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Whale Optimization Algorithm with Machine Learning Driven Intrusion Detection in Wireless Sensor Networks

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Abstract

Wireless Sensor Networks (WSNs) play a vital role in various applications, including environmental monitoring, industrial automation, and surveillance. However, the open and distributed nature of WSNs exposes them to security threats, making intrusion detection a critical concern. Traditional rule-based intrusion detection systems often struggle to cope with the evolving and complex nature of attacks. To address this challenge, this study presents a novel approach that introduces a Whale Optimization Algorithm with Machine Learning Driven Intrusion Detection in Wireless Sensor Networks (WOAML-IDWSN) technique. The presented WOAML-IDWSN technique integrates the inclusion of WOA with ML approach for effective intrusion detection in WSNs. It comprises two major processes such as WOA based feature selection and ML based intrusion detection. At the initial stage, the WOA is applied to electing an optimal subset of features. Next, in the second stage, extreme gradient boosting (XGBoost) classifier is applied for the identification of the intrusions. Extensive experiments are conducted using benchmark datasets to evaluate the effectiveness of the WOAML-IDWSN approach. Extensive comparative analyses against existing intrusion detection techniques demonstrate the superiority of the WOAML-IDWSN technique in accurately identifying various intrusion types.

Keywords: Wireless sensor networks; Intrusion detection; Whale optimization algorithm; Machine learning

1. Introduction

WSN is constructed on device network that gives a possibly supportable and green solution for increasing collection of data in a particular condition and it providing to the end user [1]. WSN is a robust and efficient infrastructure-free network composed of tens to large numbers of lower power detectors, which can be structured randomly [2]. These devices can receive feedback from the environment, it can be analyzed, and

after communicated [3]. Sensors are distributed deliberately or randomly in external environments, work as the sensing layer of IoT devices, and have an extensive range of applications. WSNs are frequently utilized in military and non-military activities for tool, detection, and feedback to an event at a remote or unavailable location. The major objectives of advanced education are to develop autonomous learning abilities and long-lasting learning capabilities [4]. A WSN exploits many SNs internally or around the allocated area. The sensors may be in some arrangement and do not need some preplanning, creating models for hard and unaccepting environments. Types of sensors are employed in WSN clusters namely acoustic sensors, infrared sensors, thermal sensors, magnetic sensors, seismic sensors, and so on [5]. With the emergence of wireless transmission, mobile sensor networking is newly provoked the attention of both industry and scientific researchers fascinated with real-time solutions. WSN is a network of special SNs distributed through space to monitor and detect physical environmental conditions before organizing the data at a centralized position [6]. Fig. 1 depicts the structure of IDS.

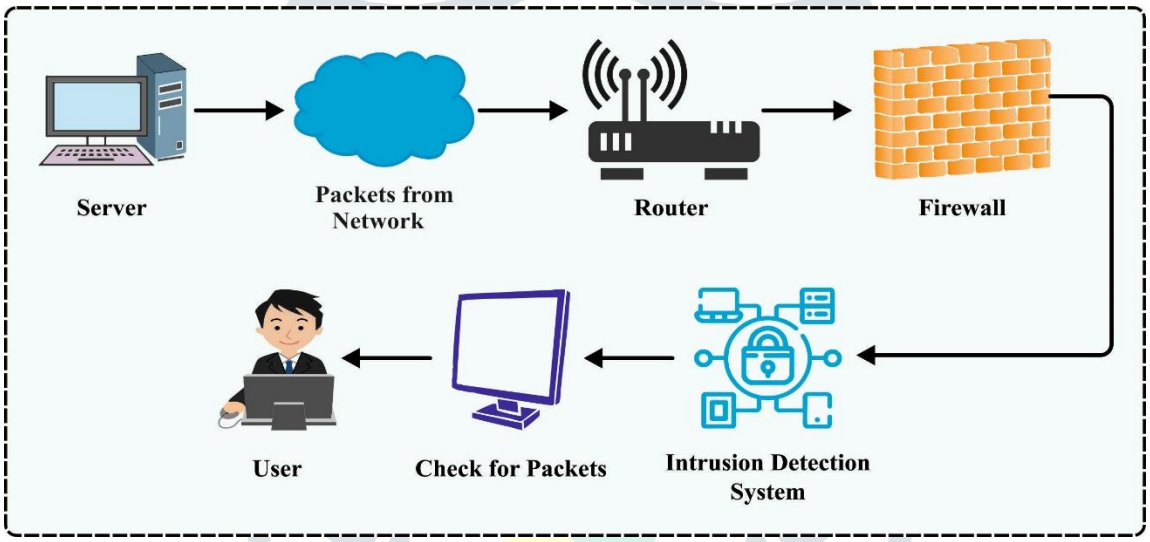

Fig. 1. Structure of IDS

WSNs can be susceptible to security threats and attacks [7]. Securing them becomes a challenge as their shortage of resources namely storage space, memory, battery power, communication bandwidth, and processing ability [8]. Additionally, SNs are detectable to physical occurrences due to their exploitation in unsupervised locations. The most common type of occurrence against WSN is DoS attack. These have occurred in different kinds to empty the node sources, specifically the energy and its capacity for executing other tasks [9]. Subsequently, particular security systems are crucial to protect WSNs from DoS attacks. Many researchers are developed different intrusion detection systems (IDS) supports for detection of these security attacks [10]. Machine learning (ML) and Deep learning (DL) approaches are deployed in various analyses and often represented high-rate of accuracy.

Alalayah et al. [11] developed a new Bear Smell-based-RF (BSbRF) for accurately detecting intrusion by monitoring the threshold values and activity of every user. Thereafter, preprocessing was employed for eliminating the errors existing in the datasets. Besides, feature extraction is exploited for extracting important features from datasets. Later, update bear smell fitness in the RF classification layer that supervises the

activities and accurately identifies the intrusion from the resultant layer. Singh et al. [12] presented an Automatic ML (Auto-ML) technique to automatically choose the ML method and automate the hyperparameters optimization for accurately predicting count of k-barriers then, rapid intrusion detection and avoidance employing Bayesian optimization. Four synthetic predictors are extracted such as transmission number of sensors, sensing various sensors, area of the region, and multiple sensors through Monte Carlo simulation. Alruhaily and Ibrahim [13] introduced a multilayer-IDS for WSN; that adopted a defense overall security method, but a 2-layers of identification were employed. The 1st layer is positioned on the network edge sensors that could be allocated; it utilizes a NBs method for actual-time decision making of the analyzed packets. In 2nd layer, has been positioned on the cloud, and applied an RF multiclass technique for a detailed analysis of the checked packets.

In [14], a novel k-means clustering is developed with optimum SVM (KM-OSVM) based IDS for WSN. Mainly, K-means clustering and data preprocessing techniques are implemented for classifying the data samples into cluster sets. Also, SVM based classification method is utilized for allocating classes, and parameters in SVM are optimally adopted by using CSO algorithm. Saif et al. [15] introduced an ML based IDS (ML-IDS) for BA-WSN based health monitoring technique. Five famous classification methods namely RF, NBs, k-NN, J48, and SVM are implemented for selecting and generating an effective technique with respect to identification accuracy. A particular dataset WSN-DS is employed for training the intrusion detection method. Pan et al. [16] suggested a lightweight Intelligent Intrusion Detection method for WSN incorporating SCA and K-NN approaches. The compact mechanism is executed to SCA (C-SCA) for saving the computation period, and space, and the polymorphic mutation (PM) approach has been employed to compensate for reducing accuracy of optimization.

This study presents a novel approach that introduces a Whale Optimization Algorithm with Machine Learning Driven Intrusion Detection in Wireless Sensor Networks (WOAML-IDWSN) technique. The presented WOAML-IDWSN technique integrates the inclusion of WOA with ML approach for effective intrusion detection in WSNs. It comprises two major processes such as WOA based feature selection and ML based intrusion detection. At the initial stage, the WOA can be applied to electing an optimal subset of features. Next, in the second stage, extreme gradient boosting (XGBoost) classifier is applied for the identification of the intrusions. Extensive experiments are conducted using benchmark datasets to evaluate the effectiveness of the WOAML-IDWSN approach.

2. The proposed model

This study presents a novel approach that introduces a WOAML-IDWSN technique for effective intrusion detection in WSNs. It comprises two major processes such as WOA based feature selection and XGBoost based classification.

2.1. WOA based feature selection

At the initial stage, the WOA is applied to electing an optimal subset of features. The Whale algorithm has been employed in the present study for optimizing the classification methods hyperparameter and

determining the suitable features [17]. This approach comprises 2 major steps: the exploration step, but this method explorations for prey, and the exploitation step, where the prey can be surrounded utilizing a spiral bubble-net feeding maneuver. Whales are trapping and detecting prey, where the correct place of prey can frequently be unidentified; this method is considered to be optimum performance is possible nearby the prey or closer to the optimal whale position.

During the "Exploitation step", the humpback whales (searching agents) use Eqs. (1) & (2) to move nearby the best performance if identifying the place of prey.

$$\vec{D} = \left|\vec{C} \cdot \vec{X}^*(t) \rightarrow -\vec{X}(t)\right| \quad (1)$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \quad (2)$$

During the present iteration defined by "t", the coefficient vectors A and C are computed employing Eqs. (3) and (4). The place vector of existing optimum whale and the existing whale is denoted by X^* and X, correspondingly It is vital to upgrade X^* in each iteration once the optimum performance or position can create:

$$\vec{A} = 2 \cdot \vec{a} \cdot \vec{r} - \vec{a} \quad (3)$$

$$\vec{C} = 2 \cdot \vec{r} \quad (4)$$

During all the iterations, the value of "a" reduces in [2-0] based on Eq. (5), whereas "MaxIteration" denotes the maximal possible iteration counts. For determining the novel whale place, arbitrary vectors of r are elected from the range of -1 to 1. These values can be employed for establishing the whale's position among the existing optimum whale as well as original whale place.

$$a = 2\left(1 - \frac{t}{\text{Max}Iteration}\right) \quad (5)$$

Two approaches can be employed for modeling the bubble-net performance of humpback whales: the shrinking encircling method and spiral upgrading position. The shrinking encircling method can be carried out by decreasing the value of "a" in Eq. (3). During the spiral upgrading position mechanism, Eqs. (6) and (7) are utilized for calculating the distance among whales as well as their optimum performance. These formulas are employed for replicating this design.

$$\vec{X}(t+1) = \vec{D}, \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) \quad (6)$$

$$\vec{D}, = \left|\vec{X}^*(t) - \vec{X}(t)\right| \quad (7)$$

The distance among the whale as well as prey (an optimum performances attained so far) is represented by $D,$. According to the value of p, the whale method is elect among circular and spiral movements. This formula is defined by Eq. (8):

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) \to -\vec{A} \cdot \vec{D} & if\ p < 0.5 \\ \vec{D}, \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}^*(t) & if\ p \geq 0.5 \end{cases} \quad (8)$$

whereas p implies the arbitrary integer among zero and one; whales search for prey arbitrarily along with the bubble-net system.

During the "Exploration step (Search for Prey the searching agents concentrate on broadening the scope of searching and moving far from the establish performance (before depending on only the optimum performance). Compared to the exploitation step, the exploration step employs arbitrary whale election for updating the whale position, permitting greater searching space exploration.

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_{rand}(t) - \vec{X}(t)\right| \quad (9)$$

$$\vec{X}(t+1) = \vec{X}_{rand}(t) - \vec{A} \cdot \vec{D} \quad (10)$$

In Eqs. (9) and (10), X_{rand} refers to the arbitrarily elected whale in the existing population. Once the absolute number of $|A|$ is superior to one, an arbitrary whale can elect for upgrading the whale's position. However, Once the absolute number of $|A|$ is lesser than one, optimum performance is to upgrade the whale positions. At last, the whale technique ends with sufficient end conditions (maximal iterations).

2.2. Classification using XGBoost method

Next, in the second stage, XGBoost classifier is applied for the identification of the intrusions. XGBoost concept with the features of high accuracy, low computation difficulty, fast running speed, and avoiding over-fitting [18]. The objective function of XGBoost involves a constant term, loss function, and a regularization term:

$$Obj(\theta) = L(\theta) + \Omega(\theta) + C \quad (11)$$

The loss function measures the model prediction, and the regularization term controls the model complexity to prevent overfitting. The modelling process of XGBoost is to keep the original model remain the same and take the generated error through the prior prediction as a reference to construct the next tree. It takes the residual difference among the true and the predicted values as the input to the next tree, and it can be formulated by the following expression:

(1) Initialization:

$$\hat{y}_t^{(0)} = 0 \quad (12)$$

(2) Add the first tree to the model:

$$\hat{y}_t^{(1)} = f_1(x_i) = \hat{y}_t^{(0)} + f_1(x_i) \quad (13)$$

(3) Add the second tree to the model:

$$\hat{y}_t^{(2)} = f_1(x_i) + f_2(x_i) = \hat{y}_t^{(0)} + f_2(x_i) \quad (14)$$

(4) Add the t-th tree to the model:

$$\hat{y}_t^{(t)} = \sum_{k=1}^{t} f_k(x_i) = \hat{y}_t^{(t-1)} + f_t(x_i) \quad (15)$$

Here $f_t(x_i)$ refers to the predictive outcome of the present t-th tree. $\hat{y}(t)$ shows the prediction value of i^{th} sample at time t, keep the model predictive outcome of t- 1 time:

$$\begin{cases} L(t) = \sum_{i=1}^{n} \left[l\left(y_j - \hat{y}_i^{(t-1)}\right) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] \\ g_i = \partial_{\hat{y}_i^{(t-1)}} l\left(y_i - \hat{y}_i^{(t-1)}\right) \\ h_i = \partial^2_{\hat{y}_i^{(t-1)}} l\left(y_i - \hat{y}_i^{(t-1)}\right) \end{cases} \quad (16)$$

In Eq. (16), I_j denotes the sample at j^{th} leaf nodes and wi indicates the weight of j^{th} leaf nodes, as follows:

$$G_j = \sum_{i \in I_j} g_i \, , H_j = \sum_{i \in I_j} h_j \quad (17)$$

Substitute the above formula and takes the partial derivative of wi to attain the optimal weight:

$$w_j^* = -\frac{G_j}{H_j + \lambda} \quad (18)$$

In such cases, the optimum objective function is attained as follows:

$$OBJ(\theta) = -\frac{1}{2} \sum_{j=1}^{T} \frac{G_j}{H_j + \lambda} + \gamma T \quad (19)$$

In Eq. (19), γ and λ denotes the weighting factor, and T indicates the node count. The small the value of objective function, the small the prediction error, and the better the model performance.

3. Performance validation

The ID results of the WOAML-IDWSN methodology are studied here. Fig. 2 reveals the confusion matrices attained by the WOAML-IDWSN algorithm on 80:20 and 70:30 of TRP/TSP. The outcome implied the effective recognition and classification of 5 classes accurately.

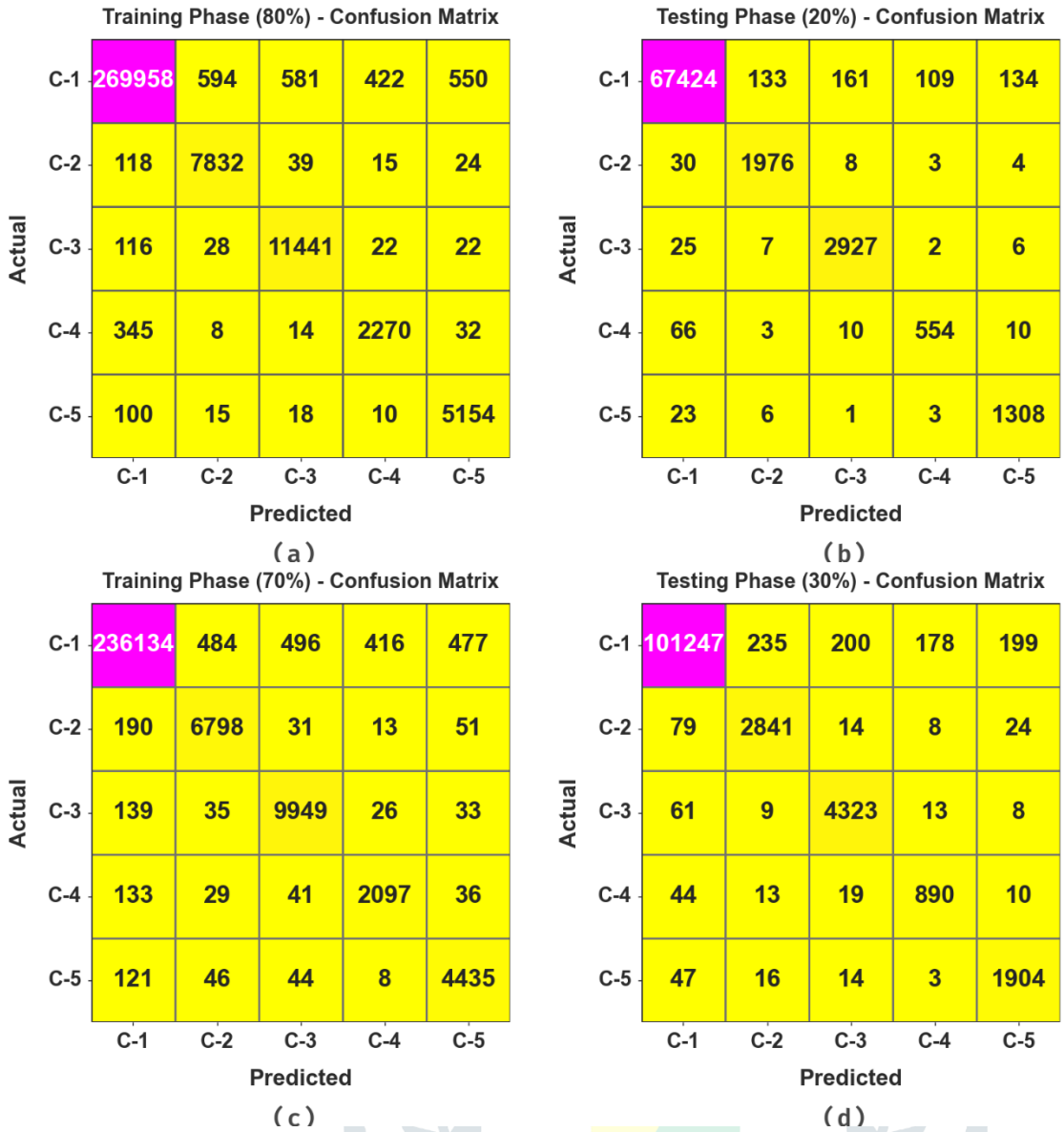

Fig. 2. Confusion matrices of (a-b) 80:20 of TRP/TSP and (c-d) 70:30 of TRP/TSP

The ID result of the WOAML-IDWSN system with 80:20-TRP/TSP is studied in Table 1 and Fig. 3. The outcome referred that the effective recognition of five classes. On 80%-TRP, the WOAML-IDWSN approach accomplishes average $accu_y$, $sens_y$, $spec_y$, F_{score}, and MCC of 99.61%, 95.73%, 99.49%, 93.59%, and 92.62% correspondingly. Afterward, on 20%-TSP, the WOAML-IDWSN methodology accomplishes average $accu_y$, $sens_y$, $spec_y$, F_{score}, and MCC of 99.62%, 96.60%, 99.56%, 94.04%, and 93.11% correspondingly.

Table 1 ID outcome of WOAML-IDWSN approach with 80:20-TRP/TSP

Class	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}	MCC
Training Phase (80%)					
C-1	99.06	99.21	97.54	99.48	94.54
C-2	99.72	97.56	99.78	94.90	94.80
C-3	99.72	98.38	99.77	96.46	96.33
C-4	99.71	85.05	99.84	83.95	83.81
C-5	99.74	97.30	99.79	93.04	93.00
Average	**99.59**	**95.50**	**99.34**	**93.57**	**92.50**
Testing Phase (20%)					
C-1	99.09	99.21	97.93	99.50	94.79
C-2	99.74	97.77	99.80	95.32	95.22
C-3	99.71	98.65	99.75	96.38	96.25
C-4	99.73	86.16	99.84	84.32	84.20
C-5	99.75	97.54	99.79	93.33	93.29
Average	**99.60**	**95.87**	**99.42**	**93.77**	**92.75**

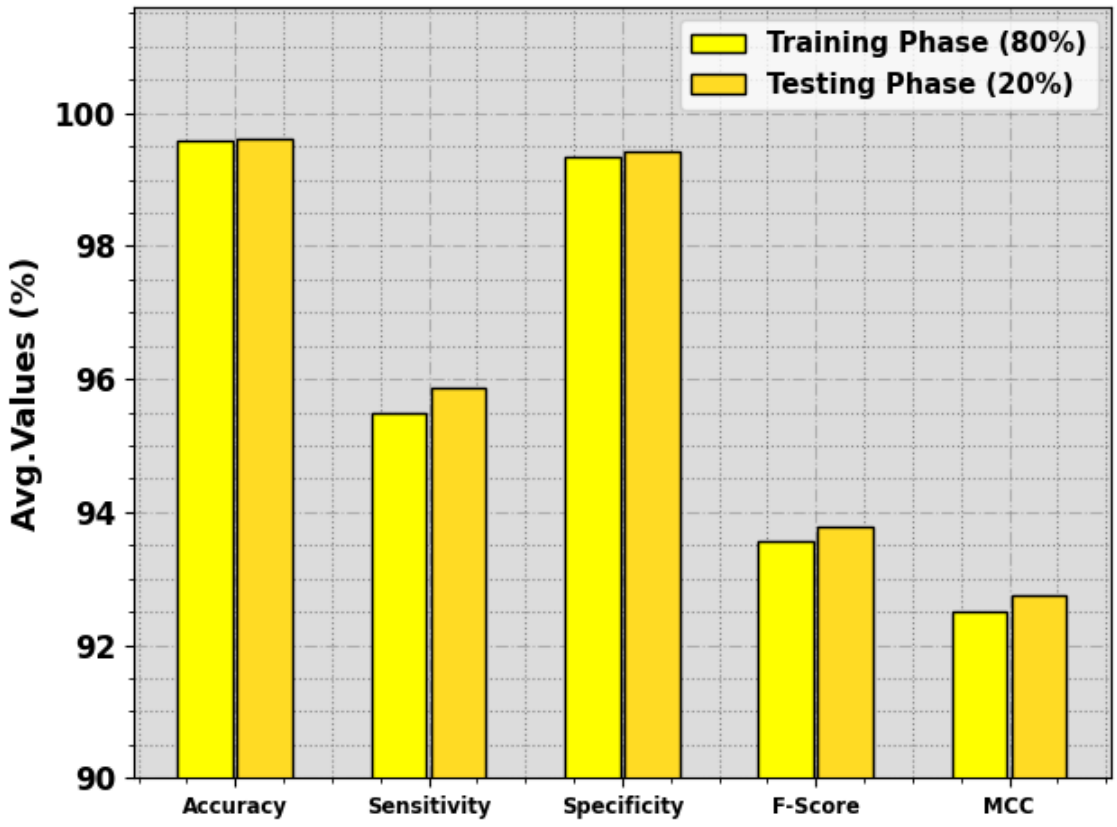

Fig. 3. Average of WOAML-IDWSN approach with 80:20-TRP/TSP

The ID outcome of the WOAML-IDWSN system with 70:30-TRP/TSP is studied in Table 2 and Fig. 4. The simulation value denoted the efficient recognition of five classes. On 70%-TRP, the WOAML-IDWSN method gains average $accu_y$, $sens_y$, $spec_y$, F_{score}, and MCC of 99.61%, 97.25%, 99.48%, 94.22%, and 93.25% correspondingly. Next, on 30%-TSP, the WOAML-IDWSN method attains average $accu_y$, $sens_y$, $spec_y$, F_{score}, and MCC of 99.62%, 97.36%, 99.46%, 94.63%, and 93.68% correspondingly.

Table 2 ID outcome of WOAML-IDWSN approach with 70:30-TRP/TSP

Class	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}	MCC
Training Phase (70%)					
C-1	99.06	99.21	97.60	99.48	94.59
C-2	99.66	95.98	99.77	93.93	93.78
C-3	99.68	97.71	99.76	95.93	95.78
C-4	99.73	89.77	99.82	85.66	85.62
C-5	99.69	95.29	99.77	91.58	91.49
Average	**99.57**	**95.59**	**99.34**	**93.31**	**92.25**
Testing Phase (30%)					
C-1	99.07	99.20	97.77	99.49	94.63
C-2	99.65	95.79	99.75	93.45	93.30
C-3	99.70	97.94	99.77	96.24	96.10
C-4	99.74	91.19	99.82	86.07	86.08
C-5	99.71	95.97	99.78	92.23	92.15
Average	**99.58**	**96.02**	**99.38**	**93.50**	**92.45**

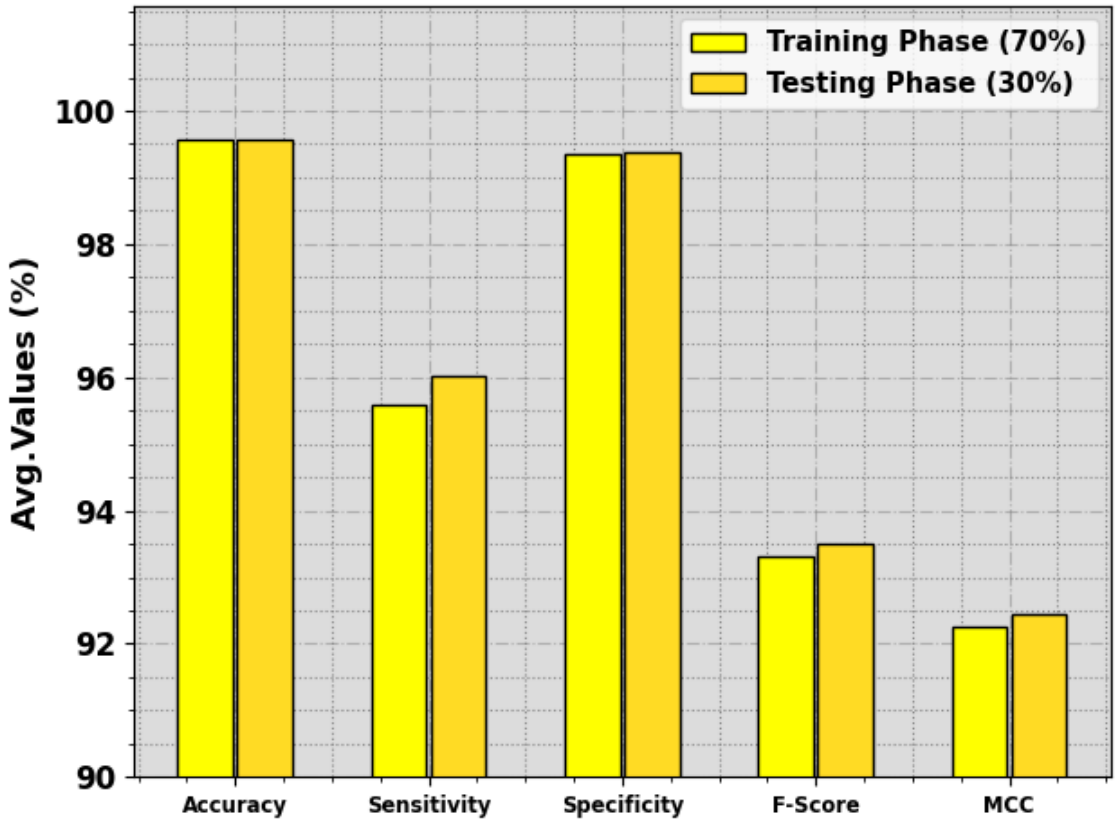

Fig. 4. Average of WOAML-IDWSN approach with 70:30-TRP/TSP

Fig. 5. $Accu_y$ curve of WOAML-IDWSN approach with 80:20-TRP/TSP

Fig. 5 represents the training accuracy TR_accu_y and VL_accu_y of the WOAML-IDWSN algorithm on 80:20-TRP/TSP. The TL_accu_y is determined by the evaluation of the WOAML-IDWSN approach on TR dataset whereas the VL_accu_y is computed by evaluating the performance on a separate testing dataset. The outcomes exhibit that TR_accu_y and VL_accu_y increase with an upsurge in epochs. Accordingly, the performance of the WOAML-IDWSN technique gets improved on the TR and TS dataset with a rise in amount of epochs.

In Fig. 6, the TR_loss and VR_loss curve of the WOAML-IDWSN system on 80:20-TRP/TSP is shown. The TR_loss defines the error among the predictive performance and original values on the TR data. The VR_loss represents the measure of the performance of the WOAML-IDWSN method on individual validation data. The results indicate that the TR_loss and VR_loss tend to decrease with rising epochs. It portrayed the improved performance of the WOAML-IDWSN technique and its capability to generate accurate classification. The reduced value of TR_loss and VR_loss demonstrates the superior performance of the WOAML-IDWSN technique on capturing patterns and relationships.

Fig. 6. Loss curve of WOAML-IDWSN approach with 80:20-TRP/TSP

The WOAML-IDWSN methodology is compared with other ML classifiers in Table 3. In Fig. 7, the ID outcome of the WOAML-IDWSN system is examined interms of $accu_y$ and F_{score}. The outcome displayed the effective performance of the WOAML-IDWSN approach. Based on $accu_y$, the WOAML-IDWSN method reaches improving $accu_y$ of 99.60% while the Adaboost, GB, XGBoost, KNN, and KNN-PSO approaches attain lower $accu_y$ of 96.30%, 94.23%, 95.91%, 96.40%, and 96.47% correspondingly. Besides, based on F_{score}, the WOAML-IDWSN algorithm reaches enhance F_{score} of 93.77% while the Adaboost, GB, XGBoost, KNN, and KNN-PSO approaches accomplish reducing F_{score} of 91.09%, 92.43%, 90.70%, 90.79%, and 92.59% correspondingly.

In Fig. 8, the ID analysis of the WOAML-IDWSN methodology is examined in terms of $sens_y$ and $spec_y$. The results exhibited the effectual performance of the WOAML-IDWSN approach. Based on $sens_y$, the WOAML-IDWSN method reaches improving $sens_y$ of 95.87% while the Adaboost, GB, XGBoost, KNN, and KNN-PSO approaches attain minimal $sens_y$ of 94.96%, 96.95%, 94.75%, 96.99%, and 94.10% correspondingly. In addition, based on $spec_y$, the WOAML-IDWSN system achieves enhance $spec_y$ of 99.42% while the Adaboost, GB, XGBoost, KNN, and KNN-PSO systems attain lesser $spec_y$ of 94.47%, 94.55%, 94.14%, 96.20%, and 94.21% correspondingly.

Table 3 Comparative outcome of WOAML-IDWSN approach with other systems

Methods	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}
The Proposed Model	99.60	95.87	99.42	93.77
AdaBoost	96.30	94.96	94.47	91.09
GB	94.23	94.95	94.55	92.43
XGBoost	95.91	94.75	94.14	90.70
KNN	96.40	94.99	96.20	90.79
KNN-PSO	96.47	94.10	94.21	92.59

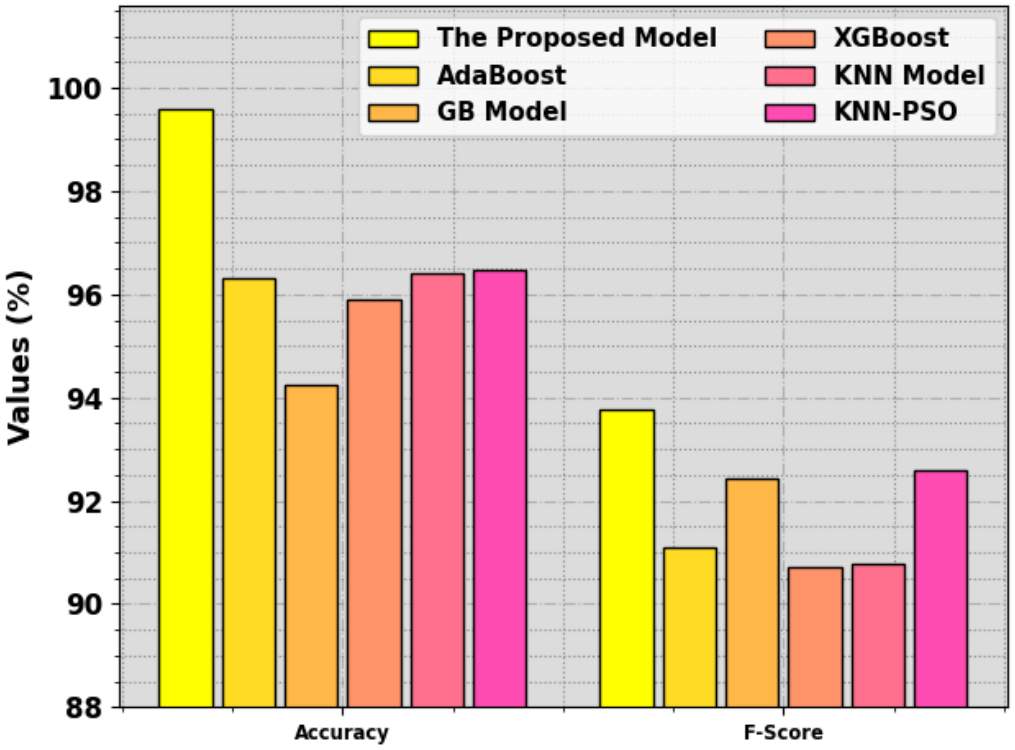

Fig. 7. $Accu_y$ and F_{score} outcome of WOAML-IDWSN approach with ML systems

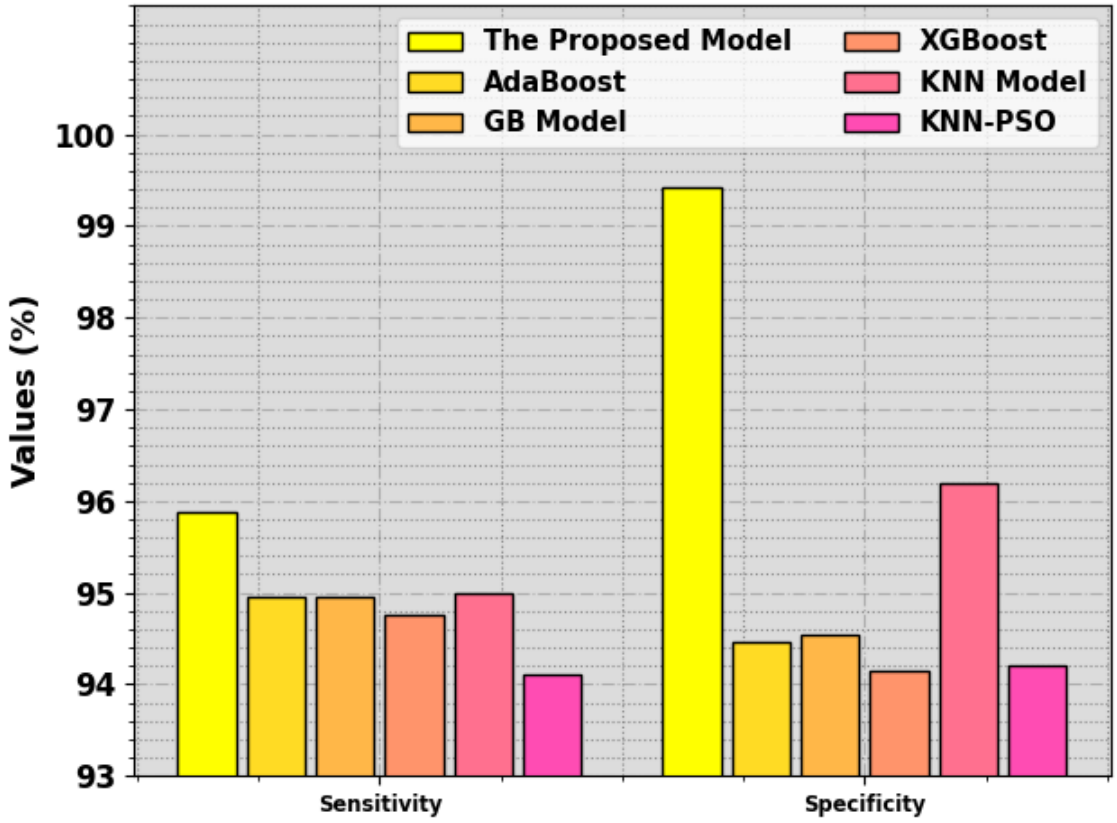

Fig. 8. $Sens_y$ and $Spec_y$ outcome of WOAML-IDWSN approach with ML systems

4. Conclusion

This study presents a novel approach that introduces a WOAML-IDWSN technique for effective intrusion detection in WSNs. It comprises two major processes such as WOA based feature selection and ML based intrusion detection. At the initial stage, the WOA can be applied to electing an optimal subset of features. Next, in the second stage, XGBoost classifier is applied for the identification of the intrusions. Extensive experiments are conducted using benchmark datasets to evaluate the effectiveness of the WOAML-IDWSN approach.

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