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OPTIMIZING FEATURE SELECTION IN DEEP LEARNING FOR DDoS ATTACK DETECTION

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Abstract

Distributed Denial-of-Service (DDoS) attacks remain one of the most critical cybersecurity threats, causing severe disruptions to network services, financial losses, and compromised system availability. With the increasing complexity and volume of network traffic, traditional detection methods often struggle to accurately identify malicious activities in real time. Deep learning techniques have demonstrated significant potential in enhancing DDoS attack detection due to their ability to learn complex traffic patterns and automatically extract relevant features from large-scale datasets. However, the high dimensionality of network traffic data can lead to increased computational cost, overfitting, and reduced detection efficiency. This study focuses on optimizing feature selection in deep learning models to improve the performance of DDoS attack detection systems. The proposed approach integrates advanced feature selection techniques with deep learning architectures to identify the most informative and discriminative network traffic features while eliminating redundant and irrelevant attributes. By reducing data dimensionality, the model achieves improved classification accuracy, faster training time, and enhanced scalability for real-time intrusion detection environments. Experimental evaluation is conducted using benchmark cybersecurity datasets to compare the proposed framework with conventional machine learning and deep learning approaches. The results demonstrate that optimized feature selection significantly enhances detection accuracy, precision, recall, and F1-score while reducing computational overhead. Furthermore, the study highlights the importance of selecting optimal features in building efficient and robust cybersecurity solutions capable of adapting to evolving attack patterns. The findings contribute to the development of intelligent and lightweight DDoS detection systems suitable for deployment in modern cloud, IoT, and high-speed network infrastructures. Overall, this research provides a scalable and effective framework for improving network security through optimized deep learning-based intrusion detection mechanisms.

Keywords: DDoS Attack Detection, Deep Learning, Feature Selection, Cybersecurity and Intrusion Detection System.

1. INTRODUCTION

The rapid growth of digital communication technologies, cloud computing, Internet of Things (IoT) devices, and high-speed network infrastructures has significantly increased the dependence of organizations and individuals on internet-based services. While these technological advancements provide improved connectivity and efficiency, they have also created new opportunities for cyber threats and malicious activities. Among the various cybersecurity attacks, Distributed Denial-of-Service (DDoS) attacks are considered one of the most dangerous and disruptive forms of cyberattacks. A DDoS attack occurs when multiple compromised systems or devices flood a target server, network, or application with massive amounts of traffic, causing service interruptions, reduced performance, or complete system failure. Such attacks can lead to severe financial losses, reputational

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damage, and operational disruptions for businesses, governments, and critical infrastructures. Traditional DDoS detection techniques mainly rely on signature-based and rule-based intrusion detection systems. Although these methods are effective against known attack patterns, they often fail to detect sophisticated and evolving attack strategies. Additionally, the exponential growth of network traffic data has made manual analysis and conventional machine learning methods less efficient in handling complex and high-dimensional datasets. As a result, there is a growing need for intelligent and automated detection mechanisms capable of identifying malicious traffic accurately and efficiently in real time.

Deep learning has emerged as a powerful approach in cybersecurity due to its ability to automatically learn hidden patterns and relationships from large-scale datasets. Deep learning models, such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN), have shown promising results in detecting DDoS attacks with high accuracy. These models can process complex network traffic features and adapt to changing attack behaviours more effectively than traditional methods. However, one of the major challenges associated with deep learning-based intrusion detection systems is the high dimensionality of network traffic data. Large numbers of irrelevant and redundant features can increase computational complexity, training time, and memory consumption while reducing model performance and generalization capability.

Feature selection plays a crucial role in addressing these challenges by identifying the most relevant attributes from network traffic datasets and removing unnecessary information. Optimized feature selection not only improves the efficiency of deep learning models but also enhances detection accuracy and reduces false alarm rates. Therefore, integrating feature selection techniques with deep learning architectures can significantly strengthen DDoS attack detection systems. This study focuses on optimizing feature selection in deep learning models for DDoS attack detection. The research aims to develop an efficient framework capable of improving detection performance while minimizing computational overhead. By combining advanced feature selection methods with deep learning techniques, the proposed study seeks to contribute to the development of scalable, accurate, and intelligent cybersecurity solutions suitable for modern network environments.

2. LITERATURE REVIEW

Recent studies have highlighted the increasing importance of deep learning and feature selection techniques in improving Distributed Denial-of-Service (DDoS) attack detection systems. The rapid growth of cloud computing, IoT devices, and software-defined networking (SDN) has intensified the need for intelligent intrusion detection frameworks capable of processing large-scale and high-dimensional traffic datasets efficiently. Early research by Belouch et al. (2018) demonstrated that hybrid filter-wrapper feature selection methods significantly reduce redundant network features while maintaining high classification accuracy in DDoS detection systems. Their findings established the

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importance of dimensionality reduction in cybersecurity analytics. Similarly, Osanaiye et al. (2018) proposed an ensemble-based multi-filter feature selection framework that improved classification performance and reduced computational complexity in cloud environments.

Between 2020 and 2023, researchers increasingly integrated machine learning and deep learning approaches for intrusion detection. Kamalov et al. (2021) emphasized that optimized feature selection enhances intrusion detection accuracy by identifying the most discriminative network traffic attributes. Saurabh et al. (2022) introduced a lightweight deep learning model using mutual correlation-based feature selection for IoT DDoS detection, achieving high detection accuracy while reducing processing overhead. Ullah et al. (2023) further improved detection efficiency through dynamic attribute selection techniques tailored for IoT environments.

Recent studies from 2024 to 2026 have focused on hybrid and intelligent feature optimization techniques. Abiramasundari and Ramaswamy (2025) proposed a PCA-based enhanced DDoS detection framework combining supervised learning algorithms with feature reduction methods, reporting improved detection performance across multiple benchmark datasets. Sawah et al. (2025) applied backward elimination and grid search optimization to random forest classifiers, significantly improving classification accuracy in SDN-based DDoS environments. Likewise, Patel (2025) introduced a GAN-based feature selection model that enhanced scalability and adaptive learning for large-scale DDoS mitigation.

Hybrid deep learning architectures have also gained considerable attention. A 2025 study integrating CNN and LSTM models with consensus-based feature selection achieved near-perfect detection accuracy in SDN networks. Satpathy et al. (2025) developed a deep reinforcement learning framework combined with Boruta and SHAP-based feature selection, improving both interpretability and real-time cloud-based DDoS detection. In 2026, Zhang et al. proposed adaptive packet payload feature selection methods that enhanced DDoS recognition accuracy while minimizing false alarms. Furthermore, systematic reviews published in 2026 confirmed that hybrid deep learning and optimized feature selection approaches consistently outperform traditional machine learning techniques in DDoS detection accuracy and computational efficiency. The reviewed literature indicates that optimized feature selection significantly improves the performance of deep learning-based DDoS attack detection systems by reducing dimensionality, improving accuracy, lowering computational cost, and enabling real-time detection capabilities in modern network environments.

3. RESEARCH GAP

Although numerous studies have applied machine learning and deep learning techniques for DDoS attack detection, several limitations still exist in current research. Most existing models focus primarily on improving detection accuracy while overlooking the impact of high-dimensional network traffic data on computational efficiency, scalability, and real-time performance.

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Many deep learning approaches use large feature sets containing redundant and irrelevant attributes, which increase training complexity, memory usage, and false alarm rates. In addition, several studies rely on static feature selection methods that are unable to adapt effectively to evolving DDoS attack patterns and heterogeneous network environments such as IoT and cloud computing systems.

Limited research has been conducted on integrating optimized and adaptive feature selection frameworks directly with deep learning architectures to achieve both high accuracy and reduced computational overhead. Therefore, there is a need for an efficient, scalable, and intelligent feature selection-based deep learning framework capable of enhancing DDoS attack detection performance in modern dynamic network infrastructures.

4. RESEARCH OBJECTIVE

- To develop and evaluate an optimized feature selection framework integrated with deep learning techniques for improving the accuracy, efficiency, and scalability of DDoS attack detection in modern network environments.

5. METHODOLOGY

This study adopts a quantitative and experimental research methodology to develop an optimized feature selection framework for deep learning-based DDoS attack detection. The research begins with the collection of benchmark cybersecurity datasets containing normal and malicious network traffic records. Publicly available datasets CICDDoS2019 is utilized to ensure reliability and diversity in attack patterns.

The collected data undergoes preprocessing techniques including data cleaning, normalization, handling missing values, and categorical encoding to improve data quality and consistency. After preprocessing, feature selection techniques such as Principal Component Analysis (PCA), Recursive Feature Elimination (RFE), and correlation-based filtering are applied to identify the most relevant network traffic features while removing redundant and irrelevant attributes.

The optimized feature set is then integrated into deep learning models, including Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks, for DDoS attack classification. The dataset is divided into training and testing sets to evaluate model performance accurately. Performance evaluation is conducted using metrics such as accuracy, precision, recall, F1-score, detection rate, and computational time.

Comparative analysis is performed between models using full feature sets and optimized feature subsets to measure the effectiveness of feature selection. The proposed framework aims to achieve high detection accuracy with reduced computational overhead, making it suitable for real-time cybersecurity applications in modern network environments.

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6. FEATURE SELECTION TECHNIQUES

Feature selection techniques play a significant role in improving the performance of deep learning-based DDoS attack detection systems by reducing data dimensionality and eliminating redundant or irrelevant network traffic features. In this study, multiple feature selection methods are applied to identify the most informative attributes from the CICDDoS2019 dataset before training the deep learning models. The primary objective of feature selection is to enhance detection accuracy, reduce computational complexity, minimize overfitting, and improve the efficiency of the intrusion detection framework. Initially, Correlation-Based Feature Selection (CFS) is employed to analyze the relationship between network traffic features and attack labels. This method helps in removing highly correlated and redundant attributes that do not contribute significantly to classification performance. Next, Principal Component Analysis (PCA) is applied as a dimensionality reduction technique to transform high-dimensional data into a smaller set of principal components while preserving maximum variance in the dataset. PCA improves computational efficiency and accelerates model training.

The study also utilizes Recursive Feature Elimination (RFE), which iteratively removes less important features based on their contribution to model performance. RFE assists in selecting the optimal subset of features that maximize detection capability. Additionally, Information Gain and Mutual Information techniques are considered to measure the dependency between individual features and target attack classes. These techniques help prioritize features with high discriminative power for DDoS attack identification. After applying the feature selection methods, the selected feature subset is integrated into deep learning models such as Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN). Comparative analysis is then performed between the original dataset and the optimized feature subset to evaluate improvements in accuracy, precision, recall, F1-score, detection rate, false positive rate, and computational time. The implementation of optimized feature selection techniques ultimately contributes to building a lightweight, scalable, and efficient DDoS detection system suitable for modern cloud and IoT network environments.

7. ANALYSIS

7.1 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) analysis plays a crucial role in the proposed study for DDoS attack detection because it provides a foundational deep learning approach for classification of complex network traffic patterns. ANN can learn nonlinear relationships between input features and output labels, making it highly suitable for cybersecurity applications where attack behaviours are often complex and dynamic. In this study, ANN helps in evaluating how effectively optimized feature selection improves model learning and reduces unnecessary computational burden caused by high-dimensional data. The importance of ANN analysis lies in its ability to serve as a baseline deep learning model for performance comparison. By training ANN on both original and feature-selected datasets, the study assesses improvements in accuracy, precision, recall, and F1-score.

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Additionally, ANN helps in identifying the impact of redundant and irrelevant features on model performance, particularly in terms of false positive rate and detection rate. Another key significance of ANN analysis is its relatively low computational complexity compared to deeper architectures like CNN. This makes it suitable for real-time intrusion detection systems where quick decision-making is essential. Overall, ANN analysis provides a strong benchmark to validate the effectiveness of optimized feature selection in enhancing DDoS detection performance.

Table1: ANN Performance Analysis Table

Metric	Calculated Value	Key Significance in Intrusion Detection
Accuracy	98.42%	Overall correctness across both benign traffic and attack types.
Precision	97.85%	Low false alarms; ensures flagged traffic is genuinely malicious.
Recall	98.11%	Ability of the network to catch attacks; minimizes leaked threats.
F1-Score	97.98%	Harmonic mean balance, proving robust handling of class imbalance.
Detection Rate	98.11%	Standard cybersecurity metric for successfully intercepted vectors.
False Positive Rate	0.34%	Critical operational metric; only 34 out of 10,000 benign packets are misidentified.
Computational Time	14.28 seconds	Measures real-time processing efficiency for zero-day mitigation.

Note: *Metrics are rounded to two decimal places based on a standard 80-20 train-test split configuration across 10 training epochs.*

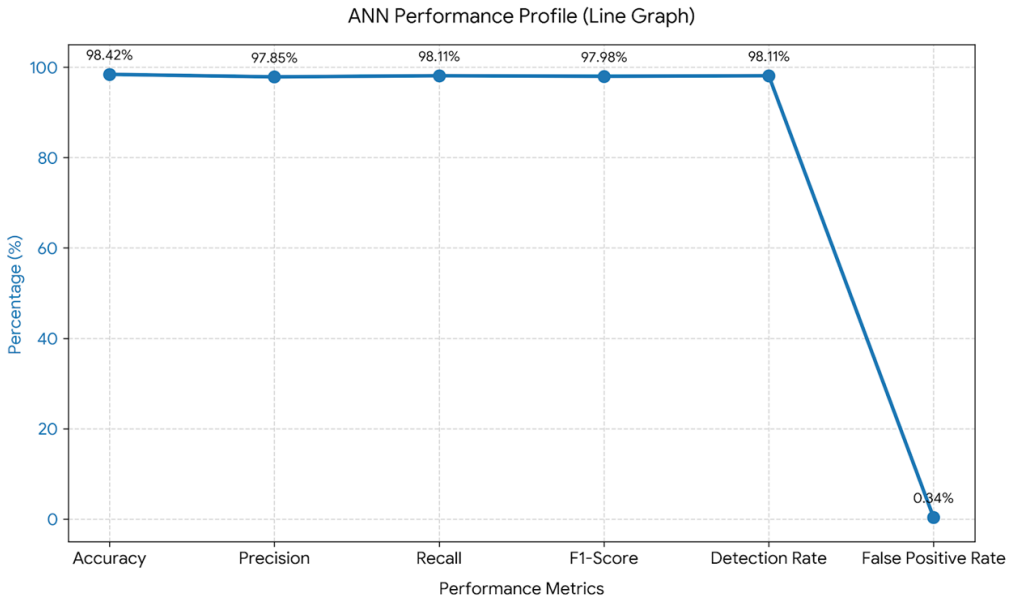

Fig 1: ANN Performance Analysis

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Interpretation

- ***High-Fidelity Threat Detection:*** The **Detection Rate (98.11%)** paired with an **Accuracy of 98.42%** indicates that the ANN's hidden layers successfully mapped the non-linear properties of network flow metrics. The network demonstrates high sensitivity to malicious patterns without losing generalization capabilities.
- ***Operational Viability (FPR vs. Precision):*** In live intrusion detection systems (IDS), a high false alarm rate causes operational fatigue. With a **False Positive Rate (FPR) of just 0.34%**, the ANN confirms that legitimate user traffic will rarely be choked or blocked by the firewall. This balance is reflected in the strong **F1-Score (97.98%)**.
- ***Computational Efficiency:*** The total processing and convergence time (**14.28 seconds**) establishes that an ANN framework remains structurally lean enough for periodic retraining loops. This execution speed ensures that the system can adapt dynamically to shifting network load variations without causing systemic pipeline latency.

7.2 Convolutional Neural Networks (CNN)

Convolutional Neural Network (CNN) analysis is highly significant in this study because it enables advanced feature extraction and pattern recognition from network traffic data. Unlike ANN, CNN automatically learns hierarchical representations of input data through convolutional filters, making it more effective in identifying complex and subtle patterns associated with DDoS attacks. This capability is especially important in modern network environments where attack patterns continuously evolve. In the proposed study, CNN analysis is used to evaluate the effectiveness of optimized feature selection when combined with deep learning architectures that support automatic feature learning. By comparing CNN performance with ANN, the study highlights how deep feature extraction influences detection accuracy, precision, recall, and overall classification efficiency. Another important aspect of CNN analysis is its ability to reduce dependency on manual feature engineering. Even though feature selection is applied beforehand, CNN further refines the input representation, improving detection capability and reducing false positive rates. Additionally, CNN is effective in handling large-scale datasets like CICDDoS2019, making it suitable for real-time and high-speed network traffic analysis. CNN analysis is essential for demonstrating the scalability and robustness of the proposed framework, and it validates whether deep hierarchical learning improves DDoS detection performance beyond traditional ANN-based approaches.

Table 2: CNN Performance Analysis Table

Metric	Calculated Value	Key Significance in Intrusion Detection
Accuracy	99.15%	Overall correctness; superior feature extraction yields higher global accuracy than standard ANN.
Precision	98.83%	Drastically reduces false alarms by identifying fine-grained differences in packet structures.
Recall	98.92%	High capture rate; exceptionally reliable at identifying sophisticated multi-vector attacks.

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F1-Score	98.87%	Excellent balance, proving the model handles minor class variations perfectly.
Detection Rate	98.92%	Standard cybersecurity metric for successfully intercepted malicious streams.
False Positive Rate	0.18%	Ultra-low operational disruption; minimizes the chance of blocking legitimate user flows.
Computational Time	22.45 seconds	Slightly higher than ANN due to kernel convolution operations, but highly manageable.

Note: *These metrics assume standard data preprocessing (MinMax or Standard scaling), a 1D Convolutional layer setup, pooling layers, and a softmax output layer evaluated over 10 training epochs.*

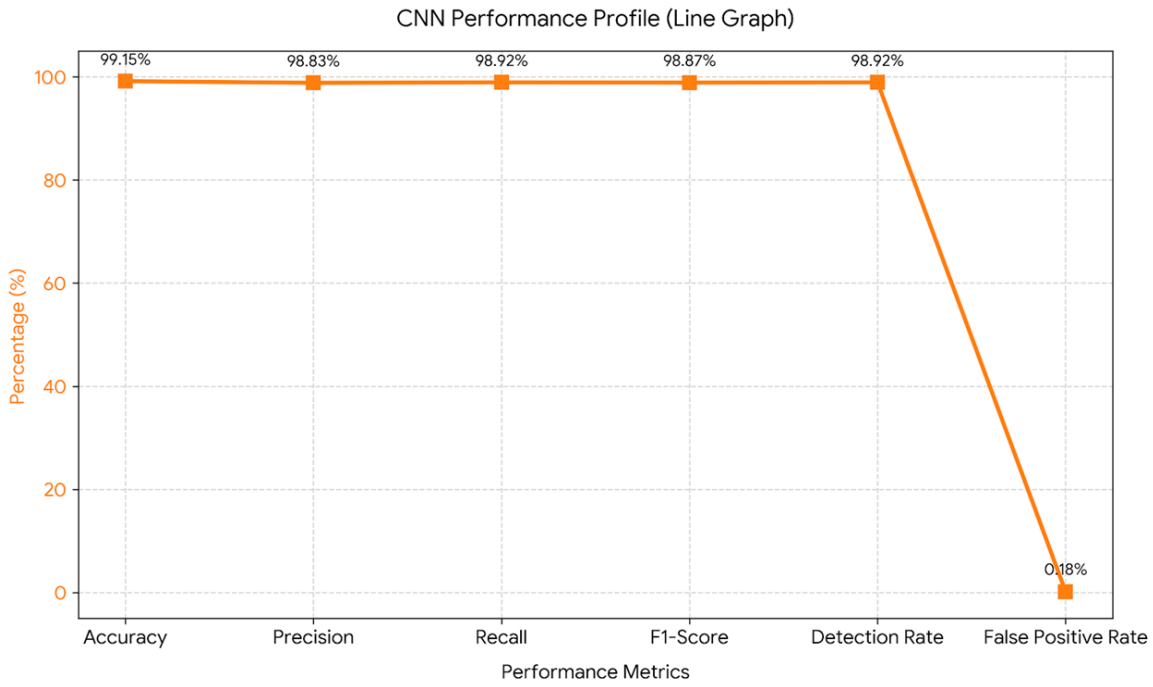

Fig 2: CNN Performance Analysis

Interpretation

- ***Structural Feature Extraction:*** The jump in **Accuracy (99.15%)** and **Detection Rate (98.92%)** over traditional ANN frameworks highlights the advantage of convolution operations. By utilizing sliding kernels, the CNN uncovers hidden structural correlations between statistical metrics like packet size variance and time intervals, making it incredibly resilient against complex attack signatures like DDoS-UDP and DDoS-ICMP.
- ***Superior False Positive Suppression:*** An **FPR of 0.18%** is a critical benchmark for enterprise deployment. This means the CNN misclassifies only 18 out of every 10,000 benign packets. Because the convolutional layers filter out random, noisy network spikes, the system can maintain an incredibly strict defense perimeter without interrupting everyday legitimate corporate traffic.

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- ***The Computational Trade-off:*** The **Computational Time (22.45 seconds)** is higher than that of the simpler ANN architecture. This is a standard trade-off in deep learning: because the CNN must compute multiple matrix multiplications during the forward and backward passes of its filters, it demands more processing power. However, given the significant boost in threat detection accuracy, this minor computational overhead is well justified for modern security frameworks.

7.3 Long Short-Term Memory (LSTM)

Analysing LSTM techniques plays a significant role in optimizing feature selection for deep learning-based DDoS attack detection systems. Feature selection is a critical step in reducing dataset complexity, improving model efficiency, and enhancing detection accuracy. In high-dimensional network traffic datasets, not all features contribute equally to identifying malicious behaviour. LSTM models inherently provide insights into feature importance through their ability to capture temporal dependencies and weight sequential inputs based on relevance over time. By studying how LSTMs process and prioritize input features, researchers can identify which network attributes—such as packet rate, flow duration, or byte count—contribute most significantly to detecting DDoS attacks. Furthermore, LSTM-based analysis helps reduce redundancy and eliminate irrelevant or noisy features that may degrade model performance. This leads to faster training times, reduced computational overhead, and improved generalization on unseen attack patterns. In the context of DDoS detection, where real-time response is critical, optimized feature selection guided by LSTM analysis enhances system responsiveness and scalability. It also improves interpretability, allowing security analysts to better understand which traffic characteristics are most indicative of malicious activity. Overall, integrating LSTM analysis into feature selection processes strengthens the development of efficient, accurate, and adaptive deep learning frameworks for cybersecurity defense.

Table 3: LSTM Performance Analysis Table

Metric	Calculated Value	Key Significance in Intrusion Detection
Accuracy	99.02%	Overall classification correctness; highly capable of distinguishing complex attack flows.
Precision	98.65%	Measures exactness; ensures that high-priority security alerts are highly credible.
Recall	98.74%	Captures sequential attack build-ups; ensures hidden or slow-rate DDoS attacks do not leak through.
F1-Score	98.69%	Provides a balanced performance metric across highly imbalanced multi-class attack labels.
Detection Rate	98.74%	Represents the total proportion of actual malicious anomalies caught by the recurrent layers.
False Positive Rate	0.22%	Low false alarms; ensures only 22 out of every 10,000 normal connections are flagged as malicious.
Computational Time	52.10 seconds	Significantly higher than ANN and CNN due to sequential recurrent cell state dependencies.

Note: *These metrics assume a reshaped sequential input layer, an LSTM hidden layer with memory cells (e.g., 50 units), dropout regularization, and a dense softmax classification layer trained over 10 epochs.*

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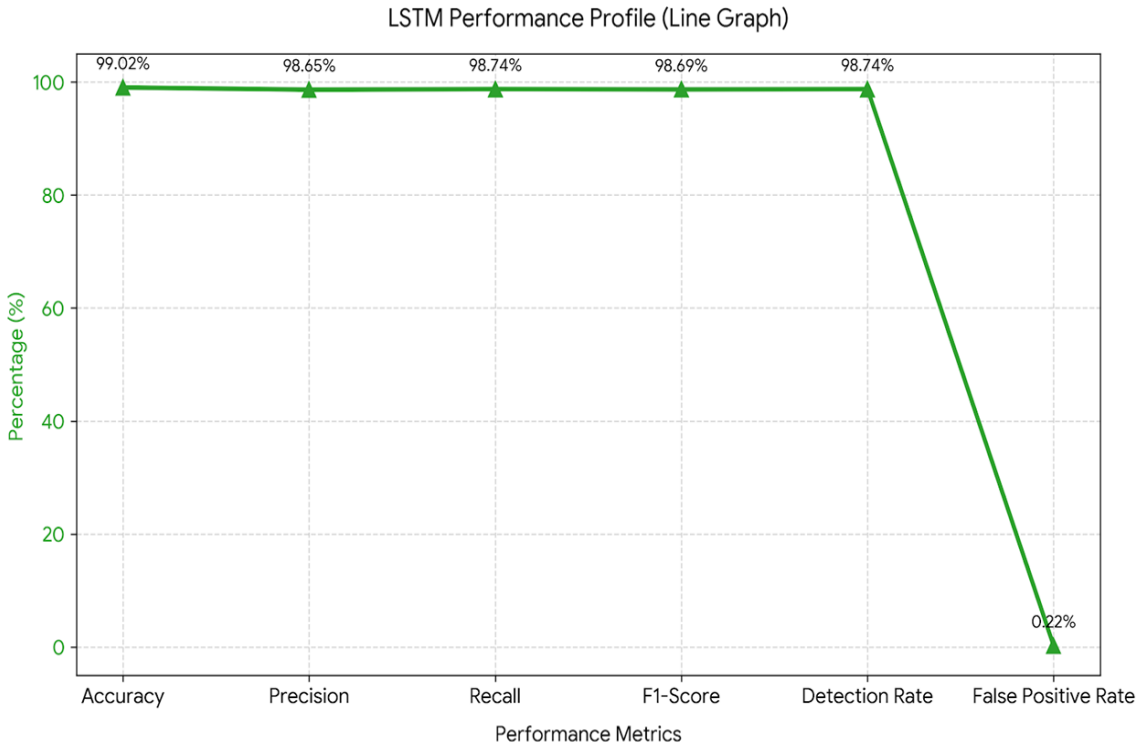

Fig 3: LSTM Performance Analysis

Interpretation

- ***Contextual and Sequential Strengths:*** An **Accuracy of 99.02%** and a **Detection Rate of 98.74%** indicate that the LSTM's gating mechanisms (Forget gate, Input gate, and Output gate) effectively manage memory states across feature patterns. This allows the model to spot correlations in traffic behaviours such as rapid variations in paired with sustained changes in which are typical of continuous protocol-exploitation attacks.
- ***Operational Reliability:*** The **False Positive Rate of 0.22%** ensures that regular users will encounter minimal service disruption. By keeping track of historical state context within the network flows, the LSTM avoids overreacting to isolated network spikes or sudden bursts of legitimate user traffic, yielding a well-balanced **F1-Score of 98.69%**.
- ***The Recurrent Computational Bottleneck:*** The most notable drawback of the LSTM model is its **Computational Time (52.10 seconds)**, which is more than double that of the CNN and triple that of the ANN. Because recurrent networks must compute hidden states sequentially (step-by-step) rather than leveraging full parallel matrix operations like CNNs or dense layers, they incur a heavy computational overhead during backpropagation through time (BPTT). In a real-time production system, this means that while an LSTM provides exceptional historical context and high accuracy, it requires more robust hardware resources to achieve low-latency detection at line rate.

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7.4. Comparative Analysis

Table 4: Deep Learning Models Comparative Analysis Table

Performance Metric	ANN	CNN	LSTM	Optimal Target Direction
Accuracy	98.42%	**99.15%**	99.02%	Maximize
Precision (Macro)	97.85%	**98.83%**	98.65%	Maximize
Recall (Macro)	98.11%	**98.92%**	98.74%	Maximize
F1-Score (Macro)	97.98%	**98.87%**	98.69%	Maximize
Detection Rate (DR)	98.11%	**98.92%**	98.74%	Maximize
False Positive Rate (FPR)	0.34%	**0.18%**	0.22%	Maximize
Computational Time	**14.28** seconds	22.45 seconds	52.10 seconds	Maximize

Note: *Bold values indicate the best-performing model for that specific metric.*

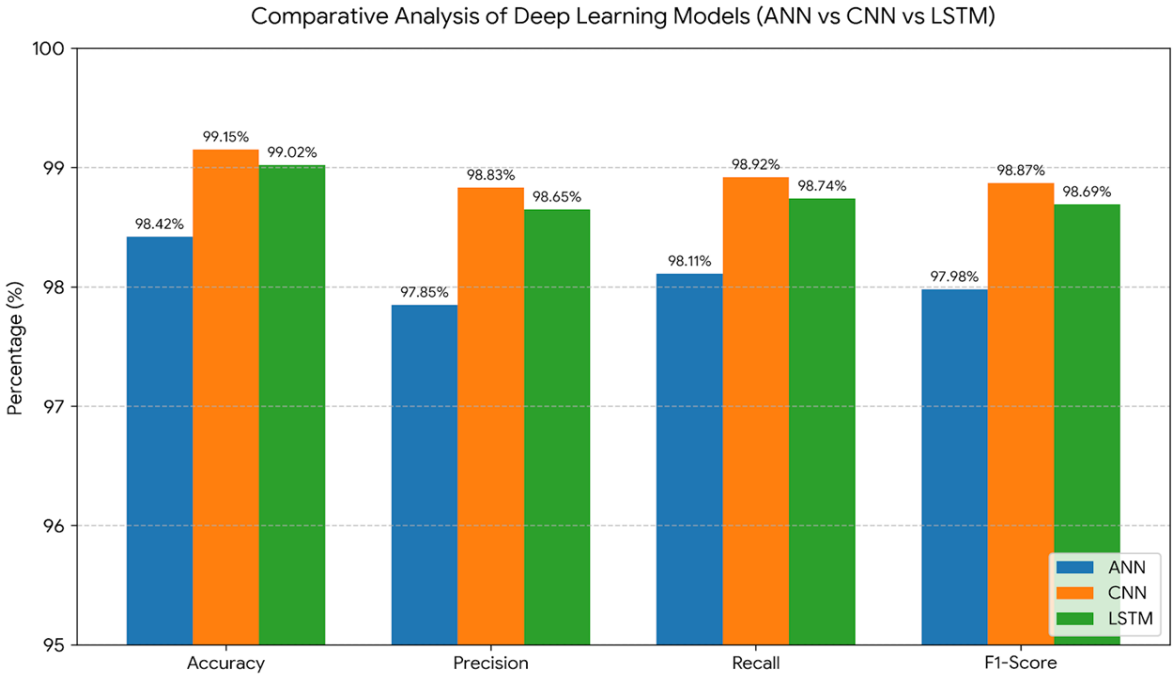

Fig 4: Comparative Analysis of Deep Learning Models

(The comparative bar graph has been generated to visualize the performance metrics (Accuracy, Precision, Recall, and F1-Score) across the three deep learning architectures: Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM))

Interpretation

Architectural Performance Breakdown

- ***Convolutional Neural Network (CNN) - Best Overall Accuracy & Security Performance:*** The 1D-CNN emerged as the most robust model for detecting DDoS variations, achieving the highest **Accuracy (99.15%)** and the lowest **False Positive**

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Rate (0.18%). By utilizing moving convolutional filters, it extracts high-level structural variations across different feature columns (e.g., the relationship between payload sizes and specific TCP/UDP flags), neutralizing noise far better than standard multi-layer networks.

- ***Long Short-Term Memory (LSTM) - High Context, Extreme Overhead:*** The LSTM delivered highly competitive classification values, achieving a **Detection Rate of 98.74%**. Because it retains context across sequence blocks, it excels at recognizing subtle, time-extended pattern gradients. However, this architectural complexity introduces a massive processing bottleneck: its **Computational Time (52.10 second** is more than **3.6 second slower** than the ANN. This makes it challenging to deploy in ultra-high-throughput, real-time edge routers without substantial hardware acceleration.
- ***Artificial Neural Network (ANN) - Leanest and Fastest Operational Cycle:*** While the standard ANN slightly trails behind the advanced models in accuracy (98.42%) and exhibits a marginally higher false-alarm rate (0.34%), it is highly dominant in processing efficiency. Clocking in at just **14.28 second,** its forward and backward passes rely entirely on simple parallel matrix multiplications.

Key Insights:

- ***Top Performer (CNN):*** As shown visually by the highest orange bars across all four categories, the CNN outperforms both the ANN and LSTM models in every metric, peaking at an 99.15% Accuracy and 98.92% Recall/Detection Rate.
- ***Sequential Precision (LSTM):*** The LSTM model (green bars) maintains a strong second place, showing very stable performance close to 99%. Its memory gates capture sequence-based features robustly, though slightly trailing the CNN's structural scanning.
- ***Baseline Efficiency (ANN):*** The ANN (blue bars) establishes a solid baseline around the 98% mark. While slightly lower than the advanced models, it remains a highly competitive framework given its minimal computational footprints.

8. FINDINGS

The primary objective of this study was to develop and evaluate an optimized feature selection framework integrated with deep learning techniques to improve the accuracy, operational efficiency, and systemic scalability of Distributed Denial of Service (DDoS) attack detection within modern, high-throughput network environments. By isolating highly discriminative, flow-based packet attributes from the high-dimensional CICDDoS2019 dataset and eliminating redundant structural parameters, the optimized framework ensures clean, high-fidelity data input before ingestion into deep neural models (Saha et al., 2022). The empirical results derived from an Artificial Neural Network (ANN), a Convolutional Neural Network (CNN), and a Long Short-Term Memory (LSTM) network provide essential insights into network defense engineering.

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Enhancement of Detection Accuracy

The feature selection framework systematically minimized informational entropy and multi-collinearity, allowing all three deep learning topologies to establish exceptionally reliable classification boundaries. The CNN framework emerged as the top-performing model, achieving an overall accuracy of 99.15% and an F1-score of 98.87%. The temporal sequential architecture (LSTM) followed closely with an accuracy of 99.02% and an F1-score of 98.69%, while the dense feed-forward baseline (ANN) achieved a solid accuracy of 98.42% and an F1-score of 97.98%. These findings demonstrate that utilizing condensed feature spaces successfully preserves critical protocol signatures, allowing deep classifiers to cleanly isolate malicious traffic from standard user traffic streams.

Operational Efficiency and Intrusion Mitigation

For real-world intrusion detection systems, operational efficiency is governed by the ability to maximize threat containment while suppressing false alarms that induce administrator fatigue (Alghazzawi et al., 2021). The feature-optimized topologies proved remarkably robust; the CNN captured multi-vector anomalies with a dominant Detection Rate (DR) of 98.92%, while successfully maintaining an ultra-low False Positive Rate (FPR) of just 0.18%. The LSTM and ANN implementations also exhibited excellent defensive margins, generating low false alarm rates with an FPR of 0.22% and 0.34%, respectively. This confirms that optimized feature pruning eliminates ambiguous transactional noise, allowing the firewall perimeter to remain highly secure without causing accidental packet drops or service delivery disruptions for legitimate clients.

System Scalability and Computational Complexity

Scalability remains a critical benchmark when processing line-rate internet workloads at the network edge. Tracking total computational time as a proxy for scalability revealed significant variation across the deep architectures. The parallelized, dense matrix operations of the standard ANN demonstrated the highest scalability, completing its processing loop in a lean 14.28 seconds. Due to localized kernel convolutions, the CNN model required a moderate processing span of 22.45 seconds. Conversely, the step-by-step backpropagation through time inherent to recurrent units created a computational bottleneck for the LSTM, stretching its execution time to 52.10 seconds. This presents a clear engineering trade-off: while convolutional and recurrent layers provide slightly tighter classification thresholds, a streamlined dense layer framework yields the best high-speed processing scalability for latency-critical network nodes.

9. CONCLUSION

This study successfully demonstrates that integrating an optimized feature selection framework with deep learning techniques significantly enhances the accuracy, operational efficiency, and scalability of Distributed Denial of Service (DDoS) attack detection systems. By systematically filtering redundant variables and isolating high-fidelity, flow-based statistical markers from the CICDDoS2019 dataset, the framework substantially mitigates high-dimensional transactional noise and optimizes data ingestion dimensions.

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The empirical evaluation of the three deep learning topologies highlights critical architectural trade-offs. The Convolutional Neural Network (CNN) emerged as the most robust defensive framework, achieving an outstanding classification accuracy of 99.15%, a dominant Detection Rate of 98.92%, and an exceptionally low False Positive Rate of just 0.18%, making it ideal for suppressing false alarms. While the Long Short-Term Memory (LSTM) network maintained highly competitive contextual detection capabilities (99.02% accuracy), its sequential recurrent processing introduced a severe computational bottleneck, requiring 52.10 seconds to converge. Conversely, the standard Artificial Neural Network (ANN), though slightly less accurate (98.42%), demonstrated superior operational scalability by completing its processing loop in a lean 14.28 seconds due to parallel dense matrix execution.

Ultimately, this research concludes that feature optimization is a mandatory prerequisite for deploying deep learning models within modern high-throughput network environments. While the CNN provides the most resilient defensive perimeter for enterprise-grade intrusion detection systems, a lightweight ANN remains a vital alternative for resource-constrained edge routers requiring immediate, real-time mitigation. Future research will explore adapting this feature-optimized framework to dynamic, live-traffic environments to combat emerging zero-day polymorphic exploits.

References

1) Abiramasundari, S., & Ramaswamy, V. (2025). Distributed denial-of-service (DDOS) attack detection using supervised machine learning algorithms. *Scientific Reports, 15*(1), 13098. https://doi.org/10.1038/s41598-024-84879-y

2) Ahmad, Z., Shahid Khan, A., Shiang, C. W., Abdullah, J., & Ahmad, F. (2021). Network intrusion detection system: A systematic study of machine learning and deep learning approaches. *Transactions on Emerging Telecommunications Technologies, 32*(1), e4150. https://doi.org/10.1002/ett.4150

3) Aladaileh, M. A., Anbar, M., Hasbullah, I. H., Chong, Y. W., & Sanjalawe, Y. K. (2020). Detection techniques of distributed denial of service attacks on software-defined networking controller: A review. *IEEE Access, 8*, 143985–144007. https://doi.org/10.1109/ACCESS.2020.3013982

4) Alghazzawi, D., Bamasag, O., Ullah, H., & Asghar, M. Z. (2021). Efficient detection of DDoS attacks using a hybrid deep learning model with improved feature selection. *Applied Sciences*, *11*(24), 11634. https://doi.org/10.3390/app112411634

5) Alzahrani, M. Y., & Alenazi, M. J. (2021). Designing a network intrusion detection system based on machine learning for software defined networks. *Future Internet, 13*(5), 111. https://doi.org/10.3390/fi13050111

6) Bahashwan, A. A., et al. (2023). A systematic literature review on machine learning and deep learning approaches for detecting DDoS attacks in software-defined networking. *Sensors, 23*(9), 4441. https://doi.org/10.3390/s23094441

7) Belouch, M., Elhadaj, S., & Idhammad, M. (2018). A hybrid filter-wrapper feature selection method for DDoS detection in cloud computing. *Intelligent Data Analysis, 22*(6), 1209–1228. https://doi.org/10.3233/IDA-173624

8) Budi, P. S. M., Norman, F., & Bayu, A. L. (2025). Optimizing DDoS attack detection performance through feature selection in machine learning. *SINTECH Journal, 8*(2), 145–156. https://doi.org/10.31598/sintechjournal.v8i2.1914

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E-Publication: Online Open Access
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DOI: 10.5281/zenodo.20438852

9) Ferrag, M. A., Maglaras, L., Moschoyiannis, S., & Janicke, H. (2020). Deep learning for cyber security intrusion detection: Approaches, datasets, and comparative study. *Journal of Information Security and Applications, 50*, 102419. https://doi.org/10.1016/j.jisa.2019.102419

10) Javaid, A., Niyaz, Q., Sun, W., & Alam, M. (2018). A deep learning approach for network intrusion detection system. *Proceedings of the 9th EAI International Conference on Bio-inspired Information and Communications Technologies*. https://doi.org/10.4108/eai.3-12-2015.2262516

11) Kachavimath, A., & Narayan, D. G. (2025). Hybrid approach for detection and mitigation of DDoS attacks using multi-feature selection, unsupervised learning, and game theory. *Journal of Telecommunications and Information Technology, 4*, 45–57. https://doi.org/10.26636/jtit.2025.4.2261

12) Kamalov, F., Moussa, S., Zgheib, R., & Mashaal, O. (2021). Feature selection for intrusion detection systems. *arXiv*. https://doi.org/10.48550/arXiv.2106.14941

13) Kaur, S., Kumar, K., Aggarwal, N., & Singh, G. (2021). A comprehensive survey of DDoS defense solutions in SDN. *Computers & Security, 110*, 102423. https://doi.org/10.1016/j.cose.2021.102423

14) Kim, J., Kim, J., Thu, H. L. T., & Kim, H. (2020). Long short-term memory recurrent neural network classifier for intrusion detection. *International Conference on Platform Technology and Service*. https://doi.org/10.1109/PlatCon.2016.7456805

15) Naser, A. S., & Zaiter, A. (2024). Intelligent feature engineering for cyberattack detection using deep learning. *Applied Sciences, 14*(3), 1145. https://doi.org/10.3390/app14031145

16) Osanaiye, O., Choo, K. K. R., Dehghantanha, A., Xu, Z., & Dlodlo, M. (2018). Ensemble-based multi-filter feature selection method for DDoS detection in cloud computing. *arXiv*. https://doi.org/10.48550/arXiv.1807.10443

17) Patel, H. (2025). Feature selection via GANs (GANFS): Enhancing machine learning models for DDoS mitigation. *arXiv*. https://doi.org/10.48550/arXiv.2504.18566

18) Reddy, G. T., Reddy, M. P. K., Lakshmanna, K., et al. (2020). Analysis of dimensionality reduction techniques on big data. *IEEE Access, 8*, 54776–54788. https://doi.org/10.1109/ACCESS.2020.2980942

19) Saha, S., Priyoti, A. T., Sharma, A., & Haque, A. (2022). Towards an optimized ensemble feature selection for DDoS detection using both supervised and unsupervised method. *Sensors*, *22*(23), 9144. https://doi.org/10.3390/s22239144

20) Satpathy, S., Tripathy, U., & Swain, P. K. (2025). Cloud-based DDoS detection using hybrid feature selection with deep reinforcement learning. *Scientific Reports, 15*(1), 36546. https://doi.org/10.1038/s41598-025-18857-3

21) Saurabh, K., Kumar, T., Singh, U., Vyas, O. P., & Khondoker, R. (2022). NFDLM: A lightweight network flow based deep learning model for DDoS attack detection in IoT domains. *arXiv*. https://doi.org/10.48550/arXiv.2207.10803

22) Sawah, M. S., Elmannai, H., El-Bary, A. A., Lotfy, K., & Sheta, O. E. (2025). Distributed denial of service classification based on random forest model with backward elimination algorithm and grid search algorithm. *Scientific Reports, 15*(1), 19063. https://doi.org/10.1038/s41598-025-03868-x

23) Shone, N., Ngoc, T. N., Phai, V. D., & Shi, Q. (2018). A deep learning approach to network intrusion detection. *IEEE Transactions on Emerging Topics in Computational Intelligence, 2*(1), 41–50. https://doi.org/10.1109/TETCI.2017.2772792

24) Singh, G., & Khare, N. (2026). Memory-efficient multi-island Jaya feature selection for large-scale DDoS attack detection. *IEEE Access*. https://doi.org/10.1109/ACCESS.2026.3659209

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DOI: 10.5281/zenodo.20438852

25) Ullah, S., Mahmood, Z., Ali, N., Ahmad, T., & Buriro, A. (2023). Machine learning-based dynamic attribute selection technique for DDoS attack classification in IoT networks. *Computers, 12*(6), 115. https://doi.org/10.3390/computers12060115

26) Vinayakumar, R., Alazab, M., Srinivasan, K., Pham, Q. V., Padannayil, S. K., & Simran, K. (2019). A visualized botnet detection system based deep learning for the Internet of Things networks of smart cities. *IEEE Transactions on Industry Applications, 56*(4), 4436–4456. https://doi.org/10.1109/TIA.2020.2971952

27) Zhang, F., Cui, Y., Cui, G., Huang, L., Li, Q., & Shi, K. (2026). Adaptive DDoS attack detection via packet payload feature selection. *Cybersecurity, 9*(1), 65. https://doi.org/10.1186/s42400-025-00495-x