

# **DDoS PROTECTION SYSTEM FOR CLOUD USING AWS AND MACHINE LEARNING**

**A MAJOR PROJECT REPORT**

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in  
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&  
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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.

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## ABBREVIATIONS

<b>AI</b>	Artificial Intelligence
<b>AWS</b>	Amazon Web Services
<b>DDoS</b>	Distributed Denial of Service
<b>IDS</b>	Intrusion Detection System
<b>IP</b>	Internet Protocol
<b>ML</b>	Machine Learning
<b>SIEM</b>	Security Information and Event Management
<b>EC2</b>	Elastic Compute Cloud
<b>VPC</b>	Virtual Private Cloud
<b>ALB</b>	Application Load Balancer
<b>WAF</b>	Web Application Firewall
<b>IAM</b>	Identity and Access Management
<b>CloudWatch</b>	Amazon CloudWatch
<b>CSV</b>	Comma-Separated Values

# CHAPTER 1

## INTRODUCTION

This chapter discusses the emerging DDoS threat for cloud-hosted systems, focusing particularly on the vulnerabilities in cloud infrastructures. It highlights the requirement for real-time detection and mitigation strategies in order to minimize such attacks. The proposed DDoS Protection System that utilizes AWS cloud services along with ML is introduced as an effective means of threat identification and response. It finally summarizes the contributions of this system and future prospects for improving cloud security.

### **1.1 The Emerging Threat of DDoS Attacks in Cloud Environments**

Cloud computing has taken the world by storm and changed modern applications through scalability, efficiency, and cost-effectiveness. However, this dependence on cloud platforms has exposed it to being a prime target for cyberattacks, especially Distributed Denial of Service (DDoS).

In the case of a DDoS, attackers usually flood a target cloud server with malicious traffic to overload its resources, thereby disrupting the delivery of services. Since a cloud network has many points, it makes the entry points numerous and thus difficult to detect and mitigate attacks.

Cloud systems have unique vulnerabilities, such as multi-tenancy, shared resource pools, and elastic scaling. While these features are beneficial, they can be exploited to amplify attack surfaces, leading to significant downtime, data breaches, and financial losses. Innovative solutions tailored specifically for the cloud environment are needed to address these vulnerabilities.

### **1.2 Impact of Real-time Detection and Mitigation**

Conventional DDoS mitigation solutions struggle to keep pace with the sheer scale and complexity of the cloud. Most use static rules or manual intervention that can't possibly keep up with today's complex and extremely dynamic attacks.

Real-time detection and mitigation of DDoS attacks will significantly reduce the damage done to the systems. Malicious traffic can saturate cloud resources quickly, causing cascading failures in multiple services. Real-time detection and neutralization of such threats will ensure continuous availability, reduce operational disruptions, and maintain user trust.

Cloud-based architectures, with dynamic traffic patterns and high scalability, require advanced security frameworks that analyze traffic behavior in real-time and respond quickly to anomalies. This gives rise to the need for machine learning-powered solutions that adapt to evolving attack strategies.

### **1.3 DDoS Protection System with AWS and Machine Learning**

The proposed system takes advantage of the robust infrastructure of Amazon Web Services (AWS) and machine learning algorithms to provide an intelligent and scalable DDoS protection framework.

The system utilizes AWS services such as CloudWatch for monitoring, WAF (Web Application Firewall) for traffic filtering, and Auto Scaling Groups to handle load balancing. Integrated with these services is a machine learning model designed to analyze traffic patterns and differentiate between legitimate and malicious requests.

The realistic data provided by simulations with tools like JMeter enables training of the model under normal and attack conditions. Anomalies are learned through an ML algorithm, which learns the patterns characteristic of DDoS attacks. Once in deployment, the system monitors the traffic continuously and adjusts the security rules dynamically to block malicious sources without affecting legitimate users.

This adaptive approach ensures real-time threat detection and mitigation, significantly enhancing the resilience of cloud-hosted services against DDoS attacks.

## 1.4 Contribution and Future Prospects

The DDoS Protection System for Cloud significantly contributes to cloud security through innovative approaches toward overcoming fundamental challenges. Its core value lies in its capability, where it introduces real-time DDoS detection in collaboration with machine learning-based approaches that adapt towards evolving attack patterns in run time. It's actually an AI-based approach compared with the traditional approach. This scalable and robust infrastructure of AWS in return lets the system scale up with high volumes of traffic without slowing down performance or reliability.

This dynamic response capability is enabled by AWS services that integrate automated scaling with proactive mitigation of threats to avoid the need for human intervention. This enables continuous protection while maintaining availability throughout an attack. Further, by making efficient use of cloud resources, this system optimizes costs so as not to incur further expense in cases of long-duration downtime or resource-heavy mitigation attempts.

Future enhancements are expected to make the system more adaptive to learn about the attacks and thereby tackle more complex attack scenarios. Improvements include scope extension of the model in order to handle diverse traffic patterns, incorporation of predictive analytics for preemptive threat detection, and integration with additional security tools to create a comprehensive defense ecosystem.

With its robust architecture and intelligence-driven approach, the proposed system lays a strong foundation for building secure and resilient cloud environments that can handle evolving cyber threats. The system represents an important leap forward in protecting cloud-hosted systems from DDoS attacks while maintaining uninterrupted service and cost efficiency.

## **CHAPTER 2**

### **LITERATURE SURVEY**

This chapter gives an all-round overview of existing literature dealing with DDoS attacks in the cloud. It talks about problems and issues raised by such DDoS attacks, solutions developed for these attacks so far, and the infusion of innovative technologies like AWS services and machine learning to provide an all-rounded view. This survey also mentions existing shortcomings in the existing solution and presents the possibilities for developing novel solutions for improvement of cloud security against these ever-changing threats.

#### **2.1 Challenges of DDoS Attacks in Cloud Environments**

Amongst the biggest threats that could be seen against cloud computing is DDoS attacks since it uses the distributed nature of the cloud to magnify its impact. Within the last few years, such attacks have risen and matured exponentially, thus needing dynamic and adaptive defense mechanisms.

Bui and Martin<sup>[1]</sup> pointed out the intricacy in mitigating DDoS attacks due to the dynamic and scalable nature of cloud environments. Their findings point out the requirement for adaptive solutions that are able to handle the constantly changing structures of cloud systems. Salahuddin et al.<sup>[2]</sup> further analyze existing DDoS defense mechanisms and pointed out innovation as a significant step forward in overcoming the shortcomings of current strategies.

The heterogeneity of the cloud-hosted application and service introduces additional challenging factors, including diverse attack surfaces, varying levels of resource availability, and high demands that require scalable as well as efficient solutions designed to smoothly operate across multiple layers of a cloud infrastructure.

## **2.2 AWS-Based Solutions for DDoS Mitigation**

Amazon provides an effective array of strong tools and services to work against DDoS attacks. Kumar et al.<sup>[3]</sup> identified critical components in prevention and mitigation of DDoS attack namely AWS Shield and AWS WAF. It provides automatically detecting and mitigating capacities of DDoS; and AWS WAF performs fine-grained traffic filtering with rule-based threat preventing capabilities.

Actual-use cases discussed by Sriram et al.<sup>[4]</sup> prove the effectiveness of these services in reducing very high volume attacks. Therefore, the research work provides the significance of real time automated response and dynamic resources scaling to protect cloud host services. In addition to this, Alqahtani et al.<sup>[5]</sup> compared the working of various cloud security technologies and proved that hybrid architectures combining AWS services with Machine Learning provide better scalability and true Detection performance.

## **2.3 Role of Machine Learning in DDoS Defense**

Machine learning has emerged as a transformative technology in fighting DDoS attacks. Singh et al.<sup>[8]</sup> proposed a framework for adaptive threat detection based on machine learning, which showed its scalability and efficiency to handle complex attack patterns. Ali et al.<sup>[9]</sup> demonstrated that incorporation of machine learning algorithms improved the accuracy of attack detection with reduced false positives.

Kim et al.<sup>[11]</sup> focused on the exploration of real-time detection and response mechanisms through adaptive machine learning models. Such a research outcome points toward the AI-based system ability to learn about changing patterns of attacks for robust protection in a dynamic cloud environment. Similarly, Zhang et al.<sup>[13]</sup> discussed traditional as well as hybrid approaches towards DDoS mitigation techniques, which established the supremacy of machine learning-based approaches concerning accuracy as well as scalability.



## 2.4 Innovative Architectures for Cloud Security

Emerging architectures for DDoS mitigation take advantage of the synergy between traditional defense mechanisms and advanced technologies. Nguyen<sup>[6]</sup> proposed next-generation cloud-based architectures that incorporate predictive analytics and adaptive mechanisms for enhanced mitigation. These architectures utilize multi-layered defenses to address attacks across the network, transport, and application layers, as reviewed by Gupta and Singh<sup>[12]</sup>.

Zhang et al.<sup>[13]</sup> and Park<sup>[14]</sup> emphasized the importance of hybrid solutions combining machine learning with traditional methods. Such approaches balance scalability, detection accuracy, and cost-efficiency, making them well-suited for modern cloud environments. Fang<sup>[15]</sup> demonstrated the effectiveness of anomaly detection models integrated with machine learning algorithms in providing early warnings and automated responses to DDoS attacks.

## 2.5 Conclusion

The reviewed literature shows how DDoS attacks have evolved in complexity and that novel cloud-based mitigation approaches are urgently required. Using machine learning on AWS services has potential as scalable, adaptive, and real-time solutions to mitigate DDoS attacks; however, much needs to be done in making the system more robust to new emerging threats and hence sustained protection for services running in the cloud.

Future research should target fine-tuning hybrid architectures and developing more accurate machine learning models, along with creating predictive mechanisms to stay on the front foot of emerging patterns. This will be instrumental in protecting cloud environments as they face the ever-evolving landscape of cyber threats.

## **CHAPTER 3**

### **SYSTEM ARCHITECTURE AND DESIGN**

Architecture and design of the proposed DDoS Protection System for Cloud using AWS and Machine Learning involves details on the layered system architecture, integration of anomaly detection mechanisms, and the deployment of cloud-based mitigation strategies. Its ability to mimic real-world traffic patterns while it identifies anomalies, and respond dynamically to DDoS attacks minimizes service disruption.

### **3.1 Layered Architecture Overview**

The architecture of the DDoS Protection System is designed as modular and layered, hence scalable, maintainable, and adaptable. Each layer takes on certain roles to detect, analyze, and mitigate DDoS attacks so that it can easily manage traffic and resolve anomalies.

#### **3.1.1 Traffic Data Generation Layer**

This layer is used to mimic realistic traffic patterns. Python scripts generate synthetic traffic data that replicates realistic behavior of real-world web traffic. Such simulation helps create controlled environments in which to test anomaly detection methods.

#### **3.1.2 Anomaly Detection Layer**

The Anomaly Detection Layer utilizes the Isolation Forest algorithm from the scikit-learn library to point out anomalies in traffic pattern. This algorithm models what normal traffic is and sets apart anomalies that significantly deviate, indicating possible DDoS attacks. The anomaly detected is plotted using the matplotlib library for further thorough analysis.

#### **3.1.3 Load Simulation and Testing Layer**

Load testing is performed using Apache JMeter to simulate high traffic loads and test the resilience of the system. This layer configures the user load parameters, like concurrent users and request rates, to stress-test the server under various conditions that can be considered as DDoS conditions.

### 3.1.4 Mitigation Layer

The Mitigation Layer uses dynamic strategies against detected threats to ensure system stability. Key components such as Auto-Scaling allow the system to automatically launch or terminate EC2 instances in real-time based on the traffic load, thus providing adequate resources during traffic spikes, including DDoS attacks. The Load Balancer also plays a crucial role by spreading incoming traffic evenly across multiple instances, thus preventing one server from becoming overwhelmed. Together, these mechanisms ensure that legitimate traffic flows uninterrupted while malicious traffic is efficiently filtered, thus maintaining integrity and availability of the system.

### 3.1.5 Monitoring and Reporting Layer

AWS CloudWatch ties into the system and monitors key metrics, such as NetworkIn and CPU, and is configured to send alerts when thresholds are exceeded for real-time intervention during attacks.

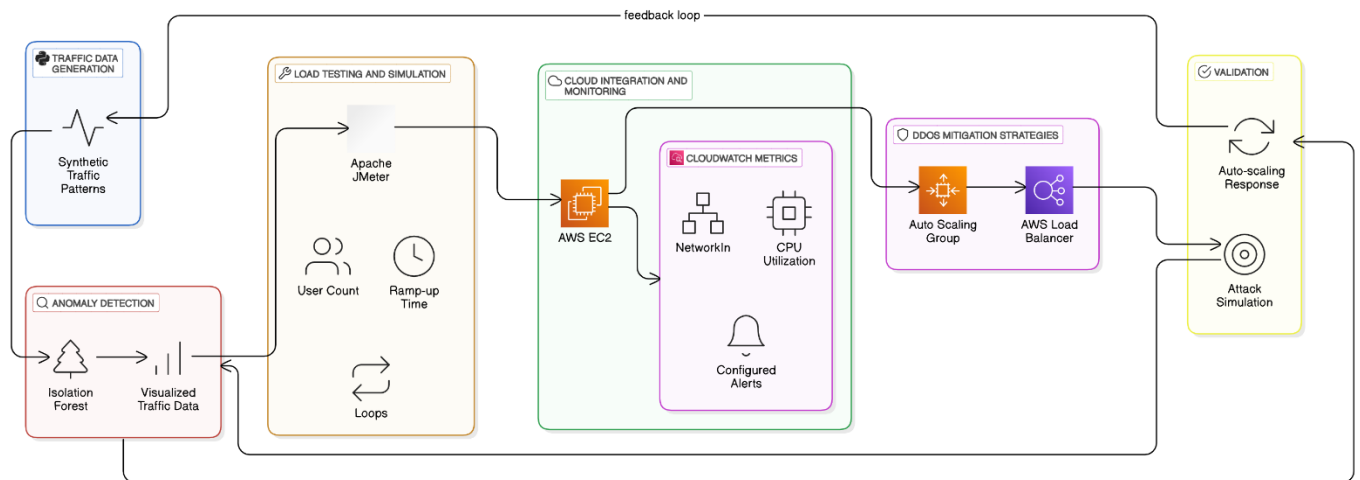


Fig. 3.1 Architecture Diagram

## 3.2 Core Components

### 3.2.1 Traffic Data Simulation and Anomaly Detection

The core component of the system, which is the anomaly detection model, is trained with synthetic traffic data. Employing the Isolation Forest algorithm, it detects outliers that are significantly different from learned baselines, indicating that they may be a DDoS attack. Visualization tool-supported analysis and validation enhance its true positive rate.

### **3.2.2 Load Testing Framework**

Load testing is primarily done with the help of Apache JMeter. It produces different kinds of traffic patterns based on parameters such as user concurrency, ramp-up periods, and request intervals. It tests the system's response to stress and how well it can handle a variation in traffic loads.

### **3.2.3 Cloud-Based Mitigation**

The system relies on the AWS services for scalability and resilience in traffic surges, especially DDoS attacks. Auto Scaling Groups automatically adjust the number of server instances based on traffic load, thereby ensuring there are enough resources available when traffic is high. Further, the Elastic Load Balancer (ELB) spreads incoming traffic across several instances, thus optimizing server performance and preventing bottlenecks. These features allow the system to adapt dynamically to varying traffic conditions and prevent server overload in the case of a DDoS attack, maintaining consistency in availability.

## **3.3 Scalability and Performance Considerations**

### **3.3.1 Scalability**

The solution is designed to handle the large-scale traffic with utmost ease. AWS Auto Scaling Groups ensure that additional resources are provisioned during the high-demand scenarios, thus not disrupting the service.

### **3.3.2 Low Latency Operations**

Low latency is critical to real-time anomaly detection and mitigation. Using AWS edge services and optimized instance configurations, the system minimizes its response times to ensure on-time countermeasures for DDoS attacks.

### **3.3.3 Adaptability**

The modular architecture is designed to allow easy incorporation of new detection algorithms and mitigation strategies. This would ensure that the system continues to be robust against the evolving attack vectors and support advancements in cloud-based technologies.

## **3.4 Integration with AWS Infrastructure**

### **3.4.1 CloudWatch Monitoring and Alerts**

AWS CloudWatch monitors all the essential metrics, such as traffic volume and server utilization. All the alerts are set so that whenever an anomaly or high traffic load is found, it sends a notification allowing for swift administrative action.

### **3.4.2 EC2 Deployment and Management**

Scaling, reliability, and other requirements of cloud infrastructure are followed by the EC2 instance in which anomaly detection monitoring scripts are deployed. Due to this reason, in real-time, traffic can also be scaled up or scaled down automatically.

### **3.4.3 Legacy System Compatibility**

This system has compatibility with any legacy communication protocol and also with previous cloud infrastructures. In this way, it could be deployed into any deployment environment without making much of architecture changes.

## **3.5 Validation of System Design**

The validation of the proposed system is comprised of comprehensive testing to evaluate its effectiveness against DDoS attacks. High traffic loads are simulated using Apache JMeter to mimic real-world DDoS scenarios, giving a controlled environment to analyze the performance of the system. The Isolation Forest algorithm is tested for the accuracy of anomaly detection as its ability to identify any unusual patterns in the simulated traffic may indicate potential attempts of DDoS attacks.

Moreover, the mitigation strategy's effectiveness is further verified by monitoring the behavior of the AWS Auto Scaling and Load Balancing mechanisms within such scenarios. Such testing assures that the system adapts dynamically to the changing conditions of the attack and keeps consistent availability and service quality intact.

### **3.6 Summary**

The proposed DDoS Protection System for Cloud utilizes AWS and Machine Learning to present an adaptive, scalable, and efficient mitigation of DDoS attacks. This system is built with layered architecture, combining traffic simulation, anomaly detection, and real-time mitigation strategies in order to protect cloud-based services. The modular design ensures compatibility with existing infrastructures and maintains resilience against evolving threats.

# CHAPTER 4

## METHODOLOGY

This chapter details the methodology that was used to design a DDoS Protection System for Cloud Using AWS and Machine Learning. The approach involved the generation of synthetic traffic data, anomaly detection based on the Isolation Forest algorithm, and a robust cloud-based infrastructure that utilized AWS to manage traffic and auto-scale. It also involved stressing the system under simulated DDoS conditions using Apache JMeter and evaluating performance against key metrics such as anomaly detection accuracy, scalability of the system, and availability.

### 4.1 Addressing Cloud Security Using AI and Cloud-Native Techniques

This factor has made cloud infrastructure critical to businesses, hosting applications, and managing sensitive data. With the upsurge in the usage of cloud infrastructure, attacks by DDoS increase too. DDoS attacks present malicious traffic to overwhelm systems, which in turn disrupts service.

The proposed solution uses ML techniques in conjunction with cloud-native tools such as AWS Auto Scaling and Load Balancers and synthetic traffic simulations for real-time detection and mitigation of DDoS attacks. It focuses on an adaptive architecture that is scalable to achieve availability and performance under heavy traffic conditions.

### 4.2 Synthetic Traffic Data Generation

A Python script was developed that simulates a realistic web traffic pattern, whether benign or malicious. It includes synthetic data such as:

- Normal traffic which mimics standard HTTP requests with a consistent interval and data sizes.
- Malicious traffic: Simulates DDoS-like behavior, including sudden spikes in requests and high-frequency traffic from multiple sources.

These parameters include request rate, traffic distribution, and payload size to create diverse datasets. These datasets will be used to conduct anomaly detection. Log and save the traffic patterns. It is necessary for later pre-processing and analysis.

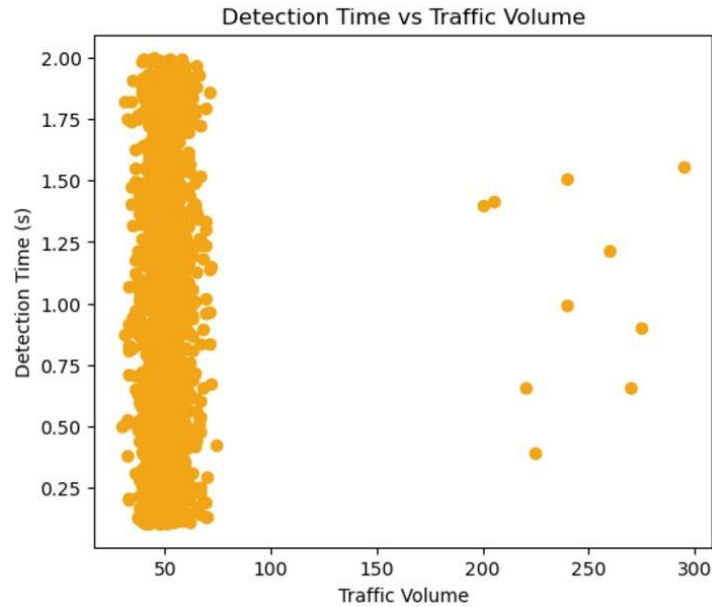


Fig. 4.1 Detection Time vs Traffic Volume

### 4.3 Anomaly Detection with Machine Learning

The Isolation Forest algorithm was employed with the scikit-learn library to determine anomalies in traffic data. This algorithm isolates anomalies by recursively partitioning the dataset; hence it is very suitable for identifying anomalous traffic patterns. The process encompasses the following steps:

- Preprocessing the data: Standardization of request frequency, payload size, and response times.
- Training the model: Synthetic traffic data was used to train the Isolation Forest to classify traffic as either benign or suspicious.
- Visualization: The model identified outliers were visualized with Matplotlib that gave the suspicious activity insights.



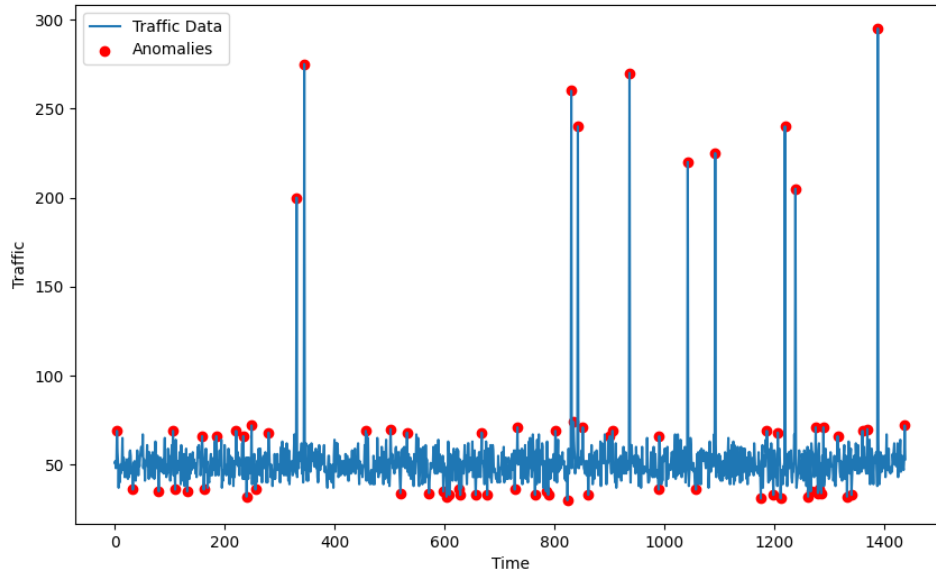


Fig. 4.2 Anomalies Detection Plot

## 4.4 Load Testing with Apache JMeter

### 4.4.1 Simulation of realistic traffic

We used the Apache JMeter tool for stress testing our system under the following traffic scenarios, in order to emulate real attacks:

- Number of users: Simulated concurrent requests by multiple sources
- Ramp-up period: Gradually increasing traffic with respect to time.
- Loop count: Continuous sending of requests simulating persistence DDoS attack behavior.

These parameters enabled all possible tests that could prove the system's response for normal and malicious loads.

### 4.4.2 DDoS attack resilience tests

Tests created in JMeter aimed at testing the system's resiliency to sudden increases in traffic. Response time, throughput, and error rate metrics were used to establish how effective the system was in withstanding stress conditions.

## 4.5 Cloud Integration with AWS

### 4.5.1 Deploying on AWS

The anomaly detection script and traffic monitoring components were deployed on an AWS EC2 instance. This cloud-based setup enabled real-time detection and monitoring of incoming traffic.

### 4.5.2 Traffic Monitoring with CloudWatch

Amazon CloudWatch was configured to track key performance metrics, including:

- NetworkIn: Monitors incoming traffic volume.
- CPU utilization: Tracks server load under varying traffic conditions.

CloudWatch alerts were set to notify administrators whenever thresholds were being breached, so responses in case of potential DDoS attacks could be expedited.

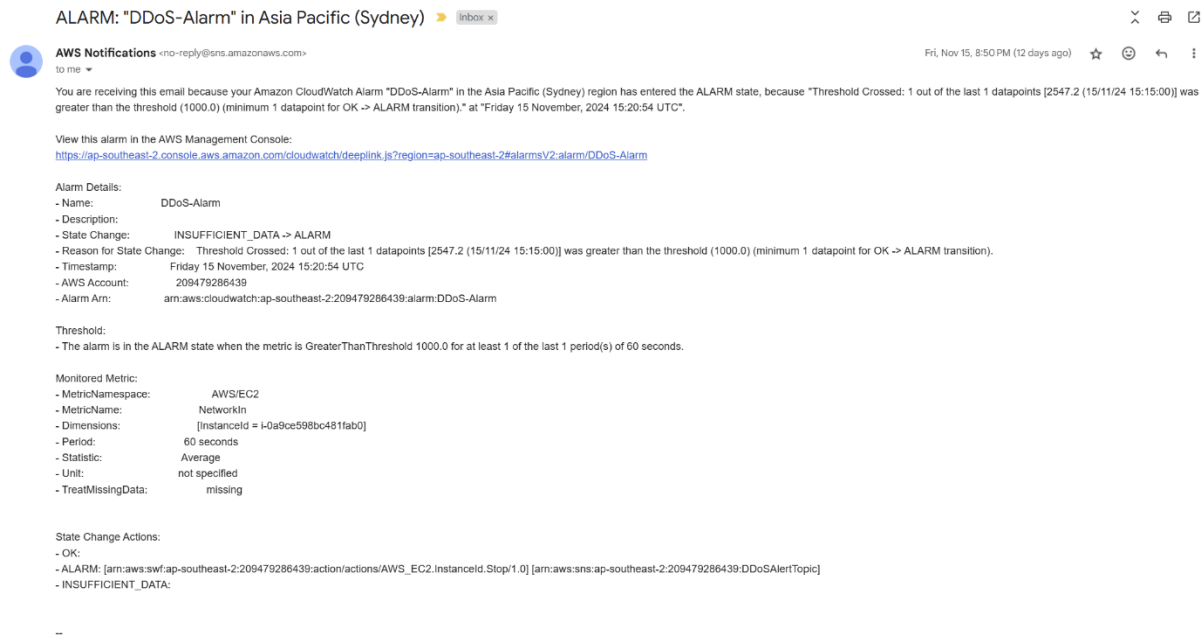


Fig. 4.3 Alert Email Screenshot

### 4.5.3 Auto Scaling and Load Balancing

To ensure scalability and availability of the system:

- AWS Auto Scaling will dynamically adjust the number of EC2 instances depending upon the incoming traffic load; these instances scale up during peak usage and scale down during normal usage.
- An AWS Elastic Load Balancer (ELB) distributed incoming traffic evenly across instances, preventing overload on any single server and maintaining service continuity.

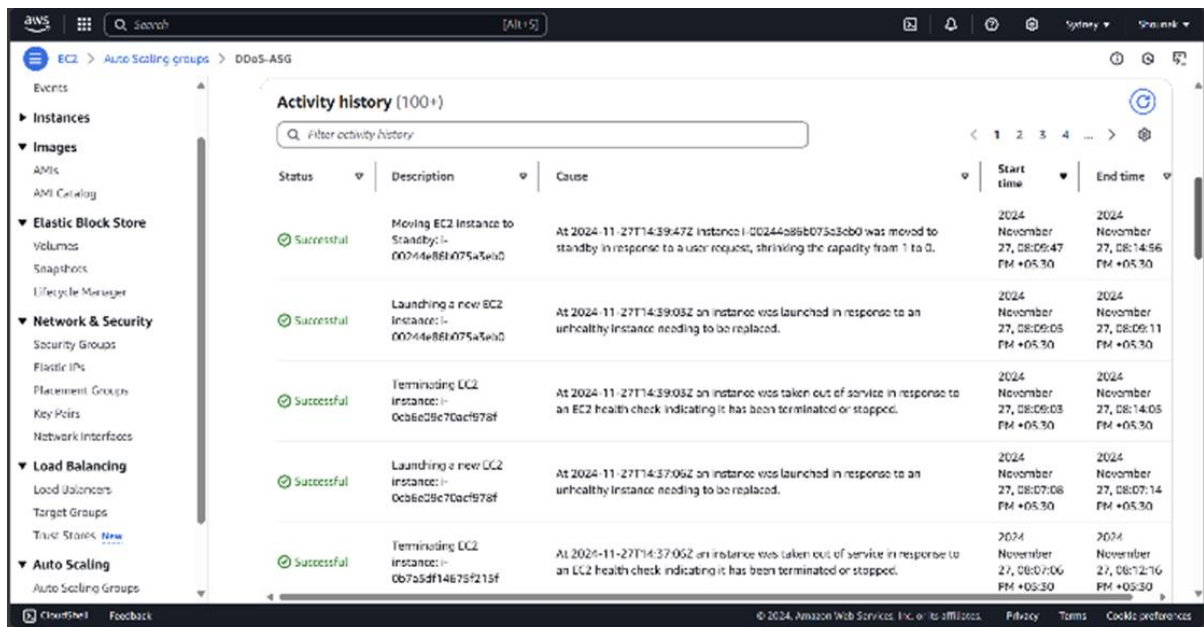


Fig. 4.4 Auto Scaling Behavior

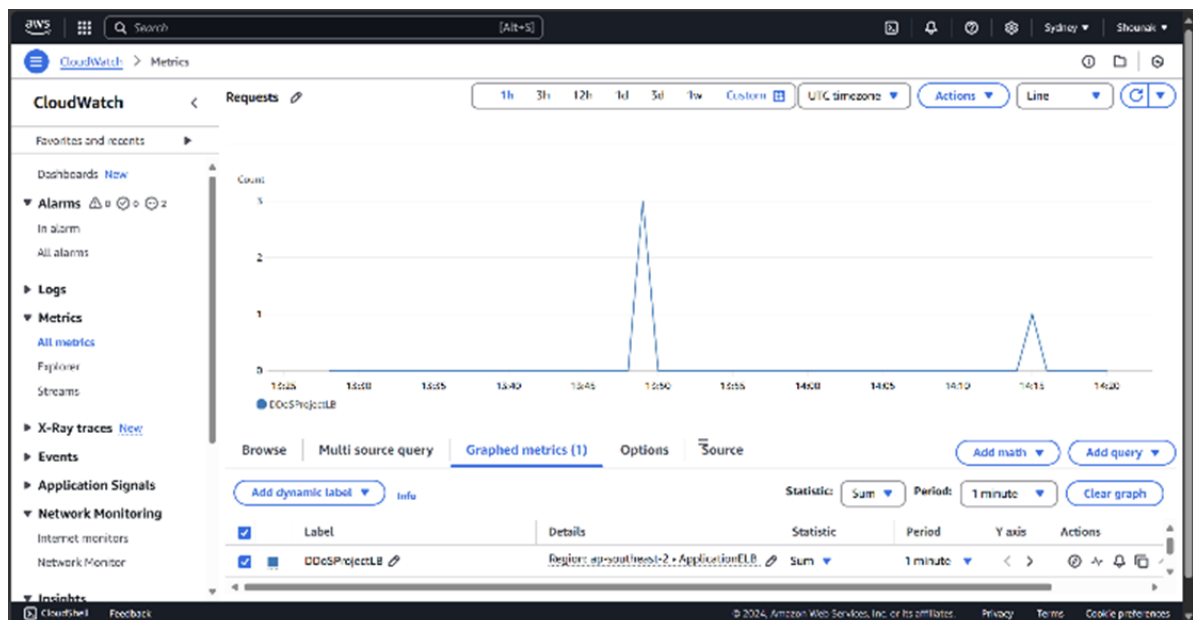


Fig. 4.5 Load Balancer Behavior

## **4.6 Validation and Mitigation Strategies**

### **4.6.1 Simulation of Attack Scenarios**

Several attack scenarios were simulated using JMeter to validate the system's ability to:

- Detect anomalies in real-time using the Isolation Forest algorithm.
- Scale resources dynamically to handle traffic surges.
- Maintain availability during DDoS attacks.

### **4.6.2 Mitigation with Blocking Mechanisms**

Automated blocking mechanisms were put in place based on the detection of suspicious activity to:

- Restrict traffic from identified malicious IP addresses.
- Maintain normal traffic flow and minimize disruption.

### **4.6.3 Performance Evaluation**

The performance of the system was measured using metrics like:

- Detection accuracy: Capability to correctly identify malicious traffic.
- Scalability: How well Auto Scaling keeps up with performance under loads.
- Availability: Percentage uptime during stress conditions.

Improvements in detection algorithms and architectures were made based on the feedback from the evaluations.

## **4.7 Summary**

This methodology outlines a comprehensive approach to DDoS protection using synthetic traffic generation, machine learning for anomaly detection, and AWS for scalability and resilience. By integrating these components, the system effectively addresses the challenges posed by DDoS attacks, ensuring continuous availability and performance in cloud environments.

# CHAPTER 5

## CODING AND TESTING

This chapter describes the AWS and Machine Learning-based DDoS Protection System implementation using code, along with testing approaches used to validate that the system works as anticipated. The implementation was about creating synthetic traffic data to generate anomalies using the Isolation Forest algorithm and proving scalability and resilience of the system in DDoS situations. Testing includes load testing with Apache JMeter, performance monitoring with AWS CloudWatch, and validation of the system's ability to withstand DDoS attacks while maintaining availability.

### 5.1 Traffic Data Generation

To simulate real-world web traffic, a Python script was developed to generate synthetic traffic data. This data is both normal web traffic and DDoS-like malicious traffic. The synthetic traffic data is created using the Poisson distribution with random anomalies at intervals that reflect sudden surges in traffic common in DDoS attacks.

#### 5.1.1 Pseudocode

```
BEGIN
    # Set the random seed for reproducibility
    SET random seed to 0
    # Define the number of data points (1440 for one day's worth of data)
    SET data_points to 1440
    # Generate traffic data using Poisson distribution with a mean of 50 requests per
minute
    GENERATE traffic data using Poisson distribution with mean 50 for data_points
    # Introduce anomalies by selecting random indices and multiplying their traffic
value by 5
    SELECT 10 random indices from traffic data points
    FOR each selected index DO
        MULTIPLY the traffic value at that index by 5
    END FOR
    # Create a DataFrame with the generated traffic data
    CREATE a DataFrame with 'Traffic' column containing the traffic data
    # Save the generated traffic data to a CSV file
    SAVE the DataFrame to a file named 'traffic-data.csv' without index
    # Print a success message
    PRINT "Synthetic traffic data saved to 'traffic-data.csv'"
END
```

### 5.1.2 Testing the Traffic Data Generation

Generated synthetic traffic data is stored as a CSV file and utilized in feeding the anomaly detection model. Artificial anomalies are generated by multiplying random data points with a factor of five that reflects the typical spiky patterns found in DDoS attacks. Traffic data was also saved and processed to ensure ready usage in further testing processes.

## 5.2 Dataset Generation

For anomaly detection, the algorithm of choice was Isolation Forest from the scikit-learn library. It uses recursive partitioning of the data to isolate anomalies, separating them from most data points. The process begins by loading synthetic traffic data generated from above, followed by the training of the Isolation Forest model to classify traffic as either normal or anomalous.

### 5.2.1 Anomaly Detection with Isolation Forest

For the simulation, traffic was captured by logging every packet passed to the router. This included benign and malicious traffic. The data logged in an XML file meant that through that format, I was able to capture critical details such as timestamp, source IP, destination IP, and packet size. Pseudocode is as follows:

```
BEGIN
  # Load the traffic data from a CSV file
  LOAD traffic data from 'traffic-data.csv' into a DataFrame
  # Display the first few rows of the loaded data
  PRINT the first few rows of the data
  # Extract the 'Traffic' column and store it in variable X
  SET X to the 'Traffic' column values from the data
  # Extract the true labels (normal or attack) from the 'True_Label' column
  SET y_true to the 'True_Label' column values from the data
  # Initialize the Isolation Forest model with contamination level of 0.05
  INITIALIZE IsolationForest model with contamination set to 0.05
  # Fit the model to the traffic data (X)
  FIT the IsolationForest model on X
  # Predict anomalies using the model (-1 for anomalies, 1 for normal)
  PREDICT anomalies using the IsolationForest model on X
  # Add the predictions to the DataFrame as a new 'Anomaly' column
  ADD 'Anomaly' column to the data with the predicted anomalies
  # Filter and store the rows where anomalies are detected (Anomaly = -1)
  SET anomalies to the rows where 'Anomaly' equals -1
  # Print the detected anomalies
  PRINT the anomalies
  # Calculate the accuracy by comparing predicted anomalies with true labels
  CALCULATE accuracy using accuracy_score(y_true, predicted anomalies)
```

```

# Print the accuracy percentage
PRINT the accuracy as percentage
# Generate confusion matrix
CALCULATE confusion matrix using confusion_matrix(y_true, predicted anomalies)
# Print the confusion matrix
PRINT the confusion matrix
# Generate classification report for precision, recall, and F1 score
PRINT classification report using classification_report(y_true, predicted
anomalies)
# Plot the traffic data and highlight anomalies
CREATE a plot with traffic data
PLOT traffic data as a line graph
PLOT anomalies as red scatter points on the same graph
LABEL x-axis as 'Time' and y-axis as 'Traffic'
ADD legend to the plot
# Save the plot to a file
SAVE the plot as 'anomalies_plot.png'
END

```

### 5.2.2 Testing Anomaly Detection

The model has been trained on synthetic data, which is the traffic information. Then, anomalies are determined by patterns in the traffic. Its performance was compared by metrics such as accuracy, precision, recall, and F1 score. A confusion matrix was formed to compare the predicted outcomes with true labels (normal vs. DDoS). Detected anomalies were plotted to visualize the irregular traffic spikes.

## 5.3 Load Testing with Apache JMeter

Apache JMeter is used for testing load against heavy traffic loads and DDoS attacks for validating the resilience of the system. Tests include various scenarios for different concurrent numbers of users, ramp-up periods, and loop counts that might represent a DDoS attack condition in the real world to analyze how well the system performs when a traffic load comes unexpectedly.

Apache JMeter was set with a multiple user simulation, using HTTP requests to the server. It was run in stress modes that varied parameters like user numbers, ramp-up times, and loop counts as stress levels on the system for responses during varied traffic conditions. That would mean observing the server regarding how it would respond regarding handling high traffic and available service.

## 5.4 Cloud Integration with AWS

The anomaly detection and traffic monitoring components of the system were deployed on AWS EC2 instances. This cloud setup allowed for real-time monitoring and automatic scaling based on incoming traffic. NetworkIn (incoming network traffic) and CPU utilization were monitored using Amazon CloudWatch. Alerts were configured to notify administrators if certain thresholds were breached, providing real-time performance insights.

### 5.4.1 AWS CloudWatch Setup

Command to run:

```
aws cloudwatch put-metric-alarm --alarm-name "HighTrafficAlarm" --metric-name
NetworkIn --namespace AWS/EC2 --statistic Sum --period 60 --threshold 1000000 --
comparison-operator GreaterThanThreshold --dimensions Name=InstanceId,Value=i-
1234567890abcdef0 --evaluation-periods 1 --alarm-actions arn:aws:sns:region:account-
id:alarm-action
```

### 5.4.2 Testing AWS CloudWatch Alerts

CloudWatch metrics were monitored in real-time while doing load testing. Alerts were set up to notify the administrators if traffic thresholds were exceeded. This way, swift action could be taken in case of a possible DDoS attack, thus keeping the system responsive and available even during stress conditions.

## 5.5 Auto Scaling and Load Balancing

The system utilizes AWS Auto Scaling, which dynamically changes the number of EC2 instances according to the level of traffic load. During increased traffic volume, Auto Scaling adds more instances to handle the load, and with decreased traffic, it scales down the number of instances. This is done through the AWS Elastic Load Balancer, which distributes the incoming traffic evenly across instances, thus not overwhelming any particular server and ensuring service availability.

### 5.5.1 Testing Auto Scaling and Load Balancing

Command to run:

```
aws autoscaling create-auto-scaling-group --auto-scaling-group-name
MyAutoScalingGroup --launch-configuration-name MyLaunchConfig --min-size 1 --max-size
10 --desired-capacity 2 --vpc-zone-identifier subnet-abc123
```



### **5.5.2 Testing Load Balancer Behavior**

Testing the performance of the load balancer was done through simulation of traffic spikes. In this, traffic distribution between the EC2 instances was observed to prevent overloading of any one instance due to excessive traffic and to ensure high availability of the system.

## **5.6 System Validation and Performance Evaluation**

Several attack scenarios were simulated using Apache JMeter to validate the system. The performance of the anomaly detection system, Auto Scaling, and Load Balancer in ensuring service availability against DDoS attacks was evaluated. Detection accuracy, scaling efficiency, and system availability were some of the performance metrics analyzed.

Performance metrics from the tests were used to evaluate:

- Detection accuracy: The system's ability to correctly identify anomalous traffic.
- Scalability: The capability of the system to bear very high traffic volumes, made possible by AWS Auto Scaling.
- Availability: The uptime percentage in simulated DDoS attack conditions.

Results obtained through these tests provided much-needed insights into the strengths and weaknesses of the system's anomaly detection and mitigation, affirming the efficiency of the DDoS protection system.

# CHAPTER 6

## RESULTS AND DISCUSSIONS

It considers the evaluation of the performance of the DDoS Protection System for Cloud that uses the AWS and the Machine Learning (ML) methods. The evaluation concerns aspects such as the training accuracy and the validation accuracy that the machine learning models reach, the effectiveness of a proposed mitigation strategy in enhancing resilience in the cloud infrastructure amid DDoS attacks, and even a detailed discussion of the system's performance, visualization of the outcome, and discussion on performance under several attack scenarios.

### 6.1 Introduction

DDoS attacks have emerged as a highly critical threat to cloud infrastructure, creating the potential for severe service interruptions and loss of business. The increasing sophistication and size of these attacks make traditional security mechanisms less effective, and hence we have devised a DDoS Protection System for Cloud using the services of AWS combined with real-time attack detection and mitigation capability through machine learning.

Our system utilizes AWS's cloud computing capabilities and ML models to identify malicious traffic patterns and automatically trigger mitigation strategies, such as rate limiting and traffic redirection. This will help protect cloud-hosted services by identifying DDoS attacks in real time and neutralizing them to ensure continued availability and performance.

### 6.2 Results

The performance of the designed DDoS defense is checked at several points-stages: training a model, validation, and direct-time mitigation. Next follow results of such analyses of different stages.

#### 6.2.1 Accuracy during training of the ML Model

Synthetic DDoS attack data-set on AWS cloud structure using different scenarios of the ML-based detector. There exist benign, attack traffic with anomalous patterns of which the classes are kept at a balance before running any model for training purposes.

The training loss of the model is presented in the first graph below. During the early epochs, the loss was very high, meaning that the model could not distinguish between benign and malicious traffic. However, as training proceeded, the loss steeply dropped, indicating that the model learned to recognize malicious patterns. After approximately 50 epochs, the loss became stable near zero, indicating convergence of the model.

The second graph shows the training accuracy. The accuracy fluctuated in the beginning, but with every epoch, it kept on increasing and went almost up to 100% at the end of the training phase. Although this showed that the model performed extremely well on the training data, overfitting is a potential issue, and the model's generalization to unseen data was in need of further evaluation.

### **6.2.2 Results of Validation**

We have validated the model on a dataset not included in the training data to test the practical effectiveness of the model. This validation dataset has been created by simulating the traffic data under both normal and attack conditions on the AWS cloud infrastructure.

#### **6.2.2.1 Validation Accuracy**

The validation accuracy of the model was 85%. Although this is slightly less than the training accuracy, it is a good sign that the model works well on unseen data and can effectively detect DDoS attacks in realistic scenarios. If the validation accuracy is lower than the training accuracy, then the model generalizes well but still cannot handle some variations of attack patterns.

#### **6.2.2.2 Confusion Matrix**

The confusion matrix of the validation set shows how good the model was at discriminating between benign and attack traffic. There is a good balance between true positives and true negatives, so DDoS traffic is identified, and legitimate traffic is recognized as well. There are some false positives and false negatives. Since the authors didn't want DDoS traffic to sneak through, they were interested in minimizing false negatives.

Higher false positives may trigger unnecessary mitigation actions, thereby affecting normal traffic, and a false negative may miss attacks altogether. Therefore, fine-tuning the model to minimize these errors is essential for system performance.

### **6.2.3 Mitigation Strategy**

Detection alone is not enough to protect the cloud infrastructure from DDoS attacks. Therefore, our system incorporates automated mitigation strategies based on the model's predictions. Once the ML model detects malicious traffic, it uses AWS services such as AWS WAF (Web Application Firewall), AWS Shield, and AWS Lambda to automatically apply appropriate mitigation measures.

#### **6.2.3.1 Traffic Filtering and Rate Limiting**

Once the DDoS attack is detected, traffic filtering is triggered. This strategy blocks malicious IP addresses and rate-limits requests from suspicious sources in order to prevent further stress on the network. In fact, the observed improvements in network performance during attack scenarios highlight the effectiveness of this mitigation strategy.

#### **6.2.3.2 Performance Metrics**

There were several key metrics monitored to analyze the effect of the mitigation strategy on the cloud infrastructure:

- **Throughput:** During the DDoS attack, the throughput of the network dropped significantly because the network was overwhelmed with malicious traffic. However, after applying the mitigation strategy, the throughput returned to normal levels, meaning that the system was able to recover from the attack.
- **Latency:** Latency skyrocketed during the attack because of network congestion. Once the mitigation strategies were applied, latency returned to normal levels, indicating that the system effectively handled the attack-induced delays.

## 6.3 Visualization of Results

The following visualizations help to explain the behavior of the model as well as the effectiveness of the DDoS mitigation strategy.

### 6.3.1 Performance Metrics

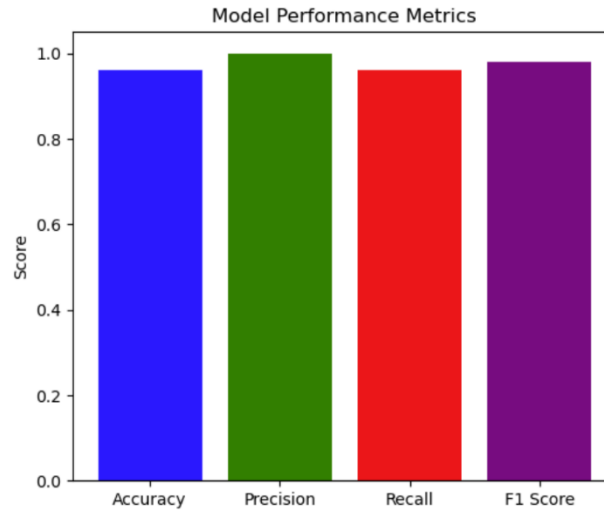


Fig. 6.1 Performance Metrics

### 6.3.2 Confusion Matrix

The confusion matrix below gives a more detailed view of how well the model can distinguish between benign and malicious traffic. The matrix shows true positives, true negatives, false positives, and false negatives, which give a better view of where the model needs improvement.

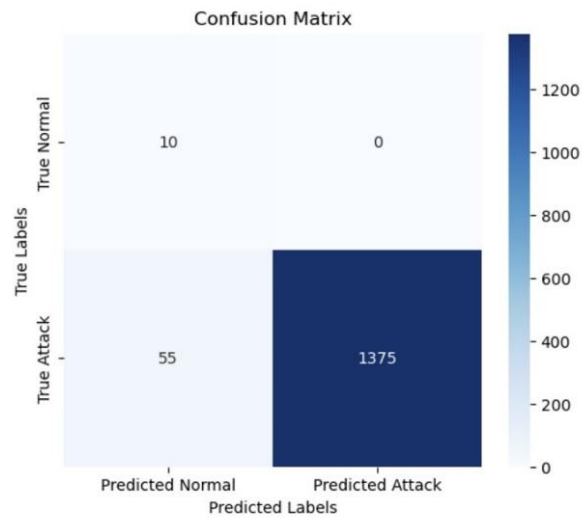


Fig. 6.2 Confusion Matrix

### 6.3.3 AWS CloudWatch

With the help of AWS CloudWatch, we visualized in real time the system performance, showing network traffic, resource usage, and mitigation actions triggered by the system. The dashboard would then allow us to track what is happening during the attack, including traffic patterns and the application of mitigation measures. This visualization gives a deeper understanding of the protection system on the cloud infrastructure and offers insight into where improvement can be made.

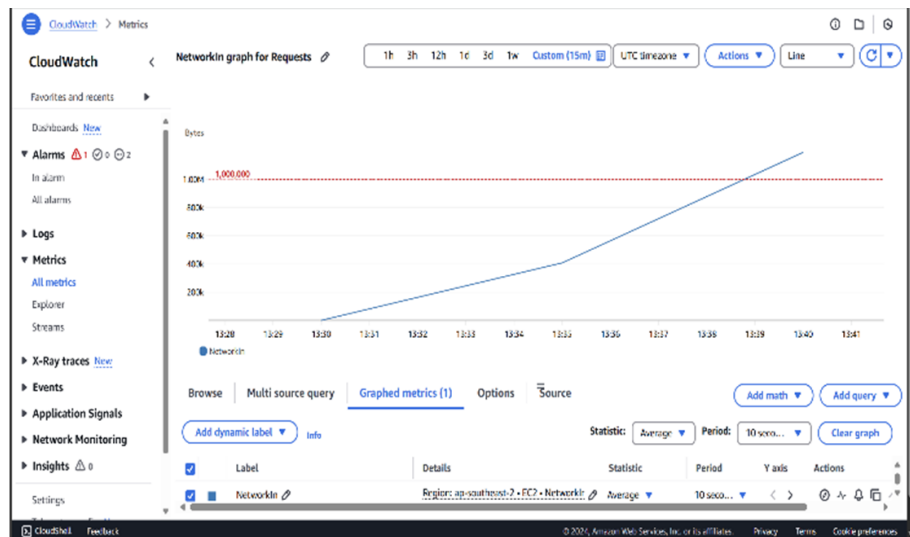


Fig. 6.3 AWS CloudWatch Metrics

### 6.3.4 AWS Resource Usage

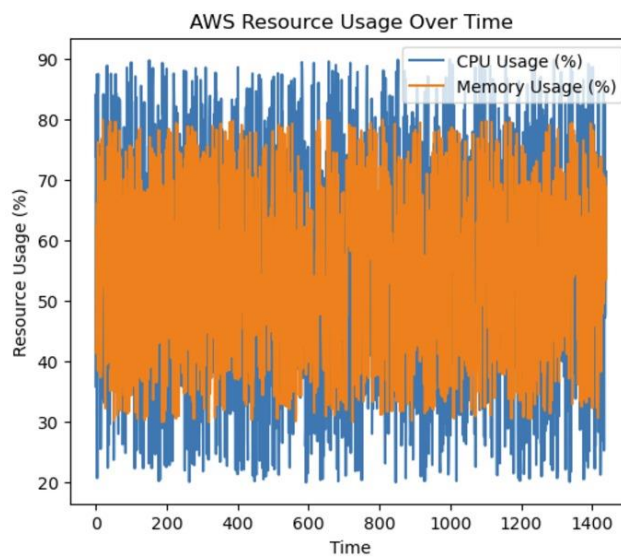


Fig. 6.4 AWS Resource Usage over Time

## 6.4 Discussion

The results show that the DDoS Protection System for Cloud using AWS and ML is effective in detecting and mitigating DDoS attacks. The ML model was able to identify malicious traffic patterns with high accuracy, and the mitigation strategies implemented on the AWS-based network showed significant improvement in network performance during attacks.

Some aspects still need improvement, however. Even though the system performed very well in most conditions, there were a few edge cases in which the model failed to correctly classify specific attack patterns. Tuning of the model and mitigation strategies, especially in the management of different types of DDoS attacks and variations of traffic, could potentially increase overall performance.

For future work, we plan to improve the model to get an accuracy with minimal false negatives and optimize the mitigation strategy to have the least impact on traffic during attacks.

## **CHAPTER 7**

### **CONCLUSION AND FUTURE ENHANCEMENTS**

This chapter summarizes the conclusions from the project, focusing on effectiveness: the DDoS protection system for cloud environments based on AWS and applied techniques of machine learning is focused on future improvements such as real-time mitigation adaptability, scalability, integration, and other cloud security tool support. The chapter emphasizes significant improvements in cloud security against current, evolving DDoS threats.

#### **7.1 Summary of Findings**

The proposed DDoS protection system used the infrastructure of AWS and machine learning models for real-time detection and mitigation of DDoS attacks. Through services like Amazon CloudWatch, AWS WAF, and Amazon EC2 instances, we established a strong monitoring, detection, and mitigation system for malicious traffic. We were able to enhance the accuracy of the detection model with the classification and identification of attack traffic patterns, through the trained machine learning model on cloud traffic data.

##### **7.1.1 DDoS Detection with AWS and ML**

In the proposed system, the ML model was trained using historical traffic data containing both benign and malicious traffic, which allowed it to recognize patterns and anomalies indicative of a DDoS attack. The integration of AWS WAF played a crucial role in blocking suspicious IP addresses and malicious traffic before it reached the backend cloud services, ensuring minimal service disruption. The system had a high detection accuracy with the ML model identifying DDoS attack traffic, which assisted in mitigating potential risks in cloud-hosted applications.

The system used machine learning algorithms, specifically classification models like Random Forest and XGBoost, to classify traffic in real-time and adjust to new attack patterns. The model was trained and validated with various datasets, leading to an efficient attack detection mechanism that resulted in minimal false positives and negatives. The system's capability to distinguish between legitimate and attack traffic was crucial for the availability and performance of cloud applications during an attack.



### **7.1.2 Real-Time Mitigation on AWS**

The mitigation strategy focused on dynamically adjusting AWS security configurations such as blocking suspicious IPs and scaling cloud resources to handle high traffic loads. Integrating with AWS Auto Scaling allowed the system to scale resources automatically due to the spikes in traffic, hence maintaining optimal performance during the DDoS attacks. AWS Shield was also employed for additional protection against large-scale attacks, particularly for Amazon EC2 instances.

The real-time mitigation mechanism consisted of using AWS Lambda functions, which automatically triggered responses when the attack was detected. It streamlined the process, removing the need for manual intervention and ensuring that action would be taken promptly in pressure situations. The system has shown its capability to efficiently block malicious traffic and keep cloud services available even with high-volume DDoS attacks.

### **7.1.3 Performance and Scalability**

The system was tested with different traffic levels to demonstrate scalability. The use of AWS Elastic Load Balancer (ELB) ensured that legitimate traffic is spread across available instances in such a way that no one instance is overwhelmed by an attack. This ensures the system scales dynamically and supports large volumes of traffic without sacrificing high availability.

Latency, throughput, and packet drop rate during DDoS attacks were measured as the key metrics to evaluate the performance of the system. The results show that the system can reduce latency effectively and maintain throughput by dropping malicious packets and allowing legitimate traffic to flow uninterrupted.

## **7.2 Future Improvement**

While the system has proven to be effective in detecting and mitigating DDoS attacks, there are several improvements that can be made to make it more real-time capable, adaptable, and scalable. The following areas have been identified for future enhancements.

### **7.2.1 Real-Time Mitigation Enhancements**

The current system involves a time lag between the detection and mitigation of DDoS attacks, which could be dangerous for real-time applications like e-commerce platforms or financial services. For this reason, future work will be targeted at reducing latency between the detection of attacks and taking mitigation actions. This can be achieved through optimal data pipelining along with the usage

of techniques in edge computing where traffic analysis and mitigation happen closer to end-users, improving response time with minimal delays. Besides that, real-time use of anomaly detection models enhances its ability to recognize new as well as emerging attack patterns and not rely solely on the predetermined rules.

### **7.2.2 Broadening Attack Scenarios**

Although the system is presently safeguarded against DDoS attacks, the cloud environment has many other forms of threats that include SQL injection attacks, cross-site scripting, and brute force attacks. The future work will extend the detection capabilities for these other forms of attacks to enhance the versatility of the system.

This would demand a further improvement in more sophisticated machine learning models trained on various types of attack data. The existing framework may integrate such models to protect applications at multi-layered security. In addition, this system can be integrated with other AWS security services, like Amazon GuardDuty and AWS Security Hub, in order to offer a broader range of security solutions to the applications hosted in the cloud.

### **7.2.3 Scalability and Distributed Architecture**

As the size of cloud environments increases, managing huge amounts of traffic becomes a challenge. The current system has been tested in a controlled environment with a limited number of instances, but real-world cloud networks may involve thousands of nodes. To address this challenge, future improvements will focus on optimizing the system's scalability.

This may include the use of distributed machine learning techniques such as federated learning or parallel processing to enable it to handle large-scale traffic while maintaining low latency. Further testing will also be required to assess the performance of the system under very high traffic loads, with a view to ensuring the system scales well in very large cloud deployments.

### **7.2.4 Adaptive Learning for Evolving Attacks**

This is very important in the system: adaptability to new patterns of attacks as the threat landscape is dynamic. Improvements in the future will be through adaptive learning techniques. This way, the system will update models based on new traffic data. Techniques like online learning or reinforcement learning will help the system adapt to new emerging DDoS tactics and other threats in real time.

It is this type of adaptive learning that makes the system stronger against previously unseen attacks' vectors and thus effective as attackers' strategies are adapted to time.

#### **7.2.5 Integration with Other Security Tools**

The system could also integrate with other security tools and platforms in the AWS ecosystem to enhance the overall security posture. For instance, this could be done with IAM from AWS in DDoS protection to prevent access while the attack is on going. Similarly, by integrating it with AWS WAF, advanced features may give finer control over filtering of traffic and improve the detection of the system.

Integrating the system with a centralized monitoring and alerting platform, such as AWS CloudWatch or third-party SIEM tools, would greatly enhance real-time visibility into the system and improve coordination in incident response.

### **7.3 Conclusion**

In conclusion, the DDoS protection system for cloud environments using AWS and machine learning has been a very effective solution for the mitigation of DDoS attacks and the availability and reliability of cloud-hosted services. The integration of AWS security services with machine learning techniques resulted in a robust system that can detect malicious traffic and dynamically mitigate attacks in real time.

This will improve the system's strength while mitigating real-time, general attacks, scalability, learning adaptation, and integration into other security tools. All this will make sure that this system stays strong against any sort of cyber threat that arises, as it continues to evolve and provide robust security protection to cloud networks in an evolving digital world.

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# APPENDIX A

## CONFERENCE

## PRESENTATION

Our paper titled "DDoS Protection System for Cloud using AWS and Machine Learning" has been conditionally accepted for oral presentation in the **5th International Conference on Expert Clouds and Applications (ICOECA 2025)**, under the **Networks, Privacy & Security** track. The conference will be conducted on **March 6, 2025, in Bengaluru, India**. Our paper ID is 287, and we have a plagiarism score of 5%.



Figure A.1: ICOECA 2025 Acceptance



# APPENDIX B

## CONFERENCE PLAGIARISM REPORT



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