



## RESEARCH ARTICLE

## OPEN ACCESS

# STARFISH OPTIMIZED AI-BASED DEEP LEARNING MODEL FOR ACCURATE BROKEN ROTOR BAR FAULT DETECTION IN INDUCTION MOTORS

Killamsetti Vijeta<sup>\*1</sup>, Sri Suyambulinga Perumal B<sup>2</sup>, R. Tharwin Kumar<sup>3</sup>, Nirani I R<sup>4</sup>, Jinsha Lawrence<sup>5</sup>, Gunasekar M<sup>6</sup>

<sup>1</sup>Assistant Professor, Department of Electrical Engineering, Medicaps University, Indore, India.

<sup>2</sup>Assistant Professor, Department of Chemistry, Vel Tech High Tech Dr.Rangarajan Dr.Sakunthala Engineering College, Chennai, India.

<sup>3</sup>Department of Electrical and Electronics Engineering, Mohan Babu University, Tirupati, Andhra Pradesh, India.

<sup>4</sup>Lecturer, Department of Mechanical Engineering, Edumentor, Thrissur, Kerala, India.

<sup>5</sup>Assistant Professor, Department of Computer Science and Engineering, Faculty of Engineering, Karpagam, India.

Academy of Higher Education (Deemed to be University), Coimbatore, Tamil Nadu, India.

<sup>6</sup>Assistant Professor, Department of Computer Science and Business Systems, Vel Tech Multi Tech Dr.Rangarajan Dr.Sakunthala Engineering College, Avadi, Chennai, Tamil Nadu, India.

<sup>1</sup><http://orcid.org/0000-0002-7925-5596>, <sup>2</sup><http://orcid.org/0000-0001-8006-7202>, <sup>3</sup><http://orcid.org/0000-0002-3438-4562>,

<sup>4</sup><http://orcid.org/0009-0007-7087-7413>, <sup>5</sup><http://orcid.org/0009-0003-0291-9272>, <sup>6</sup><http://orcid.org/0009-0007-3921-5403>,

Email: \*vijetha258@gmail.com, bsslperumal@gmail.com, tharwin.eee@gmail.com, niraniyyani@gmail.com, jinshalarence@gmail.com, gunaceg2017@gmail.com

## ARTICLE INFO

**Article History**

Received: February 17, 2026

Reviewed: June 7, 2026

Accepted: July 7, 2026

Published: July 31, 2026

**Keywords:**

Induction motor,  
fault diagnosis,  
EDEWF,  
RBFNN- MHAT,  
SFOA.

## ABSTRACT

To maintain the safety and reliability of industrial applications, it is important to analyse faults in three-phase induction motors. Traditional methods have difficulty in identifying the complex characteristics of errors in three-phase induction motors because the signals associated with three-phase induction motors are often noisy and exhibit non-linear dynamics. In this paper, a comprehensive method to analyse errors in three-phase induction motors are proposed that utilises advanced signal preprocessing, feature extraction, and Deep Learning (DL) methods to address these issues. Initially, an Entropy-Driven Empirical Wavelet Filter (EDEWF) are applied to clean the raw motor signal, and a Min-Max scaling is used to normalise the signal to create useful features. Next, an integrated hybrid model combining a Radial Basis Function Neural Network (RBFNN) with a Multi-Head Adaptive Transformer (MHAT) are used for capturing local non-linear characteristics and global context. The features extracted from both models are combined into one feature vector and passed through a fully connected layer for classification. The Starfish Optimization Algorithm (SFOA) is implemented to adjust the hyperparameter of the proposed integrated hybrid model to improve the overall performance. The results obtained from the proposed method showed that it achieved a greatest accuracy, precision, recall, F1-Score of 0.9960 and robustness in the diagnostic of three-phase induction motors compared to traditional diagnostic methods, with respect to classifying the motor states as normal, healthy, and Broken Rotor Bar (BRB) faulted.



Copyright ©2026 by authors and Galileo Institute of Technology and Education of the Amazon (ITEGAM). This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

## I. INTRODUCTION

Induction motors represent a significant aspect of industrialization, as they are extremely tough and do not have their integrity impaired by the environment in which they operate. However, over time, parts of an induction motor will experience wear and deformation, which can result in decreased life expectancy and poor operation output from the motor [1]. An induction motor malfunction can also cause damage to surrounding materials, waste time, and cause workplace accidents, which will lower system reliability. For this reason, fault diagnosis technologies are necessary for timely fault detection, proper action, and safe and secure operation of the equipment.

Induction motor faults are divided into electrical and mechanical faults [2]. The different types of electrical faults found in induction motors are overload, open phase and short-circuit faults. The various ways mechanical faults occur include the bearing, rotor, and stator. Among these three types of mechanical faults, the most typical is the bearing fault; approximately 40 % of all induction motors have a bearing fault. The traditional method for diagnosing faults relies on the use of a mathematical model of the system and the user's input. Due to the complex nature of nonlinear systems, accurately representing them mathematically has always presented challenges. User input techniques rely upon visual and auditory signals gathered from direct observation of the equipment and have resulted in excessive maintenance from over-maintaining equipment due to unexpected faults and unnecessary costs [3-5]. Induction motors fault diagnosis has the purpose of detecting motor component failure, located in the magnetic or mechanical parts of the motor, and assess the motor operating conditions to identify what repair actions must take place. Fault diagnosis in induction motors has two types of diagnostic testing methods to detect the faults such as invasive methods and non-invasive methods [6]. Invasive testing methods measure electrical phase lines, insulation, winding, and polarisation indexes, to consider only the windings that may fail. This test type usually requires expensive Test and Measurement Equipment (T&M), which has its associated risks for testing personnel. Invasive testing is generally completed when an induction motor is not powered and all types of faults must be tested at the same time [7]. Due to the high costs and risks involved in completing the invasive fault test method, there is an increased acceptance of the non-invasive fault tests in monitoring a motor's operational condition and diagnosing a variety of faults at a time, when the induction motor is running. However, non-invasive diagnostic methods, employ mathematical models and physical mechanisms combined with actual operating data to assess and predict degeneration of the induction motor component based on specific motor operating parameters and operating conditions. At this time, there are many categories of these non-invasive fault diagnostic tests include electromagnetic field monitoring, temperature monitoring, infrared monitoring, noise monitoring, vibration monitoring, and current monitoring based on the specific sensor being used [8-13].

In addition, fault diagnosis techniques continue to rely on model-based approaches. Model-based fault diagnosis is heavily reliant on the user's in-depth knowledge of the fault mechanisms along with deep understanding of the processing of signals that are generated during motor operation. The models utilize the generated vibration signal from the motor by creating an indicator representing sensitivity towards a fault and performing the following tasks to detect a fault [14]. Additionally, a mode decomposition technique is proposed that uses variational mode decomposition and improved teager energy operators to extract fault characteristics early in motor operation. Despite the advantages of the techniques, the inherent limitations of these techniques are high computational cost associated with model development and the inability to utilize all available information contained within the monitoring data. Furthermore, the model is task dependent and thus the resulting models will require re-optimization if new tasks are presented [15-17]. To overcome this issue, the proposed model develop an AI-based approach for induction motor fault diagnosis. In this process, the raw data undergoes preprocessing to reduce noise and to clean the data [18]. Due to the computational simplicity, straightforward implementation, and extensive support through conventional signal processing techniques, the classical Fourier transform method is particularly suited towards online applications used for surveillance within industrial environments. However, since this method does not maintain temporal and spatial localization of failures, it poses significant difficulties when attempting to identify early or developing failures [19]. To tackle this issue EDEWF method is implemented. The preprocessed data is passed to a feature engineering stage to normalize the signal features to a common range. Histogram Equalization (HE) enhances the visibility of low-amplitude fault indicators when converting time-frequency images from vibration or current signal data. However, HE enhance the noise levels along with the fault signal which gives rise to false positives [20]. To deal with this constraint, the proposed system uses a Min-Max scaling. Next to enhance the diagnostic accuracy, RBFNN with MHAT is executed in this proposed system. Though, various existing methods are deliberated in this paper to completely analyze each model's respective performance compared with each other, indicating where each model is limited in effectively addressing motor signals that do not follow linear values.

## 1.1 RELATED WORKS:

By [21] have developed a machine learning approaches, in particular through the usage of Random Forest Classifiers, it has been found to provide extremely high classification accuracies for motor faults due to its ability to utilize ensemble learning, where many Decision Trees are used to increase generality while at the same time reduce overfitting of the Decision Trees. However, with regard to real-time monitoring systems and the number of trees required for high accuracy of Random Forest Classifiers, it becomes computationally expensive particularly when using large amounts of data. In turn [22] have proposed an Induction motor bearing fault diagnostics utilizing Continuous Wavelet Transform (CWT) possess an exceptional time -frequency resolution and, therefore, it is an effective tool in the analysis of non-stationary and transient signal characteristics. Nevertheless, data redundancy and volume provided from the CWT increase the complexity of the extraction and classification of feature information. By [23] have established a CNN-LSTM for the analysis of faults in three-phase induction motors from an AI perspective. The CNN is capable of effectively capturing local characteristics and fault features, while also modelling time-dependent behaviour and dynamics by implementing the LSTM, resulting in High diagnostic accuracy and reliable early fault detection. Nonetheless, CNN-LSTM require large labelled datasets for training and it suffer from poor performance due to insufficient or unbalanced datasets. According to [24] have suggested a ClasLoc, a reliable fault management methodology for transmission lines, based on RBFNN and ANFIS, which provide distinct benefits for the management of transmission line faults because of the combined approach used in the ClasLoc methodology to classify and localize faults more accurately and reliably under various operating conditions. ClasLoc's performance could potentially deteriorate when implemented on large-scale systems due to the increased quantity of rules that need to be created. Though, the overall ClasLoc model lacks interpretability and scalability, which limit ClasLoc's ability to be implemented in real time in large or limited resource power system environments. By [25] have recommended a CNN-RNN observers for predictive maintenance and fault detection for industrial robot drive systems. By automatically learning to identify both spatial and temporal features from sensor data, these observers accurately predict degradation before it occurs and detect faults once they occur. The CNN portion of the observer learns to identify localized fault patterns, while the RNN portion learns to model the dynamic behavior of the system over time, therefore this method is particularly effective for the control of robotic drive systems that are complex, nonlinear and time-varying in their nature.

However, the fault prediction decisions provide lack of interpretability. Additionally, because of the high level of complexity in the design, training and tuning of hyperparameter in CNN-RNN networks, the costs involved in developing these systems possibly be prohibitively high for implementation in an industrial environment.

## I.2 OBJECTIVES:

The main objectives of this research includes,

- ❖ To design an intense and intelligent fault diagnosis model for three-phase induction motors, the proposed system is implemented.
- ❖ To enhance signal quality and fault information, entropy-based empirical wavelet filtering is used in preprocessing stage.
- ❖ To provide an accurate assessment of the fault classification, min-max scaling normalization is introduced.
- ❖ To capture both global and local fault characteristics, a hybrid RBFNN-multi-head Adaptive Transformer model is executed.
- ❖ To optimise the RBFNN model performance for accurate and steady recognition of the induction motor faults, especially for the broken rotor bar condition, starfish optimisation method is employed.

## I.3 PAPER ORGANIZATION:

This paper is organized as follows: Section II provides an explanation of the suggested system description. The study methodology is thoroughly described in Section III, which also includes examples of the process, methods, and mathematical representations. The experimental results of this work are described in Section IV, which also include the simulation setup, comparison analysis, and research summary. The conclusion of the proposed investigation is explained in Section V.

## II. PROPOSED SYSTEM DESCRIPTION

The proposed system provides a reliable fault diagnosis system for three-phase induction motors. The block diagram of the proposed system is depicted in figure 1.

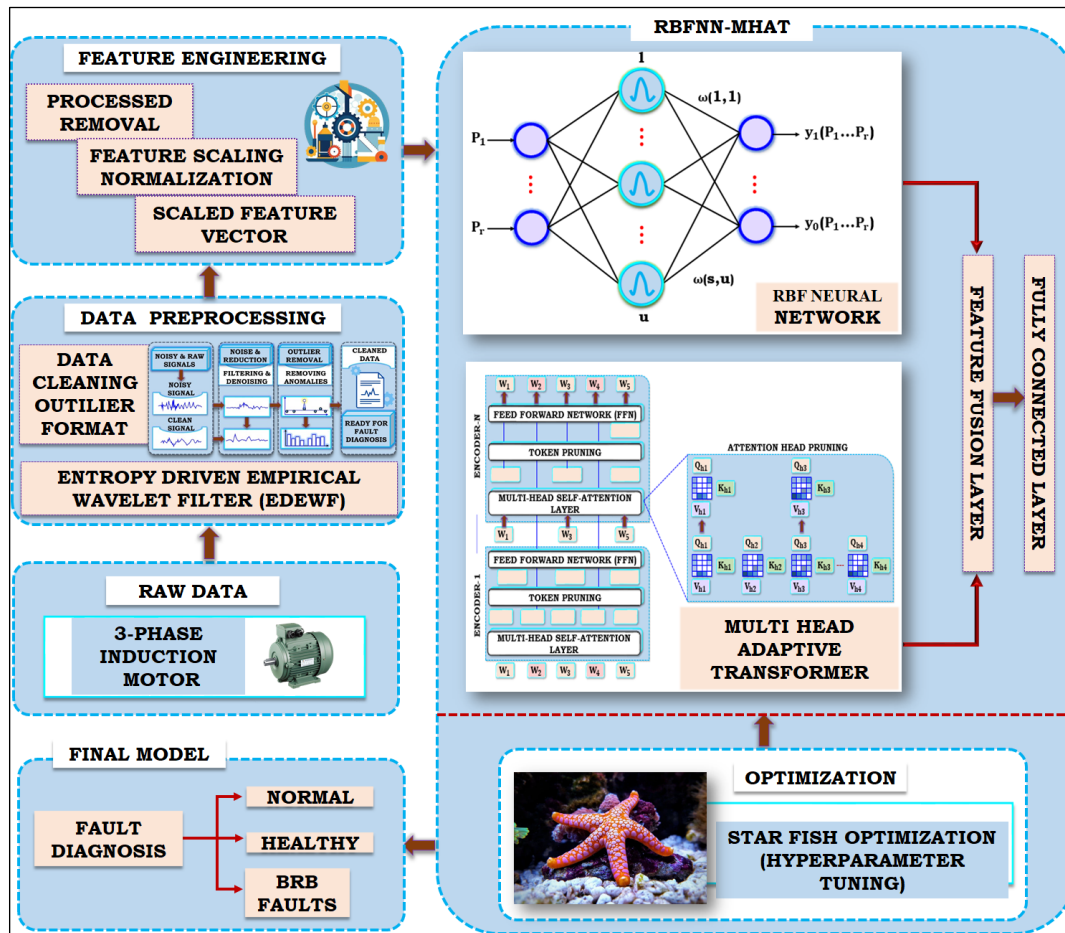


Figure 1: Proposed block diagram.

Source: Authors, (2026).

The suggested fault diagnosis system begins with the collection of raw motor data, which then undergoes data preprocessing via data cleaning, removal of outliers, EDEWF, and other signal enhancement techniques. Following the information enhancement of the raw motor data, feature engineering is performed to create feature vectors through feature scaling and feature normalization. After feature vector creation, a hybrid model that incorporates both a RBFNN and a MHAT are utilized. The RBFNN is used to capture global context features through the use of multi-head self-attention and adaptive weighting, whereas the transformer focuses on extracting local pattern features through the use of an RBF kernel layer.

After the feature extraction process, both models are combined, at which each model is treated as a separate input, and delivered to a fully connected layer for final classification. Optimizing performance is achieved by applying SFOA to tune hyper parameters, providing the capability for the system to diagnose motor operating conditions with high levels of accuracy, whether they are normal operating conditions, healthy working conditions, or failure modes associated with the broken rotor bars supporting effective condition monitoring and predictive maintenance for all motor installations.

### III. PROPOSED SYSTEM MODELLING

#### III.1 DATA PREPROCESSING

##### III.1.1 Data Cleaning

In diagnosing faults with induction motors, the first step is to identify sensor readings that show irregularities or potential failure. Some of these readings recommend problems with the rotor bars, insulation, or bearings. The diagram of data cleaning process is shown in figure 2.

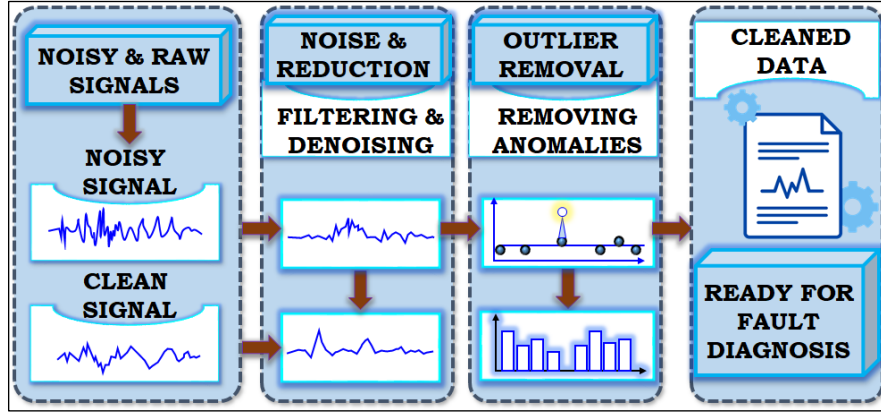


Figure 2: Data cleaning process.

Source: Authors, (2026).

For identifying errors in data systems, each individual measurement in an induction motor fault diagnosis is classified according to its measurement type such as current, voltage and vibration. In some cases, only a single reading is analysed in isolation. In other cases, multiple readings from the same time period are combined to identify context-dependent faults that occur through interactions of several parameters. By converting signals generated by the induction motor into sequences and applying techniques to classify those sequences, faults are identified and classified, thereby improving the effectiveness of condition monitoring and predictive maintenance effectively.

##### III.1.2 Entropy Driven Empirical Wavelet Filter (EDEWF)

The process of analysis within the EDEWF starts with the decomposition, using Empirical Wavelet Transform (EWT), of a time-dependent function (current or vibration) from a motor into two components such as an approximation mode and detail modes as follows,

$$f_0(t) = EWT(0, t) * \phi_1(t) \quad (1)$$

$$f_k(t) = EWT(k, t) * \psi_k(t) \quad (2)$$

Where,  $EWT(0, t)$  and  $EWT(k, t)$  is represented as an approximation coefficients and detail coefficients respectively.

$$EWT(0, t) = \langle f, \phi_1 \rangle \quad (3)$$

$$EWT(k, t) = \langle f, \psi_k \rangle \quad (4)$$

Each mode's entropy  $f_k(t)$  is computed to determine the information aspect of that mode. Entropy is referred to as Shannon Entropy or Energy Entropy, and works by measuring the energy distribution across the selection of modal frequencies, as provided by:

$$H(f_k) = -\sum_i P_i \log(P_i) \quad (5)$$

In the above expression,  $P_i$  is the normalized distribution of energy across the selected modal frequencies. Therefore, when a fault has occurred, the energy distribution is concentrated on those modes of increased entropy. And for the other modes, it is automatically suppressed. The reconstructed fault signal is determined by the addition of only those selected modes:

$$f_{fault}(t) = \sum_{k \in \text{selected}} f_k(t) \quad (6)$$

Thus, the EDEWF enhances weak mark components in relation to the fault and suppresses noise. This makes the approach suitable for diagnosing fault conditions in induction motors.

### III.2 FEATURE ENGINEERING- MIN-MAX SCALING

Min-Max scaling method of normalizing the signals extracted from induction motors are large variances between the signals being analysed due to differences in measurement units and ranges. The Min-Max scaling method allows to set all outputs from different signals on a common scale of 0 to 1. For each signal that has been normalised using the Min-Max Scaling formula, a new normalised value is calculated using the formula in the following way,

$$X_{ij}^{MM} = \frac{X_{ij} - X_{min}}{X_{max} - X_{min}} \quad (7)$$

Where,  $X_{min}$  and  $X_{max}$  are value of features. By using the Min-Max Scaling method to normalise the EDEWF-derived features associated with the induction motor fault diagnosis application, it makes it possible to have a consistent method to compare the EDEWF-derived features across multiple different modes to determine which mode contain weak fault-related marks, provide signal characteristic information and a method to interpret differences in the condition of an induction motor while eliminating variable ranges and the influence of variable units on the comparison between modes.

### III.3 HYBRID MODEL- RBFNN- MHAT

An RBFNN represents a kind of nonlinear mapping from a feature space obtained from induction motor signal data to types of motor faults. An input vector  $x \in R^d$ , represents a set of features created using data taken from an induction motor's stator current, vibration sensor, and/or audio microphone, while the prototype  $c_i \in R^d$  for the  $i^{th}$  RBF unit represents a typical operating condition (or fault) for that motor. The RBF unit outputs the Euclidian distance between the input vector and the prototype.

$$\phi_i(x) = \exp\left(\frac{-\|x - c_i\|^2}{2\sigma_i^2}\right) \quad (8)$$

Where,  $\|\cdot\|$  denotes the Euclidean norm and  $\sigma_i$  is the Gaussian width of the  $i^{th}$  RBF unit. The Gaussian function is popular for establishing a relation between localizing, smoothness, hence modelling delicate changes that occur on induction motor fault marks. The diagram of RBFNN- MHAT is shown in figure 3.

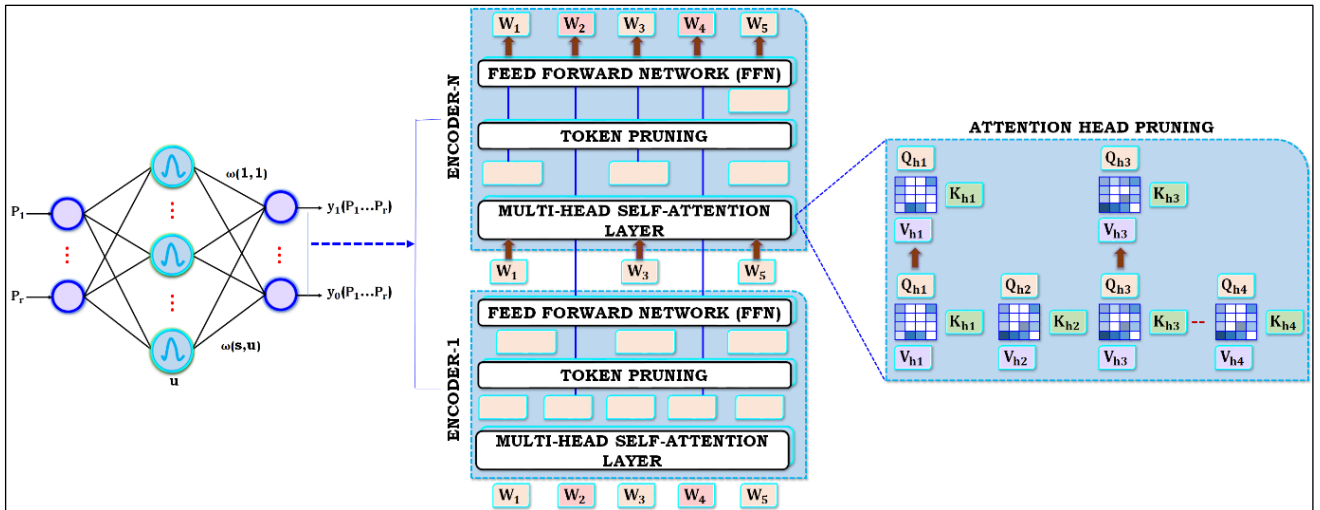


Figure 3: HYBRID MODEL- RBFNN- MHAT.

Source: Authors, (2026).

An RBF unit produces localized responses, which represents the similar or dissimilar observed condition of the motor with any of all fault prototypes stored in its memory. The Gaussian width  $\sigma_i$  determines the region over which the total influence of that prototype occurs. Low values of  $\sigma_i$  render an RBF unit very sensitive to small variations in the motor's features, while higher values of  $\sigma_i$  produce RBF units that are tolerant variations resulting from load changes, speed fluctuations, and measurement noise that are a common occurrence during the operation of induction motors. The output of the RBF neural network for the  $k^{th}$  fault class is calculated as a weighted linear combination of the output from all RBF units,

$$y_k = \sum_{i=1}^M w_{ik} \phi_i(x) \quad (9)$$

Where,  $w_{ik}$  represents the connection weight between the  $i^{th}$  RBF unit and the  $k^{th}$  output neuron, and  $M$  denotes the total number of Gaussian units. The bias term is neglected to reduce network complexity. The formulation above shows that the RBF neural network linearly discriminates in a transformed feature space created using the non-linear mapping,  $\phi_i(x)$ . Therefore, decision boundaries for different induction motor fault classes are hyperplanes in this high-dimensional RBF feature. According to Cover's theorem, mapping to a higher dimension with a non-linear function increases the probability of making the induction motor fault pattern linearly separable. Hence, as  $M$  increases, the induction motor fault classes are more distinct from one another. However, too high a value of  $M$  cause the model to over fit; therefore, it decrease its ability to generalize when the fault data available were small in volume.

RBFNN partitions feature space into hyper spherical sectors centred around  $c_i$  and width  $\sigma_i$ . Clustering methods typically supply the clustering centres for RBFNNs. Most conventional clustering methods are based on unsupervised techniques, which typically do not take into the differences between fault categories and create clusters that consist of samples from more than one fault category, this results in a low level of diagnostic accuracy. The supervised methods are more effective at producing homogeneous clusters for the purposes of diagnostic accuracy. In addition to the distance  $\|x - c_i\|$  between a feature vector and a cluster centre, the Gaussian width  $\sigma_i$  determines the factor in assigning fault connection. Thus, a feature vector have a closer distance to one cluster centre than another, a properly selected  $\sigma_i$  produce a greater activation for the other fault class, enabling the accurate handling of overlapping fault feature sets and variable operating conditions of induction motors. Clustering methods of RBFNN is depicted in figure 4.

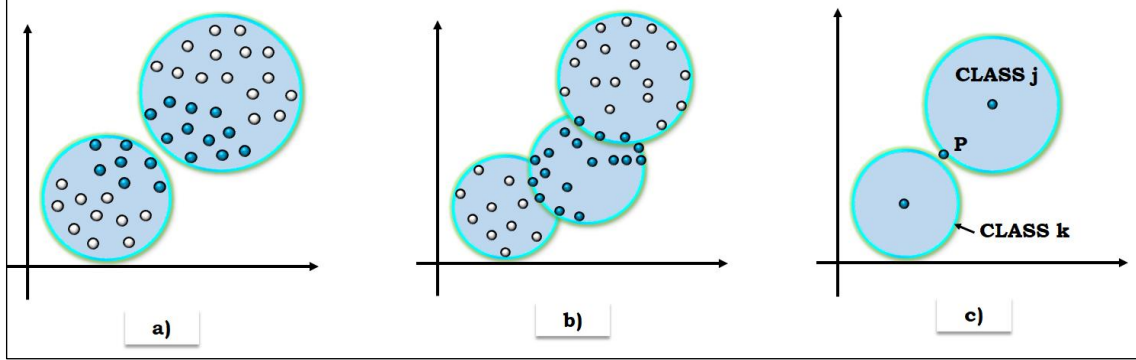


Figure 4: Clustering methods of RBFNN.  
Source: Authors, (2026).

The MHAT is from the base Multi-Head Attention framework that extracts the additional fault features from induction motor signals appropriately without computing redundantly. Let  $x = x_1, x_2, \dots, x_T$ , where  $x_t \in R^d$ , denote the sequence of embedded induction motor signal marks that were derived from either the stator current or vibration signals, and let  $q \in R^d$  represent a query vector resulting from the same sequence of induction motor signals. The manner in which the elastic form of scaled dot product is used to model temporality-related dependencies through induction motor data is,

$$Attention(x, q) = W_o \sum_{t=1}^T \alpha_t(q) W_v x_t \quad (10)$$

The attention weights are calculated as follows,

$$\alpha_t(q) = softmax\left(\frac{q^T W_q^T W_K x_t}{\sqrt{d}}\right) \quad (11)$$

$W_o, W_v, W_q, W_k \in R^{d \times d}$  represent the weight vectors used for each signal in the multi-head attention mechanism. Each attention head is designed to target a specific fault feature of a motor signal that occur in time, such as an intermittent burst of bearing defects or rotor bar harmonics. Once the focus of the individual head is established, the output of the multi-head attention is the sum of  $H$  parallel attention heads is given by,

$$MH\ Attention(x, q) = \sum_{h=1}^H Attention_h(x, q) \quad (12)$$

Where, each  $Attention_h$  represents a low-rank decomposition of the output of the previous attention heads. In the analysis of faults in induction motors, many of the attention heads are considered interchangeable or provide only minimal assistance. To assist in the identification of which heads to keep for training purposes, a head sensitivity score is generated from a forward pass through a transformer model, fine-tuned specifically for classifying faults. Once these scores have been computed, the heads reflect the highest levels of usefulness included in training. When training is completed, each layer  $i + 1$ , the retention  $m_{i+1}$  is the number of heads, is selected randomly based on,

$$m_{i+1} \in [m_{i+1}, m_i] \quad (13)$$

Where,  $m_i$  is the number of heads retained from prior  $i$  layer,  $m_{i+1}$  is the minimum number of heads retained in the next layer, and only one head retained in the final layer. This reflects that the deeper layers have fewer but more important heads for recognizing anomalies related to fault marks. The MHAT offers a computationally efficient methodology for induction motor fault diagnosis. The approach allows for an improved accuracy relationship when compared to traditional transformer models. Hence the proposed system is more effective, reliable, and scalable approach for performing induction motor fault diagnosis that is employed on a real-time basis as part of an industrial condition monitoring system.

### III.4 HYPERPARAMETER TUNING- SFOA

Induction motor fault identification is approached through optimization by minimizing misclassification errors or maximizing fault separation using the features generated from stator current, vibration or acoustic signals. In SFOA, each starfish requires its own candidate fault detection solution, representing a classifier parameter vector, with an assigned position expressed as,

$$X = \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1D} \\ X_{21} & X_{22} & \dots & X_{2D} \\ \vdots & \vdots & \ddots & \vdots \\ X_{N1} & X_{N2} & \dots & X_{ND} \end{bmatrix} \quad (14)$$

Where  $N$  should be the size of the starfish population and  $D$  is the number of decision variables for induction motor fault detection. Starfish are initialized to relative position with respect to the allowable dimension of the induction motor fault detection parameter space by,

$$X_{ij} = l_j + r(u_j - l_j), i = 1, 2 \dots N, j = 1, 2, \dots D \quad (15)$$

Where  $l_j$  stands for the lower bounds of the fault detection parameters,  $u_j$  denotes the upper bounds, and  $r \in \{0,1\}$  is a random number. Each starfish's utility is evaluated through a fault detection objective function that is expressed as,

$$F = \begin{bmatrix} f(X_1) \\ f(X_2) \\ \vdots \\ f(X_N) \end{bmatrix}_{N \times 1} \quad (16)$$

The SFOA uses a hybrid exploration strategy to cover the complete feature space for induction motor faults.

Pseudo-code: SFOA.

```

01: Initialize population  $X = \{x_1, x_2, \dots, x_N\}$  randomly within  $[LB, UB]$ 
02: Evaluate fitness  $F(i)$  for each  $x_i$ 
03: Identify global best solution:
    xpos_best = argmin(F)
    fval_best = min(F)
04: Set iteration counter  $T = 1$ 
05: While  $T \leq \text{MaxIt}$  do
06: Update control parameters:
     $\theta = 2 \times (1 - T / \text{MaxIt})$  // decay factor
     $t_{EO} = T / \text{MaxIt}$  // exploitation-exploration balance
07: For each individual  $i = 1$  to  $N$  do
08: Generate random number  $r \in [0,1]$ 
09: If  $r < GP$  then // ===== Exploration Phase =====
10: If  $D > 5$  then
11: Perform 5D Starfish Search:
     $x_{\text{new}} = x_i + \theta \times \text{randn}(1,D) \times |x_{\text{best}} - x_i|$ 
12: Else
13: Perform 1D Starfish Search:
     $k = \text{random dimension} \in [1, D]$ 
     $x_{\text{new}}(k) = x_i(k) + \theta \times \text{rand}() \times (x_{\text{best}}(k) - x_i(k))$ 
14: End If
15: Else // ===== Exploitation Phase =====
16: // Predation behavior
17:  $x_{\text{pred}} = x_i + \text{rand}() \times (x_{\text{best}} - x_i)$ 
18: // Regeneration behavior
19:  $x_{\text{new}} = x_{\text{pred}} + t_{EO} \times \text{randn}(1,D)$ 
20: End If
21: Apply boundary constraints:
     $x_{\text{new}} = \min(\max(x_{\text{new}}, LB), UB)$ 
22: Evaluate new fitness  $F_{\text{new}} = F(x_{\text{new}})$ 
23: If  $F_{\text{new}} < F(i)$  then
24:  $x_i = x_{\text{new}}$ 
25:  $F(i) = F_{\text{new}}$ 
26: End If
27: If  $F_{\text{new}} < fval_{\text{best}}$  then
28:  $xpos_{\text{best}} = x_{\text{new}}$ 
29:  $fval_{\text{best}} = F_{\text{new}}$ 
30: End If
31: End For
32: Store convergence value:
    Curve( $T$ ) =  $fval_{\text{best}}$ 
33:  $T = T + 1$ 
34: End While
35: Return xpos_best, fval_best, Curve

```

For instance, for  $D > 5$ , the concurrent five-dimensional search pattern updates five randomly chosen fault-sensitive features such as sideband amplitude, statistical vibrations, or typical values of non-typical faults.

$$Y_{i,p}^T = \begin{cases} X_{i,p}^T + a_1(X_{best,p}^T - X_{i,p}^T)\cos\theta, & r \leq 0.5 \\ X_{i,p}^T - a_1(X_{best,p}^T - X_{i,p}^T)\sin\theta, & r > 0.5 \end{cases} \quad (17)$$

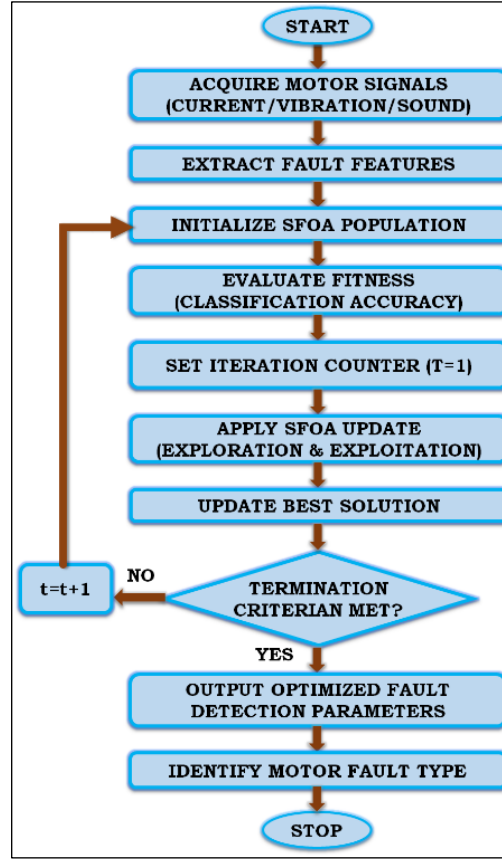


Figure 5: Flowchart of SFOA.  
Source: Authors, (2026).

Flowchart of SFOA is shown in figure 5. Where,  $X_{best,p}^T$  represents the most effective method of recognizing faults in iteration  $T$  within the  $p^{th}$  dimensional space.

$$a_1 = (2r - 1)\pi, \theta = \frac{\pi}{2} - \frac{T}{T_{max}} \quad (18)$$

The values of the other variables define the step size and convergence behaviour for feature exploration. A starfish that is updated to a value beyond the range retain its last value.

$$X_{i,p}^{T+1} = \begin{cases} Y_{i,p}^T, & l_p \leq Y_{i,p}^T \leq u_p \\ X_{i,p}^T, & \text{otherwise} \end{cases} \quad (19)$$

When the total number of parameters associated with faults is relatively low ( $D \leq 5$ ), only unidirectional searches are implemented during feature searching. The above equation summarizes a generic form of the searching procedure.

$$Y_{i,q}^T = E_t X_{i,p}^T + A_1(X_{k1,p}^T - X_{i,p}^T) + A_2(X_{k2,p}^T - X_{i,p}^T) \quad (20)$$

Where  $X_{k1,p}^T$  and  $X_{k2,p}^T$  are two randomly selected starfish which represents an alternative fault detection methods with  $A_1, A_2 \in (-1, 1)$  and the energy of a starfish is computed according to equation,

$$E_t = \frac{T_{max} - T}{T_{max}} \cos(h) \quad (21)$$

The exploitation phase enables the enhancement of fault detection capabilities through a naturalistic simulation of the collective hunting habits of starfish. Thus, a distance calculation must be performed between the best fault detection method provided at present and the selected starfish.

$$d_m = X_{best}^T - X_m^T, m = 1, 2, \dots, 5 \quad (22)$$

A parallel bidirectional search method is employed for updating the positions of the starfish is,

$$Y_i^T = X_i^T + r_1 d m_1 + r_2 d m_2 \quad (23)$$

The parameters  $r_1, r_2 \in (0,1)$  for the starfish. This method provides the ability for the fault detection model to converge to their respective discriminative decision boundaries while maintaining diversity. To prevent stagnation in local optima due to non-stationarity of the motor signal and interference due to noise in the motor signal, a regeneration mechanism is applied to the last starfish in the group.

$$Y_i^T = \exp\left(\frac{T-N}{T_{max}}\right) X_i^T \quad (24)$$

This mechanism allows the addition of controlled perturbations to the starfish and further increases the convergence of the global. The boundary constraints of each starfish are applied as,

$$X_i^{T+1} = \begin{cases} l_b, Y_i^T < l_b \\ u_b, Y_i^T > u_b \\ Y_i^T, otherwise \end{cases} \quad (25)$$

Table 1: Optimization values of SFOA.

| PARAMETERS              | VALUES  |
|-------------------------|---------|
| RBF Units               | 96.000  |
| Transformer Heads       | 4.000   |
| Transformer Layers      | 2.000   |
| Learning Rate           | 0.001   |
| Batch Size              | 64.000  |
| Dropout Rate            | 0.200   |
| Dense Units             | 128.000 |
| Number of Starfish      | 30.000  |
| Maximum Iterations      | 50.000  |
| Exploration Probability | 0.500   |

Source: Authors, (2026).

The starfish determine only the search within a specified area. By applying the equations in these processes within the SFOA, it designed specifically for the induction motor fault detection system, when the SFOA is applied to improve the fault sensitivity and detection parameters of the induction motor fault detection system, it leads to enhanced accuracy, robustness to a performance effect of noise, and assures that motor faults are accurately identified under several operational conditions.

#### IV. RESULT AND DISCUSSION

This research work highlights a Starfish Optimized AI-based DL framework for accurately detecting broken rotor bar faults on induction motors by making use of the BBIM2023 dataset. The BBIM2023 dataset consists of 24,000 samples containing 36 inputs features related to the time, three phase stator currents, multiple rotor bar current, ring current, rotor speed, and rotor position; as well as a target class indicating the motor's health condition. The data divided into 70% for training and 30% for testing to enable proper evaluation of the reliability of the model's performance. In order to obtain effective analysis of non-stationary and nonlinear characteristics in the electrical signals related to electrical motors, it used an additional advanced signal processing methods including the Entropy Driven Empirical Wavelet Filter (EDEWF), the Empirical Wavelet Transform (EWT), the Wavelet Packet Transform (WPT) and the Hilbert–Huang Transform (HHT), which were used as part of the procedure to reduce noise and to extract features that are sensitive to faults. The features that were extracted were then applied to a couple of different intelligent classification models including Radial Basis Function Neural Network (RBFNN) and Multi-Head Adaptive Transformer (MHAT). These intelligent classification models were able to represent complex nonlinear relationships and long-term temporal dependencies present within the dataset. Additionally, to improve the overall classification accuracy of the developed motor model and to improve the robustness of the classification models, the SFOA was used for optimally tuning the model parameters and for performing feature selection.

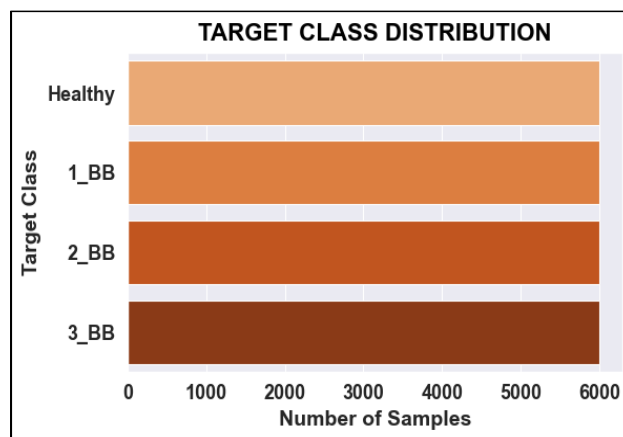


Figure 6: Distribution of target class.

Source: Authors, (2026).

Figure 6 shows the distribution of target class. The classes include a uniform number of the four Target Classes (i.e., Healthy, 1\_BB, 2\_BB, 3\_BB), each class has approximately 6,000 samples of data for use during model training.

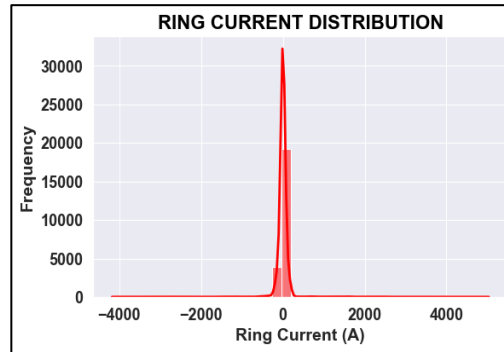


Figure 7: Distribution of ring current.  
Source: Authors, (2026).

Distribution of ring current is depicted in figure 7. There is a strong concentration of recorded Ring Currents, the majority of recorded Ring Currents are in the 0A region with very few outliers in either positive or negative directions.

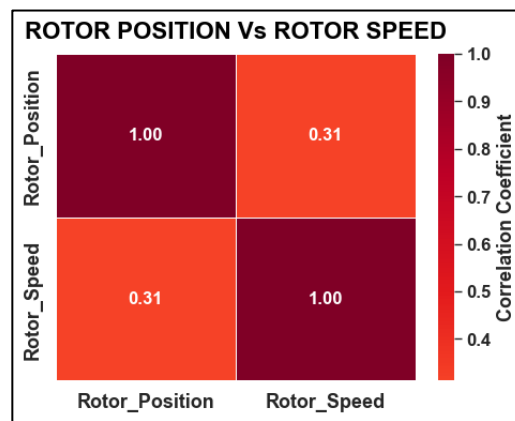


Figure 8: Rotor position vs Rotor speed.  
Source: Authors, (2026).

The diagram of Rotor position vs Rotor speed is illustrated in figure 8. There is a moderate positive correlation between the Rotor Position (RP) and Rotor Speed (RS) (CP=0.31), with the CP of RP being 1.00 and the CP of RS being 1.00.

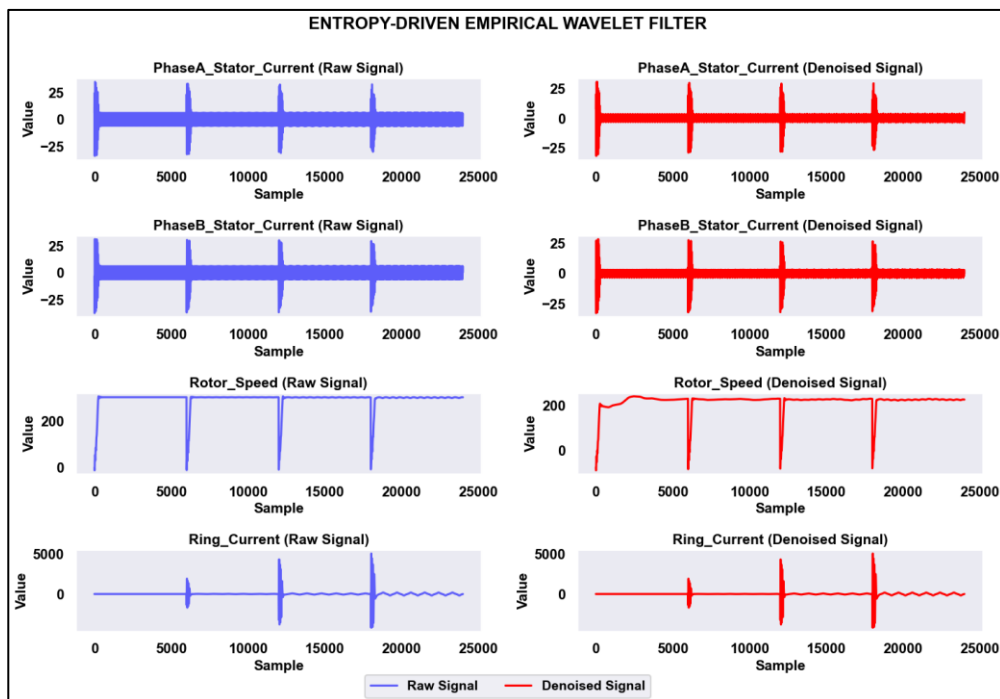


Figure 9: Entropy driven Empirical Wavelet Filter.  
Source: Authors, (2026).

Figure 9 shows a high level of consistency when the signals were processed with an Entropy-Driven Empirical Wavelet Filter (EDEWF). The denoised signals represent an accurate representation of the most important transients and fault-related events, producing smooth and interpretable representations of the signals, while significantly reducing noise, fluctuations, and unwanted oscillations.

Table 2: Comparison of performance metrics.

| SI.NO | FILTER | SNR (dB) | PSNR (dB) | MSE       | RMSE     | SSIM   |
|-------|--------|----------|-----------|-----------|----------|--------|
| 1     | EDEWF  | 35.4238  | 55.8329   | 1920.3489 | 43.8232  | 0.9991 |
| 2     | EWT    | 31.1615  | 50.7602   | 2821.3994 | 47.9306  | 0.9987 |
| 3     | WPT    | 30.9846  | 49.9126   | 3050.2765 | 55.2749  | 0.9979 |
| 4     | HHT    | 12.4512  | 18.2150   | 6043.1248 | 340.9597 | 0.2812 |

Source: Authors, (2026).

Table 2 illustrates the filtered image quality comparison table. EDEWF was the best filtering method due to highest SNR, PSNR, and SSIM and RMSE. It has obtained the best classification of information and provides the maximum noise reduction and image quality. EWT and WPT will deliver moderate performance, however HHT demonstrates weaker performance across all measures.

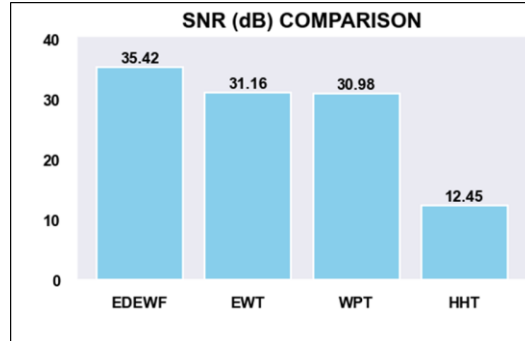


Figure 10: Comparison of SNR.

Source: Authors, (2026).

The bar graph in figure 10 compares the SNR performance of EDEWF, EWT, WPT, and HHT. The highest SNR was recorded from EDEWF (35.42dB), followed by EWT (31.16dB) and WPT (30.98dB). In contrast, HHT recorded the lowest SNR of all methods tested (12.45dB).

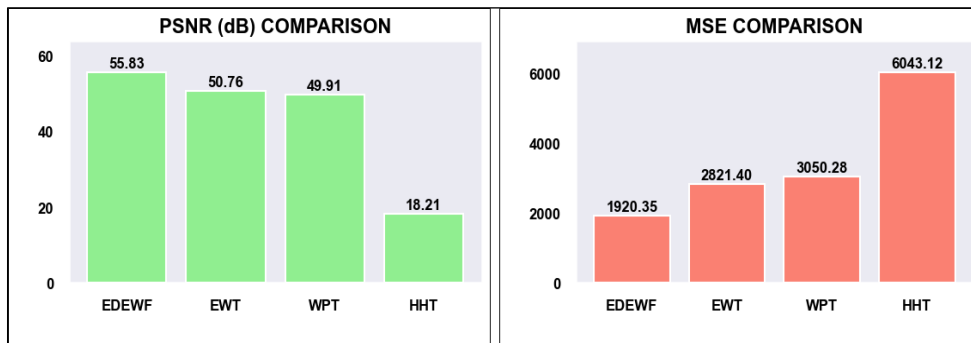


Figure 11: Comparison of PSNR and MSE.

Source: Authors, (2026).

As shown in figure 11, EDEWF achieved the highest PSNR (55.83dB) and the lowest MSE (1920.35) of any method tested, indicating the highest reconstruction accuracy, while EWT and WPT achieved moderate performances (PSNR= 50.76/ MSE=2821.40 & PSNR= 49.91dB/ MSE=3050.28), while HHT achieved the lowest PSNR (18.21dB) and the highest MSE (6043.12).

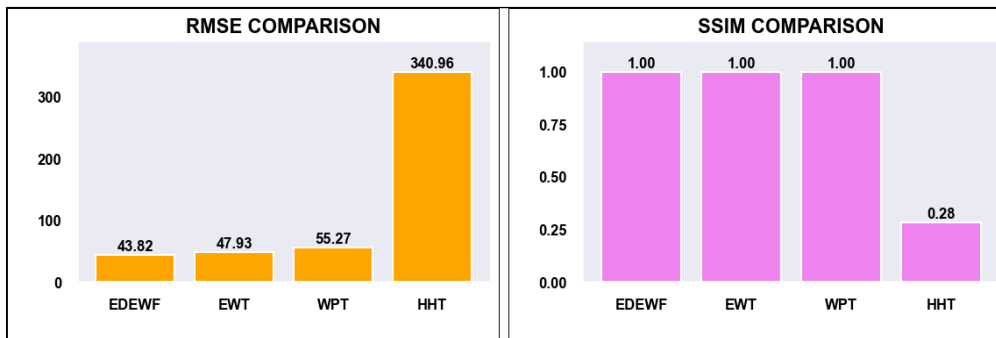


Figure 12: Comparison of RMSE and SSIM.

Source: Authors, (2026).

Figure 12 shows the comparison of RMSE and SSIM. The charts suggest that EDEWF, EWT, and WPT have excellent performance due to their low error rates and high structural similarities to one another. In contrast, HHT's performance is poor due to its high errors and low structural similarity to the other models.

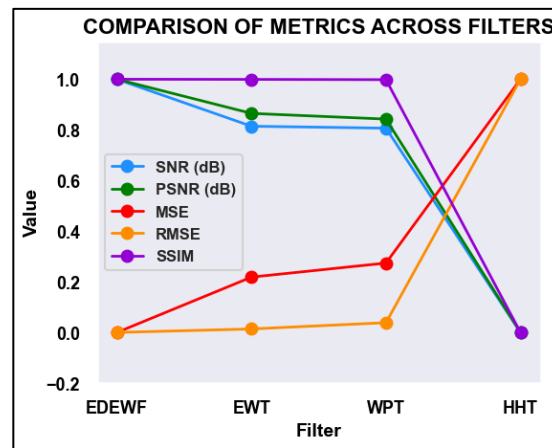


Figure 13: Comparison of metrics across filters.  
Source: Authors, (2026).

Figure 13 indicates that EDEWF, EWT, and WPT have strong signal quality based on high similarity and low errors, while HHT has lower signal quality and therefore produces worse metrics and higher errors.

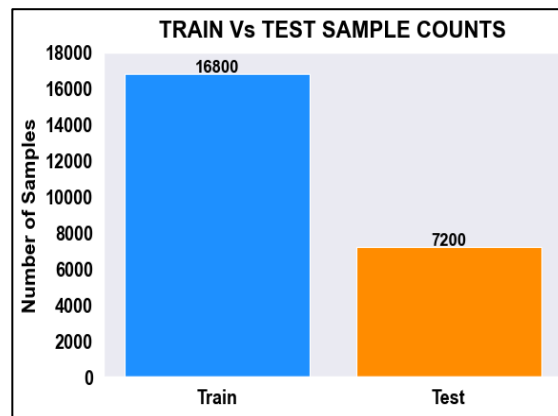


Figure 14: Train vs Test sample counts.  
Source: Authors, (2026).

Figure 14 depicts the comparison of train and test sample counts. In addition to splitting the dataset into more training samples than testing samples, the plot shows that the emphasis of the model design is on learning the model rather than evaluating the model.

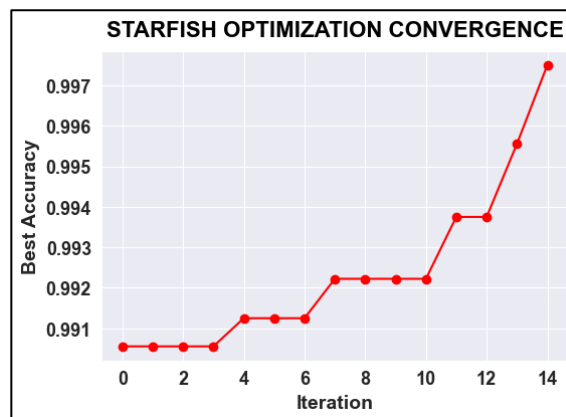


Figure 15: Starfish optimization convergence.  
Source: Authors, (2026).

Figure 15 displays that Starfish Optimization is converging steadily, with the best accuracy increasing steadily over iterations until reaching its final iteration, where it improves dramatically to approximately 0.998.

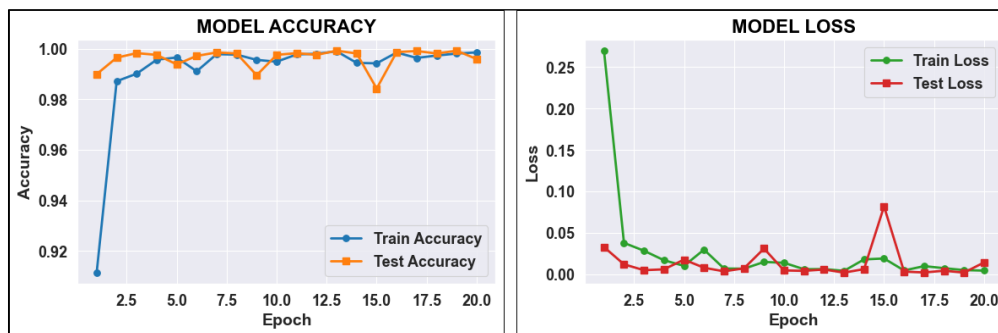


Figure 16: Model accuracy and Model loss for SFOA-Hybrid RBFNN-MHAT.

Source: Authors, (2026).

Figure 16 demonstrates that the model achieves near-perfect accuracy on both the training and testing datasets very quickly and is stable throughout all epochs. Training and testing losses drop quickly during the early epochs and remain low with only slight fluctuations, indicating the model's ability to converge properly without overfitting.

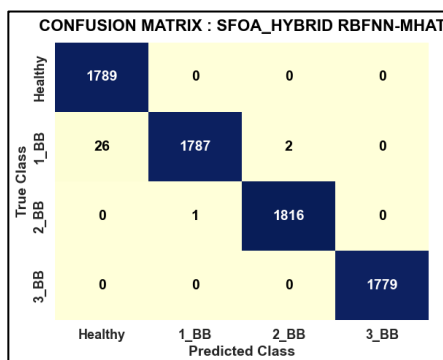


Figure 17: Confusion matrix of SFOA-Hybrid RBFNN-MHAT.

Source: Authors, (2026).

Confusion matrix of SFOA-Hybrid RBFNN-MHAT is illustrated in figure 17. The confusion matrix illuminates near-perfect classification performance, wherein nearly all samples were correctly classified. The only two misclassified categories are among Healthy vs. 1\_BB or 1\_BB vs. 2\_BB, while the 3\_BB category was perfectly classified.

Table 3: Performance metrics of SFOA-Hybrid RBFNN-MHAT.

| SI.NO | METRICS       | VALUES |
|-------|---------------|--------|
| 1     | Accuracy      | 0.9960 |
| 2     | Precision     | 0.9960 |
| 3     | Recall        | 0.9960 |
| 4     | F1-Score      | 0.9960 |
| 5     | Cohen's Kappa | 0.9946 |
| 6     | MCC           | 0.9946 |
| 7     | ROC-AUC       | 1.0000 |

Source: Authors, (2026).

In table 3, the SFOA-Hybrid RBFNN- MHAT model demonstrates approximately the highest possible performance for each metric at 99% accuracy, precision, recall and F1-score, a very high Cohen's Kappa and MCC at 0.99, and an ideal ROC-AUC score of 1.0, indicating very strong classification reliability and robustness.

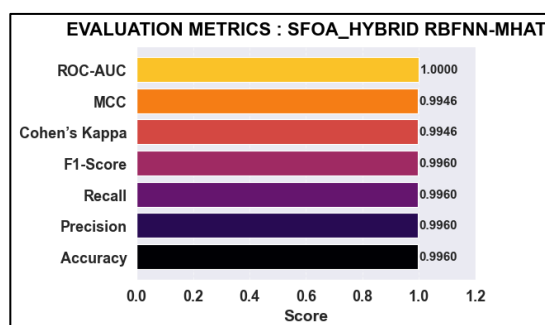


Figure 18: Evaluation metrics of SFOA-Hybrid RBFNN-MHAT.

Source: Authors, (2026).

Figure 18 demonstrates impressive performance for the SFOA-HYBRID RBFNN-MHAT model as evidenced by its near-perfect measures, ROC-AUC of 1.0; Accuracy/Precision/Recall/F1 score of 0.996 and MCC & Cohen's Kappa of 0.9964 and 0.9946. The model has been consistently classified as high quality and as a result provides reliable and consistent classification.

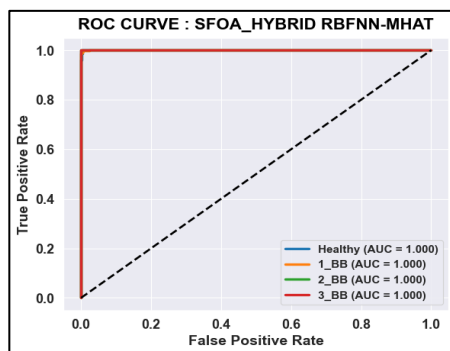


Figure 19: ROC curve of SFOA-Hybrid RBFNN-MHAT.  
Source: Authors, (2026).

Figure 19 illustrate the indicating AUC = 1.000 and perfect classification performance with exceptional separation of the classes from one another.

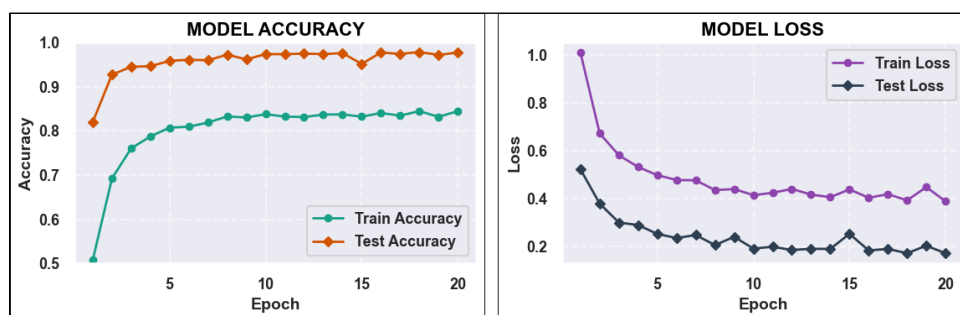


Figure 20: Model accuracy and model loss for Hybrid RBFNN-MHAT.  
Source: Authors, (2026).

Figure 20 explains the model accuracy and model loss for Hybrid RBFNN-MHAT. The learning of the model is consistent and it generalizes well. The accuracy for both training and testing continues to increase until stabilizing (Test 97% and Train  $\approx$  84%). Training and testing losses have consistently decreased over time, demonstrating effective convergence without overfitting.

| CONFUSION MATRIX : HYBRID RBFNN-MHAT |         |         |      |      |      |
|--------------------------------------|---------|---------|------|------|------|
| True Class                           | Healthy | 1730    | 19   | 40   | 0    |
|                                      | 1_BB    | 0       | 1738 | 77   | 0    |
|                                      | 2_BB    | 0       | 0    | 1817 | 0    |
|                                      | 3_BB    | 11      | 14   | 0    | 1754 |
|                                      |         | Healthy | 1_BB | 2_BB | 3_BB |

Figure 21: Confusion matrix for Hybrid RBFNN-MHAT.  
Source: Authors, (2026).

The confusion matrix demonstrates high classification performance in figure 21. There is high percentage of samples that were accurately classified along the diagonal (Healthy = 1730; 1\_BB = 1738; 2\_BB = 1817; and 3\_BB = 1754), which indicates the model's strong overall accuracy and low confusion rates among the classes.

Table 4: Performance metrics of Hybrid RBFNN-MHAT.

| SI.NO | METRICS       | VALUE  |
|-------|---------------|--------|
| 1     | Accuracy      | 0.9776 |
| 2     | Precision     | 0.9786 |
| 3     | Recall        | 0.9776 |
| 4     | F1-Score      | 0.9778 |
| 5     | Cohen's Kappa | 0.9702 |
| 6     | MCC           | 0.9704 |
| 7     | ROC-AUC       | 0.9965 |

Source: Authors, (2026).

In table 4, the Hybrid RBFNN - MHAT model demonstrates sustained and strong performance, exhibiting approximately 97% accuracy, precision, recall, and F1-score, strong Cohen's Kappa and MCC factors, with an extraordinary ROC-AUC of 0.99, signalling dependable and robust classification evaluation.

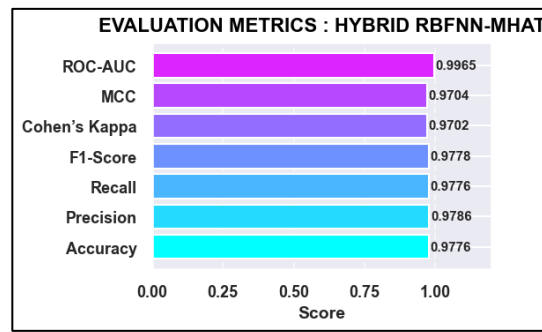


Figure 22: Evaluation metrics of Hybrid RBFNN-MHAT.

Source: Authors, (2026).

The performance of the model is superior in terms of the metrics which is depicted in figure 22. The high reliability and balance of classification are supported by the robustness and close agreement of the high MCC and Cohen's Kappa.

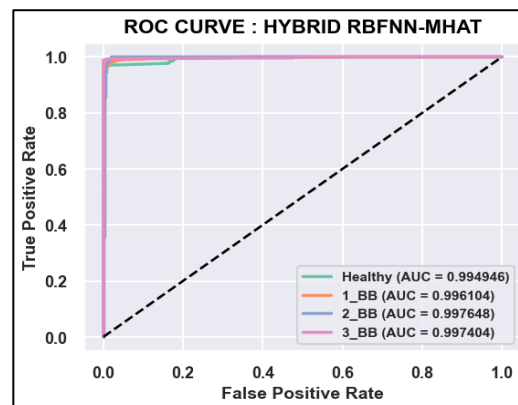


Figure 23: ROC curve of Hybrid RBFNN-MHAT.

Source: Authors, (2026).

The ROC curves show that there is a near-perfect separation of all classes, with AUCs, which is showed in figure 23. This indicates excellent discrimination between the different classes with very low false-positive rates for both Healthy and all classes of BB.

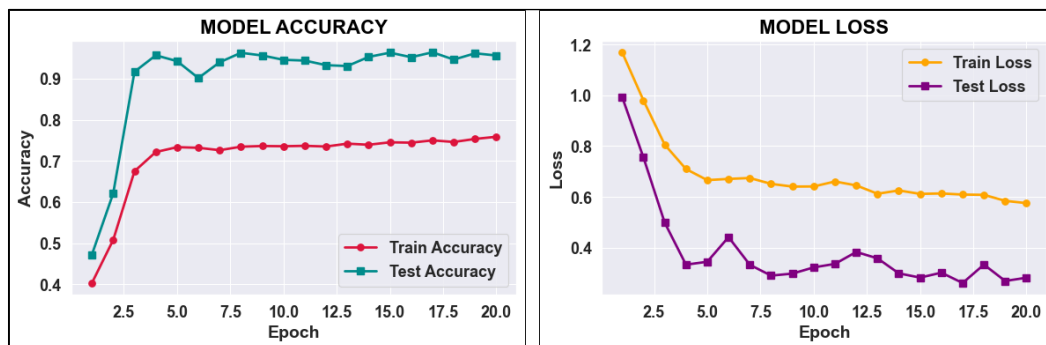


Figure 24: Model accuracy and model loss for MHAT.

Source: Authors, (2026).

Figure 24 shows the Model accuracy and model loss for MHAT. In the first few epochs of training, the model learns very quickly; however, it then stabilizes, with a final training accuracy of roughly 75% and test accuracy between 93 and 95%. The training and test losses have declined at a steady rate and have shown no signs of pronounced overfitting, which indicates that the model has performed well and has exhibited stable performance.

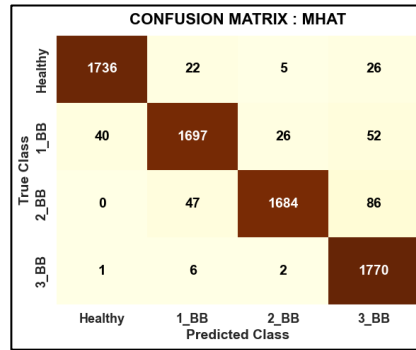


Figure 25: Confusion matrix for MHAT.  
Source: Authors, (2026).

Figure 25 displays the confusion matrix for MHAT. From the confusion matrix, there was a strong classification performance, as evidenced by the detail that the diagonal had most of the correctly predicted samples for every class. Hence, the overall accuracy was quite high but that there was some minor misclassifications between the different BB classes.

Table 5: Performance metrics of MHAT.

| SI.NO | METRICS       | VALUES |
|-------|---------------|--------|
| 1     | Accuracy      | 0.9565 |
| 2     | Precision     | 0.9576 |
| 3     | Recall        | 0.9568 |
| 4     | F1-Score      | 0.9566 |
| 5     | Cohen's Kappa | 0.9420 |
| 6     | MCC           | 0.9425 |
| 7     | ROC-AUC       | 0.9919 |

Source: Authors, (2026).

In table 5, the MHAT method exhibited reliable overall quality at approximately 0.95 of accuracy, precision, recall and F1-score, as well as the highest Cohen's Kappa and MCC (0.94 each) and a very strong ROC-AUC at 0.99, confirming that it is an effective and less optimal.

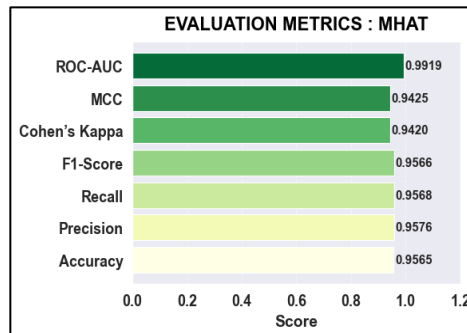


Figure 26: Evaluation metrics for MHAT.  
Source: Authors, (2026).

The evaluation metrics are indicative of the model's performance which is depicted in figure 26. There is high accuracy, precision, recall and F1-score, strong agreement in terms of MCC and Cohen's Kappa (approximately 0.94), and excellent ROC-AUC (approximately 0.99), indicating that the model has demonstrated reliable classification with robustness.

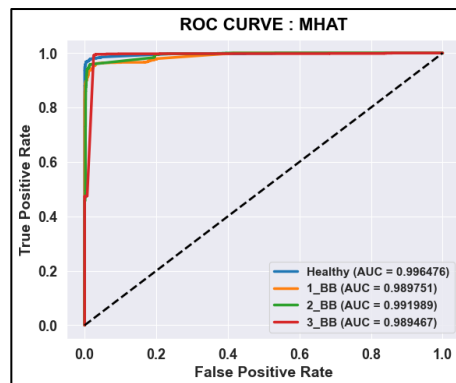


Figure 27: ROC curve for MHAT.  
Source: Authors, (2026).

The ROC curves produced during evaluation also indicate that there has been an excellent classification performance across the various classes which is mentioned in figure 27, and the curves are well positioned toward the upper left corner of the graph. The AUC values, which were found to be all very high, demonstrate strong discrimination by the model, and the Healthy class was determined to deliver the best performing model.

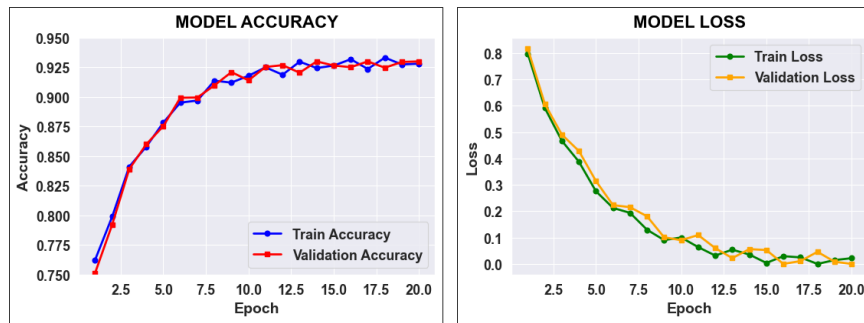


Figure 28: Model accuracy and model loss for RBFNN.

Source: Authors, (2026).

Figure 28 exhibits a progression in terms of the development of the model's performance during the training process by increased training and validation accuracy and decreased training and validation loss; both were observed to be steadily converging and demonstrated no significant evidence of overfitting.

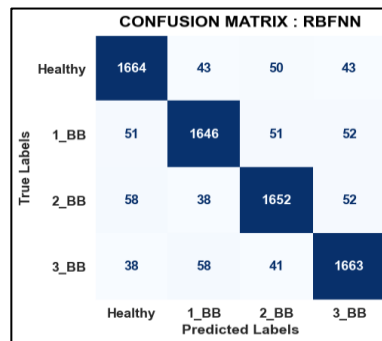


Figure 29: Confusion matrix for RBFNN.

Source: Authors, (2026).

The confusion matrix in figure 29 provided an evidence of the overall strength of the classification, with the majority of correctly predicted samples positioned along the diagonal; and, on average, there were very few instances of misclassification, and they were distributed relatively evenly across the various classes, indicating that there was no significant bias toward one or another class.

Table 6: Performance metrics of RBFNN.

| SI.NO | METRICS       | VALUES |
|-------|---------------|--------|
| 1     | Accuracy      | 0.935  |
| 2     | Precision     | 0.938  |
| 3     | Recall        | 0.932  |
| 4     | F1-Score      | 0.935  |
| 5     | Cohen's Kappa | 0.910  |
| 6     | MCC           | 0.915  |
| 7     | ROC-AUC       | 0.970  |

Source: Authors, (2026).

The RBFNN model has a stellar reputation which is depicted in table 6. High accuracy, combined precision and recall, Good Kappa and MCC agreement, plus outstanding classification accuracy demonstrated by ROC-AUC values of nearly 0.97.

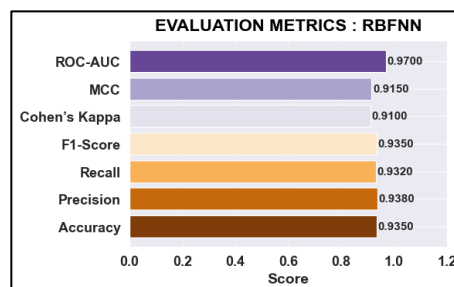


Figure 30: Evaluation metrics for RBFNN.

Source: Authors, (2026).

The RBFNN Model demonstrated in figure 30 is measured by AUC-ROC of 0.970, accuracy of 0.935, precision of 0.938, Recall of 0.932, F1 Score of 0.935, MCC of 0.915 and Cohen's Kappa of 0.91, demonstrating that this model has excellent reliability and demonstrates a high level of balanced classification capability.

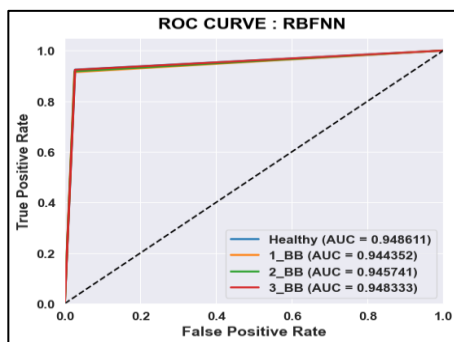


Figure 31: ROC curve for RBFNN.  
Source: Authors, (2026).

Figure 31 demonstrates the great class-wise separation of classes by showing similar AUCs in the 0.94–0.95 range; thus, RBFNN class access the class in a more reliable manner.

Table 7: Comparative analysis of various methods.

| SL.NO | METRICS       | SFOA-Hybrid RBFNN-MHAT | Hybrid RBFNN-MHAT | MHAT   | RBFNN |
|-------|---------------|------------------------|-------------------|--------|-------|
| 1     | Accuracy      | 0.9960                 | 0.9776            | 0.9565 | 0.935 |
| 2     | Precision     | 0.9960                 | 0.9786            | 0.9576 | 0.938 |
| 3     | Recall        | 0.9960                 | 0.9776            | 0.9568 | 0.932 |
| 4     | F1-Score      | 0.9960                 | 0.9778            | 0.9566 | 0.935 |
| 5     | Cohen's Kappa | 0.9946                 | 0.9702            | 0.9420 | 0.910 |
| 6     | MCC           | 0.9946                 | 0.9704            | 0.9425 | 0.915 |
| 7     | ROC-AUC       | 1.0000                 | 0.9965            | 0.9919 | 0.970 |

Source: Authors, (2026).

As illustrated in table 7, the performance of the SFOA-Hybrid RBFNN-MHAT method consistently surpassed the performance of every other method across every metric of measurement evaluated, attaining excellent results for accuracy, precision, recall, and F1-score (0.996 for accuracy, precision, recall, F1, and ROC-AUC score of 1.0). There was a progressive decrease in performance for Hybrid RBFNN-MHAT, MHAT, and RBFNN indicating the efficacy of the proposed Hybrid Optimization method.

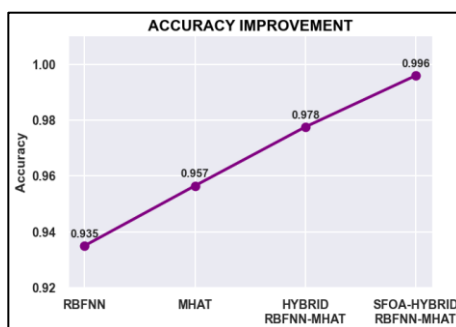


Figure 32: Accuracy improvement.  
Source: Authors, (2026).

Figure 32 displays the tracking of accuracy via plotting results demonstrates the improvements in accuracy attained by use of the RBFNN, 0.935 through the use of the MHAT, 0.957 through the use of Hybrid RBFNN- MHAT, and highest with SFOA-Hybrid RBFNN-MHAT of 0.996.

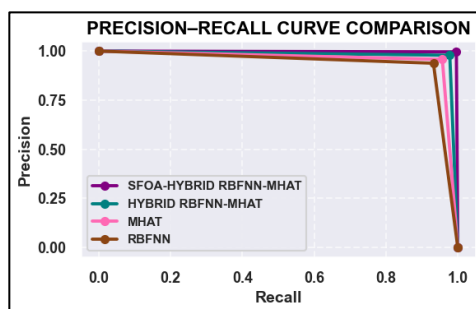


Figure 33: Comparison of precision-recall curve.  
Source: Authors, (2026).

Figure 33 compares the performance of the model across all metrics was tracked through plotting of the Precision-Recall curve to indicate that SFOA-Hybrid RBFNN-MHAT obtains the highest precision with almost all values of recall, therefore allowing for the most accurate results. The Precision-Recall curve shows that Hybrid RBFNN-MHAT-MHAT perform close in terms of precision, RBFNN, had lower results in precision at high recall values and was associated with greater drops in accuracy.

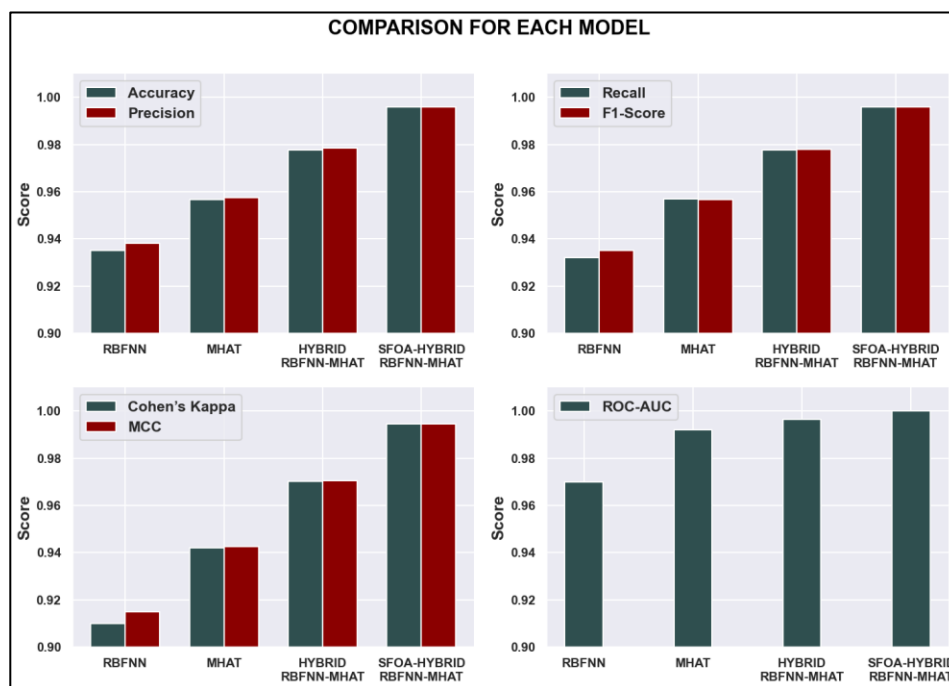


Figure 34: Comparison for each model.

Source: Authors, (2026).

Figure 34 shows the clear performance improvement of the class across all metrics. The SFOA-Hybrid RBFNN-MHAT continues to produce the highest accuracy, Precision, Recall, F1 Scores, Cohen's Kappa, MCC and ROC-AUC indicating itself as the most robust and reliable overall class performance.

Table 8: Comparative analysis of accuracy for different methods.

| Sl.NO | MODEL         | ACCURACY |
|-------|---------------|----------|
| 1     | RF [21]       | 0.91     |
| 2     | CWT [22]      | 0.97     |
| 3     | CNN-LSTM [23] | 0.976    |
| 4     | ClasLoc [24]  | 0.90     |
| 5     | CNN-RNN [25]  | 0.977    |
| 6     | PROPOSED      | 0.99     |

Source: Authors, (2026).

Table 8 displays the accuracy of each model, showing that the proposed model achieved the highest accuracy at 99%, followed closely by CNN-RNN and CNN-LSTM with accuracies of 97.7% and 97.6%, respectively, while RF and ClasLoc both have lower accuracies.

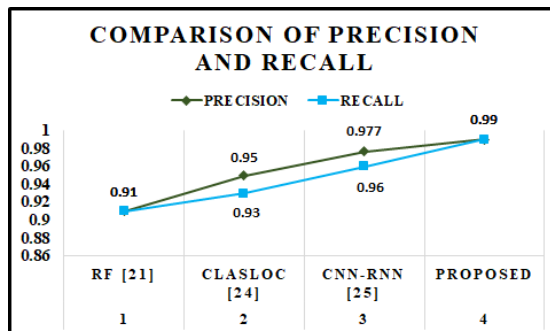


Figure 35: Comparative analysis of precision and recall.

Source: Authors, (2026).

Figure 35 depicts the metrics of accuracy, precision, recall and F1-score measured by four models including RF, ClasLoc, CNN-RNN and the proposed model. Performance on each metric progressed from RF to the proposed model producing the best results (0.99) for every metric.

Table 9: Comparative analysis of F1-Score for different methods.

| SI.NO | MODEL        | F1-SCORE |
|-------|--------------|----------|
| 1     | RF [21]      | 0.91     |
| 2     | ClasLoc [24] | 0.94     |
| 3     | CNN-RNN [25] | 0.98     |
| 4     | PROPOSED     | 0.99     |

Source: Authors, (2026).

Table 9 had a gradual increase in their respective F1-scores, from the lowest to the highest. The proposed model achieving the highest F1-score at 99%. This demonstrates that the presented model achieves significantly improved than all other models.

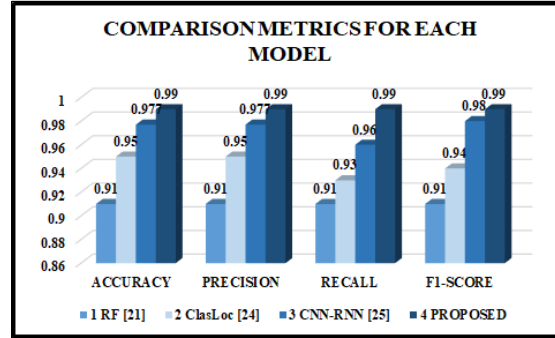


Figure 36: Comparison metrics for each model.

Source: Authors, (2026).

Figure 36 indicates a steady increase in the F1-score achieved by each model as their performance progressed (RF F1-score=0.91, ClasLoc F1-score=0.94, CNN-RNN F1-score=0.98, proposed model F1-score of 0.99); this indicates the suggested model attained higher enactment overall.

## V. CONCLUSION

The proposed framework incorporates an organised workflow of data collection, preprocessing, feature engineering, parameter optimisation and combination of automated and manual models incorporated into a comprehensive fault diagnostic structure, the proposed system uses the highest superiority operational signal from initial data collection and provide excellent results for removing noise from cleansed operational data while preserving the relevant information regarding electrical faults. The feature engineering stage used the data produced from preprocessing to both prepare and standardise the data when developing the feature vector for use in training the DL model. The starfish optimising algorithm provides for the optimal tuning of the model hyper-parameters that offer the higher performance and assurance in prediction. The hybrid model that consists of RBFNN along with MHAT captures both the high-level contextually expressive features and the details of the localised fault marks. The fusion layer allows for the best representation of both the global context and localised signature features, leading to the combined strength for the final diagnostics through an accurate classification of induction motor conditions as either Normal/Healthy or BRB Failure. Finally, the hybrid model provides a substantially higher degree of diagnostic accuracy, precision, recall, F1-Score of 0.9960, robustness and real-world utility for intelligent condition monitoring systems.

## VI. AUTHOR'S CONTRIBUTION

**Conceptualization:** Killamsetti Vijeta, Sri Suyambulinga Perumal B, R. Tharwin Kumar, Niran I R, Jinsha Lawrence, and Gunasekar M.

**Methodology:** Killamsetti Vijeta and Sri Suyambulinga Perumal B.

**Investigation:** Killamsetti Vijeta and Sri Suyambulinga Perumal B.

**Discussion of results:** Killamsetti Vijeta, Sri Suyambulinga Perumal B, R. Tharwin Kumar, Niran I R, Jinsha Lawrence, and Gunasekar M.

**Writing – Original Draft:** Killamsetti Vijeta.

**Writing – Review and Editing:** Vijeta and Sri Suyambulinga Perumal B.

**Resources:** Sri Suyambulinga Perumal B.

**Supervision:** Sri Suyambulinga Perumal B and Sri Suyambulinga Perumal B.

**Approval of the final text:** Killamsetti Vijeta, Sri Suyambulinga Perumal B, R. Tharwin Kumar, Niran I R, Jinsha Lawrence, and Gunasekar M.

## VII. REFERENCES

- [1] K. Barrera-Llana, J. Burriel-Valencia, A. Sapena-Bano, and J. Martinez-Roman, "Fault detection in induction machines using learning models and Fourier spectrum image analysis", *Sensors*, vol. 25, no. 2, pp. 471, Jan. 2025.
- [2] M. Samiullah, H. Ali, S. Zahoor, and A. Ali, "Fault diagnosis on induction motor using machine learning and signal processing", *arXiv preprint arXiv: 2401.15417*, Jan. 2024.
- [3] S.M. Yoo, H.G. Lee, W.K. Hao, and I.S. Lee, "Induction Motor Fault Diagnosis Using Low-Cost MEMS Acoustic Sensors and Multilayer Neural Networks", *Applied Sciences*, vol. 15, no. 17, pp. 9379, Aug. 2025.
- [4] P. S. Kartik, L. Padmasuresh and P. Muthukumar, "AI-Enhanced Power Electronics for Electric Mobility: A Review of Recent Developments and Future Trends", 2025 8th International Conference on Circuit, Power & Computing Technologies (ICCPCT), Kollam, India, pp. 2035-2039, Aug. 2025.

- [5] J. Guo, Q. He, and F. Gu, "DNOCNet: A novel end-to-end network for induction motor drive systems fault diagnosis under speed fluctuation condition", *IEEE Transactions on Industrial Informatics*, vol. 20, no. 6, pp. 8284-8293, Mar. 2024.
- [6] S. Ayankoso, A. Dutta, Y. He, F. Gu, A. Ball, and S.K. Pal, "Performance of vibration and current signals in the fault diagnosis of induction motors using deep learning and machine learning techniques", *Structural Health Monitoring*, pp. 14759217241289874, 2024.
- [7] U. Calderon-Urbe, R.A. Lizarraga-Morales, and I.V. Guryev, "Fault Diagnosis in Induction Motors through Infrared Thermal Images Using Convolutional Neural Network Feature Extraction", *Machines*, vol. 12, no. 8, pp. 497, Jul. 2024.
- [8] H.C. Chang, R.G. Liu, C.C. Li, and C.C. Kuo, "Fault Diagnosis of Induction Motors under Limited Data for Across Loading by Residual VGG-Based Siamese Network", *Applied Sciences*, vol. 14, no. 19, pp. 8949, Oct. 2024,
- [9] K. Karthika and R. Devi Priya. "Image processing-based protection of privacy data in cloud using NTRU algorithm", *Signal, Image and Video Processing*, vol. 18, no. 5, Jul. 2024.
- [10] V.I. Vlachou, T.S. Karakatsanis, S.D. Vologiannidis, D.E. Efstathiou, E.L. Karapalidou, E.N. Antoniou, A.E. Efraimidis, V.E. Balaska, and E.I. Vlachou, "Intelligent Fault Diagnosis of Ball Bearing Induction Motors for Predictive Maintenance Industrial Applications", *Machines*, vol. 13, no. 10, pp. 902, Oct. 2025.
- [11] M. Sehri, M. Ertagrin, O. Yildirim, A. Orhan, and P. Dumond, "Deep Learning Approach to Bearing and Induction Motor Fault Diagnosis via Data Fusion", *arXiv preprint arXiv:2506.11032*, May. 2025.
- [12] M.A. Saleh, A. Ghayeb, S.S. Refaat, H. Abu-Rub, S.P. Khatri, and J. Kammermann, "Attention-enhanced agru framework for induction motor incipient fault diagnosis in electric vehicles", *IEEE Transactions on Instrumentation and Measurement*, Nov. 2024.
- [13] J. Choi, S.H. Kim, W. Lee, and J.S. Lee, "Rapid Control Prototyping and Analysis of a Fault Diagnosis and Amplifying Algorithm for Broken Rotor bar Induction Motor Drives", *IEEE Access*, Jan. 2025.
- [14] U. Ali, U. Ramzan, W. Ali, and K.A. Al-Jaafari, "An Improved Fault Diagnosis Strategy for Induction Motors Using Weighted Probability Ensemble Deep Learning", *IEEE Access*, Jun. 2025.
- [15] G. Himaja, G.S. Rao, G.A. Naidu, T. Nagothi, and S. Dalli, "Recommendation system: national institute rank prediction using machine learning", *Journal of Algebraic Statistics*, vol. 13, no. 3, pp. 146-152, May. 2022.
- [16] J.A. Reyes-Malanche, E. Ramirez-Velasco, F.J. Villalobos-Pina, and S.K. Gadi, "Short-circuit fault diagnosis on the windings of three-phase induction motors through phasor analysis and fuzzy logic", *Energies*, vol. 17, no. 16, pp. 4197, Aug. 2024.
- [17] G.U. Oh, S.T. Kim, and J.S. Ko, "Bearing Fault Diagnosis Using Torque Observer in Induction Motor", *Energies*, vol. 18, no. 22, pp. 5872, Nov. 2025.
- [18] S. Wang, Y. Vidal, and F. Pozo, "Two-dimensional color distribution entropy: validation and application on non-contact fault diagnosis for induction motor", In *2024 32nd European Signal Processing Conference (EUSIPCO)*, pp. 556-560, Aug. 2024.
- [19] B. Xu, H. Li, R. Ding, and F. Zhou, "Fault diagnosis in electric motors using multi-mode time series and ensemble transformers network", *Scientific Reports*, vol. 15, no. 1, pp. 7834, Mar. 2025.
- [20] J. Ahn, J. Lee, and H. Kim, "Impedance-Based Inter-Turn Fault Diagnosis in Integrated Induction Motor and Drive Systems Using Space Voltage Vectors", *Applied Sciences*, vol. 15, no. 11, pp. 6065, May. 2025.
- [21] A. Abdulkareem, T. Anyim, O. Popoola, J. Abubakar, and A. Ayoade, "Prediction of induction motor faults using machine learning", *Heliyon*, vol. 11, no. 1, Jan. 2025.
- [22] R. Boudiaf, B. Abdelkarim, and H. Issam, "Bearing fault diagnosis in induction motor using continuous wavelet transform and convolutional neural networks", *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 15, no. 1, pp. 591-602, Mar. 2024.
- [23] R. Rahim, "AI-Driven Fault Diagnosis in Three-Phase Induction Motors Using Vibration and Thermal Data", *National Journal of Electrical Machines & Power Conversion*, pp. 21-28, Mar. 2025.
- [24] K.M. Shahiduzzaman, A.A. Koly, M. Maria, and B. Mymensingh, "ClasLoc: A Robust Fault Management Methodology for Transmission Lines Using RBFNN and ANFIS", 2024.
- [25] C. Eang, and S. Lee, "Predictive maintenance and fault detection for motor drive control systems in industrial robots using CNN-RNN-based observers", *Sensors*, vol. 25, no. 1, pp. 25, Dec. 2024.