Sandcat Optimized ANN-LSTM Framework for Advanced Fault Detection in Electric Vehicle Drive Motor

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Abstract*— In order to guarantee the longevity, safety and efficiency of drive motors, there is an urgent need for sophisticated and dependable defect detection systems due to the growing dependence on Electric Vehicles (EVs). Conventional diagnostic techniques frequently struggle to handle intricate, time-varying sensor data and are unable to adjust to changing operational circumstances. A novel framework for EV motor defect detection utilizing a Sandcat Optimized ANN-LSTM model is proposed in this study to overcome these limitations. To ensure high-quality inputs for learning, the system first gathers raw sensor data from the motor and refines it using a systematic preprocessing model that includes data cleaning, one-hot encoding, and normalization. In order to standardize input magnitudes and enhance the learning dynamics of the model, feature engineering is utilized through feature scaling. Accurate fault state classification is made possible by the use of a hybrid ANN-LSTM network, which captures the motor signals' temporal and spatial features. Sandcat Optimization, which adjusts hyperparameters to attain the best accuracy and efficiency, further improves the model's performance. The designed framework provides a better performance analysis from python software, which provides a reliable and clever way to detect faults in EVs drive systems by successfully differentiating between normal and defective motor characteristics with higher accuracy of (97%).

Keywords*— *Electric Vehicles, Sandcat Optimized ANN-LSTM model, preprocessing model, feature scaling.

I. INTRODUCTION

A. Background and Motivation

EVs are quickly changing the way people travel across the world because of their advantages for the environment, energy efficiency, and technology [1]. The drive motor is a crucial part of an EV that converts energy and propels the vehicle forward. But much like any other mechanical or electrical system, drive motors have problems such rotor imbalances, bearing corrosion, and winding failures [2]. If ignored, these issues results in decreased efficiency, worsened performance, and in extreme situations, complete motor failure. Consequently, one of the most important areas of research in the fields of smart diagnostics and electric mobility is the creation of precise and intelligent defect detection systems [3].

B. Challenges in Existing topologies

The Conventional defect diagnostic methods, which generally rely on rule-based systems, signal thresholding, or custom feature extraction, are incapable of observing the non-linear and dynamic nature of motor function under different conditions. Further, such methods tend to be inflexible and not very scalable when faced with large scales of real-time sensor data [4]. While some machine learning (ML) models have been developed to detect faults automatically, they tend to struggle with capturing sequential patterns and require significant manual parameter tuning [5]. These limitations highlight a need for a more intelligent and automated problem detection services.

C. Role of Deep Learning and Optimization Model

Deep learning has revolutionized fault detection systems by removing the need for time-consuming manual preprocessing and handcrafted features, as it allows features to be automatically learned from raw sensor data. Long Short-Term Memory (LSTM) networks [6], recurrent neural networks (RNNs) [7], and convolutional neural networks (CNNs) [8] are traditional DL architectures that have been thoroughly investigated in industrial defect diagnosis applications, because of their ability to model complex nonlinear relationships. LSTMs are particularly effective at capturing temporal dependencies in sequential data (e.g., voltage, current, and speed signals over time), whereas CNNs are effective at detecting spatial features in vibration or image based signals [9-10]. In spite of their advantages, these models do have some disadvantages relating to high processing requirements, settings for hyperparameters, and overfitting on small or unbalanced datasets.

To tackle these issues and improve the performance of deep learning models, researchers have progressively turned to optimization methods for automated hyperparameters tuning [11]. The structure and the learning parameters of neural networks have been enhanced by well-established met heuristic methods (i.e., Genetic Algorithms (GA) [12], Particle Swarm Optimization (PSO) [13], Grey Wolf Optimizer (GWO) [14], and Whale Optimization Algorithm (WOA) [15]. These techniques aid in avoiding local minima, enhancing model generalization, and speeding up convergence. However, the complexity of the task and algorithm-specific parameters have a substantial impact that leads to higher complexity and takes more time to converge.

D. Objectives and Contributions

- The framework incorporates robust preprocessing techniques, including data cleaning, one-hot encoding, and normalization to ensure high-quality inputs motor for the model.
- Feature engineering using scaling technique ensures uniform feature distribution, enabling balanced training and improving model generalization
- A novel architecture combining ANN-LSTM for effective fault classification in EVs motors.
- The sandcat optimization algorithm is applied to automatically tune the ANN-LSTM hyperparameters, enhancing convergence speed and classification performance.

II. PROPOSED SYSTEM DESCRIPTION

The proposed system's whole flow is depicted in the block diagram in Fig. 1. First, input motor failure signals are acquired and then directed through a data preparation step. Data normalization, which adjusts input features to a consistent range, one-hot encoding, which transforms categorical fault labels into binary vectors appropriate for classification tasks, and data cleaning, which deals with noise and missing values, are all included in this step. The feature engineering module receives the preprocessed data after which feature scaling is used to standardize numerical values and guarantee that each characteristic contributes equally.

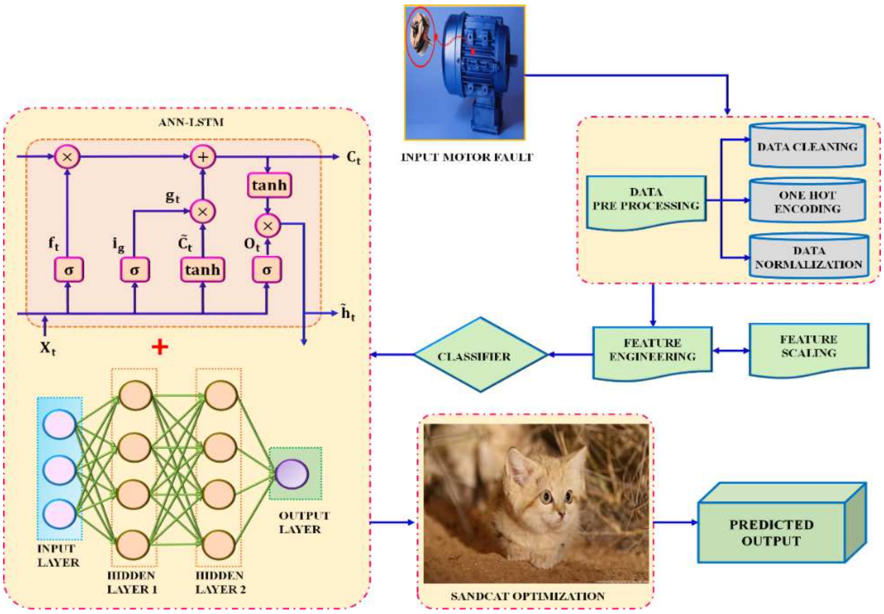

Fig. 1. Block diagram for the proposed work

After that, the input is processed by the classifier, which is made up of an ANN and an LSTM network. While the LSTM records the temporal dependencies necessary for fault pattern recognition, the ANN layers extract spatial relationships. By fine-tuning the ANN-LSTM network's hyper parameters, the Sandcat optimization algorithm optimizes the entire framework and generates a high-confidence projected output that represents the motor's fault status.

III. PROPOSED SYSTESM MODELLING

1. Data Preprocessing

In order to improve quality of input motor fault data and guarantee the dependability and effectiveness of the classification model, data preprocessing is essential. To get raw data ready for analysis and model training, the preprocessing stage usually entails data cleaning, one-hot encoding, and normalization techniques.

- **Data Cleaning-** Data cleaning, the initial stage of preprocessing, deals with missing, incorrect, or noisy values in the dataset. The Missing values due to miscommunication, errors in collecting manual data or sensor failures. Defines noise and outliers through statistical analysis, and this helps to keep the data in the input signals intact. The potential of the model being inaccurate is reduced through this as it ensures the dataset accurately reflects the motor's operational characteristics

- **One-Hot Encoding-** It is often necessary to transform categorical labels, including fault types (bearing, stator, rotor fault, etc.), into machine-readable numbers that are effectively different values; this is typically performed by engaging a process called one-hot encoding, which converts each category class into a binary vector. For the three-class classification problem, for example, the labels could be defined as [1, 0, and 0] for bearing fault, [0, 1, 0] for rotor fault, and [0, 0, 1] for stator fault. This provides an effective learning process in their classifications by not permitting the model to presume any ordinal nature between the different categories of faults.

- **Data Normalization-** When the data includes characteristics of different magnitudes, such current, voltage, and vibration signals, normalization is essential to bringing all the input properties to a single scale. One popular technique is min-max normalization, which uses the following equation to rescale the feature values to a specified range, usually [0, 1],

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Where, x represents the initial value, x_{min} and x_{max} represents feature's minimum and maximum values, and x' represents normalized value.

2. Feature Engineering

The process of feature engineering is crucial to the discovery of IM faults because it has a direct impact on model's capacity to extract discriminative patterns from input data. Among the several methods, feature scaling is one that is essential for improving model performance since it guarantees that each feature contributes proportionately during the training process. Numerical characteristics obtained from sensor readings, such as current, voltage, vibration, or temperature, frequently make up the data. The ranges of these characteristics differ greatly, for instance, vibration levels may be in fractions of a unit, whereas current may vary in tens of amperes. Features with larger magnitudes dominate the learning process if they are not properly scaled, leading the model to misinterpret their relative relevance to features with smaller magnitudes.

Feature scaling is used to counteract this, bringing all features into a similar range. This not only speeds up convergence and eliminates bias toward high-magnitude features, but it also increases the numerical stability of algorithms, particularly those based on gradient descent or distance metrics.

Z-score normalization, also known as standardization, is one of the best scaling methods, it changes the features so that their mean is zero and their standard deviation is one. It is stated numerically as:

$$x' = \frac{x - \mu}{\sigma} \tag{2}$$

Here, x stands for the original feature value, μ refers mean of feature, σ signifies standard deviation of feature and x' signifies standardized feature value. Subsequently, the features gets classified through ANN-LSM model.

A. Modelling of SCO with ANN-LSTM Model

ANN-LSTM model

This work focuses on employing LSTM networks for temporal data and ANN for time-invariant data. LSTMs use input, output, and forget gates to define sequential time dependencies. These networks use inputsx_t,h_{t-1}, and C_{t-1} to generate outputs $h_t$and C_t. ANNs, on the other hand, have a hidden layer with units connected to all preceding and subsequent layers. Fig. 2 depicts a combined LSTM-ANN network with input (x), output (h), nonlinear activation functions$(\sigma(\cdot)$ and $tanh(\cdot)$, point-wise multiplication and addition $(*$ and $+)$, and cell state (C).

Three LSTM units sending outputs to the ANN layers. Nonlinear activation functions are used by ANN layers to process time-invariant input data. The cellulose DP and Kappa number are shown in output layer. Temporal dependencies are made simpler by using LSTM layers first, which enable network to collect time-varying data straight from input layer. At time instant t, cell state,c is sent through LSTM block and modified by the gates, as shown in the equations below.

$$f_t = \sigma\left(W_f.[h_{t-1}x_t] + b_f\right) \tag{3}$$

$$i_t = \sigma(W_i, h_{t-1} + b_i) \tag{4}$$

$$C_t = tanh(W_c.h_{t-1} + b_c) \tag{5}$$

$$g_t = i_t.C_t \tag{6}$$

$$C_t = f_t * C_{t-1} + g_t \tag{7}$$

$$\sigma_t = \sigma(W_O.[h_{t-1}x_t] + b_O) \tag{8}$$

$$h_t = o_t * \tanh(C_t) \tag{9}$$

The first gate in an LSTM network is forget gate denoted by f_t in (3). The amount of data kept in cell state is determined by input gate (g_t) in (4-6). Equation (7) defines the updated cell state. The input layer decides which cell state needs to be changed, while $C_t$represents possible updating values. The output gate, denoted byo_t, determines the output of the LSTM block. Equations (8) and (9) define the quantity of cell state output determined by this gate. W_f,W_i, W_c and W_O indicate the trainable weights for each gate layer, while b_f, b_i, b_c, and reflect the corresponding bias.

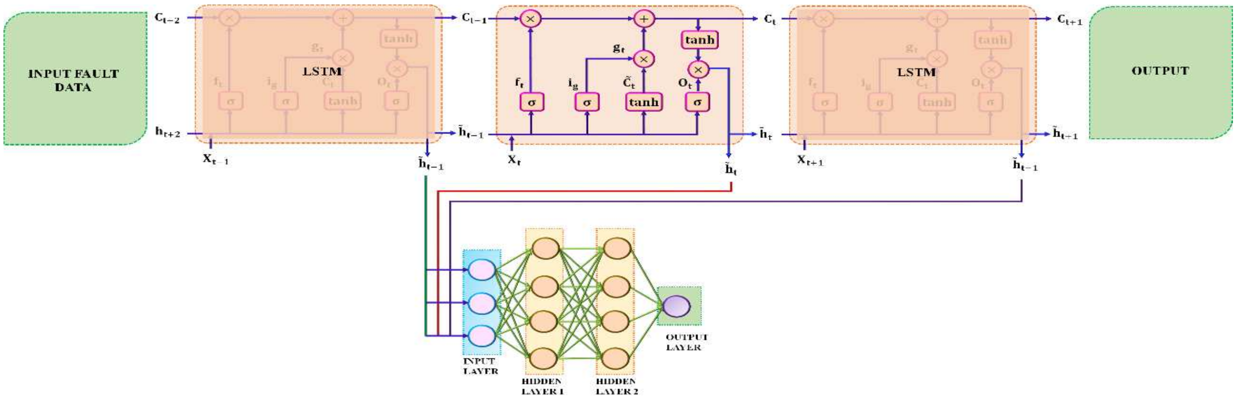

Fig. 2. Structure of ANN-LSTM model

Following equation defines output state of time-step t in layer l:

$$h_t^{(l)} = LSTM(x_t, h_{t-1}^{(l)} \tag{10}$$

The ANN layer comes after the LSTM layers have produced their outputs. W_a And b indicate this layer's trainable weights and biases. The output of the ANN layer, indicated by y, is supplied by the following equations.

$$y_t = \sigma(W_a . h_t + b_a) \quad (11)$$

After training LSTM-ANN model parameters of this ANN-LSTM model gets fine-tuned with the help of SCO as discussed below.

SandCat Optimization

Depending on the degraded input data, modify hyperparameters such hidden layers, neural network layers, and filtered redundant information to create an efficient RUL prediction model. In addition to being time-consuming or experience-based, traditional hyperparameters optimization techniques are unable to guarantee the best possible parameter combination. Sand Cat Swarm is an optimization algorithm that uses swarm intelligence. The unique ability of sand cats to find its food both above and below ground is used to show an optimization technique that detects low-frequency, which expressed as

$$r_G = S_M - \left(\frac{S_M * t}{t_{max}}\right) \quad (12)$$

$$R = 2 * r_G * rand - r_G \quad (13)$$

$$r = r_G * rand \quad (14)$$

Where t and t_{max} denotes current iteration number and maximum iteration, respectively and S_M is set to 2. r_G Indicates that as the number of iterations grows, it decreases from 2 to 0. . R indicates parameter that is selected during the attack and search phases. Interestingly, when $|R| \leq 1$, the sand cat moves into attack state; then, it remains in search state. Each sand cat's sensitivity range is indicated by r. A random number between 0 and 1 is represented by $rand$. The attack's mathematical model is shown as follows.

$$P_r = |rand * P_{bc}^t - P_c^t| \quad (15)$$

$$P_c^{t+1} = P_c^t - r * P_r * \cos(\theta) \quad (16)$$

P_r Indicates a random point around the optimal position, allowing the sand cat to approach it. P_c^{t+1} Reflect the updated location. To avoid a local optimum, θ is determined at random using roulette. When $|R| > 1$, sand cats look for prey within their sensitivity range. The position expressed as

$$P_c^{t+1} = r * (P_b^t - P_c^t * rand) \quad (17)$$

Where, the optimal candidate solution is represented by P_b^t, respectively.

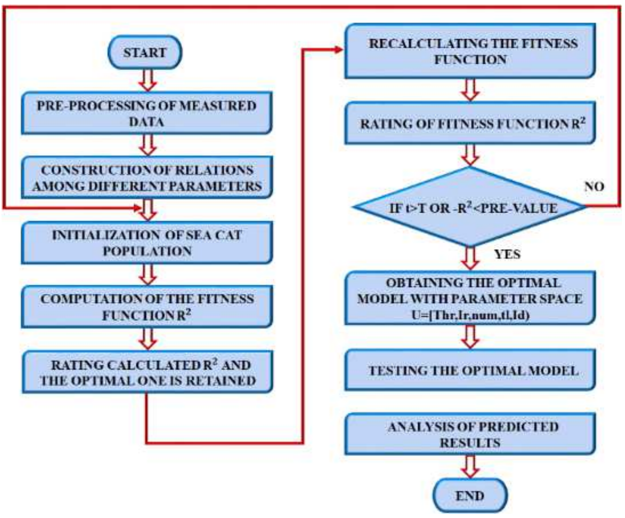

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Fig. 3. Flowchart of SCO-ANN-LSTM model

The utilized SCO model helps to categorize the faults identification of EV motor very accurately. Also, it aids to minimize error and complexity.

IV. Results And Discussion

For the validation of proposed system works for categorizing motor fault prediction, it is evaluated in python software, the results are discussed clearly in this section. Also the comparison performance of classical utilized models are also discussed here for showing the importance of proposed topology.

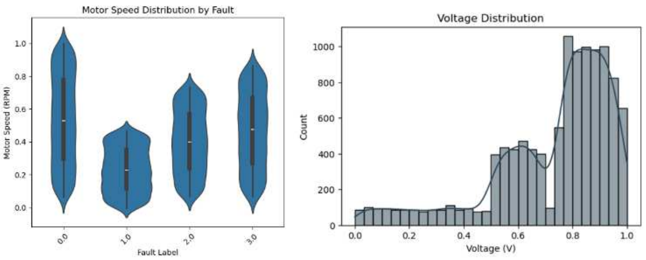

Fig. 4. Motor speed and voltage distribution Plots

The motor speed distribution by Fault in Fig. 4 displays clear variations in speed across different fault categories, confirming that motor speed is a strong discriminating feature. The voltage distribution histogram illustrates voltage varies across samples, highlighting fault-induced deviations in voltage levels.

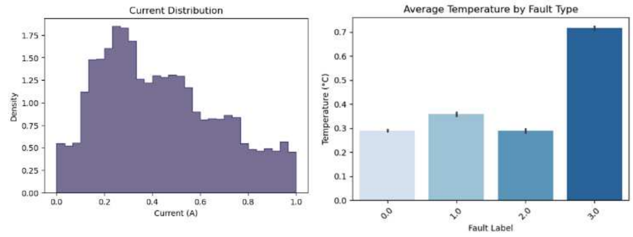

Fig. 5. Current and average temperature distribution fault type

Figure 5 illustrates current distribution, which shows the spread of current values and identifies potential shifts under different fault states. The average temperature by fault type reveals rising trends in temperature under specific faults, indicating overheating patterns.

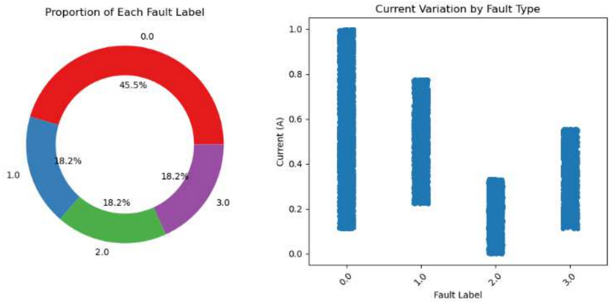

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Fig. 6. Proportion of each fault label and current variation fault type \

The proportion of each fault label figure in Fig. 6 demonstrates the class balance, revealing the data spread across different fault classes. The current variation by fault class indicates the distinction in current levels assigned for each fault label, thus enhancing the model's performance in identifying fault labels on the input signal.

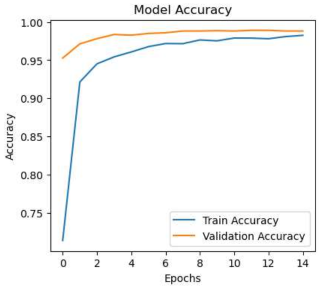

Fig. 7. Accuracy and Loss curve

The model accuracy graph in Fig. 7 shows rapid convergence, with both training and validation accuracy exceeding 97%, while the loss graph shows a steep decline in loss values, indicating strong generalization and minimal overfitting.

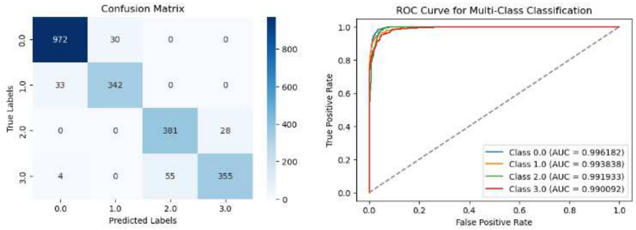

Fig. 8. Confusion Matrix graph and ROC curve

Figure 8 indicates confusion matrix proves model's effectiveness, displaying high diagonal values which reflect correct predictions for each class with minimal misclassification. The ROC Curve for Multi-Class Classification shows AUC values close to 1.0 for all fault classes, which signifies excellent classification capability across the board.

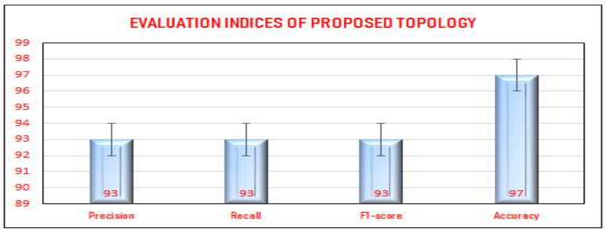

Fig. 9. Obtained values of various metrics

The proposed system's different indices are illustrated in Fig. 9, which demonstrated that that higher value of precision, recall, F1-score and accuracy are attained with the help of ANN-LSTM with SOA.

TABLE I. Comparison Of Losses

Classifiers	Loss
ResNet [7]	0.75
CNN [6]	1.2
LSTM [10]	0.85
Proposed ANN-LSTM	0.71

The losses comparison of ANN-LSTM over various classifiers are illustrated in TABLE I. According to table it is proven that compare to the other models proposed approach maintains minimal losses of 0.71.

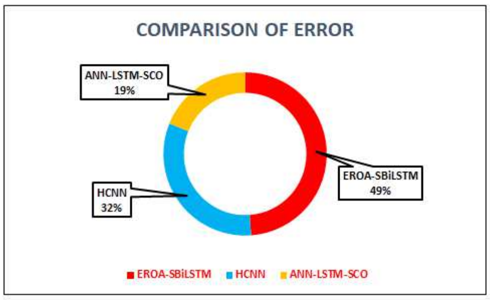

Fig. 10. Comparison of Error over other topologies

The error comparison over different models are shown in Fig. 10. The pie chart represents that the proposed ANN-LSTM-SCO model achieves minimal error compare to the other models utilized in the recent studies refer in [2-11].

V. CONCLUSION

This paper addresses the increasing need for sophisticated, real-time diagnostic solutions in the field of electric mobility by proposing a novel sandcat optimized ANN-LSTM framework for enhanced defect identification in EV drive motors. The model guarantees high-quality inputs for the classifier by combining efficient feature scaling with strong data pretreatment approaches. Accurate classification of different failure states is made possible by the hybrid ANN-LSTM architecture, which captures both the spatial and temporal properties of motor sensor data. By adjusting crucial hyperparameters, the sandcat optimization approach improves model performance even more, resulting in quicker convergence, lower computing overhead, and better generalization. Comparing the presented approach to traditional techniques, experimental results confirm its superiority in terms of classification accuracy of (97%) and minimal error.

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