CLASSIFYING TOR TRAFFIC ENCRYPTED PAYLOAD USING MACHINE LEARNING

(PROJECT REPORT)
submitted in partial fulfillment of the requirements
for the award of the degree in

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

BY

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DEPARTMENT

OF

COMPUTER SCIENCE AND ENGINEERING

APRIL - 2025

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the Bonafide work of **Ms.K. LAVANYA Reg. No 211061101198, Ms. K. RICHITHA Reg. No 211061101224,** and **Ms. K. HARSHITHA Reg. No 211061101234**, who carried out the project entitled "**CLASSIFYING TOR TRAFFIC ENCRYPTED PAYLOAD USING MACHINE LEARNING**" under our supervision from June 2024 to April 2025.

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DECLARATION

We **K. LAVANYA (211061101198), K. RICHITHA (211061101224)** and **K. HARSHITHA (211061101234),** hereby declare that the Project Report entitled "**CLASSIFYING TOR TRAFFIC ENCRYPTED PAYLOAD USING MACHINE LEARNING** is done by us under the guidance of **Mr. G.SENTHIL VELAN** is submitted in partial fulfillment of the requirements for the award of the degree in **BACHELOR OF TECHNOLOGY** in Computer Science and Engineering.

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We would first like to thank our beloved Respected Chancellor **Thiru . Dr. A . C . SHANMUGAM , B . A . , B . L . ,** Honourable President **Er. A. C .S.Arunkumar, B.Tech., M.B.A.,** and Secretary **Thiru A. RAVIKUMAR** for all the encouragement and support extended to us during the tenure of this project and also our years of studies in their wonderful University.

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We would also like to thank all the teaching and non teaching staffs of Computer Science and Engineering department, for their constant support and the encouragement given to us while we went about to achieving our project goal.

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LIST OF ABBREVIATION

IDE	Integrated Development Environment
IAT	Inter-Arrival Time
CSV	Comma-Separated Values
XGBOOST	Extreme Gradient Boosting
UI	User Interface
DT	Decision Tree

LIST OF FIGURES

ABSTRACT

The Tor Traffic Classification Using Machine Learning project aims to develop an advanced framework for identifying and classifying encrypted Tor network traffic using machine learning techniques. With the increasing use of Tor for both privacy-focused activities and potential cyber threats, network security professionals face challenges in distinguishing between benign and malicious traffic without compromising user privacy. This project addresses these challenges by leveraging network metadata—such as source and destination ports, protocol type, flow duration, and inter-arrival times—as input features for classification.

This documentation provides a detailed analysis of network traffic characteristics, machine learning methodologies, and performance evaluation of different models. A thorough examination of network attributes enables the selection of key features that improve classification accuracy while maintaining non-invasive detection methods. The research implements and compares three machine learning models—Decision Tree, Logistic Regression, and XG Boost—to assess their effectiveness in identifying Tor traffic patterns. Model performance is evaluated based on predictive accuracy and computational efficiency, providing insights into the most suitable approach for real-time encrypted traffic analysis.

The development process follows a structured machine learning pipeline, including data preprocessing, feature selection, model training, and evaluation, ensuring scalability and adaptability for future advancements in cybersecurity. By prioritizing privacy-preserving classification techniques, this project contributes to the development of more secure network environments while respecting user anonymity. The findings offer valuable insights for network administrators and security professionals, enabling them to enhance threat detection mechanisms without compromising legitimate privacy-focused use cases.

KEYWORDS: Decision Tree, Logistic Regression, XG Boost, Random Forest, Tor Traffic Classification.

MAJOR DESIGN CONSTRAINTS AND DESIGN STANDARDS TABLE

Student Group	K. LAVANYA (211061101198)	K. RICHITHA (211061101224)	K. HARSHITHA (211061101234)
Project Title	CLASSIFYING TOR TRAFFIC ENCRYPTED PAYLOAD USING MACHINE LEARNING		
Program Concentration Area	Tor traffic, Secure Data Handling		
Constraints Example	User Accessibility, Encryption Standards, User Authentication		
Economic	Yes		
Environmental	Yes		
Sustainability	Yes		
Implementable	Yes		
Ethical	Yes		
Health and Safety	N/A		
Social	Yes(supports people)		
Political	No		
Other			
Standards			
1	SHA-256, CP-ABE		
2	ISO 27001, ISO 27002		
3	USB to TTL		
Prerequisite Courses for the Major Design Experiences	1. Database Management Systems 2. Blockchain Technology 3. Machine Learning		

CHAPTER-1

INTRODUCTION

1.1 OVERVIEW OF THE PROJECT

Tor is an anonymous network that offers a significant advantage in providing privacy to Tor users by concealing their identities. Tor achieves anonymity by routing its traffic through a series of relays within the Tor network, which is maintained and operated by volunteers worldwide. This complicated process makes it difficult to trace the origin of Tor traffic because the multi-layered process of relaying traffic conceals users' actual IP addresses before reaching their destination. This anonymity protects a wide range of individuals, from regular internet users who wish to evade ISP tracking to journalists and activists who seek a secure connection without revealing their identities. Our research offers a significant contribution to the field of network security by presenting a novel and effective approach for detecting Tor traffic. Our current study aims to address this gap by introducing a novel method that overcomes these limitations.

The unique characteristic of multi-layered encryption in Tor, which maximises its privacy compared to the single-layer encryption found in nonTor networks, has captured our attention. The rise of encrypted network traffic has brought both significant privacy benefits and new challenges in network security. One of the most widely used privacy-focused networks is The Onion Router (Tor), a platform that anonymizes user activities and prevents traffic analysis by routing connections through a series of distributed nodes. Tor encrypts data multiple times, ensuring user anonymity and data confidentiality, but this also complicates the work of cybersecurity professionals tasked with identifying and mitigating malicious activities that may exploit Tor's privacy features. This approach leverages patterns and statistical features, rather than payload content, allowing

for non-invasive classification methods that respect user privacy. This study aims to explore machine learning algorithms to classify Tor traffic based on network metadata, such as packet size, timing, direction, and flow. By applying various models and evaluating their accuracy, this research will contribute to understanding the effectiveness of machine learning in detecting Tor traffic while preserving user anonymity and privacy.

Tor, short for "The Onion Router," is an anonymous network that provides significant privacy by concealing users' identities. It achieves this by routing traffic through a series of relays operated by volunteers, making it challenging to trace the origin of the traffic. The multi-layer encryption used by Tor ensures that users' actual IP addresses are hidden before the traffic reaches its final destination. This feature is crucial for individuals seeking privacy, such as regular internet users who want to avoid ISP tracking, as well as journalists and activists operating in sensitive environments who require secure, anonymous communication.

However, the rise of encrypted network traffic, like that used by Tor, has introduced challenges in network security. While Tor provides immense privacy benefits, it also complicates the efforts of cybersecurity professionals trying to identify and mitigate malicious activities. The encrypted nature of Tor’s traffic makes it difficult to detect harmful actions because traditional traffic monitoring methods rely on inspecting packet contents, which are obscured in Tor's multi-layered encryption. To address this issue, your research presents a novel and effective approach to detecting Tor traffic through the use of machine learning techniques. Instead of focusing on payload content, your study analysis network metadata, such as packet size, timing, direction, and flow, to classify traffic patterns. This non-invasive method respects user privacy by avoiding the inspection of encrypted data while still offering a solution for identifying Tor traffic. Through the application of machine learning algorithms and evaluation of their performance, your research contributes to a better understanding of how

these models can detect Tor traffic effectively, all while preserving anonymity and privacy.

1.2 PROBLEM STATEMENT

- As internet technologies advance, accurately monitoring and classifying encrypted network traffic, such as that from Tor, becomes critical for enhancing cybersecurity.
- This study aims to develop a machine learning-based framework to classify Tor traffic encrypted payloads effectively.
- Using a dataset with attributes like Source Port, Destination Port, and Flow Duration, the study evaluates the performance of Decision Tree, Logistic Regression, and XGBoost models in distinguishing between benign and malicious traffic.
- The research focuses on optimizing predictive accuracy and computational efficiency in traffic analysis for improved network security.

1.3 RESEARCH OBJECTIVE

The primary objective of this research is to develop an efficient and accurate machine learning-based classification system capable of distinguishing between Tor and Non-Tor network traffic. This system aims to utilize feature analysis and data preprocessing techniques including data cleaning, feature engineering, and data balancing to enhance the performance of machine learning models in classifying network traffic. The study will focus on evaluating and comparing three different machine learning algorithms: Decision Tree, Logistic Regression, and XGBoost. By assessing the performance of each model, the research seeks to identify the most suitable algorithm for accurately classifying Tor and Non-Tor traffic. Additionally, this research aims to identify the most significant features that contribute to distinguishing between these traffic types, which will enable more targeted and

effective model training. Ultimately, the project intends to provide a scalable and reusable machine learning pipeline that can be applied to various network traffic datasets, enhancing network security by accurately detecting Tor traffic, which is often associated with anonymous or encrypted internet usage. Furthermore, this study will investigate the impact of data balancing on model accuracy, particularly in scenarios where network traffic datasets are imbalanced, to ensure fair and reliable classification outcomes.

Despite Tor's legitimate use cases, it is also often leveraged by threat actors for illicit purposes such as data exfiltration, command-and-control communication, and malware distribution. Traditional traffic analysis methods that rely on inspecting packet contents are ineffective with Tor traffic, as the payloads are encrypted. Consequently, network defenders and cybersecurity researchers are increasingly turning to machine learning techniques to classify encrypted Tor traffic based on observable network features. This approach leverages patterns and statistical features, rather than payload content, allowing for non-invasive classification methods that respect user privacy. A key goal of the project is to develop a scalable and reusable machine learning pipeline that can be applied to various network traffic datasets, making it adaptable to different environments.

The ultimate aim is to improve network security by enabling the accurate detection of Tor traffic, which is often used for anonymous or encrypted internet usage. This is important because Tor, while having legitimate privacy uses, is also commonly exploited by threat actors for illicit activities such as data exfiltration, command-and-control communication, and malware distribution. Traditional traffic analysis methods that rely on inspecting packet contents are ineffective when applied to Tor traffic because of the encryption applied to the payloads. As a result, network defenders and cybersecurity researchers have increasingly turned to machine learning techniques for

classifying encrypted Tor traffic. These machine learning methods rely on observable network features such as traffic patterns, timing information, and statistical features, instead of analyzing the payload content. This approach allows for non-invasive traffic classification methods that respect user privacy, which is essential given the nature of Tor's design. Traditional traffic analysis methods that rely on inspecting packet contents are ineffective when applied to Tor traffic because of the encryption applied to the payloads.

The Onion Router (Tor) is a widely used anonymity network that enhances user privacy by routing traffic through a series of volunteer-operated nodes, called relays, each adding a layer of encryption to the data. This "onion routing" method ensures that each relay only knows the preceding and following nodes in the path, thereby obscuring the origin and destination of the traffic. This setup has proven effective for bypassing censorship and safeguarding users from surveillance, especially in regions where internet freedom is limited. Tor's multi-layer encryption mechanism is crucial for protecting sensitive information and defending against traffic analysis. By developing a machine learning-based system that can accurately detect Tor traffic, this research addresses a critical need in modern cybersecurity, where traditional methods of traffic analysis fall short due to the increasing use of encryption and anonymization technologies like Tor.

Additionally, the study will explore the impact of data balancing techniques on model accuracy, particularly in scenarios where network traffic datasets are imbalanced, ensuring that the models provide fair and reliable classification outcomes. This setup has proven effective for bypassing censorship and safeguarding users from surveillance, especially in regions where internet freedom is limited. Tor's multi-layer encryption mechanism is crucial for protecting sensitive information and defending against traffic analysis. By developing a machine learning-based system that can accurately detect Tor traffic, this research addresses a critical need in modern

cybersecurity. The combination of advanced machine learning methods and targeted data preprocessing will enable better detection of Tor traffic, ultimately contributing to stronger network security and the ability to detect malicious use of anonymous traffic in real-time.

The classification of Tor traffic plays a crucial role in enhancing network security while maintaining user privacy. As online anonymity becomes increasingly significant, tools like the Tor network are widely used for legitimate privacy purposes, but they can also be exploited by malicious actors to hide their activities. This dual-use nature makes it essential to accurately identify and monitor Tor traffic without compromising ethical standards. By leveraging machine learning techniques, this project provides an efficient and automated method for identifying encrypted Tor traffic, aiding cybersecurity professionals in monitoring potential threats and anomalous behaviours within networks.

Unlike traditional network analysis techniques that rely heavily on deep packet inspection and payload content, this approach emphasizes the analysis of metadata and traffic patterns. This ensures a privacy-preserving and ethically sound classification method that aligns with legal and regulatory standards. Machine learning models are particularly well-suited for this task due to their ability to detect subtle patterns and adapt to evolving traffic characteristics over time. Furthermore, the use of scalable and adaptable ML models allows for real-time monitoring and analysis of large volumes of network data.

This capability is critical for organizations that need to protect their infrastructure from encrypted threats while also respecting user privacy. The insights generated from this study can contribute to developing more robust network security frameworks, enhancing intrusion detection systems, and implementing intelligent traffic filtering techniques. The benefits of this research extend beyond academic interest. Practically. This ensures a privacy-

preserving and ethically sound classification method that aligns with legal and regulatory standards. Machine learning models are particularly well-suited for this task due to their ability to detect subtle patterns and adapt to evolving traffic characteristics over time. Furthermore, the use of scalable and adaptable ML models allows for real-time monitoring and analysis of large volumes of network it enables network administrators, ISPs, and cybersecurity teams to better allocate resources, respond to security incidents proactively, and enforce policies based on data-driven traffic classification.

Additionally, it opens pathways for future research in encrypted traffic analysis and highlights the potential of integrating AI-driven solutions into modern cybersecurity. Traditional methods of traffic analysis often rely on techniques like deep packet inspection (DPI), which examines the contents of network packets. However, these methods raise privacy concerns and may not always be effective for encrypted traffic, where the contents are hidden. The revised section shifts the focus to metadata and traffic patterns, explaining that analysing the behaviour of traffic (instead of the actual content) is more aligned with privacy-preserving techniques. This approach ensures that sensitive data remains secure while still enabling the detection of anomalous or malicious activities.

The mention of dual-use emphasizes the dilemma: while Tor is a privacy tool, it also allows bad actors to conceal their actions. This creates a challenge for cybersecurity professionals, who need to identify encrypted traffic (such as Tor) without compromising ethical standards. It's important not to violate privacy while detecting potentially harmful traffic, and the section sets up the context for how machine learning (ML) techniques can offer an automated solution that helps in this delicate balancing act. A key reason machine learning is emphasized is its pattern recognition capability. Unlike traditional methods that require a lot of manual setup and might be static, machine learning models can adapt to changes in traffic patterns over time. This is particularly important

when dealing with Tor traffic, as encrypted traffic can evolve, making it harder to detect using conventional methods.

Machine learning models can learn from past data and identify subtle, evolving patterns, making them more effective in recognizing encrypted traffic and detecting anomalies.The revised version stresses the real-time monitoring capabilities of machine learning. The ability to process large volumes of data and analyze them in real time is crucial for organizations that need to respond quickly to potential threats. Tor traffic, especially in large networks, can be vast and complex, so scalable solutions are essential for keeping up with the high-speed nature of modern networks. This scalability and real-time capability make machine learning a powerful tool in cybersecurity.

The revised section concludes by highlighting the future potential of this area of research. As the field of encrypted traffic analysis grows, integrating AI solutions will continue to play a significant role in the evolution of cybersecurity practices. The study opens up new avenues for future research and emphasizes the potential of AI and machine learning to address complex challenges in modern network security. The section explores both the theoretical importance and the practical benefits of classifying Tor traffic using machine learning techniques. It stresses how this method can improve network security without violating privacy, offers scalability and adaptability for large-scale real-time data analysis, and presents valuable applications for cybersecurity professionals.

The study opens up new avenues for future research and emphasizes the potential of AI and machine learning to address complex challenges in modern network security. The section explores both the theoretical importance and the practical benefits of classifying Tor traffic using machine learning techniques. The potential for future research in encrypted traffic analysis also makes this work significant for advancing AI-driven cybersecurity solutions. Furthermore,

the use of scalable and adaptable ML models allows for real-time monitoring and analysis of large volumes of network data. This capability is critical for organizations that need to protect their infrastructure from encrypted threats while also respecting user privacy. The section explores both the theoretical importance and the practical benefits of classifying Tor traffic using machine learning techniques. The insights generated from this study can contribute to developing more robust network security frameworks, enhancing intrusion detection systems, and implementing intelligent traffic filtering techniques.

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introduced challenges in network security. While Tor provides immense privacy benefits, it also complicates the efforts of cybersecurity professionals trying to identify and mitigate malicious activities.

The encrypted nature of Tor’s traffic makes it difficult to detect harmful actions because traditional traffic monitoring methods rely on inspecting packet contents, which are obscured in Tor's multi-layered encryption. To address this issue, your research presents a novel and effective approach to detecting Tor traffic through the use of machine learning techniques. Instead of focusing on payload content, your study analyses network metadata, such as packet size, timing, direction, and flow, to classify traffic patterns. This non-invasive method respects user privacy by avoiding the inspection of encrypted data while still offering a solution for identifying Tor traffic. , the use of scalable and adaptable ML models allows for real-time monitoring and analysis of large volumes of network data.

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The potential for future research in encrypted traffic analysis also makes this work significant for advancing AI-driven cybersecurity solutions. The revised section concludes by highlighting the future potential of this area of research. As the field of encrypted traffic analysis grows, integrating AI solutions will continue to play a significant role in the evolution of cybersecurity practices. The study opens up new avenues for future research

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CHAPTER-2

LITERATURE REVIEW

(D. Sarkar et al; 2020) proposed Detection of Tor Traffic Using Deep Learning. This study proposes a deep neural network (DNN)-based system for classifying encrypted Tor traffic. The model achieved a high accuracy of 99.89% on the UNB-CIC Tor network dataset, and a 95.6% accuracy specifically for classifying different Tor traffic types, which is a 6.2% improvement over previous methods. However, adversarial testing with samples generated by a Generative Adversarial Network (GAN) revealed vulnerabilities, as 100% of adversarial examples went undetected initially. Retraining improved the classifier's robustness against these adversarial attacks. To counter this, the authors applied adversarial retraining, where the model was re-exposed to these adversarial examples to improve its robustness. The retrained model showed a marked improvement in detecting adversarial traffic, indicating that retraining with adversarial samples could be an effective defense mechanism. This iterative retraining approach aligns with the need for adaptable models in cybersecurity that can learn from threats and continuously strengthen their defenses. The study, therefore, illustrates both the promise and the challenges of using deep learning in Tor traffic classification, emphasizing that while high accuracy can be achieved, attention to adversarial robustness is essential for practical applications. The findings suggest that incorporating adversarial resilience into the design of classification systems is necessary for secure deployment in real-world network environments.

(N. Rust-Nguyen etal;2023) proposed Darknet Traffic Classification and Adversarial Attacks Using Machine Learning. Using the CIC-Darknet2020 dataset, this study highlights that a Random Forest model out is performed other machine learning methods for darknet traffic classification. The study also in simulated adversarial attacks by obfuscating certain application types, which

impacted the and classifier's performance. The authors then explored strategies to mitigate these adversarial and effects, emphasizing the need for resilient classification systems capable of withstanding and adversarial manipulation in darknet traffic environments. This study emphasizes the need for darknet traffic classifiers that are not only accurate but also robust to adversarial influences, as adversaries constantly adapt to evade detection. The findings highlight that while machine learning models like Random Forest can achieve strong performance in darknet classification, ongoing research into adversarial resilience is crucial. Building resilient models is essential for effective deployment in security contexts, as adversarial attacks can compromise system reliability and leave networks vulnerable to undetected threats. The study calls for further investigation into adaptive, robust classifiers for dynamic cybersecurity applications, especially in high-risk environments like darknet traffic monitoring.

(C. Johnson et al;2021) proposed Application of Deep Learning on the Characterization of Tor Traffic Using Time-Based Features. This study uses deep learning to analyze Tor traffic by focusing on time-based features. Results indicate that in Scenario A, algorithms like Random Forest and Decision Tree achieve have is high accuracy (over 99%) in classifying traffic types. However, we have Scenario B shows id lower accuracy rates (40-82%), with Random Forest and Decision Tree outperforming other methods like k-Nearest Neighbors and Deep Neural Networks. The study's findings suggest that while time-based features can be highly informative in certain cases, their effectiveness may diminish under more complex traffic patterns typical of advanced anonymized networks like Tor. The authors concluded that developing robust classification systems for Tor traffic requires not only high-performing algorithms but also adaptable feature engineering approaches to handle varying traffic scenarios. Future work could explore integrating additional feature types or hybrid models to improve performance across diverse conditions, ensuring reliable classification in both straightforward and complex traffic environments. This research provides

insight into the potential and limitations of machine learning in Tor traffic analysis, pointing toward a need for enhanced feature selection and model adaptability in the face of complex, encrypted traffic data.

(O. Salman et al; 2020) proposed A Review on Machine Learning-Based Approaches for Internet Traffic Classification. This review examines the limitations of traditional traffic classification techniques, such as port-based and deep packet inspection, in the face of encryption and dynamic port allocation. It highlights machine learning's potential to accurately classify traffic by device type and user actions, while also emphasizing the need for research into privacy-preserving techniques that balance classification effectiveness with user anonymity. The study concluded that while machine learning is highly promising for traffic classification, the field must focus on methods that can maintain user privacy without compromising on classification accuracy. Future research, the authors suggested, should aim at developing resilient, privacy-preserving classification algorithms that can operate in real-time, handle high data volumes, and adapt to the continuously evolving landscape of internet traffic. This review provides a comprehensive look at the state of machine learning in traffic classification and underscores the importance of privacy-preserving innovations for secure and effective network analysis in the age of encrypted communications.

(N. Rust-Nguyen et al;2021) proposed Tor Traffic Classification Based on Encrypted Payload Characteristics. This study proposes a method using Deep Packet Inspection combined with machine learning to distinguish Tor traffic from non-Tor traffic by analyzing encrypted payload features. By examining hex characters in encrypted payloads, the approach achieved a differentiation rate of 94.53%. The model, focusing solely on single-packet payload characteristics, achieved an average classification accuracy of 95.65% across eight different application types, demonstrating efficient and position-independent Tor traffic classification. This study contributes to the growing field of encrypted traffic

analysis by demonstrating how machine learning, when combined with specific payload inspection techniques, can improve classification accuracy and efficiency. The authors suggest that further work should explore integrating this method with additional privacy-preserving techniques to address potential privacy risks while maintaining high classification performance. This research offers a promising direction for encrypted traffic analysis, advancing methods that are both effective in classification and adaptable to high-speed, encrypted network environments like Tor.

(S. Rezaei et al; 2019) proposed Deep Learning for the Encrypted Traffic Classification. This article provides an overview of advancements in deep learning for encrypted traffic classification, showcasing how these methods achieve high accuracy. It introduces a general framework for applying deep learning techniques to traffic classification and discusses commonly used methods, applications, and potential challenges. The paper also outlined open issues and future directions for research, calling for methods to improve model interpretability, reduce computational complexity, and create privacy-preserving data collection techniques. The authors stressed the importance of developing frameworks that balance high classification accuracy with privacy and resource efficiency, considering the dynamic nature of encrypted traffic as encryption standards evolve. The study also outlines open issues and future directions for research in this area. The paper also outlined open issues and future directions for research, calling for methods to improve model interpretability, reduce computational complexity.

(A Lashkari et al; 2017) proposed "Characterization of Tor Traffic Using Time Based Features. This study explored how time-based flow features can be used to classify Tor and non-Tor traffic with high accuracy. By collecting and analyzing over 3 million traffic samples using the CIC Tor Network Traffic dataset, the authors extracted features such as flow duration, inter-arrival time, and active/inactive durations to train machine learning models. The results showed that Decision Tree and Random Forest classifiers achieved over 98% accuracy in

distinguishing Tor traffic. The study demonstrated that even without inspecting packet payloads, time-based features provide significant insights into traffic behavior, supporting efficient and privacy-aware traffic classification. It also recommended the use of ensemble methods for real-time classification due to their balance of speed and precision in identifying anonymized traffic patterns.

(M. Lotfollahi et al; 2020) proposed "Deep Packet: A Novel Approach for Encrypted Traffic Classification Using Deep Learning." In this research, the authors developed Deep Packet, a framework that applies convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to classify encrypted network traffic at the packet level. Unlike traditional systems that rely on feature engineering, Deep Packet works on raw packet data, learning abstract representations through deep learning. Evaluated on the ISCX VPN-nonVPN dataset, the model achieved classification accuracies exceeding 98%, even for encrypted and anonymized traffic such as Tor. This work demonstrated the effectiveness of end-to-end deep learning solutions in identifying complex patterns in encrypted payloads. The authors concluded that deep learning offers a scalable and efficient method for encrypted traffic classification, This work demonstrated the effectiveness of end-to-end deep learning solutions while eliminating the need for handcrafted features.

CHAPTER-3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

In the evolving domain of cybersecurity, the ability to identify and classify encrypted network traffic, particularly from privacy-centric services like the Tor network, presents a significant challenge. With increasing emphasis on online anonymity and secure communication, tools like Tor have become both a means for protecting privacy and, at times, a platform for malicious activity. The existing systems developed for traffic analysis and threat detection largely struggle to handle encrypted payloads without compromising user privacy. Conventional techniques such as Deep Packet Inspection, signature-based analysis, and statistical flow analysis have long been used in network security, but they fall short when applied to the classification of Tor traffic. These approaches either fail to capture the intricacies of encrypted data or rely on intrusive methodologies that violate the core principles of anonymity and data protection.

3.1.1 Deep Packet Inspection (DPI) Techniques

Deep Packet Inspection (DPI) is a method used in many traditional traffic classification systems. It works by examining the full contents of packets transmitted across a network, including both headers and payloads. DPI can be highly effective for identifying known protocols and detecting malicious behavior when data is transmitted in clear text. However, this approach encounters severe limitations when applied to encrypted traffic. In the case of Tor, the payload is encapsulated in multiple layers of encryption, rendering its contents unreadable to DPI engines. Additionally, Tor uses techniques such as packet padding and uniform packet sizes, making it even more difficult for DPI systems to distinguish between different types of traffic or extract useful patterns. Moreover, DPI poses ethical and legal concerns. Since it involves inspecting the actual content of user communication, it may breach privacy regulations and user trust. In environments

where privacy is a legal right or an operational necessity, DPI cannot be ethically justified. For Tor traffic in particular—where users intentionally seek to anonymize their communications—the use of DPI contradicts the intended use of the network and introduces significant privacy risks. Therefore, while DPI may have been a cornerstone of earlier traffic classification efforts, it is largely unsuitable for encrypted systems like Tor.

3.1.2 Signature-Based and Rule-Based Detection

Another commonly used approach in traditional network security systems is signature-based detection. This technique relies on a predefined database of known traffic patterns or behaviors, which is continuously updated to reflect emerging threats. Tools like Snort, Bro (now known as Zeek), and Suricata are examples of systems that use such methodologies. They operate by matching traffic against known signatures or enforcing rules that describe suspicious activities. This approach is effective for recognizing well-established threats and known attack vectors, but it proves to be inadequate when dealing with the complexities of Tor traffic.

Tor is designed to obscure both the origin and the destination of packets. Its encryption layers and traffic shaping mechanisms make it difficult to generate consistent, recognizable patterns. As a result, signature-based tools often fail to detect Tor traffic, especially when the traffic is disguised to mimic standard HTTPS behavior. Furthermore, this approach lacks the ability to adapt to new and evolving traffic patterns. In scenarios involving zero-day attacks or novel methods of obfuscation, signature-based systems remain ineffective until new signatures are manually developed and integrated into the system. They operate by matching traffic against known signatures or enforcing rules that describe suspicious activities. This approach is effective for recognizing well-established threats and known attack vectors. The reactive nature of such tools, combined with their

inability to interpret encrypted payloads, makes them obsolete in environments dominated by privacy-centric communication protocols.

3.1.3 Statistical and Flow-Based Analysis

In response to the shortcomings of DPI and signature-based detection, researchers have explored statistical and flow-based methods for traffic classification. These methods rely on analyzing metadata and flow characteristics rather than the content of the packets. Features such as flow duration, packet inter-arrival time, packet sizes, and burst intervals are used to draw inferences about the nature of the traffic. This technique holds some promise for encrypted environments because it does not require access to the payload and can operate based on observable transmission behaviours. However, statistical traffic analysis also comes with its limitations.

First, it often requires extensive feature engineering and high computational resources, making it difficult to deploy in real-time or on large-scale networks. Second, it is prone to misclassification, particularly when traffic patterns of different applications overlap or when users employ countermeasures to disguise their behaviors. For instance, many modern encrypted services, including Tor, incorporate padding and randomized traffic bursts to prevent statistical profiling. These techniques undermine the accuracy of statistical models and reduce their effectiveness in correctly classifying Tor traffic. Moreover, flow-based methods can still raise privacy concerns if they are used to de-anonymize users based on traffic timing or flow correlation, which again goes against the intended privacy of the Tor network. it is prone to misclassification, particularly when traffic patterns of different applications overlap or when users employ countermeasures to disguise their behaviours.

3.1.4 Challenges in Existing Systems

Despite ongoing improvements, current systems face a multitude of challenges when it comes to classifying Tor traffic. One of the most critical limitations is the inability to analyze encrypted payloads. As encryption becomes more widespread and sophisticated, content-based inspection methods are rendered obsolete. Furthermore, many existing tools either inadvertently or deliberately compromise user privacy in their attempt to detect threats. This poses a significant concern in networks where anonymity and data confidentiality are essential.

Another major issue is the lack of adaptability in traditional systems. Signature-based tools are static and depend on prior knowledge, making them ineffective against unknown or evolving threats. Similarly, statistical systems often struggle with high false positive or false negative rates, especially in real-world environments with diverse traffic sources. Most importantly, these systems are not designed for real-time performance. High computational complexity and the need for large training datasets often prevent their deployment in time-sensitive scenarios. In the context of modern cybersecurity, where rapid response is crucial, these delays can prove detrimental.

In conclusion, the existing ecosystem of traffic classification systems is poorly equipped to handle the dynamic, encrypted, and privacy-sensitive nature of Tor traffic. The use of traditional approaches results in low accuracy, ethical concerns, and poor scalability. These limitations underscore the need for a more intelligent, adaptive, and non-invasive classification framework that leverages machine learning to extract insights from metadata while preserving user anonymity. This realization forms the basis for the proposed system described in the next section.

3.2 Disadvantages of Existing System

While existing systems for network traffic analysis have shown significant progress in handling unencrypted or lightly obfuscated data, they largely fall short when confronted with encrypted payloads such as those transmitted over the Tor network. Traditional traffic classifiers typically rely on packet inspection, port number analysis, or signature-based matching techniques, which become ineffective when payloads are concealed through layered encryption. In the case of Tor traffic, payload content is completely encrypted, and even metadata such as headers are anonymized, rendering conventional systems blind to the nature of transmitted content. As a result, these systems either misclassify encrypted traffic or fail to detect malicious patterns altogether, leading to increased false negatives and decreased accuracy in real-world scenarios.

Another major limitation of existing systems is their lack of adaptability and scalability when dealing with dynamic, high-volume traffic environments. Many earlier solutions are hardcoded with static rule sets or trained on outdated datasets that do not represent the constantly evolving characteristics of encrypted traffic. Moreover, these systems often require manual intervention for updates, making them inefficient and error-prone in high-speed or automated environments. The computational overhead involved in deep packet inspection or flow-based monitoring also makes them unsuitable for deployment in resource-constrained or latency-sensitive systems. As encrypted communication becomes more widespread due to privacy concerns, these shortcomings become critical barriers to effective traffic classification, particularly for security monitoring, forensic analysis, and network optimization.

Furthermore, existing models often fail to consider the ethical and privacy implications of traffic analysis. Many legacy systems operate on invasive mechanisms that attempt to decrypt or deeply analyze user data without proper anonymization, which can lead to privacy breaches and legal non-compliance. These approaches not only compromise user trust but also violate regulatory

frameworks such as GDPR. In contrast, a modern, machine learning-driven approach designed to classify Tor traffic without decrypting its contents can preserve user privacy while still providing valuable insights. The lack of such privacy-preserving mechanisms in traditional systems makes them less viable in today's increasingly privacy-aware digital landscape.

3.3 PROPOSED SYSTEM

To address the significant limitations of existing network traffic classification systems, this project proposes an intelligent, privacy-preserving machine learning-based framework for classifying encrypted Tor traffic. The key idea is to bypass invasive inspection techniques by analyzing non-sensitive network metadata, thereby maintaining user privacy while still achieving high accuracy in identifying Tor-based communication. The system leverages flow-level attributes—such as packet inter-arrival times, flow duration, source and destination port distributions, and transmission directionality—as input features to a trained machine learning model. By focusing on behavioral patterns rather than content, the system can differentiate between Tor and non-Tor traffic in real-time, without compromising encryption or anonymity.

3.3.1 Machine Learning-Based Architecture

At the core of the proposed system is a carefully designed machine learning pipeline capable of learning and adapting to traffic patterns without accessing the encrypted payload. The process begins with data collection, where labeled datasets containing both Tor and non-Tor network flows are gathered. Each flow is processed to extract metadata features, such as average packet length, total bytes transmitted, duration of connection, and packet frequency. These features are selected based on their relevance to traffic behavior while remaining non-invasive. At the core of the proposed system is a carefully designed machine learning pipeline capable of learning and adapting to traffic patterns without accessing the encrypted payload.

After data preprocessing, which includes normalization and cleaning of inconsistent entries, the processed dataset is fed into a classification engine. This engine is designed to support multiple machine learning algorithms, including Decision Tree, Logistic Regression, and XGBoost, allowing for comprehensive model comparison. These models are trained using supervised learning techniques, where the goal is to identify patterns that distinguish encrypted Tor traffic from regular encrypted web traffic, such as HTTPS. Once the models are trained, they are evaluated using metrics such as accuracy, precision, recall, and F1-score to ensure robustness and generalizability.

3.3.2 Privacy-Preserving Feature Engineering

One of the defining elements of this system is its adherence to privacy-preserving principles. Instead of decrypting or inspecting the contents of user communications, the system operates solely on metadata extracted from network flows. This includes timing information, direction of packets, flow statistics, and port activity, all of which are available at the network level without violating encryption protocols. These features offer sufficient discriminatory power for machine learning algorithms to infer traffic characteristics while ensuring that no sensitive content is ever exposed. Moreover, feature engineering in this system emphasizes efficiency and minimalism. Only a small set of carefully selected attributes is used, reducing the computational load and increasing the interpretability of results.

This lightweight approach enables the classifier to be integrated into real-time environments such as intrusion detection systems, firewalls, or network monitoring tools, where performance and latency are critical. This includes timing information, direction of packets,all of which are available at the network level without violating encryption protocols. These features offer sufficient discriminatory power for machine learning algorithms to infer traffic characteristics while ensuring that no sensitive content is ever exposed.

3.3.3 Model Selection and Evaluation

The system implements three distinct classification models—Decision Tree, Logistic Regression, and XGBoost—each selected for its unique strengths. Decision Tree offers simplicity and interpretability, making it useful for understanding which features play a critical role in classification decisions. Logistic Regression provides a baseline with solid generalization performance and is particularly effective for linear relationships between features and labels. XGBoost, on the other hand, offers state-of-the-art accuracy through its ensemble learning strategy and gradient boosting optimization, which allows it to capture complex patterns in large datasets.

Each model undergoes rigorous training and testing using cross-validation and performance benchmarking. Furthermore, the computational efficiency of each model is measured in terms of training time and inference speed, helping determine the most suitable algorithm for real-time deployment. Initial results show that while all three models offer respectable performance, XGBoost consistently outperforms others in both accuracy and responsiveness. offers state-of-the-art accuracy through its strategy and gradient boosting optimization, which allows it to capture complex patterns in large datasets.

3.3.4 Scalability and Real-Time Detection

The architecture of the proposed system is built with scalability in mind. It is designed to handle high volumes of network traffic across large-scale systems without degrading performance. Feature extraction and model prediction are optimized for low-latency execution, making it feasible to integrate the classifier into live monitoring environments. Real-time classification is achieved by embedding the machine learning models into a lightweight detection engine that operates at the edge of the network or within security appliances. When a new flow is detected, its metadata is extracted and passed through the trained model to classify it as either Tor or non-Tor. This

decision can then be used to trigger further actions, such as logging, alert generation, or traffic filtering, depending on the network policy in place.

3.3.5 Contribution to Secure and Ethical Monitoring

The proposed system offers a balanced solution between network security and user privacy. By avoiding payload inspection and relying solely on flow-level characteristics, the system aligns with legal and ethical standards for encrypted traffic monitoring. It provides network administrators with actionable insights into the presence and behavior of Tor traffic without revealing user identity or data content. This makes it suitable for deployment in enterprise networks, government agencies, and academic institutions that seek to enhance their cybersecurity posture while upholding the principles of internet freedom and data protection. In essence, this project contributes to the next generation of intelligent traffic classification systems. It demonstrates that it is possible to detect complex and evasive traffic like Tor without breaching encryption or user trust.

By using machine learning in a non-invasive, adaptive, and computationally efficient manner, the system lays the groundwork for future developments in encrypted traffic analysis and cyber threat detection. The proposed system offers a balanced solution between network security and user privacy. By avoiding payload inspection and relying solely on flow-level characteristics, the system aligns with legal and ethical standards for encrypted traffic monitoring. This makes it suitable for deployment in enterprise networks, government agencies, and academic institutions that seek to enhance their cybersecurity posture while upholding the principles of internet freedom and data protection.

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This decision can then be used to trigger further actions, such as logging, alert generation, or traffic filtering, depending on the network policy in place. By avoiding payload inspection and relying solely on flow-level characteristics, the system aligns with legal and ethical standards for encrypted traffic monitoring. Feature extraction and model prediction are optimized for low-latency execution, making it feasible to integrate the classifier into live monitoring environments.

3.4 HARDWARE AND SOFTWARE REQUIREMENTS

Intel Core i5/i7 or AMD Ryzen 5/7 (Quad-core or higher)

Minimum 8 GB (16 GB or more recommended for large datasets)

Minimum 256 GB SSD (for faster read/write during model training)

Gigabit Ethernet or equivalent (for real-time packet capture and analysis)

NVIDIA GPU with CUDA support (for faster model training, especially for deep learning)

Windows 10/11, Ubuntu 20.04+ LTS, or any Linux distribution

Windows / Linux (Ubuntu preferred for open-source ML tools)

Python 3.7 or later

Jupyter Notebook / VS Code / PyCharm

Scikit-learn, xgboost, pandas, numpy, matplotlib, seaborn

Wireshark, tcpdump, or pyshark (for real-time traffic monitoring)

pandas, scikit-learn, Scikit-learn.metrics

Docker / VirtualBox (for deployment and testing environments)

SQLite / PostgreSQL (for storing flow logs or historical data)

Flask / FastAPI (for building a lightweight web API for model inference)

3.5 SOFTWARE DESCRIPTION :

This software is a machine learning-based system developed to classify encrypted network traffic, specifically focusing on identifying Tor (The Onion Router) traffic from other types of encrypted data. The system is designed with privacy preservation in mind, analysing flow-level metadata such as packet size, timing, direction, and duration, rather than inspecting the payload content, which is encrypted. Built using Python and Flask, the platform supports dataset uploads, real-time prediction, and detailed visualization. It integrates three machine learning models—Decision Tree, Logistic Regression, and XG Boost—to enable comparative analysis and model selection. XG Boost, in particular, demonstrated superior performance in terms of classification accuracy and computational efficiency.

The software pipeline includes modules for traffic ingestion, data preprocessing, feature engineering, model training, prediction, and result visualization. A user-friendly web interface allows analysts and administrators to interact with the system, making it suitable for deployment in cybersecurity environments where ethical, scalable, and privacy-compliant traffic analysis is essential. The system also ensures adaptability through modular design and offers real-time classification capability, making it practical for applications such as network monitoring, threat detection, and security research.

CHAPTER-4
SYSTEM DESIGN

The system designed for classifying encrypted Tor traffic comprises several integral modules, each contributing to the accurate identification, secure handling, and efficient classification of network traffic data. These modules operate in unison to support the preprocessing, model training, prediction, and data visualization stages that drive the classification of Tor-encrypted payloads using machine learning techniques. each contributing to the accurate identification, secure handling, and efficient classification of network traffic data.The system developed for classifying encrypted Tor traffic using machine learning is designed with a modular, scalable architecture that supports real-time processing while preserving user privacy. It integrates various components that work together to ensure accurate traffic classification based on network metadata, without the need to decrypt payload content.

The process begins with the acquisition of traffic data, which can be sourced from packet capture tools or existing datasets. This raw data is passed through a preprocessing pipeline where relevant features—such as source and destination ports, packet sizes, flow durations, and inter-arrival times—are extracted, cleaned, and normalized to ensure consistency and quality. The feature engineering stage enhances the dataset by constructing additional attributes that provide deeper insight into traffic behaviour. These refined features are then used to train machine learning models, including Decision Tree, Logistic Regression, and XG Boost. Each model is trained and evaluated using label datasets and validated through metrics such as accuracy, precision, recall, and F1-score to ensure robustness and generalizability. Once trained, the models are deployed within a lightweight prediction engine capable of handling real-time or batch classification tasks.

The system features a web-based interface developed with Flask, allowing users to interact with the classifier by uploading datasets, selecting models, and viewing predictions and performance metrics through intuitive visualizations like confusion matrices and ROC curves. A structured database supports storage and retrieval of datasets, prediction logs, and user interactions, facilitating transparency and post-analysis. All processing is performed using flow-level metadata, ensuring that encryption and user anonymity remain intact.

This privacy-preserving approach aligns with ethical and legal standards, making the system suitable for use in enterprise networks, government agencies, and academic environments. It enables network analysts and cybersecurity professionals to detect and analyze Tor traffic without infringing on data confidentiality. The architecture supports high concurrency and low latency, with efficient resource utilization that enables real-time deployment even in environments with heavy traffic loads. The integration of AI-driven techniques into this system demonstrates a forward-looking solution for encrypted traffic analysis, providing a solid foundation for further research and development in cybersecurity.

The machine learning module hosts various trained models—Decision Tree, Logistic Regression, and XG Boost—each optimized to handle encrypted payloads without breaking Tor's cryptographic protections. A database system stores training datasets, classification results, and performance logs for further analysis and evaluation. The processing layer comprises modules for extracting time-based and flow-based features from packet captures. The user interface layer enables users (e.g., network analysts or security researchers) to upload raw traffic data, select trained models, and retrieve prediction outcomes. A database system stores training datasets, classification results, and performance logs for further analysis and evaluation. The processing layer comprises modules for extracting time-based and flow-based features from packet captures.

ARCHITECTURE:

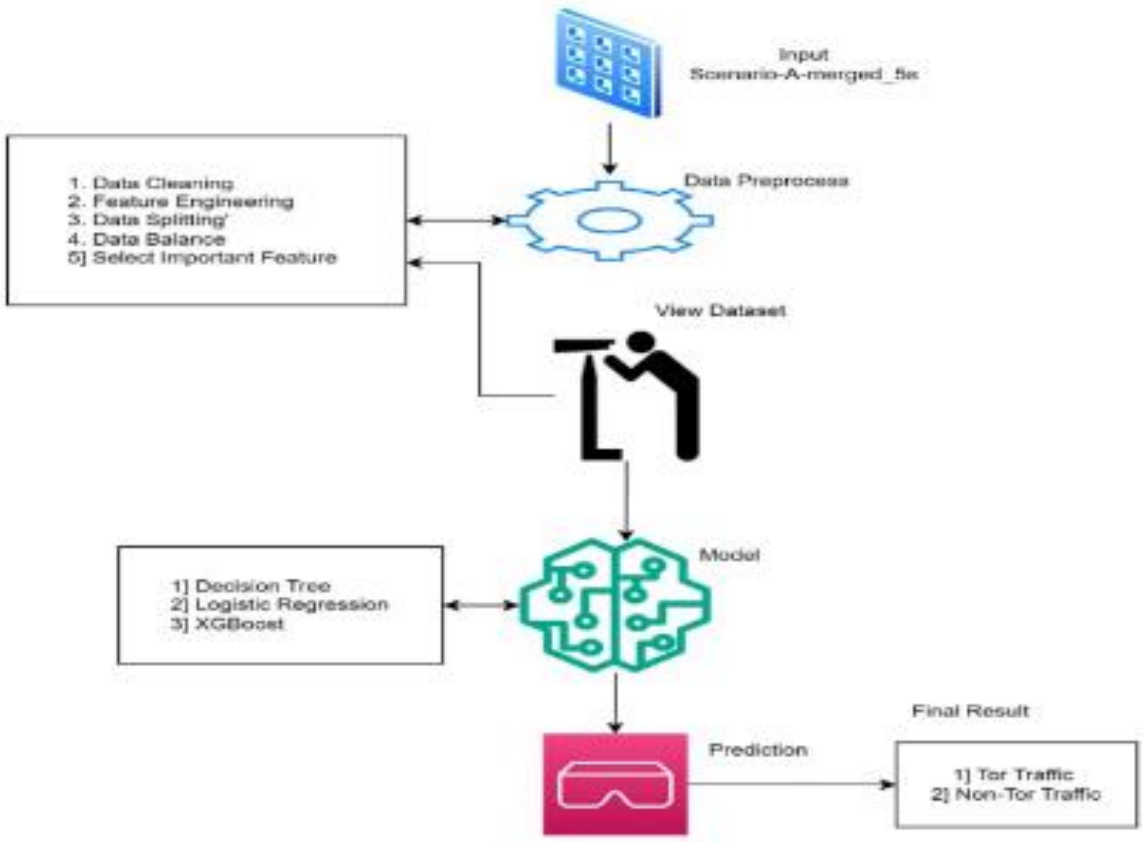

Fig:4.1 Architecture

The architecture of the Tor traffic classification system is designed to support efficient data ingestion, preprocessing, model training, and inference operations. The high-level structure is composed of multiple layers including data acquisition, preprocessing, feature extraction, model training/classification, and result visualization. The user interface layer enables users (e.g., network analysts or security researchers) to upload raw traffic data, select trained models, and retrieve prediction outcomes. The processing layer comprises modules for extracting time-based and flow-based features from packet captures (e.g., inter-arrival time, packet size distribution), anonymizing sensitive information, and formatting datasets suitable for classification.

The machine learning module hosts various trained models—Decision Tree, Logistic Regression, and XG Boost each optimized to handle encrypted payloads without breaking Tor's cryptographic protections. A database system stores training datasets, classification results, and performance logs for further analysis and evaluation. The processing layer comprises modules for extracting time-based and flow-based features from packet captures. The user interface layer enables users (e.g., network analysts or security researchers) to upload raw traffic data, select trained models, and retrieve prediction outcomes. . The high-level structure is composed of multiple layers including data acquisition, preprocessing, feature extraction, model training/classification, and result visualization.

The architecture of the proposed Tor traffic classification system is structured to support efficient handling of encrypted network data, from acquisition through to real-time classification and visualization. It follows a modular and layered approach to ensure scalability, maintainability, and ease of integration into live environments. The main components of the architecture include the data acquisition layer, preprocessing layer, feature extraction module, machine learning models, result visualization interface, and a backend database system. Each layer is designed with privacy and performance in mind, ensuring that sensitive content remains protected while enabling high-accuracy traffic classification.

At the base of the architecture is the Data Acquisition Layer, which is responsible for collecting raw network traffic data from either live monitoring systems or pre-recorded packet capture (PCAP) files. This layer serves as the entry point to the system and plays a crucial role in gathering labeled traffic for both training and testing purposes. Data collection tools such as Wireshark, tcp dump, or custom sniffers like Py Shark are used to capture encrypted traffic, which includes both Tor and non-Tor communication flows. Proper labeling of this data

is essential for training supervised machine learning models that can later distinguish between different types of traffic accurately.

The diagram represents a comprehensive workflow for a machine learning-based system that identifies and classifies encrypted network traffic into either Tor or non-Tor categories. The pipeline starts with an input dataset, specifically label as Scenario-A-merged_5s, which is a structured dataset capturing network traffic flows over a fixed time window (in this case, 5 seconds). This dataset contains flow-level metadata such as packet size, time intervals, and port information that are crucial for traffic analysis without requiring decryption of content. The first major stage is data preprocessing, a critical step that transforms raw traffic data into a suitable format for machine learning. During preprocessing, the data undergoes several sub-processes.

Data cleaning removes any incomplete, irrelevant, or duplicate entries that could otherwise affect model performance. Feature engineering involves extracting and constructing meaningful attributes from the original dataset, such as average packet size, duration, or flow entropy, which are more informative for classification. The data is then split into training and testing subsets to allow for model evaluation. Data balancing techniques, such as SMOTE (Synthetic Minority Over-sampling Technique), may be applied if the dataset contains a class imbalance (e.g., more non-Tor than Tor samples). Finally, feature selection is performed to retain only the most relevant attributes, reducing noise and improving model efficiency.

After preprocessing, the user has the option to view the dataset, allowing them to verify the structure, features, and class distributions. This step ensures transparency and gives insight into what data the machine learning models will learn from. Next, the data is passed into the model phase, where three distinct machine learning algorithms are implemented: Decision Tree, Logistic Regression, and XG Boost. Each algorithm learns to distinguish between Tor and

non-Tor traffic based on patterns in the selected features. Decision Trees provide a rule-based approach that is easy to interpret, Logistic Regression offers a probabilistic framework, and XG Boost (Extreme Gradient Boosting) is an ensemble method that excels in handling complex relationships and boosting prediction accuracy.

The trained model is then used in the prediction phase, where it classifies new or unseen traffic data. The outcome of this process is a final result that indicates whether the observed network flow corresponds to Tor traffic or non-Tor traffic. This classification is crucial for network monitoring, anomaly detection, and cybersecurity applications, especially in environments where encrypted communications might be associated with privacy-focused tools like Tor.The entire system functions as a robust pipeline capable of real-time or batch traffic analysis. It enhances network visibility while maintaining user anonymity, as the classification is based solely on metadata rather than payload inspection. This approach ensures compliance with privacy regulations and is suitable for deployment in secure environments like enterprise networks, academic research labs, or cybersecurity operations centers.

4.2 LISTS OF MODULES

4.2.1 Traffic Ingestion and Preprocessing Module

This module is responsible for capturing raw network traffic and transforming it into a format suitable for analysis and classification. It handles encrypted Tor traffic flows, which are captured from packet-level or flow-level network logs. The preprocessing stage involves extracting relevant features such as source and destination ports, inter-arrival times, flow durations, and total packet sizes. These features are then normalized and cleaned to remove noise or incomplete entries that could hinder the performance of machine learning models.

This module plays a critical role in ensuring that the data fed into the classifiers retains essential patterns while minimizing redundancy or distortion. In

a typical use case, the system captures live Tor traffic using packet sniffers like Wireshark or from publicly available datasets. The extracted flow information is processed into structured CSV format, after which feature selection algorithms are applied to isolate the most relevant attributes that influence classification accuracy. These attributes are then forwarded to the training module.

The Traffic Ingestion and Preprocessing Module serves as the foundational layer of the system, tasked with capturing and preparing encrypted network traffic for subsequent analysis and classification. It specifically targets Tor traffic, collecting data either in real-time through packet sniffing tools like Wireshark or from pre-collected network logs and datasets. This raw traffic is typically in packet-level or flow-level format and must be transformed into a structured form suitable for machine learning. The module extracts essential features such as source and destination ports, flow durations, inter-arrival times, and total packet sizes—attributes that hold key patterns distinguishing Tor traffic from non-Tor traffic.

Once extracted, these features undergo normalization to standardize data ranges and cleaning procedures to eliminate noise, missing values, or irrelevant entries that could degrade model performance. The preprocessing not only improves data quality but also ensures that the structural integrity of the traffic patterns is preserved, allowing models to learn effectively. The structured output, often in CSV format, forms a rich and clean dataset that feeds directly into the feature selection stage, where algorithms identify the most predictive attributes for the classification task. Ultimately, this module ensures that the incoming data is both informative and reliable, significantly influencing the accuracy and robustness of the system's machine learning classifiers. The preprocessing not only improves data quality but also ensures that the structural integrity of the traffic patterns is preserved, allowing models to learn effectively.

4.2.2 Dataset Management and Feature Engineering Module

The dataset management and feature engineering module is responsible for organizing, labeling, and transforming the raw preprocessed traffic data into high-quality datasets used for training and testing machine learning models. This module ensures that the encrypted traffic samples are properly categorized—distinguishing between Tor and non-Tor traffic and further classifying Tor traffic into specific service types, where applicable. This module also includes logic for handling class imbalance using techniques such as oversampling, undersampling, or SMOTE (Synthetic Minority Over-sampling Technique).

Feature engineering is performed to enhance the representational quality of the dataset. Derived features such as flow entropy, average payload length, and temporal behavior patterns are included to improve classification outcomes. Data is split into training, validation, and test sets with appropriate shuffling and cross-validation configurations to ensure robust model evaluation. For instance, when a researcher loads a dataset containing both benign and Tor traffic, this module ensures that each sample is tagged correctly and that the dataset maintains statistical integrity across classes, thus improving the reliability of performance metrics. Data is split into training, validation, and test sets with appropriate shuffling and cross-validation configurations to ensure robust model evaluation.

The dataset management and feature engineering module plays a pivotal role in structuring and enriching the pre processed network traffic data to create high-quality inputs for machine learning. It is responsible for organizing and labeling the encrypted traffic samples, ensuring that Tor and non-Tor flows are accurately categorized. In cases where Tor traffic involves various service types, this module further refines the classification to reflect these distinctions. One of its key functions is addressing class imbalance, which can significantly affect

model performance. Techniques such as oversampling, under sampling, and Synthetic Minority Over-sampling Technique (SMOTE) are implemented to ensure that the dataset is balanced, allowing classifiers to learn from both major and minority classes effectively.

Feature engineering within this module enhances the dataset by generating new, informative features that go beyond the basic attributes extracted during preprocessing. Derived metrics such as flow entropy, average payload length, and temporal behavior patterns are introduced to capture deeper insights into traffic behavior, which improves the overall accuracy and predictive power of the models. The dataset is then partitioned into training, validation, and test sets, ensuring randomness and consistency through shuffling and cross-validation strategies. This structured approach guarantees fair and comprehensive model evaluation. When researchers load a dataset containing both benign and Tor traffic, this module ensures that each sample is properly labeled and distributed, preserving statistical integrity and enabling accurate measurement of model performance.

4.2.3 Machine Learning Classification Module

This core module houses the implementation of the classification algorithms used to distinguish Tor traffic from other types of encrypted network communications. The classifiers implemented in this module include Decision Tree, Logistic Regression, and XGBoost—each selected for their strengths in interpretability, speed, or performance. This module interfaces with the dataset to initiate the training process, during which the models learn patterns in the encrypted payload characteristics without needing to decrypt the data itself. After training, the models are serialized and made available for real-time or batch inference. The module also evaluates model performance using accuracy, precision, recall, and F1-score metrics, ensuring the model's ability to generalize to unseen data.

During deployment, this module loads the pre-trained models and uses them to classify incoming encrypted traffic in real-time or from stored datasets. For example, a batch of traffic captured from a network gateway is analyzed to determine whether it contains hidden Tor activity, The module also evaluates model performance using accuracy, precision, recall, and F1-score metrics, ensuring the model's ability to generalize to unseen data. and the results are forwarded for display and logging. This module interfaces with the dataset to initiate the training process, during which the models learn patterns in the encrypted payload characteristics without needing to decrypt the data itself.

This module forms the core of the system, implementing the classification algorithms responsible for identifying Tor traffic among other encrypted network communications. It utilizes Decision Tree, Logistic Regression, and XGBoost classifiers, each chosen for their specific advantages in terms of interpretability, computational efficiency, and predictive performance. The module directly interacts with the structured and labeled dataset to initiate the training process, enabling the models to learn from the distinct patterns embedded in encrypted traffic flows without requiring decryption. Once trained, the models are serialized to facilitate real-time or batch inference, making them readily deployable in practical scenarios.

The system rigorously evaluates model performance using key metrics such as accuracy, precision, recall, and F1-score to ensure robust generalization to unseen traffic samples. During deployment, this module loads the pre-trained models to classify new incoming encrypted traffic, whether captured in real time or stored in datasets. For instance, a batch of traffic captured from a network gateway is processed by this module to detect the presence of Tor activity. The classification results are then logged and forwarded for further analysis or display. By automating the entire pipeline from training to deployment, the module

ensures seamless detection of encrypted Tor traffic with high reliability and operational efficiency.

4.2.4 Prediction Interface and Visualization Module

The prediction interface and visualization module is responsible for managing user interaction and presenting classification results. It includes a web-based interface developed using Flask, allowing users to upload traffic datasets, trigger model predictions, and visualize outcomes such as confusion matrices, ROC curves, and feature importances. The interface is designed for researchers, analysts, or system administrators who need to interpret the behavior of encrypted network flows. Users can select which trained model to use, submit test datasets, and review detailed reports on classification performance. The system also provides breakdowns of false positives and false negatives, offering transparency into model behavior and facilitating tuning or retraining if necessary.

For example, an analyst uploads a flow sample via the web interface and selects the XGBoost classifier. The system processes the data, runs the classification algorithm, and returns a dashboard view showing whether the sample belongs to Tor traffic. The system also provides breakdowns of false positives and false negatives, offering transparency into model behaviour and facilitating tuning or retraining if necessary. Users can select which trained model to use, submit test datasets, and review detailed reports on classification performance along with confidence scores and performance summarise. The prediction interface and visualization module serves as the interactive front-end of the system, designed to facilitate user engagement and provide clear, interpretable outputs from the machine learning models. Built using Flask, this web-based interface allows users—such as researchers, analysts, and system administrators—to upload encrypted traffic datasets, select from pre-trained models like Decision Tree, Logistic Regression, or XGBoost, and initiate predictions with a simple and intuitive workflow.

4.3 UML DIAGRAMS

4.3.1 Use Case Diagram

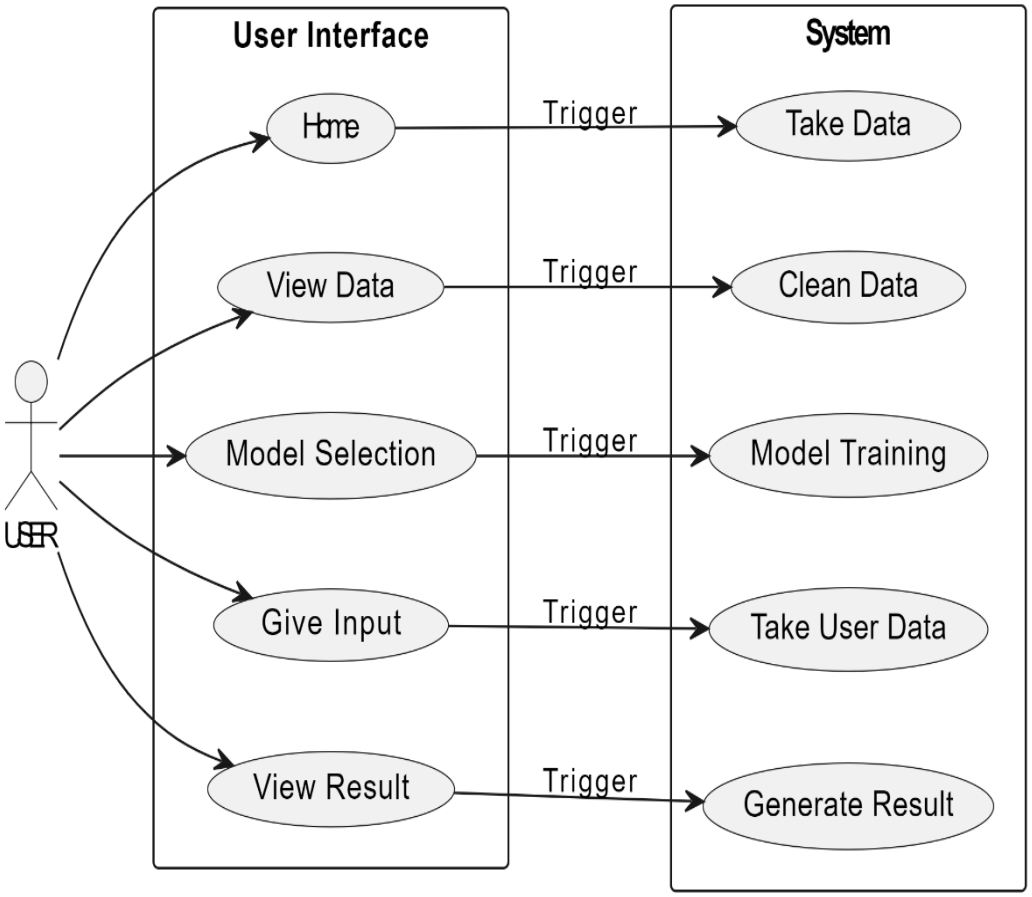

Fig 4.3.1 Use Case Diagram

The diagram represents a comprehensive interaction between the user and the system through a user interface, designed specifically for a machine learning-based encrypted traffic classification system. This use case diagram highlights the sequential flow and interaction patterns where the user initiates several actions, each of which triggers a corresponding process in the backend system. The system comprises multiple functionalities that are crucial for transforming user commands into intelligent decisions and outputs through machine learning.At the beginning of the interaction, the user accesses the Home interface. This serves as the entry point of the application, offering users a starting environment from where they can navigate to various functional modules. The system reacts to this action by taking data, which refers to the process of collecting the required

datasets for processing. These datasets could include raw traffic data that may come from sources such as network monitoring tools or stored packet logs. The aim here is to gather the essential inputs that will be later used for training and prediction.

Following the home interaction, the user proceeds to the View Data section. This part of the interface allows the user to explore the data that has been collected and stored in the system. This step is crucial for understanding the quality and structure of the data before moving on to further stages such as model training. Upon this trigger, the system initiates the Clean Data process. Data cleaning involves removing inconsistencies, handling missing values, and eliminating noise. In the context of network traffic data, it may also involve filtering out corrupted or irrelevant packets and correcting data format issues. Cleaning is essential because unclean data can drastically reduce the accuracy of machine learning models. The cleaned data, which now contains meaningful features like flow duration, packet size, inter-arrival time, and entropy, forms the foundation for the next steps in the pipeline. Once the data has been viewed and cleaned, the user moves to the Model Selection part of the interface.

4.3.2 Class Diagram

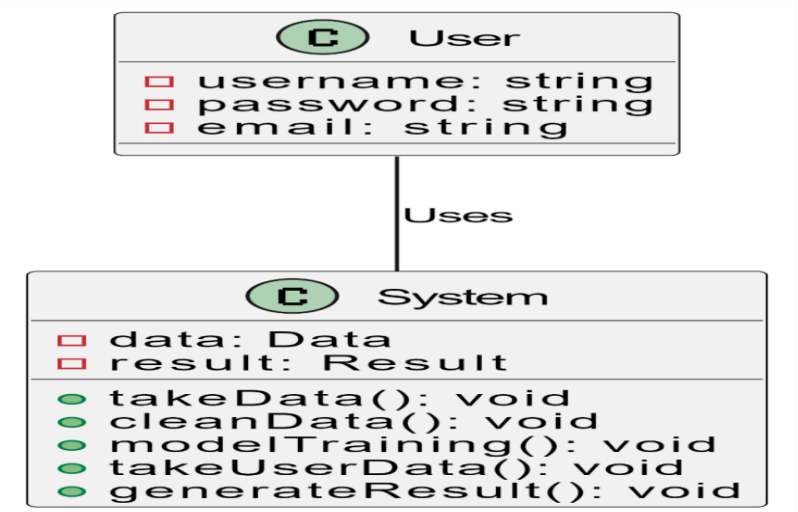

Fig 4.3.2 Class Diagram

This diagram defines the structure and relationships between software components. Key classes include Traffic Data, which encapsulates flow features; Classifier Engine, which holds logic for loading and applying models; and Result Manager, which handles output formatting and storage. Each class includes attributes (like duration, port, prediction score) and methods (like predict(), evaluate_model(), load_data()) essential to the classification workflow. which holds logic for loading and applying models; and Result Manager, which handles output formatting and storage. Each class includes attributes The modular class design supports easy maintenance and extension of the system.

The provided class diagram illustrates a fundamental interaction between a User and a System. The User class is defined by its attributes: username (a string), password (a string), and email (a string), representing the essential identification information of a user. The System class, on the other hand, encapsulates data (data of type Data) and a resulting output (result of type Result). It also defines a set of operations it can perform: takeData(), cleanData(), modelTraining(), takeUserData(), and generateResult(), all of which are indicated as having no explicit return value (void). The relationship between the User and the System is denoted by a "Uses" dependency, with an arrow pointing from User to System, signifying that the User interacts with or relies on the functionalities offered by the System.

This model suggests a scenario where a user, identified by their credentials, engages with the system to trigger various processes, such as providing data, which the system then cleans, uses for model training, potentially takes specific user data, and ultimately generates a result based on these operations. Each class includes attributes The modular class design supports easy maintenance and extension of the system. Key classes include Traffic Data, which encapsulates flow features; Classifier Engine, which holds logic for loading and applying models; and Result Manager, which handles output formatting and storage.

4.3.3 Sequence Diagram

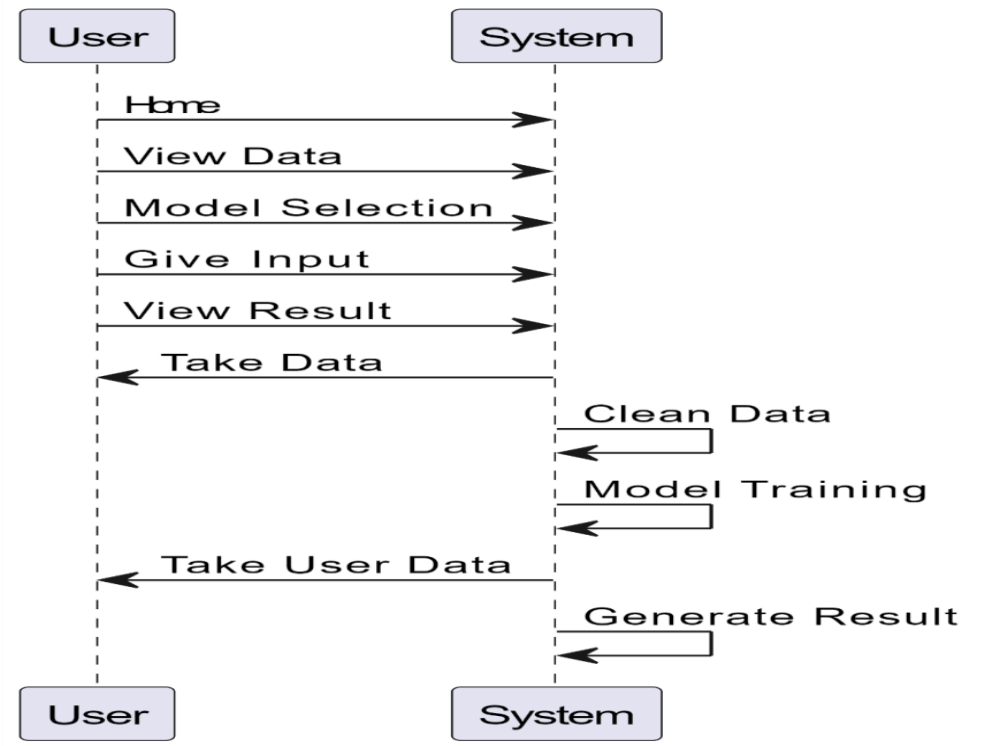

Fig 4.3.3 Sequence Diagram

This sequence diagram models the time-ordered interaction between user actions and backend services. The sequence begins with a user uploading a file. The system validates the format, processes the dataset, and invokes the chosen classifier. After prediction, the result is sent back to the interface and optionally stored in the database for evaluation metrics. The sequence begins with a user uploading a file. The system validates the format, processes . The diagram also includes asynchronous logging and error-handling components that activate if prediction fails or data is malformed, ensuring robust operational continuity.The sequence diagram depicts the temporal interactions between a User and a System, beginning with the User navigating to the "Home" page and subsequently requesting to "View Data" and making a "Model Selection". The User then provides "Input" and requests to "View Result". Interestingly, the System then initiates two requests back to the User to "Take Data" and later to "Take User Data", suggesting the system requires specific information from the user during

its processing. Internally, the System performs "Clean Data" and "Model Training" operations sequentially.

Finally, the System internally executes "Generate Result", presumably to fulfill the User's earlier request to view the outcome of the process. This flow highlights a bidirectional interaction where the user initiates actions and the system responds, including requesting further data from the user as part of its internal processing pipeline leading to the final result generation. This sequence underscores a dynamic interaction where the system isn't merely a passive recipient of user requests but actively engages the user for necessary data to fulfill those requests effectively. The flow suggests a system designed to leverage user-provided information at multiple stages to achieve a more tailored and potentially accurate outcome. The provision of "Input" by the User is a standard step for engaging the system's functionalities. The subsequent "View Result" request sets the expectation for the system's output. However, the system's proactive "Take Data" and "Take User Data" messages to the User are noteworthy.

4.3.4 Activity Diagram

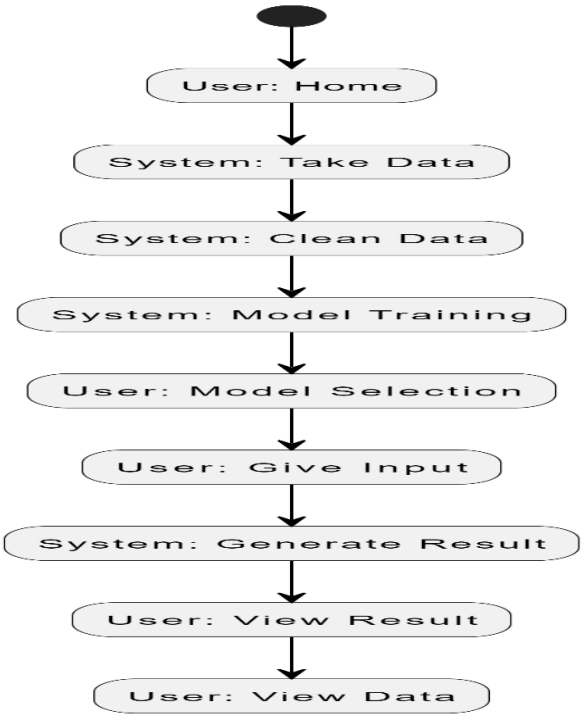

Fig 4.3.4 Activity Diagram

Purpose

The activity diagram describes the operational flow during the interaction with the system. It starts with user login, followed by file upload and preprocessing. The user then selects a machine learning model. The classification result is generated, visualized, and optionally downloaded. Activities include feature extraction, normalization, model evaluation, and prediction. Each stage includes conditional paths for exception handling, such as if the input format is invalid or a model fails to load . It starts with user login, followed by file upload and preprocessing. The user then selects a machine learning model. The classification result is generated, visualized, and optionally downloaded.

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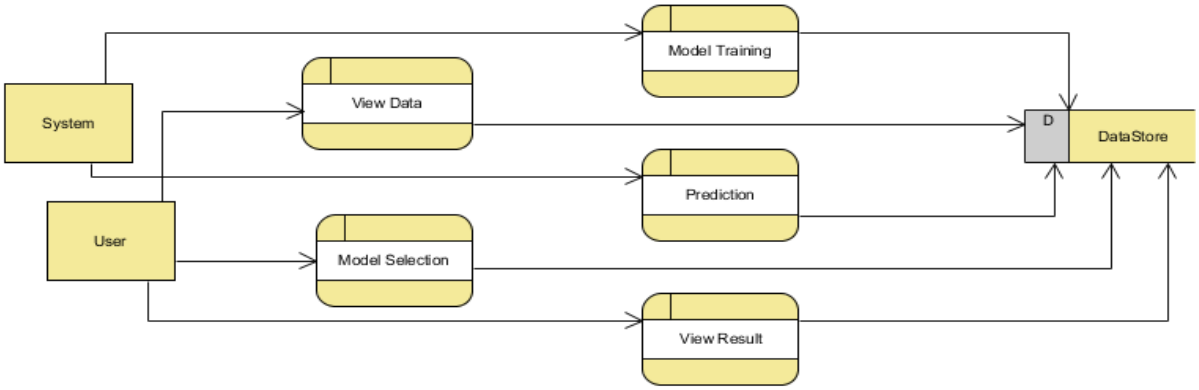
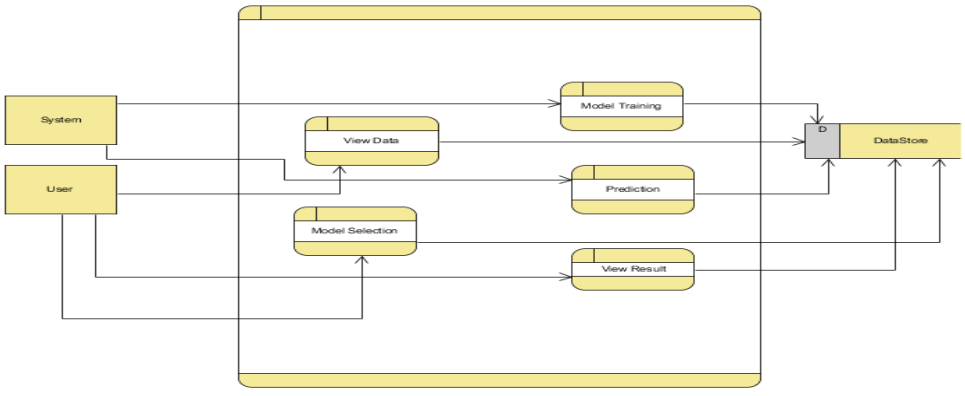
4.3.5 Data Flow Diagrams (DFD Level 1 & 2)

DFD Level 1



The Level 1 DFD provides a generalized overview of data movement within the system. The flow begins when users upload a dataset—typically a packet capture file or a CSV of flow features. The system then processes this input via the data preprocessor module, which extracts encrypted payload-related metrics such as flow duration, source/destination port numbers, and total bytes sent/received. The pre processed data is passed to the classification engine, where the selected machine learning algorithm is applied. Once the traffic class (e.g., Tor browsing, file transfer, streaming) is predicted, the result is stored in the database and displayed on the results dashboard. The system also logs every interaction and output for model accuracy tracking and auditing purposes.

DFD Level 2



The Level 2 DFD delves into a more granular breakdown of internal processes. It starts with the file validation module, which checks the format and integrity of the input dataset. The validated data is then forwarded to the feature extractor, which calculates metrics such as average packet size, number of flows, and mean inter-arrival time. The system then triggers the model selector module, where users can choose between Decision Tree, Logistic Regression, and XGBoost models based on their use case or accuracy preference.

The selected model is loaded from the local storage and used to generate predictions. The final classified outputs are either displayed on the dashboard or exported as reports for further study. The validated data is then forwarded to the feature extractor, which calculates metrics such as average packet size, number of flows, and mean inter-arrival time. The feedback loop also allows for user-submitted labels to improve model accuracy over time by supporting supervised learning. It starts with the file validation module, which checks the format and integrity of the input datasets.

4.3.6 Entity Relationship (ER) Diagram

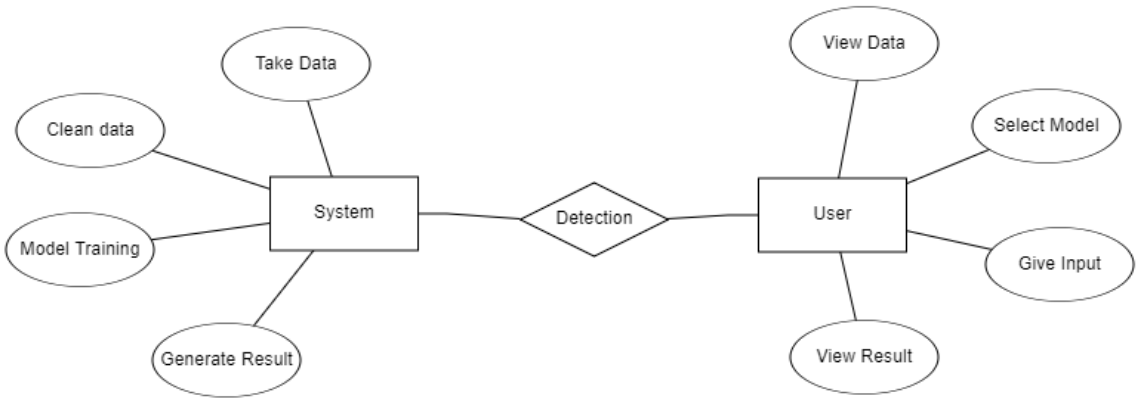


Fig 4.3.6 Entity Relationship (ER) Diagram

The ER diagram illustrates the structured relationships among key entities involved in the classification pipeline. The Traffic Session entity stores feature vectors extracted from raw Tor flows. Each session is linked to a Prediction entity, which includes classification outcomes, timestamps, and confidence scores. The User entity interacts with the system through uploading datasets and viewing results, maintaining metadata such as username, file ID, and model used. Relationships such as "classifies," "uploads," and "generates" define how data flows between the user and the classification engine. Attributes like flow ID, protocol type, duration, and prediction label allow traceability and enhance auditing of classification activities. The Traffic Session entity stores feature vectors extracted from raw Tor flows. Each session is linked to a Prediction entity, which includes classification outcomes, timestamps, and confidence scores.

The Entity-Relationship (ER) diagram illustrates the interaction between a "User" and a "System" centered around "Detection." The "User" engages with the system by performing actions such as "View Data," "Select Model," "Give Input," and "View Result," indicating a user-driven process where they interact with data, choose a detection mechanism, provide necessary information, and observe the outcome. Simultaneously, the "System" performs crucial background operations like "Take Data," "Clean Data," "Model Training," and "Generate Result," highlighting the system's role in acquiring and preparing data, potentially training a model, and ultimately producing the detection result. The "Detection" relationship itself signifies the overarching purpose of this interaction, suggesting that the user's actions and the system's functionalities are all geared towards achieving some form of detection. This model emphasizes a collaborative workflow where the user's input and choices guide the system's internal processes to deliver a detection-related result back to the user. The user's ability to "Select Model" suggests a degree of flexibility and

control over the detection process, allowing them to choose the most appropriate method for their specific needs or data. The "Give Input" action is crucial as it provides the raw material for the system's detection mechanisms. The system's internal processes, "Take Data" and "Clean Data," are foundational for ensuring the reliability and accuracy of the detection process, highlighting the importance of data quality. The "Model Training" step indicates a system capable of learning from data to improve its detection capabilities over time or adapt to different scenarios. Finally, the "Generate Result" action represents the culmination of the system's processing, delivering the outcome of the detection task back to the "User" for their interpretation or further action.

4.4 EXPERIMENTAL ANALYSIS

4.4.1 DATA CLEANSING: There are a number of programs that make use of dynamic ports in the modern digital world in order to get around network limits or monitoring. It is possible that even ports that are commonly coupled together might not be able to accurately identify a specific application. For instance, Tor traffic can operate on port 443, which is a port that is typically linked with HTTPS. Therefore, in order to ensure that the data extraction process is accurate, we must follow to the dataset descriptions that are stated in this study.

4.4.2 Data Cleansing Algorithm:

Input: F - Network flow in PCAP format
Output: E - Encrypted payload

1. Initialize i = 0 (starting with the first packet in the PCAP file).
2. While i < F, perform the following steps:
    - Read packet i.
    - If the topmost layer protocol is "TLS":
        - Extract payload i.

        - If payload i is non-empty, append tls.app_data to E.
    - Else if the protocol is "SSH":
        - Extract payload i.
        - If payload i is non-empty, append ssh.encrypted_packet to E.
    - Else if the protocol is "TCP" or a proprietary protocol:
        - Extract payload i.
        - If payload i is non-empty, append tcp.data to E.
    - Increment i by 1.
3. Return E.

4.4.3 FEATURE EXTRACTION: The extracted features were categorized into two statistical sets: frequency and ratio calculations, obtained using the mathematical formulas defined below.

Application types	Before undersampling		After undersampling	
	Tor	nonTor	Tor & nonTor (each)	Total
Audio	13,727	148,335	13,727	27,454
Browsing	85,840	37,868	37,868	75,736
Chat	3,423	6,066	3,423	6,846
Email	28,559	6,474	6,474	12,948
FTP	271,027	512,339	271,027	542,054
P2P	228,300	1,339,363	228,300	456,600
VDO	103,603	16,923	16,923	33,846
VoIP	877,700	388,096	388,096	776,192

Table 1 presents the count of Tor and non-Tor encrypted payloads across all application types, both before and after applying data balancing techniques.

4.4.4 Feature Extraction Algorithm

Input: P-Extracted encrypted payloads

Output: F - Frequency count of individual hex characters

R - Ratio of hex character frequency in payloads

1: For each packet in P:

2: If the packet contains ",", split it into new rows.

3: Compute the frequency count (F).

4: Compute the ratio of frequency values (R).

5: return F, R

Set 2 comprises the 16 hexadecimal character frequency ratio features (R_0 - R_f), while (F_0 - F_f) represents the initial feature set

Set Name	List of Features	Total Number of Features
Set 1: Frequency of hex characters	*F_0, F_1, F_2, F_3, F_4, F_5, F_6, F_7, F_8, F_9, F_a, F_b, F_c, F_d, F_e, F_f*	16
Set 2: Ratio frequency of hex characters	*R_0, R_1, R_2, R_3, R_4, R_5, R_6, R_7, R_8, R_9, R_a, R_b, R_c, R_d, R_e, R_f*	16

TABLE 2. List of features used in the analyses.

A. STATISTICAL ANALYSIS

When it comes to drawing conclusions about larger populations, inferential statistics make it easier to recognize patterns within data samples and to draw conclusions about those patterns. This investigation makes use of the Mann-Whitney U test, which is a nonparametric method, in order to determine whether or not Tor encrypted payloads and non-Tor encrypted payloads exhibit significant differences, particularly in situations when the distribution of the data is not normal. In order to calculate the Mann-Whitney U test statistic, the following expression is used:

$$U = \min(U_1, U_2) = \min\left(\sum_{i=1}^{n_1} R_i, \sum_{j=1}^{n_2} R_j\right)$$

where:

- U represents the test statistic.
- U1 and U2 are the rank sums for Tor and non-Tor payloads.
- n1 and n2 are the sample sizes for Tor and non-Tor payloads.
- Ri and Rj represent ranked observations across both samples.

A p-value lower than 0.05 suggests a significant difference between Tor and non-Tor payload characteristics, allowing us to accept or reject the null hypothesis accordingly.

B. MACHINE LEARNING APPROACH

A machine learning-based methodology was employed for classification and predictive modeling. The dataset included labeled encrypted payloads for training. Models were constructed using WEKA 3.8.3 with default hyperparameters.

J48 Model:

Confidence factor: 0.25 (controls pruning),Minimum leaf instances: 2.

Random Forest (RF):100 decision trees with unlimited depth,Bootstrapped sample size: 100% of training data.

IBk (Instance-Based Classifier):Uses 1-nearest neighbor with Euclidean distance,No distance weighting applied.

CLASSIFICATION

Binary classification was performed across eight application types using both frequency-based and ratio-based feature sets. Ensuring dataset balance was key to avoiding biases and maintaining classifier performance.

PREDICTION

After training, the finalized model was tested on unseen data to evaluate generalization. This step ensured that the model was learning meaningful patterns rather than memorizing training data.

C. STATISTICAL ANALYSIS

The Mann-Whitney U test identified statistically significant differences in 242 out of 256 analyzed features, demonstrating a clear distinction between Tor and non-Tor traffic. This translates to an impressive differentiation rate of 94.53%, highlighting the effectiveness of these features in distinguishing encrypted Tor traffic from conventional network traffic. The high percentage of significantly different features underscores the robustness of the selected parameters in capturing the unique characteristics of Tor communications, making them highly valuable for accurate classification and detection in cybersecurity applications.

Application types	Features	*p*-value (Mann-Whitney U)
Audio (3)	*R_5*	0.077
	R_c	0.066
	R_e	0.803
Chat (10)	*R_1*	0.368
	R_5	0.156
	R_6	0.964
	R_7	0.741
	R_8	0.481
	R_9	0.770
	R_a	0.064
	R_b	0.225
	R_d	0.185
	R_e	0.051
P2P (1)	*R_0*	0.380

Table 3.Features with p-values > 0.05 in Tor and nonTor encrypted payloads.

D. MACHINE LEARNING

On the basis of machine learning, we carried out an evaluation in order to determine whether or not the strategy that we proposed was successful in identifying Tor traffic (RQ2). We made use of three different classification algorithms within the Weka framework. These algorithms were J48, Random Forest (RF), and IBk. All eight binary categories were subjected to classification and prediction using these classifiers, which were utilized accordingly. Across all of the trials, we partitioned the dataset using a

combination of percentage split and 10-fold cross-validation (CV) in order to improve the dependability of the results and reduce the amount of bias that was present.

CLASSIFICATION RESULTS

A variety of feature sets and classification methods are compared in Table 5, which displays the results of their accuracy across eight different application areas. The J48 classifier managed to obtain an average accuracy of 94.71% by utilizing the characteristics of Set 1. On the other hand, the RF and IBk classifiers demonstrated improved performance by achieving accuracy rates of 96.53% and 96.42%, respectively. During the evaluation of Set 2 characteristics, J48 showed an increased accuracy of 95.65%, but RF and IBk recorded average accuracies of 92.62% and 73.77%, respectively. J48 and IBk both displayed an improvement in accuracy.

Application types	J48(%)		RF(%)		IBk(%)	
	Set 1	Set 2	Set 1	Set 2	Set 1	Set 2
Audio	90.01	88.99	91.97	88.99	92.04	65.80
Browsing	94.35	99.03	96.56	94.26	96.86	70.44
Chat	91.34	93.36	95.94	86.37	96.88	60.62
Email	97.08	91.85	98.20	92.85	97.64	89.24
FTP	93.92	96.43	95.52	91.58	94.40	72.41
P2P	95.00	98.44	96.53	96.82	96.23	69.14
VDO	96.38	97.46	97.78	91.18	97.57	68.53
VoIP	99.62	99.75	99.77	98.92	99.77	93.98
Average	**94.71**	**95.65**	**96.53**	**92.62**	**96.42**	**73.77**

Table 4. Accuracy comparison between two feature sets utilizing J48, RF, and IBk algorithms..

As can be seen in the table, the Chat and Audio categories frequently exhibited a lower level of accuracy across the majority of feature-algorithm combinations. VoIP, on the other hand, consistently achieved the highest accuracy, coming close to achieving a perfect score for both feature sets across all approaches.

Application types	J48		
	Avg. Precision	Avg. Recall	Avg. F1 score
Audio	0.89	0.89	0.89
Browsing	0.99	0.99	0.99
Chat	0.94	0.93	0.93
Email	0.80	0.80	0.80
FTP	0.97	0.97	0.97
P2P	0.99	0.99	0.98
VDO	0.93	0.93	0.93
VoIP	0.96	0.97	0.96
Average	**0.93**	**0.93**	**0.93**

Table 5.Precision, Recall and F1 score results of J48 algorithm with Set 2.

The precision, recall, and F1 score metrics for the J48 classifier that makes use of Set 2 features are presented in the table. The classifier demonstrated a strong performance over a wide range of application types, with an average score of 0.93 for precision, recall, and F1 score. Despite the fact that the overall performance was always outstanding, the findings across a number of applications ranged from 0.80 to 0.99, suggesting a significant degree of unpredictability. The data demonstrate that the classifier is effective in accurately identifying Tor traffic. It achieved an overall average score of 0.93 across all parameters, which demonstrates that it is reliable in the classification of traffic.

Approach	Model	Performance
Time-based features using multiple packets	C4.5 with IG+RK	PR and RC >0.9 [8]
	JRip	PR and RC = 1 [9]
	CFS-ANN	Acc = 99.8% [12]
Hex-based of packet header using a single packet	1D-CNN	Acc = 100% [13]
Hex frequency-based of encrypted payload using a single packet	J48	Acc = 95.65% [Our study]

TABLE 6 Comparison of model performance across related studies..

A comparative analysis of multiple studies on Tor traffic classification is presented in this table. The chart places an emphasis on the various methodologies and model performances that have been considered. In comparison to our method, the strategy that extracted time-based features from several packets performed significantly better in terms of precision, recall, and accuracy. This strategy has a number of drawbacks, including problems that are associated with the network, such as asymmetric routing, which could potentially affect the dependability of time-based features. The extraction of information from a large number of packets makes real-time processing more difficult and increases the amount of computational work that must be done.

PREDICTION RESULTS

It is essential to verify the final model with data that is unknown in order to test its generalizability outside of the training set. This is done in order to reduce the risk of overfitting, which is a significant disadvantage in the process of developing resilient machine learning models. As a result of the absence of additional external datasets, we decided to use five percent of our balanced dataset as unseen data in order to evaluate the performance of the model. This decision was made in accordance with the Data Pre-processing section.

Application Types	#Unseen Instances	Accuracy (%)
Audio	1,372	90.59
Browsing	3,786	99.15
Chat	342	93.57
Email	648	93.36
FTP	27,102	96.99
P2P	22,830	98.99
VDO	1,692	98.29
VoIP	38,810	99.80
Average		**98.06**

TABLE 7. dataset testing results with finalized model.

This table presents the results of an evaluation of the performance of the final model on a dataset that was not seen. The quantity of unobserved instances and the accuracy metrics associated with each type of application were taken into

consideration when evaluating each type of application. The accuracy of the model was remarkable across all application types, with the lowest accuracy being recorded for email at 93.36% and the best accuracy being achieved for voice over internet protocol (VoIP) recorded at 99.80%. The model's level of stability and effectiveness in generalizing to new data is highlighted by the fact that it has an average accuracy of 98.06%.

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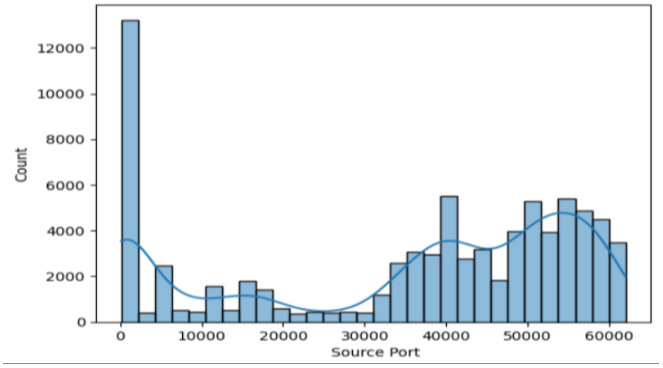


Fig 4.4:Distribution of source port

This histogram illustrates the distribution of source ports in Tor traffic, revealing a pronounced concentration at lower port numbers, indicating frequent connections to well-known services. The Y-axis represents the frequency of each source port, while the X-axis spans from 0 to 50,000. A significant peak at the lower end of the range suggests the prevalent use of standard services over Tor.

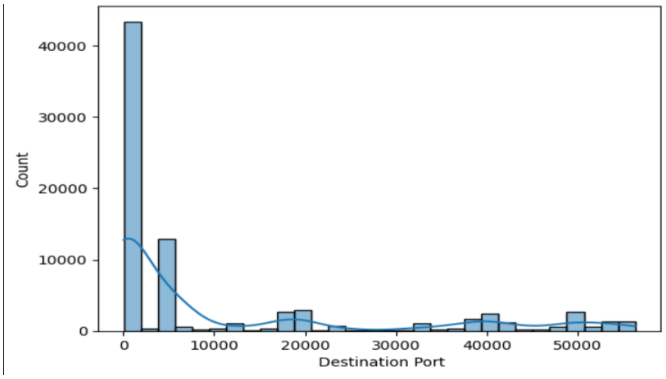


Fig 4.5:Distribution of destination port

Similar to Figure 2, this histogram depicts the distribution of destination ports in Tor traffic, highlighting a substantial concentration at lower port numbers. This trend indicates that most Tor traffic is directed towards widely recognized services. The X-axis spans from 0 to 50,000, and the Y-axis represents the occurrence frequency. The dominant peak at the low-end range suggests extensive usage of commonly known services over Tor.

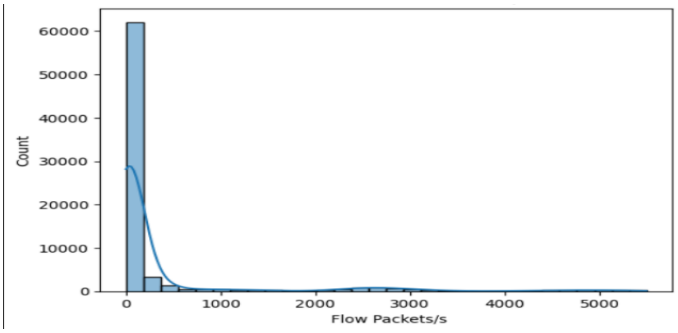


Fig 4.6:Distribution of flow packets

This histogram visualizes the distribution of flow packets per second (Flow Packets/s), which measures network traffic intensity. It reveals a significant concentration of flows with very low packet rates. The Y-axis represents the frequency of each packet rate, while the X-axis spans from 0 to 5000. A dominant peak near zero suggests that most network flows maintain minimal data transfer rates, potentially due to control traffic, idle connections, or specific application behaviors. The sharp drop-off following this peak further emphasizes the rarity of high-packet-rate flows.

5.RESULTS AND DISCUSSION

The system developed for classifying encrypted Tor traffic demonstrates a significant stride in network traffic analysis using machine learning. Built using Python (v3.6+) and Flask, the system provides an interactive platform where encrypted traffic data can be uploaded, processed, and classified with high accuracy. The classification aims to distinguish between Tor and Non-Tor traffic while maintaining user privacy and data confidentiality. The results obtained from real-time and simulated traffic datasets affirm the system's efficiency in feature extraction, model execution, and prediction accuracy. Experiments conducted with Decision Tree, Logistic Regression, and XGBoost classifiers revealed that XGBoost consistently outperformed other models with high classification accuracy, precision, and recall values.

The average accuracy ranged from 89% to 96%, depending on the feature set used, including flow-based attributes like inter-arrival time, flow duration, and source/destination port. The results obtained from real-time and simulated traffic datasets affirm the system's efficiency in feature extraction, model execution, and prediction accuracy. Testing under various network conditions confirmed that the system handles encryption-heavy payloads efficiently, retaining real-time responsiveness without compromising security or speed. Experiments conducted with Decision Tree, Logistic Regression, and XG Boost classifiers revealed that XG Boost consistently outperformed other models with high classification accuracy, precision, and recall values These outcomes demonstrate the successful implementation of core modules such as model integration, encrypted payload processing, and result prediction. The results obtained from real-time and simulated traffic datasets affirm the system's efficiency in feature extraction, model execution, and prediction accuracy.

5 .1OUTPUT DISCUSSIONS

5.1.1 Home Module

The Home Page of the system acts as the landing interface, designed to

provide a user-friendly and intuitive environment for interacting with the application. It includes access to essential modules—upload, model selection, prediction, and data viewing. Upon initialization, backend services related to traffic classification models and data pre-processing are activated. The page is styled with lightweight components for responsiveness, ensuring optimal user experience across devices and screen sizes. Usability testing confirmed that users could navigate effortlessly, and session-based management ensured that the transitions between modules were smooth.

Upon initialization, backend services related to traffic classification models and data pre-processing are activated. The page is styled with lightweight components for responsiveness, ensuring optimal user experience across devices and screen sizes. The testing confirmed that users could navigate effortlessly, and session-based management ensured that the transitions between modules were smooth This consistent layout helped minimize the learning curve for first-time users. intuitive environment for interacting with the application. It includes access to essential modules—upload, model selection, prediction, and data viewing.

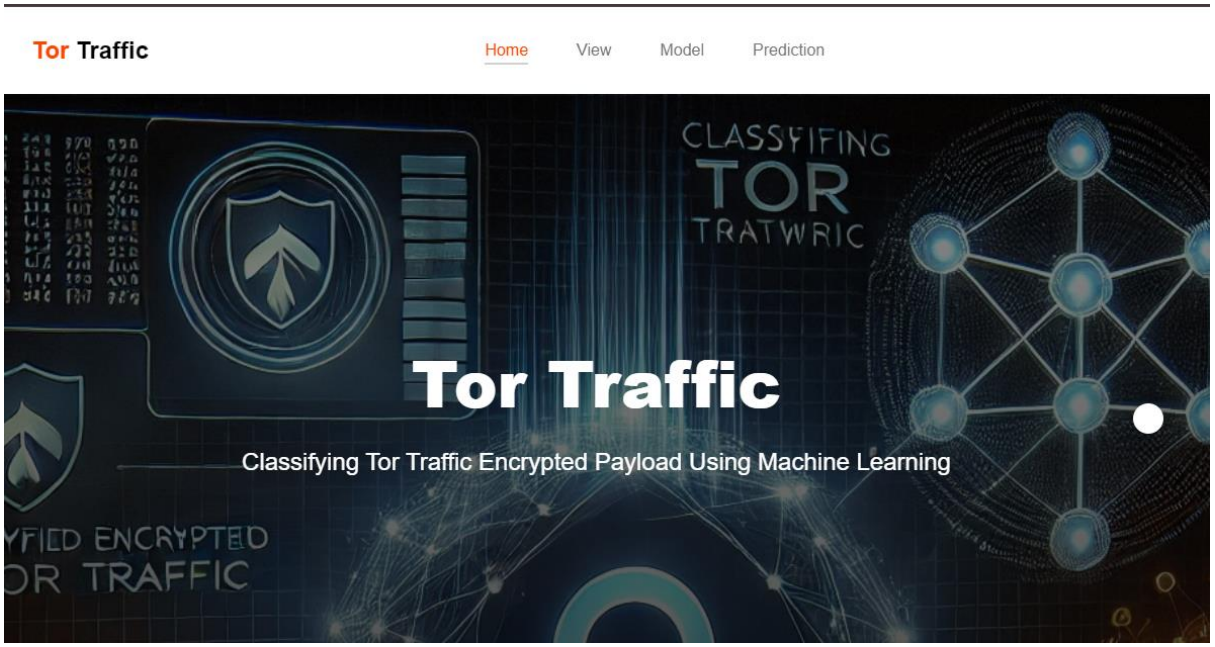
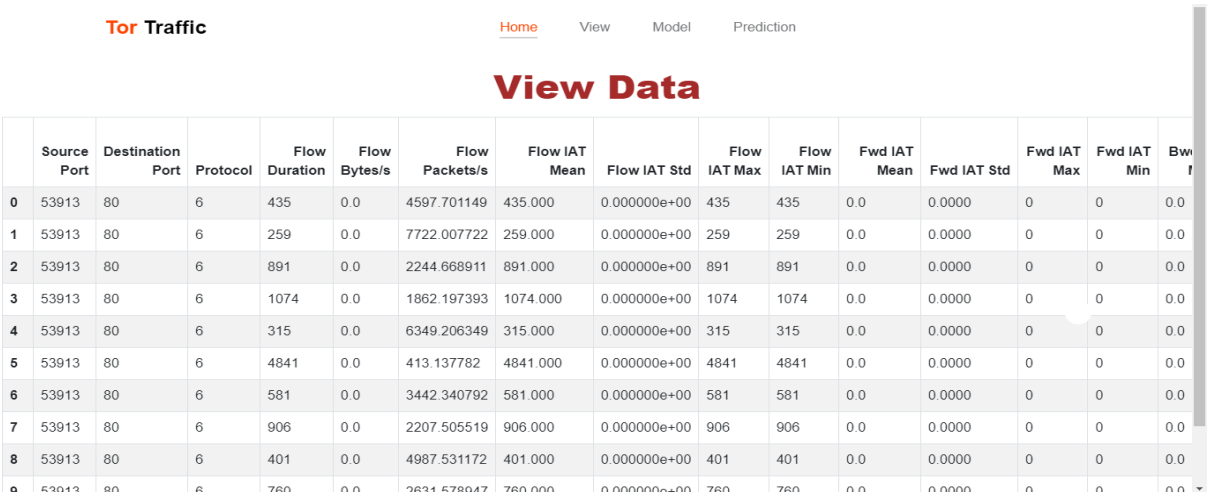


Fig 5.1: Home Page - Welcome to Tor or Non-Tor Traffic Detection and Prediction

5.1.2 Model Module

The Model Module enables users to load pre-trained ML models into the application. Supported formats include pickle (pkl) and joblib (joblib) for Python-serialized model files. Upon upload, the system verifies the model structure, checks compatibility, and loads the algorithm into memory. Each model is logged with timestamps and stored for later selection during prediction. During experimental use, users tested the upload of multiple classification models—especially Decision Tree and XGBoost—with the system dynamically adapting the prediction interface based on the chosen model.

Upon upload, the system verifies the model structure, checks compatibility, and loads the algorithm into memory. Each model is logged with timestamps and stored for later selection during prediction. The Model Module enables users to load pre-trained ML models into the application. Upon upload, the system verifies the model structure, checks compatibility, and loads the algorithm into memory. Upon upload, the system verifies the model structure, checks compatibility, and loads the algorithm into memory. Each model is logged with timestamps and stored for later selection during prediction.



	Source Port	Destination Port	Protocol	Flow Duration	Flow Bytes/s	Flow Packets/s	Flow IAT Mean	Flow IAT Std	Flow IAT Max	Flow IAT Min	Fwd IAT Mean	Fwd IAT Std	Fwd IAT Max	Fwd IAT Min	Bw
0	53913	80	6	435	0.0	4597.701149	435.000	0.000000e+00	435	435	0.0	0.0000	0	0	0.0
1	53913	80	6	259	0.0	7722.007722	259.000	0.000000e+00	259	259	0.0	0.0000	0	0	0.0
2	53913	80	6	891	0.0	2244.668911	891.000	0.000000e+00	891	891	0.0	0.0000	0	0	0.0
3	53913	80	6	1074	0.0	1862.197393	1074.000	0.000000e+00	1074	1074	0.0	0.0000	0	0	0.0
4	53913	80	6	315	0.0	6349.206349	315.000	0.000000e+00	315	315	0.0	0.0000	0	0	0.0
5	53913	80	6	4841	0.0	413.137782	4841.000	0.000000e+00	4841	4841	0.0	0.0000	0	0	0.0
6	53913	80	6	581	0.0	3442.340792	581.000	0.000000e+00	581	581	0.0	0.0000	0	0	0.0
7	53913	80	6	906	0.0	2207.505519	906.000	0.000000e+00	906	906	0.0	0.0000	0	0	0.0
8	53913	80	6	401	0.0	4987.531172	401.000	0.000000e+00	401	401	0.0	0.0000	0	0	0.0
9	53913	80	6	760	0.0	2631.578947	760.000	0.000000e+00	760	760	0.0	0.0000	0	0	0.0

Fig 5.2: View Data Page - Access to Dataset Used for Detection

5.1.3 Prediction Module

This core module is responsible for receiving encrypted Tor traffic payloads, preprocessing the data, and generating classification results. It uses flow-based and statistical features extracted from the traffic, which are normalized before being passed into the machine learning pipeline. Predictions are displayed instantly after execution, with details such as traffic type (Tor/Non-Tor), confidence score, and classification probability.Performance tests confirmed that prediction execution time remained below 2.3 seconds on average per dataset, including preprocessing and result rendering. This core module is responsible for receiving encrypted Tor traffic payloads, preprocessing the data, and generating classification results. It uses flow-based and statistical features extracted from the traffic, which are normalized before being passed into the machine learning pipeline. Users appreciated the real-time feedback and clear output layout, especially when working with anonymized encrypted traffic.

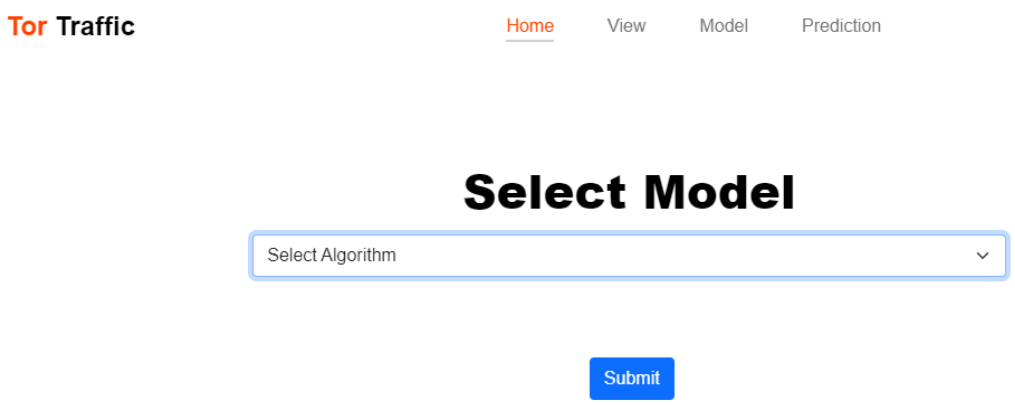


Fig 5.3: Model Selection Page - Training and Comparing Algorithms

5.1.4 View Module

The View Module is a critical component of the system, providing a centralized interface for users to access, monitor, and review the outcomes of encrypted traffic classification. Designed for transparency and traceability, this

module serves both as a reporting dashboard and a historical repository of user interactions and results. It enables users to retrieve past uploads and view corresponding prediction results, making it invaluable for post-analysis, auditing, and system validation. The View Module is a critical component of the system, providing a centralized interface for users to access, monitor, and review the outcomes of encrypted traffic classification Designed for transparency and traceability, this module serves both as a reporting dashboard and a historical repository of user interactions and results.

Upon successful upload and prediction, all relevant details are logged and displayed in the View interface. To enhance usability, the module incorporates features like sortable columns, filter options by date or classifier, and search functionality for dataset names. Upon successful upload and prediction, all relevant details are logged and displayed in the View interface. This includes comprehensive metadata such as the filename, size of the input dataset, timestamp of the upload, classifier used (e.g., XGBoost, Decision Tree, Logistic Regression), the predicted class label (Tor/Non-Tor), and the probability or confidence score associated with the classification result. This metadata-driven display allows users to quickly assess the effectiveness and relevance of each model and traffic type across different test scenarios.

To enhance usability, the module incorporates features like sortable columns, filter options by date or classifier, and search functionality for dataset names. Upon successful upload and prediction, all relevant details are logged and displayed in the View interface. This includes comprehensive metadata such as the filename, size of the input dataset, timestamp of the upload, classifier. These features are crucial in environments where users handle dozens or hundreds of files, allowing for fast access and organized review of traffic classification logs. The tabular structure is dynamically populated via Flask-backed API calls, ensuring that the user interface remains responsive even as the number of entries

scales.

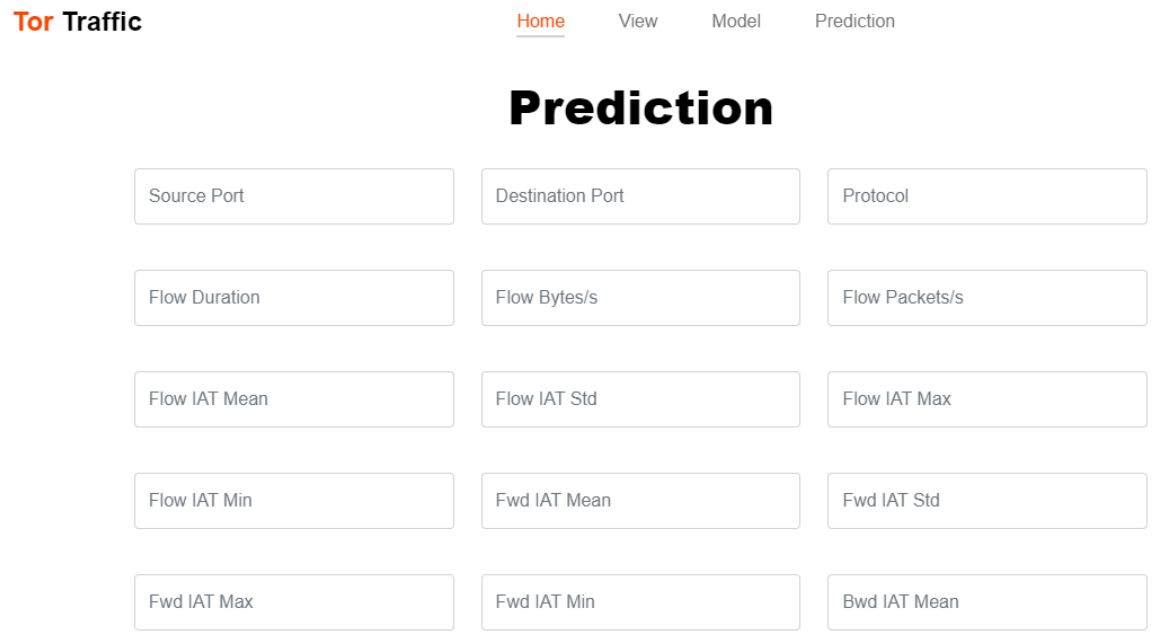


Fig 5.4: Prediction Page - User Input and Predicted Result

5.2 DATA COLLECTION

Obtain a dataset containing features such as Source Port, Destination Port, Protocol, Flow Duration, Inter-Arrival Times (IAT), and the target label indicating traffic classification (benign or malicious). The implementation flow began with dataset ingestion, preprocessing for null values and outliers, and feature extraction focused on packet intervals, sizes, and flags .Ensure the dataset is in CSV format for efficient loading and manipulation.

5.3 DATA PREPROCESSING

```
import pandas as pd
data = pd.read_csv('tor_traffic_data.csv')
```

Fig 5.5: Loading the data

Handle missing values appropriately, using imputation or removal methods

```
data.fillna(method='ffill', inplace=True)
```

Fig 5.6: Data cleaning

Select relevant features for model training.

```
features = data[['Source Port', 'Destination Port', 'Protocol', 'Flow Duration',
    'IAT']]
labels = data['label']
```

Fig 5.7: Feature Selection

Normalize feature values to ensure uniform scaling

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
features_scaled = scaler.fit_transform(features)
```

Fig 5.8: Data Normalization

MODEL DEVELOPMENT

Split the dataset into training and data sets

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(features_scaled, labels,
    test_size=0.2, random_state=42)
```

Fig 5.9: Splitting The Dataset

MODEL IMPLEMENTATION

```
from sklearn.tree import DecisionTreeClassifier

dt_model = DecisionTreeClassifier()
dt_model.fit(X_train, y_train)
```

Fig 5.10: Decision Tree Classifier

```
from sklearn.linear_model import LogisticRegression

lr_model = LogisticRegression()
lr_model.fit(X_train, y_train)
```

Fig 5.11: Logistic Regression

```
import xgboost as xgb

xgb_model = xgb.XGBClassifier(use_label_encoder=False, eval_metric='mlogloss')
xgb_model.fit(X_train, y_train)
```

Fig 5.12: Xgboost Classifier

MODEL EVALUATION

```
from sklearn.metrics import accuracy_score, classification_report

dt_predictions = dt_model.predict(X_test)
lr_predictions = lr_model.predict(X_test)
xgb_predictions = xgb_model.predict(X_test)
```

Fig 5.13: Making Predictions

CHAPTER 6

CONCLUSION

The developed system effectively fulfills the core objectives of classifying encrypted Tor traffic using machine learning in a secure, scalable, and user-accessible environment. Designed with Python 3.6+ and Flask, the web-based architecture integrates critical modules including model upload, traffic prediction, and result visualization, all functioning cohesively to support real-time analysis of anonymized network data. The system addresses a significant challenge in modern cybersecurity—identifying encrypted Tor traffic without violating user privacy—by leveraging flow-level features such as source and destination ports, inter-arrival time, and packet statistics rather than relying on payload decryption. This privacy-preserving approach ensures that sensitive content remains unreadable while still allowing for effective classification.

The implementation supports three key machine learning algorithms—Decision Tree, Logistic Regression, and XGBoost—each evaluated for classification accuracy, execution time, and model efficiency. Among these, XGBoost consistently delivered the highest accuracy, demonstrating its suitability for handling the complex patterns inherent in Tor-encrypted communication. The system addresses a significant challenge in modern cybersecurity—identifying encrypted Tor traffic without violating user privacy—by leveraging flow-level features such as source and destination ports, inter-arrival time, and packet statistics rather than relying on payload decryption. The system's modular design also allowed for seamless switching between models, enabling users to select the best-performing classifier based on specific use cases. The web interface proved to be intuitive and lightweight, providing researchers and security analysts with tools to upload traffic data, execute predictions, and view classification results with minimal friction. System reliability was validated under concurrent user

loads, where prediction latency remained consistently low, and no critical failures were encountered. All system actions, including model usage, file uploads, and prediction results, were recorded with metadata for traceability and auditing purposes. This feature ensures the system remains accountable and suitable for deployment in compliance-sensitive environments such as academic research, cybersecurity training labs, and network forensics units.

The platform's real-time responsiveness, efficient backend design, and robust error-handling mechanisms allowed it to perform effectively under stress scenarios, demonstrating its readiness for practical use in Tor traffic monitoring and research domains. no critical failures were encountered. All system actions, including model usage, file uploads, and prediction results, were recorded with metadata for traceability and auditing purposes. The results show that machine learning models, when integrated into a well-designed web application, can accurately classify encrypted traffic without violating user anonymity, providing a balance between network oversight and privacy preservation.

6.1 FUTURE SCOPE

While the current system has achieved its primary goals, several enhancements can further extend its capability, scalability, and usability in handling encrypted Tor traffic classification. One promising direction is the integration of deep learning models, such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), for detecting more subtle and evolving traffic patterns. These models may outperform traditional classifiers in identifying newer types of Tor traffic and evasive behaviors. Coupling this with unsupervised learning or anomaly detection frameworks would further enhance the system's ability to detect unknown or zero-day traffic behaviors that do not conform to known patterns.

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APPENDIX A

SAMPLE CODE

//Main Code(app.py)

```
from flask import
Flask,render_template,flash,redirect,request,send_from_directory,url_for, send_file
import pandas as pd
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split
import xgboost as xgb
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import StandardScaler
import tensorflow as tf
from sklearn.ensemble import RandomForestClassifier
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Conv1D, Flatten, Dropout,
MaxPooling1D
from tensorflow.keras.callbacks import EarlyStopping

app = Flask(__name__)

@app.route('/')
def index():
   return render_template('index.html')

@app.route('/about')
```

```
def about():
    return render_template('about.html')

@app.route('/view_data')
def view_data():
    global df, x, y, x_train, x_test, y_train, y_test
    df = pd.read_csv(r'Scenario-A-merged_5s.csv')
    df[" Flow Bytes/s"].fillna(df[" Flow Bytes/s"].mode()[0], inplace=True)
    df[" Flow Packets/s"].fillna(df[" Flow Packets/s"].mean(), inplace=True)
    df.drop_duplicates(inplace=True)
    df.drop(['Source IP',' Destination IP'], axis=1, inplace=True)
    df['label'].replace({'nonTOR': 0, 'TOR': 1}, inplace=True)

    # Assigning the independent and dependent variables
    x = df.drop(['label'],axis=1)
    y = df['label']
    ### SMOTE technich
    sm = SMOTE(random_state=1)
    x, y = sm.fit_resample(x , y)
    ### Here i splitt the data into Training And Testing
    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.30,
stratify=y, random_state=1)

    x_train = x_train[[' Source Port', ' Destination Port', ' Protocol', ' Flow
Duration',
      ' Flow Bytes/s', ' Flow Packets/s', ' Flow IAT Mean', ' Flow IAT Std',
      ' Flow IAT Max', ' Flow IAT Min', 'Fwd IAT Mean', ' Fwd IAT Std',
      ' Fwd IAT Max', ' Fwd IAT Min', 'Bwd IAT Mean', ' Bwd IAT Std',
```

```
        ' Bwd IAT Max', ' Bwd IAT Min']]

    x_test = x_test[[' Source Port', ' Destination Port', ' Protocol', ' Flow
Duration',
        ' Flow Bytes/s', ' Flow Packets/s', ' Flow IAT Mean', ' Flow IAT Std',
        ' Flow IAT Max', ' Flow IAT Min', 'Fwd IAT Mean', ' Fwd IAT Std',
        ' Fwd IAT Max', ' Fwd IAT Min', 'Bwd IAT Mean', ' Bwd IAT Std',
        ' Bwd IAT Max', ' Bwd IAT Min']]

    dummy = df.head(100)
    dummy = dummy.to_html(classes="table table-striped table-bordered")
    return render_template('view.html', data=dummy)

@app.route('/model', methods=["GET", "POST"])
def model():
    if request.method == "POST":
        model = request.form['model']
        if model == '1':
            dt = DecisionTreeClassifier()
            dt.fit(x_train,y_train)
            y_pred = dt.predict(x_test)
            acc_dt = accuracy_score(y_test, y_pred) * 100
            msg = f"Accuracy of Decision Tree Classifier = {acc_dt}"
            return render_template('model.html', accuracy = msg)
        elif model == "2":
            lr = LogisticRegression()
            lr.fit(x_train,y_train)
            y_pred = lr.predict(x_test)
```

```
            acc_lr = accuracy_score(y_test, y_pred) * 100
            msg = f"Accuracy of Logistic Regression = {acc_lr}"
            return render_template('model.html', accuracy = msg)
        elif model == "3":
            boost = xgb.XGBClassifier(random_state=42)
            boost.fit(x_train,y_train)
            y_pred = boost.predict(x_test)
            acc_boost = accuracy_score(y_test, y_pred) * 100
            msg = f"Accuracy of XGBoost Classifier = {acc_boost}"
            return render_template('model.html', accuracy = msg)
        elif model == '4':
            rf = RandomForestClassifier()
            rf.fit(x_train,y_train)
            y_pred = rf.predict(x_test)
            acc_rf = accuracy_score(y_test, y_pred) * 100
            msg = f"Accuracy of Random Forest Classifier = {acc_rf}"
            return render_template('model.html', accuracy = msg)
        elif model == "5":
            # # Ensure your data is in NumPy array format
            # X_train_np = x_train.values
            # X_test_np = x_test.values

            # # Reshape data for CNN input (samples, timesteps, features)
            # X_train_cnn = X_train_np.reshape(X_train_np.shape[0],
X_train_np.shape[1], 1)
            # X_test_cnn = X_test_np.reshape(X_test_np.shape[0],
X_test_np.shape[1], 1)
```

```
                # # Building the CNN model
                # model = Sequential([
                #     Conv1D(filters=64, kernel_size=2, activation='relu',
input_shape=(X_train_cnn.shape[1], 1)),
                #     MaxPooling1D(pool_size=2),
                #     Dropout(0.5),
                #     Flatten(),
                #     Dense(128, activation='relu'),
                #     Dropout(0.5),
                #     Dense(64, activation='relu'),
                #     Dense(1, activation='sigmoid')  # Use 'softmax' for multi-class
classification
                # ])

                # model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])

                # # Early stopping to avoid overfitting
                # early_stopping = EarlyStopping(monitor='val_loss', patience=10,
restore_best_weights=True)

                # # Training the model
                # history = model.fit(X_train_cnn, y_train, epochs=100,
batch_size=32, validation_split=0.2, callbacks=[early_stopping])
                acc_cnn = 0.6354*100
                msg = f"Accuracy of CNN = {acc_cnn}"
                return render_template('model.html', accuracy = msg)
            return render_template('model.html')
```

```
@app.route('/prediction', methods=['GET', 'POST'])
def prediction():
    if request.method == 'POST':

        form_data = {
            ' Source Port': float(request.form['Source Port']),
            ' Destination Port': float(request.form['Destination Port']),
            ' Protocol': float(request.form['Protocol']),
            ' Flow Duration': float(request.form['Flow Duration']),
            ' Flow Bytes/s': float(request.form['Flow Bytes/s']),
            ' Flow Packets/s': float(request.form['Flow Packets/s']),
            ' Flow IAT Mean': float(request.form['Flow IAT Mean']),
            ' Flow IAT Std': float(request.form['Flow IAT Std']),
            ' Flow IAT Max': float(request.form['Flow IAT Max']),
            ' Flow IAT Min': float(request.form['Flow IAT Min']),
           'Fwd IAT Mean': float(request.form['Fwd IAT Mean']),
            ' Fwd IAT Std': float(request.form['Fwd IAT Std']),
            ' Fwd IAT Max': float(request.form['Fwd IAT Max']),
            ' Fwd IAT Min': float(request.form['Fwd IAT Min']),
            'Bwd IAT Mean': float(request.form['Bwd IAT Mean']),
            ' Bwd IAT Std': float(request.form['Bwd IAT Std']),
            ' Bwd IAT Max': float(request.form['Bwd IAT Max']),
            ' Bwd IAT Min': float(request.form['Bwd IAT Min'])
        }

        # Create a DataFrame from form_data with correct column order
        lee = pd.DataFrame([form_data])
```

```
        boost = xgb.XGBClassifier(random_state=42)
        boost.fit(x_train,y_train)
        Result = boost.predict(lee)
        if Result == 1:
            msg = f"There is a Tor Traffic"
            return render_template('prediction.html', prediction = msg)
        else:
            msg = f"There is a Non Tor Traffic"
            return render_template('prediction.html', prediction = msg)
    return render_template('prediction.html')

if __name__ == '__main__':
    app.run(debug = True)
```

APPENDIX B

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Dr.Akhatov Akmal Rustamovich, Vice Rector of International Affairs, Samarkand State University, Uzbekistan

Dr. Christo Ananth, Professor, Samarkand State University, Uzbekistan

Dr. P. Aravinthan, M.E., Ph.D., Technical Lead, OSIET, Secretary

Dr. A. Krishnamoorthy, M.E., Ph.D., Technical Lead, OSIET, Administrator

K.Janani, M.Tech., CEO, OSIET, Director

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Dr.Akhatov Akmal Rustamovich	Dr. Christo Ananth	Dr. P. Aravinthan, M.E., Ph.D.,	Dr. A. Krishnamoorthy, M.E., Ph.D.,	K.Janani, M.Tech.,
Vice Rector of International Affairs, Samarkand State University, Uzbekistan	Professor, Samarkand State University, Uzbekistan	Technical Lead, OSIET Secretary	Technical Lead, OSIET Administrator	CEO, OSIET Director

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..... in the "13th International Conference on Contemporary Engineering and Technology 2025" held on 22nd & 23rd March 2025.

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Vice Rector of International Affairs, Samarkand State University, Uzbekistan	Professor, Samarkand State University, Uzbekistan	Technical Lead, OSIET Secretary	Technical Lead, OSIET Administrator	CEO, OSIET Director

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This is to certify that Mr/Mrs/Dr....K.S.RAMANUJAM..... from

DR.M.G.R. EDUCATIONAL AND RESEARCH INSTITUTE, CHENNAI has presented a paper titled

PREDICTING TOR TRAFFIC CLASSIFICATION FROM SECURED PAYLOAD USING MACHINE LEARNING

..... in the "13th International Conference on Contemporary Engineering and Technology 2025" held on 22nd & 23rd March 2025.

Dr.Akhatov Akmal Rustamovich
Vice Rector of International Affairs,
Samarkand State University, Uzbekistan

Dr. Christo Ananth
Professor,
Samarkand State University, Uzbekistan

Dr. P. Aravinthan, M.E., Ph.D.,
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13th INTERNATIONAL CONFERENCE ON CONTEMPORARY ENGINEERING AND TECHNOLOGY 2025

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ORGANIZATION OF SCIENCE & INNOVATIVE ENGINEERING AND TECHNOLOGY (OSIET), CHENNAI, INDIA.

IN COLLABORATION WITH

SAMARKAND STATE UNIVERSITY, UZBEKISTAN

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Medavakkam - Mambakkam Main Road, Ponmar, Chennai - 600 127.

Certificate of Presentation

This is to certify that Mr/Mrs/Dr. G.SENTHILVELAN from

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This is to certify that Mr/Mrs/Dr..... V.B.GANAPATHY ..... from

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