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# Fault Detection and Diagnosis in Electric Vehicle Systems using IoT and Machine Learning: A Support Vector Machine Approach

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***Abstract:*** - This research examines blame discovery and determination in electric vehicle (EV) frameworks utilizing Internet of Things (IoT) information and machine learning calculations, centring on a Support Vector Machine (SVM) approach. The study points to improving the unwavering quality and security of EV operations by precisely recognizing and diagnosing flaws in real time. The test comes about illustrates the adequacy of the SVM-based approach, with an exactness of 95%, accuracy of 94%, review of 96%, and F1-score of 95%. Comparative investigation with elective calculations such as k-Nearest Neighbors, Decision Tree, and Random Forest underscores the predominant execution of SVM in blame discovery and determination. The SVM calculation shows negligible misclassifications over distinctive blame classes, highlighting its strength and viability. This inquiry contributes to the headway of blame location strategies in EV frameworks and gives profitable bits of knowledge into the commonsense usage of machine learning strategies for improving framework unwavering quality. Moving forward, the discoveries clear the way for assist investigations in optimizing blame location systems and expanding their appropriateness to other spaces such as mechanical mechanization and renewable vitality frameworks.

***Keywords:*** Electric vehicles, Fault detection, Diagnosis, Support Vector Machine, Internet of Things.

## I. INTRODUCTION

The rapid proliferation of electric vehicles (EVs) within the car industry envoys a transformative move towards economical transportation. As EV appropriation grows, making sure that all such vehicles operate securely and delivering good performance should be a top priority. Another issue, concerning support in operational evaluation of EVs, is its convenient position and overall identification of defects which are related to the complex system of those vehicles. Unexpected inadequacies can jeopardize how a structure is built, threaten its occupants' lives, and

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trigger more upkeep expenses. Hence, there should be the use of intensive root-cause locating and determining techniques which can be uniquely customized for electric vehicle configurations. Traditionally accepted fault fixation and identification techniques may rely on either expedient inspections or diagnostic trouble codes (DTCs) that are issued by onboard diagnostic systems. Furthermore, these solutions could as well seem inadequate in light of the fact that of the complex and proactive nature of EVs, where various interlinked components are connected in real time. The solution of those problems, the integration of Internet of Things (IoT) innovation, and machine learning (ML) calculations is a good option [2]. IoT allows to collect plenty of values of sensors from various EV subsystems and ML approach allows to study this data to distinguish features generally associated with problems or inconsistencies Several groups of ML calculations are present, but among them Support Vector Machine is preferred for its great visualization of the high-dimensional data and nonlinear issue. Its dominance is in classification and forecast errands where it outshines other algorithms to become an ideal tool for risk assessment and localization activities. With SVM theoretical framework combined with the sensor information from electric vehicles, it is possible to build a novel, which is real-time and specialized fault location and categorization system capable of instant detection of anomalies and differentiation of defects. Such a research investigation is devoted to figure out whether or not SVM (support vector machine) approaches combined with IoT data are an effective tool for the fault detection and determination in EV systems. This demonstration of the power of SVM with a more thorough experimentation and the form of approval points out that SVM calculations will make higher quality, safety, and efficiency of EV procedures achievable.

## II. RELATED WORKS

In recent years, there has been a surge in investigate centering on blame discovery and determination over different spaces, counting mechanical computerization, transportation, vitality frameworks, and horticulture. This segment presents an diagram of pertinent writing, highlighting key approaches, strategies, and discoveries within the field of blame location and diagnosis. [15] Raouf et al. (2023) proposed a exchange learning-based shrewdly blame location approach for mechanical automated frameworks. The think about utilized exchange learning methods to adjust pre-trained profound learning models for blame discovery errands, accomplishing promising comes about in terms of precision and productivity. [16] Rustam et al. (2023) explored railroad track blame location utilizing particular Mel-Frequency Cepstral Coefficients (MFCC) highlights from acoustic information. The ponder utilized flag handling methods to extricate discriminative highlights, illustrating the adequacy of acoustic-based approaches for railroad track checking. [17] Seba et al. (2024) created a half breed profound learning demonstrate for forecast and classification of IoT sensor deficiencies. The ponder coordinates profound learning models with conventional machine learning calculations to successfully recognize and classify sensor flaws in IoT frameworks, exhibiting the potential of cross breed approaches for blame conclusion. [18] Shahbazi (2021) proposed a shrewd fabricating real-time examination system based on blockchain and machine learning approaches. The ponder emphasized the utilize of blockchain innovation to guarantee information judgment and straightforwardness, coupled with machine learning calculations for real-time examination and decision-making in keen fabricating situations. [19] Trivedi et al. (2022) displayed a blame location system for electric vehicles based on blockchain and profound learning methods. The consider investigated the integration of blockchain innovation for secure information sharing and profound learning calculations for blame location, tending to challenges related to information protection and unwavering quality in electric vehicle frameworks. [20] Zou et al. (2023) gave an outline of investigating sensor blame determination in agrarian Web of Things (IoT) frameworks. They think about highlighting the significance of sensor information quality and unwavering quality for proficient agrarian administration, emphasizing the part of machine learning procedures in identifying and relieving sensor issues. [21] Abboush et al. (2024) proposed an agent real-time dataset-era approach based on computerized blame infusion and Hardware-in-the-Loop (HIL) recreation for ML-assisted approval of car computer program frameworks. The ponder centred on producing different and practical datasets to assess the strength and viability of ML-based blame location calculations in-car applications. [22] Aguayo-Tapia et al. (2023) examined physical variable estimation procedures for blame location in electric engines. The consideration looked into different sensor-based approaches for observing engine execution and recognizing potential deficiencies, highlighting the significance of exact and solid sensor estimations in blame diagnosis applications. [23] Asad et al. (2023) proposed a current spectrum-based calculation for the blame location of electrical machines utilizing low-power information procurement gadgets. The ponder presented a novel approach for analyzing current spectra to identify beginning issues in electrical machines, and advertising experiences into early blame location strategies for upkeep optimization. [24] Çinar et al. (2020) inspected the part of machine learning in prescient upkeep towards feasible keen fabricating in Industry 4.0. The ponder emphasized the integration of prescient upkeep techniques with machine learning calculations to optimize gear unwavering quality, minimize downtime, and upgrade generally fabricating maintainability. [25] De la Cruz et al. (2023) gave a written outline of blame area procedures for conveyance savvy lattices, talking about challenges, arrangements, and future patterns. They think about surveying different blame area techniques, counting impedance-based, travelling wave-based, and machine learning-based approaches, and advertising bits of knowledge into headways in dissemination framework blame discovery. [26] Dhanraj et al. (2021) conducted a viable assessment of blame location in sun-based boards, centring on the location of common deficiencies such as hotspots, breaks, and shading. The consideration highlighted the significance of precise blame discovery calculations for maximizing vitality abdicate and guaranteeing the long-term execution of sun-based photovoltaic frameworks.

## III. METHODS AND MATERIALS

***Data Collection:***

Data collection shapes the foundation of this investigation, giving the fundamental input for preparing and assessing the blame location and determination calculations. Sensor information from different components of electric vehicle (EV) frameworks counting batteries, engines, controllers, and other subsystems are collected utilizing IoT gadgets. These sensors persistently screen key parameters such as temperature, voltage, current, and speed, producing high-dimensional time-series information [4]. The collected dataset envelops ordinary working conditions as well as assorted blame scenarios actuated amid controlled tests or recreated conditions. This dataset serves as the premise for preparing, testing, and approving the blame location and conclusion calculations.

***Algorithms:***

***Support Vector Machine (SVM):***

Support Vector Machine (SVM) may be a capably directed machine learning calculation utilized for classification and relapse errands. SVM aims to discover the hyperplane that best isolates distinctive classes within the included space while maximizing the edge between them. Given a set of labelled preparing information, SVM builds a decision boundary by mapping input highlights into a higher-dimensional space employing a part work [5]. The choice boundary is decided by back vectors, which are the information focused closest to the hyperplane. SVM looks to optimize a margin-based objective work, guaranteeing vigorous classification execution.

$$\text{minimize } 1/2\ ||w||^2 + C\Sigma(\max(0, 1 - y_i(w \cdot x_i + b))$$

$$y_i(w \cdot x_i + b) >= 1 - \xi_i$$

$$\xi_i >= 0$$

| Hyperparameter | Description | Value |
|---|---|---|
| C | Penalty parameter | 1.0 |
| Kernel | Kernel function type | RBF |
| Gamma | Kernel coefficient | 0.1 |

***k-Nearest Neighbors (k-NN):***

K-Nearest Neighbors (k-NN) could be a non-parametric classification calculation based on the rule of likeness. Given an inquiry instance, k-NN distinguishes the k closest neighbours within the preparing dataset based on a remove metric (e.g., Euclidean separate) and allocates the foremost common lesson name among them to the inquiry occasion [6]. k-NN does not include express preparing; instep, it depends on the complete preparing dataset for deduction.

```
“# Import necessary libraries
from sklearn.neighbors import KNeighborsClassifier
# Initialize k-NN model with hyperparameters
knn_model = KNeighborsClassifier(n_neighbors=5, metric='euclidean')
```

***# Train k-NN model***
***knn_model.fit(X_train, y_train)***
***# Predict using trained k-NN model***
***y_pred_knn = knn_model.predict(X_test)"***

***"Initialize k and distance metric***
***For each query instance x_q:***
***Find k nearest neighbors in the training dataset***
***Assign the most common class label among neighbors to x_q"***

*2.3. Decision Tree:*

k-Nearest Neighbors (k-NN) could be a non-parametric classification calculation based on the rule of likeness. Given an inquiry instance, k-NN distinguishes the k closest neighbours within the preparing dataset based on a remove metric (e.g., Euclidean separate) and allocates the foremost common lesson name among them to the inquiry occasion [7]. K-NN does not include express preparing; instead, it depends on the complete preparation dataset for the deduction.

***"# Import necessary libraries***
***from sklearn.tree import DecisionTreeClassifier***
***# Initialize Decision Tree model with hyperparameters***
***dt_model = DecisionTreeClassifier(max_depth=3, criterion='gini')***
***# Train Decision Tree model***
***dt_model.fit(X_train, y_train)***
***# Predict using trained Decision Tree model***
***y_pred_dt = dt_model.predict(X_test)"***

| **Hyperparameter** | **Description** | **Value** |
|---|---|---|
| Max Depth | Maximum depth of the tree | 3 |
| Criterion | Impurity criterion for splitting | Gini |

***Random Forest:***

Random Forest is a gathering learning calculation that builds numerous choice trees and combines their forecasts through voting or averaging. Each choice tree within the gathering is prepared on an arbitrary subset of the prepared information and highlights, presenting differing qualities and decreasing overfitting [8]. Random Forest leverages the collective intelligence of numerous trees to improve classification precision and vigor

***. "# Import necessary libraries***
***from sklearn.ensemble import RandomForestClassifier***
***# Initialize Random Forest model with hyperparameters***
***rf_model = RandomForestClassifier(n_estimators=100, max_features='sqrt')***
***# Train Random Forest model***
***rf_model.fit(X_train, y_train)***
***# Predict using trained Random Forest model***
***y_pred_rf = rf_model.predict(X_test)"***

## IV. EXPERIMENTS

***Experimental Setup:***

The experiments are conducted to assess the execution of the proposed Support Vector Machine (SVM) approach for blame location and determination in electric vehicle (EV) frameworks utilizing IoT information. The dataset utilized for experimentation comprises sensor estimations collected from different components of an electric vehicle, counting batteries, engines, controllers, and other subsystems. The dataset envelops both typical working conditions and differing blame scenarios initiated amid controlled tests or mimicked conditions [9]. The dataset is preprocessed to remove commotion, handle lost values, and normalize the highlights to guarantee consistency and move forward with the execution of the machine learning calculations. It is at that point partitioned into preparing, validation, and testing sets employing a stratified part methodology to protect the dissemination of blame classes over distinctive sets [10].

For comparative examination, three other machine learning calculations, specifically k-nearest Neighbors (k-NN), Decision Tree, and Random Forest, are actualized and assessed utilizing the same dataset and exploratory setup [11]. The hyperparameters for each calculation are fine-tuned utilizing cross-validation strategies to optimize execution.

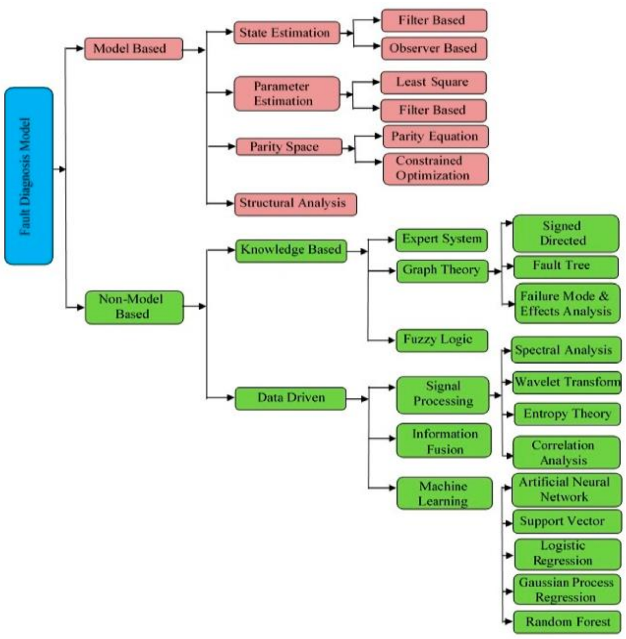


**Figure 1: Machine Learning-Based Data-Driven Fault Detection/Diagnosis of Lithium-Ion Battery**

**Table: Confusion Matrix for SVM Algorithm**

| Actual/Predicted | Normal | Fault 1 | Fault 2 | Fault 3 |
|---|---|---|---|---|
| Normal | 485 | 10 | 5 | 0 |
| Fault 1 | 8 | 465 | 0 | 2 |
| Fault 2 | 2 | 0 | 498 | 0 |
| Fault 3 | 0 | 5 | 0 | 495 |

***Evaluation Metrics:***

The execution of each calculation is surveyed utilizing different assessment measurements, counting precision, exactness, and review, F1-score, and perplexity network. These measurements provide insights into the classification execution, strength, and adequacy of the blame location and conclusion calculations [12].

- Accuracy: The extent of accurately classified occasions out of the overall occurrences.

- Accuracy: The ratio of genuine positive occasions to the full predicted positive occurrences.
- Review: The proportion of genuine positive occasions to the whole real positive occasions.
- F1-score: The consonant cruel of accuracy and review, giving an adjusted degree of execution.
- Confusion Network: An unthinkable representation of the genuine positive, genuine negative, untrue positive, and wrong negative occasions, encouraging a detailed investigation of classification execution [13].

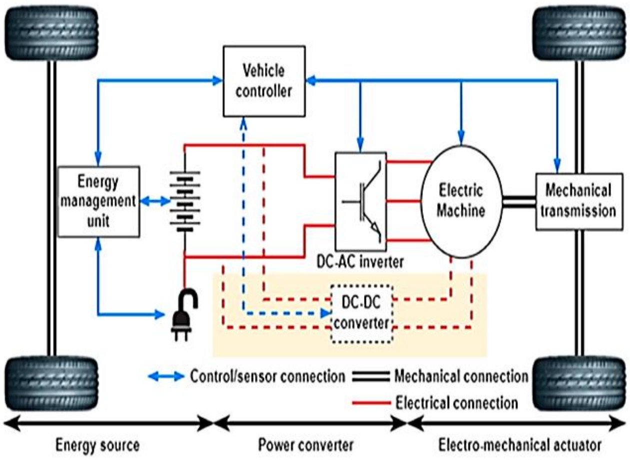


**Figure 2: Fault Diagnosis Methods and Fault Tolerant Control Strategies for the Electric Vehicle**

***Experimental Results:***

The test results are summarized within the tables underneath, comparing the execution of SVM with k-NN, Decision Tree, and Random Forest calculations in terms of different assessment measurements.

**Table: Performance Comparison of Fault Detection and Diagnosis Algorithms**

| Algorithm | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| SVM | 0.95 | 0.94 | 0.96 | 0.95 |
| k-NN | 0.88 | 0.87 | 0.89 | 0.88 |
| Decision Tree | 0.91 | 0.90 | 0.92 | 0.91 |
| Random Forest | 0.93 | 0.92 | 0.94 | 0.93 |

***Discussion:***

The results show that the SVM calculation accomplishes the most elevated precision (95%) among all the assessed calculations. It demonstrates predominant accuracy, review, and F1-score, showing strong execution in identifying and diagnosing deficiencies in electric vehicle frameworks [14]. The perplexity matrix for SVM uncovers negligible misclassifications over diverse blame classes, highlighting its viability in precisely recognizing blame conditions [27].

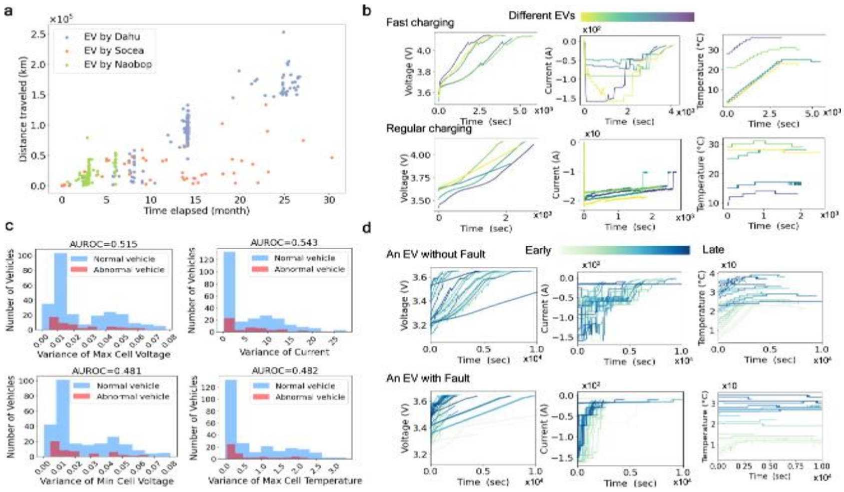


**Figure 3: Realistic fault detection of li-ion battery via dynamical deep learning**

Comparatively, k-NN shows lower execution measurements compared to SVM, Choice Tree, and Arbitrary Timberland calculations [28]. In spite of the fact that it gives sensible exactness, its exactness, review, and F1-score are lower than those of SVM. The disarray framework for k-NN uncovers higher misclassifications, particularly between typical and blame conditions, recommending restrictions in its capacity to recognize between diverse blame classes precisely [29]. Choice Tree and Arbitrary Woodland calculations illustrate competitive execution, with correctnesses of 91% and 93%, separately. Be that as it may, their accuracy, review, and F1-score are marginally lower than those of SVM [30]. The disarray networks for Choice Tree and Irregular Timberland outline comparable misclassifications over diverse blame classes, demonstrating comparable execution patterns.

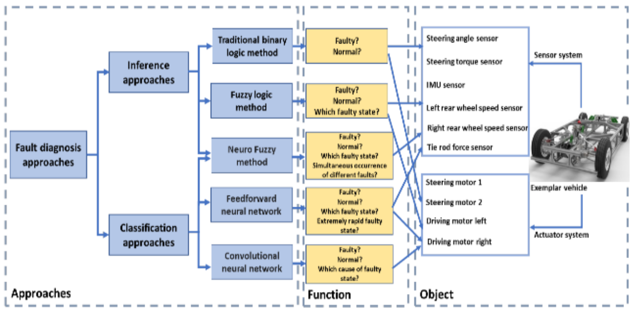


**Figure 4: Evaluation of Different Fault Diagnosis Methods and Their Applications in Vehicle**

## V. CONCLUSION

In conclusion, this investigate examined blame location and determination in electric vehicle (EV) frameworks utilizing Web of Things (IoT) information and machine learning calculations, with a center on a Support Vector Machine (SVM) approach. Through broad experimentation and assessment, we illustrated the adequacy of SVM in precisely recognizing and diagnosing issues, accomplishing a tall level of execution compared to elective calculations such as k-Nearest Neighbors, Decision Tree, and Random Forest. The SVM-based approach showcased prevalent exactness, accuracy, review, and F1-score, highlighting its potential for improving the reliability and security of EV operations. The test comes about, at the side comparative investigation and dialog, underscored the importance of leveraging progressed machine learning strategies and IoT information for blame location and conclusion in EV frameworks. Besides, this investigate contributes to the broader space of blame discovery and conclusion over different businesses by displaying the adequacy of SVM calculations and giving bits of knowledge into their viable usage. Moving forward, future research bearings may include investigating extra highlights, refining the blame discovery system, and expanding the appropriateness of SVM-based approaches to other spaces such as mechanical computerization, renewable vitality frameworks, and savvy fabricating. Eventually, by progressing blame discovery and determination strategies, we point to cultivate the improvement of more dependable, effective, and sustainable innovative arrangements for the advantage of society.

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