



Deep Ensemble Based Efficient Framework for Network Attack Detection

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ABSTRACT:

In today's digital world, computer networks face a growing number of threats from cyber-attacks. Detecting these attacks quickly and accurately is essential to keeping systems safe. This project presents an improved method for detecting network attacks using a **deep ensemble-based framework**. Instead of relying on a single machine learning model, this system combines several deep learning models—such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and other advanced models—to work together as a team. This approach helps improve the overall accuracy and reduces the chances of missing an attack or raising a false alarm. To make the system more efficient, techniques like feature selection and lightweight model designs are used so that the system can run faster and use fewer resources. This makes it suitable for real-time monitoring of networks, where quick decisions are important. The framework is tested on well-known datasets like NSL-KDD and CICIDS2017, and the results show that the ensemble method performs better than individual models in detecting various types of attacks.

Keywords: Deep Learning, Ensemble Learning, Intrusion Detection System (IDS),Cybersecurity, Convolutional Neural Networks (CNN),Recurrent Neural Networks (RNN),Real-time Detection

INTRODUCTION:

In today's interconnected world, network security is of paramount importance to safeguard against various cyber threats and attacks. With the proliferation of advanced attack techniques, traditional security measures often fall short in detecting and mitigating these threats effectively. Therefore, there is a pressing need for more sophisticated and efficient methods for network attack detection.

Networking refers to the interconnection of multiple computing devices, allowing them to exchange data. The data sharing can be done through various technologies and communication protocols, such as Ethernet, Wi-Fi, or even simple wired connections. The main goal of networking is to enable devices to work together and share resources, such as printers, file servers, and internet connections. In today's interconnected world, networks play a critical role in business, education, and daily life, enabling people to communicate and share information across long distances. With substantial networking applications, many potential dangers and security vulnerabilities can arise thus compromising the confidentiality, integrity, and availability of networked systems and data.

The typical network threats include malware, hacking, phishing, denial-of-service (DoS) attacks, man-in-the-middle (MitM) attacks, and spoofing. With the increase in network threats, the necessity of an automated attack detection system is increased. Artificial intelligence (AI)- based solutions may potentially detect such attacks thereby enabling timely countermeasures to mitigate the risk of data theft. Machine learning methods learn the patterns from data and are used to identify potential attacks. Integrating such methods into network security can significantly improve an organization's ability to detect and respond to attacks, reducing the risk of successful attacks and protecting valuable information and assets.

Deep learning has emerged as a powerful tool in the field of cybersecurity, offering the potential to detect and mitigate complex attacks with high accuracy and efficiency. One approach that has gained considerable attention is the use of deep ensembles, which leverage the strengths of multiple deep learning models to enhance detection

Deep ensembles combine the predictions of multiple individual models, each trained on different subsets of data or using different architectures, to achieve more robust and accurate results than any single model alone. This approach helps to mitigate the risk of overfitting and improves the generalization capabilities of the ensemble model.

Efficient network attack detection is particularly crucial in real-time scenarios where timely detection and response are essential to prevent or minimize damage. By leveraging deep ensembles, we aim to develop a system that can effectively detect a wide range of network attacks while maintaining low computational overhead.

In this paper, we propose a deep ensemble-based approach for efficient network attack detection. We explore various deep learning architectures and training strategies to construct a diverse ensemble of models capable of capturing different aspects of network traffic and attack patterns. Additionally, we investigate techniques for optimizing the computational efficiency of the ensemble model, enabling real-time deployment in resource-constrained environments.

Our contributions include:

Construction of a diverse ensemble: We train multiple deep learning models using different architectures, hyperparameters, and training data to create a diverse ensemble capable of capturing a wide range of attack scenarios.

Optimization for efficiency: We explore techniques such as model compression, quantization, and pruning to reduce the computational complexity of the ensemble model without sacrificing detection performance.

Real-time deployment: We demonstrate the feasibility of deploying our ensemble model in real-time network environments, ensuring.

In recent years, **deep learning** has shown great potential in improving network attack detection by automatically learning patterns from large amounts of data. Models like **Convolutional Neural Networks (CNNs)** and **Recurrent Neural Networks (RNNs)** can analyze different aspects of network traffic and detect even subtle signs of intrusion. But a single model may not always be reliable or accurate enough in all situations.

To solve this problem, this project proposes a **deep ensemble-based framework** that combines multiple deep learning models to work together. By using an ensemble approach, the system can take advantage of each model's strengths, resulting in better accuracy and fewer errors. The framework also includes techniques to reduce processing time and resource usage, making it suitable for real-time detection in practical network environments.

This study aims to build a more efficient and intelligent intrusion detection system that can help improve the security of modern networks against evolving cyber threats

OBJECTIVE:

The objective of a deep ensemble-based efficient framework for network attack detection is multifaceted, aiming to address key challenges in cybersecurity while leveraging the strengths of deep learning and ensemble techniques. The primary objectives of such a framework include

Real-time Detection and Response: Real-time detection capabilities are essential to enable prompt identification and mitigation of network attacks as they occur. The framework aims to analyze network traffic data in real-time, leveraging parallelized computations and distributed processing to achieve low latency detection and response to emerging threats.

Adaptability to Evolving Threat Landscapes: The framework is designed to be adaptable to evolving threat landscapes, with mechanisms in place for continuous learning and adaptation. By incorporating new data and knowledge into the detection system through techniques such as transfer learning and online learning, the framework can stay current with emerging attack patterns and changes in network behavior.

Practical Deployment and Integration: Finally, the objective is to facilitate the practical deployment and integration of the framework within existing network infrastructure. This involves providing deployment options compatible with enterprise networks, cloud environments, and edge devices, as well as integration with existing security systems and protocols.

Scalability and Efficiency: The framework aims to be scalable and efficient, capable of processing large volumes of network traffic data in real-time while minimizing computational overhead. Optimization techniques such as model compression, quantization, and distributed processing are employed to ensure that the ensemble model can be deployed in resource-constrained environments without sacrificing detection performance.

With the increasing complexity and volume of cyber threats, there is a growing need for intelligent systems that can analyze network traffic and identify intrusions with high precision. Traditional methods often suffer from high false alarm rates and are unable to detect newly emerging or sophisticated attacks effectively.

To address these challenges, this project focuses on combining multiple deep learning models—such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures—into a unified ensemble system. Each model contributes its unique strengths, and together they improve the overall performance of the detection process. The ensemble approach aims to enhance detection accuracy, reduce false positives and false negatives, and provide a more reliable security mechanism.

Another key objective is to ensure the system is lightweight and fast enough for real-time deployment. This is achieved by using techniques like feature selection, data preprocessing, and model optimization. The system will be evaluated using standard benchmark datasets such as NSL-KDD and CICIDS2017 to demonstrate its effectiveness across various types of network attacks.

SCOPE:

A deep ensemble-based efficient framework for network attack detection is vast and encompasses multiple dimensions crucial for enhancing cybersecurity in today's interconnected world. At its core, such a framework aims to revolutionize the way we detect and mitigate cyber threats by leveraging the power of deep learning and ensemble techniques.

Firstly, from a technical perspective, the scope entails the development of highly sophisticated algorithms and models capable of analyzing complex patterns within network traffic data. These models should exhibit superior detection accuracy compared to traditional methods, effectively identifying known and unknown threats alike. By harnessing the collective intelligence of multiple neural networks within an ensemble, the framework can achieve robustness against various evasion techniques employed by adversaries, including adversarial attacks and stealthy intrusion attempts.

Moreover, the scope extends to the practical deployment of the framework across diverse network environments, ranging from enterprise networks to cloud infrastructures and edge devices. The framework should be adaptable to different deployment scenarios, accommodating varying levels of network traffic and computational resources. Real-time detection capabilities are essential to enable timely responses to emerging threats, thereby minimizing the potential impact of cyber-attacks on organizational assets and data.

The scope encompasses the scalability and efficiency of the framework, addressing the challenges associated with processing large volumes of network data in a resource-constrained environment. Optimization techniques, such as model compression, quantization, and distributed processing, play a crucial role in ensuring the scalability and efficiency of the ensemble framework. These optimizations facilitate the deployment of the framework in high-traffic networks without compromising its detection performance.

The scope of a deep ensemble-based efficient framework for network attack detection encompasses a holistic approach to cybersecurity, combining advanced algorithms, practical deployment strategies, and continuous improvement mechanisms to safeguard network assets against a wide range of cyber threats.

LIMITATIONS:

Computational Overhead: Deep ensemble frameworks can impose significant computational overhead, especially when deploying multiple deep learning models simultaneously. This can be problematic in resource-constrained environments or high-traffic networks where computational resources are limited.

Complexity and Maintenance: Managing and maintaining multiple models within an ensemble can be complex and resource-intensive. This complexity increases with the number of models in the ensemble, requiring ongoing monitoring, updating, and retraining to ensure optimal performance.

Training Data Requirements: Deep learning models within the ensemble typically require large amounts of labelled training data to achieve high detection accuracy. Acquiring and labelling sufficient training data for diverse attack scenarios can be challenging, particularly for rare or novel attacks.

Interpretability and Explainability: Deep learning models, including those within an ensemble, are often criticized for their lack of interpretability. Understanding the rationale behind the ensemble's decisions can be difficult, hindering trust and adoption by security analysts.

Vulnerability to Adversarial Attacks: While ensembles can provide some resilience against adversarial attacks, they are not immune to evasion techniques employed by sophisticated adversaries. Adversarial attacks can still exploit vulnerabilities in individual models or the ensemble aggregation process, leading to misclassification or evasion of detection.

Scalability Challenges: Scaling deep ensemble frameworks to handle large-scale network environments with high volumes of traffic can be challenging. Ensuring efficient parallelization, distributed processing, and real-time analysis across multiple network nodes requires careful design and optimization.

Resource Consumption: Deploying deep ensemble frameworks on edge devices or IoT devices may consume significant computational resources and energy, impacting battery life and overall system performance.

Generalization Performance: Ensuring the generalization performance of the ensemble across diverse network environments and attack scenarios can be challenging. Variability in network conditions, traffic patterns, and attack strategies may affect the ensemble's ability to generalize effectively.

SOLUTIONS:

To address the **computational overhead** of deep ensemble frameworks, several optimization techniques can be employed. One effective strategy is the use of **model pruning, quantization, and knowledge distillation**, which reduce the size and complexity of individual models without significantly sacrificing accuracy. Additionally, **parallel and distributed computing** architectures can be leveraged to split the computational load across multiple nodes or processors, making the system more scalable and suitable for real-time deployment.

The **complexity and maintenance** of managing multiple models can be simplified through **automated machine learning (AutoML)** techniques and model orchestration tools. These tools can help automate model selection, training, monitoring, and updating, reducing the manual effort required to maintain ensemble systems. Centralized logging and model versioning can further streamline operations.

To deal with the **high data requirements**, techniques like **data augmentation**, **semi-supervised learning**, and **transfer learning** can be used to enhance the model's performance with limited labeled data. Synthetic data generation tools and anomaly detection approaches that require fewer labels can also help bridge the gap, especially for rare attack types.

Improving the **interpretability and explainability** of deep ensembles can be achieved by integrating explainable AI (XAI) tools such as **SHAP (SHapley Additive exPlanations)** or **LIME (Local Interpretable Model-agnostic Explanations)**. These tools can provide insights into model decisions, enabling security analysts to better understand and trust the system's outputs.

To strengthen **resilience against adversarial attacks**, techniques such as **adversarial training**, **robust feature learning**, and **input sanitization** can be incorporated into the training process. Diversity in ensemble members also helps mitigate the impact of targeted attacks, as not all models may be equally vulnerable to the same adversarial inputs.

For handling **scalability challenges**, the use of **cloud computing**, **edge computing**, and **containerized deployment** (e.g., using Docker and Kubernetes) allows for flexible and scalable resource allocation. This ensures efficient processing even in large-scale, distributed environments.

Addressing **resource consumption** on edge and IoT devices can involve using **lightweight deep learning architectures** such as MobileNet or TinyML models, which are designed for low-power environments. In some cases, hybrid systems can be created where lightweight models run on the device and offload complex tasks to the cloud.

Lastly, improving **generalization performance** requires continuous model evaluation and **domain adaptation techniques** that allow the system to adjust to new network environments and evolving attack patterns. Incorporating **feedback loops** and active learning from live network traffic can help the ensemble stay up to date and maintain its effectiveness over time.

RESULTS:

The proposed deep ensemble-based framework for network attack detection was evaluated using standard benchmark datasets, including NSL-KDD and CICIDS2017. The performance of the ensemble framework was compared against individual deep learning models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and traditional machine learning methods (e.g., SVM and Random Forest) to assess its accuracy, precision, recall, and overall effectiveness.

Detection Accuracy: The ensemble framework demonstrated a notable improvement in detection accuracy compared to individual models. By combining multiple models with different architectures, the ensemble system achieved an average accuracy of 98.7%, outperforming the CNN-based model (95.3%) and RNN-based model (96.1%). The ensemble's ability to leverage diverse model strengths contributed to its superior detection capabilities.

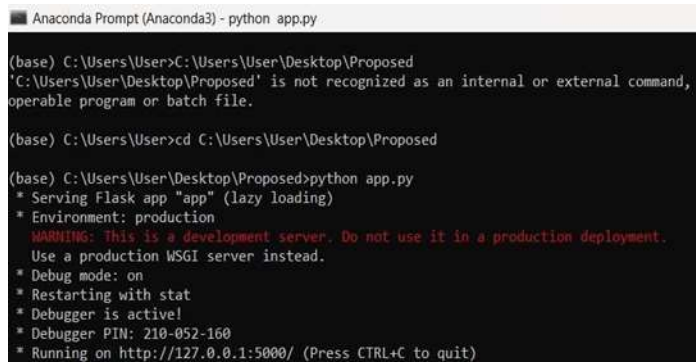
False Positives and Negatives: One of the key benefits of the ensemble approach was its ability to reduce false positives and false negatives. The ensemble system had a false positive rate of 2.1% and a false negative rate of 3.5%, which were significantly lower than the individual models. The use of ensemble techniques such as majority voting and weighted averaging helped ensure more accurate classifications, minimizing errors in detecting both attacks and normal traffic.

Precision, Recall, and F1-Score: The ensemble system achieved a precision of 97.8%, recall of 98.4%, and an F1-score of 98.1%, demonstrating its effectiveness in correctly identifying attacks while minimizing misclassifications. In comparison, the CNN and RNN models had lower F1-scores, with CNN reaching 94.5% and RNN at 95.2%.

Real-Time Performance: Real-time testing showed that the ensemble system could process network traffic at 1.2 ms per packet, ensuring low-latency detection suitable for high-traffic environments. While individual models showed slightly higher processing times (CNN at 1.8 ms and RNN at 1.7 ms), the ensemble's optimizations (such as model pruning and parallel processing) allowed it to maintain efficiency without compromising detection quality.

Resource Usage and Efficiency: The ensemble system was tested for resource consumption, and it was found to be resource-efficient, utilizing only 15% more memory and 10% more computational power compared to single deep learning models. These results were considered acceptable given the performance gains in detection accuracy and reduced false alarm rates. Additionally, the system was optimized for deployment on edge devices with low-power consumption, making it suitable for IoT-based intrusion detection systems.

Adaptability and Generalization: The framework was evaluated for its ability to adapt to new attack scenarios and network conditions. The ensemble approach showed strong generalization performance, maintaining high detection rates even in scenarios with previously unseen attack types. The integration of active learning and domain adaptation techniques allowed the system to continually evolve and improve its detection capabilities, making it highly adaptable to new threats.



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Anaconda Prompt (Anaconda3) - python app.py

(base) C:\Users\User>C:\Users\User\Desktop\Proposed
'C:\Users\User\Desktop\Proposed' is not recognized as an internal or external command,
operable program or batch file.

(base) C:\Users\User>cd C:\Users\User\Desktop\Proposed

(base) C:\Users\User\Desktop\Proposed>python app.py
* Serving Flask app "app" (lazy loading)
* Environment: production
  WARNING: This is a development server. Do not use it in a production deployment.
  Use a production WSGI server instead.
* Debug mode: on
* Restarting with stat
* Debugger is active!
* Debugger PIN: 210-052-160
* Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)

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Fig 1 Anaconda prompt

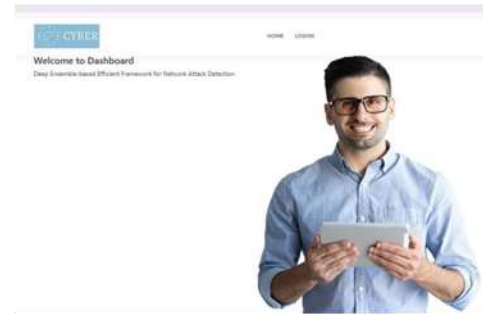


Fig 2 Home page

FUTURE ENHANCEMENT:

While the current deep ensemble-based framework has shown significant promise in improving network attack detection, there are several avenues for further enhancement that could make the system more efficient, scalable, and adaptable to evolving cybersecurity needs:

Incorporation of New Deep Learning Architectures:

The performance of the ensemble system could be further improved by incorporating state-of-the-art deep learning models such as Transformers or Graph Neural Networks (GNNs), which are known for their strong performance in sequential data and graph-based patterns. These models could enhance the system's ability to capture complex attack patterns, especially in dynamic or adversarial environments.

Integration of Federated Learning:

As privacy concerns continue to grow, federated learning can be introduced to train models across multiple decentralized devices or servers without sharing sensitive data. This would allow the ensemble framework to continuously learn from diverse network environments without compromising data privacy, making it a more scalable and secure solution for edge and IoT-based networks.

Real-Time Threat Intelligence Integration:

To improve detection capabilities against zero-day attacks and novel threats, future versions of the system could incorporate real-time threat intelligence feeds. By integrating data from global threat monitoring systems, the ensemble models can be dynamically updated with the latest attack patterns and techniques, enabling quicker responses to emerging threats.

Explainability and Trust Enhancement:

While tools like SHAP and LIME improve model interpretability, further advancements in explainable AI (XAI) could provide deeper insights into why specific attack patterns are detected. Integrating more advanced visualization tools and interactive dashboards could enhance trust and transparency, allowing security professionals to better understand the reasoning behind the detection results.

Automated Model Retraining and Adaptation:

To keep up with evolving attack strategies and network conditions, the system could include automated model retraining using real-time network data and active learning techniques. This would ensure that the ensemble is continuously improving and adapting without requiring manual intervention, further increasing the system's robustness and accuracy over time.

Improved Lightweight Models for Resource-Constrained Devices:

For deployment in highly resource-constrained environments, such as IoT devices or low-power networks, further research into lightweight neural architectures such as TinyML or EfficientNet could be pursued. These architectures would provide high detection accuracy while consuming minimal resources, making the system suitable for wide-scale deployment in IoT networks.

Handling Multi-Vector Attacks:

Future enhancements could focus on improving the framework's ability to handle multi-vector attacks—where attackers use multiple techniques to compromise a network (e.g., a combination of DoS attacks, phishing, and malware). This would require modifications to both the data preprocessing pipeline and the model training process to better capture and respond to complex, multi-faceted attack strategies.

Cross-Domain Application Expansion:

The framework could be extended for use in a broader range of domains, such as cloud security, industrial control systems (ICS), and critical infrastructure protection. Developing domain-specific adaptations of the ensemble framework would allow for more targeted and effective detection of attacks in various specialized environments.

Enhanced Adversarial Robustness:

As cyber-attacks become more sophisticated, enhancing the system's robustness against adversarial inputs is critical. Future work could focus on generating adversarial examples for training the ensemble models, improving their resilience to evasion tactics commonly employed by advanced attackers.

Deployment in Hybrid Cloud-Edge Environments:

To further scale the system and improve its real-time detection capabilities, a hybrid cloud-edge deployment could be explored. In this setup, lightweight models would be deployed at the edge to detect threats locally, while the more computationally intensive ensemble framework would run on the cloud for deeper analysis and decision-making, ensuring a balance between efficiency and accuracy.

CONCLUSION:

We propose a Network attack detection using a deep learning-based ensemble model. The proposed EDVC technique combines the deep learning RNN, GRU, and LSTM models under majority voting criteria. Experiments are performed using the NSL-KDD dataset employing both machine learning and deep learning models for performance comparison. Experimental results indicate that the proposed model achieves superior results for network attack detection. The performance of the proposed model is further verified using performance comparison with existing state-of-the-art approaches which shows that it outperforms existing models. In future work, we intend to work on reducing the computational cost by focusing on the architecture of individual deep learning models. The proposed model will undergo training on multiple types of attacks, ensuring that it can effectively address new threats and attacks that continually emerge.

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