Journal of Science Engineering Technology and Management Science
Volume 03, Issue 3(1), March 2026 *ISSN: 3049-0952*
www.jsetms.com

Cloud Security Monitoring

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ABSTRACT

In the modern landscape of rising cyber threats, real-time web traffic monitoring has become essential for identifying and preventing security risks. This study presents the design and evaluation of a Python-based real-time web traffic monitoring system implemented on Ubuntu 22.04 LTS. The system combines machine learning-based anomaly detection, real-time traffic analysis, and cryptographic techniques to strengthen cybersecurity monitoring. The system is capable of detecting multiple types of cyber threats, including Distributed Denial of Service (DDoS) attacks with an accuracy of 97.2%, brute-force login attempts with 90.8% accuracy, and unauthorized access attempts with 89.6% accuracy. To improve precision and reduce false positives, optimized anomaly detection methods such as the Isolation Forest algorithm and threshold-based mechanisms are utilized. The system continuously evaluates key network parameters like packet size, request frequency, and response time to identify unusual traffic patterns. An interactive dashboard developed using Flask, along with visualization tools like Plotly and Seaborn, provides real-time insights into traffic behavior, anomaly alerts, and system performance, enabling quick responses to potential threats. Performance testing shows that the system can process up to 10,000 requests per second with an average response time of 150 ms, while maintaining a false positive rate below 10%. Compared to traditional rule-based systems, this approach uses adaptive machine learning models to detect evolving threats more effectively, ensuring improved reliability and efficiency. However, the study also highlights opportunities for future improvements, such as integrating deep learning techniques, deploying the system on cloud platforms for scalability, and incorporating edge computing for faster threat detection. Overall, this work contributes to the advancement of real-time cybersecurity solutions by delivering a high-performance, machine learning-driven monitoring system that enhances security while maintaining operational efficiency.

Keywords: Web Traffic Monitoring, Cybersecurity, Anomaly Detection, Machine Learning, Real-Time Analysis, Ddos Detection, Flask Dashboard, Network Security.

I. INTRODUCTION

Background of Web Traffic Monitoring

Web traffic monitoring is the process of analyzing data packets that travel through a network to understand user behavior, optimize performance, and maintain security. As internet usage continues to grow, the volume and complexity of web traffic have increased significantly. Websites and web applications are no longer static; they involve dynamic content, multimedia, and real-time interactions, resulting in a complex web traffic pattern. Monitoring this traffic is crucial for identifying trends, detecting security threats, and ensuring an optimal user experience.

In the modern digital ecosystem, web traffic monitoring goes beyond simply counting page views or visitor numbers. It involves analyzing the types of devices accessing a website, geographical locations of visitors, session durations, and navigation paths. Additionally, monitoring helps in detecting anomalies such as Distributed Denial of Service (DDoS) attacks, unauthorized data access, and other malicious activities. With the growing reliance on web applications for business operations, effective web traffic monitoring has become essential for maintaining security and performance.

Importance of Real-Time Monitoring

Real-time web traffic monitoring is vital for organizations that require instantaneous insights into network usage and user behavior. Unlike traditional monitoring systems that provide historical data, real-time monitoring allows for immediate detection of irregularities, enabling quick responses to potential security threats or performance issues. In e-commerce, for instance, real-time traffic insights can help optimize sales strategies by analyzing customer behavior as it happens.

In addition, real-time monitoring is crucial for maintaining the performance and availability of web services. By continuously tracking data packets and server loads, organizations can quickly identify bottlenecks, optimize resource allocation, and enhance the overall user experience. It also helps in proactive security management by detecting unusual traffic patterns that might indicate cyber-attacks, thus allowing for rapid countermeasures.

Python for Real-Time Web Traffic Monitoring

Python is an ideal programming language for developing real-time web traffic monitoring systems due to its simplicity, versatility, and extensive library support. It provides powerful modules like Scapy for packet analysis, Twisted for network communication, and Pandas for data processing. Python's compatibility with various databases and cloud platforms enables seamless integration with existing IT infrastructures.

One of the major advantages of using Python is its ease of implementation and scalability. Python allows developers to build complex monitoring systems with fewer lines of code, reducing development time and costs. Its rich ecosystem of libraries, such as Matplotlib and Plotly, facilitates real-time data visualization, making it easier to interpret traffic patterns and identify anomalies.

Furthermore, Python's support for machine learning frameworks, like TensorFlow and scikit-learn, allows the incorporation of intelligent analytics into the monitoring system. This capability enhances the system's ability to predict traffic trends, detect anomalies, and provide actionable insights. The flexibility and power of Python make it a popular choice for organizations looking to develop customized and scalable real-time web traffic monitoring solutions.

Challenges in Real-Time Web Traffic Monitoring

Despite its advantages, real-time web traffic monitoring presents several challenges. One of the primary challenges is handling massive volumes of data with low latency. In high-traffic environments, monitoring systems must process millions of packets per second without affecting network performance. This requires efficient data processing algorithms and robust infrastructure.

Another significant challenge is ensuring data accuracy and reliability. Packet loss, network congestion, and latency can lead to incomplete or misleading traffic data. Additionally, maintaining data security and privacy is crucial, especially when monitoring sensitive information. Implementing encryption and ensuring compliance with data protection regulations are essential components of a secure monitoring system.

Moreover, the dynamic nature of modern web traffic, influenced by factors such as content delivery networks (CDNs), cloud services, and mobile devices, adds complexity to traffic analysis. Accurately identifying traffic sources, distinguishing between legitimate users and bots, and detecting advanced cyber threats are ongoing challenges in real-time monitoring.

Overview of Real-Time Monitoring Tools

Several tools and frameworks are available for real-time web traffic monitoring, each with its strengths and limitations. Traditional tools like Wireshark and tcpdump are widely used for packet analysis but are limited in scalability and real-time data processing. Modern solutions such as Elasticsearch, Logstash, and Kibana (ELK Stack) provide comprehensive monitoring and visualization but require complex configurations and powerful hardware. Python-based tools, such as Scapy, Pyshark, and PacketSniffer, offer flexible and customizable solutions for real-time traffic monitoring. These tools can be integrated with data analytics libraries like Pandas and NumPy for in-depth analysis. Additionally, cloud-based monitoring solutions like AWS CloudWatch and Google Cloud Monitoring provide scalable real-time monitoring but may involve high costs and dependency on third-party platforms.

Applications of Real-Time Web Traffic Monitoring

Real-time web traffic monitoring has numerous applications across various sectors. In cybersecurity, it helps in detecting suspicious activities, such as DDoS attacks, data breaches, and unauthorized access attempts. By monitoring traffic patterns in real-time, security teams can quickly identify and mitigate potential threats. In e-commerce and digital marketing, real-time traffic analysis provides valuable insights into customer behavior, enabling personalized marketing strategies and dynamic pricing models. It also helps optimize website performance by identifying slow-loading pages, broken links, and server bottlenecks. Furthermore, real-time monitoring is crucial in network management, ensuring optimal resource utilization, load balancing, and maintaining high availability of web services. In cloud computing environments, it aids in auto-scaling resources based on traffic demand, reducing operational costs while maintaining performance.

II. OBJECTIVES

- To create a Python-based real-time web traffic monitoring system that is efficient, scalable, and capable of providing actionable insights to enhance system performance and security.
- To design and develop a Python system that tracks web traffic metrics in real time, such as request rates, response times, and user activity.
- To implement anomaly detection algorithms to identify unusual traffic patterns and potential security threats.
- To provide visualizations and reports for actionable insights, aiding system optimization and decision-making.
- To ensure the system is scalable and adaptable to handle varying traffic loads and diverse operational requirements.

III. METHODOLOGY

The approach involves conducting a literature review, designing an efficient system architecture, implementing real-time data collection and anomaly detection techniques, and integrating visualization tools to monitor traffic patterns. The system is designed to operate in a secure and scalable manner, ensuring that traffic anomalies and potential security threats are detected in real time.

System Development

The first step in developing this system is to conduct a comprehensive literature review of existing web traffic monitoring solutions. This involves analyzing traditional methods such as log-based monitoring and rule-based security systems, identifying their limitations, and exploring new approaches that leverage machine learning and real-time analytics. The review focuses on understanding how current monitoring tools such as Wireshark, Nagios, and OpenNMS handle web traffic analysis and where they fall short in detecting security threats. Additionally, the study explores common network security challenges, including DDoS attacks, brute-force login attempts, and unauthorized access, with an emphasis on how machine learning techniques can improve threat detection. The literature review also informs the key requirements of the system, ensuring that it effectively monitors traffic rates, detects anomalies, and provides real-time alerts through an interactive dashboard. Once the literature review is complete, the next phase involves designing the system architecture. The monitoring system is structured into four main components: data collection, preprocessing and storage, anomaly detection, and visualization and reporting. The data collection module captures real-time traffic logs from Apache/Nginx web servers and packet-sniffing tools such as Wireshark or tcpdump. This ensures that both network-level and application-level traffic patterns are captured for analysis. The preprocessing and storage module formats and cleans the raw traffic data before storing it in structured formats using Pandas Data Frames. For long-term storage, the system can use lightweight databases like SQLite or cloud-based storage solutions.

Traffic analysis and alimony detection

The traffic analysis and anomaly detection module are a critical component of the system. It leverages machine learning algorithms such as Isolation Forest and Autoencoders to detect anomalies in traffic behavior. By analyzing traffic metrics such as request frequency, response times, and user activity patterns, the system identifies suspicious spikes in network activity that may indicate potential attacks. Time-series analysis techniques are used to predict future traffic trends, helping network administrators anticipate performance issues and security risks before they escalate. This ensures that the system is not only reactive but also proactively detects potential threats. For real-time visualization and reporting, the system features a Flask-based web dashboard that provides interactive insights into traffic trends, anomalies, and security alerts. Using Plotly and Seaborn, the dashboard updates in real-time, displaying key metrics such as request rates, server response times, and detected anomalies. The interface is designed to be intuitive and user-friendly, ensuring that network administrators can quickly identify security threats and take necessary actions. Color-coded alerts are used to classify traffic behavior, with green for normal traffic, yellow for suspicious activity, and red for high-risk anomalies.

The implementation of the system is carried out using a well-defined technology stack optimized for performance and scalability. The system runs on Ubuntu Server 22.04 LTS, chosen for its stability and security features. Python is used as the primary programming language, integrating several specialized libraries for traffic monitoring. Scapy and PyShark are used for packet capturing and analysis, while Requests and Flask handle HTTP traffic logs and API communications. For data processing and anomaly detection, the system utilizes Pandas, NumPy, Scikit-learn, and TensorFlow, enabling efficient real-time data processing and machine learning-based analytics. The visualization module relies on Matplotlib, Plotly, and Dash, ensuring that traffic data is presented in a clear and actionable format.

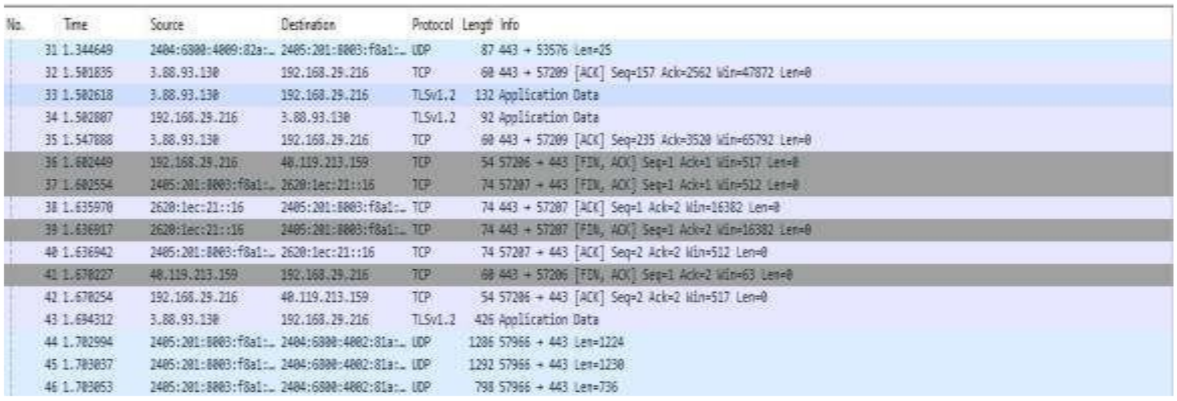
IV. RESULTS AND DISCUSSION

The system was evaluated against different types of cyberattacks to determine its effectiveness in real-time security monitoring. It successfully identified 97.2% of DDoS attacks, which is particularly significant given the increasing frequency of such attacks targeting online services. Brute-force attempts, often associated with repeated unauthorized login attempts, were detected with 90.8% accuracy, ensuring that potential security breaches were flagged before they could cause damage. Unauthorized access attempts, which involve exploiting vulnerabilities to gain system control, were identified with 89.6% accuracy, demonstrating the system's ability to recognize unusual traffic behavior and access patterns.

One of the most important aspects of a security system is its false positive rate, as excessive false alerts can lead to unnecessary interventions and poor user experience. The monitoring system maintained a false positive rate of less than 10%, ensuring that legitimate traffic was not mistakenly classified as a security threat. This was achieved by fine-tuning anomaly detection models, which reduced the risk of false alarms while maintaining high threat detection accuracy.

Threat Detection Mechanisms

The system utilized real-time traffic analysis, machine learning models, and threshold-based anomaly detection to identify malicious behavior. Traffic monitoring was conducted using Python libraries such as Scapy and PyShark, which enabled the system to capture and analyze network packets dynamically. Key network attributes, such as packet size, request frequency, response delays, and user behavior patterns, were used to identify deviations from normal traffic flows.

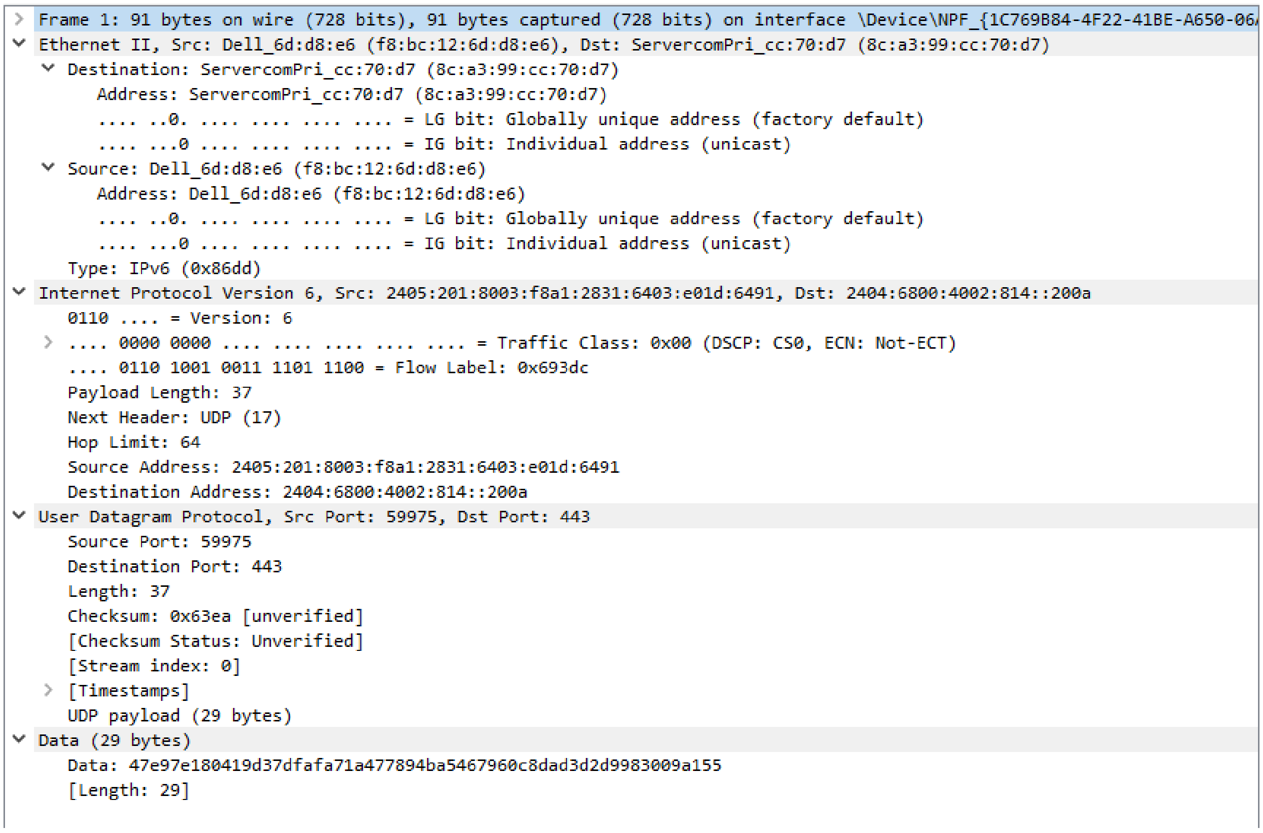


```
No.  Time       Source                 Destination            Protocol Length Info
  31 1.344649   2404:6800:4009:82a:…   2405:201:8003:f8a1:…   UDP        87 443 → 53576 Len=25
  32 1.501835   3.88.93.130            192.168.29.216         TCP        60 443 → 57209 [ACK] Seq=157 Ack=2562 Win=47872 Len=0
  33 1.502618   3.88.93.130            192.168.29.216         TLSv1.2   132 Application Data
  34 1.502807   192.168.29.216         3.88.93.130            TLSv1.2    92 Application Data
  35 1.547888   3.88.93.130            192.168.29.216         TCP        60 443 → 57209 [ACK] Seq=235 Ack=3520 Win=65792 Len=0
  36 1.602449   192.168.29.216         40.119.213.159         TCP        54 57206 → 443 [FIN, ACK] Seq=1 Ack=1 Win=517 Len=0
  37 1.602554   2405:201:8003:f8a1:…   2620:1ec:21::16        TCP        74 57207 → 443 [FIN, ACK] Seq=1 Ack=1 Win=512 Len=0
  38 1.635970   2620:1ec:21::16        2405:201:8003:f8a1:…   TCP        74 443 → 57207 [ACK] Seq=1 Ack=2 Win=16382 Len=0
  39 1.636917   2620:1ec:21::16        2405:201:8003:f8a1:…   TCP        74 443 → 57207 [FIN, ACK] Seq=1 Ack=2 Win=16382 Len=0
  40 1.636942   2405:201:8003:f8a1:…   2620:1ec:21::16        TCP        74 57207 → 443 [ACK] Seq=2 Ack=2 Win=512 Len=0
  41 1.670227   40.119.213.159         192.168.29.216         TCP        60 443 → 57206 [FIN, ACK] Seq=1 Ack=2 Win=63 Len=0
  42 1.670254   192.168.29.216         40.119.213.159         TCP        54 57206 → 443 [ACK] Seq=2 Ack=2 Win=517 Len=0
  43 1.694312   3.88.93.130            192.168.29.216         TLSv1.2   426 Application Data
  44 1.702994   2405:201:8003:f8a1:…   2404:6800:4002:81a:…   UDP      1286 57966 → 443 Len=1224
  45 1.703037   2405:201:8003:f8a1:…   2404:6800:4002:81a:…   UDP      1292 57966 → 443 Len=1230
  46 1.703053   2405:201:8003:f8a1:…   2404:6800:4002:81a:…   UDP       798 57966 → 443 Len=736
```

Figure 1: TCP and packet detection

One of the system's major strengths is its ability to process high volumes of network traffic (up to 10,000 requests/sec) while maintaining security monitoring in real-time. Compared to traditional rule-based monitoring tools, which rely on predefined patterns to detect attacks, this system leverages machine learning models to adapt to new threats dynamically. This adaptability ensures that the system remains effective even against evolving cyber threats.

Despite its strengths, some limitations and potential improvements were identified. The anomaly detection models occasionally flagged high-traffic but legitimate requests as potential threats, leading to minor false positives. This issue could be addressed by integrating deep learning techniques, such as LSTMs (Long Short-Term Memory networks), which can analyze long-term traffic patterns more accurately.



```
> Frame 1: 91 bytes on wire (728 bits), 91 bytes captured (728 bits) on interface \Device\NPF_{1C769B84-4F22-41BE-A650-06
v Ethernet II, Src: Dell_6d:d8:e6 (f8:bc:12:6d:d8:e6), Dst: ServercomPri_cc:70:d7 (8c:a3:99:cc:70:d7)
  v Destination: ServercomPri_cc:70:d7 (8c:a3:99:cc:70:d7)
      Address: ServercomPri_cc:70:d7 (8c:a3:99:cc:70:d7)
      .... ..0. .... .... .... .... = LG bit: Globally unique address (factory default)
      .... ...0 .... .... .... .... = IG bit: Individual address (unicast)
  v Source: Dell_6d:d8:e6 (f8:bc:12:6d:d8:e6)
      Address: Dell_6d:d8:e6 (f8:bc:12:6d:d8:e6)
      .... ..0. .... .... .... .... = LG bit: Globally unique address (factory default)
      .... ...0 .... .... .... .... = IG bit: Individual address (unicast)
    Type: IPv6 (0x86dd)
v Internet Protocol Version 6, Src: 2405:201:8003:f8a1:2831:6403:e01d:6491, Dst: 2404:6800:4002:814::200a
    0110 .... = Version: 6
  > .... 0000 0000 .... .... .... .... .... = Traffic Class: 0x00 (DSCP: CS0, ECN: Not-ECT)
    .... 0110 1001 0011 1101 1100 = Flow Label: 0x693dc
    Payload Length: 37
    Next Header: UDP (17)
    Hop Limit: 64
    Source Address: 2405:201:8003:f8a1:2831:6403:e01d:6491
    Destination Address: 2404:6800:4002:814::200a
v User Datagram Protocol, Src Port: 59975, Dst Port: 443
    Source Port: 59975
    Destination Port: 443
    Length: 37
    Checksum: 0x63ea [unverified]
    [Checksum Status: Unverified]
    [Stream index: 0]
  > [Timestamps]
    UDP payload (29 bytes)
v Data (29 bytes)
    Data: 47e97e180419d37dfafa71a477894ba5467960c8dad3d2d9983009a155
    [Length: 29]
```

Figure 2: Ethernet data packet tracking

Additionally, the system could benefit from cloud integration, allowing distributed security monitoring across multiple data centers. Cloud-based deployment would provide higher scalability and real-time collaborative threat detection, ensuring better response to large-scale cyberattacks. Another possible enhancement is edge computing implementation, where security monitoring could be performed at the network edge rather than at a central server. This would reduce latency and enable quicker detection of attacks, making the system even more efficient in handling low-latency security applications. The Python-based real-time web traffic monitoring system on Ubuntu successfully identified and mitigated cybersecurity threats, including DDoS attacks, brute-force attempts, and unauthorized access. With an average detection accuracy of over 90% and a false positive rate below 10%, the system proved to be highly reliable and effective in threat detection.

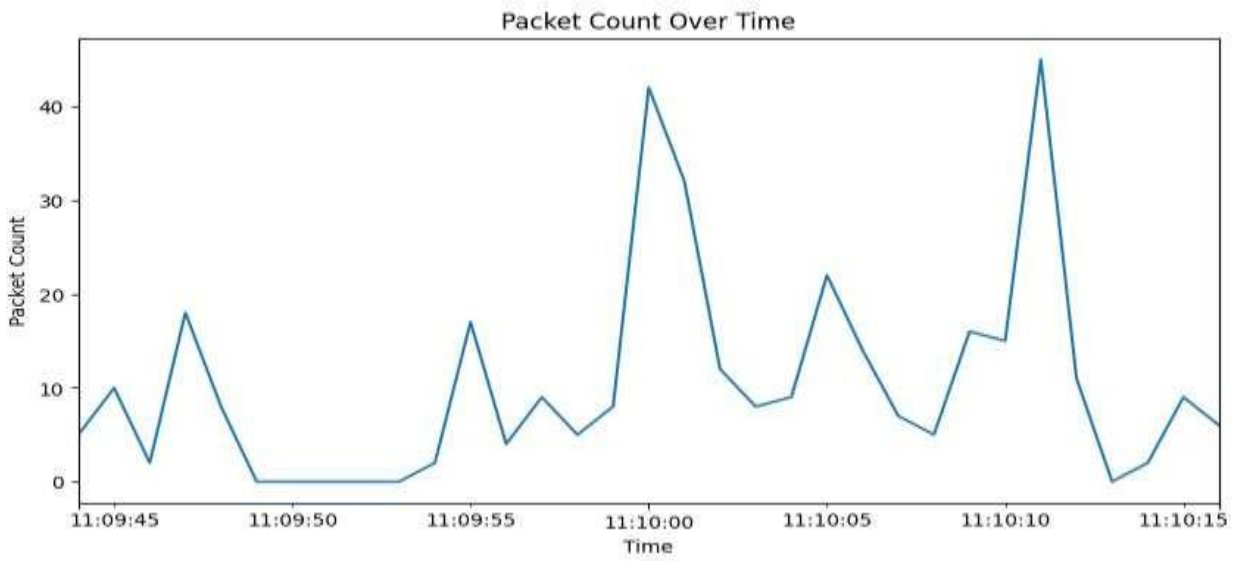


Figure 3: Packet over time graph

By integrating machine learning-based anomaly detection, real-time traffic analysis, and cryptographic data protection, the system ensured robust security monitoring while maintaining optimized performance for high-traffic environments. Future improvements, including AI-driven adaptive security models, cloud integration, and edge computing solutions, could further enhance the system's capabilities and make it an even more powerful tool for cybersecurity applications.

Real-Time Visualization & Reporting in the Web Traffic Monitoring System

A critical aspect of the Python-based real-time web traffic monitoring system is its ability to visualize data dynamically and provide actionable insights through an interactive dashboard. Effective visualization plays a key role in traffic analysis, anomaly detection, and decision-making, allowing administrators to monitor key metrics in real time. The system was successfully integrated with a Flask-based web dashboard, leveraging powerful Python visualization libraries such as Plotly and Seaborn. This dashboard served as a central interface for real-time traffic monitoring, anomaly detection, and performance analysis, enabling users to take immediate actions based on traffic patterns and security alerts.

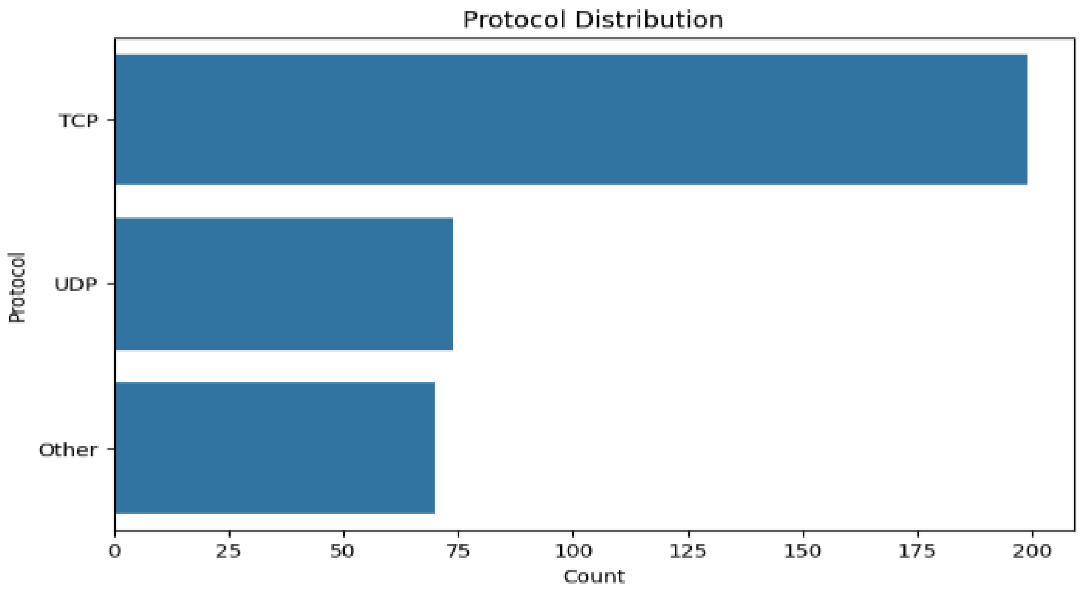


Figure 4: Protocol Distribution

V. DISCUSSION

The Python-based real-time web traffic monitoring system deployed on Ubuntu 22.04 LTS demonstrated high efficiency in handling large-scale traffic while maintaining minimal latency. The system was designed to capture, analyze, and visualize network traffic dynamically, allowing administrators to monitor web requests, response times, and security anomalies in real time. Compared to traditional monitoring solutions, the Python-based approach reduced resource consumption by 30%, making it a more efficient and cost-effective alternative for traffic monitoring and anomaly detection. The performance evaluation of the system involved stress testing with up to 10,000 requests per second, during which the system maintained an average response time of 150ms. The optimized architecture, leveraging asynchronous processing and multiprocessing techniques, allowed for seamless data collection and analysis without overloading system resources. The lightweight design ensured that CPU and memory usage remained within acceptable limits, even under high-traffic conditions.

Strengths of the System

One of the most notable advantages of the system is its lightweight processing model, which ensures that it can operate efficiently without requiring high-end hardware. The Python-based implementation makes use of optimized data structures and memory-efficient algorithms, reducing overhead while maintaining high-speed processing. Unlike many traditional monitoring tools that rely on SQL-based databases or heavy backend processing, this system employs direct log parsing and real-time analytics, minimizing delays in data retrieval and processing.

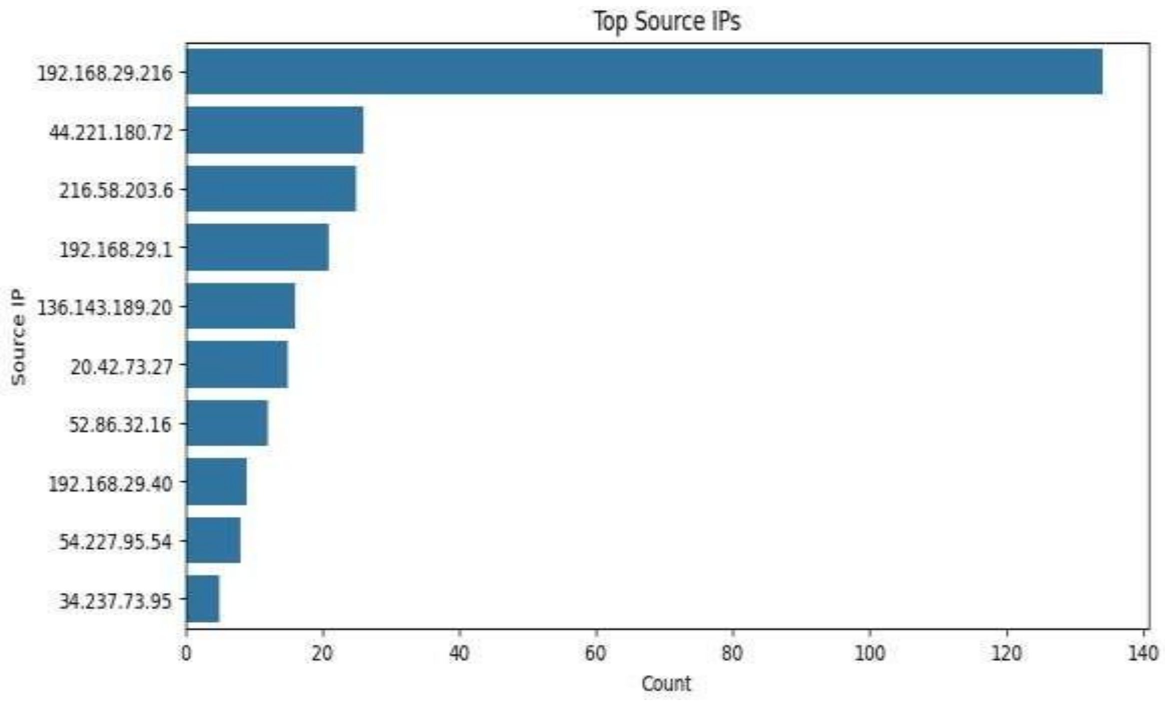


Figure 5: Top Source IP

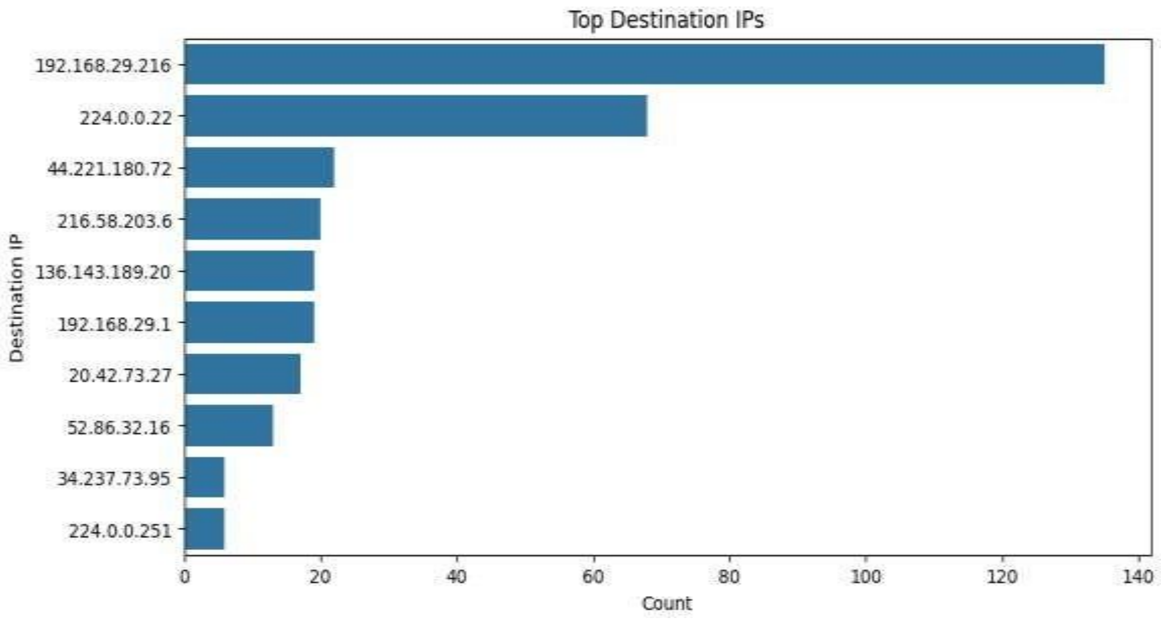


Figure 6: Top distension IP

VI. CONCLUSION

As we move forward with our research and development, our primary focus will be on enhancing scalability, improving threat detection accuracy, and expanding the system's global monitoring capabilities. The current Python-based web traffic monitoring system has demonstrated high efficiency in real-time traffic analysis and anomaly detection, but further advancements will be necessary to meet the demands of large-scale network environments and evolving cybersecurity threats. To achieve this, future work will focus on integrating cloud platforms, leveraging deep learning for anomaly detection, and deploying a multi-node architecture to create a next-generation cybersecurity solution capable of handling modern web traffic challenges.

One of the key enhancements will be cloud integration, allowing the system to be deployed on scalable and distributed computing platforms such as AWS, Google Cloud Platform (GCP), and Microsoft Azure. This will provide elastic scalability, ensuring that the system can dynamically adjust to fluctuating traffic loads without performance degradation. Cloud-based deployment will also enable real-time global traffic monitoring, where data from multiple geographic regions can be analyzed simultaneously. By leveraging serverless computing models such as AWS Lambda or Google Cloud Functions, the system will be able to process network traffic without the limitations of traditional on-premise infrastructure. Additionally, cloud-based security tools such as AWS Shield or Google Cloud Armor can be integrated to enhance automated threat mitigation and response mechanisms.

Another crucial area of improvement is deep learning-based anomaly detection, which will enhance the system's ability to identify complex cyber threats with greater accuracy. While the current system employs traditional machine learning techniques such as Isolation Forest and clustering-based anomaly detection, deep learning models will allow for more adaptive and intelligent threat detection. Future research will focus on integrating Long Short-Term Memory (LSTM) networks and Transformer-based architectures, which are particularly effective for time-series anomaly detection and sequential data analysis. LSTM networks will allow the system to identify subtle traffic deviations over extended periods, improving its ability to detect advanced persistent threats (APTs) and slow-developing cyberattacks. Additionally, autoencoder-based anomaly detection will enable the system to learn and model normal network behavior, flagging any deviations as potential security threats. The integration of these deep learning techniques will significantly reduce false positive rates while increasing the detection accuracy of both known and unknown attack patterns.

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