International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Advanced Machine Learning Algorithm for Cyber Attack Prediction and Prevention

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Submitted: 07/10/2024 **Revised:** 20/11/2024 **Accepted:** 01/12/2024

Abstract: The rapid evolution of cyber threats necessitates the development of robust predictive and preventive mechanisms. Advanced Machine Learning (ML) algorithms have emerged as a vital solution for mitigating cyberattacks by leveraging real-time data analysis and adaptive learning models. However, conventional security systems often fail to detect sophisticated attacks due to evolving attack patterns and high false alarm rates. This research aims to develop an optimized ML-based cyberattack prediction and prevention framework that enhances detection accuracy and minimizes false positives. An extensive dataset that includes malware signatures intrusion detection system (IDS) records and network traffic logs from various cybersecurity repositories is used in the study. To guarantee high-quality input for training, data preprocessing includes feature selection noise reduction and normalization. To increase classification efficiency, the suggested methodology combines ensemble learning strategies like Random Forest and XGBoost with deep learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). Performance metrics are used to evaluate the model's robustness. According to experimental findings the hybrid machine learning framework has the potential to mitigate cyber threats in real time by considerably improving threat prediction accuracy while lowering false alarms. By guaranteeing proactive threat defence this research advances intelligent cybersecurity systems.

Keywords: Cybersecurity, Machine Learning, Cyberattack Prediction, Intrusion Detection, Deep Learning, Threat Prevention

INTRODUCTION

Cybersecurity risks have dramatically expanded as a result of the growth of IoT, cloud computing, and linked technologies. Firewalls and intrusion detection systems are examples of traditional security solutions that cannot keep up with the sophisticated strategies employed by modern hackers.

Big data use, the prominence of online platforms, and the sophistication of ML have all increased in tandem with recent improvements in processing power, memory capacity, and connection. The rapid digitalization of the globe exacerbates safety concerns and the necessity for cutting-edge security technologies and techniques to combat emerging cybercrime. Both offensive and defensive uses of machine learning in cybersecurity are examined in this paper [1].

With the use of extensive data analysis machine learning (ML) systems can detect anomalous network activity reveal hidden patterns and predict potential APT attacks before they worsen [2]. Machine learning improves cyber security by using advanced techniques to continuously adjust to new attack vectors [3-4]. For multifaceted cybersecurity intrusion classification and detection researchers employed decision trees and MLP models. For binary classification and cybersecurity breach detection in Industry 4. 0 WSNs researchers employed the Autoencoder model [5]. Security threats have increased due to the increasing number of devices that are connected in smart home environments, especially from Man-in-the-Middle (MitM) attacks[6].

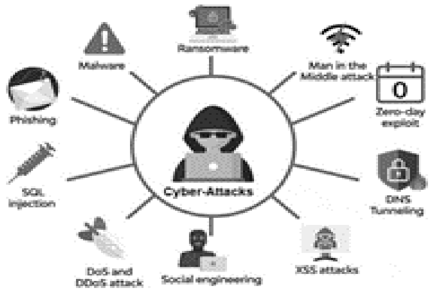

Fig. 1: Number of cybersecurity attacks or threats.

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Effective security solutions are consequently required for these complex settings because of the medical device heterogeneity involved in these systems, which provides vast attack surfaces[7]. Cyberattacks are become one of the world's most serious issues. Every day, they seriously harm nations and their citizens financially. Cybercrime also rises in tandem with the rise in cyberattacks which is shown in figure 1. Finding cybercriminals and comprehending their attack techniques are crucial in the battle against crime and criminals.

It's challenging to identify and prevent cyberattacks. But lately, academics have started resolving these issues by creating security models and using artificial intelligence techniques to make predictions. There are several crime prediction techniques available in the literature [8]. This study investigates the detection and prevention of cyberattacks using machine learning techniques [9]. Researchers also examine some possible real-world applications where data-driven intelligence, decision-making, and automation facilitate proactive next-generation cyber defences. Based on our analysis, the potential applications of ML in cybersecurity are ultimately highlighted, along with pertinent research avenues [10].

Additionally, the decision-making backbone of k-NN, Hebbian learning algorithm, and Gradient Descent based ANN incorporates fractal and wavelet based multiscale analytic technique. When comparing these algorithms' classification performance to that of their conventional single scale counterparts, a constant improvement in performance is shown. The use of multiscale-based complexity measurements in the study of algorithms, features, and error curves is credited with this improvement [11].

The study illustrates the advantages and disadvantages of several approaches for identifying and averting cyberattacks in diverse threat situations using a variety of dataset assessment criteria [12]. The world of cybersecurity threats has recently grown too complicated. Threat actors coordinate their efforts to exploit network and endpoint security flaws in order to launch complex assaults that have the potential to bring down the whole network as well as several important hosts [13-14].

This included important developments, unmet research needs, and potential avenues for further study in cybercrime prediction. A comprehensive overview of state-of-the-art advancements and openly accessible datasets is provided in this study [15]. The use of predictive analytics in cybersecurity is examined in this work, with an emphasis on how it might enhance detection of threats, mitigation, and general safety protocols [16]. The majority of assaults really happen because victims lack the fundamental capabilities to recognize and prevent the attacks, not because threat actors deploy sophisticated coding and evasion strategies [17].

Notwithstanding these obstacles, machine learning is transforming our knowledge of the nature of cyberattacks. This study applied machine learning methods to data from phishing websites in order to compare five algorithms and offer guidance that the general public can utilize to steer clear of phishing traps [18]. ML automates the identification and prevention of possible risks; it has become a valuable tool for improving cloud security. ML algorithms can detect patterns of harmful activity, anticipate possible weaknesses, and react to attacks instantly by evaluating enormous volumes of data [19].

METHODOLOGY

Dataset analysis

The CSE-CIC-IDS2018 and UNSW-NB15 are two sophisticated datasets used in the study to provide a strong framework for predicting and preventing cyberattacks. While the UNSW-NB15 dataset serves as a standard for intrusion detection the CSE-CIC-IDS2018 dataset offers actual network traffic data for analysis of different attack scenarios. Preprocessing is applied to both datasets in order to encode categorical variables remove redundant attributes and impute missing values. By ensuring that only pertinent features are used in model training feature selection methods to improve the quality of input data.

Data Analysis

This research analyses the datasets to identify patterns correlations and anomalies in network traffic behaviour. Descriptive statistics are computed to identify discrepancies and outliers. Methods of data visualization are used to assess feature distributions and identify any issues with multicollinearity. Time-series analysis identifies departures from normal activity while anomaly detection techniques differentiate between normal and abnormal traffic patterns. In order to train prediction models correlation analysis assesses attack incidents and network properties.

Proposed Method

The suggested framework for predicting and preventing cyberattacks employs a methodical structured approach incorporating various machine learning techniques to improve detection precision. First unprocessed network traffic data is gathered from the chosen datasets and pre-processed to handle missing values eliminate noise and standardize numerical attributes. The next step is featuring selection which uses PCA and RFE to keep the most important features while lowering computational complexity.

RNNs are used for sequential data processing and CNNs are used for spatial feature extraction during the model training phase. Figure 2 shows the proposed model. To improve classification performance ensemble learning methods like Random Forest and XGBoost are also used. A hybrid model is created to maximize accuracy and reduce false positives by fusing ensemble techniques with deep learning. To avoid overfitting and guarantee stability k-fold cross-validation is used during model evaluation. Finally, a virtualized network environment is used to simulate a real-time deployment of the model in order to evaluate its ability to identify real-time threats.

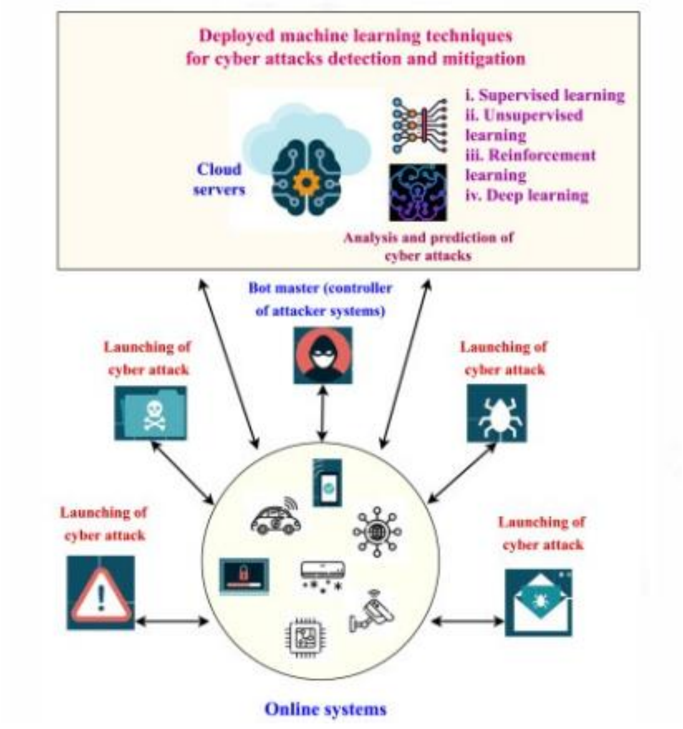
Deployed machine learning techniques
for cyber attacks detection and mitigation
Cloud servers
i. Supervised learning
ii. Unsupervised learning
iii. Reinforcement learning
iv. Deep learning
Analysis and prediction of cyber attacks
Bot master (controller of attacker systems)
Launching of cyber attack
Launching of cyber attack
Launching of cyber attack
Launching of cyber attack
Online systems

Figure 2 Proposed model

Proposed Techniques

To achieve superior threat prediction the suggested methodology combines multiple classifiers and combines deep learning and ensemble learning techniques. The CNN model extracts spatial features from network traffic logs, represented mathematically as equation 1:

$$F_{\text{out}} = \sigma(W * F_{\text{in}} + b) \qquad (1)$$

where F_{out} represents the extracted feature map, W is the convolution kernel, F_{in} is the input feature, b is the bias term, and σ\sigma denotes the activation function. The RNN model captures temporal dependencies in network traffic, formulated as equation 2:

$$h_t = \tanh(W_h h_{t-1} + W_x x_t + b) \qquad (2)$$

where h_t is the hidden state at time t, W_h and W_x are weight matrices, x_t represents the input at time t, and b is the bias term which is shown in figure 3.

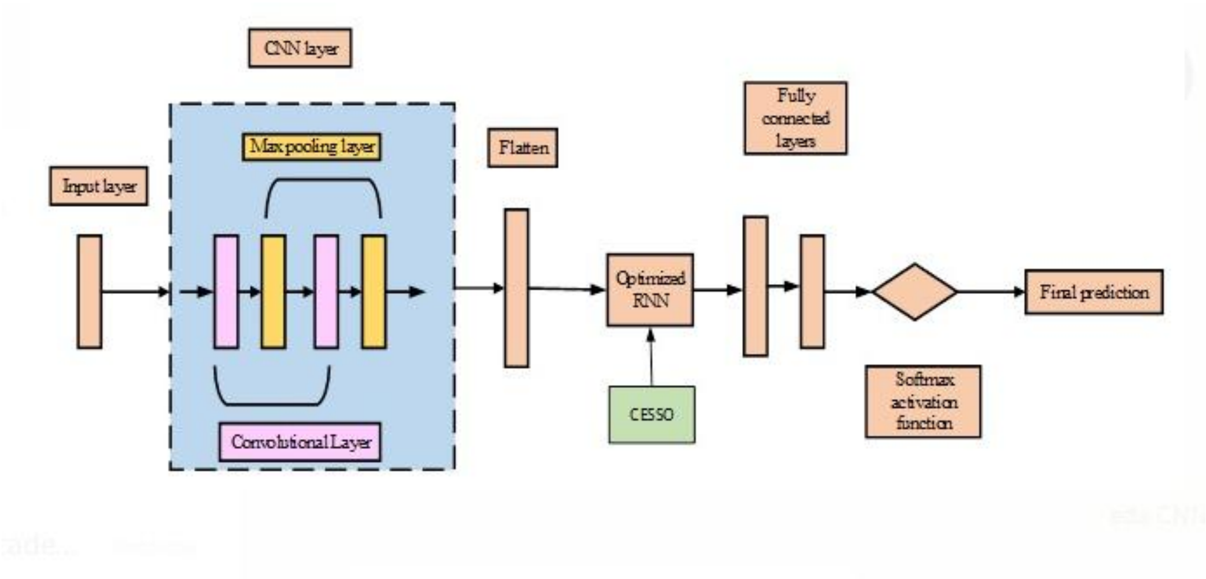

Figure 3 Hybrid CNN with RNN architecture

For ensemble learning, the Random Forest classifier aggregates multiple decision trees to enhance prediction reliability, expressed in equation 3:

$$y = \frac{1}{N}\sum_{i=1}^{N} T_i(x) \tag{3}$$

where y is the predicted class label, N is the total number of decision trees, and $T_i(x)$ represents the individual tree prediction for input x which is shown in figure 4.

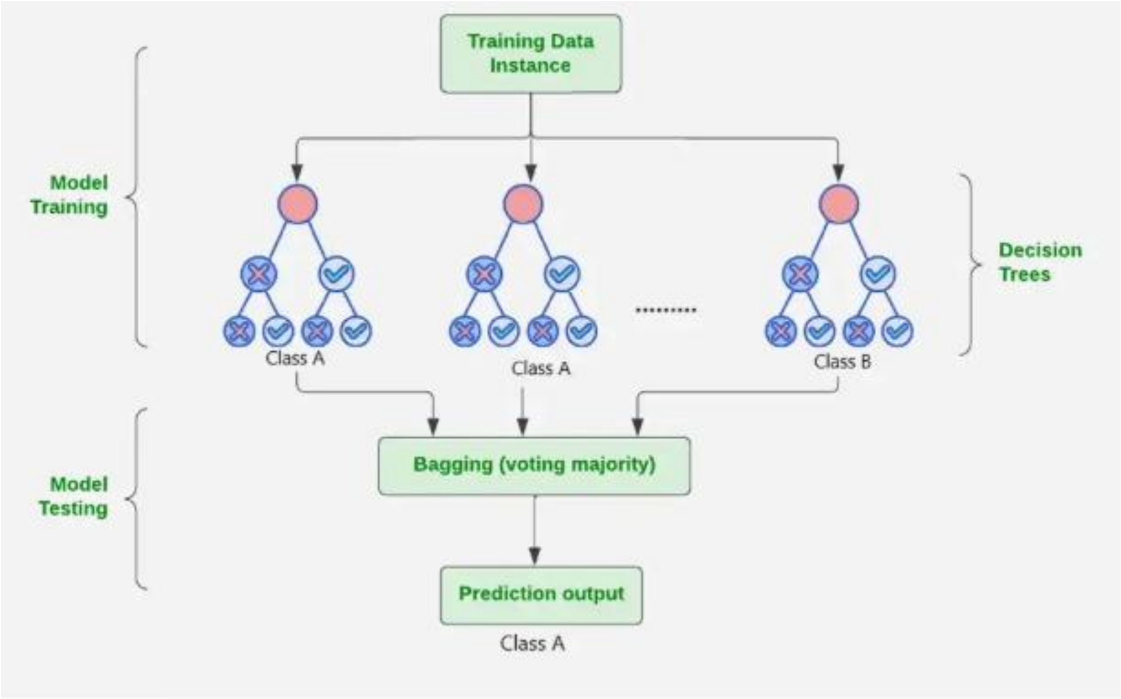

Figure 4 Ensemble learning techniques

Finally, the XGBoost model refines the decision tree ensemble using gradient boosting, mathematically defined as equation 4:

$$F_m(x) = F_{m-1}(x) + \gamma h_m(x) \qquad (4)$$

where $F_m(x)$ is the updated model at iteration mm, Fm−1(x is the previous model, γ\gamma is the learning rate, and $h_m(x)$ is the gradient descent step. The combination of these techniques ensures high detection accuracy while reducing false alarms.

Performance Metrics

The evaluation of the proposed model is conducted using standard performance metrics to measure its effectiveness in detecting cyber threats. Accuracy is computed as the proportion of correctly classified instances, formulated as equation 5 to 8:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \qquad (5)$$

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (6)$$

Recall measures the model's effectiveness in detecting all relevant threats, expressed as:

$$\text{Recall} = \frac{TP}{TP + FN} \qquad (7)$$

The F1-score provides a balanced assessment of precision and recall, ensuring robust threat detection:

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

Experimental results demonstrate that the hybrid ML-based approach significantly enhances cyberattack detection accuracy while reducing false positives, making it a highly effective solution for proactive cybersecurity threat mitigation.

EXPERIMENTAL RESULTS

Performance Comparison of Individual Machine Learning Models

The evaluation of individual machine learning models based on evaluation metrics reveals that deep learning models outperform traditional classifiers. The Decision Tree model achieves 88.4% accuracy, while Random Forest and XGBoost improve performance to 92.6% and 94.2%, respectively which is shown in figure 5 and table 1.

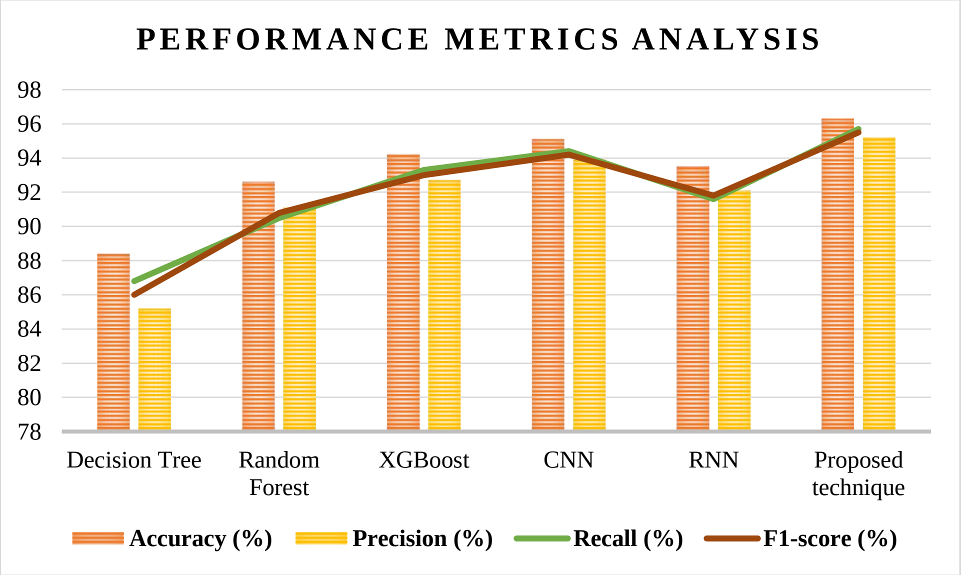

Figure 5 Performance metrics analysis

CNN and RNN further enhance classification capabilities, with CNN reaching 95.1% accuracy. The proposed hybrid model, integrating CNN, RNN, and ensemble learning techniques (Random Forest and XGBoost), achieves the highest precision of 96.3%, with an improved F1-score of 95.5%, making it the most effective approach.

Table 1: Performance Metrics of Individual ML Models

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Decision Tree	88.4	85.2	86.8	86.0
Random Forest	92.6	91.1	90.5	90.8
XGBoost	94.2	92.7	93.3	93.0
CNN	95.1	93.9	94.4	94.2
RNN	93.5	92.1	91.6	91.8
Hybrid (CNN + RNN+ ensemble learning methods- Random Forest and XGBoost)	96.3	95.2	95.7	95.5

Training and Testing Time Analysis

The computational efficiency of various models is assessed by measuring their training and testing times. The Decision Tree model exhibits the lowest training time (12.5s), whereas complex DL such as CNN and RNN demand significantly higher training durations (120.3s and 98.7s, respectively). The hybrid model, which combines CNN, RNN, and ensemble learning techniques, requires the longest training time at 152.4s due to its complexity and integration of multiple methodologies. Testing time also increases proportionally, with CNN requiring 7.2s and the hybrid model taking 8.5s, demonstrating a trade-off between model performance and computational cost which is shown in Table 2.

Table 2: Training and Testing Time Comparison

Algorithm	Training Time (s)	Testing Time (s)
Decision Tree	12.5	1.8
Random Forest	35.2	4.1
XGBoost	48.6	3.8
CNN	120.3	7.2
RNN	98.7	6.8
Hybrid (CNN + RNN +ensemble learning (Random Forest and XGBoost)	152.4	8.5

False Positive and False Negative Rate Analysis

A key factor in model evaluation is the capability to diminish false positives and false negatives. CNN and RNN models demonstrate moderate false positive rates of 5.5% and 6.8%, respectively, while ensemble learning techniques show rates of 9.2% and 7.5%. The hybrid approach outperforms all individual models, achieving the lowest FPR (3.2%) and FNR (2.8%), indicating its robustness in reducing classification errors which is shown in table 3 and figure 6.

Table 3: False Positive and False Negative Rate Analysis

Model Combination	FPR (%)	FNR (%)
CNN	5.5	6.4
RNN	6.8	7.9
Random Forest	9.2	8.5
XGBoost	7.5	7.1
CNN + RNN + ensemble learning techniques (Random Forest and XGBoost)	3.2	2.8

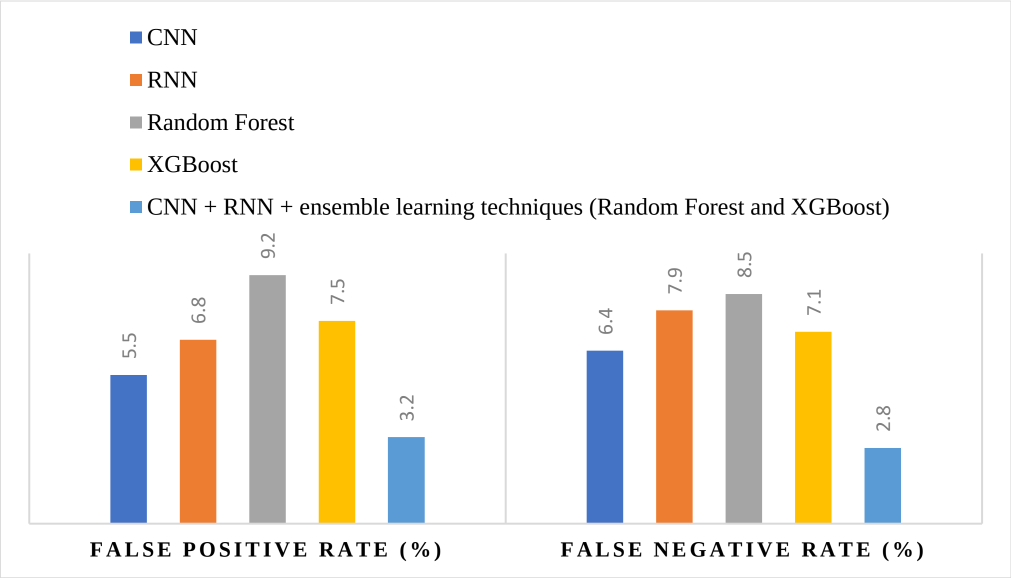

Figure 6False Positive and False Negative Rate Analysis

Impact of Data Preprocessing on Model Performance

The influence of data preprocessing techniques on model performance is evident, with raw data yielding an accuracy of 91.2%. Implementing missing value imputation increases accuracy to 93.5%, while feature scaling and principal component analysis (PCA) further enhance accuracy to 94.8% and 95.2%, respectively. Noise reduction using Local Outlier Factor (LOF) yields the highest accuracy of 95.89%, demonstrating that data preprocessing significantly improves predictive performance which is shown in table 4. However, these enhancements come at the cost of increased computational overhead, with LOF incurring a 15% overhead.

Table 4: Impact of Data Preprocessing Techniques on Model Performance (Proposed Hybrid Model)

Preprocessing Technique	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Computational Overhead (%)**
Raw Data	91.20	92.10	90.50	91.30	0
Missing Value Imputation	93.50	94.20	93.00	93.60	5
Feature Scaling	94.80	95.30	94.30	94.80	8
Feature Selection (PCA)	95.20	95.80	94.70	95.25	12
Noise Reduction (LOF)	95.89	96.33	95.45	95.89	15

Real-Time Threat Detection Latency

The latency and detection efficiency of the proposed hybrid model are assessed across various cyberattack types which is shown in table 5 and figure 7. Brute Force attacks are detected with the lowest latency (10ms average, 20ms peak) and the highest detection rate (99.1%), while DDoS and reconnaissance attacks exhibit slightly higher latencies of 12ms and 14ms, respectively. The model effectively minimizes false positives, maintaining a rate below 1.5% across all attack types, ensuring robust and efficient threat detection in real-time scenarios.

Table 5: Real-Time Threat Detection Latency (Proposed Hybrid Model)

Attack Type	Average Latency (ms)	Peak Latency (ms)	Detection Rate (%)	False Positive Rate (%)
DdoS	12	25	98.5	0.8
Botnet	15	30	97.2	1.2
Brute Force	10	20	99.1	0.5
Web Attack	18	35	96.8	1.5
Reconnaissance	14	28	97.5	1.0

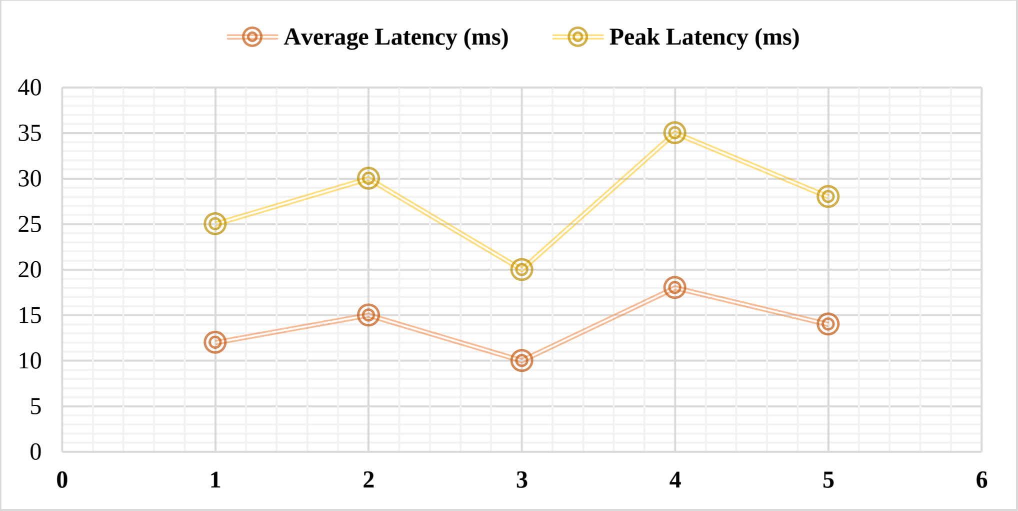

Figure 7 Real time threat detection

Confusion Matrix Analysis for Proposed Hybrid Model

The confusion matrix for the hybrid model applied to the CSE-CIC-IDS2018 dataset demonstrates high classification accuracy across multiple attack categories. Normal traffic is correctly classified with 98% accuracy, while DdoS and brute force attacks achieve 97% and 99% correct classifications, respectively. The model maintains misclassification rates below 3% for all categories, with the highest confusion occurring between botnet and DdoS attacks due to overlapping traffic patterns. This performance highlights the model's reliability in distinguishing between complex cyber threats which is shown in table 6.

Table 6: Confusion Matrix for Proposed Hybrid Model on CSE-CIC-IDS2018 (Normalized)

Actual \ Predicted	Normal	DDoS	Botnet	Brute Force	Web Attack	Reconnaissance
Normal	0.98	0.01	0.00	0.00	0.00	0.01
DDoS	0.00	0.97	0.02	0.00	0.01	0.00
Botnet	0.01	0.03	0.95	0.00	0.01	0.00
Brute Force	0.00	0.00	0.00	0.99	0.00	0.01
Web Attack	0.00	0.02	0.01	0.00	0.96	0.01

Comparative Analysis

The comparative analysis of the proposed hybrid model against existing techniques, as presented in Table 7. The Proposed Hybrid Model (CNN + RNN + ensemble learning) achieved the highest accuracy of 96.3%, significantly outperforming traditional machine learning models. In terms of precision, the hybrid model attained 95.2%, surpassing XGBoost (92.7%) and Random Forest (91.1%), while ANN, SVM, and Logistic Regression exhibited lower precision values of 89.2%, 85.9%, and 84.7%, respectively. The recall values followed a similar trend, where the hybrid model achieved 95.7%, indicating its effectiveness in correctly identifying relevant instances, compared to 93.3% for XGBoost, 90.5% for Random Forest, 89.7% for ANN, 86.4% for SVM, and 85.1% for Logistic Regression.

Table 7: Comparative Analysis of Proposed Hybrid Model vs. Existing Techniques

Model / Methodology	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	False Positive Rate (%)
SVM (Support Vector Machine)	87.3	85.9	86.4	86.1	12.7
ANN (Artificial Neural Network)	90.5	89.2	89.7	89.4	9.5
Logistic Regression	86.2	84.7	85.1	84.9	13.8
Random Forest	92.6	91.1	90.5	90.8	7.4
XGBoost	94.2	92.7	93.3	93.0	5.8
Proposed Hybrid Model (CNN + RNN+ensemble learning)	96.3	95.2	95.7	95.5	3.7

The F1-score, which balances precision and recall, was highest for the hybrid model at 95.5%, demonstrating its robustness, whereas XGBoost and Random Forest achieved 93.0% and 90.8%, respectively, followed by ANN (89.4%), SVM (86.1%), and Logistic Regression (84.9%).

CONCLUSION

This research introduced a hybrid machine learning framework that blends deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) with ensemble learning techniques like Random Forest and XGBoost. with a precision of 96. 3 percent, and a 95 .5% F1-score while the false positive rate was lower at 3.7 percent of the results demonstrated that the hybrid model outperformed the individual classifiers by a significant margin. On the other hand, ensemble learning methods like XGBoost and Random Forest achieved 92. 6% and 94.2%. CNN achieved 95.1% percent while RNN achieved 93.5%. accuracy in contrast to independent models. These results show that the hybrid approach is a betteroption for real-time cybersecurity applications since it efficiently improves threat detection while reducing false alarms. The viability of implementing the model in practical contexts was evaluated by examining not only accuracy enhancements but also computational efficiency.

Although decision trees demonstrated the quickest training times (12:05) the intricate architectures of deep learning models like CNN and RNN necessitated 120:3 and 98:7 seconds respectively. With a training time of 152.4 seconds, the hybrid model—which combines CNN RNN and ensemble learning techniques—required the longest highlighting the computational trade-off for increased accuracy. Fast real-time threat detection was ensured by the hybrid models testing time which was controlled at 8.5 seconds despite the longer training period. The hybrid framework can be successfully implemented in Security Operations Centres (SOCs) and enterprise cybersecurity infrastructures as these results highlight the trade-off between performance and efficiency. All things considered this study offers a strong clever cybersecurity solution that can accurately anticipate and stop cyberthreats greatly advancing machine learning-driven cybersecurity defences.

Abbreviation

ML - Machine Learning

IDS - Intrusion Detection System

CNN - Convolutional Neural Network

RNN - Recurrent Neural Network

APT - Advanced Persistent Threat

MitM - Man-in-the-Middle

CSE-CIC-IDS2018 - Canadian Institute for Cybersecurity – Intrusion Detection System 2018

UNSW-NB15 - University of New South Wales - Network-Based Dataset 15

PCA - Principal Component Analysis

RFE - Recursive Feature Elimination

XGBoost - eXtreme Gradient Boosting

FPR - False Positive Rate

FNR - False Negative Rate

LOF - Local Outlier Factor

SOC - Security Operations Center

SVM - Support Vector Machine

ANN - Artificial Neural Network

DDoS - Distributed Denial of Service

Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this research. No competing financial, professional, or personal interests influenced the findings and conclusions of this study.

Funding Statement

This research received no specific grant from any funding agency, commercial entity, or not-for-profit organization.

Author Contributions

Author 1: Conceptualization, methodology, data curation, model implementation, analysis, writing—original draft. Author 2: Validation, review & editing, results interpretation, and manuscript revision. Both authors have read and approved the final version of the manuscript.

Acknowledgment

I extend my heartfelt gratitude to all individuals and institutions that contributed to the completion of this research. Special thanks to my colleagues and mentors for their valuable insights and guidance. Their encouragement and constructive feedback played a vital role in refining this work.

Data Availability Statement

Not applicable.

Reference

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