**DDoS Protection System for Cloud using AWS and Machine Learning**

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Abstract— The increasing reliance on cloud computing has made it a critical target for Distributed Denial of Service (DDoS) attacks, which threaten the availability, performance, and reliability of cloud-hosted applications. This paper introduces the DDoS Protection System for Cloud using AWS and Machine Learning, a comprehensive and adaptive solution for real-time detection and mitigation of DDoS attacks. The proposed framework exploits both the scalability of AWS cloud services and the intelligence of machine-learning algorithms to perform advanced traffic analysis in order to differentiate legitimate users from malicious entities. The system integrates anomaly-based detection techniques, dynamic resource allocation, and automated mitigation workflows to handle high-volume, complex attack patterns while minimizing latency in operational activities. Key features are real-time alerting, seamless scalability, and efficient use of cloud resources, making the solution practical for dynamic cloud environments. The experimental evaluations clearly indicate effectiveness in neutralizing various vectors of DDoS attacks and maintaining high availability and optimising resource consumption. With a combination of cloud-native tools and intelligent analytics, the research work here has a positive impact on advancing cloud security and provides the groundwork for further development in hybrid and multi-cloud architectures. Such findings therefore present insight for organizations that seek to fortify defences against evolvement of cyber threats.

Keywords—DDoS attacks, AWS, cloud security, machine learning, anomaly detection, dynamic resource allocation.

# INTRODUCTION

Distributed Denial of Service attacks are one of the most serious and emerging threats to cloud environments, which is attributed to the widespread adoption of cloud computing across industries. DDoS attacks interrupt service availability by flooding resources with malicious traffic, causing a lot of financial and reputational damage to organizations. Traditional security measures are often inadequate in detecting and mitigating these sophisticated attacks in real-time, especially in dynamic and scalable cloud infrastructures. This paper proposes a new DDoS Protection System for Cloud using AWS and Machine Learning, combining the advanced capabilities of cloud-native tools with intelligent traffic analysis to overcome this challenge.

The system utilizes AWS services to design a robust and scalable architecture that integrates machine learning models trained on diverse traffic patterns to identify and mitigate DDoS threats dynamically. By using anomaly detection techniques and automated response mechanisms, while real-time traffic monitoring assures the continuity and reliability of cloud-hosted applications and does not disrupt legitimate activity, experimental evaluations demonstrate efficacy in neutralizing various attack vectors while maintaining optimal resource usage. This research is a significant stride toward improving cloud security and, hence, provides a platform for developing advanced DDoS protection systems for hybrid and multi-cloud environments. The rest of this paper discusses the design, implementation, and experimental validation of the system.

# LITERATURE SURVEY

Distributed Denial of Service attack is found to be one of the vital threats for cloud computing environment thus lately, the increase in frequency and intensity attracts great interest toward an efficient mechanism of protection. Recent past few years, there were many approaches to counter-acting DDoS attack proposed in recent days related to the development of technologies of cloud and machine learning. This paper outlines the state-of-the-art solutions, which presents the issues and gaps in research and discusses the role of AWS and machine learning in the solution for DDoS attacks.

Difficulties along with strategies for DDoS attacks that are associated with the mitigations within the cloud computing environment have brought out the need to handle dynamically changing cloud structures Bui and Martin [1]. They need more efficient and adaptive solutions scalable and effective for the current mitigation strategies. Salahuddin et al. [2] have done an excellent survey of the current mechanisms of DDoS defence in cloud-based environments. The paper has highlighted the requirement for further innovation in the area of DDoS defences based on clouds and has discussed potential future research areas.

Kumar et al. [3] has identified the security features offered by Amazon Web Services (AWS) that counter DDoS attacks. Further, the paper details that among the must-have defence mechanisms for prevention and mitigation of DDoS attacks are AWS services AWS Shield and AWS WAF (Web Application Firewall). Sriram et al. [4] discuss real-life attacks and defence mechanisms against DDoS attacks through clouds. Their work illuminates how important real-time automated mitigations are for cloud systems and the dynamic nature of resources in a cloud environment.

Alqahtani et al. [5] made a comparative study about security methods implemented on cloud platforms against DDoS attacks, wherein relative performance of various mitigation techniques is compared. Their findings show that the hybrid approach can achieve great improvement in terms of detection accuracy and scalability, using the integration of traditional DDoS defence with machine learning. Nguyen [6] advances the discussion into more sophisticated architectures for DDoS mitigation, especially within the context of cloud environments. He mentions next-generation cloud-based architectures using adaptive and predictive mechanisms for effective DDoS attack mitigation.

Brown [7] has presented the problems of cloud-hosted DDoS defence systems that include traditional solution limitations and new defence architectures. Singh et al. [8] focused on the prevention of DDoS attacks in the cloud environment by introducing a preventive framework that makes use of machine learning for threat identification. Their framework is adaptive and scalable, which is very important in handling the growing complexity of DDoS attacks.

Ali et al. [9] emphasizes detection and countermeasure strategies in DDoS attacks on cloud computing. In this paper, how the detection mechanism has been integrated with the machine learning algorithms to enhance accuracy of detection and also decreases false positives. Johnson et al. [10] have described the real-world testing of cloud DDoS prevention tools. They tested a variety of commercial as well as open-source solutions against the real-world performance in that. Their results indicate that although the solutions proposed till date have worked, there is still much scope for improvement in handling emerging and evolving attack patterns.

Kim et al. [11] present machine learning-based adaptive approaches for DDoS in cloud networks, real-time detection, and response mechanisms during attacks. Their results strongly indicate that AI-driven systems can learn as well as adapt in time-varying attack patterns. Gupta and Singh [12] have provided a review of cloud-based DDoS mitigation techniques, which are classified into network-layer, transport-layer, and application-layer defences. They believe that the key to effective defence is a multi-layered approach combining these methods with machine learning.

Zhang et al. [13] have compared the various approaches to DDoS mitigation for cloud systems, which analyses the pros and cons of the techniques that are available. Both of them have their merits according to their study, but hybrid one using machine learning with traditional defence gives the best result with high accuracy and scalability. Park [14] has used machine learning in DDoS attack detection, specifically in cloud-based networks. His research is about applicability of AI models in identifying attack patterns and decreasing time taken in detection and mitigation of attacks.

Finally, Fang [15] described the technique for anomaly detection to suppress the DDoS attack in the cloud environment. In an anomaly detection model with ML algorithm integration, Fang has proven that it could probably provide a means of early detecting any anomaly within the traffic patterns due to the DDoS attack with an automated response.

Conclusion As DDoS attacks become more sophisticated, so will the wave of innovation for DDoS mitigation. Cloud-based solutions, especially those built on top of AWS services and machine learning techniques, have a great promise for augmenting the capabilities of DDoS detection and mitigation. These systems need further engineering to enhance their scalability, adaptability, and response in real time for sustained robust protection against changing threats for cloud-hosted services.

# METHODOLOGY

The present study utilizes synthetic traffic data generation by creating a Python script to simulate real web traffic patterns. The synthesized traffic data is then subjected to further processing by Isolation Forest algorithm from the scikit-learn for finding anomalies, which may correspond to DDoS attacks or suspicious activities. Matplotlib is then used to analyse the outliers of the Isolation Forest model.

The use of Apache JMeter for load testing the system is used to test it under heavy load. It is set to simulate the number of requests coming from different users to the server through HTTP requests with varying levels of traffic. Parameters varied include the number of users, ramp-up period, and loop count in testing the response of the system under different stress conditions.

This load testing simulates real-world traffic patterns and tests the server's resilience to sudden surges in requests, mimicking conditions under a potential DDoS attack. Real-world cloud integration is demonstrated by deploying the anomaly detection scripts and traffic monitoring components on an AWS EC2 instance. To monitor the system's performance, Amazon CloudWatch is used to track key metrics such as NetworkIn (incoming network traffic) and CPU utilization. It's configured to alert administrators on the thresholds that are breached with these metrics, giving them real-time performance insights.

AWS automatically creates an Auto Scaling Group, which dynamically scales up and down the number of running EC2 instances depending upon traffic load. Additionally, there is an AWS Load Balancer, which distributes incoming traffic across instances, allowing high loads without affecting service availability.

Finally, the system is validated to be effective in handling high traffic and potential DDoS attacks by simulating various attack scenarios using JMeter. The performance of the system in detecting anomalies, scaling the number of instances based on the load of traffic, and ensuring continuous system availability during stress tests is evaluated. The results of these tests are used to determine the strength of the anomaly detection and mitigation strategies.

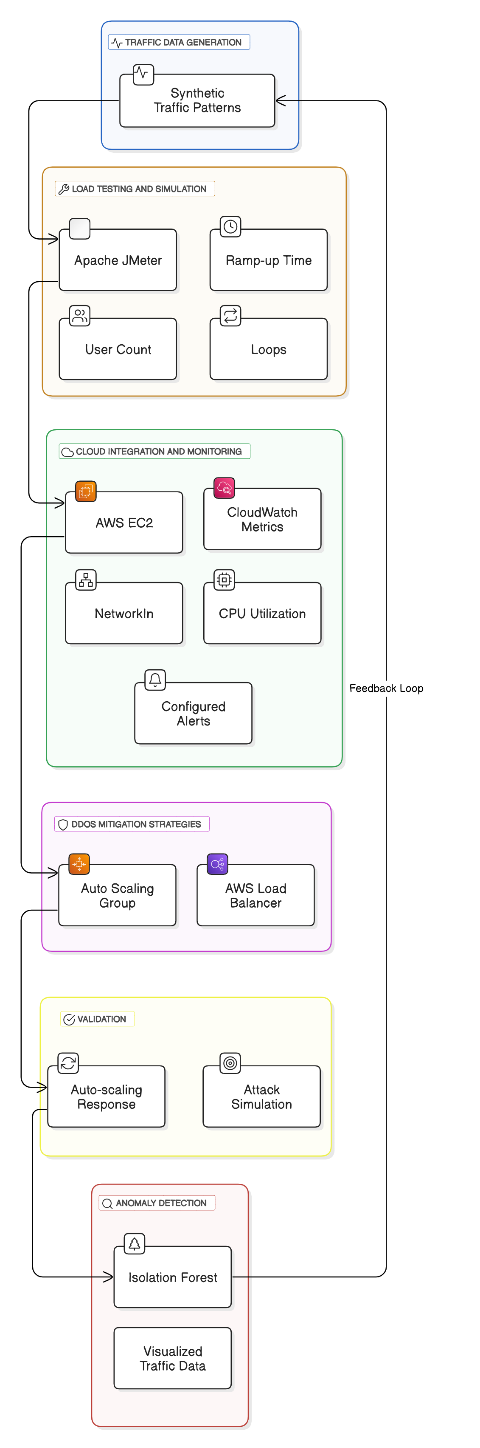


Fig. 1. Architecture Diagram of the workflow

# RESULTS

The performance of the proposed system was tested with regards to its anomaly detection and handling of simulated DDoS attacks under varying traffic loads. The results obtained show the effectiveness of the anomaly detection algorithm and the overall capacity of the system to mitigate traffic surges while maintaining system availability.

The Isolation Forest algorithm is able to isolate anomalies in the traffic data, which appear in the produced graphs. As traffic was increasing, the algorithm detected deviations in normal patterns of traffic flow, thereby indicating DDoS attempts. The scatter plots in which the x-axis represents traffic volume and the y-axis represents the detected anomaly scores are able to show anomalies. The higher the score, the more likely the data point is an anomaly. Figures showing the results of anomaly detection visually illustrate how well the algorithm isolated these irregular traffic patterns.

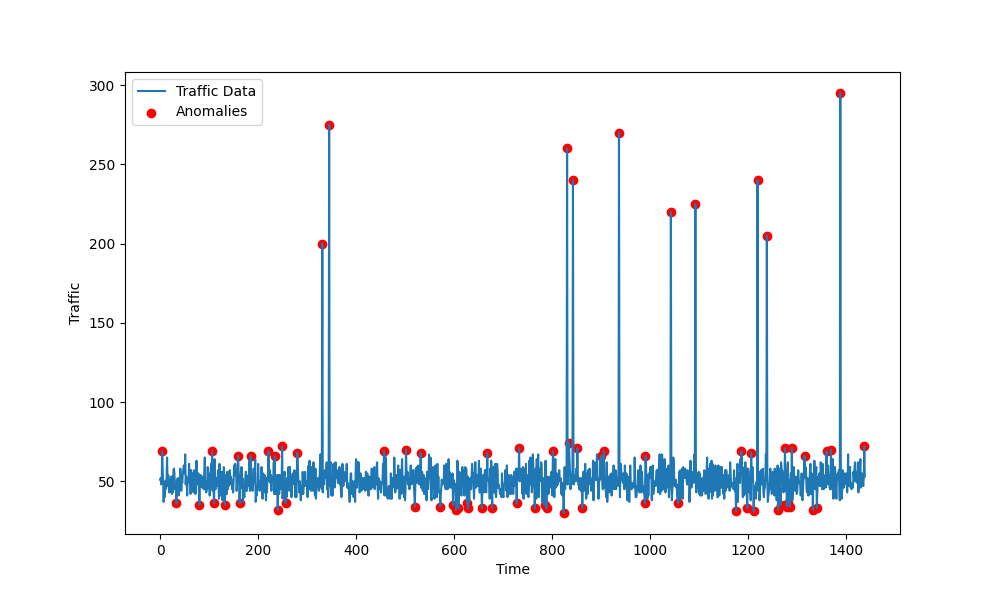


Fig. 2. Anomaly Detection Graph

During the load testing, the Apache JMeter simulated a high traffic condition. Results of the load test were obtained in terms of requests per second and show that it has a good handling capability, thus mimicking a level of traffic observed during a DDoS attack. The system response is monitored using key performance indicators, namely CPU utilization and network traffic. The graphs show how well a server performs when put through its paces in a scenario called load testing. Scenarios vary by the different quantities of users and styles of traffic.

Fig. 3. Apache JMeter Config

The cloud-based solution performed well under stress testing. AWS Auto Scaling Group automatically scaled the number of EC2 instances based on the volume of traffic to ensure the system maintained high availability even with load spikes. Throughout the tests, AWS CloudWatch metrics were monitored, and the results confirm that the system responded promptly to traffic changes and triggered appropriate alerts when predefined thresholds were exceeded.

Fig. 4. AWS CloudWatch Metrics

AWS CloudWatch was used to validate the alerting mechanism of the system. The key performance thresholds, like CPU utilization and network traffic, were set up for alerts to notify when those thresholds are exceeded during load tests. Figure 5. An example alert e-mail from the system; it had detected an anomaly: There is a vital piece of information contained within the body of the message about time, the anomaly type found, and a particular threshold that has been violated. All this shows how the system can track what's wrong and raise appropriate alarms and alerts for such problems before they develop.

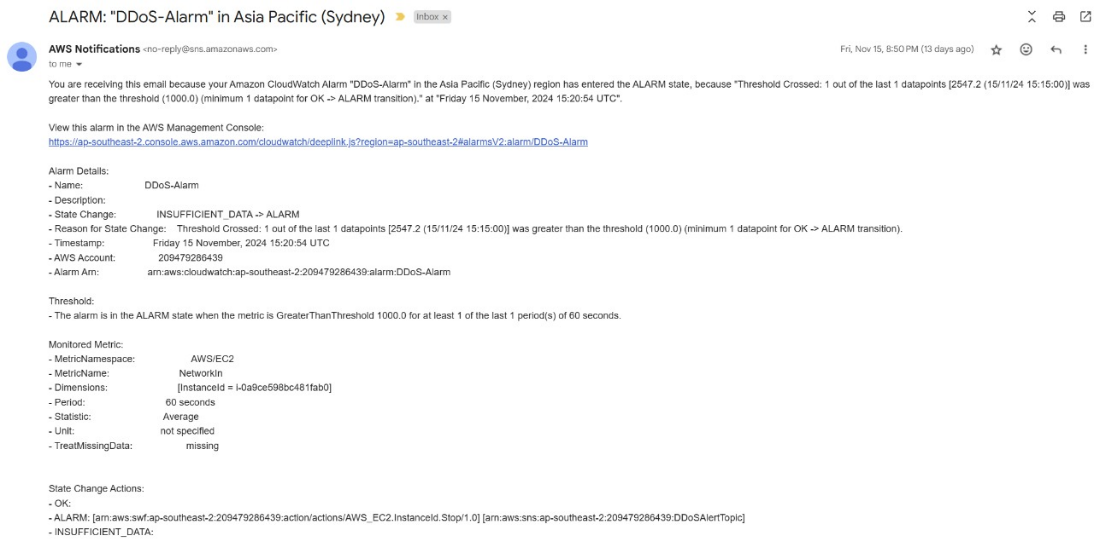
The results also validate the mitigation strategies used to address DDoS attacks. Using AWS Load Balancers, incoming traffic was distributed evenly across the EC2 instances, and no instance was overwhelmed by the incoming traffic. The Auto Scaling of the system also ensured that there were sufficient resources to handle high traffic volumes. Distribution of traffic and system scaling behaviour are included in figures to show how the system was resilient.

Fig. 5. Alert Email

Fig. 6. Auto Scaling and Load Balancer Behavior

Fig. 7. Traffic Distribution via Load Balancer

Therefore, this paper's results indicate that the proposed anomaly detection system together with load testing and DDoS mitigation strategies, it is shown to adequately address the problem of system performance under heavy traffic. The system performed with an ability to detect and react to anomalies without having an influence on the availability of the services even in cases of simulated attacks with DDoS.

# CONCLUSION AND FUTURE ENHANCEMENTS

This research was very successful in demonstrating the design and implementation of a DDoS protection system for cloud-hosted websites using a combination of anomaly detection, load testing, and cloud services. The system made use of synthetic traffic generation, which emulated real-world web traffic patterns; it used the Isolation Forest algorithm for anomaly detection.

The system was able to identify anomalies in traffic, which might indicate potential DDoS attacks. Deployment on AWS EC2 with monitoring and alerting by CloudWatch allowed the system to scale dynamically as the load of traffic increased, thereby offering a robust solution to DDoS attacks. Apache JMeter was used to perform load testing, which simulated high traffic loads and thus provided useful insights into how the system behaves under stress.

The Auto Scaling Group and AWS Load Balancer successfully distributed traffic and dynamically scaled resources based on demand, demonstrating the system's capacity for maintaining high availability during simulated DDoS attacks. The results validated the system's ability to detect anomalous behaviour, automatically scale infrastructure, and maintain system stability, while also generating automated alert notifications to inform stakeholders in real-time.

Overall, the research has established a foundational framework for DDoS protection in cloud environments. Scalable cloud services, real-time monitoring, and machine learning-based anomaly detection prove to be an effective strategy against DDoS threats.

Although the current system effectively prevents DDoS attacks, there are a few areas of improvement in the future. The anomaly detection currently relies on the Isolation Forest algorithm, which is good for identifying outliers but might not capture all the complexities of an attack pattern.

Future improvements can be in the form of more advanced machine learning algorithms, like deep learning models or ensemble methods, to increase the detection rate and accuracy of anomalous traffic patterns. Currently, the system dynamically scales depending on detected anomalies, and the future versions may also support more real-time mitigation techniques by rate-limiting traffic coming from specific sources or firewalls to block malicious traffic on detection. Real-time threat intelligence can also be utilized for faster identification of known attack vectors.

Enhanced visualization tools may be integrated to present real-time data and anomaly detections in an intuitive dashboard for better decision-making and quicker analysis. Administrators would be able to monitor traffic in real-time, view alerts, and take corrective actions more efficiently. Integrating the system with external threat intelligence feeds would help detect and block known malicious IP addresses and DDoS attack signatures, thereby improving the accuracy and speed of attack mitigation.

By integration of this with the present anomaly detection system, it will present multi-layered defence. This time, the system is spread out only on a single AWS EC2 instance. In the near future, improvements may include spreading it all over various geographic regions, such that in case of an even broader global-scale DDoS attacks, its fault tolerance enhances along with availability.

More detailed reporting, customizable thresholds and channels for notifications could be part of future enhancements of the alerting system. Automated responses to a type of alert, such as invoking a custom script or executing preconfigured countermeasures, can further increase operational efficiency.

As the load increases, the performance optimization of the anomaly detection algorithm will play an important role in reducing latency and false positives.

This can be achieved through more efficient data structures, optimization of the detection algorithm, and processing large volumes of traffic data using distributed computing frameworks. Continued refinement and expansion on these features will result in an evolution of the system into a more robust and adaptable solution for protection against DDoS attacks on cloud-hosted services, ensuring their availability and resilience in the face of increasing threats.

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