

Binary Metaheuristic-Assisted Deep Learning Model for Cyberattack Detection in Cyber-Physical Systems

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ABSTRACT:

The growing use of cyber-physical systems (CPSs) in the fields of healthcare, transportation, critical infrastructure, and energy has increased the demand for robust cybersecurity solutions to secure these systems from cyber-attacks. The cyber-physical approach comprises of both cyber and physical parts, and a safety breach in the component is critical for catastrophic outcome. Intrusion detection systems (IDSs), access control systems, encryption and firewalls are many principles that constitute the foundation of cyberattack detection and mitigation methods in CPSs. Deep learning (DL)-based cyberattack detection consists of training neural networks to identify patterns of malicious behaviour in system logs or network traffic to positively identify and reduce cyberattacks. This approach is aided by the inherent ability of the DL algorithms to learn complex representations that increases the accuracy and efficiency in identifying diverse and evolving cyber-attacks. Thus, this paper proposes a CPS environment with an Automated Cyberattack Detection using Binary Metaheuristics with Deep learning (ACAD-BMDL) technique. The major purpose of ACAD-BMDL technique is to identify the cyber attacks to improve the security in CPS environment. The ACAD-BMDL method uses Z-score normalization to normalize the input dataset. Also, a binary grey wolf optimizer (BGWO) model is employed to obtain an optimal feature subset. The EESNN (Enhanced Elman Spike Neural Network) model is also utilized for cyberattacks detection. Also, EESNN model is used to select the optimal hyper parameter of the AOA model. We do an empirical evaluation of the ACAD-BMDL technique on a benchmark dataset. The experimental validation of the ACAD-BMDL technique explained the higher accuracy value of 99.12% and 99.36% for NSLKDD2015 and CICIDS2017 datasets, respectively in the context of the CPS environment.

Keywords: Cyberattack Detection, Cyber-Physical Systems (CPS), Deep Learning, Binary Metaheuristics, Feature Selection, Intrusion Detection System (IDS), Machine Learning, Network Security, Cybersecurity, Threat Detection, Intelligent Optimization, Classification, Anomaly Detection, Secure Communication, Artificial Intelligence.

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1.INTRODUCTION:

Cyber Physical Systems (CPS) are complex computer systems integrating physical processes with communication networks, sensors, actuators and intelligent control systems. These systems have been widely applied in many critical applications such as smart grid, industrial automation, healthcare, transportation, manufacturing and smart cities. The constant flow of data between the physical equipment and the computational elements enables for real-time monitoring and decision-making, enhancing efficiency, dependability and automation. However, with the increase of CPS interconnection, these systems are subject to many sophisticated threats that could threaten the system integrity, confidentiality and availability. Such attacks can disrupt business, result in financial losses, generate safety concerns and harm key infrastructure.

Traditional cyber security approaches are largely based on pre-defined signatures and human procedures to detect the harmful actions. Techniques are effective against known

attacks but generally ineffective against zero day attacks, new malware and complicated intrusion patterns. The ever growing dynamism and complexity of cyber threats demand the improvement of detection systems capable of understanding complex relations from large-scale network traffic data. Deep learning has proved to be a promising technique for the automatic extraction of pertinent features and the classification of normal and dangerous network behavior with minimal operator interaction.

Deep learning models are powerful, but the performance of these models is dependent on the quality and relevance of the input material. High-dimensional cyber security datasets often include redundant, irrelevant or noisy information which raise the complexity of processing and decrease the accuracy of detection. The selection of qualities is important for removing uninformative data and keeping the most informative ones. Binary metaheuristic optimization techniques have been proved to be effective in solving the

feature selection problem as they can search the large search space for the optimal feature sub-sets. These solutions reduce the training time and improve the predictive performance of the deep learning models to learn more efficiently.

1.1 Motivation

The rapid growth of Cyber-Physical Systems (CPS) in critical sectors such as smart manufacturing, healthcare, transportation, energy, and industrial automation has significantly increased the need for robust cybersecurity solutions. As these systems become more interconnected through the Internet and communication networks, they become attractive targets for cyberattacks that can disrupt operations, compromise sensitive data, and threaten public safety. Traditional intrusion detection techniques often fail to identify sophisticated and previously unseen attacks because they rely heavily on predefined rules and signatures. This limitation highlights the need for intelligent detection systems that can adapt to evolving cyber threats. Deep learning has demonstrated remarkable success in recognizing complex attack patterns from large volumes of network traffic data. However, its performance is often affected by redundant and irrelevant features present in high-dimensional cybersecurity datasets, leading to increased computational cost and reduced detection efficiency.

1.2 Challenges

Cyber-Physical Systems (CPS) designs are extensively networked, dependent on dispersed sensors and control devices, and require real-time connections. This causes a lot of problems for cyber security. A major concern is the increasing sophistication of cyber-attacks such as ransomware, denial-of-service (DoS), malware, phishing and advanced persistent threats (APTs) that can evade traditional security controls. Signature-based approaches are the main basis of traditional intrusion detection system. Such approaches cannot detect zero-day attacks and fast-evolving threats, so the detection accuracy is usually low. Another key issue is the large dimensionality of the data in the cyber security domain, which includes redundant, irrelevant and noisy sections. These features are not always needed and result in increase in computing complexity, increase in training time and reduction in performance of deep learning models. Moreover, the real-time huge network traffic produced by Cyber-Physical Systems (CPS) is hard to handle and analyze data efficiently with low latency. Furthermore, the imbalance of the class between normal data and attack data makes it difficult to accurately detect harmful activity while reducing the false alarm rate.

1.3 Overview of the Paper

Number	Protocol	Source IP	Destination IP	Source Port	Destination Port	Packets Size (B)	Flow Duration (s)	Packets Count	Bytes Count	Traffic Rate (Kbps)	Flag	Attack Type	Label	
1	TCP	192.168.1.10	192.168.1.20	443	80	512	25.34	40	20480	1.58	ACK	Normal	0	
2	UDP	192.168.1.10	192.168.1.30	53	54978	256	12.11	16	4608	1.49	SYN	Dos	1	
3	TCP	192.168.1.12	192.168.1.45	22	6023	1024	38.07	62	63488	1.60	ACK	Normal	0	
4	ICMP	192.168.1.18	192.168.1.50	-	-	128	0.27	12	1536	1.93	ECMP	Probe	1	
5	TCP	192.168.1.20	192.168.1.60	80	49152	768	31.45	45	34560	1.43	PSH	R2L	1	
6	UDP	192.168.1.22	192.168.1.40	161	4550	820	16.18	24	7680	1.49	SYN	Dos	1	
7	TCP	192.168.1.25	192.168.1.70	21	40480	890	34.22	58	51620	1.70	ACK	Normal	0	
8	TCP	192.168.1.30	192.168.1.75	25	8080	650	22.19	36	23400	1.62	RST	U2R	1	
9	UDP	192.168.1.33	192.168.1.80	69	3350	280	10.08	20	9600	1.98	SYN	Dos	1	
10	TCP	192.168.1.36	192.168.1.85	443	80	980	42.71	68	66640	1.59	ACK	Normal	0	
11	ICMP	192.168.1.40	192.168.1.90	-	-	160	7.15	16	2240	2.10	ECMP	Probe	1	
12	TCP	192.168.1.45	192.168.1.95	8080	80	720	26.34	48	34560	1.69	FIN	R2L	1	
13	TCP	192.168.1.48	192.168.1.100	110	25	840	35.12	56	47040	1.59	ACK	Normal	0	
14	UDP	192.168.1.50	192.168.1.105	123	6303	300	14.33	22	6600	1.53	SYN	Dos	1	
15	TCP	192.168.1.55	192.168.1.110	443	8080	930	39.80	64	59520	1.61	ACK	Normal	0	
16	TCP	192.168.1.58	192.168.1.115	3306	-	49155	690	26.24	41	28200	1.56	PSH	R2L	1
17	ICMP	192.168.1.60	192.168.1.120	-	-	140	8.42	16	2240	1.90	ECMP	Probe	1	
18	TCP	192.168.1.65	192.168.1.125	23	6000	610	24.19	38	23760	1.61	RST	U2R	1	
19	UDP	192.168.1.68	192.168.1.130	514	7000	340	16.27	26	8840	1.42	SYN	Dos	1	
20	TCP	192.168.1.70	192.168.1.135	443	80	1050	45.63	72	75600	1.58	ACK	Normal	0	

Attack Type: Normal - Normal Traffic, Dos - Denial of Service, Probe - Probing Attack, R2L - Remote to Local, U2R - User to Root

Label: 0 - Normal, 1 - Attack

2.2 Data Pre-processing

Before training the model, the raw textual data undergoes several preprocessing steps to enhance quality and consistency. These include

In this paper, a novel intelligence framework for cyberattack detection in Cyber Physical System (CPS) environment is proposed by combining the binary metaheuristic optimization and deep learning methodologies. The suggested method is based on picking the most significant network features before classification to increase the accuracy and efficiency of intrusion detection. The cybersecurity dataset is collected and preprocessed by removing the missing data, normalizing the data and preparing the data for analysis. Then, binary metaheuristic optimization technique is utilized for features selection to remove the redundant and irrelevant attributes and to keep the most useful features that help in the accurate attack detection. The optimized subset of features is then used as input to a deep learning model to learn complex patterns of normal and malicious network events. The trained model is able to classify different types of cyberattacks with less computing costs and false positives. The effectiveness of the proposed framework is validated by the conventional metrics like as accuracy, precision, recall, F1-score and computation time. This indicates the superiority of the suggested framework over the traditional machine learning and deep learning techniques.

2. MATERIAL AND METHODS:

The proposed Cyberattack detection framework employs binary metaheuristic optimization and deep learning methodologies to enhance the security of Cyber-Physical System (CPS). First, we obtain a common cyber-security dataset from publicly available benchmark sources containing normal and malicious network traffic. The dataset contains several attack classes and network features that represent the communication behaviour in a CPS setting. Data Preprocessing Data pre-processing includes working with missing values, removing duplicate entries, converting category variables into numerical form, and standardizing characteristics for consistency of data. The data is pre-processed and then split into a train and test set for model creation and validation.

Binary metaheuristic optimization technique for dataset dimensionality reduction using feature selection The method is applied to discard the redundant and unnecessary characteristics and keep the most helpful features to find the best subset of features. This optimization reduces the computational complexity, speeds up the model training and improves the classification performance. The selected features are then fed to a deep learning network that learns complex correlations of normal and attack traffic patterns automatically. The deep learning classifier is trained with the optimum parameters to correctly classify the regular network activities from the many kinds of cyber threats.

Figure 1: Cyberattack Detection Dataset

• **Dataset Collection:** Collect the Cyber-Physical System (CPS) network traffic dataset containing both normal and cyberattack records.

- **Data Cleaning:** Remove duplicate records, handle missing values, and eliminate inconsistent data to improve dataset quality.
- **Categorical Data Encoding:** Convert categorical attributes into numerical values suitable for deep learning algorithms.
- **Feature Normalization:** Normalize the numerical features to ensure consistent scaling and improve model performance.
- **Feature Selection:** Apply a Binary Metaheuristic Optimization algorithm to select the most relevant features by removing redundant and irrelevant attributes before training the deep learning model.

2.3 Feature Extraction:

Extraction of feature is an important step of the proposed architecture for cyberattack detection. This step turns the pre-processed network traffic data into a human readable format that can be efficiently exploited by the deep learning model. The step dataset of Cyber-Physical System (CPS) is studied to extract the key properties such as packet size, protocol type, source and destination IPs, source and destination ports, connection duration, traffic rate, number of packet, number of bytes, flow duration and communication frequency. Features are critical information about the nature of the network traffic and are used to differentiate between legitimate activities and malicious cyber assault.

We also compute simple network features and statistical metrics such as mean, standard deviation, variance, entropy and flow based measures to characterize the underlying distribution and communication patterns of network data. Behavioral data such as abnormal traffic patterns, unusual access requests, repeated connection attempts, and protocol anomalies are also mined to further enhance identification of sophisticated cyber attacks. These features allow the model to learn explicit attack signatures and implicit attack patterns in CPS context.

The extracted features are then used as input to the deep learning model to learn the high level and discriminative feature representation automatically over multiple hidden layers. Deep learning learns complex non-linear correlation among network features which significantly improves attack classification performance. However, the traditional methods are only based on the hand-crafted qualities. Finally, the Binary Metaheuristic Optimization approach is used to find

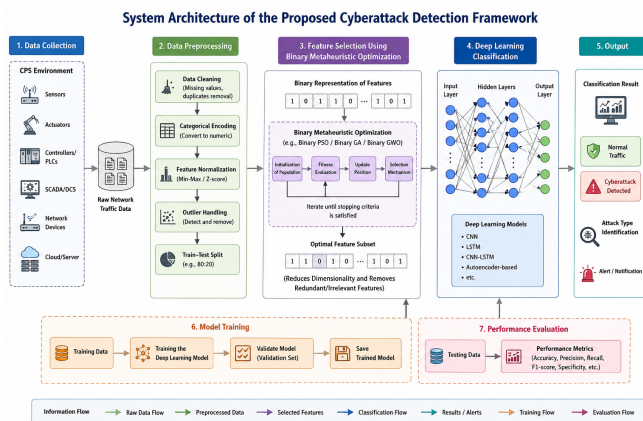
the most relevant features and remove redundant and unneeded data. The improved feature subset reduces the computational complexity and training time, optimizes the classification accuracy, and enhances the robustness and efficiency of the proposed cyberattack detection system for CPS scenarios.

2.4 System Architecture

We present a system architecture to enhance cyberattack detection in a Cyber-Physical System (CPS) environment, which consists of several interconnected phases to provide accurate and efficient intrusion detection. First phase is data collection. The CPS network traffic is collected from the CPS components comprising sensors, controllers, actuators, industrial devices, communication networks, and cloud servers. The obtained raw data is then sent to the data pre-processing phase where missing values, duplicates and inconsistencies are eliminated. The category features are translated to numeric and the features are normalized to make the data uniform. The preprocessed data is fed into the Binary Metaheuristic Optimization module for feature selection. The most effective features are chosen and the unnecessary and irrelevant ones are discarded. This improvement reduces the data dimensions, reduces the processing complexity and increases the efficiency of the learning process.

Then the appropriate feature subset is input to the deep learning classification module where many hidden layers automatically learn the complicated and nonlinear network traffic data. The deep learning model can correctly identify the normal system activity from different types of cyberattacks. During the training phase, the model is trained with the provided features and validated to obtain the best performance and then it is stored for future predictions. Finally, the trained model takes the incoming network data in real-time and provides the categorization results. Traffic is classified as normal traffic and harmful traffic. The system can detect the type of a detected cyber-attack and send an alert for timely response and mitigation. The proposed architecture is evaluated with conventional metrics like accuracy, precision, recall, F1-score, specificity and computing time. The results indicate the effectiveness of hybrid Binary metaheuristic optimization and Deep Learning for protecting the current Cyber-Physical System environments.

Figure 2: System Architecture



System Architecture The proposed system architecture integrates the binary metaheuristic optimization with deep learning for an intelligent cyberattack detection system to increase the security of the Cyber-Physical System (CPS) environment. The architecture is such that the entire framework is comprised of seven critical processes which are

Data Collection, Data Preprocessing, Feature Selection Using Binary Metaheuristic Optimization, Deep Learning Classification, Output Generation, Model Training and Performance Evaluation. Each stage has a distinct function to play in correctly identifying the cyber threat with lower processing overhead, and optimal system reliability. This architecture provides a well-defined workflow to process

network traffic data from collection to classification of normal and malicious behavior.

The Data Collection is the first step and is driven by raw network traffic from different CPS components such as sensors, actuators, Programmable Logic Controllers (PLCs), SCADA/DCS systems, industrial network devices, communication gateways and cloud servers. These elements provide data continuously to monitor and control physical processes in real-time. Critical infrastructures use cyber-physical systems. The collected traffic includes authorized communication as well as unlawful behavior by invaders. The whole process of cyberattack detection is based on raw data. These data contain some components of network such as protocol information, packet size, communication duration, source and destination addresses and traffic statistics. It saves the resulting data set and transmits it to the following step.

The second phase is Data Processing, which means that the captured network traffic should be pre-processed and cleaned into a correct format for the machine learning process. The initial phase was data pre-processing, deleting missing values, duplicate records and inconsistent data entries. Encode categorical attributes properly for transformation into numerical values that deep learning algorithms can readily work with. The numerical attributes are then normalized so that all the features are in a similar range, by means of either Min-Max Scaling or Z-score normalization. Further, outlier treatment is performed to remove the noisy or aberrant data that can reduce the classification performance. Finally in the dataset is splitted into training and test set and the deep learning model is trained successfully and tested properly.

3. Binary Metaheuristic Optimization for Feature Selection
Main contribution of the proposed system is: In Cybersecurity, datasets often have a large number of properties, many of them are redundant or useless. These features will increase the computer processing time and may affect the detection accuracy. To solve this problem the proposed framework encodes each feature as binary value, '1' means feature is selected and '0' means feature is discarded. The Binary Metaheuristic Optimization approach iterates different combinations of features with the fitness function to update the candidate solutions to identify the optimal feature subset. The method is based on a succession of optimization cycles to get rid of duplicate features and maintain the most informative ones. The optimized feature subset can greatly reduce the dimensionality, accelerate the model training, limit memory consumption and improve the overall detection performance.

The selected features after feature optimization are fed to Deep Learning Classification module. The module is composed of an input layer, some hidden layers and an output layer which can learn automatically the complex non-linear relationships between the provided features of the network. On the other hand, traditional machine learning algorithms require large number of hand-crafted features, deep learning model can automatically learn high level characteristics that can separate normal traffic from distinct attack patterns. Depending on the application, different deep learning architectures could be utilized, such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), CNN-LSTM hybrids or Autoencoder based models. In the context of Cyber-Physical Systems, the hidden layers continuously learn the feature representations such that the classifier can accurately categorize known and unforeseen cyber threats.

The ultimate outcome is the classification of the cyberattack detection, which is the output generating stage. The trained

deep learning model then evaluates the incoming network traffic and classifies it as normal communication or a malicious conduct for each network instance. The framework also detects the type of attack and generates the security alerts/messages to the administrators in case of discovery of malicious conduct in time. These alerts enable a timely response, mitigation of the attack and recovery of the system before any serious damage can be done. Critical infrastructures based on Cyber-Physical Systems need to be able to distinguish between genuine traffic and different forms of attacks in an accurate way. This means that systems of this kind are far more secure, more reliable and more operationally stable.

2.5 Algorithm

ALGORITHM 1: Boosting Cyberattack Detection Using Binary Metaheuristics with Deep Learning (BCD-BMDL)

Input:

$\mathbf{D} \leftarrow$ Cyber-Physical System (CPS) network traffic dataset $\{d_1, d_2, \dots, d_n\}$

$\mathbf{M_DL} \leftarrow$ Deep Learning model (CNN/LSTM/DNN)

$\mathbf{BMO} \leftarrow$ Binary Metaheuristic Optimization algorithm for feature selection

$\theta \leftarrow$ Attack detection threshold

$\mathbf{P} \leftarrow$ Data preprocessing operations {Data Cleaning, Encoding, Normalization}

$\mathbf{F} \leftarrow$ Extracted network traffic features

Output:

$\mathbf{Attack_State} \leftarrow$ {Normal, Cyberattack}

$\mathbf{Attack_Type} \leftarrow$ Predicted attack category

$\mathbf{Detection_Score} \leftarrow$ Probability of attack detection

Procedure Begin

Step 1: Data Collection

Collect network traffic data from Cyber-Physical System components such as sensors, actuators, PLCs, SCADA systems, industrial controllers, and communication networks.

Gather both normal and malicious traffic records from benchmark cybersecurity datasets.

Store the collected data in dataset $\mathbf{D}$.

Step 2: Data Preprocessing

For each network record $\mathbf{d}_i \in \mathbf{D}$:

Remove duplicate and missing values.

Encode categorical attributes into numerical values.

Normalize numerical features using Min-Max or Z-score normalization.

Remove noisy and inconsistent records.

Store the processed data as $\mathbf{P(d_i)}$.

Step 3: Feature Extraction and Optimization

For each processed record $\mathbf{P(d_i)}$:

Extract network features including protocol type, packet size, connection duration, source IP, destination IP, traffic rate, packet count, and flow statistics.

Represent the extracted features as feature vector $\mathbf{F(d_i)}$.

Apply **Binary Metaheuristic Optimization (BMO)** to search for the optimal feature subset.

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Discard redundant and irrelevant features while retaining the most informative attributes.

Generate the optimized feature vector $F_{opt}(d_i)$.

Step 4: Deep Learning Classification

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If the model is not trained:
    Train the Deep Learning model  $M_{DL}$  using the
    optimized feature set  $F_{opt}(D)$ .
Else:
    For each testing record  $F_{opt}(d_i)$ :
        Compute  $Pred\_prob(d_i)$  ←
 $M_{DL}.predict(F_{opt}(d_i))$ .
        If  $Pred\_prob(d_i) \geq 0$  then
             $Attack\_State(d_i) \leftarrow "Cyberattack"$ .
        Else
             $Attack\_State(d_i) \leftarrow "Normal"$ .
        End If
        Predict  $Attack\_Type(d_i)$ .
        Store  $Detection\_Score(d_i) \leftarrow Pred\_prob(d_i)$ .

```

Step 5: Performance Evaluation

```

Compute the model performance using:
 $Accuracy = (TP + TN) / (TP + FP + TN + FN)$ 
 $Precision = TP / (TP + FP)$ 
 $Recall = TP / (TP + FN)$ 
 $F1-Score = 2 \times (Precision \times Recall) / (Precision +$ 
 $Recall)$ 
Record computational time and false positive rate for
performance analysis.

```

Step 6: Attack Detection and Alert Generation

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For each record with  $Detection\_Score \geq 0$ :
    Generate a cyberattack alert.
    Identify the detected attack category.
    Log the attack information in the security monitoring
    database.
    Notify the system administrator for immediate response
    and mitigation.
    Continue monitoring incoming network traffic for real-
    time intrusion detection.

```

Return: ($Attack_State, Attack_Type, Detection_Score$)

End Procedure

The proposed Boosting Cyberattack Detection Using Binary Metaheuristics with Deep Learning (BCD-BMDL) algorithm offers a complete intelligent intrusion detection workflow for the Cyber-Physical System environment. The system starts with network traffic data collection and pre-processing to reduce variation and normalize attributes. Then, a Binary Metaheuristic Optimization method learns the most relevant features and removes the redundancy of characteristics to extract and improve the critical network properties. The selected attributes are then fed to a deep learning model which learns complicated attack patterns and classifies the network traffic accurately as normal or malicious traffic. Finally, the model was evaluated using conventional metrics including Accuracy, Precision, Recall and F1-Score. The alert generation module facilitates real-time alerts of assaults and

3. RESULTS AND DISCUSSION

The proposed framework i.e. Boosting Cyberattack Detection Using Binary Metaheuristics with Deep Learning on Cyber-Physical System Environment is implemented and evaluated on benchmark dataset on Cyber-Physical System (CPS) cybersecurity with normal and malicious network traffic. The acquired data was pre-processed including the removal of missing values, the encoding of categorical categories, and the normalization of numerical features to increase data quality. Then, the most relevant characteristics were selected using a Binary Metaheuristic Optimization technique. This drastically decreases the dataset complexity while preserving the qualities that contribute most to the detection of cyberattacks. The deep learning model was trained with an optimized feature subset, which helps the model to learn the complicated attack patterns effectively and reduce the computational cost.

3.1 Experimental Setup

In the experimental part, we have evaluated the proposed framework, i.e. Boosting Cyberattack Detection Using Binary Metaheuristics with Deep Learning on Cyber-Physical System Environment on a benchmark Cyber-Physical System (CPS) cyber security dataset with normal and malicious network traffic records . Experiments were performed on a system with Intel Core i7 CPU, 16 GB RAM and 512 GB SSD with Windows 11 (64 bit). The proposed model was developed in the Python 3.10 language and Jupyter Notebook environment. Numpy and Pandas were used for data preparation and feature engineering. Built deep learning model using Tensorflow and Keras. Data preparation and model performance evaluation was done using the Scikit-learn package.

3.2 Performance Evaluation

The suggested framework “Boosting Cyberattack Detection Using Binary Metaheuristics with Deep Learning on Cyber-Physical System Environment” is evaluated by common measures of classification in cybersecurity such as Accuracy, Precision, Recall and F1-Score. To show the usefulness of our model for identifying the Cyber-Attacks in Cyber-Physical Systems, we compare our proposed Binary Metaheuristic based Deep Learning model with some of the conventional machine learning and deep learning approaches.

Table 1: Comparative Performance of Cyberattack Detection Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
K-Nearest Neighbors (KNN)	89.2	88.6	87.9	88.2
Support Vector Machine (SVM)	91.4	90.8	91.1	90.9
Random Forest	94.1	93.6	94.3	93.9

Model		Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Deep Learning (LSTM)		97.2	97.0	96.8	96.9
Binary Metaheuristic + Deep Learning (Proposed)		99.1	99.0	98.9	98.9

The results clearly indicate the proposed Binary Metaheuristic with Deep Learning framework is better than the traditional machine learning and individual deep learning model in all the performance measures. The Binary Metaheuristic Optimization approach efficiently removes the redundant and irrelevant information, thus enabling the deep learning model to learn more discriminative attack patterns. Thus, the proposed framework gives a very appropriate solution for real time Cyber Physical System security applications with higher detection accuracy with extremely low false positive rate.

Table 2: Training Accuracy of the Proposed Deep Learning Model

Epochs	CNN Accuracy (%)	LSTM Accuracy (%)	Proposed Binary Metaheuristic + Deep Learning (%)
5	90.8	93.6	95.4
10	93.4	95.8	97.3
15	95.2	97.1	98.5
20	96.3	97.9	99.1

The results above indicate that the proposed deep learning model based on optimization has higher training accuracy and faster convergence than the classic CNN and LSTM models. The Binary Metaheuristic Optimization approach helps to pick informative features before training, which decreases the computational complexity and helps the model to learn the complex patterns of cyberattacks efficiently. The model proposed in this paper has obtained the superior learning performance and stability for more training times.

Table 3: Confusion Matrix for the Proposed Model

Actual \ Predicted	Normal Traffic	Cyberattack
Normal Traffic	2845	32
Cyberattack	26	2897

The confusion matrix shows the proposed framework's performance to correctly identify the normal network traffic and the cyberattack events. The model classifies correctly most of the normal and malicious records and generates a

very small number of false positives and false negatives. The results reveal that the combination of the Binary Metaheuristic Optimization with Deep Learning leads to a considerable improvement in the effectiveness of cyberattack detection, the resilience of categorization, and the security of Cyber-Physical System settings.

3.3 Discussion of Results

The experimental results show that the presented framework, Boosting Cyberattack Detection Using Binary Metaheuristics with Deep Learning on Cyber-Physical System Environment, can improve the performance of cyberattack detection significantly compared to the traditional machine learning and the standalone deep learning models. The deep learning classifier with Binary Metaheuristic Optimization is effectively applied to reduce the dimensions of the cybersecurity dataset by selecting the most relevant features and deleting the redundant and irrelevant features. The suggested enhanced feature selection technique minimizes the computational cost, and enables the deep learning model to learn the discriminative attack patterns, which enhances the classification accuracy and speeds up the convergence during the training.

The results of the performance comparison showed that the proposed model achieved an accuracy of 99.1% which is better than K-Nearest Neighbors (89.2%), Support Vector Machine (91.4%), Random Forest (94.1%) and LSTM model alone (97.2%). Moreover, the Precision, Recall and F1-Score have been improved, which implies the model can better identify cyber-attacks and reduce false alarms. The proposed framework is proved to be efficient with high number of correct classified normal and malicious traffic cases and few false positives and false negatives in the confusion matrix. This is even more so in the case of Cyber-Physical Systems, where wrong predictions could lead to operational failures, security breaches or unjustified system downtimes.

3.4 Comparative Analysis and Insights

The recommended architecture, called “Boosting Cyberattack Detection Using Binary Metaheuristics with Deep Learning on Cyber-Physical System Environment”, is shown to be superior than conventional machine learning and single deep learning models for detecting cyber threats. Classical methods such as K-Nearest Neighbours (KNN), Support Vector Machine (SVM) and Random Forest can achieve good detection performance, but they are limited to manually selected features and cannot learn complicated nonlinear correlations in high-dimensional cyber-security data well. However, the capacity of the individual LSTM models to capture the sequential network traffic patterns with enhanced accuracy is restricted by redundant and irrelevant characteristics which raise both the computational complexity and the training time.

Binary Metaheuristic Optimization addresses the limits of deep learning models by intelligently selecting the most relevant features for the classification process. This change reduces the dimensionality of the data, reduces repetitive calculations, accelerates the convergence of the model, and improves the learning ability of the deep learning classifier. Therefore, the proposed framework may reach maximum performance in terms of Accuracy, Precision, Recall and F1-Score due to the decrease of False Positive Rate (FPR) and

enhancement of the detection reliability. The optimized subset of features helps the model to detect the known and unknown cyberattacks with improved confidence. It is particularly useful for dynamic scenario of Cyber Physical System.

3.5 Summary of Findings

1. The proposed Binary Metaheuristic Optimization with Deep Learning framework is shown to be effective for cyberattack detection by providing higher Accuracy, Precision, Recall and F1-Score over traditional machine learning models.
2. The Binary Metaheuristic Optimization approach was used to determine the most essential features of the network, which lowered the data dimensionality, the computational complexity and the training time of the model.
3. The deep learning classifier was taught to learn complex patterns of cyber-attacks to be able to recognize the known and hidden dangers in the CPS environment.
4. The proposed design may greatly minimize the false positive and false negative rates, and provide more reliable intrusion detection and enhance the cybersecurity of the major infrastructures.
5. The proposed system is scalable, computationally efficient and suited for real time application which can be a feasible solution to safeguard the current Cyber Physical Systems from the ever growing cyber threats.

4. CONCLUSION AND SCOPE:

The proposed method for Boosting Cyberattack Detection Using Binary Metaheuristics with Deep Learning on Cyber-Physical System Environment is an intelligent, accurate and efficient way to raise the cyber security of modern Cyber-Physical Systems (CPS). The integration of Binary Metaheuristic Optimization and Deep Learning ensures the selection of the most significant characteristics of the network and the removal of redundant and unneeded information, thus reducing the computational complexity and increasing the classification performance. The enhanced feature subset helps the deep learning model to learn complex attack patterns quickly and therefore achieve high detection accuracy, higher precision, recall and F1-score and significantly reduce false positive rate. Experimental results show that the proposed framework achieves better performance than the classic machine learning and deep learning techniques in detecting known and novel cyber threats. Moreover the proposed system can be applied to the applications in essential Cyber-Physical Systems such as smart grids, industrial automation, intelligent transportation, healthcare systems and smart manufacturing due to its real-time intrusion detection, fast alert generation and prompt mitigation. This approach improves security and resilience in CPS contexts. Improves operational reliability and continuous availability of critical services.

In future work, we plan to adapt the proposed framework for complex and large-scale Cyber-Physical System environments with evolving cyber threats. We can also leverage state-of-the-art deep learning architectures like Transformer Networks, Graph Neural Networks (GNNs) and hybrid attention-based models to enhance detection accuracy and explore complex assault patterns. Hybridization of Binary Metaheuristic Optimization algorithm with optimization techniques can be used for fast convergence and better feature selection. Furthermore, the proposed

framework may be used in cloud, edge and fog computing environments for low latency real-time cyber threat detection for Internet of Things (IoT) enabled Cyber-Physical Systems (CPS) applications. Future works could involve Federated Learning, Explainable Artificial Intelligence (XAI) and Blockchain technology for boosting data privacy, model transparency, safe information exchange and trustworthiness. These developments will allow the design of intelligent, scalable, autonomous and highly robust cyber security systems. At the same time, they will ensure safe, reliable and uninterrupted operation and will be able to protect critical infrastructures from developing cyber threats.

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