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Review Article

Federated Learning for DDoS Attack Detection in Cloud Computing: A Review of Privacy-Preserving and Scalable Security Approaches

M. Usman, M. Olalere and B.A. Ajayi

Department of Computer Science, Faculty of Natural and Applied Science,
Nasarawa State University, Keffi, Nigeria.

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Abstract

This study examines critical issues in cloud-based cybersecurity, focusing on the application of machine learning and privacy-preserving techniques for Distributed Denial of Service (DDoS) detection. It evaluates existing approaches to DDoS mitigation, emphasizing the scalability and real-time challenges encountered in dynamic cloud environments. The research further explores federated learning, homomorphic encryption, and differential privacy as emerging methods for decentralized and secure data analysis. By integrating insights from recent studies, the work highlights both the limitations of current detection frameworks and the potential of advanced learning paradigms to enhance security and scalability. The findings contribute to developing robust, privacy-conscious, and adaptive DDoS detection models suitable for modern cloud infrastructures.

Keywords: Cloud Computing, DDoS Detection, Machine Learning, Federated Learning, Privacy Preservation, Differential Privacy, Homomorphic Encryption, Scalability, Cybersecurity.

Introduction

The rapid adoption of cloud computing has transformed the way organizations manage, store, and process data. Its advantages such as scalability, flexibility, and cost efficiency have made it a cornerstone of modern digital infrastructure. However, these same features also introduce new security vulnerabilities, particularly in relation to Distributed Denial of Service (DDoS) attacks. The growing frequency and sophistication of DDoS incidents pose significant threats to the availability and integrity of cloud services, potentially disrupting business operations and compromising user trust.

DDoS attacks overwhelm target systems with massive amounts of malicious traffic, rendering services unavailable to legitimate users. In cloud environments where resources are distributed across multiple

Correspondence addressed to Muhammed Usman, email:mdusman7292@gmail.com

servers and geographical regions such attacks can have far-reaching consequences, sometimes incapacitating entire infrastructures. Attackers often exploit the very distributed nature of cloud systems to coordinate large-scale assaults, emphasizing the urgent need for advanced and adaptive defense mechanisms.

Recent research has explored the application of federated learning (FL) as a promising strategy for detecting and mitigating DDoS attacks in cloud computing. For instance, the study [1] demonstrated that federated learning enables collaborative DDoS detection without centralizing sensitive data, thereby enhancing both scalability and privacy compliance. In [2], the study highlighted its potential for securing IoT and cloud environments simultaneously.

Despite these advances, traditional centralized detection systems continue to struggle with the vast scale and evolving dynamics of modern cyber threats. Consequently, strengthening cloud security demands a distributed, scalable, and privacy-preserving approach. This review therefore examines the role of federated learning in addressing DDoS attacks within cloud computing infrastructures, highlighting its potential to balance performance, data privacy, and system resilience.

A Survey on DDoS Attack Detection Techniques in Cloud Computing

The detection of Distributed Denial of Service (DDoS) attacks in cloud computing environments has become an essential area of research due to the growing sophistication and frequency of such attacks. This survey presents an in-depth analysis of existing DDoS detection strategies, emphasizing their applicability, effectiveness, and limitations within cloud infrastructures. The techniques are broadly classified into signature-based, anomaly-based, and hybrid approaches, each offering distinct advantages and challenges in ensuring the security and availability of cloud services.

Signature-based detection techniques rely on known attack patterns to identify malicious activities. While these systems are highly accurate against previously encountered threats, they often fail to detect new or evolving attack types. Conversely, anomaly-based methods employ statistical, heuristic, or machine learning models to identify deviations from normal network behavior. These techniques are more adaptive but can suffer from high false positive rates, especially in dynamic and heterogeneous cloud environments. Hybrid approaches combine both paradigms, striving to balance detection accuracy and adaptability while minimizing computational costs.

Recent studies have contributed significantly to the advancement of DDoS detection methodologies. The study [3] applied deep learning, particularly Convolutional Neural Networks (CNNs), to DDoS detection in cloud environments. Their results demonstrated CNNs' strong adaptability across diverse network scenarios but also highlighted their high computational overhead, which may hinder real-time deployment. Similarly, [4] proposed an integrated framework combining supervised and unsupervised learning for early detection of DDoS attacks in Software-Defined Networks (SDN). Although their hybrid system achieved

commendable detection accuracy, its processing complexity limits scalability in large-scale, high-speed networks.

The study [5] introduced a time series-based detection model employing Recurrent Neural Networks (RNNs) to identify compromised SDN switches in cloud infrastructures. This method demonstrated improved temporal learning capabilities but was constrained by its dependency on large volumes of historical data, which may be impractical in rapidly evolving network environments. In another approach, [6] developed a statistical user-behavior scoring model for DDoS detection using the CICDDoS2019 dataset. The model achieved a low false positive rate but its performance consistency across varying network conditions remains limited due to reliance on specific statistical characteristics.

Moreover, the study [7] combined deep learning with information entropy to enhance DDoS attack detection precision and accuracy. Despite promising results, this approach requires careful threshold calibration, which can be challenging to maintain in dynamic and distributed cloud settings.

Critical Insights and Future Directions

The survey emphasizes that while machine learning and hybrid approaches have significantly advanced DDoS detection in cloud computing, their performance remains constrained by scalability, training data diversity, and real-time applicability. The integration of distributed intelligence, such as federated learning and edge analytics, represents a promising direction for overcoming the limitations of centralized systems. Future research should focus on developing lightweight, adaptive models capable of identifying emerging threats without compromising data privacy or increasing system latency. There is also a need for standardized benchmark datasets and evaluation protocols to enhance comparability across studies and improve reproducibility. Furthermore, efforts should be directed toward designing energy-efficient detection frameworks that can operate seamlessly in multi-tenant, geographically distributed cloud infrastructures.

By addressing these challenges, the next generation of DDoS detection systems can achieve higher resilience, precision, and efficiency ultimately strengthening the reliability and trustworthiness of cloud computing environments.

Federated Learning: Challenges, Methods, and Future Directions

Federated learning (FL) represents a transformative shift in machine learning, enabling decentralized model training across multiple devices or institutions without requiring the exchange of raw data. This privacy-preserving paradigm has emerged as a promising solution to the growing concerns surrounding data confidentiality, regulatory compliance, and distributed data ownership. The approach allows local devices to collaboratively train a shared global model through iterative communication with a central aggregator, thereby enhancing data protection while maintaining predictive performance.

This section provides a comprehensive overview of the challenges, methodologies, and future prospects of federated learning. It explores key technical issues such as model heterogeneity, privacy preservation,

and communication efficiency, as well as highlights diverse application areas, including healthcare, finance, industrial automation, and smart city systems. By examining recent advancements and ongoing research efforts, the discussion underscores how federated learning can serve as a foundation for building secure, scalable, and efficient decentralized intelligence in modern data-driven environments.

Federated learning has gained attention in contexts where centralized data aggregation is impractical or poses significant privacy and security risks. Despite its advantages, FL still encounters challenges such as non-independent and identically distributed (non-IID) data, limited computational resources on edge devices, and communication bottlenecks during model updates. Addressing these challenges remains critical for achieving real-world adoption and maintaining the integrity of federated systems.

Notable contributions in this field have shaped the evolution of FL research. In their study, [8] examined the broad implications of federated learning, emphasizing the pressing need to tackle privacy and communication constraints. The study [9] offered a landmark survey outlining open problems related to scalability, robustness, and standardization of privacy-preserving methods. Similarly, [10] provided a conceptual framework for understanding FL and its applications across multiple industries, forming the basis for later, domain-specific advancements.

Further developments include the work by [11] that investigated system architectures necessary for large-scale federated deployments and proposed strategies to overcome synchronization and communication inefficiencies. The study [12], introduced FedCM, an innovative framework combining clustering and data masking to enhance data privacy in federated systems, demonstrating the feasibility of integrating privacy enhancement with computational efficiency.

Critical Insights and Future Directions

This survey emphasizes that, while federated learning has revolutionized the concept of privacy-preserving machine learning, it continues to face significant research and engineering challenges. Key limitations include data heterogeneity, uneven client participation, and restricted communication bandwidth, all of which can affect model convergence and global performance. Furthermore, the absence of standardized evaluation frameworks complicates fair comparison across studies and slows the translation of research findings into practical systems.

Future work should prioritize the development of adaptive aggregation algorithms capable of managing dynamic participation and diverse data distributions among clients. Integrating differential privacy, secure multiparty computation, and blockchain-based trust frameworks can further enhance the transparency, confidentiality, and accountability of FL systems. Equally important is the creation of lightweight, energy-efficient models optimized for deployment on resource-constrained edge devices.

Beyond these technical dimensions, the establishment of collaborative benchmarking datasets and cross-domain experimental platforms is essential to promote reproducibility and interoperability. By addressing these emerging challenges, federated learning can mature into a robust and trustworthy paradigm one that

enables large-scale, decentralized intelligence across sectors while safeguarding data privacy and system reliability.

DDoS Detection in Cloud Environments Using Machine Learning Techniques

The application of machine learning (ML) in detecting Distributed Denial of Service (DDoS) attacks has emerged as one of the most promising approaches for securing cloud computing environments. With the exponential growth of network traffic and the complexity of modern cloud infrastructures, traditional rule-based intrusion detection systems have become insufficient. Machine learning techniques, through their ability to learn from historical traffic data, enable intelligent classification of normal and malicious behaviors, thereby enhancing both detection accuracy and response speed.

This section explores the use of various machine learning methodologies for identifying DDoS attacks in cloud systems. It focuses on the analysis of network traffic patterns to distinguish legitimate requests from malicious ones, evaluating the strengths, weaknesses, and applicability of different algorithms. These include classical learning models such as Support Vector Machines (SVMs), Decision Trees, and Random Forests, as well as more recent advances in Deep Learning (DL) and Ensemble Learning. The discussion also highlights scalability and real-time performance challenges inherent to deploying ML-based detection systems within distributed cloud architectures.

Machine learning approaches have shown great potential for proactive DDoS mitigation. In [13], ML was combined with big data analytics to improve detection accuracy and system responsiveness, demonstrating how large-scale data processing frameworks can enhance model performance in real-world scenarios. The study [14] conducted a comparative evaluation of multiple ML algorithms for DDoS detection, revealing that ensemble-based and deep learning models generally outperform traditional classifiers in dynamic network settings.

Further developments include [15] that investigated deep learning frameworks—particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models—for recognizing complex DDoS attack signatures within high-dimensional traffic data. Their study confirmed that deep learning architectures can effectively capture temporal and spatial correlations in network flows, resulting in improved detection precision. Building on this, [16] proposed a real-time ensemble-based detection system capable of balancing speed and accuracy, addressing the growing demand for responsive mitigation in live cloud environments.

In addressing the scalability problem of centralized detection, [17] introduced a federated learning-based approach for distributed DDoS detection. Their model allows multiple cloud nodes to collaboratively train detection systems without sharing raw data, thereby ensuring data privacy while maintaining detection efficiency. This approach aligns with the broader industry trend toward decentralized, privacy-aware cybersecurity frameworks.

Critical Insights and Future Directions

The integration of machine learning into DDoS detection frameworks represents a major leap toward intelligent and adaptive cloud security. However, this field still faces several unresolved challenges. Chief among them are issues of data imbalance, model interpretability, real-time adaptability, and computational scalability. Many ML models, particularly deep learning architectures, demand extensive labeled datasets and high computational resources, which can be difficult to maintain in dynamic, resource-constrained cloud environments.

Future research should prioritize the development of lightweight, explainable ML models capable of operating efficiently under real-time constraints. Integrating online learning and transfer learning mechanisms may enable adaptive systems that evolve alongside emerging attack patterns. Additionally, combining federated learning with privacy-preserving analytics could enhance collaboration among cloud providers without compromising sensitive data.

Another crucial direction involves the establishment of standardized datasets and performance benchmarks for evaluating DDoS detection methods across diverse cloud environments. This would facilitate consistent assessment and reproducibility of results. By addressing these gaps, machine learning-driven approaches can evolve into robust, scalable, and privacy-conscious solutions, strengthening the resilience and reliability of cloud computing infrastructures against sophisticated DDoS attacks.

Privacy-Preserving Machine Learning in Cloud Computing

As the adoption of machine learning (ML) in cloud computing continues to grow, ensuring data privacy during model training and deployment has become a critical challenge. Machine learning systems often require access to large volumes of user data, which can expose sensitive information if not properly secured. Consequently, privacy-preserving machine learning (PPML**)** has emerged as a key research area aimed at enabling intelligent data analysis without compromising confidentiality.

This section explores various methodologies designed to protect user privacy in ML applications within cloud environments. Core strategies include homomorphic encryption**,** differential privacy**,** secure multiparty computation (SMC), and federated learning. These approaches allow organizations to harness the predictive power of machine learning while maintaining compliance with data protection regulations and ethical standards.

- **Homomorphic encryption:** enables computations on encrypted data, ensuring that raw inputs remain inaccessible throughout the learning process.
- **Differential privacy:** introduces statistical noise to data or gradients, preventing adversaries from identifying individual records.
- **Secure multiparty computation:** distributes computation across multiple parties without revealing their respective data inputs.

- **Federated learning**: perhaps the most transformative of these methods, facilitates collaborative model training across decentralized devices or servers while keeping the data local to each client.

Collectively, these techniques are redefining how machine learning models are trained and deployed in the cloud, striking a balance between utility and privacy protection**.**

Several studies have made noteworthy contributions to this evolving field. In [17] revealed vulnerabilities in federated learning architectures, demonstrating that private data can be inferred from model gradients, thereby emphasizing the urgent need for robust privacy safeguards. In response, [18] integrated differential privacy mechanisms into federated learning systems to reduce information leakage during collaborative model updates. Moreover, [1] proposed efficient homomorphic encryption schemes tailored for privacy-preserving machine learning, achieving improved computational performance without sacrificing security.

Expanding on these foundations**,** [19] conducted a comprehensive privacy analysis of deep learning systems, exposing vulnerabilities to both passive **and** active white-box inference attacks in centralized and federated settings. Their work underscores the need for continuous evaluation of emerging privacy risks as machine learning models become more complex and interconnected.

Critical Insights and Future Directions

The growing integration of privacy-preserving methodologies into cloud-based machine learning frameworks mark a paradigm shift toward secure and ethical AI**.** Nonetheless, significant challenges persist. Current PPML techniques often introduce trade-offs between model accuracy**,** computational cost, and privacy strength**.** For instance, homomorphic encryption can significantly slow down model training, while differential privacy may degrade accuracy when excessive noise is applied.

Future research should focus on developing lightweight, adaptive, and hybrid PPML frameworks that optimize this trade-off. Integrating federated learning with advanced encryption and differential privacy mechanisms offers a promising direction for achieving scalable, privacy-preserving intelligence in real-world cloud applications. Additionally, there is a pressing need for standardized privacy benchmarks, regulatory compliance models, and explainable privacy metrics to evaluate and compare PPML approaches across diverse use cases.

By advancing these directions, privacy-preserving machine learning can become a foundational element of trustworthy AI systems, ensuring that innovation in cloud-based analytics proceeds without compromising the privacy and security of individual users.

Scalability Challenges in DDoS Detection for Cloud Environments

As cloud infrastructures expand to accommodate the growing demand for distributed computing and data-intensive applications, maintaining robust and scalable security mechanisms has become increasingly complex. Among the most persistent threats to cloud environments are Distributed Denial of Service

(DDoS) attacks, which can cripple network performance and availability by overwhelming systems with malicious traffic.

This section examines the scalability challenges that arise in the design and implementation of DDoS detection systems within cloud environments. Traditional detection methods often developed for static or smaller-scale networks struggle to maintain both accuracy and real-time responsiveness when deployed in highly dynamic and virtualized cloud infrastructures. The difficulty lies in efficiently processing massive, fluctuating traffic volumes while minimizing false positives and computational overhead.

Key factors contributing to scalability issues include:

- Dynamic cloud traffic patterns, which fluctuate due to multi-tenant workloads and elastic resource allocation;
- Massive data throughput, requiring real-time feature extraction and classification across geographically distributed nodes;
- Algorithmic limitations, where existing machine learning and rule-based models fail to adapt quickly to evolving attack signatures; and
- Resource constraints, as DDoS detection consumes significant bandwidth, CPU, and storage resources in large-scale environments.

Recent advances in big data analytics, machine learning, and federated intelligence are being explored as potential solutions to overcome these challenges.

The study [20] conducted an extensive review of scalability issues in cloud-based DDoS detection systems, identifying fundamental bottlenecks in current algorithms and proposing architectural improvements to enhance efficiency. In [1], the study introduced a hierarchical DDoS detection framework, which distributes detection tasks across multiple network layers, improving scalability and fault tolerance in large-scale deployments.

In a related direction, [21] demonstrated how big data analytics can address scalability limitations by enabling real-time processing of massive traffic datasets. Their work highlights how integrating streaming analytics and distributed data pipelines can facilitate early detection and adaptive response.

Building upon these foundations, [22] explored federated learning as a promising approach to scalable and privacy-preserving DDoS detection. Their model leverages decentralized data processing to reduce latency and improve adaptability across distributed cloud nodes. Similarly, the study [23] focused on enhancing the real-time responsiveness of DDoS detection systems, emphasizing the need for algorithmic optimizations and lightweight architectures capable of operating at cloud scale.

Critical Insights and Future Directions

The challenge of scalability in DDoS detection is not merely a technical obstacle but a fundamental issue that determines the resilience and reliability of modern cloud infrastructures. The reviewed studies collectively reveal that effective scalability requires a multi-layered approach, combining architectural optimization, distributed computation, and intelligent automation.

Future research should prioritize:

- Adaptive detection frameworks that dynamically adjust to fluctuating workloads and network topologies;
- Federated and edge-based learning models to decentralize computation while preserving data privacy;
- Integration of real-time analytics pipelines capable of handling exabyte-scale network traffic; and
- Energy-efficient detection mechanisms, ensuring that scalability does not compromise sustainability in large cloud systems.

By addressing these dimensions, the next generation of DDoS detection frameworks can achieve the balance between accuracy, responsiveness, and scalability, ultimately strengthening the security posture of global cloud computing infrastructures.

Conclusion

This study underscores the growing importance of integrating advanced machine learning and privacy-preserving techniques in addressing DDoS detection challenges within cloud environments. While conventional detection systems face scalability and adaptability limitations, emerging models such as federated learning, homomorphic encryption, and deep neural frameworks demonstrate significant potential for enhancing detection accuracy and security. Future research should prioritize optimizing these methods for real-time applications and multi-cloud interoperability to build more resilient, intelligent, and privacy-aware cloud infrastructures.

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