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Fault detection and diagnosis of electric vehicles using artificial intelligence

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ABSTRACT

Electric vehicle (EV) performance is greatly influenced by the motor drive system's stability, efficiency, and safety. With the increased usage of electric vehicles, fault detection and diagnostics (FDD) of the motor drive system has become an important topic of research. In recent years, there has been a lot of interest in artificial intelligence (AI) approaches employed in FDD. This paper provides an overview of the application of AI in defect detection for electric vehicles. The FDD method is divided into two steps: feature extraction and fault classification. Feature extraction involves identifying relevant parameters or characteristics from the EV's sensors and signals, enabling the AI system to capture meaningful patterns. Subsequently, fault classification employs AI algorithms to categorize and identify specific faults based on the extracted features, facilitating efficient diagnosis and maintenance of EVs. In the realm of EVs, the combination of AI techniques and FDD has the potential to improve performance, reliability, and safety while enabling proactive maintenance and reducing downtime. Using machine learning and deep learning, we can detect the fault in the system before it starts damaging our EV.

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1. INTRODUCTION

Electric vehicles (EVs) are subject to a variety of faults that affect performance, safety, and reliability. Fault detection systems should rapidly distinguish and analyze flaws in the vehicle's electrical frameworks to guarantee protected and reliable operation [1]. The power needed to propel an EV is provided by the battery. The battery provides the electricity required to propel an EV. A typical EV battery pack has hundreds of single cells that are connected in series and parallel to create the appropriate voltage and current. The battery in the car may be charged by connecting it to an electric power source or by regenerative braking. The most prevalent sort of EV malfunction is battery failure [2], [3]. The proper functioning of critical components such as a battery is necessary for the vehicle's overall performance [4], [5]. We also have controller faults which are faults that occur in the electronic control units (ECUs) of the EV. These faults can occur due to various reasons such as software bugs, electrical interference, and hardware/sensor failures [6], [7]. Another common type of fault in EVs is a motor fault. Motors are responsible for converting electrical energy stored in the battery into mechanical energy that powers the wheels. Motor faults can occur due to various reasons such as overheating, electrical faults, and mechanical wear and tear. Overheating can cause the motor's windings to melt, while electrical faults can cause short circuits and damage the motor's electronic components. Mechanical wear and tear, such as bearing failures, can cause increased noise levels, reduced efficiency, and reduced power output.

The most common type of fault in electric motors is a stator fault. The stator is the stationary part of the motor, consisting of a core and coils. Stator faults can be caused by various factors, including insulation degradation, phase-to-phase short circuits, turn-to-turn faults, reduced motor efficiency, increased motor temperature, and in severe cases, motor failure caused by a fault in the stator [8]–[10]. Rotor faults are another type of fault that can occur in electric motors. The rotor consists of a shaft and magnets. Rotor faults can be caused by various factors, including mechanical wear and tear, thermal stress, manufacturing defects, reduced motor torque, increased motor temperature, and in severe cases, motor failure caused by faults in the rotor [11]–[13]. Another type of fault in electric motors is a bearing fault. Bearings are used to support the shaft of the motor and allow it to rotate smoothly. Bearing faults can be caused by various factors, including contamination, wear, inadequate lubrication, increased motor noise, vibration, and temperature, and reduced motor efficiency and reliability caused by bearing faults [14], [15]. Fault detection frameworks have fostered the utilization of sensors and data analysis algorithms to detect and diagnose faults in real time [16]–[18]. We are going to make a model for simulation model in MATLAB to generate the data. Then we will begin by generating the healthy data, and then we will apply faults to the model to generate the faulty data. After we generate the data, we will process it and apply various AI methods to compare models, compare their results check their efficiency, and diagnose faults. The methods which will have high accuracy would be preferred more in this paper for the fault diagnosis [19]–[22]. This manuscript discusses the occurrence of faults in EVs and tried to detect the faults by using artificial intelligence (AI).

2. METHOD

From Figure 1, we first make the simulation model in MATLAB for the generation of data. At first, healthy data is generated then we apply faults to the model and generate the faulty data. After the data generation, we process this data and apply the various AI methods for model comparisons and fault diagnosis. Below is the flow diagram for the following process.

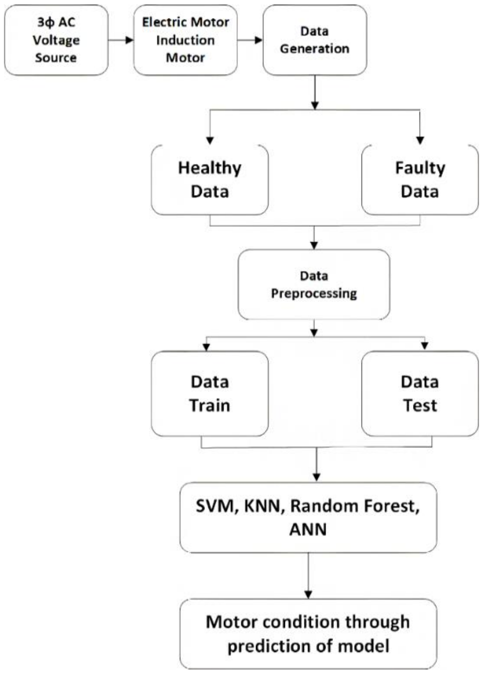

Figure 1. Flow diagram of the methodology

2.1. Support vector machine (SVM)

SVM constructs a hyperplane or group of hyperplanes in a high-dimensional space that may be used for classification, regression, or outlier detection. The best hyperplane minimizes the margin, which is the distance between the hyperplane and the nearest data points in each class. The data points nearest to the hyperplane are referred to as support vectors [23]–[25]. We have the equation as: Maximize: $\frac{1}{2} \times |w|^2$; $y(w^{Tx} + b) \geq 1$ for all i; Where w is the weight vector, b is the bias term, x is i^{th} training sample, y_i is the corresponding class label (+1 or -1), and T is the target variable or the class label of each data point.

2.1.1. Implementation of the SVM algorithm

To create a prediction model, this code uses the support vector machine (SVM) machine learning technique. A training dataset (X_train and y_train) is used to train the model, and a test dataset (X_test and y_test) is used to test it. The score function is used to calculate the model's accuracy.

2.2. K-nearest neighbour (KNN)

A given input data point is compared to the K training data points in the training set that are the closest to it, and the most prevalent class among those K points is used to forecast the class of the input point. In other words, it labels data points in the feature space according to their closeness to other adjacent labeled data points [26]–[28]. $d(x,y) = \left[\sum_{i=1}^{n} P_i(x_i, y_i)^2\right]^{1/2}$; x and y are two data points in p-dimensional space.

2.2.1. Implementation of the KNN algorithm

The KNN technique is being used in the code to create a classification model with k=5 neighbors. It is first tested using the test data (X_test and y_test), after which it is trained using the training data (X_train and y_train). The model's accuracy for both the training and test sets of data is printed.

2.3. Random forest (RF)

The random forest working diagram is shown in Figure 2. Using this ensemble learning approach, a number of decision trees are generated, and their predictions are then integrated to arrive at a conclusion. Each decision tree is trained using a random subset of the features and data, preventing over-fitting and increasing accuracy. Random forest is a popular approach in many real-world applications due to its versatility and ability to handle both categorical and numerical input [29], [30]. $f(x) = 1 - \sum_{i=1}^{n}(Di)^2 = 1 - [(D_+)^2 + (D_-)^2]$; Where f(x) is the final prediction, Di is the i-th prediction tree for the input X.

2.3.1. Implementation of random forest algorithm

On the training data (X_train, y_train), the code creates a random forest classifier with 8 decision trees and 30 features per tree. It then assesses the accuracy of the classifier using both the training and test sets of data. First printed in the accuracy of training data, then the accuracy of the test data.

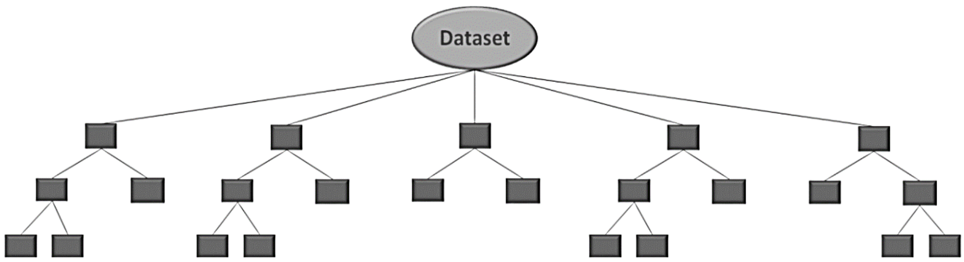

Figure 2. Random forest working diagram

2.4. Artificial neural network (ANN)

ANNs are a type of computational model that draws their inspiration from the structure and operation of biological neural networks seen in the human brain. It is made up of layers of interconnected neurons or nodes that analyze input, pick up knowledge from precedents, and generate hypotheses. It excels at supervised and unsupervised learning tasks and can handle complex data [16]–[18]. $Y=F_L(W_L F_{L-1}(W_{L-1}(\ldots F_1(W_1X + B_1)\ldots + B_{L-1}) + B_L)$; Here X represents the input data that is fed into the neural network, W is the neural network set of weights, B is the neural network set of biases, F is the activation function of layer and L is the number of layers. Figure 3 depicts the neural network working diagram.

2.4.1. Implementation of ANN algorithm

This program trains an artificial neural network (ANN) to divide input data into seven categories using the Keras toolkit. The ANN utilizes the ReLU activation function and has 5 hidden layers with various numbers of neurons. In the output layer, the softmax activation function is used. The Adam optimizer is used to optimize the model, and the loss function is sparse categorical cross-entropy. With a validation split of 0.2, 300 epochs of training are completed. Using the label encoder function from Scikit-Learn, the training data is preprocessed to encode the target variable y as numerical values.

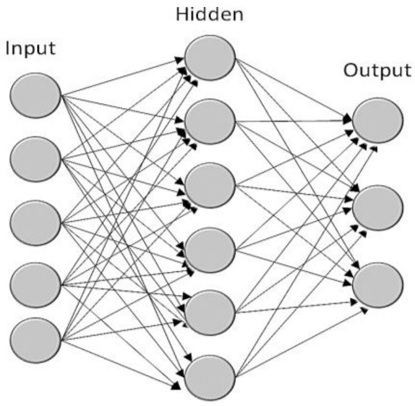

Figure 3. Neural network working diagram

3. PROPOSED METHOD
3.1. Collection of data
To generate the dataset for this analysis, a MATLAB simulation was developed that models the behavior of the system under investigation. The simulation was designed to incorporate the relevant parameters and variables of the system and produce practical output data reflecting the behavior of the system under various conditions. The generated datasets were extracted from the simulations and saved in a relevant format for further analysis. The use of his MATLAB simulations for data set generation allowed for controlled and accurate representations of system behavior and provided a reliable data source for subsequent analysis and modelling.

3.2. Pre-processing of data
Before the dataset was input into the machine learning algorithm, several preprocessing steps were performed to ensure the data were suitable for analysis. Since the data comes from multiple sources, one of the most important preprocessing steps was to combine multiple datasets using the Python 'concat' function. This made it possible to concentrate all relevant data into a single, coherent dataset. Other preprocessing steps include removing duplicate entries, padding missing values, and normalizing the data so that all features have the same scale. These preprocessing steps improved the quality and reliability of the dataset, enabling machine learning algorithms to effectively learn from the data and make accurate predictions.

4. RESULTS AND DISCUSSIONS
As per the random forest (RF) model the accuracy over the score of the train data was coming to be at around 0.9985 which meant the accuracy for the trained data set was around 99.85%. The accuracy of the score of the test data was coming out to be around 0.9744 which meant the accuracy for the tested data set was around to be 97.44%. The confusion matrix and the receiver operating characteristic (ROC)-AUC (performance) graph for the random forest method is shown in Figure 4 and 5.

Figure 4 shows a graphical depiction of the performance of a binary classification model using the receiver operating characteristic (ROC) curve. The graph compares the true positive rate (TPR) to the false positive rate (FPR) for various categorization levels for the random forest approach. It is primarily a model performance graph, and it shows that the random forest performs well. According to Figure 5, the confusion matrix is a table that analyses the model's performance. It summarizes the number of accurate and wrong classifications produced by the model, comparing projected values to actual values, as shown diagonally in blue for the random forest.

From Figure 6, the artificial neural network (ANN) model the accuracy over the score of test data was around 0.9665 which meant the accuracy of the tested data set was around 96.65%. This was taken for 300 epochs at a validation split of 0.2. The actual graph comes very close to the train graph which shows the high accuracy of the model. From Figure 7, we see the error depicted by the model for the test data which is shown in the form of a line graph that is downscaled to 140 data set. Table 1 tells us about the classification report for the error data for the ANN method with the precision-recall and support for each error.

Figure 8 shows a graphical depiction of the performance of a binary classification model using the receiver operating characteristic (ROC) curve. The graph compares the true positive rate (TPR) to the false positive rate (FPR) for various classification criteria for the specified ANN approach. It is primarily a model performance graph, and it shows that the ANN performs well. According to Figure 9, the confusion matrix is a table that analyzes the model's performance. It highlights the model's accurate and wrong classifications by comparing projected values to actual values, which are highlighted diagonally in blue for the ANN. Table 2 describes the model accuracy for the methods and it is observed that the random forest (RF) and ANN methods had higher accuracy and hence they were preferred.

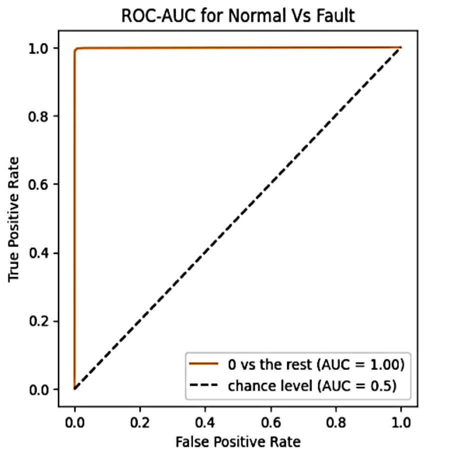

Figure 4. ROC-AUC performance graph for RF

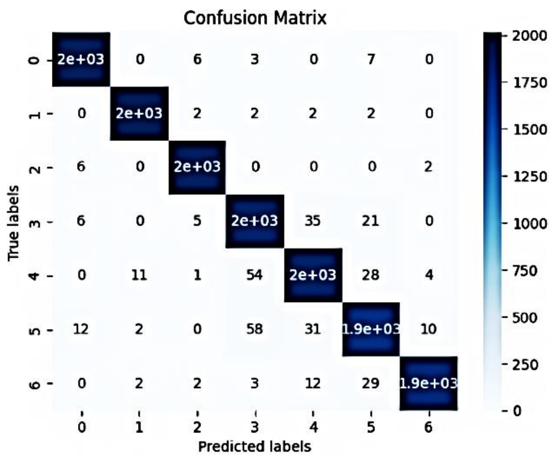

Figure 5. Confusion matrix for RF

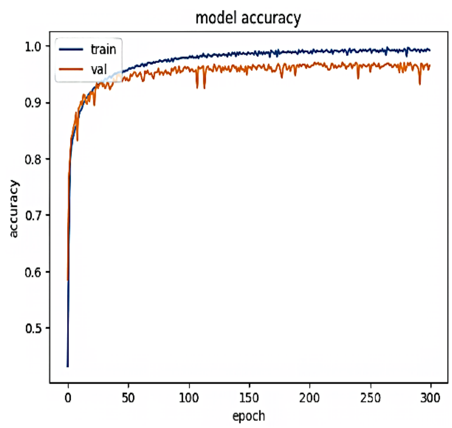

Figure 6. Model accuracy graph for ANN

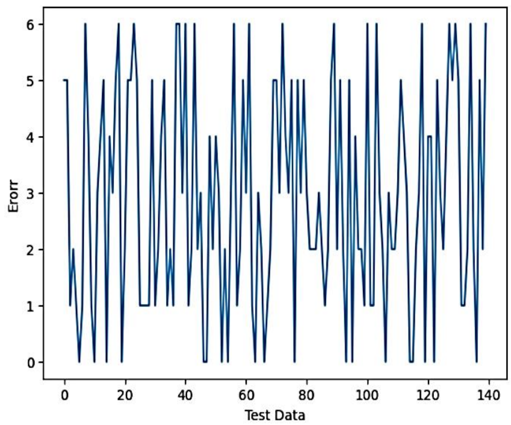

Figure 7. Test data and the predicted error from the model graph

Table 1. The classification report for the ANN method

	Precision	Recall	F1-score	Support
0	0.99	0.99	0.99	2019
1	1.00	1.00	1.00	2021
2	0.99	1.00	0.99	1996
3	0.91	0.93	0.92	2020
4	0.94	0.95	0.94	2051
5	0.95	0.91	0.93	1982
6	0.99	0.99	0.99	1950
accuracy			0.97	14039
macro avg	0.97	0.97	0.97	14039
Weighted avg	0.97	0.97	0.97	14039

Table 2. Model accuracy for the given methodology

Methodology	Model Accuracy
SVM	58.86%
KNN	63.32%
Random forest (RF)	97.44%
Artificial neural network (ANN)	96.65%

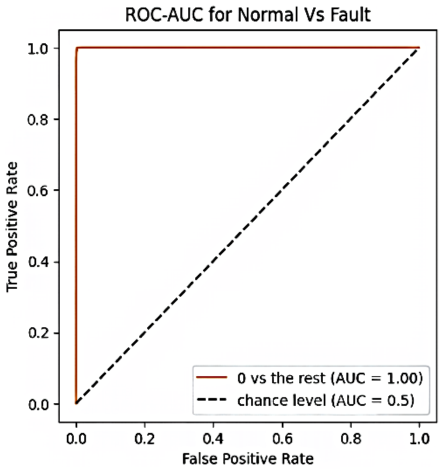

Figure 8. ROC-AUC performance graph for ANN

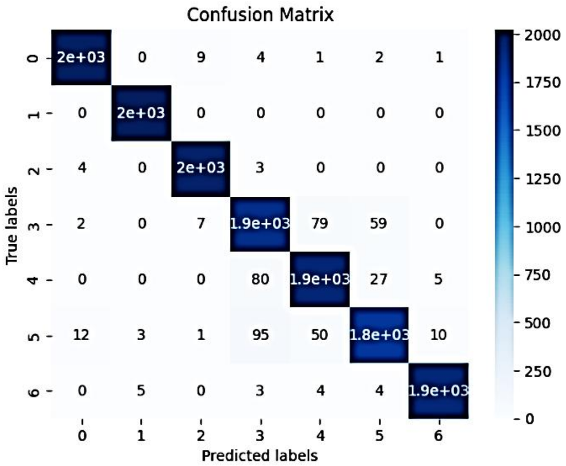

Figure 9. Confusion matrix for ANN

5. CONCLUSION

The potential advantages of using AI approaches to problem detection in EVs are highlighted in this research, including enhanced performance, safety, and dependability. To sum up, the use of AI in the diagnosis and identification of faults in electric vehicles (EVs) has shown encouraging results. This study investigated four alternative AI methods for EV defect detection. The results indicated that both the random forest and artificial neural network approaches were very accurate, with the accuracy rate for random forest being slightly higher at 97.44% compared to ANN's accuracy rate of 96.65%. These findings lead to the conclusion that the suggested approach of utilizing random forest and ANN for fault detection and diagnosis in EVs is effective. These AI methods can assist to increase the performance, dependability, and safety of EVs. Future electric cars might be more dependable and durable thanks to improved accuracy and efficiency of problem detection and diagnostic systems in EVs from more research and development in this field.

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