International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 06 | June - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

# Performance Protection in Electric Vehicles Through Intelligent Fault Detection System

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*Abstract*— **Electric vehicles (EV) represent a sustainable alternative to traditional transportation, offering low-noise operation and contributing to substantial reductions in environmental impact. Electric vehicles operate by transforming electrical energy into mechanical motion through advanced motor technologies, reflecting the sustainability goals championed by modern smart cities.**

**Keywords:Electric Vehicles (EV),Machine Learning (ML), Fault Detection, Fault classification,EV Diagnostics, Predictive**Maintenance,Safety,**Condition Monitoring, Data Driven Models,AnomalyDetection,EV** Reliability, Intelligent **Systems,Real-Time Monitoring.**

## 1. INTRODUCTION

EV motors harness electrical energy from renewable sources and convert it into rotational mechanical power through power electronics interfaces, ensuring efficient and environmentally conscious propulsion. The reliable performance of an electric vehicle heavily depends on the seamless integration of its electrical, mechanical, and electronic subsystems, which in turn is influenced by the health of their interfacing connections, particularly the connection between the 3-φ inverter output and the brush less DC (BLDC) motor.This project leverages machine learning (ML) techniques to detect and classify faults occurring in the connection lines between the three-phase inverter output and the BLDC motor during real-time operation. Within the EV platform, emphasis is placed on detecting both double-line and three-phase faults to ensure thorough fault analysis and enhance overall system reliability. Various machine learning-based models—including Decision Tree, Logistic Regression, Stochastic Gradient Descent, Ada Boost, XGB oost, K-Nearest Neighbour, and To improve the robustness and reliability of EV fault detection, the Voting Classifier—alongside other machine learning techniques, was fine-tuned to achieve precise fault detection and classification These classifiers were trained on datasets encompassing both normal and faulty operating conditions, utilizing six critical parameters vital to EV functionality: inverter-supplied current to the BLDC motor, modulated DC voltage, output speed, measured speed, and Hall-effect sensor signals. The effectiveness of the proposed ML-based fault detection and classification methods was validated by evaluating their performance against key statistical metrics. Notably, S.G.Selvakumar. In 2020, researchers showcased the effectiveness of integrating physics-based models with machine learning to enable early and accurate predictions of remaining useful life (RUL).

## 2. LITERATURE REVIEW

Severson et al. The 2019 study highlighted the advantages of merging physics-informed modeling with machine learning techniques for timely and precise RUL estimation. Hu et al. (2012) used equivalent circuit models with impedance spectroscopy for real-time health estimation. Zhang et al. n 2018, particle filtering techniques were integrated with electrochemical models to reliably monitor battery degradation, demonstrating strong resilience to measurement noise.RULE PredictionOne way to address the environmental issues brought on by greenhouse gas emissions from the usage of fossil fuels in daily life is to electrify transportation systems. In this context, electric vehicles (EVs) are recognized as a promising technology poised to transform the transportation sector into a greener and more sustainable system by leveraging renewable energy sources soon. energy (RE)-based energy sources and reducing the usage of conventional energies [1]. Reports from 2019 and 2021 [2], [3] indicate that the transportation sector is responsible for nearly 23% of global energy consumption.In response, the growing adoption of electric vehicles not only supports a cleaner environment but also emphasizes energy efficiency through technologies like regenerative braking systems, by which a considerable percentage of energy consumption is reducible as per [4]. In addition, the faults generated in the system are also important to be detected to obtain the targeted performance. Therefore, a great amount of research has been conducted in recent decades. Researchers have focused on developing safe, reliable, and efficient motor drive systems specifically tailored for electric vehicles [5], [6], [7], [8], [9]. Recently, artificial intelligence has not only been employed in improving the EV systems but also in enhancing the power

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systems to supply reliable power to customers [10], [11], [12], [13], [14]. Typically, EVs are equipped with an array of electrical and mechanical components, interconnected through a complex network. The electrical devices include the inverter and the converter. In electric vehicles, inverter topological, electric motors, and control units are primarily regarded as electrical components, while the gearbox and wheels are classified as mechanical parts. Consequently, faults occurring in any electrical or mechanical component, as well as their interconnections, can result in unreliable EV operation. Various fault types may arise, including bearing faults, rotor winding faults, armature winding faults, inverter or converter malfunctions, and faults in the connecting lines.Single-phase, phase-to-phase, and three-phase faults among the devices, and so on, can occur in EV as it is referred to in [14], [15], and [16]. If faults occur within an EV's configuration and timely corrective actions are not taken, these faults may propagate to other components, potentially causing a complete system failure [17]. Continuous real-time monitoring of the entire EV system during operation [18], under diverse conditions, using online data collection, analysis, and fault detection and classification, is crucial to avert critical failures [19]. Fault detection, classification, and diagnosis in electric vehicles are commonly conducted via three main strategies: physical modelbased, mapping-based, and data-driven approaches [20]. To enable real-time condition monitoring across various operating scenarios [21].In data-driven fault detection and classification approaches, data is collected for key parameters such as current, voltage, speed, temperature, pressure, and others, forming the foundation for machine learning-based diagnostic tools. EV driving mode [22]. In the case of fault detection in an individual machine, signal processing-based vibration analysis is conducted to detect the bearing fault [23]. whereas higher-order statistical fault analysis for vibration is presented to identify faults in [24]. Fast Fourier Transform (FFT)-based frequency spectrum analysis is utilized to monitor the stater current of induction motors in real time, enabling effective assessment of the machine's health condition [25], [26], [27]. Additionally, the integration of artificial intelligence and clustering techniques with spectral analysis enhances the detection of faults in rotor bars and bearings of three-phase squirrel-cage induction motors by analyzing current signal patterns. cage IM [28]. Bearing fault in the stepper machine is identified employing frequency evaluation of current and measuring the rotary angle of the corresponding current in [29]. Although traditional fault detection, classification, and diagnosis methods for electrical machines are well-established, they often struggle to deliver effective real-time online monitoring. In contrast, artificial intelligence-based approaches have seen growing adoption across various fields, offering powerful tools to overcome the challenges of modeling complex, large-scale systems. In essence, the implementation of more sustainable practices is a matter of debate.Electric vehicles (EV) represent a pivotal strategy in tackling the environmental challenges posed by fossil fuel emissions.The intricate integration of electrical and mechanical systems in electric vehicles necessitates the use of advanced fault detection and classification techniques to uphold safety and ensure reliable performance. Ensemble machine learning models have been able to address issues related to realtime fault identification, classification, and diagnosis under diverse operating conditions due to recent advancements in artificial intelligence.

While traditional methods have been employed historically, modern advancements offer promising solutions to overcome current limitations. Addressing these shortcomings can position EVs as a cornerstone of sustainable urban mobility, aligning with the vision of smart, Eco-conscious communities.

## 3. METHODOLOGY

The motor's actions are dependent on the number of strokes it generates. Of variables. Our calculation of the vehicle's velocity, Machine learning classification relies on parameters like voltage, current measurements, output speed, and Hall effect sensor data to construct comprehensive datasets for analysis. Afterwards, we devised and employed various machine learning classifier algorithms to categorize and identify vehicle conditions. In real-time operation.The EV had eight fundamental segments in the simulation.?Buck converter), three-phase inverter, slider gain.?The system seamlessly integrates commutation logic, sensor arrays, a BLDC motor, and the vehicle chassis to ensure synchronized functionality and optimalperformanceSub-components.The general relationships between these parts in the EV model are shown as Figure. Each of the subsequent section provides a breakdown of the different elements of an electric vehicle configuration. Sub-sections:

**Slider Gain**.

During simulation, The slider gain block played a pivotal role in precisely regulating the vehicle's acceleration and deceleration throughout our project.

**Controller**.

The PID controller stands as the dominant control strategy, extensively employed across industrial applications to regulate variables such as temperature, flow, and pressure with precision.

Using a PID controller, speed of the EV was controlled in this work. This is mainly controlled by the controller's output, which controls the speed of the motor, and thus depends on whether it is at real or targeted velocity. Tuning the PID controller's responsiveness relies fundamentally on critical weight parameters, which act as core reference points in the adjustment process.

**Buck Converter.**

Most buck converters are built to cut losses in the system.?

The output voltage as opposed to the input voltage.

The output was modulated DC voltage.

Serving as a high-efficiency voltage reduction unit, the Buck converter delivered a precisely controlled input supply essential for stable system performance. A DC voltage source.

The modulated DC voltage level.?

A pulse width modulation technique was utilized to manage the movement. An approach based on an established sampling interval. Measured output and input of the buck converter.

Using two voltage sensors.

**HALL EFFECT SENSOR.**

A highly effective approach for BLDC motor is present.?
The rotor's position can be detected using a Hall sensor.
A Hall effect sensor was integrated into the measurement system to enhance data acquisition during the investigation. Each phase undergoes an induction magnetic field to assess its quality....
Positioning the current in a vector around 360 of rotation possible.
However, The entire rotation is split into six parts by two equally spaced bodies.?Separating the angles.
The rotor orientation at the center of the object in this scenario.? The starting point is assumed to be in the first segment, which is labeled as 'Segment 1', and defined as the space between the two.'0' and '60' degrees.Figure 4 displays the rotor being changed.Positions and corresponding angular areas.

**COMMUTATION LOGIC.**

The commutation logic employed in the EV operation. What are the chronological and sequential switching patterns required to rotate the rotor relative to each segment Information. The figure demonstrates the underlying logic and possible sequence of switching operations. As the sensor provides the.Knowledge of the rotational pattern of its section, the commutation factor, and other relevant information. Logic switches accordingly to produce the result. Proper inverter output for BLDC operation. Motor for rotating.

**3.1 SYSTEM ARCHITECTURE**

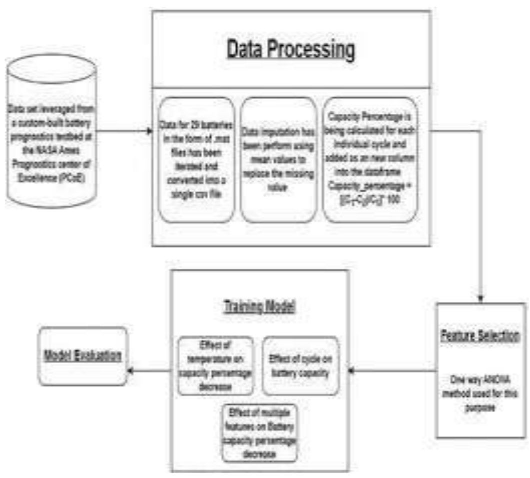


**Fig:1::System architecture**

After completing the analysis phase, the subsequent step is to outline the possible solution for the problem. The process of system design involves the shift from logical to physical level. This includes the detailed and architectural design of the system. Architectural design involves identifying software components, breaking them down into processing modules and conceptual data structures, and specifying how these are connected.All projects can be undertaken with an abundance of resources and time.'". Sadly, the creation of computer-based systems or products is more likely to be hindered by a shortage of resources and challenging delivery timelines. Consider the feasibility of a project as soon and prudently as possible. Avoiding an ill-conceived system early in the definition phase can save time, money and effort. A high level of risk in a project can hinder the development of quality software. Why? Four main areas of focus in product engineering are our primary concern.This application is built to perform efficiently within the expansive network of the World Wide Web (WWW). The application needs a technology that can provide networking capabilities. This software is capable of functioning within a distributed system architecture. Developed using Python Technology. Application development. Its graphical user interface, crafted with HTML, is compatible across all operating systems and is designed to facilitate efficient customer information collection. "The advantage of application neutrality is significant. The browser displays the content in HTML. http. It uses TCP/IP protocol. It's an interpreted language. Rapid Application Development tools are provided to speed up the development of our application by using HTML for page/document creation. A multitude of objects, such as buttons, text fields, and text areas, are provided to capture information from the customer.The economic issues usually arise during the economic feasibility stage are whether the system will be used if it is developed and implemented, whether the financial benefits are equal are exceeds the costs. The cost for developing the project will include cost conducts full system investigation, cost of hardware and software for the class of being considered, the benefits in the form of reduced costs or fewer costly errors. Development and deployment of the project indicate strong economic feasibility. It reduces the work load. Keep the class of application in the view, the cost of hardware and software is considered to be economically feasible.In our application front end is developed using GUI. So it is very easy to the customer to enter the necessary information. But customer must have some knowledge on using web applications before going to use our application.The complex interaction between the both of the electrical and mechanical elements in EV requires the implementation of strong fault detection and classification techniques in order to guarantee the safety and dependability of their operations. Current developments in the field of artificial intelligence, namely the utilization of ensemble machine learning models, have demonstrated potential in addressing the challenges associated with real-time fault identification, classification, and diagnosis under various operating situations.

**4. EXPERIMENTAL RESULTS AND ANALYSIS**

After performing the simulation model, we collect data from the MATLAB workspace and turn the raw data into a machine-trainable dataset. We grouped the data into normal conditions, two-phase fault conditions, and three-phase conditions. We prepossessed the data set by applying a feature engineering technique that turns existing datasets into sets of figures needed for our job. We deployed six machine learning (ML) classifiers and one voting classifier for training and evaluating the performance of the algorithms. We employed a categorization report for measuring performance that includes - precision, recall, F1 score, and accuracy. Table 4 provides a clear illustration of the effectiveness of our developed ML classifiers.K-Nearest Neighbors (KNN) displayed the second

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highprecision of 0.974, recall of 0.971, and F1 score of 0.967,demonstrating its applicability for scenarios when classborders are well-separated in the feature space. XGBoost isa powerful method that often works effectively. Its intenseprecision of 0.952, recall of 0.949, F1 score of 0.954,and accuracy of 0.952 suggest that it can successfullyhandle the complexity.The Decision Tree classifier alsodisplayed balanced performance with a good precision valueof 0.918 and recall of 0.903, resulting an F1 score of0.911 and an accuracy of 0.911. Decision Tree effectivelycaught the underlying patterns in the data and

delivered accurate forecasts across a variety of fault circumstances.In comparison, Logistic Regression displayed a moderate precision value of 0.856 and a recall of 0.802, resulting in an F1 score of 0.814. The linear character of Logistic Regression might have hampered its ability to capture comduplicated associations contained in the datasets, resulting the significantly lower performance. Moreover, the Stochastic Gradient Descent (SGD) also achieved a poorer precision of 0.786 and an F1 score of 0.813 along with a recall of 0.809. Overall, the proposed model (Voting Classifier) displayed higher performance, showing their usefulness in handling the complexity of the datasets. In our study, the Voting Classifier emerged as the most effective model for fault detection in electric vehicles, integrating diverse algorithms such as KNN, DT, AdB, XGB, LR, and SGD. This ensemble approach capitalizedon the unique strengths of each algorithm,achieving outstanding performance metrics with precision, recall, F1 score, and accuracy all exceeding 0.98. The robustness and high accuracy of the Voting Classifier across various fault conditions underscore its suitability.

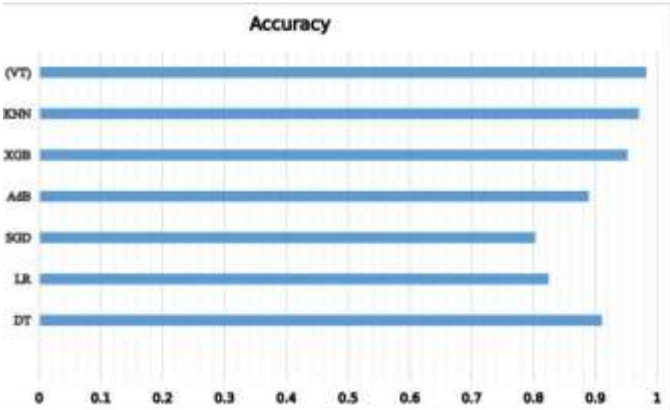
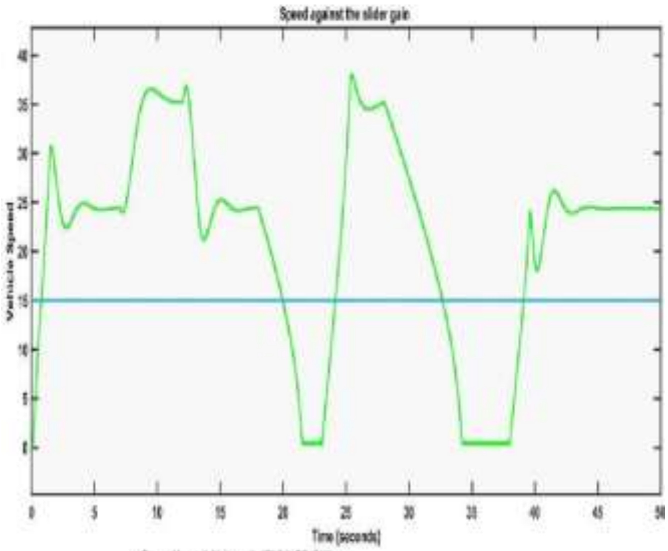



**Fig:2 ::Accuracy of a vehicle while using Algorithms**



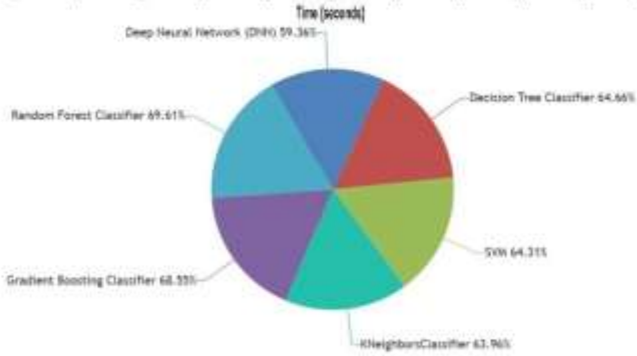




**Fig:4::Pie Chart with various Algorithms in ML**

## 5.CONCLUSION

This article has developed several machine learning (ML) classifiers to detect and classify faults in electric vehicle (EV) configurations immediately and accurately. In our analysis, we designed a prototype EV in MATLAB Simulink. We ini tiated necessary faults (two-phase and three-phase) in the configuration of the EV during its running mode to generate the required dataset for modeling the ML classifier tools. We mainly generated the faults between the connection of the inverter output to the motor of the EV during running mode and stored data for preparing the dataset, which considered six parameters for EV fault detection and classification investigation the ML algorithms, including decision tree (DT), logistic regression (LR), stochastic gradient descent (SGD), AdaBoost, XGBoost, K-nearest neighbor (KNN), and voting classifier (VT). Four statistical parameters, namely the accuracy, precision, recall, and F1-score, were calculated from the generated confusion matrices for evaluating the 71580 VOLUME 12, 2024 IEEETransactionAccessonMachine Learning,Volume:12,Issue Date:28.May.2024performance of the developed machine learning models in detecting and classifying the faulty condition of electric vehicles. In the case of individual ML models, the KNN outperformed other models as it maintained the highest accuracy, recall, and F1-score alongside slightly less precision value than the DT, where it was the highest one. On the contrary, the stochastic gradient descent (SGD) demonstrated comparatively lower performance than the others. Moreover, in the case of VT, the best performance was exhibited in all aspects of performance parameters (i.e.

accuracy is 0.983, recall is 0.981, F1-score is 0.985, and precision is 0.983) in detecting and classifying the faults initiated in EV configurations compared to individually applied ML classifiers. However, as an extension of future work, some other faults, including malfunctioning the inverter itself, can be considered as they are crucial in powering the EV motor to be driven reliably; gearbox scratches or holes can also be regarded as mechanical faults. Extensive analysis, including additional features and performance parameters.

## 6.FUTURE SCOPE

Machine learning-driven fault detection and classification is shaping up to be a game-changer for electric vehicle (EV) performance and security. Here's a glimpse into its future scope:

**1. Enhanced Fault Detection Accuracy**

**Fig:3 ::Vehcile Speed against slider gain**

Machine learning models can analyze vast amounts of real-time data from EV sensors to detect faults with higher precision than traditional methods. This reduces false positives and ensures timely interventions.

**2. Predictive Maintenance**

Instead of waiting for a fault to occur, predictive analytic can forecast potential failures based on historical data. This helps manufacturers and users prevent breakdowns before they happen.

**3. Digital Twin Technology**

A digital twin—a virtual replica of an EV—can simulate realworld conditions and detect anomalies in power train performance. This allows for remote diagnostics and proactive fault mitigation.The future of securing electric vehicle (EV) performance through machine learning and fault detection is a rapidly evolving field with immense potential. As EVs become more prevalent, ensuring their reliability, safety, and efficiency is crucial. Machine learning plays a pivotal role in achieving these goals by enabling real-time fault detection, predictive maintenance, and optimization of various EV components.

One of the most significant advancements is the ability to detect faults in real time. Machine learning models analyze sensor data from EV components such as batteries, motors, and power electronics, identifying anomalies that may indicate potential failures. This proactive approach minimizes the risk of unexpected breakdowns, improving overall vehicle performance and safety.Predictive maintenance is another key application of machine learning in EVs. By leveraging historical data and pattern recognition, AI-driven systems can forecast possible faults before they occur. This predictive capability reduces operational costs, prevents major failures, and extends the lifespan of critical vehicle components.The integration of machine learning with the Internet of Things (IoT) further enhances fault detection capabilities. Connected sensors continuously monitor EV performance and transmit diagnostic data in real time, allowing for quicker identification and resolution of issues. This approach ensures optimal functioning of the vehicle, leading to a seamless driving experience.Battery management is a crucial aspect of EV performance, and AI-powered frameworks help optimize battery usage by predicting the remaining useful life (RUL). These systems prevent premature battery degradation by implementing efficient charging and discharging strategies, ultimately enhancing EV longevity and sustainability.Safety is another area where machine learning-driven fault detection can make a significant impact. AI models can identify potential risks such as overheating, voltage fluctuations, and sudden power losses, ensuring that EVs operate under safe conditions. This level of monitoring and intervention enhances user confidence in EV technology and encourages wider adoption.

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