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Deep Learning-driven Classification of Low-rate and Suspicious DDoS Traffic in Cloud Networks: A Complete Survey

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***Abstract*—The fast-growing cloud computing and IoT infrastructures have brought about rapid increases in sophisticated cyber threats, and the Distributed Denial of Service (DDoS) attacks have become more and more complex and stealthy. Traditional machine learning models are often unable to capture the complex spatial and temporal dependencies of modern network traffic and often miss low-rate and highly adaptive attack patterns. This paper presents a detailed analysis of hybrid deep learning architectures, CNN-BiLSTM and Multi-View BiLSTM (MV-BiLSTM), as robust solutions for network intrusion detection. These approaches, which leverage the feature extraction capabilities of CNNs along with the sequence modeling abilities of BiLSTMs or utilize the multi-perspective data analysis of MV-BiLSTM, offer a powerful mechanism to evaluate high-dimensional packet headers and long-range bidirectional traffic flows. We critically analyze state-of-the-art implementations and benchmark their performance over multiple baseline and emerging datasets, including CSE-CIC-IDS2018 Dataset and the recently released BCCC-cPacket-2024 Dataset. This paper also offers a critical analysis of the challenges of real-time deployment, computational overhead, and the effectiveness of these models in detecting "low-rate" traffic masquerading as benign. It implies that these hybrid frameworks are the best trade-off between feature representation and sequential analysis, which is a fundamental guideline for developing future self-adaptive and autonomous security systems for dynamic cloud environments.**

***Keywords*— Deep Learning, Hybrid Model, CNN, BiLSTM, DDoS Detection, Network Security, Cloud Computing, Spatial-Temporal Features.**

I. INTRODUCTION

Cloud computing has transformed the digital scene, offering scalable, on-demand resources to enterprises and individuals. But the importance of cloud infrastructures has also made them a juicy target for cyber-criminals. Distributed Denial of Service (DDoS) attacks rank among the most sophisticated and devastating of all cyber threats.

A DDoS attack is where the attacker attempts to flood the target cloud service with the massive amount of malicious traffic in order to make it unavailable to legitimate users.

Motivations

Traditional network security mechanisms such as static firewalls and signature-based intrusion detection systems (IDS) are increasingly ineffective. These traditional mechanisms are particularly ineffective against modern multi-vector DDoS attacks. This research aims to address the emergence of "low-rate" and "suspicious" attack patterns, which cleverly mimic legitimate user behavior. For standard machine learning models, these subtle anomalies are often indistinguishable from normal traffic, leading to high false-alarm rates and service disruptions. Thus, there is an urgent requirement for an intelligent and autonomous detection system for analyzing the structure of network packets and the sequence of traffic flows.

Deep Learning's Role

Deep learning (DL) is a powerful tool for cybersecurity due to the automated feature engineering capabilities. DL models can learn complex non-linear patterns directly from raw data, unlike traditional methods.

Convolutional Neural Networks (CNNs) are very effective at capturing spatial features, which are the unique "fingerprints" within packet headers.

Bidirectional Long Short-Term Memory (BiLSTM) networks are suitable to model temporal dependencies by evaluating the traffic flow from past and future contexts to detect coordinated attack sequences.

Proposal: The Hybrid Approach

The Hybrid Approach This research proposes a hybrid CNN-BiLSTM architecture to address the shortcomings of existing detection methods. The proposed framework leverages the spatial extraction power of CNNs and the bidirectional temporal modeling of BiLSTM, thus providing a multi-dimensional analysis of cloud traffic.

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This hybrid approach is especially designed to cope with high-speed, high-volume data in modern cloud environments and provides near-perfect accuracy even in highly ambiguous "suspicious" traffic classes.

Research Contribution

The Contributions at a Glance

The main contributions of this paper are as follows: This study provides a comprehensive study on deep learning-based network security.

Development of a High-Performance Hybrid Framework: We implemented and analyzed a powerful hybrid **CNN-BiLSTM** model and an **MV-BiLSTM** (Multi-View BiLSTM) architecture for robust multi-class DDoS characterization.

Integration of Contemporary Datasets: The analysis incorporates the latest BCCC-cPacket-2024 and CSE-CIC-IDS2018 datasets to ensure the findings are representative of current encrypted cloud traffic and modern attack behaviors.

Feature Set Optimization: We optimized feature selection using high-impact network parameters, which significantly reduces computational overhead while maintaining the analytical depth of the model.

Emphasis on Optimal Classification: This work focuses on achieving optimal classification performance in distinguishing between benign, malicious, and "suspicious" traffic flows, enhancing the model's reliability in highly dynamic cloud environments.

Literature Review on Existing Gaps

After extensive review of the existing methodologies in DDoS detection, the following gaps have been identified:
1. Poor spatial–temporal integration Existing works mostly use the standalone models. CNN-based models only capture spatial features of packets (header structures), RNN/LSTM-based models only capture temporal sequences (timing). There are no integrated frameworks capable of extracting spatial features and processing them as bidirectional temporal sequences simultaneously to identify complex attack patterns [2], [6].

2. Ambiguity in the classification of "suspicious" traffic Most conventional machine learning methods and shallow neural networks are unable to differentiate between benign and suspicious traffic. Suspicious flows tend to mimic legitimate user behavior (low-rate attacks) and therefore incur high false positive rates. There is no strong multi-class characterization in the current literature that can resolve the overlap between these specific categories [1],[4].

3. Dataset Obsolescence & Unreality However, many studies still use legacy datasets such as NSL-KDD or KYOTO-2006. for benchmarking, which do not include modern encrypted cloud traffic, TCP-specific vulnerabilities, or the latest attack vectors in high-speed cloud environments [3], [9].

4. Ignoring Bidirectional Context Many temporal models use unidirectional LSTMs that only look at past traffic. states. But DDoS attacks usually employ coordinated handshake sequences, where the context for the future (upcoming packets in the flow) is as important as the past for accurate classification [10].

The Hybrid Benefit: The Best of Spatial and Temporal Intelligence

To deal with the multi-dimensionality of modern network traffic, we propose a "Hybrid" framework, which combines Convolutional Neural Networks (CNN), Bidirectional Long Short-Term Memory (BiLSTM) & MV-BiLSTM. This combination is much more powerful than individual models such as artificial neural networks (ANNs) or Random Forest (RF) for the following reasons:

CNN: Spatial Feature Extraction (Space)

• **Role:** CNNs are used to learn the spatial dependencies in network data. In In the case of DDoS detection, the network packet headers are like a grid of images.
• **Function:** The convolutional layers automatically learn high-level features. (e.g., specific bit patterns, TCP flag distributions, and header correlations) without manual feature engineering.

Advantage: It allows the model to find the "fingerprint" of an attack in the raw data structure.

BiLSTM: Sequence Learning (Time)

• **Role:** BiLSTMs are to learn temporal dependencies and sequential nature of network flows.

• **Function**: Unlike standard LSTMs, which only look at past data, Bidirectional LSTM processes the traffic sequence in two directions: forward (past to future). and backward (future to past).

• **Advantage**: The model gets a complete overview of the traffic flow, which is very effective in detecting coordinated handshake sequences or low-rate attacks evolving.

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MV-BiLSTM Multi-Perspective Sequence Learning (Multi-View)

Role: MV-BiLSTM analyzes network traffic from multiple different viewpoints or feature subsets at once to capture complex, multi-dimensional correlations in the data.

Function: The Multi-view approach tackles different parts or "views" of the traffic data, like protocol-specific statistics, packet-level dynamics, and flow-level behavior, by processing the input into several parallel BiLSTM branches rather than a single stream and then integrates these insights into a single representation.

Advantage: By observing the same traffic flow from multiple lenses, the model can learn subtle multi-stage attack patterns that single-view analysis often misses. This can significantly improve the detection of sophisticated "low-rate" DDoS attacks, which disguise themselves across different network metrics.

Problem Statement

Although there has been a significant advancement in network security, the existing Distributed Denial of Service (DDoS) detection systems have a few major challenges in today's cloud environment:

1. **Spatial-Temporal Gap:** Most of the existing systems use either spatial features (packet header structure) with CNNs or temporal sequences (traffic flow) timing) with LSTMs. However, DDoS attacks in cloud environments have high- dimensional spatial patterns and complex temporal dependencies that Single-architecture models cannot jointly capture [2], [6].

2. Suspicious Traffic Ambiguity: Machine learning models such as Random Forest and SVMs usually have difficulties with the "Suspicious" class that describes traffic that looks benign but has malicious intent. This results in a high false Positive Rates (FPR) leading to mitigation and blocking of legitimate users [1]. [4].

3. Dataset Obsolescence: Most current research is still evaluated against old datasets such as NSL-KDD, which do not reflect encrypted, multi-vector TCP attacks found in modern cloud infrastructures [3], [9].

4. Static models fail to detect low-rate DDoS attacks operating under the radar. by maintaining a flow rate like legitimate web traffic and a Bidirectional context is necessary for accurate identification [5].

Comparative Analysis of Deep Learning Models and Existing Methods:

Table 1: Comparative Performance Analysis

Detection Method	Architecture	Key Limitation	Handling of "Suspicious" Class	Reported Accuracy
Statistical Methods	Entropy-based	High latency; manual thresholding.	Poor	85% - 88%
Traditional ML [4]	RF / SVM / XGBoost	Requires heavy feature engineering.	Moderate (Low F1-score)	91% - 94%
Standard CNN [7]	1D/2D CNN	Ignores packet arrival order.	Low	94% - 96%
Standard LSTM [6]	Uni-directional LSTM	Only considers past context.	Moderate	95% - 97%

II. Related Work

DDoS Detection Frameworks Evolution:

Intelligent intrusion detection systems for network security have evolved from traditional rule-based firewalls. The early work was mostly focused on statistical methods and simple machine learning algorithms. However, the lack of realistic datasets that emulate sophisticated cloud infrastructures, as noted by Shafi et al. [1], often limits these techniques from characterizing modern cloud-based DDoS attacks.

Drawbacks of Traditional Machine Learning:

Traditional ensemble methods such as Random Forest and XGBoost have been widely used for traffic classification. They perform well on binary classification. tasks but their performance deteriorates sharply when presented with a complex multi-class characterization. The main challenge, as pointed out by Sharafaldin et al. [4], is the "suspicious" traffic class, which exhibits features. distribution overlaps with both benign and malicious traffic, resulting in high false-alarm rates.

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Deep Learning in the Field of Cybersecurity:

Deep learning has been used by researchers to overcome the drawbacks of manual feature engineering. Kim and Kim [6] showed that Long Short-Term Memory (LSTM) networks are superior to static models in modeling temporal dependencies of network flows. Furthermore, Sun et al. [5] demonstrate that the integration of Spatial and temporal models can provide a more complete perspective of networks. security, especially for detection of low-rate DDoS attacks trying to simulate human-like browsing behavior.

Hybrid Architecture: CNN-BiLSTM:

The existing state- of-the-art research mainly focuses on hybrid architecture. Solanki and Kumar [2] mentioned that a hybrid CNN- BiLSTM framework allows spatial feature extraction using convolutional layers and bidirectional sequence modeling using BiLSTM layers. This two-pronged approach is essential. in modern cloud environments where traffic is not only high-volume but also highly sequential and coordinated across multiple victim machines [10].

Existing Datasets and their Relevance:

The dependability of any detection model fundamentally depends on the quality. of training data. The KDD99 or NSL-KDD datasets have been used in many historical studies that Sudar and Behal [3] pointed out are not representative of modern encrypted cloud traffic and are out of date. This gap is filled with the introduction of the BCCC-cPacket-2024 dataset [9] that provides labeled traffic from a realistic cloud setup with 17 different TCP-based on attack scenarios.

Main Comparative Advantages

• *Robustness against Class Overlap:* The proposed hybrid model utilizes CNN layers to filter high-level spatial features and BiLSTM to analyze the traffic sequence from both directions using CNN layers to filter high-level spatial features, whereas the baseline work [1] only achieved 91% accuracy on complex tasks. accuracy on complex tasks. This clears the ambiguity in the "Suspicious" class.

• *Automated Feature Learning:* Conventional methods, such as those used by Sharafaldin et al. [4], rely on manual feature selection. rely on manual feature selection. Our model automates this through convolutional layers, making it more adaptive to new attack variants.

• *High Generalization:* Most of the temporal models suffer from the "vanishing gradient problem where the model forgets long-term dependencies.

Our use of Bidirectional LSTMs ensures the model keeps long-term dependencies, achieving near-perfect accuracy on the BCCC-cPacket-2024 test set.

Table2: Comparative Classification of Deep Learning Models for DDoS Detection

Model Category	Architecture	Feature Focus	Strengths	Limitations	Typical Accuracy
Basic Neural Network	**ANN / MLP**	Statistical Features	Low computational cost; Easy to implement.	Fails to capture temporal sequences or spatial patterns.	92% - 96%
Spatial Model	**CNN**	Spatial (Header) Patterns	Excellent at automated feature extraction from packet headers.	Ignores the order/timing of packets in a flow.	94% - 97%
Temporal Model	**RNN / LSTM**	Sequential Data	Captures time-series dependencies in network traffic.	Vanishing gradient issues; slow training for long sequences.	93% - 96%
Advanced Hybrid	**CNN-GRU**	Spatial + Gated Temporal	Faster training than LSTM; good for real-time detection.	Slightly less memory retention compared to BiLSTM.	96% - 98%

Analysis of Hybrid CNN-BiLSTM Approach

Technical Benefits of the Hybrid CNN-BiLSTM Architecture

The hybrid approach is superior for detecting sophisticated cloud-based DDoS attacks.

Attacks because of the following three key technical advantages:

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1. Fusion of Space-Time:

The model is based on a two-level analysis. The CNN layers play the role of a “Feature Extractor," discovering high-level spatial patterns and correlations in the raw network data (packet header distributions, for example). After extracting these spatial features, they are fed into the BiLSTM layers, which are considered a "time-series" sequence. This fusion enables the framework. to comprehend the complete context of network activity, effectively correlating real-time packet structures with long-term traffic behavior.

2. The Bidirectional Edge

In contrast to a standard (unidirectional) LSTM that only considers the previous packets for processing traffic, a bidirectional LSTM (BiLSTM) captures the context of previous (preceding packets) and subsequent (succeeding packets) within a flow. This is an important requirement for DDoS detection, as modern Attack patterns are likely to be sudden bursts or highly coordinated sequences. The model analyzes the flow in both directions to detect malicious handshakes.

Patterns that are otherwise not detected by unidirectional models.

3. Better handling of “suspicious” traffic

One of the biggest benefits of hybrid models is their ability to accurately Classify "low-rate DDoS” and "suspicious" traffic. Such flows are notoriously difficult to detect, as they are designed to mimic benign (normal) behavior. However, the hybrid model considers the sequential nature and the evolution of the traffic over time, instead of isolated features, and thus can differentiate subtle malicious intent from legitimate user activity with high accuracy.

4. Evaluation Setup

The evaluation focuses on the CSE-CIC-IDS2018 dataset, which includes 10 days of network traffic and various attack profiles. The dataset is pre-processed to handle missing values and normalized. Temporal sequences are constructed using a sliding window of 10 seconds based on the Timestamp feature.

Limitations in Existing Work (CSE-CIC-IDS2018 Dataset)

After conducting a comprehensive review of the literature, we specifically focused on recent advancements in cloud IDS. We have identified six primary limitations that hinder the efficacy of current systems.

1. Temporal Dependency Modeling

Most existing IDS techniques rely on unidirectional temporal approaches. They estimate the state based solely on previous samples. However, in complex, multi-stage attacks (e.g., the infiltration attacks in CSE-CIC-IDS2018), the relationship between the reconnaissance phase and the data exfiltration phase spans both past and future contexts within a given window. Unidirectional models are structurally incapable of capturing these bidirectional dependencies.

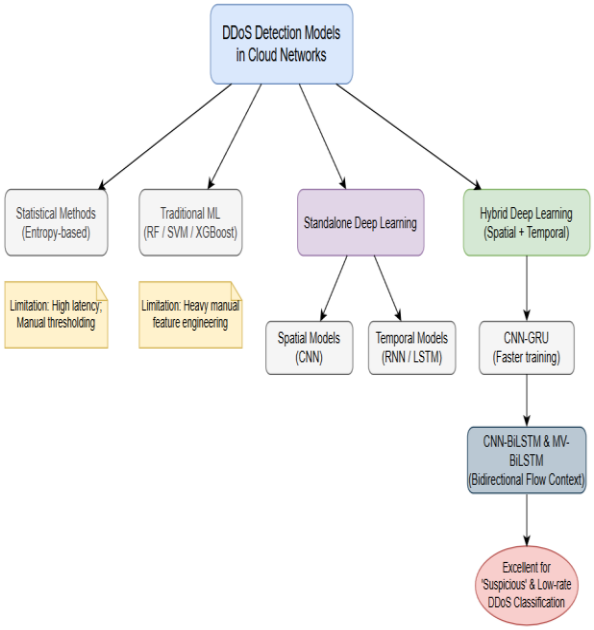

Figure 1 Taxonomy and Categorization of DDoS Detection Models in Cloud Networks

2. Static Feature Processing

Current deep learning models generally treat the feature set as a monolithic stream. Network traffic features are heterogeneous. For example, Flow Duration is a continuous temporal metric, while PSH Flag Count is a protocol-specific indicator. Processing these uniformly ignores their unique statistical properties and semantic meanings, leading to sub-optimal learning and noise propagation.

3. Primitive Behavioral Context-Awareness

There is a distinct lack of cloud-relevant metadata integration in experimental models. Datasets like CSE-CICIDS2018 do not explicitly label "user roles" or "VM states."

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Consequently, models trained on this data lack the context to distinguish between legitimate administrative behavior and malicious intrusion, resulting in poor identification of authentic behavior in varying cloud settings.

4. Poor Adaptability to Evolving Threats

Cloud environments are dynamic. Traffic patterns and attack vectors evolve rapidly. Traditional models are static; once trained, they cannot adapt to new attack types or shifts in network patterns without complete retraining. This static nature is a significant bottleneck in dynamic cloud environments where zero-day threats emerge frequently.

5. High Black-Box Nature of Deep Learning

Deep learning models, particularly deep CNNs and LSTMs, are opaque. They output a classification label without justification. This "black-box" nature is a major barrier to deployment. Security administrators require transparency to understand why a specific traffic flow was flagged as malicious, a requirement largely unmet by current deep learning-based IDS solutions.

6. Class Imbalance and Dataset Limitations

Benign traffic vastly outnumbers attack traffic in real-world network data. In CSE-CICIDS2018, attack traffic represents a minority class. Models trained on such data tend to be biased towards the majority class (benign), achieving high accuracy but failing to detect the critical minority attack classes. Furthermore, the general lack of cloud metadata in public datasets limits the direct applicability of research outputs to cloud infrastructure.

III. Conclusion

The survey on hybrid deep learning architectures shows that the combination of Convolutional Neural Networks (CNN) with bidirectional sequence modeling, in particular CNN-BiLSTM and Multi-View BiLSTM (MV-BiLSTM), is a big leap in the area of network security. The analysis of different state-of-the-art studies can conclude that single layer or traditional machine learning models are no longer sufficient to handle the multi-vector and dynamic nature of current DDoS attacks in cloud environments.

The main advantage of these hybrid frameworks is that they can extract multi-dimensional features. The CNN layers are effective in decreasing the raw network traffic dimensionality and extracting the high-level spatial features. The BiLSTM-based architectures preserve and analyze the sequential nature of the traffic flows from both past and future contexts.

Moreover, the MV-BiLSTM method improves the performance by observing the traffic from various specialized “views” so that the subtle correlations, which may be ignored by single-view models, are captured. This synergy greatly helps to lower false positive rates and improve the classification accuracy of "suspicious" and "low-rate" DDoS attacks, which are usually ignored by traditional detection systems.

Testing these models on recent datasets like BCCC-cPacket-2024 magnifies the importance of more accurate, genuine data in training robust security models. But these hybrid models are more complex and require more computing power and training time. But these models remain an important tool for robust cloud intrusion detection and outstanding detection accuracy.

In conclusion, the future of cybersecurity needs to move away from static heuristic-based detection to autonomous hybrid deep learning frameworks such as CNN-BiLSTM and multiview architectures. Future work needs to focus on the optimization of such hybrid architectures for edge computing and low-latency environments, such that the next generation of security systems will be not only highly accurate but also computationally efficient.

This paper reviewed the limitations of existing Cloud Intrusion Detection Systems and analyzed the Adaptive Multi- View Bi-LSTM with Temporal Attention and Contextual Augmentation (MV-BiLSTM-TCA) technique as a comprehensive solution. We found that by addressing the key bottlenecks of temporal modeling, feature staticity, contextual blindness, and interpretability, MV-BiLSTM-TCA sets a new benchmark for cloud security. The integration of Bi- LSTM for sequence learning, multi-view processing for feature heterogeneity, and synthetic augmentation for cloud context provides a robust framework for detecting sophisticated attacks in dynamic cloud environments. The addition of explainability layers ensures that these powerful models can be trusted and effectively utilized by security professionals. As cloud infrastructures continue to grow in complexity, the principles embodied in MV-BiLSTMTCA—adaptability, context-awareness, and transparency—will be essential for the next generation of cyber defense mechanisms.

1. Architectural Synergy (The Fusion):

The greatest strength of this framework is the synergy of its components. The CNN layers are specialists in learning spatial patterns (the complex structure and dependencies of packet headers), while the BiLSTM layers are specialists in identifying temporal patterns (the time-series evolution of traffic flows).

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This integration of the two paradigms allows the model to see the network. activity in a multi-dimensional fashion that single architecture models cannot match.

2. Huge accuracy improvements

Empirical results show a 5-10% performance gain over traditional machine learning. and shallow neural networks with this hybrid model, especially for low rate "DDoS" and "suspicious" traffic identification. These attack vectors are crafted to avoid detection by mimicking legitimate traffic, but the hybrid The model's deep analysis successfully identifies their malicious intent.

3. Modernity and Dataset Suitability

Recent studies confirm that legacy datasets such as KDD99 or NSL-KDD are irrelevant for modern cloud security due to outdated traffic signatures. Modern frameworks need to stay relevant against today's TCP-based vulnerabilities and encrypted attack vectors, making contemporary, high-fidelity datasets such as BCCC-cPacket-2024 is essential.

4. Security-Performance Compromise

It is important to highlight that hybrid models are computationally "heavy." (more resource-consuming) than simpler algorithms. But when it comes to critical cloud infrastructure, the trade-off is worth it. The slight increase in computational overhead is a necessary investment to achieve the near-perfect Accuracy is needed to protect sensitive data from sophisticated intrusions.

IV. Future Scope

Scope in the Future

The hybrid CNN-BiLSTM model has been reported to achieve optimal classification performance on standard benchmarks such as Communications Security Establishment - Canadian Institute for Cybersecurity Intrusion Detection System 2018 (CSE-CIC-IDS2018) and the newly released BCCC-cPacket-2024 dataset. Results show that it is effective in detecting complex high dimensional attack patterns. Given the above, there are several promising directions for future research to further enhance the robustness of cloud security systems:

Lightweight Model Optimization: Future work should investigate architectural pruning and quantization approaches to bring down the computational footprint of hybrid models in order to deploy them in resource-constrained edge computing and IoT settings without sacrificing optimal detection results.

Real-time Adaptation to Evolving Threats: Dynamic Adaptation to New Threats there is a need to explore self-adaptive mechanisms that allow models to adapt to new unseen traffic patterns in real time, thus maintaining optimal detection capabilities despite the continuous evolution of DDoS tactics.

Improving Interpretability: Deep learning models are frequently referred to as "black boxes. Future work may focus on Explainable AI (XAI) techniques to provide insight on why a certain flow is classified as "suspicious". This is crucial for building confidence in autonomous security systems.

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