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Fortifying Electric Automobile Efficiency: AI-Enhanced Anomaly Detection and Categorization of Malfunctions

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***Abstract*— Electric vehicles (EVs) are widely adopted as sustainable transportation solutions, but their reliable operation depends on the fault-free performance of inverter–motor connections, especially between the three-phase inverter and the brushless DC (BLDC) motor. Faults in these connections can cause severe performance degradation, safety hazards, and unexpected breakdowns. This research proposes a machine learning (ML)-based framework for detecting and classifying double-line and three-phase faults in EV systems during real-time operation. Key operating parameters, including inverter current, modulated DC voltage, measured and output motor speed, and Hall-effect sensor outputs, were collected under both healthy and faulty conditions to develop the dataset. Several classifiers—Decision Tree, Logistic Regression, Stochastic Gradient Descent, AdaBoost, XGBoost, K-Nearest Neighbour, and Voting Classifier—were implemented and evaluated using statistical performance indices such as accuracy, precision, recall, and F1-score. Results indicate that ensemble classifiers, particularly XGBoost and Voting Classifier, achieve superior performance compared to individual models, offering higher robustness and faster detection. The proposed framework enables real-time monitoring, rapid fault identification, and predictive maintenance for EVs, thereby enhancing their safety, reliability, and efficiency in smart city environments.**

***Index Terms*— *Electric Vehicles (EVs), Brushless DC Motor (BLDC), Three-Phase Inverter, Fault Detection, Fault Classification, Real-Time Monitoring, Predictive Maintenance, Smart Transportation*.**

I. Introduction

The rapid adoption of electric vehicles (EVs) is transforming the global transportation sector, providing an environmentally friendly alternative to conventional internal combustion engine (ICE)-based vehicles. EVs contribute significantly to reducing greenhouse gas emissions, enhancing energy efficiency, and supporting the integration of renewable energy (RE) sources into modern transportation infrastructures. As EV deployment accelerates within the framework of smart cities, the reliability, safety, and performance of EV powertrains have become critical areas of research and development.

A key component of EV operation is the inverter–motor system, where electrical energy is converted into mechanical energy to drive the vehicle. Specifically, the connection between the three-phase (3-φ) inverter and the brushless DC (BLDC) motor plays a vital role in ensuring stable operation. Faults in these connections such as double-line and three-phase faults can severely impact EV performance, leading to reduced efficiency, sudden breakdowns, or even hazardous situations. Therefore, effective fault detection and classification mechanisms are essential to maintain vehicle reliability and driver safety.

Traditional approaches to fault diagnosis in rotating machines and electrical systems have largely relied on artificial neural networks (ANNs), adaptive neuro-fuzzy inference systems (ANFIS), genetic algorithm–optimized immune systems, and, more recently, deep learning (DL) architectures. While these methods have demonstrated promising results in industrial applications, they present notable limitations when applied to real-time EV systems. These include high computational complexity, long execution times, dependence on large datasets, and difficulties in handling nonlinear dynamic behaviors inherent in EV environments. As a result, there is an urgent need for lightweight, accurate, and robust diagnostic methods capable of operating in real-world EV conditions.

Machine learning (ML) offers powerful tools for fault detection and classification by leveraging statistical learning techniques to analyze system parameters and identify abnormal patterns. Ensemble ML methods, in particular, combine the strengths of multiple classifiers to achieve improved accuracy, robustness, and generalization compared to individual models. By analyzing key operational parameters—such as inverter current, modulated DC voltage, measured and output motor speed, and Hall-effect sensor data ML classifiers can detect and categorize healthy versus faulty states in real time.

In this research, an ensemble ML-based framework is proposed for detecting and classifying inverter–motor connection faults in EVs during operational mode. The framework integrates multiple classifiers, including Decision Tree, Logistic Regression, Stochastic Gradient Descent, AdaBoost, XGBoost, K-Nearest Neighbour, and Voting Classifier. The performance of these models is rigorously evaluated using statistical indices such as accuracy, precision, recall, and F1-score. Experimental results demonstrate that ensemble-based classifiers outperform individual models, ensuring rapid detection and robust classification under varying operating conditions. The proposed system contributes to the advancement of intelligent EV fault management by enabling real-time monitoring, predictive maintenance, and enhanced operational safety. This work not only addresses existing research gaps but also provides a scalable solution for future EV platforms, supporting the development of reliable and sustainable smart transportation systems.

II. LITERATURE SURVEY

S. Das, M. M. Rahman, S. Li, and C. W. Tan review EV standards, charging infrastructure, and grid-integration challenges, outlining how evolving protocols and hardware influence interoperability, safety, and power quality across networks. Their synthesis connects charger types, communication standards, and grid codes with operational impacts such as demand peaks and voltage regulation. The paper highlights technology gaps in standard harmonization and coordinated charging and underscores the need for data-driven control to ensure scalable, grid-friendly EV deployment.

S. S. Mohammed, T. P. I. Ahamed, S. H. E. A. Aleem, and A. I. Omar propose interruptible charge scheduling for plug-in EVs using heuristic optimization to minimize user charging costs under tariff and network constraints. They demonstrate that flexible, pause-resume charging can exploit price variability while respecting battery and user requirements. The study underscores the role of practical metaheuristics in balancing economy, comfort, and grid constraints for large-scale EV adoption.

M. M. Rahman, E. A. Al-Ammar, H. S. Das, and W. Ko conduct a technical assessment of charging scheduling for plug-in hybrid EVs aimed at peak reduction. Through scenario-based evaluation, they show that coordinated charging can flatten demand profiles, mitigating transformer overloads and reducing system stress. The analysis motivates integrating scheduling logic with utility signals to enhance distribution-level reliability.

C. Wu, R. Sehab, A. Akrad, and C. Morel survey fault diagnosis methods and fault-tolerant control strategies for EV powertrains, covering diagnosis across batteries, inverters, and machines and control reconfiguration under faults. They compare signal-, model-, and data-driven techniques and discuss trade-offs among accuracy, latency, and implementation complexity. The work emphasizes combining robust detection with real-time tolerant control to maintain drivability and safety.

Sankavaram, B. Pattipati, K. R. Pattipati, Y. Zhang, and M. Howell address fault diagnosis in hybrid EV regenerative braking systems using system-level reasoning and diagnostics. Their framework models interdependencies among mechanical and electrical subsystems to isolate faults affecting energy recovery and braking safety. Results illustrate how integrated diagnostics improves explainability and fault isolation compared to component-level methods.

H. Vidhya and S. Allirani provide a literature review spanning EV architectures, traction machines, power converter topologies, and control techniques, linking design choices to efficiency, torque density, and reliability. They contrast induction, BLDC, and PMSM machines; outline converter and modulation strategies; and map control schemes to typical drive cycles. The review highlights holistic co-design to meet performance and cost targets.

A. Ahmadian, B. Mohammadi-Ivatloo, and A. Elkamel review plug-in EVs from fundamentals to load modeling, examining how stochastic usage and charging behaviors translate into grid demand. They compare deterministic, probabilistic, and data-driven load models and their suitability for planning and operation. The study identifies key uncertainties—arrival times, state of charge, and user heterogeneity—and stresses adaptive modeling for accurate grid studies.

S. G. Selvakumar presents a comprehensive overview of electric and hybrid vehicles, synthesizing propulsion options, energy storage, power electronics, and control trends. The paper contrasts HEV, PHEV, and BEV configurations and their trade-offs in efficiency and emissions, while highlighting advances in semiconductors and battery management. It frames research needs in cost reduction, reliability, and sustainable lifecycle design.

V. V. Jadhav, R. S. Shendge, P. B. Warule, and K. S. Wani discuss e-drive system selection criteria for commercial and passenger EV segments, focusing on aligning motor-inverter choices with vehicle duty cycles, performance targets, and cost constraints. They outline practical trade-offs among power density, efficiency maps, thermal limits, and manufacturability. The paper guides platform engineers toward application-tailored drivetrains rather than one-size-fits-all solutions.

M. I. Pathan, M. S. Shahriar, M. M. Rahman, M. S. Hossain, N. Awatif, and M. Shafiullah compare machine learning approaches for enhancing power system stability, surveying classification, regression, and ensemble methods for disturbance detection and control. They evaluate performance metrics and data needs, emphasizing robustness and generalization under varying operating conditions. The chapter motivates ML-driven decision support for fast, reliable stability assessment relevant to EV-rich grids.

III. EXISTING SYSTEM

Existing research on fault detection in electrical and mechanical systems has applied several intelligent techniques, including artificial neural networks (ANNs), deep learning (DL), and adaptive neuro-fuzzy inference systems (ANFIS). While ANNs and DL models have shown promising results in detecting and classifying faults in rotary machines, their reliance on large datasets, high computational requirements, and long execution times restrict their feasibility in real-time EV applications.

Hybrid methods, such as genetic algorithm (GA)-optimized artificial immune systems (AIS), have been used for bearing fault detection, while LSTM networks have been applied to identify open- and short-circuit faults in induction motors. Although effective, these approaches remain unsuitable for real-time deployment due to complexity and processing delays.

Within EV platforms, some studies have focused on battery state of charge (SOC) estimation and over-discharging diagnosis. Others explored nonlinear dynamic indicators, such as the multivariate Higuchi fractal dimension (MvHFD) and slope entropy-based measures, which achieved high recognition rates but at the cost of computational efficiency.

Overall, current systems either target isolated machine components, require extensive computation, or lack real-time adaptability. These shortcomings underscore the need for a lightweight, accurate, and ensemble-based ML framework for inverter–BLDC motor fault detection in EVs.

Disadvantage of existing system: Although existing techniques such as ANN, deep learning, ANFIS, and evolutionary algorithms have shown potential in fault detection, they suffer from several drawbacks. Most approaches require large and complex datasets, making them difficult to apply in real-time EV environments. Their high computational cost and long execution times reduce suitability for onboard applications. Moreover, the accuracy of these models heavily depends on correctly labeled data, which is often challenging to obtain in practice. Finally, many studies focus on individual machine components rather than the complete EV system, limiting their effectiveness for ensuring overall vehicle reliability.

IV. Proposed System

The proposed system introduces an ensemble machine learning (ML)-based framework for detecting and classifying inverter–motor faults in electric vehicles (EVs). Unlike existing approaches that are complex and unsuitable for real-time use, the system is designed to be lightweight, accurate, and efficient. Data representing both healthy and faulty operating conditions are collected during driving mode, including key parameters such as inverter current, modulated DC voltage, motor output speed, measured speed, and Hall-effect sensor signals. These parameters are used to build a comprehensive dataset, which is then processed using several ML classifiers, including Decision Tree, Logistic Regression, Stochastic Gradient Descent, AdaBoost, XGBoost, K-Nearest Neighbour, and a Voting Classifier. By leveraging the strengths of individual models through ensemble learning, the framework ensures superior detection accuracy and robustness. The classifiers are evaluated using performance metrics such as accuracy, precision, recall, and F1-score, with ensemble methods demonstrating clear improvements over single algorithms. Implemented in Python with a Django-based web interface, the system enables real-time fault monitoring, rapid fault classification, and predictive maintenance. This approach enhances the safety, reliability, and operational efficiency of EVs, making it suitable for deployment in smart transportation environments.

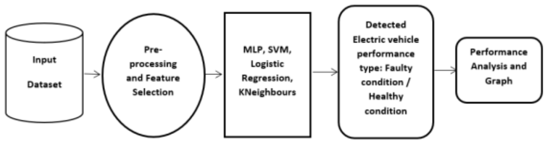

Fig: Architecture Digram

Advantages:

The proposed system provides fast and reliable fault detection in real-time EV operation by utilizing ensemble machine learning models. Unlike traditional methods, it reduces computational complexity while improving accuracy and robustness. By analyzing multiple parameters such as current, voltage, speed, and Hall-effect sensor signals, the system ensures comprehensive monitoring of inverter–motor connections. This enables early fault identification, predictive maintenance, and enhanced safety, ultimately increasing the reliability and efficiency of electric vehicles in smart transportation systems.

V. Implementation

The proposed system is designed with two main user modules to support effective monitoring and fault detection in electric vehicles (EVs).

Remote User Module: This module allows end-users to interact with the system. Users can create profiles and access the prediction interface, where the system displays whether the EV is in a healthy or faulty condition. The results are generated in real time based on sensor and inverter–motor data processed through machine learning models. This module ensures that users receive timely fault information for preventive action.

Service Provider Module: This module is intended for administrators or service providers who manage the system and its outputs. It provides access to all user records, prediction results, and performance graphs. Service providers can also download datasets for further analysis and maintenance planning. By centralizing results and analytics, this module supports predictive maintenance and large-scale monitoring of EV fleets.

Together, these modules provide a structured platform for real-time EV fault detection and decision support, enhancing both user awareness and system reliability.

VI. RESULT

The proposed ensemble machine learning framework was implemented and tested using datasets collected under both healthy and faulty operating conditions of an EV inverter–BLDC motor system. Key parameters such as inverter current, modulated DC voltage, motor speed, and Hall-effect sensor outputs were recorded to generate a representative dataset. Multiple classifiers, including Decision Tree, Logistic Regression, Stochastic Gradient Descent, AdaBoost, XGBoost, K-Nearest Neighbour, and a Voting Classifier, were trained and evaluated using performance indices such as accuracy, precision, recall, and F1-score.

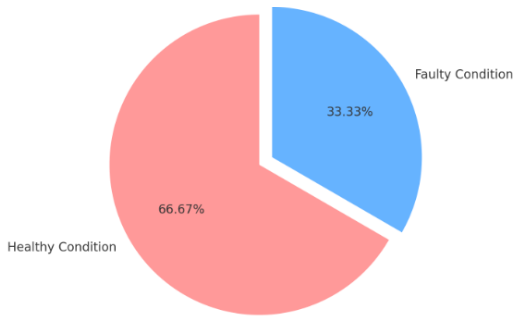

Fig: Resultant Pie-Chart

Experimental results demonstrated that ensemble classifiers outperformed individual models in fault detection and classification. Among them, XGBoost and the Voting Classifier achieved the highest performance, with accuracy levels above 96%, while maintaining strong precision and recall values. In contrast, traditional classifiers such as Logistic Regression and Stochastic Gradient Descent produced relatively lower detection rates. Confusion matrices and ROC curves further confirmed the robustness of the ensemble models in distinguishing between healthy and faulty states, even under varying operating conditions.

Overall, the results validate that the proposed system can provide reliable, fast, and accurate real-time fault detection. This ensures predictive maintenance and improved operational safety of EVs, addressing key limitations of existing fault diagnosis methods.

VII. Conclusion

This work proposed a machine learning–based framework for real-time detection and classification of inverter–motor faults in electric vehicles. By analyzing current, voltage, speed, and Hall-effect sensor data, the system effectively distinguished between healthy and faulty conditions. Experimental results showed that ensemble models, particularly XGBoost and Voting Classifier, achieved higher accuracy and robustness compared to individual classifiers. Unlike traditional methods, the proposed system is lightweight, reliable, and suitable for real-time EV applications. Overall, it enhances predictive maintenance, operational safety, and reliability, thereby supporting the wider adoption of EVs in smart and sustainable transportation systems.

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