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Energy Minimized Intrusion Detection System (IDS) For Iot Environmental Sensors Using Optimized Deep Convolutional Network

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Abstract
IoT environmental sensors are devices that use the Internet of Things (IoT) to monitor and measure various environmental conditions like temperature, humidity, air quality, and light levels. These sensors are susceptible to a variety of threats that could corrupt vital items or compromise data. To strike a balance between security and the resource limitations of IoT sensors, an Intrusion Detection System (IDS) solution that is both economical and energy-efficient is required. While preserving strong threat detection, these IDS solutions maximize processing speed and energy usage. In this paper, Energy and Cost Effective IDS for IoT, using DNN-CFOA model is proposed. In this work, Deep Convolutional Network (DNN) has been applied for the task of intrusion detection from patterns and Catch Fish Optimization Algorithm (CFOA) has been applied to optimize the weights of DNN model. According to experimental results, the suggested DNN-CFOA model performs better than the current models in terms of accuracy and F1-score metrics.
Keywords: *Internet of Things (IoT), Intrusion Detection System (IDS), Cost effective, Deep Convolutional Network (DNN), Catch Fish Optimization Algorithm (CFOA)*

1. INTRODUCTION

A global network of interconnected, communicative items is the vision of IoT, a technological paradigm shift. According to recent figures, there are currently over 13.8 billion IoT devices in operation, and by 2025, that number is expected to rise to 30.9 billion. New uses are made feasible by this extensive network, which enables information sharing and remote control of smart devices [1].

IoT environmental sensors are used to monitor various parameters like air and water quality, temperature, humidity, and soil conditions, providing real-time data for environmental management. These sensors, connected to the internet, transmit data to a central platform for analysis and informed decision-making. Nevertheless, a variety of threats could jeopardize data or harm necessary products on IoT devices [2].

An Intrusion Detection System (IDS), which is intended to identify malicious activity or cyber attacks, is one efficient security solution. Based on the kind of data source they employed, IDS can be categorized as either host-based or network-based. Because host-based IDS monitor data from the host system logs, including operating system and application logs, it can be helpful in detecting intrusions in sensitive files or programs. However, this type's reliance on host reliability and resource availability limits its ability to detect network threats [3]. Conversely, because network-based IDS operate independently of hosts, it can be used in a range of situations to detect network-based attacks. Nevertheless, it is limited to identifying attacks that take place within a certain network segment.

The three main categories of IDS detection methods are hybrid, anomaly-based, and signature-based [4]. Even though anomaly-based intrusion detection systems are better at identifying emerging threats, they have disadvantages such as high false-positive rates and low explainability for reported anomalies. Hybrid intrusion detection systems (IDS) utilize the benefits of both approaches to provide a more comprehensive and effective intrusion detection system.

One of three methods is usually used by anomaly-based IDS: knowledge-based, statistics-based, or ML-based. The statistics-based technique can detect low-probability events as possible intrusions [5]. Nevertheless, this approach necessitates intricate mathematical expressions for variables that reflect user behavior.

Artificial Intelligence (AI) is used by ML-based IDS to identify patterns in data and make predictions without the need for explicit programming. ML-based intrusion detection systems may identify whether fresh, unseen traffic is legal or illegitimate by training models on intrusion datasets [6]. ML-based intrusion detection systems use a variety of techniques, including clustering, association rules, decision trees, closest neighbour approaches, and DL.

Accurate test data classification is made possible by supervised learning, which builds predictive models using labelled training data. Nevertheless, this approach necessitates a large amount of labelled data, it is costly and labour-intensive to produce. Conversely, unsupervised learning employs unlabeled data and classifies inputs based on statistical features, making it suitable for scenarios when labelled data is unavailable [7].

The goal of an IoT IDS that is both economical and energy-efficient is to strike a balance between security and the resource limitations of IoT devices. While preserving strong threat detection, these IDS solutions maximize processing speed and energy usage [8]. Cost effectiveness is also achieved by lowering hardware requirements and utilizing software-based, scalable techniques. Because these IDS systems ensure real-time attack detection while preserving device performance and battery life, they are suitable for large, resource-constrained IoT installations.

2. Related Works

It is difficult to develop an IDS for IoT networks because of the large amount of heterogeneous data generated, which makes real-time analysis tough. The inefficiency of traditional IDS methods emphasizes the need for sophisticated methods that use machine learning or deep learning. This study [11] proposes a deep ensemble-based IDS that utilizes Lambda architecture with a complex categorization technique. Binary classification uses LSTM to distinguish between harmful and benign data, whereas multi-class classification combines CNN, ANN, and LSTM models to identify different sorts of attacks.The speed layer evaluates the model in real time, while the batch layer trains the model.

Traditional IDSs are not appropriate for edge-cloud systems, and the deployment of DL models close to devices is hampered by the massive amounts of IoT data and processing needs. This is addressed by a new edge-cloud-based IoT IDS [12], which uses distributed processing to train a RNN with Bidirectional LSTM, segment datasets, and pick attributes on time-series data. The model, which was tested on the BoT-IoT dataset, decreases the size of the dataset by 85% without sacrificing detection accuracy. In edge-cloud deployments, this scalable DL-based solution is perfect for managing high volumes of IoT data.

For local IoT gateways, Realguard [13] is a DNN-based network IDS that offers precise, real-time cyberattack detection with low processing requirements. Realguard outperforms rivals at 98.85% in identifying ten attack types with 99.57% accuracy thanks to an effective DNN model and a lightweight feature extraction mechanism. With a high packet processing rate of 10,600 packets per second, it functions well on gateways with limited resources, such as Raspberry Pi, and provides strong IoT network security.

2.1 Research Gaps

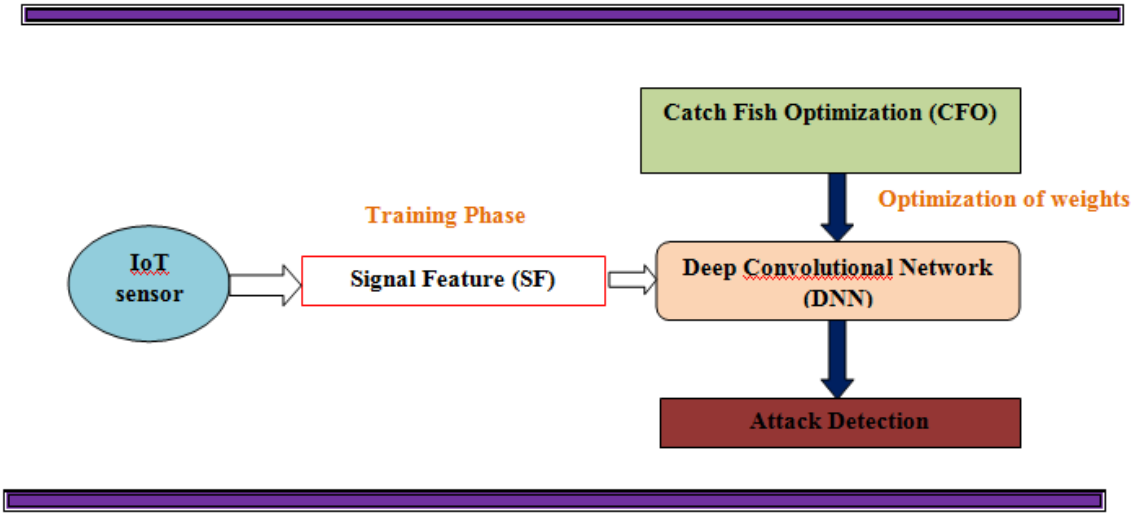
The existing works on IDS for IoT networks presents several gaps: Most studies emphasis on detecting a small set of IoT attack types, failing to address the wide and evolving range of potential attacks across diverse IoT applications and environments. Many approaches do not prioritize real-time intrusion detection, instead depending on offline datasets, which restricts the applicability of the system in actual IoT environments that necessitate dynamic and immediate threat responses. A significant number of studies utilize binary classifiers for distinguishing only between benign and malicious traffic, missing the capability to classify and recognize specific types of attacks, which is vital for effective IoT network security. Most of the existing IDS models do not combine ensemble-based methods, which combine multiple classifiers to enhance detection accuracy and precision, causing lower detection rates when compared with more advanced approaches.

3. PROPOSED METHODOLOGY

3.1 Overview

In this paper, energy and cost effective IDS for IoT, using DNN-CFOA model is proposed. Figure 1 shows the architecture of the proposed DNN-COFA model. In this work, DNN has been applied for the task of intrusion detection from patterns and CFOA has been applied to optimize the weights of DNN model

such that the IDS attains highest accuracy with least energy usage. The KDD cup dataset which comprises 42 characteristics with 494021 entries has been used in this work.



3.2 DNN based detection

Until the model satisfied the objectives for optimizing the number of hidden nodes and effectively identifying assaults while using the fewest resources, hidden layers and neurons were progressively added to the DNN. Our enhanced model, which has five hidden layers and roughly 34,315 parameters, balances simplicity and detection performance. Each hidden layer in the assault detection model's architecture, which is shown in Figure 2, is made up of neurons that are fully connected to those in the layer below.

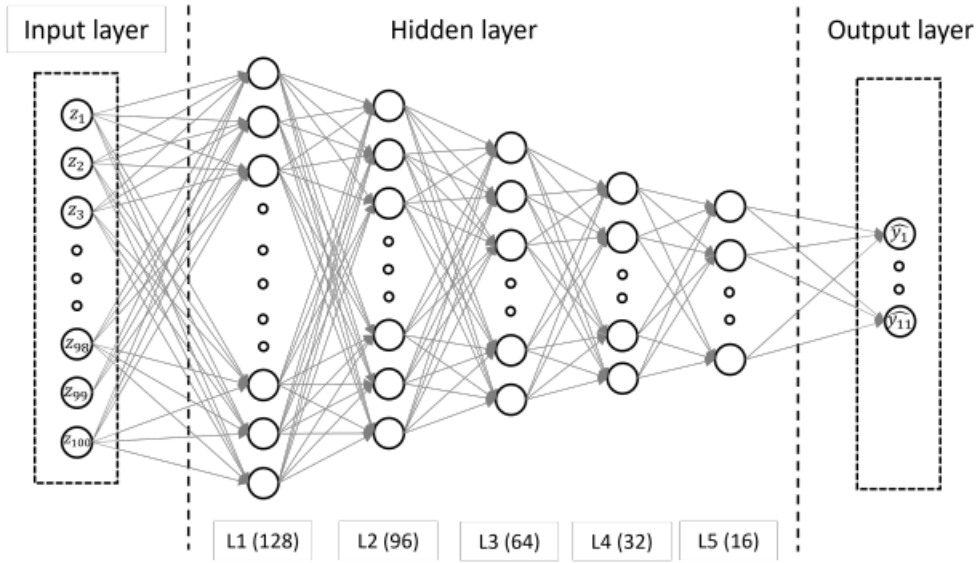


Figure 2. Architecture of the attack detection model

Information will be processed forward across the levels. The input layer, which has n neurons, receives a normalized vector $z \in R_m$ (m = 100) from the feature extractor. The following is the definition of each hidden layer H_i's calculation, which processes the input vector $x \in R^{(d(i-1))}$ (from H_{i-1} or z):

$$H_i(x) = f(w_i^T x + c_i) \quad (1)$$

The weight matrix and bias vector are represented by w_i and c_i, respectively, and the activation function is represented as 〖f:R〗^(d_(i-1))⟶R^(di). The process $w_i T\ x+c_i$ maps the values from layer H_{i-1} to layer H_i. To solve vanishing gradient issues and enhance convergence, the ReLU activation function is employed. The following formula is used to determine the output of each hidden layer or the element j^{th} of vector $H_i(x)$:

$$f(x_j^r) = \max(0, x_j^r) \quad (2)$$

Furthermore, this system requires that inputs be categorized into numerous attack types. To do this, a popular method for these types of tasks is the softmax function. The softmax function determines the probability that an input belongs to each class by setting the size of the final layer to the number of attack types. This probability is given by:

$$\hat{y}_k = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_i}} \quad (3)$$

where y^_k is the probability that the input vector x belongs to the k^{th} attack class and n is the number of assault kinds

3.3 Optimization of Weights using CFOA

To optimize the weights of DNN, CFOA is applied. It includes the following steps:

3.3.1 Initialization Process

As with many metaheuristic algorithms, the populations are produced at random during the CFOA initialization. N fishermen are taken into consideration in a D-dimensional search space, where the mathematical representation of the fishermen's population matrix is as follows:

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} x_{1,1}\ x_{1,2} \ldots x_{1,j} \ldots x_{1,D} \\ x_{2,1}\ x_{2,2} \ldots x_{2,j} \ldots x_{2,D} \\ \vdots \quad \vdots \quad \ddots \quad \vdots \quad \ddots \quad \vdots \\ x_{i,1}\ x_{i,2} \ldots x_{i,j} \ldots x_{i,D} \\ \vdots \quad \vdots \quad \ddots \quad \vdots \quad \ddots \quad \vdots \\ x_{N,1} x_{N,2} \cdots x_{N,j} \cdots x_{N,D} \end{bmatrix} \quad (4)$$

Every fisher represents a possible fix. The objective function of the problem can be evaluated using its values for the choice variables. For the fishermen, the objective function value is provided by:

$$F(X)=[F_1,F_2,\ldots F_N]=[f(X_1),f(X_2),\ldots f(X_N)] \quad (5)$$

In this case, the value of the objective function for the ith fisher is indicated by F_i and $f(X_i)$. The position of the fisherman is indicated by each Xi, which is initialized using the following formula:

$$X_{i,j} = L_j + rand * (U_j - L_j), i = 1,2, \ldots N \quad (6)$$

where U_j and L_j represent the upper and lower bounds for the jth dimension in the problem space, and $X_{i,j}$ represents the i^{th} fisher's location in the j^{th} dimension. The two stages of metaheuristic algorithms are typically exploration and exploitation. The parameter W in CFOA controls the transition from exploration to exploitation. CFOA does exploration when W < 0.5 and exploitation otherwise. W is calculated using

$$W = \frac{Current\ iteration\ number}{max.iteration\ number} \quad (7)$$

3.3.2 Independent Search and Group Capture

During the exploration phase, CFOA employs two search strategies: group capture and independent search. A fisherman selects one of these search strategies to capture the fish in each iteration. The catch rate parameter α determines which of the two approaches should be used. The formula for estimating the value of α is

$$\alpha = (1 - \frac{3}{2}W)^{\frac{3}{2}W} \quad (8)$$

Fishermen choose to conduct independent searches when α is high (α > p). Fish surface to breathe as a result of the fishermen's disturbance of the water during the fishing process. By watching the ripples the fish makes, the fishermen are able to determine the fish's location. Additionally, they modify their stance in response to other people's achievements. The following is the updating strategy for the fisherman's position:

$$X_{i,j}(t+1) = X_{i,j}(t) + \left(X_{r,j}(t+1) - X_{i,j}(t+1)\right) * E + rand * w_j * U \quad (9)$$

The experience of the i^{th} fisherman using $X_{r,j}(t)$ as a reference is represented by

$$E=(F_i-F_r)/(F_{max}-F_{min}) \quad (10)$$

Where D is the Euclidean distance between the reference point $X_r(t)$ and the i^{th} fisher's position $X_i(t)$, $U=D*\sqrt{E}*(1-W)$. In contrast to $X_{i,j}(t)$, $X_{r,j}(t)$ is the location of a randomly selected fisherman. The current iteration's maximum and minimum fitness values are denoted by F_{max} and F_{min}. A random unit vector in the D-dim space is denoted by w_j.

Fishermen switch to group capture when $\alpha \leq p$. In order to increase their fishing ability, fishermen often work together and use nets. A group of three or four fishermen work together. The following provides the update strategy:

$$X_{i,j}(t+1) = X_{i,j}(t) + rand * \left(C_e - X_{e,j}(t)\right) + (1-2W)^2 * r_1 \quad (11)$$

In this case, e is the group of three or four people, and Ce is the objective point of the group's encirclement. mean($X^{e(t)}$) is the average location of the group Xe(t), and r_1 is a random number between -1 and 1.

3.3.3 Collective Capture

In order to guide both free and concealed fish to a central region for encirclement and capture, all fishermen collaborate under a common search technique as the fishing continues. The distribution of fishermen is concentrated around the school of fish, with a gradual thinning of aggregation from the centre to the periphery, while the distribution range becomes more limited as it moves outward. The centre fishermen focus on capturing the school of fish while the perimeter fishermen handle any escaping fish. The most recent position of a fisherman is calculated using the algorithm below:

$$X_i(t+1) = X_G + normrnd\left(0, \frac{r_2 * \varepsilon * |mean(X) - X_G|}{3}\right) \quad (12)$$

$$\varepsilon = \sqrt{\left(\frac{2*(1-W)}{(1-W)^2+1}\right)} \quad (13)$$

The position of the fisherman with the highest fitness value is denoted by XG. $|\cdot|$ specifies the usage of absolute values, and r2 indicates a random number between 1 and 3.

3.4 The CFOA fitness function

Increasing the IDS's energy efficiency while preserving or improving its accuracy is the aim of optimization. The weighted sum of the ML model's energy expenditure per inference (E) and accuracy (A) is used to compute objective O.

$$O = \gamma A + \delta E \quad (14)$$

The weights γ and δ are used to control the trade-off between accuracy and energy efficiency. Accuracy A is the ratio of correctly classified examples to all samples. The optimization procedure aims to reduce O while ensuring that IDS achieves high accuracy without consuming excessive energy by modifying the model's hyperparameters.

4. Experimental Results

Python 3.0 and the Google Colab environment have been used to implement the suggested energy DNN-CFOA model. The studies have been conducted using the KDD cup dataset, which comprises 42 characteristics with 494021 entries.

4.1 Classification Results

Without using a feature selection procedure, the DNN-CFOA model's performance was compared to that of the DNN and ANN classifiers. The following metrics are used to assess the categorization performance:

$$\text{Accuracy} = \frac{TN + TP}{FP + FN + TP + TN} \quad (15)$$

$$\text{F1-score} = 2x\frac{precisionXrecall}{precision + recall} \quad (16)$$

Here,

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN} \quad (17)$$

The accuracy and F1-score comparison results for these three methods are displayed in Table 1 and Figure 3.

Techniques	Accuracy	F1-score
DNN-CFOA	98.35	95.25
DNN	96.27	93.72
ANN	95.15	90.68

Table 1 Comparison results of Accuracy and F1-score

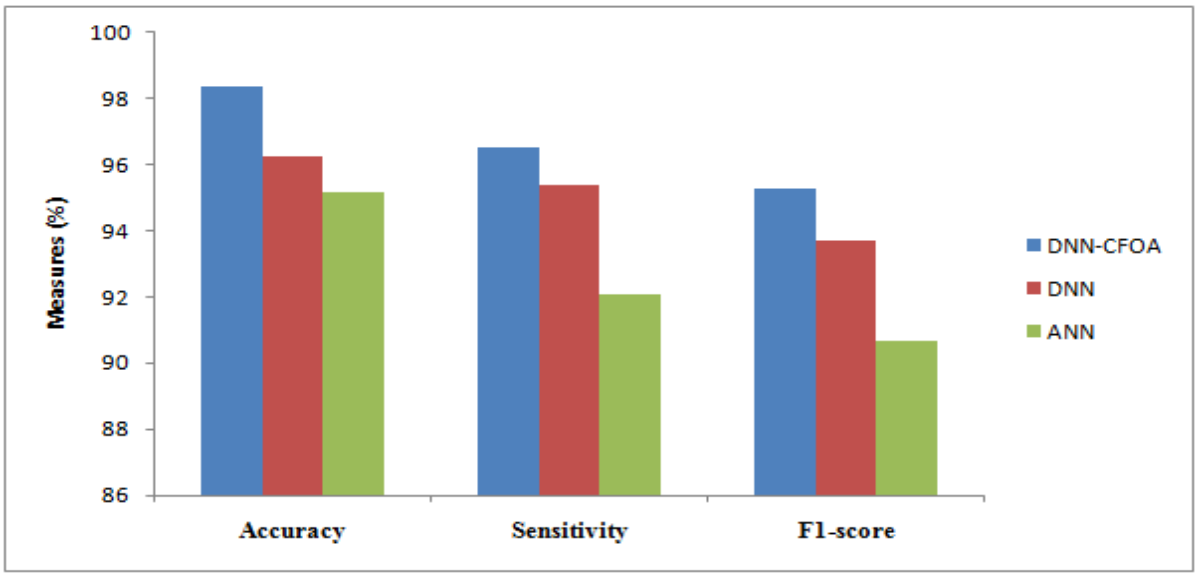


Figure 3 Comparison Results

The suggested DNN-CFOA classifier has the maximum accuracy of 98.35%, as shown in Figure 6. This is 3.25% and 2.11% greater than that of the ANN and DNN classifiers, respectively. Comparing the DNN-CFOA to the ANN and DNN classifiers, the F1-score is 95.25%, 4.8% and 1.6%, respectively.

5. CONCLUSION

In this paper, energy and cost Effective IDS for IoT environmental sensors, using DNN-CFOA model is proposed. In this work, DNN model has been applied for the task of intrusion detection from patterns and CFOA has been applied to optimize the weights of DNN model. The studies have been conducted using the KDD cup dataset, which comprises 42 characteristics with 494021 entries. According to experimental results, the suggested DNN-CFOA model performs better than the current models in terms of accuracy and F1-score metrics.

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