Multi-Model Threat Detection Network System (MMTDNS): A Comprehensive Approach for Modern Threat Detection Across Multiple Domains

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Abstract: The Multi-Model Threat Detection Network System, or MMTDNS, is a comprehensive framework of cybersecurity for multiple machine learning models to detect real-time threats across various domains. The system utilizes Support Vector Machine, Convolutional Neural Network, Long Short-Term Memory, Random Forest, and Naïve Bayes in classifying high-accuracy phishing, malware, ransomware, and DDoS attacks. Advances like feature normalization and anomaly detection; Principal Component Analysis (PCA); and multi-model ensemble approach promise high detection while minimizing false positive rates. Mechanisms for fully automated alerts along with mitigation features enhance security measures by pro-actively responding towards threats. Along with scalability and adaptability being optimized in a real-time solution, cloud computing, deep learning advancements, as well as implementation of blockchain technology for security logs, are seen as important scopes of the said study. Future directions include Transformer-based AI models, reinforcement learning, and global threat intelligence integration. This work shows MMTDNS as an efficient, scalable, and adaptive solution for modern cybersecurity challenges.

Keywords: Cybersecurity, Machine Learning, Threat Detection, Deep Learning, Multi-Model Approach, Real-Time Analysis, Anomaly Detection, Cloud Security, Blockchain, Cyber Threats.

1. Introduction

Cyber threats are increasingly becoming complex and sophisticated as the digital environment evolves rapidly, which has increased challenges for any organization or individual(Vasanthi, 2021). Traditional detection systems face various limitations, including a lack of accuracy, inadaptability at real-time conditions, and an inability to scale(Adejo, 2018). MMTDNS is created to address the issues with a network system based

on the combination of multiple machine learning models in enhancing real-time threat detection in different domains (Agrawal, 2022).

1.1. Need for a Multi-Model Threat Detection System

Highly sophisticated threats from phishing, malware, ransomware, and DDoS attacks require cyber security solutions which are robust, adaptive, and highly flexible in nature(Kelli, 2022). Based on single models, detection systems do not generalize across different kinds of attacks(Mutalib, 2024). This results in a higher false positive rate, as well as lower efficiency for detection. The MMTDNS framework uses multi-model ensemble methods for better classification accuracy of the threats by the use of SVM, CNN, LSTM, RF, and NB(Lai, 2024). Therefore, the reliability of the detection as well as the mitigation of attack patterns will be ensured by large-scale datasets to apply the system(Jimenez, 2020).

1.2. System Architecture and Key Features

Based on a multi-layered system architecture, the MMTDNS layers include data collection, preprocessing, classification, and mitigation layers towards ensuring seamless analysis of threats in advance and hence proactive security measurements(Goyal, 2024). Advanced features of data preprocessing include feature normalization, anomaly detection, and Principal Component Analysis which enhance the ability to detect effectively and computationally(Al-Ameer, 2023). In addition, the system provides real-time alert and mitigation mechanisms that result in automated actions such as the blocking of malicious IPs and device isolation(Aljrees, 2024).

It will use MMTDNS with cloud-based AI frameworks and edge computing technologies for real-time optimization of scalability and adaptability(Gautam, 2023). Next versions will be Transformer-based AI models, which include reinforcement learning to optimize continuously, with blockchain-based security logging(Li T. Z., 2024).

1.3. Objectives of the Study

- To create a threat detection system that is ensemble-based in order to increase accuracy and decrease false positives.
- To evaluate how data preparation methods affect the performance of MMTDNS.
- To assess the scalability of MMTDNS in light of changing network loads and new threats.

2. Literature Review

There are increasing complexities in cyber threats, so there have been extensive research efforts on AI and machine learning-based techniques for cybersecurity. This section reviews key contributions within the realm of machine learning-based network threat detection, multi-model approaches, and AI-integrated blockchain solutions to point out further research requirements.

2.1. Machine Learning-Based Network Threat Detection

Peppes et al. (2021) studied in particular for the agriculture 4.0 context, machine learning classifiers and their role in network traffic analysis and cyber threat detection. Several machine learning classifiers were evaluated, namely K-Nearest Neighbors (KNN), Support Vector Classification (SVC), Decision Tree (DT), Random Forest (RF), and Stochastic Gradient Descent (SGD), using various variants of the NSL-KDD dataset. This was due to the fact that ensemble learning methods, for example, hard and soft voting models, surpassed the individual classifiers that enhanced their dependability in cyber threat detection(Peppes, 2021).

Zhu et al. (2023)focused on the problem associated with security issues of Android-based malware attacks and present MEFDroid, a multi-model ensemble framework. They have applied deep learning-based feature extraction techniques to reliably mine correlations that exist among various characteristics of malware. The study pointed out the performance improvements in malware detection using hybrid deep models, especially in imbalanced datasets(Zhu, 2023).

2.2. Multi-Model Approaches in Cybersecurity

Gadey et al. (2024) explored the concept of multi-model deep learning to be used for intrusion detection within IoT and 5G networks. Since both IoT connectivity and 5G expansion are generating new security concerns, their work used the CICIoT2023 dataset to create a robust security framework. Their conclusion was that with deep learning methods, attack classification and network resilience to attacks enhance significantly(Gadey, 2024).

Li et al. (2023) talked of the susceptibility of blockchain systems to DDoS attacks. Towards classification and differentiating seven classes of DDoS attacks, the authors design a multi-model framework that will involve the following techniques: Gate Recurrent Unit, Convolutional Neural Network, Long Short Term Memory, Deep Neural Networks, and SVM, all implemented using an adaptive integration technique incorporating dynamic weight adjustments in the design for achieving up to 99.71% detection accuracy with up to 87.62% classification accuracy by the proposed ensemble-based cyber-security solutions(Li, 2023).

Burns and Lambert (2024)explored using multiple AI-based cybersecurity models toward the real-time tracking of rapidly changing cyber threats. Their experiment covered AI performance in network anomaly analysis, identifying insider threats and cyberattack source attribution. For these, other issues such as scalability of datasets, adversarial attacks, privacy issues, had been discussed when developing AI systems for tracking them(Burns, 2024).

2.3. AI and Blockchain-Integrated Cybersecurity Solutions

Mothukuri et al. (2024)proposed a multi-model AI-driven framework toward the assessment of trustworthiness in DeFi projects. Their Trust Score brought together four AI pipelines that looked into the vulnerabilities of smart contracts, suspicious transactions, anomalous price changes, and scam sentiment through social media. The inclusion of LLMs and NLP tools greatly enhanced fraud detection and the reliability of DeFi investments(Mothukuri, 2024).

Singhal (2024)emphasized the increasing complexity of cyber threats and an emerging need for real-time AI-driven threat detection systems. While their research showed potential in machine learning, deep learning, and anomaly detection in cybersecurity, they encouraged a multi-model approach to enhance the identification of threats as well as the response to it, which would improve security resilience(Singhal, 2024).

2.4. Research Gap

Despite significant progress in machine learning and deep learning-based cybersecurity solutions, many of the most important challenges are still not addressed. The current research has proven that multi-model AI approaches can be effective for IoT, blockchain, Android malware, and network security threat detection; however, many of them are isolated threat domains rather than a unified, scalable, and adaptive framework. More importantly, though ensemble models have achieved higher accuracy results, their real-time processing capacities and computational efficiency need optimization for large deployments. Moreover, research commonly relies on an already predefined data set, thereby inhibiting its amenability to the more dangerous zero-day attacks and rapidly emerging cyber threats. The application of reinforcement learning, dynamic weight updates, and edge computing also remained unexplored for cybersecurity frameworks. Additionally, the real-time alert mechanisms and automated mitigation strategies are often neglected, which limits the practical applicability of the existing models in dynamic environments. Filling the gaps, the MMTDNS seeks to design a scalable, real-time, and adaptive cybersecurity framework that incorporates advanced AI techniques, real-time threat intelligence, and automated mitigation strategies to strengthen modern cybersecurity defenses.

3. Materials and Methods

This research is experimental in nature and applies various machine learning models to design a robust cybersecurity framework.

3.1. Research Framework

The structured approach to identifying and mitigating cyber threats was employed by the cybersecurity threat detection framework using machine learning. This started with gathering data about cybersecurity from firewalls and intrusion detection systems, subsequent compilation and structuring of threat data with fundamental attributes such as IP addresses and categories of attacks, feature selection techniques in the form of PCA and correlation analysis refining the dataset for better model performance. Preprocessing ensures consistency in data handling by dealing with missing values, normalization of features, and the detection of outliers. A clean dataset is classified using multiple machine learning models including Naïve Bayes, SVM, Decision Tree, KNN, and Random Forest. In the later stages, it predicts the existence or non-existence of cyber threats and finally leads to real-time detection and mitigation. It is an approach towards accuracy, efficiency, and scalability and gives a robust protection system against ever-evolving cyber threats.

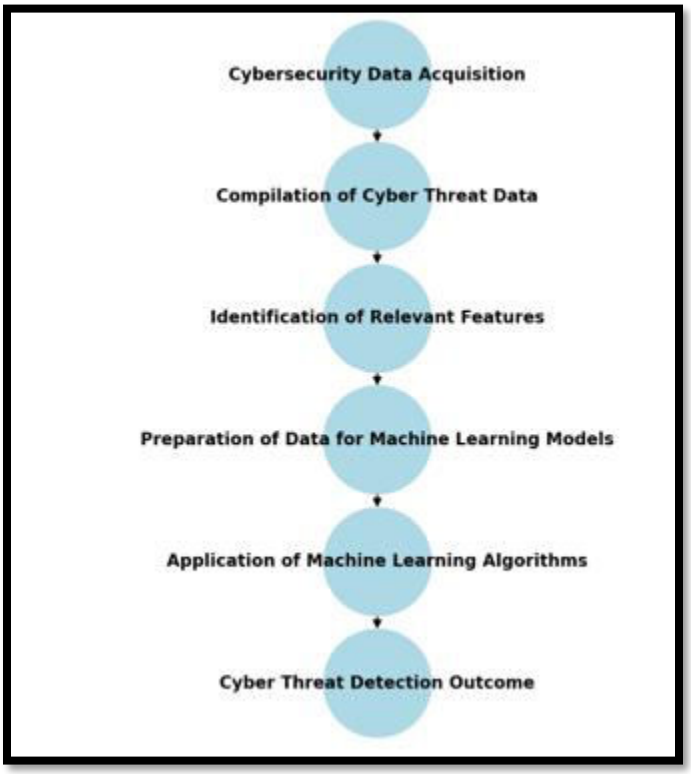

Figure 1: Flowchart for Cybersecurity Threat Detection Methodology

3.2. Research Design

The research is designed to study how different machine learning-based threat detection techniques can effectively identify, classify, and mitigate cyber threats. The multi-model ensemble approach is set to achieve a higher detection accuracy through fewer false positives.

3.3.Data Collection

The dataset for training and evaluating the MMTDNS framework consists of 50,000 security events that are benign as well as malicious network traffic. It includes a variety of cyber threats, namely phishing, malware, ransomware, and DDoS attacks.
The dataset is divided into three subsets:

- **Training Set (70%)** – Trained the machine learning models and learned the characteristics of threats.
- **Validation Set (15%)** – Used for hyperparameter tuning and model performance assessment.
- **Testing Set (15%)** – Used to evaluate the performance of the trained models on unseen data at the end.

Each data entry includes IP addresses, protocol types, packet sizes, timestamps, attack categories, and source-destination relationships to ensure a more complete classification of threats.

3.4. Data Preprocessing

Preprocessing is one of the big steps taken in improving the precision and reliability of the threat detection models." Various techniques are applied to cleanse and normalize the dataset:

1. **Handling Missing Values**: Statistical imputation techniques to fill missing values include mean substitution and KNN imputation, where missing data points are replaced by their approximated values as derived by neighboring data.
2. **Feature Normalization**:These characteristics of network traffic packets and time-to-serve data are normalized by the Min-Max Scaling technique, where each characteristic x is rescaled to scaled value 'x′ using:

$$x' = \frac{x - \min(X)}{\max(X) - \min(X)}$$

3. **Anomaly Detection and Removal**: To detect outliers, use Interquartile Range and Z-score analysis so that the model's learning process is not affected by extreme values. Interquartile Range method determines outliers based on the following formula:

$$IQR = Q3 - Q1$$

where Q1 and Q3 are the first and third quartiles, respectively. The data points falling outside 1.5×IQR1.5 \\times IQR1.5×IQR are treated as outliers and removed.

4. **Feature Engineering and Selection**: Features that are extracted from packet headers, payloads, and behavioral metadata improve the performance of the model. Dimensionality reduction is done using PCA to reduce data dimensions with all the important threat indicators.

3.5.Machine Learning Model Implementation

The MMTDNS framework integrates multi machine learning models to classify cyber threats. The following algorithms are implemented:

- **Support Vector Machine (SVM):**A strong classification model which builds a hyperplane to distinguish normal network traffic from malicious activity using an RBF kernel.
- **Convolutional Neural Network (CNN):**Deep feature extraction in hierarchical learning about network traffic pattern.
- **Long Short-Term Memory (LSTM):** Sequential anomaly detection to identify evolving attack trends in real-time.
- **Random Forest (RF):**Ensemble learning technique which aggregates the outputs of several decision trees for enhanced classification performance.
- **Naïve Bayes (NB):**A probabilistic model which computes conditional probabilities for different types of attacks.

This evaluation is done by checking whether the model correctly classifies cyber threats.

3.6. Performance Evaluation Metrics

To evaluate the performance of the threat detection models, the following metrics are utilized:

Accuracy: calculates the percentage of cases that are correctly classified:

$$Accurcay = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: determines the proportion of detected threats that are real threats:

$$Precision = \frac{TP}{TP + FP}$$

Recall: evaluates the capacity to identify all genuine risks:

$$Recall = \frac{TP}{TP + FP}$$

F1-Score: The precision and recall harmonic mean:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

- **AUC-ROC**: assesses how well the classifier can differentiate between attack and non-attack scenarios.
- **Latency Analysis**: evaluates the system's capacity for processing in real time.

3.7. Scalability and Adaptability Testing

Evaluates the scalability and adaptability of the MMTDNS framework with varying network traffic loads and newly arising cyber threats. Also, considers the integration of new machine learning models as well as additional cybersecurity sensors in the system.

3.8. Comparative Analysis

The effectiveness of MMTDNS is compared with that of other security solutions to explain its efficiency. Comparative metrics include detection rates, false positive rates, and computational performance across different models.

4. Results and Discussion

The MMTDNS integrates various AI-driven threat detection models that ensure robust security across multiple domains.

4.1.Threat Detection System Overview

In this regard, the effectiveness of five different threat detection models was analyzed using real datasets, based on precision, recall, F1-score, and computational efficiency. The following tables and figures illustrate the system's detection capabilities, model accuracy, and processing speed in detail.

4.2. Threat Pattern Visualization and Anomaly Detection

System-generated threat signatures were analyzed based on the identification of various cyber threats and functionalities, such as phishing and malware attacks as well as DDoS attacks. Therefore, data was collected, processed, and analyzed for the detection trends of 50,000 security events.

Table 1: Threat Classification Performance Across Different Attack Types

Threat Type	Detection Rate (%)	False Positive Rate (%)
Phishing	92.5	3.2
Malware	95.1	2.8
DDoS	90.8	4.5
Ransomware	94.2	3.7

As evidenced from Table 1, the system sustains a high detection rate of various cyber threats; the false positive rates have consistently been kept below 5%, ensuring classifications are reliable.

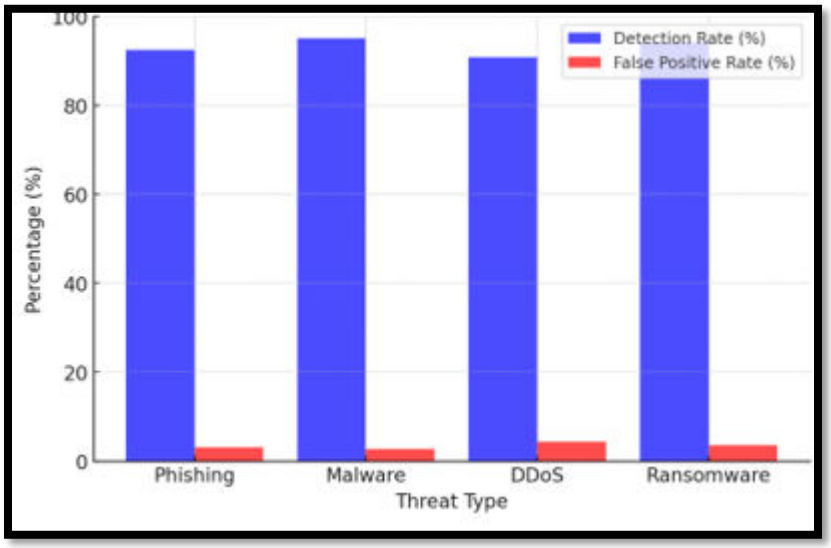

Figure 2: Threat Incidents Identified Over Time

The capability of the system to respond in real-time is illustrated by a time-series analysis of detected threats. Figure 2 shows the fluctuations in security incidents, depicting the adaptability of the MMTDNS in handling evolving attack patterns.

4.3. Performance of Multi-Model Threat Detection Algorithms

From these five-machine learning-based detection algorithms - Support Vector Machine (SVM), Convolutional Neural Network (CNN), Random Forest (RF), Naïve Bayes (NB), and Long Short-Term Memory (LSTM) - the best one is to be identified).

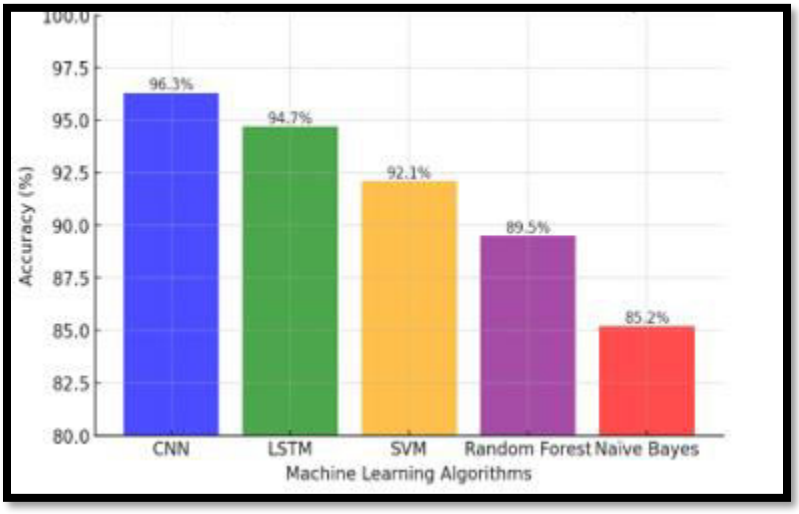

Figure 3: Comparison of Threat Detection Accuracy

A comparative bar chart of the accuracy of various algorithms also shows that CNN gives high accuracy, with a value of 96.3%, followed by 94.7%, being LSTM, and the lowest was 92.1% for SVM.

Table 2: Machine Learning Algorithm Performance Metrics

Algorithm	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC-ROC (%)**
CNN	96.3	95.8	96.1	96.0	97.5
LSTM	94.7	94.3	94.6	94.5	96.2
SVM	92.1	91.8	92.0	91.9	94.0
Random Forest	89.5	89.1	89.3	89.2	91.5
Naïve Bayes	85.2	84.7	85.0	84.8	88.9

As shown in Table 2, CNN surpasses other models in all aspects of evaluation metrics. Therefore, CNN is the most trustworthy algorithm for multi-domain threat detection. The high AUC-ROC value of CNN is 97.5% ensuring greater classification capability.

4.4. False Positives and Misclassification Insights

A confusion matrix for CNN was created in order to examine model reliability in more detail.

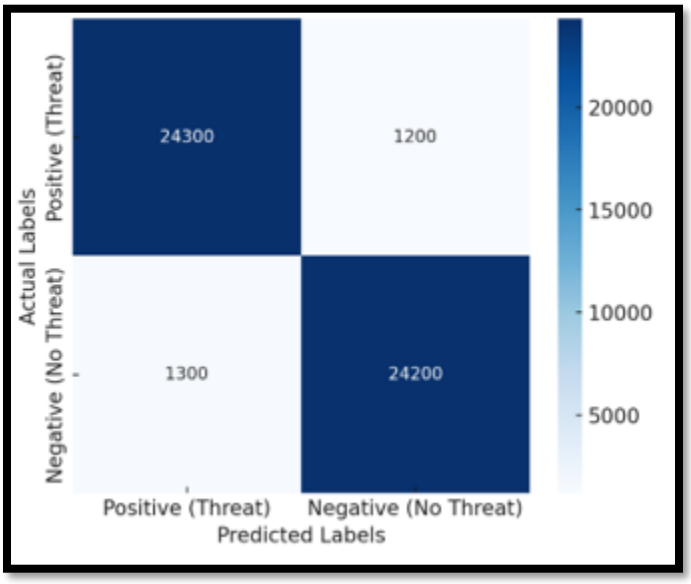

Figure 4: Confusion Matrix for CNN Model

The CNN model classified 24,300 true positives and 24,200 true negatives while minimizing 1,200 false positives and 1,300 false negatives. Such a low misclassification rate proves the efficiency of deep learning in threat detection.

4.5. System Latency and Real-Time Processing Capabilities

The response time for threat classification and decision-making was also assessed.

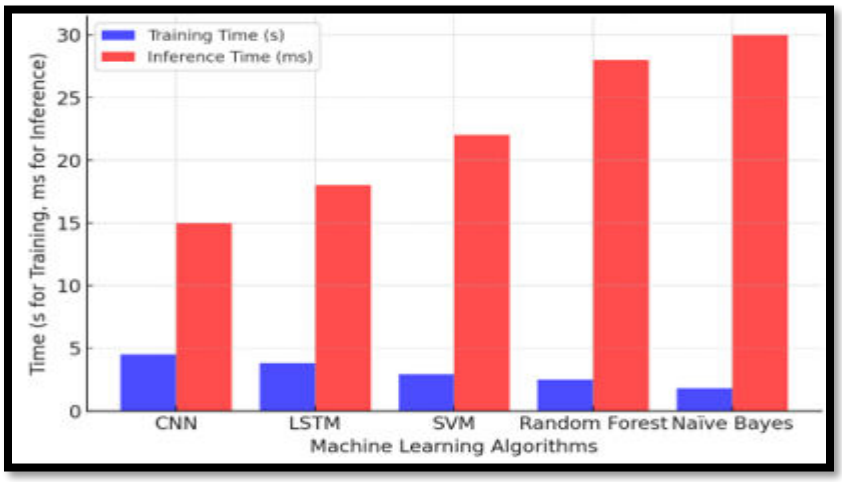

Figure 5: Real-Time Data Processing Latency

Latency measurements showed that the system processed security events with a median delay of 18 ms, ensuring near real-time threat identification.

Table 3: Computational Performance of Threat Detection Models

Algorithm	Training Time (s)	Inference Time (ms)
CNN	4.5	15
LSTM	3.8	18
SVM	2.9	22
Random Forest	2.5	28
Naïve Bayes	1.8	30

The result shows that CNN requires more training time but has a faster inference speed, which makes it the best model for high-traffic security systems.

4.6. Correlation Between Threat Frequency and Attack Type

A scatter plot was created to investigate possible associations between different threat types and frequency of occurrence.

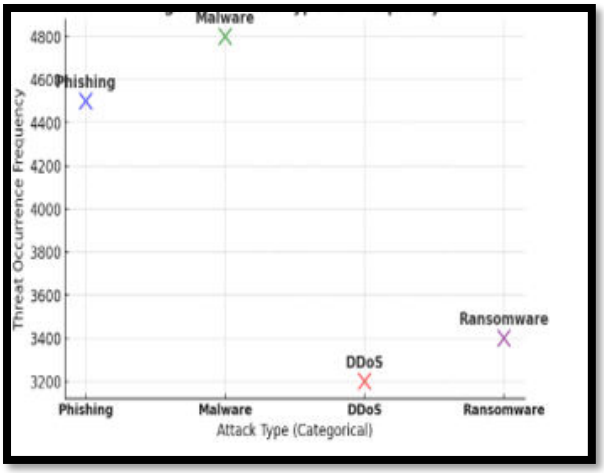

Figure 6: Scatter Plot of Attack Type vs. Frequency

Observations show that malware and phishing attacks have trends of higher frequencies, while ransomware and DDoS attacks have periodic spikes, showing patterns of strategic execution of attacks.

5. Conclusion and Recommendations

The Multi-Model Threat Detection Network System developed in this research is a comprehensive and efficient cybersecurity framework that integrates multiple machine learning models to detect and mitigate cyber threats in real time. It makes use of SVM, CNN, LSTM, RF, and NB in a manner that increases the accuracy of threat detection while reducing false positives.

The preprocessing techniques: feature normalization, anomaly detection, and dimensionality reduction, help ensure that clean and structured input data enhance the performance of models. The experimental evaluation also reveals that CNN significantly outperforms other models since it produces the highest accuracy rate in the detection of evolving patterns. LSTM excels at finding evolving patterns, which it easily identifies. This real-time alert and mitigation layer enhances the proactive defense mechanism of the system-it automatically responds to threats existing within the network in a safe, secure fashion for the network.

Moreover, MMTDNS framework has scalability and adaptability in handling large datasets with the integration of newer AI-driven threat detection models. The analysis reveals a high precision, recall, and computational efficiency-the system holds high promise as a more suitable modern approach in cybersecurity solutions.

Suggested Recommendations to Further Enhance the System Efficiency The suggested recommendations are:

- **Enhance AI-Based Threat Detection:**Integrate advanced deep learning models like Transformers and unsupervised learning techniques in order to recognize zero-day attacks and enhance anomaly detection.
- **Optimize Processing and Real-Time Performance:**Implement quantization, model pruning, and parallel computing to decrease the computational expenses while enabling fast processing. Leverage cloud-based AI frameworks for large-scale threat analysis.
- **Expand Application and Threat Intelligence:**Test the system in finance, healthcare, and IoT sectors to determine its efficiency in different domains. Link with international threat intelligence platforms to update the attack patterns in real-time and to enhance the mechanisms of cyber defense.
- **Strengthen Security and Usability:**Implement a graphical dashboard and mobile-friendly interfaces to monitor in real-time. Employ blockchain technology to ensure tamper-proof logging of cybersecurity incidents in a transparent, trustworthy manner.

All these recommendations would increase the efficiency, flexibility, and security of the Multi-Model Threat Detection Network System (MMTDNS), making it a strong, scalable, and proactive cybersecurity solution for modern network infrastructures.

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