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ENHANCING INTRUSION DETECTION USING HYBRID MODEL AND METAHEURISTIC OPTIMIZATION ALGORITHMS IN WIRELESS SENSOR NETWORKS

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Abstract

Wireless Sensor Networks (WSN) is the vital area in computer science for research owing to their broad variety of uses comprising serious civilian and military applications. Such demands have produced many security risks, particularly in unnoticed environments. To guarantee the dependability and security of WSN facilities, an Intrusion Detection System (IDS) plays a vital role. This IDS should correspond to the features of WSNs and be adequate for identifying the main potential amount of security-related challenges. It offers an efficient solution by analyzing the network to identify abnormal behavior of the sensor nodes. Investigators have presented different methods to detect intrusions in WSNs recently. Numerous deep learning (DL) and machine learning (ML) algorithms are effective tools for intrusion detection on WSNs. This paper develops a new Enhancing Intrusion Detection Using Hybrid Model and **Metaheuristic Optimization Algorithms** in Wireless Sensor Networks (EIDHM-MOAWSN) technique. The main aim of the proposed EIDHM-MOAWSN mode for detecting detect abnormal behavior of WSN in IDS using advanced techniques. At first, the data pre-processing stage applies linear scaling normalization (LSN) to transform raw data into a structured and clean format. Followed by, the proposed EIDHM-MOAWSN technique employs a dung beetle optimization (DBO) algorithm for the feature selection process. Besides, the hybrid model of a one-dimensional conventional neural network, long short-term memory with attention (1DCNN-LSTM-A) has been deployed for the classification method. At last, the multi-strategy improved chimpanzee optimization algorithm (MIChOA) adjusts the hyperparameter values of the 1DCNN-LSTM-A algorithm optimally and outcomes in greater classification performance. The efficiency of the EIDHM-MOAWSN method has been validated by comprehensive studies using the benchmark dataset. The numerical result shows that the EIDHM-MOAWSN method has better performance and scalability under various measures over the recent techniques.

Keywords: Hybrid Model**;** Intrusion Detection System; Metaheuristic Optimization Algorithms; Data Pre-processing**;** Wireless Sensor Networks

1. Introduction

Wireless Sensor Networks (WSN) have become progressively a substantial region of examination owing to their broad array of real-world applications namely forest fire monitoring, battlefields, crucial military surveillance, medical care, and building security monitoring [1]. A WSN contains a huge amount of independent sensor nodes distributed in diverse fields of interest to gather significant data and co-operatively transfer the gathered data wirelessly to a more effective node. The data transmitted around the system is based on specialized WSN protocols [2]. Consequently, protecting WSNs from multiple security attacks is needed. Inappropriately, attaining this objective becomes a major concern due to the constrained source of WSNs comprising memory, battery energy, and processing ability [3]. These restricting features make conventional security actions such as cryptography not always enough for these networks. These networks are highly susceptible to threats due to their open nature and distributed inadequate source of sensor nodes [4]. Additionally, in WSN packets broadcasting has to be done repeatedly, sensor nodes might be employed arbitrarily in a setting so an attacker adversary might be effortlessly incorporated into a WSN [5].

Intrusion is an unauthorized action in a system both attained passively and actively. In cybersecurity strategy, the Intrusion Detection System (IDS) offers few or every information to the other assistive systems: intruder's identification, location, intrusion time, activity of intrusion, types of intrusion, and layer where the intrusion arises [6]. This data would be useful to reduce and cure the outcome of threats since highly particular data relating to the intruder is attained. Thus, IDS is significant

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for network security [7]. The IDS performance is more challenging when compared to others because nodes of sensor are typically intended to be inexpensive and small, so they doesn't have tolerable hardware sources [8]. Likewise, there is no unique dataset that composes normal profiles and threats in WSN that can be employed to identify the signature of the attacker. Artificial Intelligence (AI), mainly Deep Learning (DL) and Machine Learning (ML) applications were implemented to either threat or defense measures in IP-enabled wireless systems [9]. This model offers defense approaches and resistance against security attacks to preclude and reduce the effects of casualties adaptably. Several DL and ML methodologies are employed in cyber-physical attacks, intrusion detection, data privacy protection, and malware detection [10].

This paper develops a new Enhancing Intrusion Detection Using Hybrid Model and **Metaheuristic Optimization Algorithms** in Wireless Sensor Networks (EIDHM-MOAWSN) technique. At first, the data pre-processing stage applies linear scaling normalization (LSN) to transform raw data into a structured and clean format. Followed by, the proposed EIDHM-MOAWSN technique employs a dung beetle optimization (DBO) algorithm for the feature selection process. Besides, the hybrid model of a one-dimensional conventional neural network, long short-term memory with attention (1DCNN-LSTM-A) has been deployed for the classification method. At last, the multi-strategy improved chimpanzee optimization algorithm (MIChOA) adjusts the hyperparameter values of the 1DCNN-LSTM-A algorithm optimally and outcomes in greater classification performance. The efficiency of the EIDHM-MOAWSN method has been validated by comprehensive studies using the benchmark database.

2. Related Works

The authors [11] developed an Enhanced Black Widow Optimizer (EBWO) model incorporated with an Attention Mechanism (ATTN) and Bidirectional Gated Recurrent Unit (BiGRU) method for recognizing malicious actions in IoT-based WSN. The EBWO model enhances the parameters of BiGRU-ATTN system, improving its performance. Sadia et al. [12] projected an advanced NIDS to ensure Wi-Fi-based WSN from predominant cyber-attacks, like flooding, injection and impersonation threats. Utilizing standard scaler function for pre-processing and feature scaling, this investigation train CNN-based method focus on optimum intrusion prevention and detection around multi-class classifications in WSN settings. Sedhuramalingam and Saravanakumar [13] developed an IDS depend on IDNN to resolve this concern and improve execution. Utilizing COA-GS, the succeeding hyper-parameter choice models are utilized to establish network topologies and the optimum parameter of network for DNN.

Nguyen et al. [14] introduces an innovative method named Genetic Sacrificial Whale Optimizer (GSWO) to handle the restrictions of traditional approaches. GSWO integrates a whale optimizer algorithms (WOA) and genetic algorithm (GA) adapted by employing a novel three-population division approach with a projected CIC to overwhelm premature convergence in WOA. Moreover, the CatBoost method is utilized for classification, effectually managing explicit data with complicate patterns. An innovative model for fine-tuning CatBoost's hyper-parameters is developed, utilizing GSWO approach and effectual quantization. Rajasoundaran et al. [15] projected a novel IDS with LSTM structures and Integrated Secure MAC principles for managing real-world neighbor monitoring challenges. The presented method applies GAN driven UWSN channel evaluation techniques and Secure principle of LSTM-MAC for safeguarding the data communication.

Arkan and Ahmadi [16] developed an innovative structure with an unsupervised intrusion detection model employing hierarchic method to enhance the security of incorporated software-defined WSN. In the projected structure, the sensors are not fully depends upon the SDWSN controller. Aljebreen et al. [17] projected BCOA-MLID model for secure IoT-WSN. The projected method aimed to effectually distinguish diverse kinds of threats to safeguard the IoT-WSN. The BCOA is intended for the optimum features selection to upgrade effectiveness of intrusion detection. For identifying intrusions in IoT-WSN, the presented model utilizes a class-specific cost regulation ELM categorization technique.

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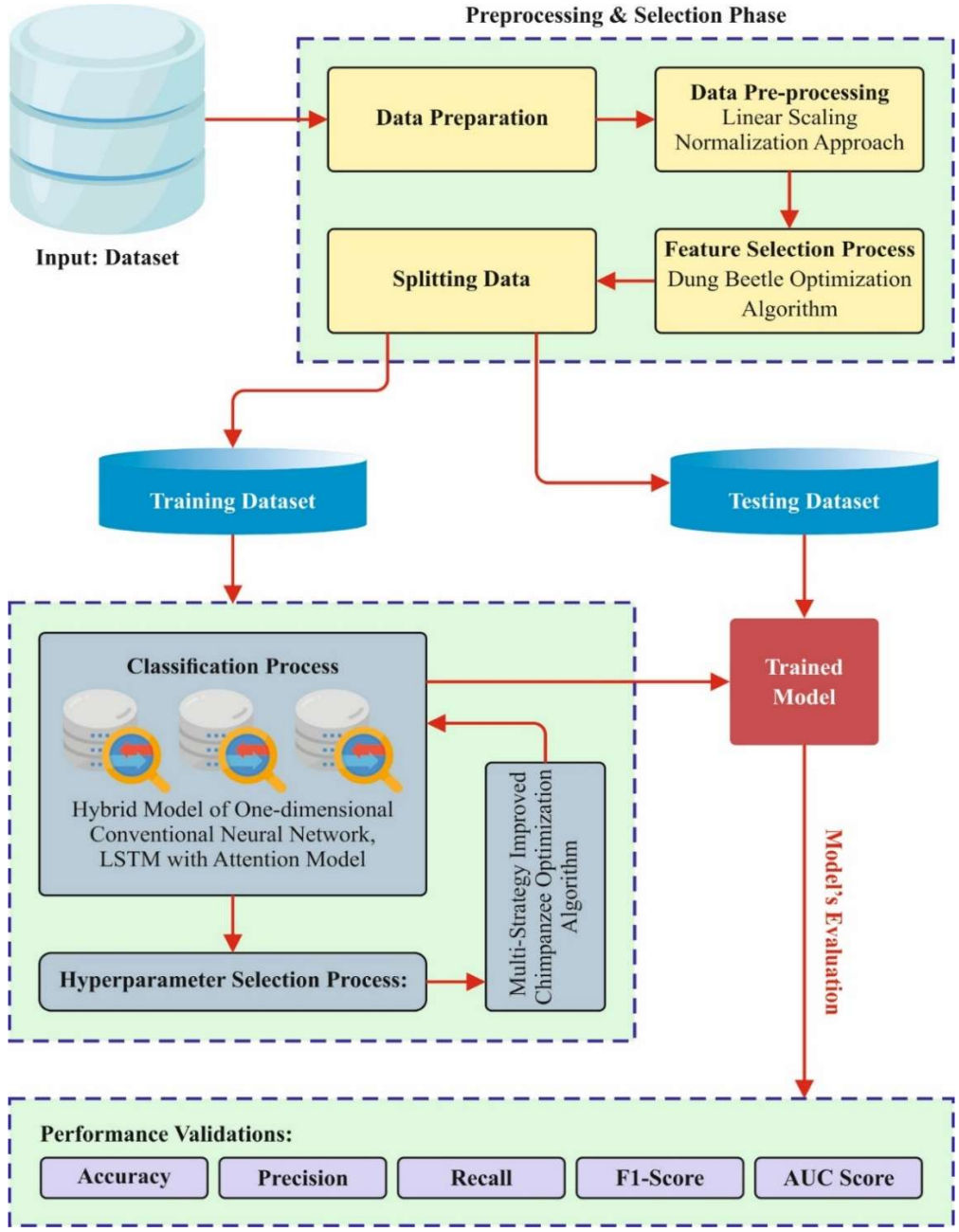

Fig. 1. Overall Working Method of EIDHM-MOAWSN algorithm

3. Proposed Methods

This paper develops a new EIDHM-MOAWSN technique. The main intention of the proposed EIDHM-MOAWSN technique is to detect abnormal behavior of WSN in IDS using advanced techniques. To accomplish that, the proposed EIDHM-MOAWSN model involves various stages such as data normalization, DBO-based feature selection, 1DCNN-LSTM-A-based classification model, and MIChOA-based hyperparameter tuning. Fig. 1 signifies the overall working process of the EIDHM-MOAWSN model.

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3.1. Data Pre-processing

At first, the LSN is applied to transform raw data into a structured and clean format. Linear scaling normalization is a model applied in **IDS** for **WSN** to normalize feature values inside a particular range, generally amongst (0,1) [18]. This method converts raw data by utilizing a linear transformation for mapping the new data to the fixed scale that guarantees consistency through various sensor nodes with changing measurement units. As regards WSNs, where sensor readings might differ considerably, linear scaling aids enhance the efficacy of ML methods by making them more responsive to anomalies and patterns. It improves the IDS performance by avoiding only particular features from dominating the study and considering quicker convergence of recognition methods. It additionally enhances the ability of the model to recognize abnormal attacks or behavior, like data manipulation or unauthorized access, by offering more balanced input for pattern recognition.

3.2. DBO-based Feature Selection Process

Followed by, the proposed EIDHM-MOAWSN technique employs the DBO algorithm for the feature selection process. DBO beetles have 4 sub-categories, foraging, rolling, stealing, and breeding classes with robust capability and rapid convergence [19]. The DBO method is discussed below:

Rolling Dung Beetle

The intensity of light impacts the movement of DB and the sun is must to remain rolling a dung ball through a direct way in lack of obstacles, the location upgrade method was depicted:

$$X_i(m+1) = X_i(m) + \omega \times k \times X_i(m-1) + b \times \Delta X \quad (1)$$

$$\Delta X = |X_i(m) - X^{worst}| \quad (2)$$

Here $X_i(m)$ represents data location of i dung beetle's at mth iteration, m specifies existing iteration counts, ω denotes natural co-efficient given a value of 1 or -1, ΔX signifies changes in the intensity of light, b is the constant in an interval to zero and one, X^{wrost} represents global worst location, and $k \in [0,0.2]$ denotes the continuous of defection co-efficient. Dung beetles should dance to attain a novel rolling position when they come through an obstacle that precludes them from forward movement. Consequently, the DB mathematical technique finding out novel rolling direction might written:

$$X_i(m+1) = X_i(m) + \tan(\theta)|X_i(m) - X_i(m-1)| \quad (3)$$

Here $\theta \in [0, \pi]$ cannot replace the position of dung beetles while θ is equal to $0, \pi/2$ or π.

Breeding Dung Beetles

The DB chooses a proper position for laying its egg after rolling the dung ball to protect its position. To pretend the area where female DB lay their eggs, the novel investigation recommended the succeeding method of boundary selection:

$$Lb^* = \max(X^* \times (1-R), Lb) \quad (4)$$

$$Ub^* = \min(X^* \times (1-R), Ub) \quad (5)$$

Here M specifies the existing maximal iteration counts, ub and lb denote the upper and lower bounds of spawn region, correspondingly Xib specifies the existing locally optimum location, Q=1−m/M, and Su and Sl represent the higher and lower borders. The location of breeding DB is likewise dynamic and defined below:

$$B_i(t+1) = X^* + b_1 \times (B_i(t) - Lb^*) + b_2 \times (B_i(t) - Ub^*) \quad (6)$$

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While, ρ_1 and ρ_2 specifies dual independent arbitrary vectors 1xD, D represents the size of optimization concern, and $X(m)$ denotes the data position of mth breeding DB at mth iteration.

Foraging Dung Beetles

The juvenile dung beetles should create the finest foraging position to guide them to feed in a way that imitates their natural behavior of foraging. The ideal foraging region boundaries are shown:

$$K_l = \max\left(X^b \times (1 - Q), lb\right) \tag{7}$$

$$K_u = \min\left(X^b \times (1 - Q), ub\right) \tag{8}$$

Here K_u and K_l specifies the upper and bottom bounds of the optimum searching region, correspondingly and X^b indicates the finest global location. The succeeding equation is utilized to upgrade the location of small DB after recognizing the optimum hunting region:

$$X_i(m+1) = X_i(m) + \beta_1 \times (X_i(m) - K_l) + \beta_2 \times (X_i(m) - K_u) \tag{9}$$

Here β_1 represents a random integer, which monitors a normal distribution, β_2 denotes the number of arbitrary variables that fall between zero and one, and $X_i(m)$ specifies the data position of ith small DB at C iteration.

Stealing Dung Beetles

The dung beetles are related to thieves because they feed upon the other DB feces. Thus, the finest region to struggle for food is thought to X^b of the surroundings. The succeeding equation defines the position information of the stealing DB that is upgraded in the iterative method:

$$X_i(m+1) = X^b + \eta \times \gamma \times \left(\left|X_i(m) - X_i^b\right| + \left|X_i(m) - X^b\right|\right) \tag{10}$$

Here $X(m)$ represents ith stealing DB data location at mth iteration, γ denotes size arbitrary vector 1xD, that mimics normal distribution, and η is constant. The fitness function (FF) imitates the accuracy of classification and the chosen feature amounts. It exploits the classifier accuracy and reduces the set dimension of the designated features in Eq. (11)

$$Fitness = \alpha * ErrorRate + (1 - \alpha) * \frac{\#SF}{\#All\_F} \tag{11}$$

Whereas $ErrorRate$ represents the classifier rate of error utilizing the designated feature. $ErrorRate$ is dignified as the incorrect percentage classified to the number of classifications completed, formulated among (0,1), $\#SF$ refers to designated feature counts and $\#All\_F$ stands for complete feature counts in the novel data set. α is utilized for controlling the significance of subset length and classification excellence.

3.3. 1DCNN-LSTM-A-based Classification Model

Besides, the hybrid model of 1DCNN-LSTM-A has been deployed for the classification method. The benefit of LSTM exists in its original 3-gate framework: the forget, the input, and the output gates [20]. These 3 gates collaborate to determine great short- and long-term memory abilities, with the related equation presented in Eq. (12).

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$$\begin{cases} f_t = \sigma\big(W_f \cdot [h_{t-1}, x_t] + b_f\big) \\ i_t = \sigma(W_i\,[h_{t-1}, x_t] + b_i) \\ \tilde{C}_t = \tanh\,(W_c \cdot [h_{t-1}, x_t] + b_c) \\ C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \\ o_t = \sigma(W_o \cdot [\mathrm{h}_{t-1}, x_t] + b_o) \\ h_t = 0_t * \tanh(C_t) \end{cases} \quad (12)$$

Whereas W and b signify weights and biases. i_t,o_t, and $f_t$represents input, output, and forget gates outputs. x_t denotes present input, C_t and C_{t-1} are present and preceding state of the cell, h_t and h_{t-l} represents present and preceding hidden layers (HLs). σ and tanh signify the Sigmoid function and the function of the hyperbolic tangent.

CNN is a deep neural networks (DNNs) structure with convolution, acting as the feature extractor for systems that are extensively applied in time-series tasks. 1D-CNN is more appropriate to handle time-series data. It successfully seizures local models in sequences, which might be closely associated with modifications in $PM_{2.5}$ focus, like periodicity and seasonal variation. The 1D-CNN structure mainly contains pooling, input, and convolutional layers. The convolution layer initially removes data features by convolution of the input data, succeeded by the layer of pooling compression of the removed features to facilitate network computational efficiency and underline main features. Owing to 1D-CNN's capability for local connectivity and weight sharing, it can lessen the complexity of the model and the modeling parameter counts while more successfully removing feature data.

As input characteristics at dissimilar time points have changing amounts of significance for $PM_{2.5}$, the AM may dynamically allocate dissimilar weighting to the feature. Whereas x_t signifies the input data at $t\ th$ time, h_t denotes x_t output in the LSTM-HL, and a_t denotes attention weight. Initially, the fully connected (FC) layer has been applied to compute the significance score for all time steps. Then, the function of the softmax was used to standardize the score, transforming them into the likelihood distribution and guaranteeing that the amount of each of the weights is one. This means that the weighting of all time steps characterizes its relative significance in model prediction. Lastly, the HLs h_t are weighted according to the attention weighting to get the novel vector of the features S_t. The equations are as shown:

$$\begin{cases} e_t = Dense(W h_t + b) \\ a_{tj} = Softmax(e_{tj}) = \frac{\exp(e_{tj})}{\sum_{k=1}^{T} \exp(e_{tk})} \\ S_t = \sum_{j=1}^{T} a_{tj}\, h_j \end{cases} \quad (13)$$

Whereas Dense signifies the FC layer, W represents the weighted matrix, b indicates the bias. e_t specifies the raw attention score. S_t denotes an attention layer output. The last forecast value y is yield over the FC layer. Fig. 2 depicts the architecture of 1DCNN-LSTM-A model.

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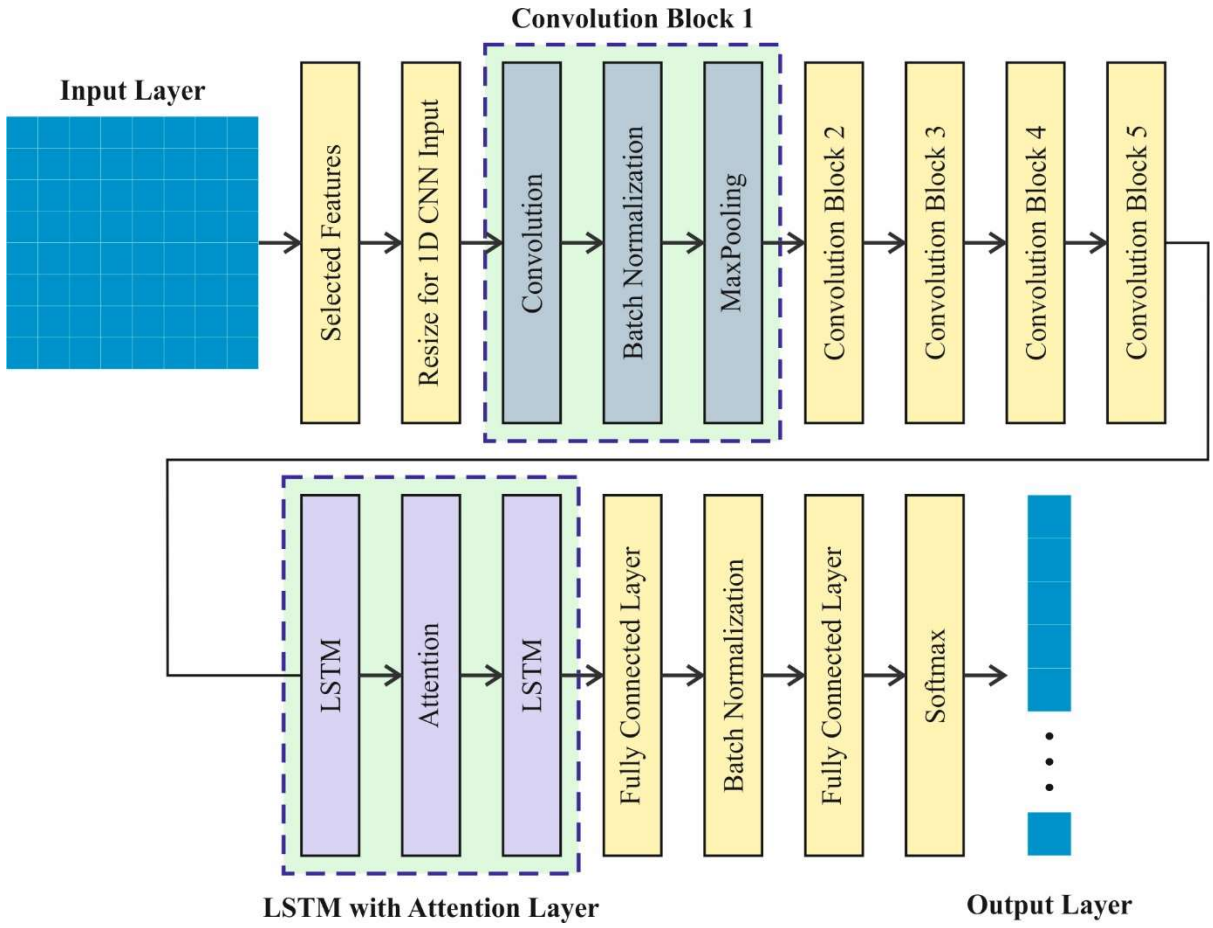

Fig. 2. Architecture of 1DCNN-LSTM-A model

3.4. MIChOA-based Hyperparameter Tuning Model

At last, MIChOA adjusts the hyperparameter values of the 1DCNN-LSTM-A algorithm optimally and outcomes in greater classification performance. The of chimpanzee populations social behavior stimulates the ChOA. Here, chimpanzees are branded into four kinds of social roles depending upon their skills such as drivers, encircles, attackers, and chasers [21]. The MIChOA is an improved form of the ChOA, which is mainly proposed for enhancing the convergence speed and accuracy. It incorporates manifold tactics, like opposition-based learning, adaptive weight adjustment, and chaotic maps, for balancing exploitation and exploration. The population range was vital to evade local goals and improve exploration of the global. The original ChOA's initialization of random wants is sophisticated. To tackle this, a hybrid approach has been developed, which unites chaotic initialization and a good point set.

Good Point Set Initialization

The initialize is beneficial model for making evenly spread points, mainly in high-dimension searching spaces, while it certifies superior distribution than initialize of random. The deviation $P_n(k) = \{(\{r_1^{(n)} \cdot k\}, \{r_2^{(n)} \cdot k\}, \ldots, \{r_s^{(n)} \cdot k\}) | 1 \leq k \leq n\}$fulfills $(n) = C(r, \varepsilon)N^{-1+\varepsilon}$, while $C(r, \varepsilon)N^{-1+\varepsilon}$ refers to a constant that relates to r and ε. n represents the amount of points. $P_n(k)$ is named a good point set, with r denoting a good point. $\{r_s^{(n)} \cdot k\}$ denotes the fractional portion, with $r =$

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$\{2\cos\left(\frac{2\pi}{p}\right)|1 \le k \le s\}$, while p means the least prime amount fulfilling$\left(\frac{p-3}{2} \ge s\right)$. This step makes low-discrepancy points, certifying even spatial distribution.

Chaos Map

It is a non-linear dynamic model, which contains ergodicity and pseudo-randomness. It enables the group of random and dissimilar points throughout the initialize stage, thus improving the model's exploration abilities. Chaos mapping is a non-linear dynamic model, which is categorized by sensitivity to an initial ergodicity and conditions. Presenting chaos map into optimizer techniques can improve population range and develop the model's capability to escape local goals in future phases. Logistic maps, Tent maps, and so on are the common chaos mappings. The formulation for Circle mapping is given below:

$$x_{i+1} = mod\left(x_i + a - \frac{b}{2\pi}\sin(2\pi x_i), 1\right) \tag{14}$$

Hybrid of Good Point Set and Chaos Initialize

The initialized tactic starts by producing a good point set, which uses a chaotic map to present perturbations, thus improving its range and randomness. This hybrid model certifies that a point set recollects even distribution while integrating adequate randomness. The main intention is to enhance the analysis of searching space, by improving the model's searchability and decreasing the convergence probability to local goals.

Comparison of Dissimilar Initialize Models

A 2D searching space is assumed within an interval of [2, 2] and 100 is the size of the population, the population delivers good point set initialize, chaos map initialize, random initialized, which have been equated. By uniting the good point set and chaos map, both benefits can be exploited to certify the even spread of an initial population while enlarging range and randomness.

Benchmark Weight Strategy

In intricate path planning issues, an easy average location upgrade frequently drops to attain quick convergence to the global optimum solution. The benchmark weight strategy has been introduced to holds the largest fitness in the present population and applies the highest impact. In every iteration, the attacker's location ($X1$) is known as reference, and locations of other parts are united for computing corresponding weight for location upgrades. This method improves the model's searchability. The enhanced location upgrade formulation is given below:

$$\begin{cases} W_1 = \dfrac{|X_1|}{|X_1| + |X_2| + |X_3| + |X_4|} \\ W_2 = \dfrac{|X_1|}{|X_2| + |X_2| + |X_3| + |X_4|} \\ W_3 = \dfrac{|X_1|}{|X_3| + |X_2| + |X_3| + |X_4|} \\ W_4 = \dfrac{|X_1|}{|X_4| + |X_2| + |X_3| + |X_4|} \end{cases} \tag{15}$$

$$X(t+1) = \frac{1}{W_1 + W_2 + W_3 + W_4} \times \frac{W_1 \cdot X_1 + W_2 \cdot X_2 + W_3 \cdot X_3 + W_4 \cdot X_4}{4} \tag{16}$$

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Every weight W_1, W_3, W_2, and W_4 contains numerator fixed as X_1, whereas the denominator has dissimilar mixtures of absolute values.

Gaussian-Modulated Cosine Factor

The convergence factor f in the ChOA is chiefly employed to balance local exploitation and global exploration throughout the search procedure, which plays a vital part in the performance of the model. The linear decay of f fails to associate with a behavior of actual convergence throughout the model's implementation. To improve the global search and local exploitation abilities of the ChOA, a factor of Gaussian-modulated cosine has been developed, as given in Eq. (17):

$$f = f_{start} + (f_{end} - f_{start}) \cdot \exp(-\frac{(t - T/2)^2}{2\sigma^2}) \cdot \left(1 - \cos\left(\frac{\pi t}{2 \cdot T}\right)\right) \quad (17)$$

Here, f_{start} and f_{end} denotes the start and end values of the convergence factor, correspondingly. t means several iteration counts, σ refers to the standard deviation of the Gaussian function, and T denotes a maximum iteration count. The function of Gaussian distribution allows a smooth adjustment in the complete search procedure. In the later phases, the exponential decay overwhelms the fluctuation of the cosine term, which allows the population to concentrate on the optimum solution and improve the exploitation of local. The term cosine variation presents periodic oscillations that increase the model's random and range in the global exploration stage. f_{start} and f_{end} controls the dynamic range, by letting the model to adaptably adjust to the desires of dissimilar searching phases. The fitness selection is the substantial feature prompting the performance of the MIChOA. The hyperparameter choice procedure includes the solution encoder model to assess the candidate solution's efficiency. During this study, the MIChOA deliberates precision as the key condition to design the FF that is expressed as shown.

$$Fitness = \max(P) \quad (18)$$

$$P = \frac{TP}{TP + FP} \quad (19)$$

Here, the true positive value indicates TP and the false positive value signifies FP.

4. Experimental Analysis

The performance estimation of the EIDHM-MOAWSN model is studied under the WSN-DS dataset [22, 23]. The databse contains 374661 instances under 5 class labels as showed in Table 1.

Table 1 Dataset details

Class labels	**No. of Instances**
"Normal"	340066
"Blackhole"	10049
"Grayhole"	14596
"Flooding"	3312
"Scheduling Attacks"	6638
Total Instances	**374661**

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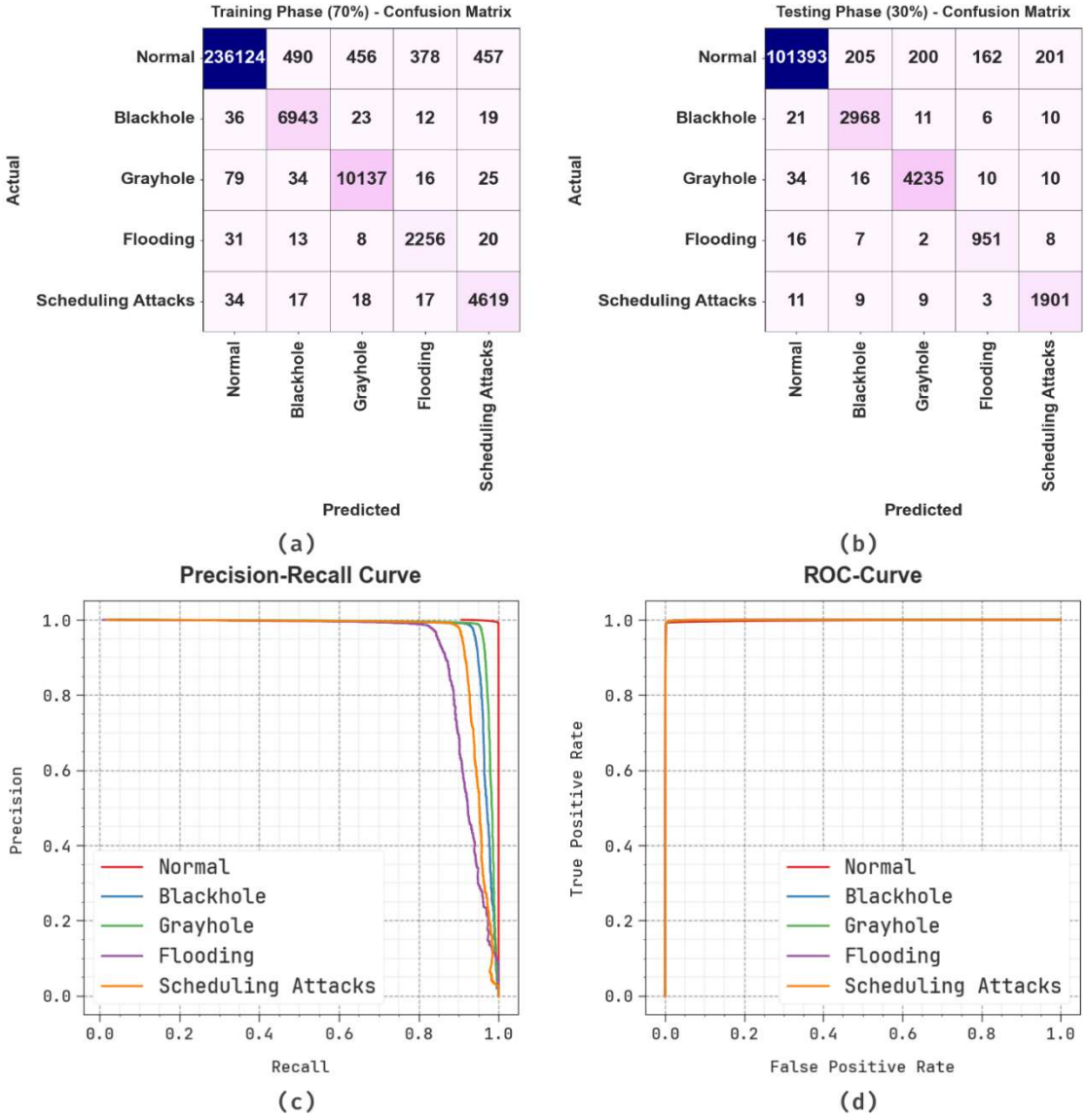

Fig. 3. Classifier result of (a-b) 70% and 30% confusion matrix and (c-d) curves of PR and ROC

Fig. 3 offerings the classifier results of the EIDHM-MOAWSN approach below 70%TRPH and 30%TSPH. Figs. 3a-3b demonstration the confusion matrix with correct recognition and classification of each class labels. Fig. 3c demonstrations the PR analysis, identifying superior performance over all classes. Followed by, Fig. 3d exemplifies the ROC values, establishing proficient outcomes with better ROC analysis for different classes.

Table 2 and Fig. 4 represents the intrusion detection of EIDHM-MOAWSN methodology under 70%TRPH and 30%TSPH. The outcomes imply that the EIDHM-MOAWSN algorithm accurately identified the samples. With 70%TRPH, the EIDHM-MOAWSN technique offers average $accu_y$, $sens_y$, $spec_y$, $F1_{score}$ and $AUC_{score}$of 99.67%, 98.31%, 99.70%, 95.19%, and 99.00%, respectively. Besides with 30%TSPH, the EIDHM-MOAWSN algorithm provides average $accu_y$, $sens_y$, $spec_y$, $F1_{score}$ and $AUC_{score}$of 99.66%, 98.20%, 99.68%, 95.03%, and 98.94%, correspondingly.

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Table 2 Intrusion detection of EIDHM-MOAWSN model under 70%TRPH and 30%TSPH

Classes	$Accu_y$	$Sens_y$	$Spec_y$	$F1_{score}$	AUC_{score}
TRPH (70%)					
Normal	99.25	99.25	99.26	99.59	99.26
Blackhole	99.75	98.72	99.78	95.57	99.25
Grayhole	99.75	98.50	99.80	96.85	99.15
Flooding	99.81	96.91	99.84	90.11	98.37
Scheduling Attacks	99.77	98.17	99.80	93.83	98.98
Average	**99.67**	**98.31**	**99.70**	**95.19**	**99.00**
TSPH (30%)					
Normal	99.24	99.25	99.20	99.58	99.22
Blackhole	99.75	98.41	99.78	95.42	99.10
Grayhole	99.74	98.37	99.79	96.67	99.08
Flooding	99.81	96.65	99.84	89.89	98.24
Scheduling Attacks	99.77	98.34	99.79	93.58	99.07
Average	**99.66**	**98.20**	**99.68**	**95.03**	**98.94**

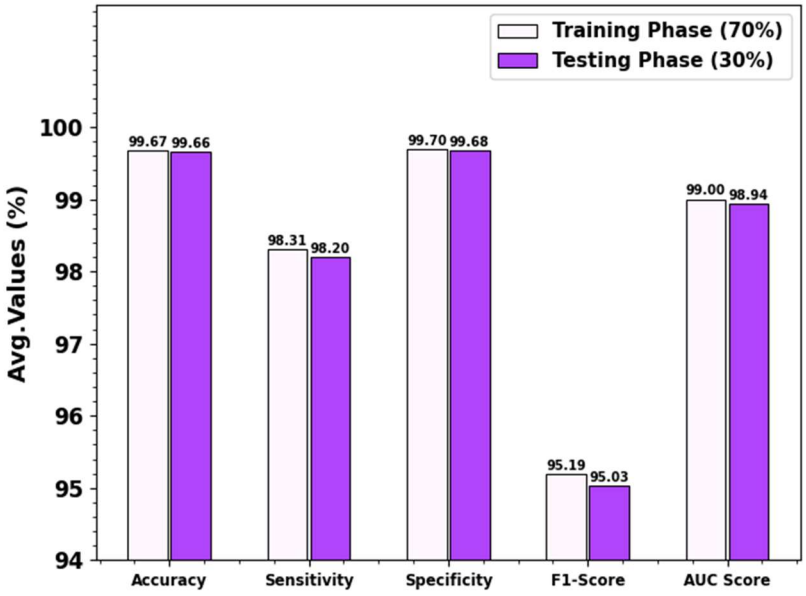

Fig. 4. Average of EIDHM-MOAWSN model under 70%TRPH and 30%TSPH

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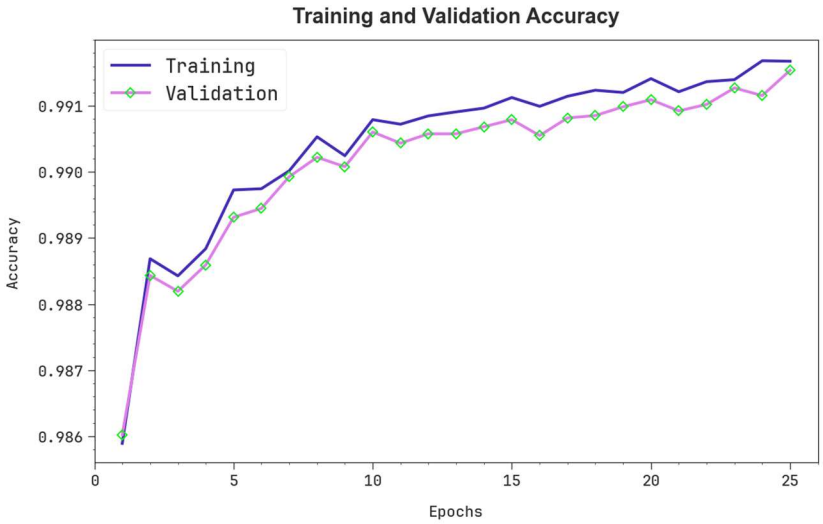

Fig. 5. $Accu_y$ curve of EIDHM-MOAWSN model

In Fig. 5, the training (TRA) $accu_y$ and validation (VAL) $accu_y$ analysis of the EIDHM-MOAWSN technique is illustrated. The $accu_y$ analysis are computed over the range of 0-25 epochs. The figure highlighting that the TRA and VAL $accu_y$ analysis exhibitions a increasing trend which informed the capacity of the EIDHM-MOAWSN algorithm with superior outcome across multiple iterations. Simultaneously, the TRA and VAL $accu_y$leftovers closer across the epochs, which identifies inferior overfitting and exhibitions maximal outcomes of the EIDHM-MOAWSN method.

In Fig. 6, the TRA loss (TRALOS) and VAL loss (VALLOS) analysis of the EIDHM-MOAWSN technique is demonstrated. The values of loss are computed across an interval of 0-25 epochs. It is identified that the TRALOS and VALLOS analysis establish a decreasing tendency, notifying the capacity of the EIDHM-MOAWSN approach in balancing a trade-off amongst data fitting and simplification. The continuous reducing in values of loss besides assurances the greater outcomes of the EIDHM-MOAWSN method.

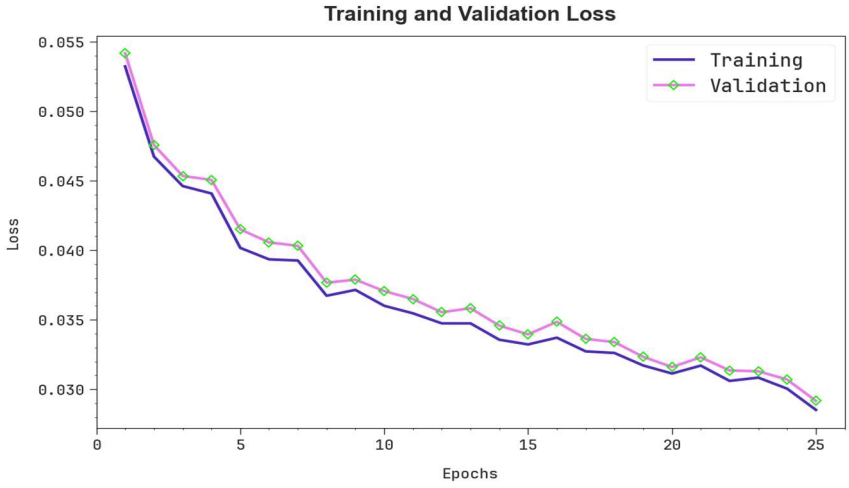

Fig. 6. Loss analysis of EIDHM-MOAWSN algorithm

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Table 3 delivers the comparative result of EIDHM-MOAWSN technique with existing approaches [24].

Fig. 7 provides $accu_y$ and $F1_{score}$ analysis of EIDHM-MOAWSN technique with existing systems. Based on $accu_y$, the proposed model EIDHM-MOAWSN has obtained higher $accu_y$ of 99.67%, whereas the existing techniques such as BCOA-MLID, AdaBoost, Gradient Boosting, XGB, KNN-AOA, and KNN-PSO have obtained lesser $accu_y$ of 99.58%, 95.76%, 94.66%, 96.90%, 97.28%, and 92.95%, respectively. In addition, depend on $F1_{score}$ the proposed technique EIDHM-MOAWSN has gained better $F1_{score}$ of 95.19%, where the existing approaches such as BCOA-MLID, AdaBoost, Gradient Boosting, XGB, KNN-AOA, and KNN-PSO have accomplished minimal $F1_{score}$ of 94.60%, 90.37%, 93.37%, 91.58%, 90.29%, and 93.06%, correspondingly.

Table 3 Comparative results of EIDHM-MOAWSN model with existing techniques

Methods	$Accu_y$	$Sens_y$	$Spec_y$	$F1_{score}$
EIDHM-MOAWSN	99.67	98.31	99.70	95.19
BCOA-MLID	99.58	97.99	99.75	94.60
AdaBoost Method	95.76	95.83	95.07	90.37
Gradient Boosting	94.66	95.32	94.16	93.37
XGB Algorithm	96.90	96.16	94.49	91.58
KNN-AOA	97.28	96.56	96.41	90.29
KNN-PSO	92.95	95.70	95.16	93.06

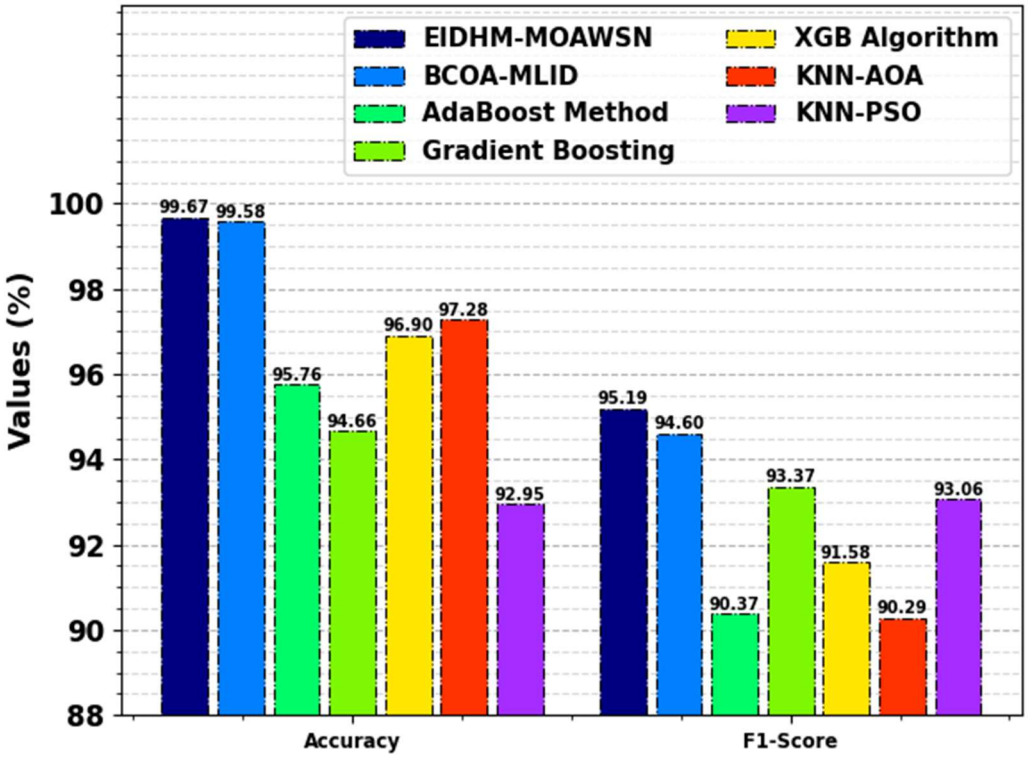

Fig. 7. $Accu_y$ and $F1_{score}$ analysis of EIDHM-MOAWSN model with existing models

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Fig. 8 inspects the $sens_y$, and $spec_y$ result of EIDHM-MOAWSN algorithm with existing methodologies. Based on $spec_y$, the proposed model EIDHM-MOAWSN has obtained higher $spec_y$of 99.70%, whereas the existing techniques such as BCOA-MLID, AdaBoost, Gradient Boosting, XGB, KNN-AOA, and KNN-PSO have obtained lesser $spec_y$ of 99.75%, 95.07%, 94.16%, 94.49%, 96.41%, and 95.16%, respectively. Besides, with respect to $sens_y$ the proposed system EIDHM-MOAWSN has achieved greater $sens_y$of 98.31%, while the existing approaches such as BCOA-MLID, AdaBoost, Gradient Boosting, XGB, KNN-AOA, and KNN-PSO have attained worst $sens_y$ of 97.99%, 95.83%, 95.32%, 96.16%, 96.56%, and 95.70%, correspondingly.

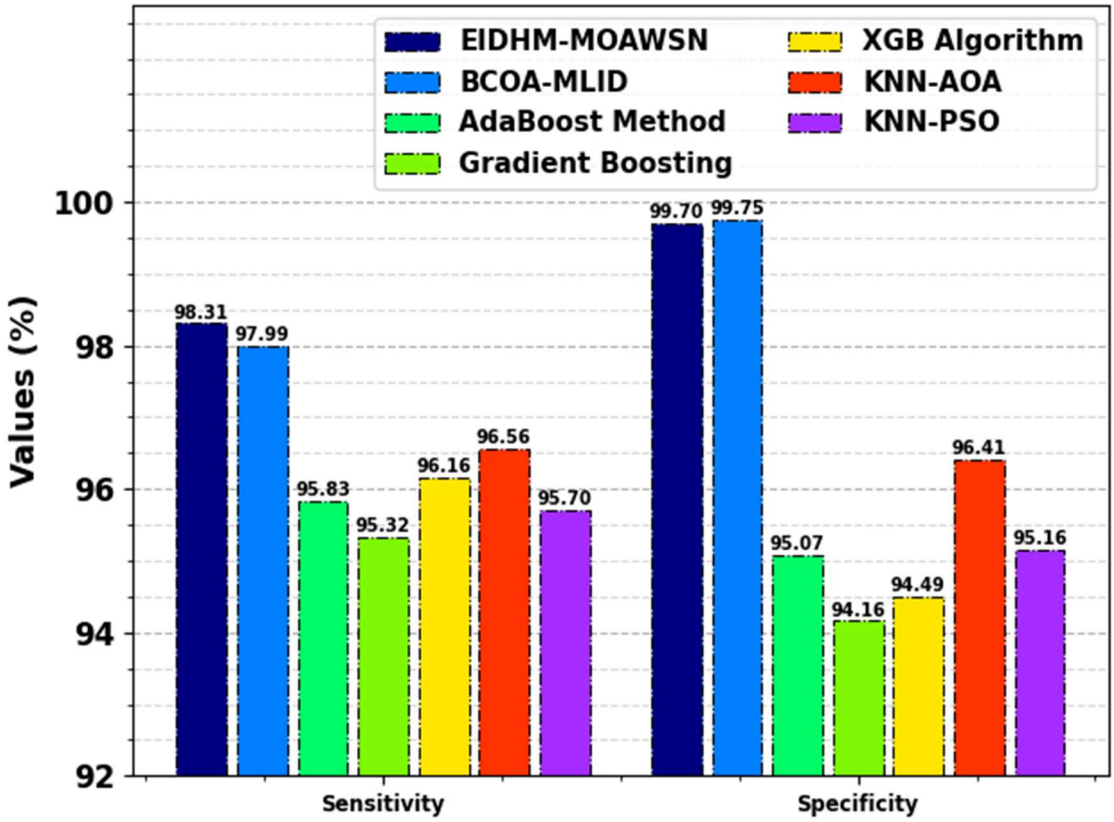

Fig. 8. $Sens_y$ and $Spec_y$ outcome of EIDHM-MOAWSN model with existing algorithms

The processing time (PT) outcome of EIDHM-MOAWSN technique with existing classifiers are displayed in Table 4 and Fig. 9. The results imply that the EIDHM-MOAWSN model gets greater performance. Based on PT, the EIDHM-MOAWSN algorithm provides minimal PT of 5.98sec whereas the BCOA-MLID, AdaBoost, GB, XGB, KNN-AOA, and KNN-PSO systems achieve maximum PT values of 16.53sec, 8.93sec, 14.99sec, 12.44sec, 13.37sec, and 9.84sec, respectively.

Table 4 PT result of EIDHM-MOAWSN approach with recent algorithms

Methods	Processing Time (sec)
EIDHM-MOAWSN	5.98
BCOA-MLID	16.53

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AdaBoost Method	8.93
Gradient Boosting	14.99
XGB Algorithm	12.44
KNN-AOA	13.37
KNN-PSO	9.84

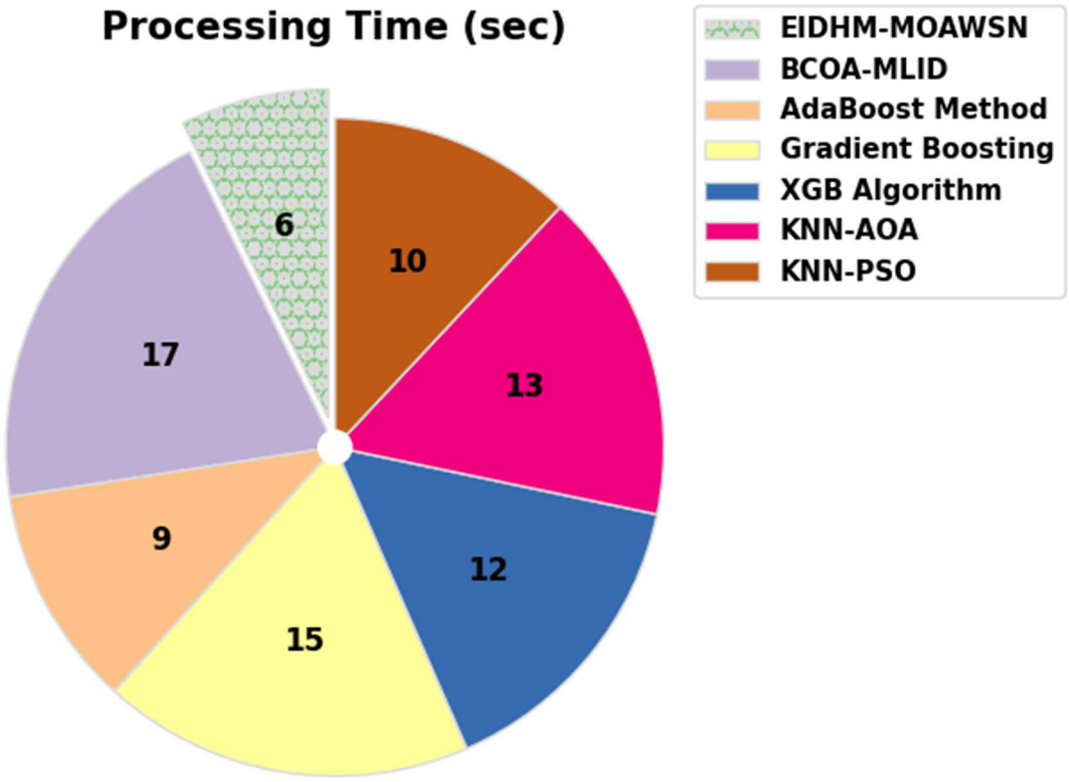

Fig. 9. PT outcome of EIDHM-MOAWSN technique with recent models

5. Conclusion

This paper develops a new EIDHM-MOAWSN technique. The main intention of the proposed EIDHM-MOAWSN technique is to perceive abnormal behavior of WSN in IDS using advanced techniques. At first, the data pre-processing step applies LSN to transform raw data into a structured and clean format. Following by, the proposed EIDHM-MOAWSN technique employs the DBO algorithm for the feature selection process. Besides, the hybrid model of 1DCNN-LSTM-A has been deployed for the classification method. At last, MIChOA adjusts the hyperparameter values of the 1DCNN-LSTM-A algorithm optimally and outcomes in greater classification performance. The efficiency of the EIDHM-MOAWSN method has been validated by comprehensive studies using the benchmark dataset. The numerical result shows that the EIDHM-MOAWSN method has better performance and scalability under various measures over the recent techniques.

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