

SALP SWARM OPTIMIZED ARBS-NET ENABLED FRAMEWORK FOR FAULT DIAGNOSIS IN ELECTRIC VEHICLES

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ABSTRACT

Electric Vehicles (EVs) represents an excellent possibility towards developing a sustainable transport sector with low carbon emissions, low noise levels, high energy-efficient and integrate with electrical grids flexibly. Thus, the process of EV begins with data collection which involves different types of data such as voltage, current, vehicle speed, temperature, vibration and humidity to create a dataset of critical parameters. Pre-processing involves normalizing the dataset to create a consistent value for every element of data and to increase the value of the informations set. Exploratory data analysis (EDA) then lead to explore the distribution of different features in the dataset and detect any underlying or hidden patterns among the data. In feature engineering, the features are determined as critical for the performance of EV extracted from the data and used to identify potential failure modes present in EV. The Salp Swarm Optimized Attentive Radial Basis Spiking Network (ARBS-Net) is developed using a combination of benefits associated with multiple feature types, including sparse convolution, attention mechanisms and evolutionary optimization, to establish high-performance prediction and classification of fault conditions present in EV systems. This model is trained in Python and attains the maximum accuracy, precision, recall and F1-Score metrics of 0.99, thus demonstrating the proposed classification's capability to effectively predict and classify the occurrence of various fault conditions within EV systems. This intelligent diagnostic framework serves as a complete solution to implement proactive maintenance and increase EV operational reliability.



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I. INTRODUCTION

Increasing reliance on EVs and increased development of electricity generation in relation to smart city control is making harder to operate. As such, EV have a large contribution to the environment when it comes to the decarbonization of individual and public transportation. When compared to traditional gasoline and diesel vehicles, EVs are more efficient in terms of energy [1]. Over the long run, EVs are considered as energy storage systems, creating numerous unique opportunities and secondary services that benefit microgrids, such as providing vehicle-to-grid capability (V2G), voltage regulation, frequency regulation, and so on. EVs, distributed energy sources, and other components associated with microgrids eventually create failures associated with these components. An EV contains many electrical devices and a long energy conversion pathway, therefore implementing a Fault Diagnosis (FD) process to maximize the service exists of the EVs. Additionally, FD process helps to increase system uptime and lower operating costs [2], [3].

An on-board microcontroller monitoring approach is employed to monitor several EV types of components, specifically the energy storage device such as batteries and supercapacitors, battery management unit, semiconductor devices, power electronic converters, electric propulsion motors and sensors [4]. EV usage has become a primary means of reducing greenhouse gas emissions associated with global warming and the cause of increasing electrical demand around the biosphere [5]. The limitation of fossil fuels, along with the number of countries that produce fossil fuels and their political instability, has further highlighted EV's importance. EV growth will continue rapidly over years across numerous countries due to government legislation aimed at growing EV market shares. As laws evolve towards achieving significant EV usage within their respective markets, electric drives and battery systems experience significant growth within EV manufacturing. The EV parts consist of multiple components, all vulnerable to various sorts of errors [6], [7]. Though, the electrical determination and sequence portions of an EV represent its core components, and typical EV component failures occur primarily within the electrical drive or battery, therefore monitoring their function is critical [8]. Some industries have a large number of electric motors and are used for many reasons including as power supplies for EV's. The transportation industry's reliability and safety requirements are necessitated by the automotive version of the EV [9]. Electrical faults, internal heat, peak performance time and electrical shifting lead to various sorts of electric motor drive faults that degrade the system's performance and reliability of the EV. Interior-Permanent Magnets Synchronized (IPMS) motors are the most commonly used motors in the EV market. The majority of other Permanent Magnet Motors (PMM) utilize similar PMSM construction with different series designed for power levels [10], [11]. Industrialists are being driven to optimize the designs of the PMSM due to increased demands for assembly and high cost materials resulting in more complex designs and increased susceptibility to failure from different types of fault mechanisms [12]. However, due to the transportation industry's demands for continuity regardless of the working atmosphere of EV motors, there are multiple varieties of errors that arise on the motor and in the driver's inverter.

Electric motor initiative errors are characterised into three primary categories such as electrical faults, mechanical faults, and sensor faults [13]. Electrical faults include Interturn Short Circuit Fault (ITSCF), phase to phase circuit faults, magnetic short circuit between windings and open or short circuits on inverter switching devices [14]. Mechanical faults include rotor faults including bearing faults, bent shafts, and airgap eccentricity. The faults associated with the various sensors in an electric motor are known as sensor faults. Identifying these faults early allow for corrective action to prevent costly damage and catastrophic failures from occurring [15]. In EVs, lithium-ion battery systems have established as superior to traditional energy-storage systems for EV applications. This is owed to their excellent resources such as high power, energy density, durability and environmental effects. The battery packs of EV's contain numerous cells linked together in both series and parallel arrangements, creating both redundancy and increased performance. There are many ways that faults develop in battery systems resulting in the batteries degrading quickly, accelerated aging of batteries, EV problems, and fatal accidents. The report indicated that approximately 30% of EV accidents were battery related [16], [17]. Consequently, the development of reliable error discovery and fault-tolerant control systems is necessary to ensure the safety and continuity of EV operation. Nonetheless, intricate processes and other unfamiliar variables sort initial discovery of faults difficult. A method for early detection and prediction of faults is the use of FD techniques to monitor and identify the operating conditions of an electric motor [18], [19]. Therefore the proposed system uses a hybrid framework for FD in EV. The collected signals go through a normalization process as part of the preprocessing stage to ensure data consistency and the stability of learning. After preprocessing an EDA is used, where statistical and distribution-related information about the operating conditions, and fault pattern detection is gained. Feature engineering is used as the third step to extract and refine informative features [20]. Then the model training stage is executed and the existing model training methods for fault diagnosis in EV is illustrated in table 1.

Table 1: Related works for existing model training methods for fault diagnosis in EV.

SI.NO	AUTHOR/YEAR	MODELS	MERITS	DEMERITS	METRICS
1.	Debani Prasad Mishra <i>et al</i> [2024] [21]	ANN	It performs automation without requiring an in-depth model of each component, and make quick decisions for monitoring real-time failures.	The temporal nature of fault propagation resulting in a less efficient fault diagnosis.	It attains an accuracy of 96.65, precision, recall and F1-Score of 97.
2.	Venkata Satya Rahul Kosuru <i>et al</i> [2023] [22]	IB-DRN	It achieves a great level of accurateness and robustness through the extraction features and the ability to accurately learn complex, non-linear patterns.	It requires a huge quantity of labeled informations to train on and lacks sufficient interpretability of diagnosis results.	The metrics for IB-DRN is 98 of accuracy, 90 of precision, 97 of recall and 94 of F1-Score.
3.	Thirunavukkarasu <i>et al</i> [2024] [23]	CatBoost	CatBoost performs well with complex, nonlinear relationships involving both continuous and mixed categorical variables.	It does not perform optimally for large datasets and high-dimensional sensor data.	CatBoost achieves an accuracy, precision, recall and F1-Score of 94.
4.	Jasmine Sabeena <i>et al</i> [2024] [24]	SVM	SVM are excellent at processing large amounts of high dimensional data from EV sensors.	SVMs are less capable of providing real time diagnosis of failures as data size and system dynamics increase.	For SVM, the accuracy and F1-Score is 95, precision is 94 and recall is 96.
5.	Moussa Attiaa <i>et al</i> [2025] [25]	RF	It provide features that are indicative of the parameters that influence faults within a subsystem of an EV.	It becomes less effective at tracking the dynamic nature of the fault behavior over time.	RF achieves an accuracy of 95, precision of 92, F1-Score of 93 and recall of 94.

Source: Authors, (2026).

Existing methods for identifying fault diagnosis in EV have various limitations and to overcome these shortcomings, the proposed ARBS-NET framework is used to capture complex nonlinear relationships and temporal characteristics in EV faults. This procedure is further hyper-tuned by Salp Swarm Optimization (SSO) to find the best model parameters.

I.1 OBJECTIVES

The main intents of this study includes,

- ❖ To decrease the impact of noise signal and improve data quality, preprocessing method termed normalization is implemented.
- ❖ To identify data distribution and fault patterns, exploratory data analysis is utilized.
- ❖ To differentiate between faults and to eliminate irrelevant information, feature engineering is executed.
- ❖ To learn complex and nonlinear characteristics of faults, ARBS-Net is employed.
- ❖ To reduce classification error rates, avoid local minima and increase the diagnostic accuracy, SSO algorithm is performed.

II. PROPOSED SYSTEM DESCRIPTION

A SSO-enabled ARBS-Net-based framework for fault diagnosis in EVs provide highly accurate and reliable detection of operational fault occurrence through the use of multi-sensory data. The diagram of fault diagnosis in EV using Salp Swarm Optimized ARBS-NET enabled framework is displayed in figure 1.

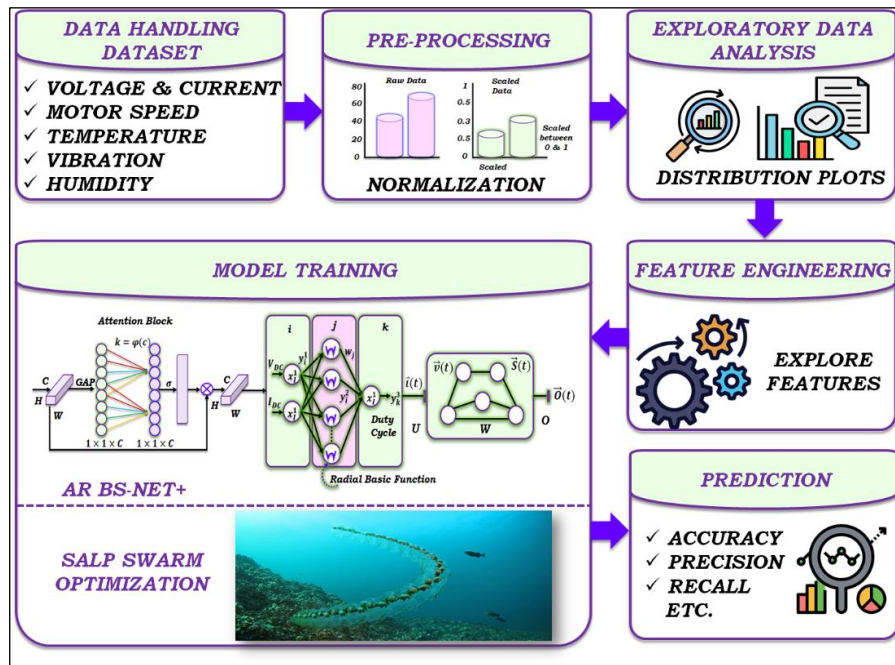


Figure 1: Proposed block diagram.

Source: Authors, (2026).

Initially, voltages, currents, motor speeds, temperatures, vibrations, humidity, and other critical parameters are collected and compiled into a single consolidated dataset. The collected data is subjected to preliminary normalization to remove scale differences among variables to improve the stability of learning and then processed further using EDA to understand the distribution and the operation of the data, before creating useful fault-related attributes to improve class separation from the features. The main feature of the proposed framework is the use of the ARBS-Net with its ability to capture nonlinear dynamics and temporal spiking of an EV component's performance. The ARBS-Net provides a robust representation of faults for diagnostic purposes. In addition, SSO is used in conjunction with the ARBS-Net, the SSO optimally tune the parameters of the ARBS-Net model, which include the network's attention weights and kernel characteristics, which reduce inaccuracies by enhancing the ARBS-Net's rate of convergence. The application of the offered framework for fault discovery and arrangement is verified through the use of standard metrics such as accuracy, precision, and recall to determine the reliability of the fault diagnosis of the EV systems.

III. PROPOSED SYSTEM MODELLING

III.1 PREPROCESSING – NORMALIZATION

III.1.1 MIN-MAX Normalization

Commonly, when diagnosing faults in EVs using multiple sensors to measure voltage, current, temperature, vibration and humidity, min-max normalization is used to standardize each of the measurements into a fixed range generally between [0,1]. Since these sensors measure the same quantity with different numerical ranges, the large numerical ranges dominate the model and reduce the ability of a diagnostic system to detect faults by an accurate model. The normalized value of a sensor measurement for min-max normalization is calculated as,

$$im_n(x, y, z) = \frac{im(x, y, z) - \min(im)}{\max(im) - \min(im)} \quad (1)$$

The benefit of using min-max normalization is that it is computationally low-cost, and relatively easily process data on real-time systems for EVs. This method is very appropriate for range applications for EVs. Figure 2 shows the diagram of Min-Max normalization.

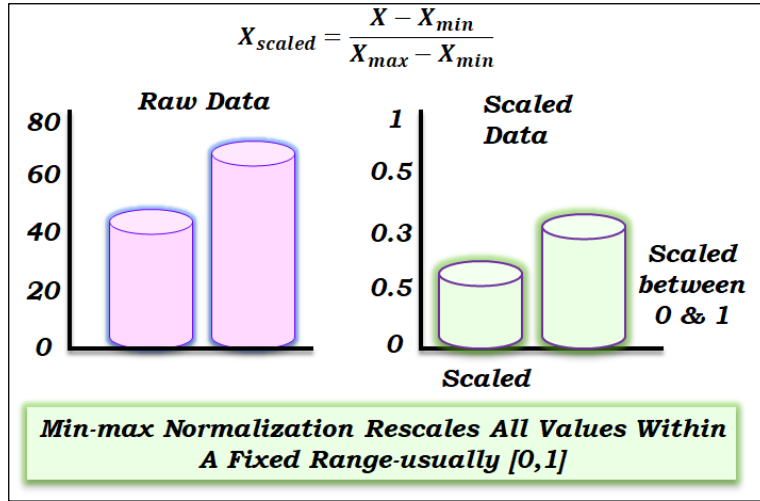


Figure 2: Min-Max normalization.
Source: Authors, (2026).

The data scaling process is done quickly and reliably along with providing information for feature representation, and allows faster processing for large amounts of sensor measurements though not having a large amount of computing overhead. It improve the fault diagnostic systems in terms of their ability to respond quickly with respect to elements such as characteristics of elements within an EV.

III.1.2 Z-Score Normalization

Sensor data from EV vary significantly depending on the type of vehicle and its operating conditions. To normalize the information of signal data from different types of EVs is to apply a Z score transformation. The Z score transformation normalizes the signal about a mean of 0 and a variance of 1, thus allowing for easier comparison and more stable models when performing data analysis. The formula for determining the normalized signal is,

$$im_n(x, y, z) = \frac{im(x, y, z) - \mu}{\sigma} \quad (2)$$

Where, μ equals the mean value of the signal and σ equals the standard deviation of the signal. By using a Z score transformation to normalize sensor data from EV, centers the signal on a mean of zero and provides an interpretation of the signal that is consistent, regardless of the type of EV. The diagram of Z-Score normalization is shown in figure 3.

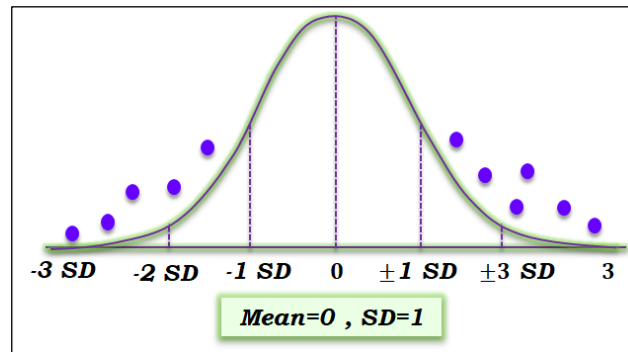


Figure 3: Z-Score normalization.
Source: Authors, (2026).

Furthermore, normalizing the data to a consistent statistical form helps facilitate the ability to effectively detect, isolate, and classify faults within the EV's subsystems such as batteries, motors, and power electronics. The Z score transformation applied to the signal data in several different ways, thus providing to improve the accurateness, reliability, and consistency of error identification for EVs.

III.2 EXPLORATORY DATA ANALYSIS

When diagnosing faults in EVs, exploratory data analysis through distribution plots shows an significant part in providing the initial insight into the characteristics of the sensor data collected from the vehicle components such as the battery management system, electric motor, power electronics, and thermal systems, prior to applying an intelligent fault detection model.

EVs produce a massive amount of data relating to these components, and distribution plots are helpful in illustrating the parameters of voltage, current, humidity, temperature, speed of a motor, and vibration signals which are statistically distributed under various operating conditions. Normal operating patterns easily identified from faulty operating patterns using distribution plots. When operating typically, an EV battery demonstrate a very tight clustering of voltages as compared to a sequence with internal faults, which establish greater spread in their distributions and present with multiple peaks in their distribution. Similarly, inverter faults naturally visible themselves with non-uniform distributions in the current and temperature outputs. All of this information gained from the distribution plots are used to identify outlier data points, data imbalances, noise, and any other hidden characteristics of the data that are not able to detect through the analysis of raw time-series data. Effective data preprocessing strategies are aided at this stage to ensure proper normalization, feature selection, and fault threshold determination through analysis of the relative distributions of healthy and faulty data. By analyzing the relative distributions of healthy and faulty states, plots are able to extract more discriminating features and reduce redundancy in the data set. By performing EDA using distribution plots, the reliability, accurateness, and stoutness of EV error analysis systems is enhanced then the method is proficient based on informations that are sensitive to faults.

III.3 FEATURE ENGINEERING

In the progression of diagnosing EV faults, the feature engineering - exploring features phase entails a further refining of the raw sensor data into useful and fault-sensitive representations of the sensor data that helps in increasing diagnostic accuracy. The battery, electric motor, inverter, and thermal subsystems continuously communicate data to the EV from their various sensors. However, raw data does not always provide a clear representation of any faults. Therefore, various feature representations from the sensor data, identify hidden patterns, relationships, and variances between normal operation and a fault. There are many statistical methods employed to represent significant features once conducting a localized search on sensors such as statistical parameter, time domain indicators, frequency domain components, energy and correlation of the different sensor readings like voltage, current, temperature, speed, and vibration. During this phase, individual attempts extract features from the various signals and assess the representative behavior of each feature during normal operations and fault conditions. Therefore, during this exploratory phase of the feature development process, all redundant or irrelevant features are deleted, while all highly discriminative features are retained to facilitate model learning. The identification of features improves the classification and measurement of faults through the use of two methods. By developing features that reduce the computational load of finding the faults, generate a higher level of fault separation and increased performance of Deep Learning fault diagnostic models. It creates an interface that captures the operating and performance characteristics of EV components thus allowing for the early identification of EV faults with more accurate classification, increases the safety of the vehicle and increases the vehicle's performance.

III.4 MODEL TRAINING - ARBS-Net

Using an attention mechanism for fault diagnosis in EV applications allows a model to focus on relevant fault data while eliminating unwanted sensor signal noise. Due to the variability of operating conditions and measurement uncertainties, EV fault data from devices like batteries, traction motors, inverters and other power conversion devices are heavily influenced by external disturbances. This noise complicates important aspects of detecting a fault. Therefore, by incorporating an attention mechanism, a diagnostic model acquires to favour more informative fault features while reducing the contributions of irrelevant or noisy feature content enhancing the robustness and accuracy of a diagnostic evaluation. This attention mechanism operates on extracted two-dimensional features in a channel-wise manner after performing convolutional processing. To allow for efficient computation with the attention mechanism, the two-dimensional features are essential to convert to a three-dimensional feature space. The three-dimensional feature space allows for inter-channel relationship modeling through cross-channel interaction modeling, enabling the network to place more emphasis on certain channels that require more distinct fault characteristics than other channels. This selective enhancement of particular channels recovers the simulation's capability to detect subtle faults and decreases the effect of noise without adding additional complexity to the structure of the model. Interactions between different channels are modelled using one-dimensional convolutional operations instead of fully connected layers, thus creating an efficient means of interaction between the channels and reducing computational burden. The extent of the convolution kernel k is adaptively determined founded on the quantity of channels C the layer ensures, allowing layers with higher numbers of channels to model more complete inter-channel dependencies. The determined convolution kernel size is expressed as follows,

$$k = \left\lceil \frac{\log_2(C)}{\gamma} + \frac{b}{\gamma} \right\rceil \quad (3)$$

The total sum of channels is given by c where, $\gamma = 2$ and $b = 1$ are the non-linear parameters. Sequentially, after creating the global average pool channel descriptor, a 1D convolution followed by a sigmoid function generates channel attention weights. The equation for producing these weights is as follows,

$$\omega = \sigma(C_1 D_k(y)) \quad (4)$$

Where, $\sigma(\cdot)$ is the sigmoid function, $C_1 D_k(y)$ is the one dimensional convolution operation, and y is a pooled feature vector. Final output feature map is created by multiplying attention weights ω with corresponding channels in original input feature map. This amplify fault sensitive features related to degradation or failure of EV components. To detect EV subsystem failures, the RBFN uses measurable electrical and mechanical signals, which act as inputs to the RBFN network. The output of the RBFN provide a fault index that corresponds to normal or faulty operation for the underlying EV subsystem based on the inputs provided to it. The RBFN utilize three layers as part of its design such as the input layer, hidden layer, and output layer. Each of the input layer resembles directly to one of the EV diagnostic signals selected by the RBFN and are forwarded to the hidden layer. An input layer's input-output response is expressed as follows,

$$net_i^1 = x_i^1(N) \quad (5)$$

$$y_i^1(N) = f_i^1(net_i^1(N)) = net_i^1(N), \text{ where } i = 1, 2, \dots \quad (6)$$

Where, x_i^1 expresses input variables associated with the fault and y_i^1 represents output data from a neuron in the input layer. The hidden layer of the RBFN consists of Gaussian radial basis function neurons, which model the nonlinear dynamics of the EV system under both normal and fault conditions. The hidden layer neurons correspond to membership functions related with precise error patterns or operation states. The relationship between the net input and output of the neurons in the hidden layer is provided by,

$$net_j^2(N) = (XM_j)^T \sum_j XM_j \quad (7)$$

$$y_j^2(N) = f_j^2(net_j^2(N)) = \exp(net_j^2(N)), \text{ where } j = 1, 2, \dots, 800 \quad (8)$$

Here, $M_j = [m_{1j}, m_{2j}, \dots, m_{ij}]^T$ and $\sum_j \text{diag}[1/\sigma_{1j}^2, 1/\sigma_{2j}^2, \dots, 1/\sigma_{ij}^2]^T$ represent the Gaussian mean vector for fault patterns and the diagonal covariance matrix that determines the spreading of the RBF, respectively. The output layer is then a direct combination of the neuron outputs from the hidden layer in order to produce the final fault condition or fault severity level of the EV. The computation of the output layer is represented by the subsequent equality,

$$net_k^3 = \sum_j w_j y_j^2(N) \quad (9)$$

$$y_k^3(N) = y_{ki}^3(net_k^3(N)) = net_k^3(N) \quad (10)$$

The adjustable weights were learned during the training phase are represented as w_j . To develop the accurateness of the error diagnostics and lower computation requirements, the selection of effective RBFN inputs were made utilizing the polynomial representation of the identified function. A polynomial representation of the identified function in relation to the key features related to certain faults was constructed using the Polynomial Basis Function (PBF). The formulated equation for the EV fault diagnostics is represented as below:

$$y(t) = \sum_{k=1}^n \theta_{k\phi_k}(\vec{X}(t)) + \varepsilon(t) \quad (11)$$

The fault indicator is denoted as, $y(t)$. $\vec{X}(t)$ is the vector of measured signals from the EV, $\varepsilon(t)$ is the modeling error, ϕ_k is an infinite number of nonlinear mapping functions and θ_k is an infinite number of linear coefficients. The system model generated for N training samples is expressed in the following equation,

$$\vec{Y} = \varphi(\vec{X}(t)) \odot + e \quad (12)$$

Where, $\vec{Y} = [y(1), \dots, y(N)]^T$ indicates the output vector containing the fault labels and $\varphi(\vec{X}) = [\varphi_1(X), \dots, \varphi_n(X)]^T$ is the plotting function matrix. To construct the nonlinear mapping functions, use the following polynomial representation,

$$\varphi_k = \prod_{j=n_{y1}}^{n_{yi}} y(t-j) \prod_{k=1}^m \prod_{j=n_{xk1}}^{n_{xki}} x_k(t-d_k-j), i = 1, \dots, p, \varphi_0 = 1 \quad (13)$$

The polynomial order allows the model to replicate the dynamic fault attributes of EV systems, thus $0 \leq n_y, k1 \leq \dots \leq n_{yki} \leq l_y, 0 \leq n_{xki} \leq \dots \leq n_{xki} \leq l_x$, and $l_x = 10, l_y = 3$. The general RBFN fault diagnosis model is described using the selected polynomial term orders as,

$$y(t) = \sum_{k=1}^n \theta_{k\phi_k}(\vec{X}(t), c_k, \sigma_k) + \varepsilon(t) \quad (14)$$

Where, $\phi_k(\cdot)$ is the Gaussian radial basis activation function with centre c_k and width σ_k . In a similar manner, the RBFN fault diagnosis model is represented in this format.

$$\vec{Y} = \varphi(X, \vec{c}, \vec{\sigma}) \odot + \vec{e}1 \quad (15)$$

Here, $\varphi(X, \vec{c}, \vec{\sigma})$ is the hidden layer output matrix comprised by the centre and width selections that provide robust and reliable means of detecting and classifying faults in EV systems. The structure of ARBS-Net is depicted in figure 4.

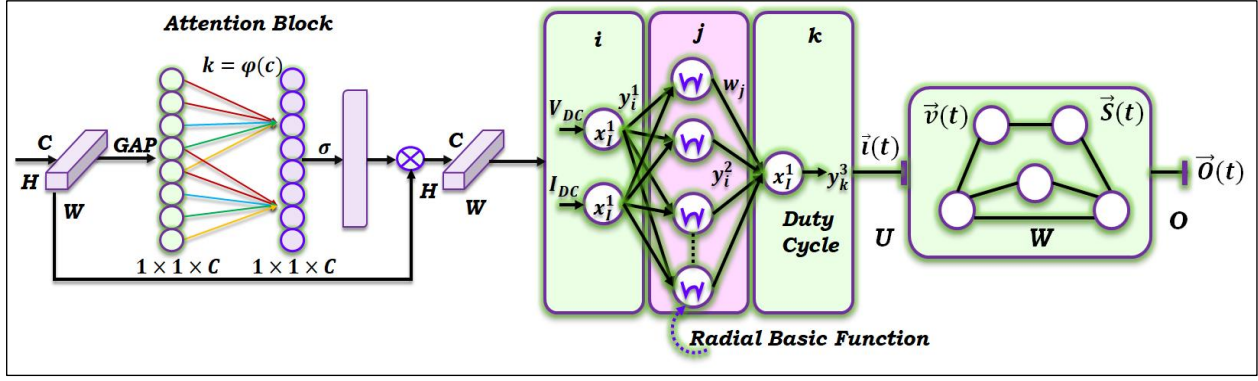


Figure 4: Structure of ARBS-Net.
Source: Authors, (2026).

A spiking neural network (SNN)-based fault diagnosis system for EVs utilizes the signals generated through measurement processes, such as battery voltage, current or temperature, as encoded neuron membrane potentials (t). When using traditional EV error analysis schemes, the actual mistake prediction mechanism is based on detecting a spike on the neuron membrane potential (t) that exceeds the predefined threshold value. Thus, fault detection occur instantaneously whenever the membrane potential exceeds the defined hard threshold causing a non-continuous fault detection response, which is expressed mathematically as,

$$\tau \dot{s} = -s + \sum_k \delta(t - t_k) \quad (16)$$

This method is sufficient for the protection of the EV from imminent failure, however, it does not provide the capability of detecting the continued gradual failure of a system, and limit the amount of time available to warn a user before failure occurs. To achieve a more sophisticated and informative fault detection capability, the hard threshold is replaced with an active fault sensitive region that is described by a gate function $g(v)$ and is defined as a narrow region in which the system is considered subject to failure due to fluctuations outside the defined threshold. In this case the synaptic dynamics is as follows,

$$\tau \dot{s} = -s + g\dot{v} \quad (17)$$

Where $g \geq 0$ and $\int g dv = 1$. In this SNN model, SNN synaptic activation gradually emerged during EV signal evolution within the active zone, inclusion of $\dot{v}$ ensures that fault representation remains rate-invariant since,

$$\int s dt = \int g \dot{v} dt = \int g dv = 1 \quad (18)$$

Consequently, both fast transients and slow degradations create equivalent spike-based fault evidence. This gate-based spiking functionality retains an event-driven fault semantic while facilitating differentiable, robust, and learning-compatible fault diagnosis in EV. Robust and adaptable fault diagnosis for EV is achieved by the ARBS-Net framework by means of the combination of Attention-based feature enhancement, RBFN Nonlinear mapping and SNN. The attention mechanism highlights features that are related to the fault while reducing background noise, the RBFN lower-order rules and correlations between multiple signals capture the nonlinear functional relationships within the data and thus generate a fault index, and spiking neurons support continuous and rate-invariant detection of both fast transients and gradually degrading systems. Thus, ARBS-Net provide early, accurate, and dependable identification of subsystem faults in an EV.

III.5 SALP SWARM OPTIMIZATION

In diagnosing faults with EVs, the process is modelled to find the best parameters, such as weights for features, hyper-parameters for classifiers, or thresholds for faults, which results in the maximum classification accuracy or a minimum error rate. In Salp Swarm Optimization algorithm, each salp is a candidate solution to an EV fault diagnostic problem, which is signified as a opinion in a d -dimensional search space defined by the number of decision variables in the EV fault diagnosis. The positions of each of the salps are stored in a two-dimensional matrix, denoted as X .

$$x_i = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_d^1 \\ x_1^2 & x_2^2 & \dots & x_d^2 \\ \vdots & \vdots & \dots & \vdots \\ x_1^n & x_2^n & \dots & x_d^n \end{bmatrix} \quad (19)$$

In forming the algorithms, for each salp, an objective function is utilized, based on actual data sources of EV operations such as currents, temperatures, and speeds, which produces the best defined solutions to the food position FP . The leader salp finds its position in relation to the food source based on the following rule,

$$x_i^1 = \begin{cases} FP_i + c_1((ub_i - lb_i)r_1 + lb_i) & r_2 \geq 0 \\ FP_i + c_1((ub_i - lb_i)r_1 + lb_i) & r_2 < 0 \end{cases} \quad (20)$$

Where, lb_i and ub_i are the lower and upper bounds of the i^{th} diagnostic constraint, r_1 and r_2 are uniformly distributed random numbers from [0 to 1]. The SSO uses each salp as a candidate solution within the diagnostic problem space to find the best possible diagnostic parameters by using iteratively updated leader–follower movements.

Pseudocode- Salp Swarm Optimized Attentive Radial Basis Spiking Network:

```

BEGIN
1: Load EV fault training and testing datasets
2: Split datasets into features X and labels y
3: Convert datasets into tensors and Data Loader batches
4: Define ARBSNN architecture with:
Input layer
Attentive hidden layer
Radial Basis Spiking layer
Output classification layer
5: Define objective function:
a) Initialize ARBSNN using candidate parameters
b) Train model for few epochs on training data
c) Evaluate classification accuracy on test data
d) Return fitness = 1 – accuracy
6: Initialize Salp Swarm Optimizer:
Population size P
Search dimension = 2 (hidden neurons, learning rate)
Maximum iterations Tmax
Parameter bounds (lb, ub)
7: Initialize salp positions randomly within bounds
8: Evaluate fitness of all salps
9: Select best salp as Food Source F
10: FOR iteration t = 1 TO Tmax DO
11:   Update control parameter c1
12:   FOR each salp i DO
13:     IF i == 1 THEN           // Leader salp
14:       Update salp position towards Food Source F
15:     ELSE                     // Follower salp
16:       Update salp position as average of previous salp
17:     END IF
18:     Apply boundary constraints
19:     Evaluate fitness of updated salp
20:     IF fitness improves THEN
21:       Update Food Source F
22:     END IF
23:   END FOR
24: END FOR
25: Extract optimal parameters from Food Source:
H* = optimal hidden neurons
η* = optimal learning rate
26: Initialize final ARBSNN using H* and η*
27: Train final ARBSNN model for predefined epochs
28: Evaluate training and testing accuracy and loss
29: Output trained SSO-ARBSNN model and performance metrics
END

```

Adaptive coefficient c_1 is utilised in SSO to help maintain both exploration and exploitation balance. As the algorithm iteratively searched through the solution space, it provided many opportunities to explore different fault signs at the beginning of the algorithm and systematically refine the diagnostic solution during subsequent iterations. This is especially important for closely fault signs to coupled together by varying operating conditions within EV environments. Coefficient c_1 is implemented to equilibrium exploration and exploitation in the optimization process and is given by,

$$c_1 = 2e^{-\left(\frac{4t}{t_{max}}\right)^2} \quad (21)$$

Where, t and t_{max} are used to denote current iterated value or maximum number of iterations. Finalisation of stable convergence and minimisation of the potential for premature stagnation, were made possible through leader and follower update strategies. The follower salps use leader and preceding salps to adjust their position which improves convergence stability based on,

$$x_i^j = \frac{1}{2}(x_i^j + x_i^{j-1}) \quad (22)$$

To ensure that the diagnostic solutions are constrained within the feasible operating limits of EV components, any salp that exceeds the search space is returned back into the allowable limit set by the boundary constraint. The flowchart of SSO is shown in figure 5.

$$x_i^j = \begin{cases} lb_i & \text{if } x_i^j \leq lb_i \\ ub_i & \text{if } x_i^j \geq ub_i \\ x_i^j & \text{otherwise} \end{cases} \quad (23)$$

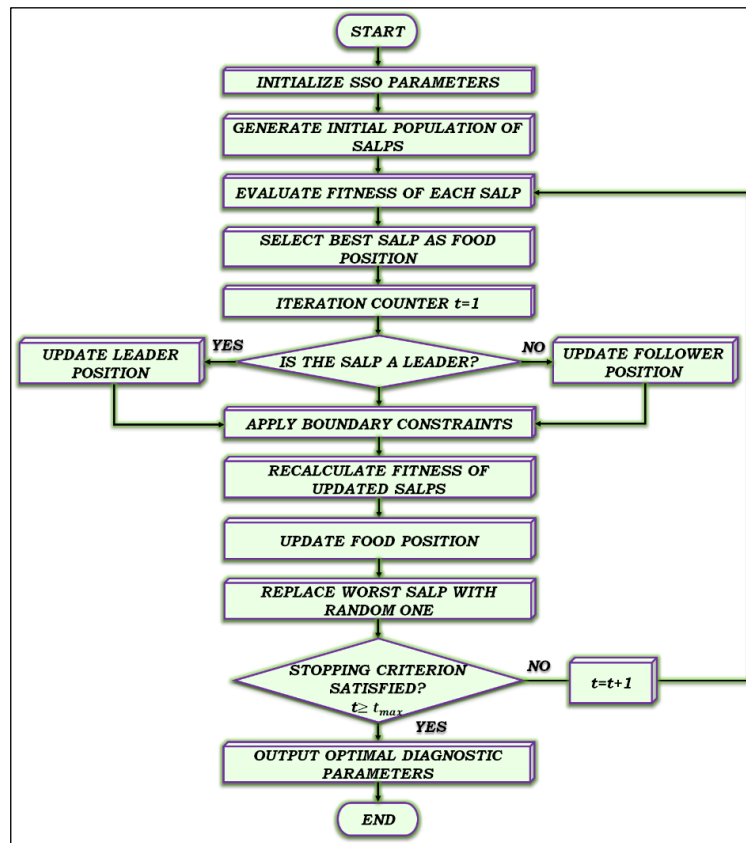


Figure 5: Flowchart of SSO.
Source: Authors, (2026).

By combining the ARBS-Net methodology using the leader-follower optimiser method and an adaptation strategy provides a balance between exploration and exploitation of actions taken by the decision maker. This research confirmed that the accuracy and operational reliability of SSO-optimized ARBS-NET successfully improve the effectiveness of EV performance. The SSO-based ARBS-NET mistake analysis produce a dependable and computationally effective classification for optimising the faults and failures of EVs, leading to improved accuracy and reliability in detecting faults. This structured process allows for the optimally constructed iterative optimisation process of all diagnostic parameters contained within the ARBS-NET providing increased accuracy of fault diagnosis performed on EV systems.

IV. RESULT AND DISCUSSION

The proposed SSO-ARBS-Net framework for diagnosing faults within EV systems is evaluated through the experimental data. The results show that integrating SSO with ARBS-Net produce substantially improved diagnostic accuracy, convergence stability and computational efficiency compared to non-optimized and conventional intelligent diagnostic approaches. Table 2 displays the report of dataset for the proposed system.

Table 2: Description of dataset.

DATASET DESCRIPTION	
Features	8
Total rows	11000
Features names	Voltage, Current, Motor Speed, Temperature, Vibration, Ambient Temperature, Humidity, Fault Label
Y label	Fault Label
Classes	Label 0: Normal Operation, Label 1: Motor-Related Faults, Label 2: Inverter-Related Faults, Label 3: Battery-Related Faults.

Source: Authors, (2026).

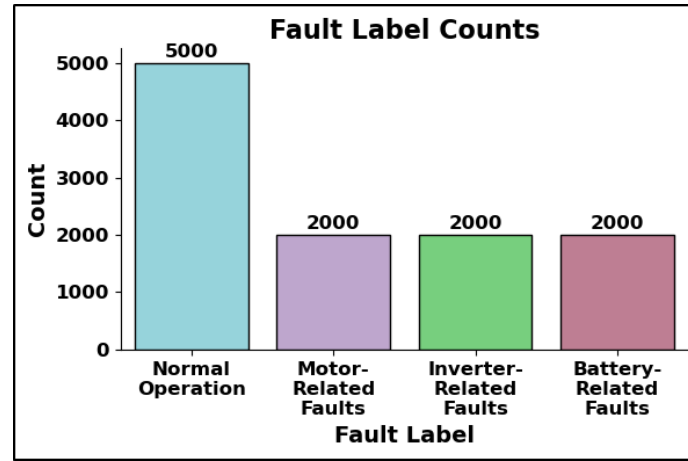


Figure 6: Fault Label Counts.
Source: Authors, (2026).

In figure 6, the data indicates that the category Usual Operation has the largest quantity of models with 5000. However, Motor faults, Inverter faults, and Battery faults each contained only 2000 samples, indicating class imbalance.

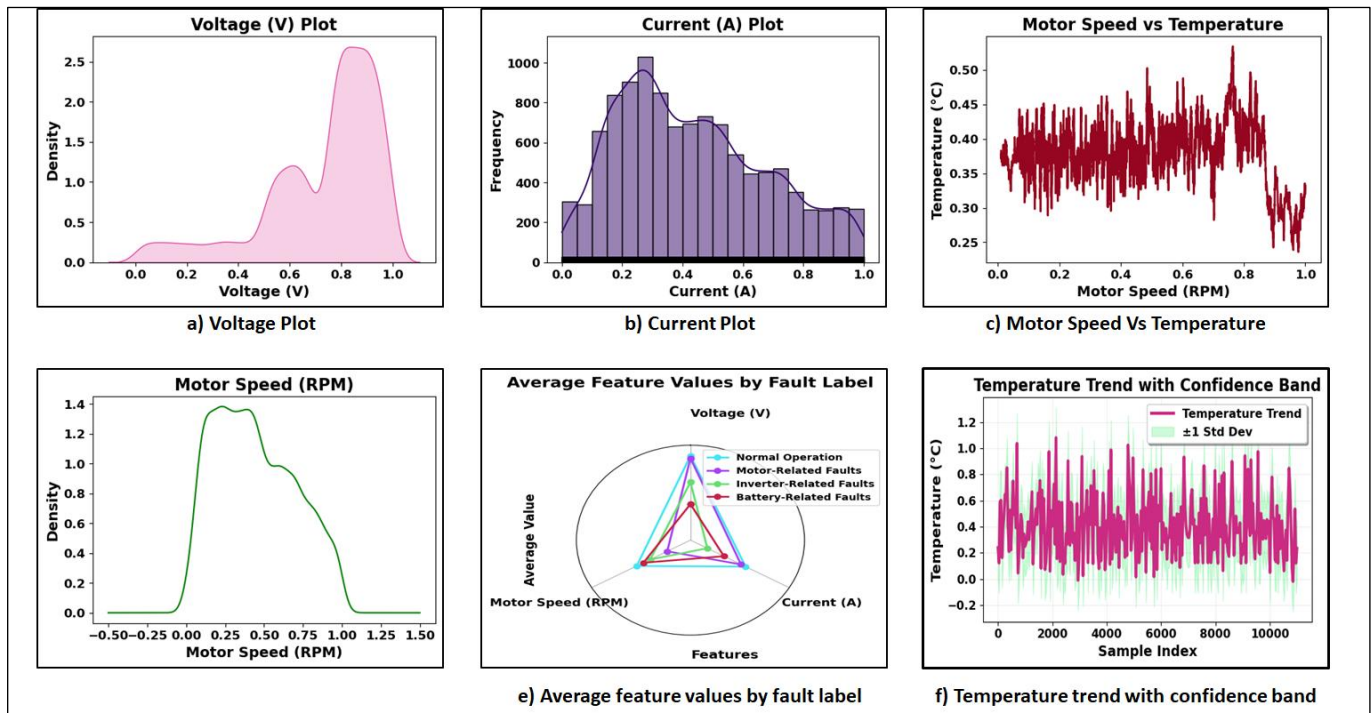


Figure 7: a) Voltage Plot, b) Current Plot, c) Motor Speed Vs Temperature, d) Motor Speed, e) Average feature values by fault label, f) Temperature trend with confidence band.
Source: Authors, (2026).

In figure 7, the data visualization has four plots such as the distribution of voltage; the distribution of motor speed; the histogram of current, and the association amongst motor speed and temperature. As a final, the average structures of the different fault classes are shown in radar chart form and the temperature trend with confidence band is displayed, both provide insight into the features behaviour and different fault classes differ under normal versus fault conditions.

Table 3: Classification report for the proposed system.

SI.NO	Performance Metrics	Values
1	Accuracy	0.99
2	Precision	0.99
3	Recall	0.99
4	F1-Score	0.99

Source: Authors, (2026).

According to the classification report in table 3, the proposed algorithm has a high accuracy, precision, recall, and F1-score of 0.99, creating it extremely accurate and providing reliable, consistent fault detection.

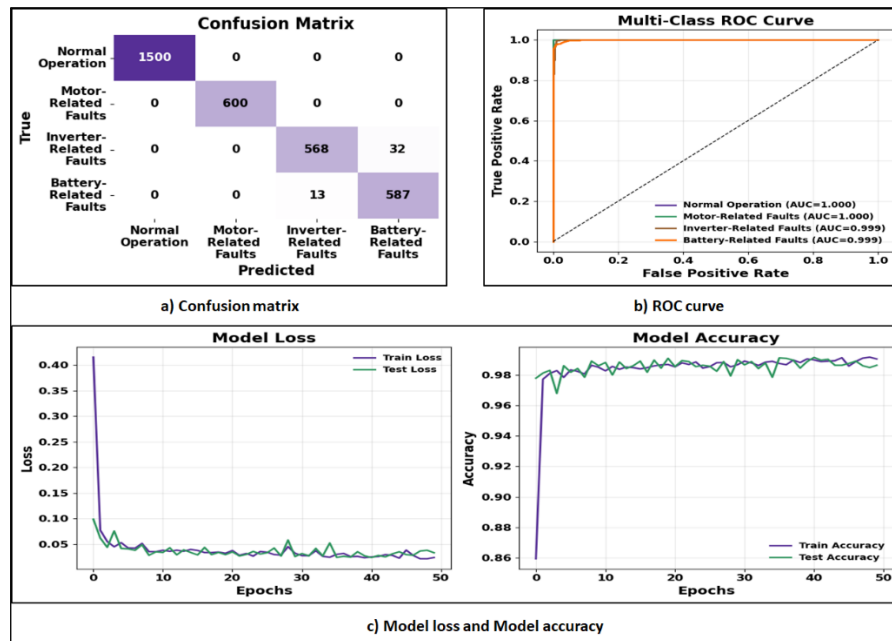


Figure 8: a) Confusion Matrix, b) ROC Curve, C) Model Loss and Model Accuracy for the Proposed System.
Source: Authors, (2026).

Figure 8 indicate a high level of confusion matrix demonstrates that very few errors occurred through all fault classes to their true classification. The ROC curves produced perfect AUC values of 1.0 which reflects excellent separability between each fault category. In addition, the model loss showed consistent decline, along with a rapid increase and stabilization of model accuracy at approximately 99%, confirming effective training of the algorithm and generalization ability.

Table 4: Classification report for Deep Neural Network.

SI.NO	Performance Metrics	Values
1	Accuracy	0.98
2	Precision	0.98
3	Recall	0.98
4	F1-Score	0.98

Source: Authors, (2026).

Table 4 illustrates a DNN to achieve an overall accuracy, precision, recall, and F1-score of roughly 98, indicating a strong performance for fault classification with very few misclassifications across the fault categories. However, the proposed system achieves the highest performance metrics.

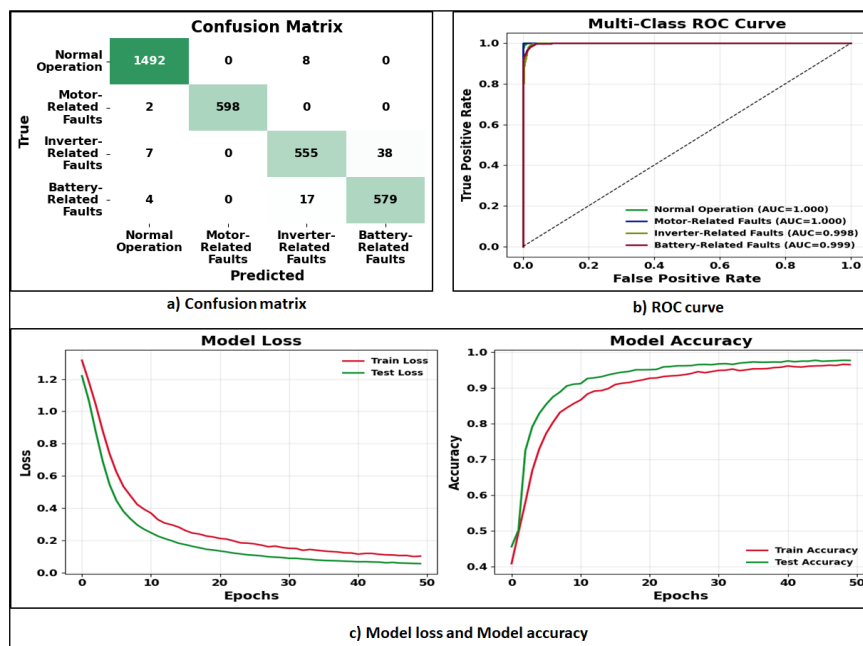


Figure 9: a) Confusion Matrix, b) ROC Curve, C) Model Loss and Model Accuracy for DNN.
Source: Authors, (2026).

In figure 9, the analysis of the confusion matrix revealed that the model potentially make several misclassifications across any of the fault types, indicating that the model has good prediction ability. The ROC curves show that the model has high AUC value 0.998-1.000 which indicates that the class separability between the faults is very high. Furthermore, as the loss decreases the model accuracy continues to increase and remains around 98 which confirms that the DNN is learning an appropriate manner to generalise the unseen data.

Table 5: Classification report for BiLSTM.

Sl.NO	Performance Metrics	Values
1	Accuracy	0.96
2	Precision	0.96
3	Recall	0.96
4	F1-Score	0.96

Source: Authors, (2026).

Table 5 depicts the BiLSTM model and produced 96% accuracy, 96% precision, 96% recall, and 96% F1 score which indicates that the BiLSTM performed lower level than the proposed models that achieved higher results.

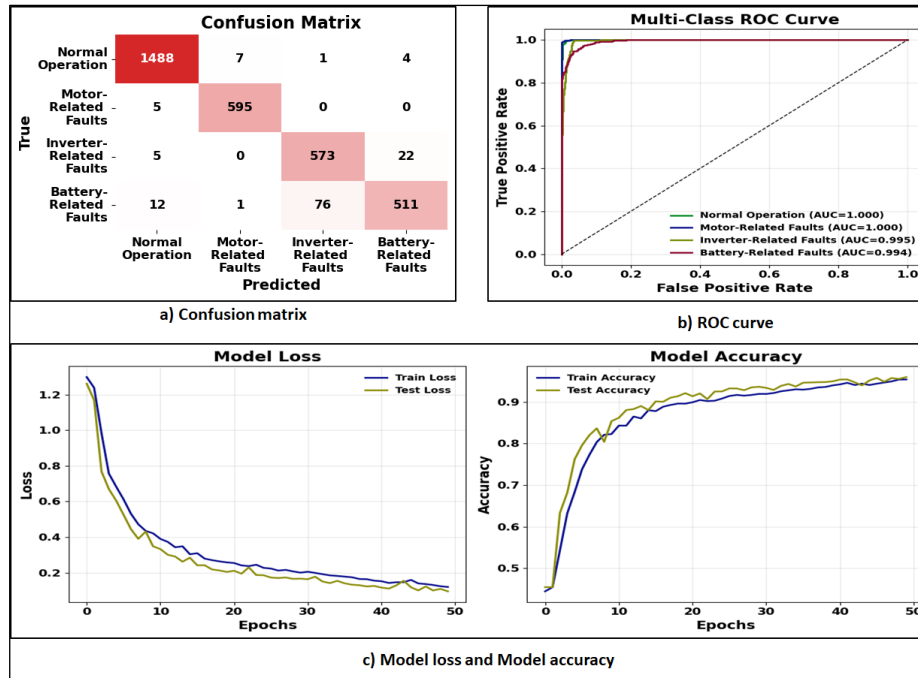


Figure 10: a) Confusion Matrix, b) ROC Curve, C) Model Loss and Model Accuracy for BiLSTM.

Source: Authors, (2026).

Figure 10 shows the analysis of the confusion matrix revealed several misclassifications, predominantly within the faults associated with the battery and inverter components, however, the predictions made from the model were accurate. The ROC curves indicate high AUC values of 0.994-1.000 such that the method has a strong capability to discriminate amongst different modules. The model has produced a decrease in loss and achieved an increase in accuracy to approximately 96%, confirming that the BiLSTM is trained consistently and performs in generalisation to new data.

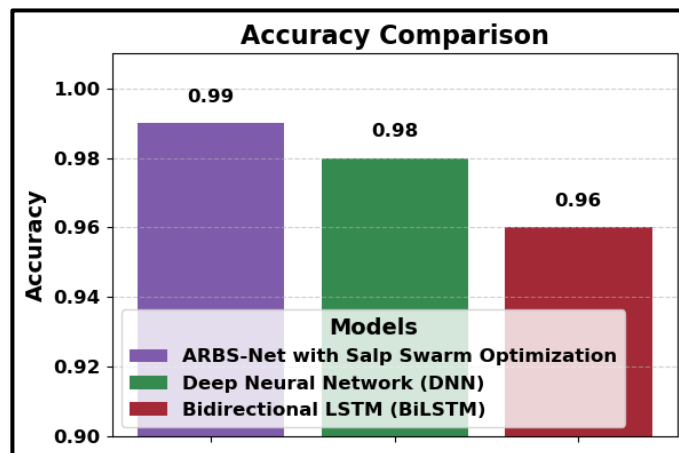


Figure 11: Comparison of accuracy.

Source: Authors, (2026).

From the accuracy comparison in figure 11, it determined that the ARBS-Net and Salp Swarm Optimisation model produced the highest accuracy (0.99), followed closely by DNN (0.98) and BiLSTM (0.96). This indicates that the proposed ARBS-Net approach has better performance than the other two systems evaluated.

Table 6: Comparison of evaluation metrics.

METRICS	PROPOSED MODEL	DNN	BILSTM
Accuracy	0.9864	0.977	0.9597
Precision	0.9815	0.9717	0.9513
Recall	0.9813	0.9703	0.9476
F1-Score	0.9812	0.9709	0.9484
Cohen Kappa	0.9804	0.9668	0.9419
MCC	0.9804	0.9669	0.9423
Hamming Loss	0.0136	0.023	0.0403
Jaccard Score	0.9638	0.9446	0.9047
Log Loss	0.0337	0.0565	0.0949
Balanced Accuracy	0.9813	0.9703	0.9476
F2-Score	0.9812	0.9705	0.9477
Zero-One Loss	0.0136	0.023	0.0403
Top-2 Accuracy	0.9997	0.9994	0.9997
Specificity	0.9958	0.9924	0.9867
G-Mean	0.9814	0.971	0.9495

Source: Authors, (2026).

In table 6, the evaluation reveals that the suggested model is higher than DNN and BiLSTM in most metrics used to evaluate models. It shows the suggested model has the best accuracy, precision, recall, F1-score, Kappa, MCC, Jaccard score, balanced accuracy, F2-score, specificity, and G-Mean of any of the models evaluated, and it produce the lowest Hamming loss, log loss, and zero-one loss. While other models produce very high Top-2 accuracies, the suggested model has the highest overall performance on all of the metrics.

Table 7: Comparative analysis of accuracy for various methods.

SLNO	MODEL	ACCURACY
1	CATBOOST [23]	0.94
2	RF [25]	0.95
3	SVM [24]	0.95
4	ANN [21]	0.96
5	IB-DRN [22]	0.98
6	PROPOSED	0.99

Source: Authors, (2026).

Table 7 demonstrates that the suggested model has the highest accuracy (0.99) compared to CATBOOST (0.94), RF and SVM (0.95), ANN (0.96) and IB-DRN (0.98), thus confirming its superior performance to other models.

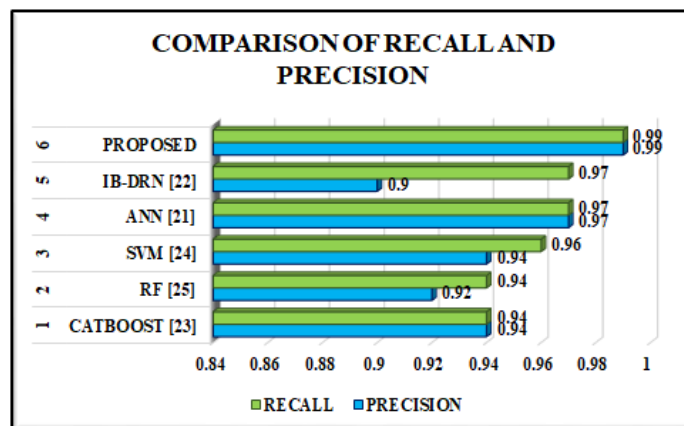


Figure 12: Comparison of recall and precision.

Source: Authors, (2026).

Figure 12 displays both recall and precision for the different models analysed. The suggested method has the maximum recall and precision (both 0.99) compared to other models including IB-DRN, ANN, SVM, RF and CATBOOST, indicating its superior and more balanced classification performance.

Table 8: Comparison of F1-Score for various methods.

SLNO	MODEL	F1-SCORE
1	CATBOOST [23]	0.94
2	RF [25]	0.93
3	SVM [24]	0.95
4	ANN [21]	0.97
5	IB-DRN [22]	0.94
6	PROPOSED	0.99

Source: Authors, (2026).

In table 8, based on F1-scores, the proposed model is superior to the other proposed methods with respect to its F1 score of 0.99. Among the other methods tested, ANNs had an F1 score of 0.97 while SVM had an F1 score of 0.95, CATBOOST had an F1 score of 0.94, IB-DRN had an F1 score of 0.94, and RF had an F1 score of 0.93. All models performed well, demonstrating the ability to accurately classify observations, however, the proposed model outperformed every existing model by having greater accuracy and robustness relative to predictions.

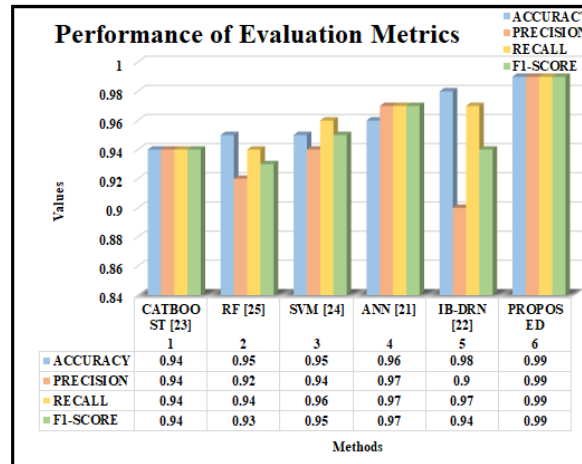


Figure 13: Comparison of performance metrics.

Source: Authors, (2026).

Figure 13 compares the accuracy, precision, recall, and F1-score of all six classifiers including CATBOOST, RF, SVM, ANN, IB-DN, and the proposed model. The proposed model outperforms all classifiers on all four measures of 0.99. IB-DN had an accuracy of 0.98 and a precision of 0.90. ANN performed consistently well throughout, while SVM and RF performed moderately. CATBOOST recorded the same performance level across all measures. Hence, the proposed model outperformed existing models for all evaluation criteria.

V. CONCLUSION

The proposed system provides a complete and intelligent framework to diagnose faults of EVs using an optimized and distributed Salp Swarm Optimized ARBS-Net. The establishment of the framework involves the acquisition of EV parameters such as voltage, current, motor speed, temperature, vibration, and humidity to create a dataset representing both electrical and mechanical characteristics of each fault. Pre-processing the dataset through normalisation improves the consistency and stability of the data for better performance when training the models. EDA provides insights into the distribution and relationship of each of the features, making it possible to locate hidden patterns in the data, which enables informed feature selection. Further, feature engineering allows for the creation of the most significant individual features connecting to fault characteristics by extraction and redundancy reduction to allow for a reduction in computational complexity when diagnosing faults. By utilizing SSO, the ARBS-Net model integrates attention mechanisms, radial basis functions, and spiking neural dynamics to create a learning model that optimizes parameters and it prevents the occurrence of local minima during training the model. Metrics used for evaluation purposes include high accuracy, precision, recall and F1-Score of 0.99. These results indicate that EV's fault conditions are correctly predicted, and thus the proposed system deliver a highly intelligent, scalable, robust and evolving diagnostic capability which allow for proactive maintenance and minimize unexpected failures and to increase the operating reliability and sustainability of EVs.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Ganapavarapu Harish, V. Suresh, D. Ravi Kishore, and B Kavya Santhoshi.

Methodology: Ganapavarapu Harish and V. Suresh.

Investigation: Ganapavarapu Harish and V. Suresh.

Discussion of results: Ganapavarapu Harish, V. Suresh, D. Ravi Kishore, and B Kavya Santhoshi.

Writing – Original Draft: Ganapavarapu Harish.

Writing – Review and Editing: Ganapavarapu Harish and V. Suresh.

Resources: V. Suresh.

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Approval of the final text: Ganapavarapu Harish, V. Suresh, D. Ravi Kishore, and B Kavya Santhoshi.

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