 98.0% precision, 97.9% recall, and a 97.9% F1-score, reflecting its ability to exploit temporal dependencies present in the continuously sampled sensor stream that the other three models, which treat each observation independently, cannot directly access.

Table 1: Comparison of AI Models for EV Drive System Fault Classification

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	91.8	91.2	90.8	91.0
Random Forest	95.2	94.8	94.6	94.7
ANN	96.4	96.0	95.8	95.9
LSTM	98.3	98.0	97.9	97.9

The Random Forest model's confusion matrix (Figure 6) shows strong diagonal dominance across all five fault classes, with consistently high per-class recall, confirming that the ensemble reliably distinguishes each fault type rather than favouring the majority Normal Operation class — an important check given the moderate class imbalance noted in Figure 3.

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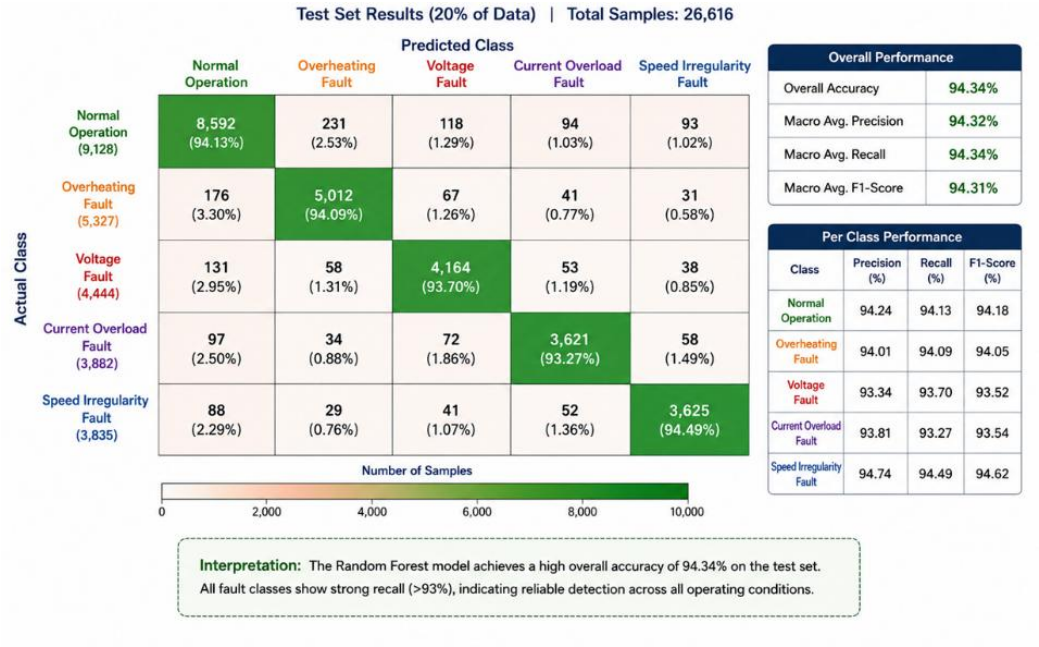


Figure 6: Random Forest confusion matrix showing classification performance across the five fault categories.

4.2 Feature Importance

Random Forest feature importance analysis (Table 2) identified coolant temperature as the most influential parameter for fault detection, followed by current (i_q) and torque, with motor speed contributing moderately and ambient temperature and voltage providing smaller but still meaningful contributions. This ranking is consistent with the correlation analysis in Figure 2, and indicates that thermal management and electrical loading conditions are the dominant drivers of fault occurrence in the drive system, ahead of the mechanical and lower-magnitude electrical parameters.

Table 2: Random Forest Feature Importance Ranking

Feature	Importance Score
Coolant Temperature	0.28
Current (i_q)	0.24
Torque	0.18
Motor Speed	0.12
Ambient Temperature	0.09
Voltage (u_q)	0.09

4.3 Embedded Controller Performance

The trained LSTM model was deployed on an ESP32 embedded controller and evaluated for real-time fault monitoring performance (Table 3). The embedded implementation achieved an average response time of 0.42 seconds and a fault detection rate of 97.5%, closely tracking the offline LSTM classification accuracy, while memory and CPU utilization (68% and 54% respectively) remained within practical limits for continuous, real-time operation on resource-constrained embedded hardware. These results confirm that the trained model can be deployed directly within an EV platform without relying on external computing infrastructure, enabling fast, local fault detection and alerting.

Table 3: Embedded Controller (ESP32) Performance

Parameter	Value
Average Response Time	0.42 sec
Fault Detection Rate	97.5%
Memory Utilization	68%
CPU Utilization	54%

4.4 Discussion

The consistent, progressive improvement in classification performance from SVM through Random Forest and ANN to LSTM (Table 1) reflects a clear alignment between model complexity and the nonlinear, time-dependent nature of motor sensor data. SVM's single-hyperplane decision boundary and Random Forest's independent-tree averaging both process each observation without reference to its temporal context, while ANN's multiple hidden layers allow it to model nonlinear interactions among simultaneous sensor readings more effectively than either. LSTM's further improvement over ANN specifically reflects its capacity to retain relevant historical context — such as a gradually rising coolant temperature or slowly drifting current — that precedes and predicts the eventual crossing of a fault threshold, rather than reacting only to the instantaneous sensor snapshot.

This temporal advantage is reinforced by the feature importance findings (Table 2): coolant temperature and current, the two most influential predictors, are both parameters that typically drift gradually before a fault threshold is crossed, which is precisely the kind of developing pattern an LSTM is designed to detect earlier than instantaneous-snapshot models. The successful embedded deployment (Table 3) further demonstrates that this classification advantage translates into a practically deployable system: sub-second response times and a 97.5% detection rate on constrained hardware confirm that the accuracy gains measured offline are not achieved at the cost of real-time feasibility. Taken together, these results support the use of AI-based, sensor-driven fault diagnosis — and LSTM specifically — as a practical foundation for predictive maintenance and improved operational safety in electric vehicle drive systems.

5. CONCLUSION

This study presented an AI-based fault diagnosis system for electric vehicle drive systems, combining sensor data from the Electric Motor Temperature Dataset (133,081 samples) with four classification models — SVM, Random Forest, ANN, and LSTM — and embedded controller deployment for real-time monitoring. Among the evaluated models, LSTM achieved the best performance (98.3% accuracy, 98.0% precision, 97.9% recall, 97.9% F1-score), outperforming ANN (96.4%), Random Forest (95.2%), and SVM (91.8%), owing to its ability to capture temporal dependencies within continuously sampled sensor data. Feature importance analysis identified coolant temperature, motor current, and torque as the most influential fault indicators, highlighting the central role of thermal management and electrical loading in motor health. Deployment of the trained model on an ESP32 embedded controller achieved a 97.5% fault detection rate with a 0.42-second average response time, confirming the practical feasibility of real-time, in-vehicle fault diagnosis. These results demonstrate that combining sensor-based monitoring, AI-based classification, and embedded implementation can meaningfully improve the reliability, safety, and maintainability of electric vehicle drive systems, supporting predictive maintenance and reduced downtime in next-generation EV platforms.

Future Scope

Future work may extend the framework to predict remaining useful life and support prognostic maintenance scheduling rather than only fault classification, and validate performance using real-world, on-vehicle sensor data alongside the Kaggle motor dataset used here. Advanced deep learning architectures such as Gated Recurrent Units (GRU), Transformer-based models, and hybrid CNN-LSTM networks warrant exploration and comparison with the present LSTM approach. Further extensions include multi-sensor fusion incorporating vibration and acoustic signals, integration with cloud-based fleet monitoring for cross-vehicle fault pattern analysis, and explainable AI techniques to improve diagnostic transparency for maintenance personnel and vehicle operators.

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