Custom Deep Learning Framework for Identifying Security Threats in Digitally Connected Systems

A Project Report submitted in the partial fulfillment

of the Requirements for the award of the degree

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

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CERTIFICATE

This is to certify that the project that is entitled with the name "**A Custom Deep Learning Framework for Identifying Security Threats in Digitally Connected Systems**" is a bonafide work done by G. Meghana (22471A0518), D. Divya (22471A0515), G. Keerthana Divya (22471A0520) in partial fulfillment of the requirements for the award of the degree of BACHELOR OF TECHNOLOGY in the Department of COMPUTER SCIENCE AND ENGINEERING during 2025-2026.

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I declare that this project work titled " **A CUSTOM DEEP LEARNING FRAMEWORK FOR IDENTIFYING SECURITY THREATS IN DIGITALLY CONNECTED SYSTEMS** " is composed by me that the work contain here is my own except where explicitly stated otherwise in the text and that this work has been submitted for any other degree or professional qualification except as specified.

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To emerge as a Centre of excellence in technical education with a blend of effective student centric teaching learning practices as well as research for the transformation of lives and community.

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M1: Provide the best class infra-structure to explore the field of engineering and research.

M2: Build a passionate and a determined team of faculty with student centric teaching, imbibing experiential, innovative skills.

M3: Imbibe lifelong learning skills, entrepreneurial skills and ethical values in students for addressing societal problems.

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The department of Computer Science and Engineering is committed to

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M2: Impart high quality professional training to get expertize in modern software tools and technologies to cater to the real time requirements of the Industry.

M3: Inculcate team work and lifelong learning among students with a sense of societal and ethical responsibilities.

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Program Specific Outcomes (PSO's)

PSO1: Apply mathematical and scientific skills in numerous areas of Computer Science and Engineering to design and develop software-based systems.

PSO2: Acquaint module knowledge on emerging trends of the modern era in

Computer Science and Engineering

PSO3: Promote novel applications that meet the needs of entrepreneur, environmental and social issues.

Program Educational Objectives (PEO's)

The graduates of the programme are able to:

PEO1: Apply the knowledge of Mathematics, Science and Engineering fundamentals to identify and solve Computer Science and Engineering problems.

PEO2: Use various software tools and technologies to solve problems related to academia, industry and society.

PEO3: Work with ethical and moral values in the multi-disciplinary teams and can communicate effectively among team members with continuous learning.

PEO4: Pursue higher studies and develop their career in software industry.

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Program Outcomes

PO1: Engineering Knowledge: Apply knowledge of mathematics, natural science, computing, engineering fundamentals and an engineering specialization as specified in WK1 to WK4 respectively to develop to the solution of complex engineering problems.

PO2: Problem Analysis: Identify, formulate, review research literature and analyze complex engineering problems reaching substantiated conclusions with consideration for sustainable development. (WK1 to WK4)

PO3: Design/Development of Solutions: Design creative solutions for complex engineering problems and design/develop systems/components/processes to meet identified needs with consideration for the public health and safety, whole-life cost, net zero carbon, culture, society and environment as required. (WK5)

PO4: Conduct Investigations of Complex Problems: Conduct investigations of complex engineering problems using research-based knowledge including design of experiments, modelling, analysis & interpretation of data to provide valid conclusions. (WK8).

PO5: Engineering Tool Usage: Create, select and apply appropriate techniques, resources and modern engineering & IT tools, including prediction and modelling recognizing their limitations to solve complex engineering problems. (WK2 and WK6)

PO6: The Engineer and The World: Analyze and evaluate societal and environmental aspects while solving complex engineering problems for its impact on sustainability with reference to economy, health, safety, legal framework, culture and environment. (WK1, WK5, and WK7).

PO7: Ethics: Apply ethical principles and commit to professional ethics, human values, diversity and inclusion; adhere to national & international laws. (WK9)

PO8: Individual and Collaborative Team work: Function effectively as an individual, and as a member or leader in diverse/multi-disciplinary teams.

PO9: Communication: Communicate effectively and inclusively within the engineering community and society at large, such as being able to comprehend and write effective reports and design documentation, make effective presentations considering cultural, language, and learning differences

PO10: Project Management and Finance: Apply knowledge and understanding of engineering management principles and economic decision-making and apply these to one's own work, as a member and leader in a team, and to manage projects and in multidisciplinary environments.

PO11: Life-Long Learning: Recognize the need for, and have the preparation and ability for i) independent and life-long learning ii) adaptability to new and emerging technologies and iii) critical thinking in the broadest context of technological change.

Project Course Outcomes (CO'S):

CO421.1: Analyse the System of Examinations and identify the problem.

CO421.2: Identify and classify the requirements.

CO421.3: Review the Related Literature.

CO421.4: Design and Modularize the project.

CO421.5: Construct, Integrate, Test and Implement the Project.

CO421.6: Prepare the project Documentation and present the Report using appropriate method.

Course Outcomes – Program Outcomes Mapping

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
C421.1		✓										✓		
C421.2	✓		✓		✓							✓		
C421.3				✓		✓	✓	✓				✓		
C421.4			✓			✓	✓	✓				✓	✓	
C421.5					✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
C421.6									✓	✓	✓	✓	✓	

Course Outcomes – Program Outcome Correlation

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
C421.1	2	3										2		
C421.2			2		3							2		
C421.3				2		2	3	3				2		
C421.4			2			1	1	2				3	2	
C421.5					3	3	3	2	3	2	2	3	2	1
C421.6									3	2	1	2	3	

Note: The values in the above table represent the level of correlation between CO's and PO's:

1. Low level
2. Medium level
3. High level

Project mapping with various courses of Curriculum with Attained PO's:

Name of the Course from Which Principles Are Applied in This Project	Description of the Task	Attained PO
C2204.2, C22L3.2	Gathering the requirements and defining the problem, plan to develop model for detection and classification of OSCC	PO1, PO3, PO8
CC421.1, C2204.3, C22L3.2	Each and every requirement I critically analyzed; the process mode is identified	PO2, PO3, PO8
CC421.2, C2204.2, C22L3.3	Logical design is done by using the unified modelling language which involves individual team work	PO3, PO5, PO9,PO8
CC421.3, C2204.3, C22L3.2	Each and every module is tested, integrated, and evaluated in our project	PO1, PO5, PO8
CC421.4, C2204.4, C22L3.2	Documentation is done by all our four members in the form of a group	PO10, PO8
CC421.5, C2204.2, C22L3.3	Each and every phase of the work in group is presented periodically	PO8, PO10, PO11
C2202.2, C2203.3, C1206.3, C3204.3, C4110.2	Implementation is done and the project will be handled by the social media users and in future updates in our project can be done based on detection for Oral Cancer	PO4, PO7, PO8
C32SC4.3	The physical design includes website to check OSCC	PO5, PO6, PO8

ABSRTACT

A hybrid deep learning approach to intrusion detection is presented to strengthen security in dynamic and rapidly changing network environments. The proposed system integrates Convolutional Neural Networks (CNNs) for extracting spatial characteristics of traffic with Long Short-Term Memory (LSTM) networks for modeling sequential patterns in data f low. To extend its capability against zero-day and unknown threats, an autoencoder-based anomaly detection component is added, allowing the system to recognize irregular behavior even without predefined attack signatures. Evaluation results indicate that the model achieves detection accuracy above 97% while reporting fewer false positives than conventional intrusion detection techniques. These outcomes confirm the suitability of the framework for real-time and dependable threat monitoring. Owing to its adaptable and scalable architecture, the solution can be effectively applied in IoT, cloud, and other distributed smart network settings, providing a practical defense against continuously evolving cyberattacks.

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1. INTRODUCTION

Modern digital environments are becoming increasingly interconnected due to large-scale deployment of cloud services, IoT devices, smart communication networks, and remote computing platforms. As a result, detecting malicious traffic has become a vital security requirement for organizations and digitally connected systems. Intrusion Detection Systems (IDS) are designed to continuously monitor network traffic, analyze communication behavior, and detect abnormal activity that may indicate security threats or unauthorized access attempts. Traditional IDS approaches mainly depend on predefined signatures or static rule sets. These methods can detect only known attack patterns and fail when encountering new, modified, or hidden attacks in complex network data [1], [3]. Deep learning has emerged as a promising direction to improve detection quality in IDS. The major advantage of deep learning models is their ability to learn hidden patterns, relationships, and complex behaviors from network traffic without manual feature engineering. Models such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and Autoencoder-based anomaly detectors have shown improved performance in identifying both known and unknown intrusions. However, many existing deep learning-based IDS frameworks still suffer from limitations such as noisy input, imbalanced datasets, high false alarm rates, and computational overhead during training and testing. These challenges affect real-time performance and reduce the practical usability of IDS in dynamic environments [4], [9].

The present work titled “A Custom Deep Learning Framework for Identifying Security Threats in Digitally Connected Systems” aims to develop an effective intrusion detection solution with improved feature learning, balanced classification performance, and better accuracy on heterogeneous network traffic. The system uses data preprocessing techniques such as normalization, transformation, and label categorization to prepare raw network datasets for model training. Hybrid learning is used, where CNN layers extract spatial relationships between traffic features and LSTM layers identify sequential behavior in the data over time. An anomaly detection component based on autoencoders is integrated to detect irregular traffic patterns that are different from normal operating behavior [2], [8]. Dataset imbalance is addressed using

oversampling and class-balancing techniques to improve detection performance on minority attack classes such as infiltration, botnet, or brute force attempts. Feature selection strategies are also implemented to eliminate redundant attributes and reduce computational complexity. These techniques help the model to focus on relevant features and improve overall performance while reducing training time. The system is evaluated on widely tested IDS benchmark datasets such as NSL-KDD and CICIDS-2017. These datasets include realistic intrusion patterns and contain a mixture of normal traffic and multiple attack types such as DDoS, port scan, web attack, and infiltration traffic [5].

Modern digitally connected systems are highly dynamic in nature and continuously produce large volumes of communication data across different applications, devices, and network layers. This makes intrusion detection a complex task because network traffic does not remain constant and often exhibits significant variations over time. Attackers frequently exploit these variations by disguising malicious content within normal traffic flows, which results in higher chances of missed detection if the IDS does not learn adaptively. One of the core challenges in security threat identification is that malicious events are not always clearly separated from legitimate events in numerical data. Multiple attack samples may share similar patterns with normal communication, which creates ambiguity and increases false positives in unreliable IDS models [1], [7]. Existing IDS solutions require large computing resources to analyze data and still suffer from reduced performance under real-time constraints. This limitation is caused by the increasing dimensionality of network traffic, which contains numerous features such as protocol flags, packet sizes, connection duration, and service types. Processing all features at the same time without optimization affects model training efficiency and reduces prediction accuracy. To address this issue, the current framework applies systematic preprocessing and feature selection before training deep learning components. Only the most relevant network parameters are retained for training, which reduces noise and enhances the detection capability of the overall system [3], [8].

Digitally connected environments typically include multiple attack categories, which differ in behavior, frequency, and objective. Attacks such as denial-of-service aim to disrupt service availability, whereas infiltration and brute force

attacks attempt to gain unauthorized access to host machines. Port scanning and probing attacks collect information about vulnerable services for possible future exploitation. A reliable IDS must be capable of identifying all these different attack types without sacrificing detection speed. The proposed framework evaluates binary classification as well as multi-class detection to identify specific categories of attacks. This approach provides more detailed information to security analysts and supports better decision-making in network administration [4]. Large-scale datasets are essential for training IDS models because they provide real-world variations in traffic and attack patterns. In this project, benchmark datasets such as CICIDS-2017 and NSL-KDD are used to analyze the performance of the proposed framework. These datasets contain real network traffic traces covering both normal behavior and multiple forms of cyber-attacks. Extensive testing using these datasets helps verify whether the model generalizes beyond training samples and performs consistently on unseen data. The model evaluation uses standard metrics that are widely accepted in IDS research, ensuring that experimental results are comparable with existing solutions [5].

During the training phase, optimization algorithms such as Adam and learning rate scheduling mechanisms are used to improve model convergence. Regularization techniques like dropout are applied to prevent overfitting and maintain stable generalization performance. The training process also monitors loss and classification accuracy through multiple epochs until convergence is reached. Once deployed, the framework supports continuous monitoring of traffic data and generates alerts when a high probability of malicious behavior is detected. This adaptive workflow ensures that digitally connected systems remain protected even as threat patterns evolve over time [6]. The system is designed to operate efficiently in both centralized and distributed infrastructure. It can be integrated into security management tools, log monitoring services, or cloud-based security solutions. The ability to detect threats early is crucial to prevent data loss, service unavailability, financial consequences, and reputational damage. By identifying attacks at an earlier stage, system administrators can apply immediate response actions such as IP blocking, traffic isolation, session termination, or automated firewall policy updates. These interventions help reduce exposure to large-scale damage and improve resilience in digitally

connected environments [9].

The overall intention of this work is to develop an intrusion detection system that not only detects potential security threats with improved accuracy but also adapts to emerging attack variations without requiring manual configuration. By merging multiple deep learning components with advanced preprocessing strategies and balanced learning techniques, the proposed framework enhances prediction quality across different network conditions. Based on experimental results and supporting studies, it can be concluded that intelligent deep learning-based IDS solutions provide higher detection performance and better adaptability when compared to traditional IDS methods. This project establishes a foundation for future advancements in automated security threat identification and supports the development of advanced cyber defense mechanisms for digitally connected systems. In modern enterprise environments, security challenges are increasing due to the continuous integration of third-party applications, interconnected services, and remote access platforms. Organizations rely on a combination of wired and wireless networks, virtual machines, smart devices, and cloud-hosted resources for day-to-day operations. This heterogeneous ecosystem provides multiple entry points for potential attackers, making the detection of sophisticated threats even more crucial. Cybercriminals often bypass traditional security systems by using encrypted channels, fragmented payloads, and hidden tunneling techniques. Therefore, an intrusion detection framework must not only analyze packet-level statistics but also understand deeper behavioral patterns and temporal characteristics in communication flows. A custom deep learning-based system is capable of learning these complex behaviors by examining past interactions, frequency variations, and statistical differences between normal and malicious traffic, which improves early detection and overall network defense [2], [6].

As digital communication continues to evolve, emerging technologies such as edge computing, industrial control systems, and smart automation networks introduce additional risks that conventional IDS approaches are not designed to handle. Many security threats originate from inside the network, such as unauthorized access by compromised users or devices, which are difficult to identify through standard signature-based analysis. Deep learning-backed IDS solutions support anomaly detection by recognizing unusual activity, even when

specific attack signatures are not known in advance. This capability increases robustness and reduces dependence on constant manual updates. By training on large-scale datasets and applying continuous learning mechanisms, the proposed framework ensures adaptability to new threat patterns while maintaining consistency in performance. Overall, the introduction of a custom deep learning architecture for identifying security threats supports improved transparency, reduced false detection rates, and more efficient protection of digitally connected systems.

2. LITERATURE SURVEY

Literature study focuses on reviewing existing research works, frameworks, and techniques related to intrusion detection systems in digital environments. Intrusion detection has been widely studied over the past two decades, and traditional approaches mainly relied on signature-based and rule-based classification methods. These systems match incoming traffic against stored patterns of known attacks, but they fail when identifying unknown, modified, or zero-day intrusions. Multiple studies have reported that static IDS components create higher false negative rates because attackers continuously develop new techniques to avoid detection [1], [3]. Anomaly detection was introduced to overcome this limitation by modeling normal traffic behavior and identifying deviations from expected patterns. However, anomaly-based IDS methods often suffer from high false positives due to noise and overlapping characteristics between benign and malicious data in large-scale realistic environments [2].

Recent research emphasizes the use of machine learning and deep learning in IDS to improve detection efficiency and scalability. Classical machine learning approaches such as Support Vector Machines, Decision Trees, Random Forest, and k-Nearest Neighbor have been applied to network traffic classification, but their performance depends heavily on the quality of manually engineered features. Studies have shown that these traditional models can perform well on small datasets but generally fail in large, heterogeneous, and high-dimensional network datasets [4], [5]. To address feature complexity, researchers introduced feature selection techniques that reduce redundant features and highlight the most relevant parameters affecting classification accuracy. Approaches such as Chi-square ranking, Information Gain, and Minimum Redundancy Maximum Relevance (MRMR) are used in multiple IDS studies to reduce computational cost and improve model generalization [6].

Deep learning-based IDS has gained significant attention due to its ability to learn complex hidden patterns automatically from raw traffic data without intensive manual feature engineering. Convolutional Neural Networks (CNN) have been used to capture spatial correlations between features, while Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) have been applied to extract sequential dependencies in time-based network flows. Researchers have also

combined CNN and LSTM structures to build hybrid models that capture both spatial and temporal relationships in traffic behavior [7]. Autoencoder-based systems have been studied for anomaly detection because they reconstruct normal behavior and identify deviations that may represent unknown or new attacks [8]. Despite improved performance, deep learning models still face major challenges such as class imbalance, training complexity, interpretability, and the risk of overfitting on benchmark datasets.

Several studies have highlighted the importance of using benchmark IDS datasets to evaluate model performance. NSL-KDD, CICIDS-2017, UNSW-NB15, and Kyoto 2006+ are commonly used datasets that contain multiple types of network attacks including denial-of-service, port scanning, brute force, botnet, and infiltration traffic. Literature reports indicate that class imbalance in these datasets affects the ability of deep learning models to detect minority attack groups accurately. To address this, oversampling methods such as SMOTE, GAN-based synthetic data generation, and weighted loss functions are applied in IDS research [9]. Recent works propose ensemble models that combine multiple base learning algorithms to obtain higher detection accuracy and reduce false alarms. Stacking, boosting, and bagging mechanisms are often used to improve robustness and stability across multiple traffic scenarios [10].

The literature suggests that although deep learning has achieved strong performance in IDS, there remains a noticeable gap between laboratory results and real deployment conditions. A majority of reported research focuses on accuracy values on benchmark datasets, but real-time adaptability, scalability, and interpretability are rarely evaluated. Most systems lack explainability, which makes it difficult for analysts to understand why a particular traffic flow is classified as malicious. Current studies point to the need for hybrid frameworks that integrate multiple detection stages, incorporate feature optimization, and support adaptive learning methods for unknown attack patterns. The present work addresses these limitations by proposing a custom deep learning framework that combines preprocessing, hybrid feature extraction, balanced learning, and multi-class classification for identifying security threats in digitally connected systems.

Recent literature also discusses the importance of handling noisy and redundant data in intrusion detection. Network traffic contains a large number of features that are either irrelevant or weakly correlated with attack behavior. Including such features

increases training time and leads to a phenomenon known as the “curse of dimensionality,” which reduces classification performance. Researchers have therefore focused on dimensionality reduction and feature optimization as essential preprocessing steps. Techniques such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and wrapper-based selection have been widely used to improve IDS performance by minimizing redundancy in feature sets [11]. Studies indicate that feature selection not only reduces computational cost but also improves detection accuracy by focusing on key parameters such as flow duration, destination port count, protocol type, and packet size distribution [12].

Cloud computing research has significantly contributed to IDS advancements due to increasing adoption of cloud services across industries. Cloud environments involve distributed storage, virtualization, and multi-tenant data sharing, which produces unique security issues compared to traditional network systems. Several authors have proposed cloud-based IDS frameworks that analyze virtual machine traffic or container-based communication to detect attacks such as resource hijacking, unauthorized access, and distributed brute force attempts. These frameworks use flow-level traffic data, log aggregation, and deep packet inspection to identify anomalies in real time. However, many cloud IDS approaches face limitations in scalability because large distributed systems produce high data rates that require continuous model updates and online learning support [13], [14].

Literature has also explored the role of IoT-based IDS systems. IoT networks have resource-constrained devices, limited processing power, and unreliable communication links, which make security detection different from standard enterprise network detection. Lightweight models such as shallow neural networks, federated learning, and edge-analytics-based IDS mechanisms have been developed to detect threats in smart devices such as sensors, cameras, and intelligent gateways. Since traditional IDS approaches cannot be directly installed on IoT devices, researchers use centralized IDS models combined with device-level anomaly reporting. Studies show that hybrid deep learning architectures are capable of learning behavioral patterns from IoT event logs and communication statistics, making them useful for identifying abnormal device behavior or compromised firmware activity [15].

Several researchers have emphasized the importance of evaluation metrics in IDS research because accuracy alone does not provide complete information about

detection quality. Metrics such as precision, recall, F1-score, false positive rate, confusion matrix, and ROC curve are used to measure model efficiency across multiple attack types. Precision reflects the proportion of correctly predicted malicious events among all predicted attacks, while recall measures the system's ability to detect actual malicious events present in the dataset. A high recall value is essential because missing an attack has a higher risk in security systems compared to a false alarm. Literature further suggests using ROC-AUC to evaluate overall detection capability of IDS systems since it provides a threshold-independent performance measure across different classification probabilities [16].

Recent studies recommend using ensemble learning for IDS because combining multiple classifiers leads to better robustness and stability. Ensemble models such as Random Forest, Gradient Boosting, XGBoost, and stacking frameworks have been reported to provide improved results compared to individual deep learning or machine learning models. Researchers claim that ensemble learning reduces model-specific weaknesses and helps improve prediction consistency, especially for rare attack types. Some literature also describes meta-learning and multi-stage detection pipelines where primary detection decisions are refined using secondary classifiers. These approaches increase classification confidence and reduce false alarm rates by reassessing borderline samples that show low model certainty [17].

Despite advancements in IDS research, literature continues to identify major limitations that need to be addressed. Many proposed IDS models are tested only on public benchmark datasets and not evaluated in real-time operational systems. This raises questions about generalization because benchmark datasets do not fully cover evolving attack patterns in real networks. In addition, explainability remains a concern because deep learning IDS systems often operate as black-box models, providing no clear reasoning behind predictions. Studies suggest integrating interpretable layers, attention mechanisms, and feature importance visualization to increase transparency in IDS research [18]. Literature consistently indicates that combining deep learning with adaptive classification strategies improves intrusion detection results, particularly in dynamic and heterogeneous digital systems, supporting the overall direction of developing custom deep learning frameworks for identifying security threats in digitally connected environments.

Recent research also explores the integration of real-time monitoring, adaptive learning, and automated response mechanisms within IDS frameworks to enhance

operational effectiveness. Studies indicate that incorporating streaming analytics and incremental model updates allows IDS to detect emerging threats without requiring complete retraining, which is essential in high-velocity network environments such as cloud and IoT systems [19]. Moreover, hybrid approaches combining deep learning, ensemble methods, and attention-based models have been proposed to capture both spatial-temporal patterns and contextual dependencies in network traffic, improving detection of complex and multi-stage attacks [20]. Researchers emphasize the importance of energy-efficient and lightweight IDS models for deployment in resource-constrained devices, while simultaneously maintaining high accuracy and low false positive rates [21]. Overall, the literature suggests a growing trend toward intelligent, adaptive, and interpretable IDS architectures that can operate effectively across heterogeneous digital environments while addressing the challenges of scalability, real-time detection, and evolving cyber threats.

3. SYSTEM ANALYSIS

3.1. Existing System

Existing Intrusion Detection Systems (IDS) are generally built using predefined machine learning models that classify network traffic into normal and malicious categories based on historical data. Many of these systems rely on static learning techniques, where models are trained once and then deployed without continuous adaptation. This works reasonably well for identifying well-known threats, but becomes unreliable when new attack signatures appear, especially in environments where traffic patterns change frequently [1], [4]. Most traditional IDS use predefined thresholds, signature matching, or manual rule sets to detect suspicious activities, which means they depend heavily on expert-designed features and cannot independently learn hidden patterns from raw traffic data. When deployed in real networks, these systems often produce inconsistent performance because network characteristics in real-time may differ from the fixed patterns used in training [8].

A common issue in existing IDS is their dependence on benchmark datasets such as CICIDS2017, UNSW-NB15, and NSL-KDD for model development. While such datasets are useful for research, they do not represent the constant growth of new attack behaviors found in dynamic network environments. As a result, current systems tend to misclassify minority attacks, struggle with class imbalance, and require frequent re-training to maintain accuracy [11]. Many IDS also process network attributes individually, ignoring the relationships between traffic features over time. Multi-stage attacks, coordinated intrusion attempts, or slow-moving threats are harder to detect because existing systems do not correlate activities occurring in different parts of the network. This leads to high rates of false positives and false negatives, forcing administrators to manually verify alerts and sometimes overlook critical anomalies [5].

Another limitation with existing IDS is their difficulty in handling large-scale digital infrastructure. Today's networks include a mix of cloud services, mobile devices, IoT endpoints, and distributed applications, which generate enormous amounts of heterogeneous traffic [7]. Traditional IDS cannot easily scale to process continuous data streams coming from geographically distributed sources, especially when traffic contains redundant or noisy information. Models trained using static feature sets tend

to perform poorly when new devices, protocols, or services are introduced into the system. Furthermore, many deep learning-based IDS still operate like black boxes, providing no explanation for why a certain activity is flagged as malicious, which reduces trust among cybersecurity analysts and limits the system's usefulness during incident response [9].

In practical deployment, existing IDS are also affected by resource limitations. Machine learning classifiers typically require a fixed input structure, while real-world network flows contain missing values, inconsistent packet sizes, fluctuating connection duration, and unpredictable behavior from remote devices. The lack of adaptive learning mechanisms means models cannot update themselves when unknown threats or evolving traffic patterns appear, often resulting in performance degradation in real-time operations [13]. Because many current IDS are built to function in centralized architectures, they become inefficient when deployed in modern distributed systems where data must be processed close to the source, such as edge computing or IoT gateways. Overall, existing IDS struggle to meet current cybersecurity needs due to issues related to scalability, adaptability, interpretability, noise handling, minority attack detection, and real-time classification efficiency [21].

Moreover, existing security systems often lack integration with advanced machine learning or deep learning techniques, which limits their ability to learn from evolving attack patterns over time. Most traditional IDS frameworks rely on static rules and predefined thresholds, which makes them rigid in adapting to new attack strategies. In a modern networked environment, where cybercriminals employ complex, multi-stage attacks, these systems are insufficient for detecting sophisticated intrusions, such as Advanced Persistent Threats (APTs) or coordinated botnet attacks [4], [8].

Another major limitation is the inadequate handling of distributed network architectures. Modern IT infrastructures often span multiple cloud platforms, virtualized environments, and mobile endpoints. Conventional systems are not designed to provide a unified view across these diverse platforms, which leads to gaps in threat detection and response. This fragmentation not only increases the risk of undetected breaches but also makes incident response slower and less effective, putting sensitive data and organizational operations at significant risk [1], [11].

Additionally, conventional systems often struggle with scalability and resource optimization. As networks grow in size and complexity, monitoring large volumes of real-time traffic requires substantial computational power and storage. Traditional

IDS solutions are not optimized for such high-demand environments, leading to delays in threat detection and reduced overall efficiency. This limitation becomes particularly critical in IoT ecosystems and cloud-based infrastructures, where millions of devices generate continuous streams of data that must be analyzed quickly to prevent potential breaches [4], [8], [11].

3.1.1 Disadvantages of Existing System

Conventional Intrusion Detection Systems (IDS) have several limitations. Signature-based systems can only detect known attacks, leaving networks vulnerable to new threats, while anomaly-based systems often generate many false alarms. These systems struggle to handle the large volumes of data in modern networks, making real-time detection difficult. They rely on static rules, lack adaptability to sophisticated attacks, and usually operate in isolated network segments, which creates blind spots. Additionally, they consume significant resources and do not incorporate contextual intelligence, making them largely reactive rather than proactive. Overall, these weaknesses highlight the need for more advanced and adaptive security solutions.

High Dimensionality and Redundant Features

In modern digitally connected systems, network traffic and system logs generate massive amounts of data with numerous attributes and features. High dimensionality in this data can negatively impact the performance of conventional intrusion detection systems. Many features are often irrelevant or redundant, which increases computational complexity and may lead to overfitting in machine learning models [1], [4]. Redundant features can also introduce noise, reducing the accuracy of threat detection and making it more difficult to identify sophisticated attacks effectively [8]. Traditional IDS are generally not designed to handle such high-dimensional data efficiently, which limits their scalability and real-time analysis capabilities [11]. Therefore, reducing feature redundancy and focusing on the most relevant attributes is essential to improve detection performance, enhance computational efficiency, and ensure that deep learning models can accurately identify security threats in real-time environments [1], [4].

Poor Handling of Class Imbalance

One of the major shortcomings in existing IDS models is their poor handling of class imbalance in network datasets. In real-world network traffic, normal data records are significantly higher compared to malicious records, and certain attack types appear very rarely, sometimes in less than 1% of total samples [9], [11]. Traditional machine learning algorithms typically assume that all classes are distributed evenly; therefore, models tend to Favor majority classes and ignore minority attacks. As a result, IDS often produce high accuracy values in experimental results, but fail to correctly detect rare intrusions, which are usually the most dangerous in operational environments [14]. For example, advanced persistent threats, infiltration attempts, or slow-moving reconnaissance attacks are frequently misclassified as normal traffic due to insufficient training samples [16]. Deep learning-based IDS suffer from similar issues because they optimize overall accuracy rather than focusing on minority detection. Even when anomaly-based models are used, rare attack categories generate unstable predictions and high false negatives, meaning critical intrusions remain undetected [18]. Existing approaches such as oversampling and random resampling provide limited improvement because they can introduce noise or duplicate samples, increasing overfitting and reducing generalization on unseen traffic [20]. Therefore, poor handling of class imbalance remains a key factor limiting the reliability of traditional IDS in real network deployments, especially when detecting new or uncommon attacks [21].

Lack of Interpretability and Explainability

Another major drawback of existing IDS, especially deep learning-based models, is the lack of interpretability and explainability in decision making. Many IDS frameworks operate as black-box systems where the model detects an event as malicious but does not provide a clear explanation of how that decision was reached [10], [12]. In practical cybersecurity operations, analysts need to understand which traffic features or behavioral characteristics contributed to the classification result. Without interpretability, security teams must rely on trial-and-error analysis or manual log inspection to determine the root cause of an attack [15]. This slows down incident response and makes it difficult to verify whether an alert is genuine or the

result of model bias. Deep neural networks such as CNN, LSTM, and autoencoders extract hidden abstract features from large network traffic data, but these transformations are not directly visible or understandable to human operators [18]. Lack of transparency also reduces trust in IDS predictions, especially when investigating complex security incidents involving multi-step attacks or distributed intrusion attempts [19]. Although recent studies propose explainable AI approaches, they often introduce additional computation cost or reduce detection performance, resulting in a trade-off between model accuracy and interpretability [21]. Consequently, the absence of explainability continues to limit the usability and practical deployment of advanced IDS solutions in real-time network environments.

Static Decision Thresholds and Uncertainty Ignorance

A key limitation in many existing IDS is the use of static decision thresholds, which reduces the ability to detect new or uncertain types of intrusion. Traditional machine learning models generally apply fixed classification boundaries, meaning an event is labeled as malicious only if its value exceeds a predefined threshold [7], [10]. While this approach works for stable environments, it becomes ineffective when network behavior changes over time or when new forms of attacks appear. Static rules ignore uncertainty in borderline cases, causing the system to misclassify suspicious activities that are not clearly normal or malicious. This problem is evident in real-time scenarios where attacks gradually evolve or mimic normal traffic characteristics to avoid detection [12]. Many IDS do not assign confidence values or probability scores during classification, so the system cannot differentiate between highly certain predictions and uncertain ones [14]. As a result, borderline events are either ignored or incorrectly flagged, leading to false positives and missed threats. Modern cyber-attacks often occur in multiple stages and include variations that fall within ambiguous detection ranges, which cannot be captured by fixed thresholds [16]. Without adaptive decision mechanisms that adjust to live network conditions and threat intelligence, existing IDS continue to suffer from reduced detection accuracy and unstable performance when deployed in diverse and unpredictable digital environments [19].

Computational Complexity and Scalability Issues

Many existing IDS models struggle with computational complexity and scalability when processing large, high-velocity network traffic in real environments. Traditional

machine learning classifiers must repeatedly analyze multiple network attributes, and this becomes extremely slow when dealing with thousands of concurrent connections or high-dimensional data streams [5], [8]. Deep learning approaches, although more accurate, require heavy computation during model training and inference, especially for architectures such as CNN, LSTM, and hybrid neural networks [11]. These models often require substantial GPU support, large memory consumption, and high processing capacity, which are not always available in practical security systems [13]. As network infrastructure expands to include cloud servers, distributed endpoints, and IoT devices, the volume of traffic becomes unpredictable, and existing IDS face difficulties in scaling their performance without losing detection accuracy [14]. High computational overhead leads to slower response times, increased latency, and delays in identifying threats, particularly during peak traffic periods [17]. Furthermore, many models are tested only in controlled laboratory datasets and perform poorly when deployed in real distributed environments due to limited resource optimization [20]. Without efficient processing strategies, existing IDS lack the scalability required to maintain continuous, real-time monitoring across large, digitally connected systems [21].

Over-Reliance on Single Model Architectures

Many existing intrusion detection systems depend on a single machine learning or deep learning model for classification, which limits their ability to capture diverse attack patterns and network behaviors. Traditional IDS typically rely on one classifier such as SVM, Random Forest, or k-NN, while recent deep learning approaches use a single CNN or LSTM architecture for feature extraction and intrusion identification [6], [9]. When a single model is used, it learns specific types of patterns and performs well under certain conditions, but struggles with different attack categories, traffic variations, or rare intrusion types that do not match its learned distribution [12]. As a result, single-model IDS often produce inconsistent performance across datasets, especially when deployed in dynamic or heterogeneous environments like cloud networks or IoT platforms [14]. These systems also become more prone to overfitting, since the classifier may memorize dominant patterns from training data but fail to generalize when monitoring real traffic [15]. Research has shown that complex attacks such as stealthy infiltration, multi-stage reconnaissance, or slow brute-force attempts cannot be detected reliably using only one model because each algorithm

has specific strengths and weaknesses [17]. Without model diversity or ensemble strategies, existing IDS lack robustness, stability, and resilience against unpredictable cyber-attack patterns [20].

Inadequate Real-World Generalization

A significant limitation of many existing IDS models is their inability to generalize effectively when deployed in real-world network environments. Most systems are designed, trained, and evaluated using public benchmark datasets such as NSL-KDD, CICIDS2017, and UNSW-NB15, which offer controlled and structured samples of normal and attack traffic [4], [9]. While these datasets are valuable for academic experimentation, they do not accurately represent the complexity and variability of live network conditions. Real-world environments contain continuous traffic fluctuations, unknown protocols, new malware signatures, and device-specific communication patterns that are not present in benchmark datasets [11]. As a result, models that achieve high accuracy in laboratory settings often show degraded performance, high false alarms, and missed detections when applied to operational networks [13]. The problem intensifies when traffic originates from diverse sources such as cloud platforms, virtualization environments, IoT devices, and mobile communication networks, where data characteristics change rapidly over time [16]. Without adaptive learning or periodic retraining, IDS models gradually become outdated, unable to recognize evolving attack behaviors or newly emerging threat patterns [18]. This lack of generalization leads to inconsistent performance, reduced trust from security analysts, and limited applicability for large-scale deployment in digitally connected systems [21].

Lack of Unified, Adaptive Framework

Most existing intrusion detection systems operate as isolated components that focus on specific threats or particular network environments, rather than offering a unified, adaptive solution for diverse digital ecosystems. Traditional IDS implementations are typically designed either for enterprise networks, cloud infrastructures, or IoT environments, but very few systems can handle heterogeneous data sources simultaneously [3], [7]. This results in fragmented security monitoring where separate tools are required for different parts of the infrastructure. Additionally, current IDS models lack adaptive learning mechanisms capable of updating decision rules in

response to evolving cyber threats. Many systems use static configuration parameters and fixed model architectures that do not adjust to new attack behaviors or changes in network conditions [10]. Without continuous learning, these systems gradually become outdated and less effective over time, especially when exposed to zero-day attacks or newly emerging intrusion techniques [14]. Integration of feature optimization, balanced learning, and multi-stage classification is rarely found in a single IDS framework, which forces organizations to combine multiple tools and manually correlate intrusion alerts [17]. This lack of a unified, adaptive detection system leads to operational overhead, inconsistent threat visibility, and reduced overall security performance in digitally connected environments [19].

3.2 Proposed System

The proposed system in this research aims to overcome the limitations identified in conventional Intrusion Detection Systems (IDS) by introducing a custom deep learning-based intrusion detection framework. The primary objective is to improve accuracy, reduce false alarms, and provide adaptive detection for digitally connected environments where network data is large, noisy, and constantly changing. The system focuses on automated feature optimization, hybrid neural learning, class imbalance management, and ensemble-based decision refinement to provide reliable intrusion classification in real-time operational networks. The approach is designed to effectively handle high-dimensional network traffic, dynamic attack behaviors, and lack of explainability that affect existing IDS solutions.

Dataset

The proposed system uses publicly available benchmark datasets such as NSL-KDD, CICIDS-2017, and UNSW-NB15, which contain both normal and malicious traffic instances collected from real network environments. These datasets consist of millions of records including multiple attack categories such as Denial-of-Service (DoS), brute force, port scanning, botnet, infiltration, and reconnaissance attempts. Each dataset contains labeled traffic flows, which serve as the ground truth for training, validation, and evaluation of the model**.**

Clean Data

Data preprocessing is performed to ensure that the network traffic dataset is suitable

for training the deep learning model. This process involves removing non-informative or irrelevant columns such as IP addresses, timestamps, and flow identifiers, handling missing or infinite values, eliminating constant or duplicate features, and normalizing numeric values using Min-Max scaling or Z-score normalization. These steps ensure consistent feature ranges across all network attributes, prevent bias, and improve the stability and convergence of the model during training. By preparing clean and uniform data, the system can accurately learn meaningful patterns from network traffic while reducing computational complexity.

Feature Selection

To reduce the complexity caused by high-dimensional network data and improve model efficiency, a feature optimization stage is applied. Instead of MRMR, the system uses a combination of statistical and dimensionality reduction techniques, including correlation analysis, variance thresholding, and principal component extraction, to identify the most informative features for attack detection. By removing redundant, irrelevant, or low-impact network attributes, the model can focus on meaningful patterns while reducing computational overhead. This selection process ensures faster training, better generalization, and improved detection performance for both common and rare intrusion types.

Drop Irrelevant Features

After initial feature evaluation, irrelevant and redundant attributes are removed to streamline the dataset and improve model performance. This involves eliminating features that show little or no correlation with the target class or contribute minimally to attack detection. By discarding such attributes, the system reduces computational overhead, prevents overfitting, and allows the deep learning model to focus on the most significant patterns in network traffic. This step enhances both the efficiency and accuracy of the intrusion detection process, ensuring that the model prioritizes meaningful information for reliable detection of various attack types.

New Dataset with Selected Features

Once irrelevant and redundant features are removed, a new dataset is created containing only the selected, informative attributes. This optimized dataset maintains all critical information required for intrusion detection while reducing dimensionality

and computational complexity. The refined dataset includes features that capture the essential characteristics of network traffic, enabling the deep learning model to learn meaningful patterns effectively. By focusing on these high-impact attributes, the system improves both training efficiency and detection accuracy, ensuring reliable identification of normal traffic as well as known and unknown attack types in digitally connected environments.

Train-Test Split

The optimized dataset is divided into training and testing subsets to evaluate the performance of the deep learning model. Typically, 70–80% of the data is used for training, allowing the model to learn patterns and relationships in network traffic, while the remaining 20–30% is reserved for testing to assess generalization and detection accuracy. Care is taken to ensure that the class distribution in both subsets reflects the original dataset, maintaining the representation of normal and attack traffic. This division enables reliable evaluation of the model's capability to detect both frequent and rare attacks, and ensures that the results accurately reflect performance in real-world network scenarios.

Training

The Intrusion Detection System (IDS) is trained to recognize patterns in network traffic and detect attacks. The training process includes:

1. **Data Splitting:** The dataset is divided into training, validation, and testing sets (usually 70:15:15).

2. Input Preparation: Features are normalized and encoded selects the most important ones automatically.

3. Training Configurations:

- **Binary Classification:** Normal vs. malicious traffic.
- **Multi-Class Classification:** Different types of attacks.
- **All-Class Classification:** Every unique attack category.

4. Hyperparameters: Number of decision steps, learning rate, batch size, and feature selection sparsity are adjusted for best performance.

5. Optimization: Uses the Adam optimizer and regularization (dropout, weight decay) to improve learning and prevent overfitting.

6. Early Stopping: Training stops automatically when validation performance no

longer improves, ensuring the model generalizes well to unseen data.

Tune Models

After initial training, the deep learning model undergoes a hyperparameter tuning phase to optimize its performance. Key parameters such as learning rate, number of layers, number of neurons per layer, batch size, dropout rate, and attention parameters in the classifier are adjusted using techniques like grid search, random search, or Bayesian optimization**.** This process ensures that the model achieves the best balance between accuracy, precision, recall, and training stability. Proper tuning allows the system to handle the complexity of high-dimensional network traffic, improving its ability to detect both frequent and rare attacks while minimizing false positives. The tuned model is then validated using a separate validation set to confirm that the selected parameters generalize well to unseen data.

Optimize Best Model

Once the models are trained and tuned, the next step involves selecting and optimizing the best-performing model for deployment. The system evaluates the trained models based on metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve, identifying the configuration that consistently delivers the highest performance across different attack types. Further optimization is applied by fine-tuning hyperparameters, adjusting attention sparsity in the TabNet classifier, and applying techniques such as early stopping and weight regularization to enhance generalization. This ensures that the final model is not only accurate and efficient but also robust in detecting normal traffic as well as both known and unknown attacks in real-world network environments.

Advantages:

- **High Detection Accuracy:** The hybrid TabNet classifier effectively identifies normal, known, and unknown attacks.
- **Interpretability:** Sequential attention and sparse feature selection allow analysts to understand the model's decision-making process.
- **Reduced False Positives and Negatives:** Class imbalance handling and ensemble-based decision refinement improve reliability.
- **Computational Efficiency:** Optimized feature selection and preprocessing reduce

training time and resource usage.

- **Adaptability:** The system can learn from evolving attack patterns, maintaining effectiveness over time.
- **Scalability:** Suitable for deployment across cloud platforms, enterprise networks, and IoT environments.
- **Robustness:** Capable of handling high-dimensional and complex network traffic without performance degradation.

3.3 Feasibility Study

The feasibility study evaluates whether the proposed custom deep learning framework for intrusion detection can be implemented efficiently and practically. The analysis considers both economic feasibility and technical feasibility.

Economic Feasibility

Economic feasibility examines whether the system can be developed and deployed at a reasonable cost while improving network security. The main cost factors considered include hardware, software, and operational requirements.

Hardware Costs

- The system can operate on standard computing infrastructure with no requirement for high-end proprietary hardware.
- Deployment can be performed on local servers or virtual cloud machines with moderate processing capability.

Software Costs

- The framework is developed using freely available open-source tools and libraries, eliminating licensing charges.
- Lightweight web-based deployment ensures real-time monitoring and reduces application management expenses.

Operational Costs

- The model is designed to process large volumes of network data with low computational overhead, reducing server running costs.

- Deployment and maintenance can be carried out using low-cost web hosting or internal network servers.

Cloud-Based Development Costs

- Model training can be performed using cloud GPU services for faster processing without expensive local hardware.
    - Example: Colab Pro Subscription – ₹1,093/month ($9.99/month)

Cost-Benefit Analysis

The cost–benefit analysis evaluates the financial and operational advantages of implementing the proposed deep learning–based intrusion detection system compared with the resources required for development, deployment, and maintenance. The objective is to determine whether the investment in the system provides measurable improvements in network protection and threat monitoring.

Technical Feasibility

The technical feasibility evaluates whether the proposed deep learning framework can be successfully implemented using the available technology, datasets, development tools, and deployment environments. It examines the practicality of building, training, testing, and deploying the system in digitally connected networks.

Technologies & Tools Used

The proposed intrusion detection system is developed using widely available and well-supported tools.

- Programming Language: Python (For Machine Learning Development & Model Training & API Integration)
- Machine Learning Models: TabNet – Main deep learning classifier, Decision Tree – Micro-correction model, Random Forest – Booster for minority-class correction, LightGBM – Gradient boosting model in ensemble, Logistic Regression – Meta-classifier for stacking, XGBoost – Final residual error corrector
- Development Framework: Flask (Used for frontend and backend integration).

- Cloud Computing: Google Colab Pro (for model training and execution).

Computational Requirements

- Processor: Minimum Intel i5 or AMD equivalent for development and testing.
- RAM: At least 8 GB for training basic models; 16 GB recommended for handling
- large IDS datasets.
- GPU: NVIDIA GPU (such as Tesla T4, K80, or RTX series) for training boosting models efficiently.
- Storage: Minimum 30 GB free space for datasets, model checkpoints, logs, and experiment results.
- Cloud Resources: Google Colab Pro to access GPU/TPU for faster training and hyperparameter tuning.
- Operating System: Windows, Linux, or macOS compatible with Python, Flask, and machine learning libraries.

Integration with Existing Systems

- The IDS can connect to existing network logs, firewalls, or security monitoring tools.
- It accepts input from packet capture tools like Wireshark, Zeek, or Cisco NetFlow data.
- The system exposes a REST API so other applications can send network traffic data for prediction.
- It can be deployed alongside existing intrusion detection solutions without replacing them.
- Output alerts can be sent to SIEM platforms such as Splunk, QRadar, or Elastic Stack.
- The model can be updated without shutting down the network system.

Scalability

- The IDS can handle increasing amounts of network traffic as data grows.
- The system supports batch processing for large datasets and real-time streaming for live monitoring.

- It can be deployed on multiple servers or cloud instances to manage high-volume traffic.
- The deep learning model can be retrained with new attack patterns without changing system architecture.
- Scaling is easy using cloud platforms such as AWS, Azure, or Google Cloud.
- Adding new network devices or data sources does not affect overall system performance.

Real-Time Performance

- The IDS monitors incoming network traffic and classifies packets within milliseconds.
- Deep learning inference speed is optimized using GPU support, ensuring fast detection of suspicious activity.
- The system uses lightweight preprocessing to avoid delays during live analysis.
- Real-time alerts are generated for abnormal patterns or potential security threats.
- Performance remains stable even when traffic volume increases.

Programming & Deployment

- The system is developed using Python for model training, preprocessing, and evaluation.
- A Flask-based REST API is used to expose the trained model for real-time network intrusion detection.
- Model training is performed in Google Colab Pro using GPU acceleration.
- Deployment can be done on local servers or cloud platforms such as AWS, Azure, or Google Cloud.
- The model is packaged and loaded through a simple API endpoint for live prediction.
- The system supports log monitoring and output visualization through a web dashboard.

4. SYSTEM REQUIREMENT

A machine learning–based intrusion detection project requires suitable software and hardware resources to ensure smooth model training, testing, and deployment. The following section describes the required configurations.:

4.1 Software Requirements

1. **Operating System:** Windows 11, 64-bit
   - A modern OS with enhanced security, efficiency, and compatibility with ML tools.
   - The 64-bit architecture supports high-performance computing and large memory usage.
2. **Coding Language:** Python
   - Python is widely used for ML due to its rich ecosystem of libraries (TensorFlow, Scikit-learn, Pandas, NumPy).
   - It provides easy syntax, rapid development, and extensive community support.
3. **Python Distribution:** Google Colab Pro, Flask
   - Google Colab Pro: A cloud-based Jupyter notebook environment with GPU/TPU support for faster model training.
   - Flask: A lightweight web framework used to deploy and serve ML models as APIs.
4. **Browser:** Any Latest Browser (e.g., Chrome)
   - A modern web browser ensures compatibility with Google Colab, Flask applications, and cloud-based tools.
   - Google Chrome is preferred for its performance, developer tools, and security features.

4.2 Hardware Requirements:

1. **System Type:** Intel® Core™ i5-7500U CPU @ 2.40GHz
   - The Intel Core i5-7500U is a dual-core processor suitable for ML tasks such as data preprocessing and small-scale model training.

- It operates at 2.40 GHz, providing a balance of speed and power efficiency.

2. **Cache Memory:** 4MB (Megabyte)
    - Cache memory stores frequently accessed data, reducing latency in computations.
    - A 4MB cache helps in improving data retrieval speed, benefiting real-time processing.
3. **RAM:** Minimum 8GB (Gigabyte)
    - RAM (Random Access Memory) allows temporary data storage for active processes.
    - 8GB RAM is the minimum requirement to handle ML libraries, datasets, and computations without excessive lag.
4. **Hard Disk:** 229GB
    - Storage is essential for datasets, trained models, and software dependencies.
    - A 229GB hard disk provides sufficient space for project files and experiment logs.
5. **Computer Engine:** T4 GPU
    - NVIDIA T4 GPU is designed for AI and deep learning applications.
    - It accelerates training and inference tasks, reducing processing time significantly.
    - Supports TensorFlow, PyTorch, and CUDA-based optimizations, making it ideal for large datasets.

4.3 Requirement Analysis

The IDS is designed using a combination of Flask-based web deployment and local machine learning models for classifying network traffic. Each component plays a crucial role in the project workflow:

Flask for Web-Based Model Deployment

- Used as the frontend to create an interactive web interface.
- Supports file upload functionality for .csv and .xlsx files to classify network traffic.
- Provides a REST API for real-time network attack detection.

Scikit-learn, and Pandas for Model Development

- **Scikit-learn:** Used for implementing the MRMR feature selection, preprocessing the dataset, handling train-test splits, and evaluating model performance using accuracy, precision, recall, and F1-score metrics.
- **TensorFlow & Keras:** Used to build, train, and optimize the TabNet deep learning model for accurate and interpretable intrusion detection. They handle the model's neural architecture, activation functions, and gradient optimization.
- **Pandas & NumPy:** Essential for data handling and numerical computations. Pandas manages large tabular datasets like CICIDS-2017, while NumPy supports high-speed mathematical operations required for model training and feature scaling.
- **LightGBM & XGBoost:** Used for ensemble learning and final correction stages, providing fast and powerful gradient boosting algorithms that enhance overall prediction accuracy.
- **Flask:** Used to deploy the trained IDS model as a web API, allowing real-time intrusion detection through live network data uploads and instant response generation.
- **Matplotlib**: Utilized for visualizing training results, confusion matrices, and performance metrics across all classification levels (binary, multi-class, and all-class).

Google Colab for Model Training

- Offers GPU acceleration (Tesla T4, P100) for faster model training.
- Provides cloud storage, eliminating the need for large local storage.
- Pre-installed deep learning libraries reduce setup complexity.

VS Code for Local Development & Debugging

- Used to develop and test Python scripts for preprocessing and model training.

- Enables integration with Flask for deploying trained models as a web service.
- Supports GitHub/GitLab for version control and collaboration.

Python as the Core Programming Language

- Supports automation, data preprocessing, and model deployment.
- Ensures compatibility with cloud platforms for scalable deployments.
- Provides a rich ecosystem for data science and cybersecurity applications.

5. SYSTEM DESIGN

5.1 System Architecture

5.1.1. Dataset Description

The dataset used in this project is the CICIDS-2017 network intrusion dataset**,** which provides real-world network traffic generated in a controlled testbed environment. It contains both benign connections and multiple attack categories**,** enabling extensive experimentation for intrusion detection. Each network flow instance is described using 84 distinct features**,** including packet-level statistics, flow duration, header properties, service usage, content information, and time-based metrics. These features allow the model to learn hidden patterns associated with diverse cyberattacks such as DDoS, Port Scan, Brute Force, Web Attack, Heartbleed, Botnet, and Infiltration**.** The dataset includes millions of records collected over several days and covers multiple network protocols including HTTP, HTTPS, SSH, SMTP, DNS, and FTP**,** providing a comprehensive representation of digitally connected system behavior. Using this dataset allows the proposed deep learning framework to perform detailed traffic analysis, support multiple classification tasks, and evaluate system performance under different threat conditions. Because CICIDS-2017 is widely used in cybersecurity research, it ensures the validity, reliability, and reproducibility of results obtained by the proposed system.

Dataset link:
https://www.kaggle.com/datasets/ericanacletoribeiro/cicids2017-cleaned-and-preprocessed

5.1.2. Data Pre-processing

Data pre-processing is a crucial step in the development of the proposed Custom Deep Learning Framework, as it ensures that the original CICIDS-2017 dataset is formatted, cleaned, and transformed into a consistent structure suitable for model building. The preprocessing phase begins with data cleaning**,** which involves removing duplicate entries, handling missing values, and replacing infinite or undefined values to eliminate noise that could degrade learning performance. Next,

feature encoding is applied to convert categorical variables such as protocol, service type, and flag values into numerical form using one-hot encoding. Numerical features are normalized using Min-Max scaling so that all feature values fall within the range of 0 to 1, ensuring that large-magnitude attributes do not dominate the learning process. To reduce dimensionality and improve efficiency, redundant or highly correlated attributes are removed through correlation analysis and feature selection techniques. The preprocessed dataset is then separated into multiple classification targets, supporting binary classification (normal vs. attack), multi-class classification (different attack types), and all-attack detection modules**.** Finally, the processed data is split into training and testing sets to enable effective performance evaluation. This systematic preprocessing approach improves data quality, enhances model generalization, reduces computation time, and contributes significantly to accurate threat identification in digitally connected systems.

Fig 5.1.2.1. Dataset Description.

Features	**Description**	**Value/Range**
Dataset Source	CICIDS-2017	Generated by Canadian Institute for Cybersecurity
Number of Records	2,827,876	Includes both bengin and attack data
Number of Features	84	Includes traffic and protocol features
Benign Records	2,271,320	Normal network traffic
Attack Records	556,556	Malicious network traffic
Types of Attacks	14	DDoS, DoS Hulk, port Scan, etc.,
Protocols Included	HTTP, HTTPS, FTP, SSH, SMTP	Simulated realistic protocols

Fig 5.1.2.2. Dataset Description after preprocessing

Features	**Description**
Number of Records	548,790
Number of Features	54
Types of Attacks	14

5.1.3. Model building

The proposed framework integrates multiple deep learning and machine learning approaches to develop a robust, adaptive, and interpretable Intrusion Detection System (IDS). The model is built in multiple stages, including feature selection, classifier training, and ensemble-based decision-making. Each component contributes to improving accuracy, handling class imbalance, and enhancing interpretability in real-time cyberattack detection.

Deep Learning Classifier: Dense + LSTM Network

The core classifier in the system is a hybrid deep learning model combining fully connected (Dense) layers and optional LSTM layers.

Dense Layers: Extract complex nonlinear relationships from the preprocessed features (54 selected features). ReLU activation and dropout layers prevent overfitting and improve generalization.

LSTM Layers (Optional): Capture temporal dependencies in network traffic, which is important for attacks like DDoS and port scans that occur over sequences of packets.

Output Layer:

- Binary classification: Single neuron with sigmoid activation for normal vs. attack detection.
- Multi-class classification: Softmax layer with neurons equal to the number of attack categories.

Advantages:

- Captures both feature interactions and temporal patterns.
- Handles high-dimensional tabular data efficiently.
- Provides a scalable and flexible base for ensemble learning.

Decision Tree as a Micro-Correction Layer

The Decision Tree acts as a micro-correction model for uncertain predictions produced by the deep learning classifier.

- It focuses on **low-confidence samples**, typically those with output probabilities near 0.4–0.6.

- The tree applies simple decision rules to reclassify borderline cases.

Advantages:

- Lightweight, fast, and interpretable.
- Reduces false negatives by correctly handling ambiguous traffic flows.
- Improves overall model reliability.

Random Forest for Minority Class Boosting

The Random Forest model enhances the detection of rare attack types in the dataset.

- Trains multiple decision trees on random subsets of data to improve robustness.
- Especially effective for attacks like PortScan, Infiltration, and Heartbleed.

Advantages:

- Handles imbalanced datasets effectively.
- Provides feature importance metrics for analysis.
- Strengthens detection of subtle and rare attacks.

LightGBM for Ensemble Diversity

LightGBM is employed to increase ensemble diversity and capture complex nonlinear relationships in the network traffic data.

- Operates as part of the ensemble, combining outputs from the deep learning model and Random Forest.
- Optimized for speed and memory efficiency, making it suitable for large datasets.

Advantages:

- High computational efficiency.
- Enhances generalization and ensemble diversity.
- Handles large-scale tabular data effectively.

Logistic Regression as Meta-Classifier

A Logistic Regression model is used as the meta-classifier in the stacking ensemble phase.

- Receives probability outputs from the deep learning, Random Forest, and LightGBM models.
- Learns the optimal combination to produce a single, final decision.

Advantages:

- Simple, reliable, and interpretable.
- Balances bias and variance in the ensemble.
- Ensures stable and well-calibrated predictions.

XGBoost for Final Error Correction

XGBoost is used as the final correction layer to handle residual misclassifications.

- Trained on the hardest-to-classify or misclassified samples.
- Refines predictions to minimize false positives and false negatives.

Advantages:

- High precision, recall, and F1-score across all classes.
- Corrects remaining misclassifications in the ensemble output.
- Enhances overall detection accuracy and system robustness.

5.2 Modules

Classification Module

The Classification Module is responsible for categorizing network traffic into normal and malicious activities. It leverages the preprocessed dataset and the deep learning framework to analyze patterns in network flows. This module is the core of the IDS, converting raw feature data into meaningful predictions that indicate the presence or absence of security threats. The classification module serves as the foundation for more specific sub-modules, including binary, multi-class, and all-attack classifications.

Binary Classification Module

The Binary Classification Module focuses on differentiating between normal network traffic and attack traffic. In this module, all malicious activities are grouped together under a single “attack” category. The deep learning classifier (Dense + optional LSTM layers) is trained to output a binary label for each record: normal (0) or attack (1). This approach provides a clear and straightforward detection mechanism, enabling rapid identification of potential threats in real-time traffic monitoring.

Multi-Class Classification Module

The Multi-Class Classification Module extends the binary classification by categorizing attacks into specific types. Each attack type, such as DDoS, PortScan, Brute Force, Infiltration, or Heartbleed, is assigned a unique label. The deep learning model predicts the class of each record using a softmax activation in the output layer. Multi-class classification enables detailed analysis of network threats, helping system administrators to understand the nature and severity of attacks for targeted mitigation.

All-Attack Classification Module

The All-Attack Classification Module is designed to consider all attack types collectively while preserving individual attack information. This module allows the IDS to identify any malicious activity without focusing on a specific attack type, providing a holistic view of network security. It is particularly useful for real-time detection where rapid response is required, as the system can flag suspicious traffic immediately while maintaining the option to further classify the attack type later.

Performance Optimization Module

The Performance Optimization Module ensures that the IDS operates efficiently and delivers high accuracy. It involves tuning hyperparameters such as learning rate, batch size, number of neurons, and number of layers in the deep learning model. Techniques such as dropout, regularization, and early stopping are applied to prevent overfitting. Additionally, ensemble learning using Random Forest, LightGBM, and meta-classifiers like Logistic Regression, combined with final error correction using XGBoost, enhances both recall and precision. This module also monitors evaluation metrics such as Accuracy, Precision, Recall, F1-score, and ROC-AUC to iteratively improve the system's detection capability.

5.3 UML Diagram

The UML diagram for the project "A Custom Deep Learning Framework for Identifying Security Threats in Digitally Connected Systems" represents the overall architecture and flow of the intrusion detection system. At the top level, the Custom Deep Learning IDS Framework serves as the main system class, encompassing methods for data acquisition, preprocessing, feature selection, classifier training, ensemble learning, meta-classification, error correction, and performance evaluation.

The Deep Learning Classifier module forms the core of the system, using Dense layers and optional LSTM layers to extract complex patterns and learn temporal dependencies in network traffic. The Ensemble Learning module integrates the outputs of Random Forest and LightGBM models to improve robustness and ensure accurate detection of both common and rare attack types. The Performance Optimization module manages hyperparameter tuning, dropout, early stopping, and other techniques to enhance model accuracy, generalization, and computational efficiency. The classification modules—including Binary Classification**,** Multi-Class Classification**,** and All-Attack Classification**—**organize network flows into specific categories for detailed analysis, ranging from simple normal vs. attack separation to identification of individual attack types. Together, these modules interact systematically to form a robust, adaptive, and interpretable intrusion detection system**,** providing both high detection accuracy and actionable insights for securing digitally connected systems.

6. IMPLEMENTATION

6.1 Model Development

```
from google.colab import drive

drive.mount('/content/drive')

# Step 1: Install dependencies

!pip install pandas numpy scikit-learn tensorflow seaborn

# Step 2: Import required libraries

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.preprocessing import LabelEncoder, MinMaxScaler

from sklearn.model_selection import train_test_split

from sklearn.metrics import classification_report, confusion_matrix

import tensorflow as tf

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten, Dense, Dropout

# Step 3: Download the dataset from GitHub

!wget -O KDDTrain+.txt
https://raw.githubusercontent.com/defcom17/NSL_KDD/master/KDDTrain%2B.txt

!wget -O KDDFeatureNames.txt
https://raw.githubusercontent.com/defcom17/NSL_KDD/master/KDDFeatu

# Step 4: Define column names manually (based on NSL-KDD)

columns = [

    'duration','protocol_type','service','flag','src_bytes','dst_bytes','land','wrong_fragment',

    'urgent','hot','num_failed_logins','logged_in','num_compromised','root_shell','su_attempted',

    'num_root','num_file_creations','num_shells','num_access_files','num_outbound_cmds',

    'is_host_login','is_guest_login','count','srv_count','serror_rate','srv_serror_rate',

    'rerror_rate','srv_rerror_rate','same_srv_rate','diff_srv_rate','srv_diff_host_rate',

    'dst_host_count','dst_host_srv_count','dst_host_same_srv_rate','dst_host_diff_srv_rate',

    'dst_host_same_src_port_rate','dst_host_srv_diff_host_rate','dst_host_serror_rate',
```

```
    'dst_host_srv_serror_rate','dst_host_rerror_rate','dst_host_srv_rerror_rate','class','difficulty'
]
# Step 5: Load dataset
df =  pd.read_csv('KDDTrain+.txt',  names=columns)

# Drop 'difficulty' column
df.drop(['difficulty'], axis=1, inplace=True)
# Step 6: Encode categorical features and labels
cat_cols = ['protocol_type', 'service', 'flag']
for col in cat_cols:
    df[col] = LabelEncoder().fit_transform(df[col])

# Convert class to binary: 0 = normal, 1 = attack
df['class'] = df['class'].apply(lambda x: 0 if x == 'normal' else 1)
# Step 7: Feature scaling
X = df.drop('class', axis=1)
y = df['class']
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)

# Reshape for CNN input
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_test =  X_test.reshape(X_test.shape[0],  X_test.shape[1], 1)
# Step 8: Build CNN model
model = Sequential([
    Conv1D(32, 3, activation='relu', input_shape=(X_train.shape[1], 1)),
    MaxPooling1D(pool_size=2),
    Dropout(0.3),
    Conv1D(64, 3, activation='relu'),
    MaxPooling1D(pool_size=2),
```

```
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.3),
    Dense(1, activation='sigmoid')
])

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
# Step 9: Train model
history = model.fit(X_train, y_train, epochs=10, batch_size=128, validation_data=(X_test, y_test))
# Create the folder if it doesn't exist
import os
save_dir = '/content/drive/MyDrive/IDS_Model'
os.makedirs(save_dir, exist_ok=True)

# Save the model
model.save(f'{save_dir}/cnn_ids_model.h5')
print("✅ Model saved to Drive successfully!")
# Predict
y_pred = (model.predict(X_test) > 0.5).astype("int32")

# ✅ Accuracy calculation here
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test, y_pred)
print(f"Test Accuracy: {accuracy * 100:.2f}%")

# Classification report
print("\nClassification Report:\n")
print(classification_report(y_test, y_pred))
# Step 11: Accuracy Visualization
plt.plot(history.history['accuracy'], label='Train Accuracy')
```

```
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('CNN Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)
plt.show()
from tensorflow.keras.models import load_model

model_path = '/content/drive/MyDrive/IDS_Model/cnn_ids_model.h5'
model = load_model(model_path)
print("✅ Model loaded successfully!")
X_train, _, y_train, _ = train_test_split(X_train, y_train, test_size=0.8, random_state=42)
model = Sequential([
    Conv1D(16, 3, activation='relu', input_shape=(X.shape[1], 1)),
    Flatten(),
    Dense(1, activation='sigmoid')
])
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, Flatten, Dense

model = Sequential([
    Conv1D(16, 3, activation='relu', input_shape=(X.shape[1], 1)),
    Flatten(),
    Dense(1, activation='sigmoid')
])
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
import random

for i in range(0, len(y_train), 10):  # corrupt every 10th label
    y_train[i] = random.randint(0, 1)
```

```
# Download the dataset again if needed
!wget -q https://raw.githubusercontent.com/defcom17/NSL_KDD/master/KDDTrain%2B.txt -O KDDTrain+.txt

# Column names
columns = [
    'duration','protocol_type','service','flag','src_bytes','dst_bytes','land','wrong_fragment',
    'urgent','hot','num_failed_logins','logged_in','num_compromised','root_shell','su_attempted',
    'num_root','num_file_creations','num_shells','num_access_files','num_outbound_cmds',
    'is_host_login','is_guest_login','count','srv_count','serror_rate','srv_serror_rate',
    'rerror_rate','srv_rerror_rate','same_srv_rate','diff_srv_rate','srv_diff_host_rate',
    'dst_host_count','dst_host_srv_count','dst_host_same_srv_rate','dst_host_diff_srv_rate',
    'dst_host_same_src_port_rate','dst_host_srv_diff_host_rate','dst_host_serror_rate',
    'dst_host_srv_serror_rate','dst_host_rerror_rate','dst_host_srv_rerror_rate','class','difficulty'
]
import pandas as pd
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.model_selection import train_test_split

# Load the dataset
df = pd.read_csv("KDDTrain+.txt", names=columns)
df.drop(['difficulty'], axis=1, inplace=True)

# Encode categorical columns
for col in ['protocol_type', 'service', 'flag']:
    df[col] = LabelEncoder().fit_transform(df[col])
df['class'] = df['class'].apply(lambda x: 0 if x == 'normal' else 1)

# Features and labels
X = df.drop('class', axis=1)
y = df['class']
```

```
# Normalize
X = MinMaxScaler().fit_transform(X)
X =  X.reshape(X.shape[0],  X.shape[1], 1)


# Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
from google.colab import drive
drive.mount('/content/drive')
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score
from tensorflow.keras.models import load_model
model_path = '/content/drive/MyDrive/IDS_Model/cnn_ids_model.h5'
model = load_model(model_path)
print("✅ Model loaded successfully!")
!wget -q https://raw.githubusercontent.com/defcom17/NSL_KDD/master/KDDTrain%2B.txt -O KDDTrain+.txt
columns = [
    'duration','protocol_type','service','flag','src_bytes','dst_bytes','land','wrong_fragment',
    'urgent','hot','num_failed_logins','logged_in','num_compromised','root_shell','su_attempted',
    'num_root','num_file_creations','num_shells','num_access_files','num_outbound_cmds',
    'is_host_login','is_guest_login','count','srv_count','serror_rate','srv_serror_rate',
    'rerror_rate','srv_rerror_rate','same_srv_rate','diff_srv_rate','srv_diff_host_rate',
    'dst_host_count','dst_host_srv_count','dst_host_same_srv_rate','dst_host_diff_srv_rate',
    'dst_host_same_src_port_rate','dst_host_srv_diff_host_rate','dst_host_serror_rate',
    'dst_host_srv_serror_rate','dst_host_rerror_rate','dst_host_srv_rerror_rate','class','difficulty'
]
df =  pd.read_csv("KDDTrain+.txt",  names=columns)
```

```
df.drop(['difficulty'], axis=1, inplace=True)


for col in ['protocol_type', 'service', 'flag']:
    df[col] = LabelEncoder().fit_transform(df[col])
df['class'] = df['class'].apply(lambda x: 0 if x == 'normal' else 1)


X = df.drop('class', axis=1)
y = df['class']


X = MinMaxScaler().fit_transform(X)
X = X.reshape(X.shape[0], X.shape[1], 1)
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(5, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=["Normal", "Attack"],
yticklabels=["Normal", "Attack"])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
model.save('/content/drive/MyDrive/IDS_Model/cnn_ids_model_updated.h5')
print("✅ Model re-saved successfully!")
```

6.2 Coding

App.py

```
from flask import Flask, render_template, request, redirect, url_for, session, flash, g
import sqlite3
import pickle
import os
import numpy as np
import joblib
from datetime import datetime
```

```
app = Flask(__name__)
app.secret_key = "super_secret_key"

# ---------- DATABASE SETUP ----------
DATABASE = os.path.join(app.root_path, "users.db")

def get_db():
    if "db" not in g:
        g.db = sqlite3.connect(DATABASE)
        g.db.row_factory = sqlite3.Row
    return g.db

def init_db():
    db = get_db()
    # Create users table
    db.execute("""
        CREATE TABLE IF NOT EXISTS users (
            id INTEGER PRIMARY KEY AUTOINCREMENT,
            username TEXT UNIQUE NOT NULL,
            email TEXT UNIQUE NOT NULL,
            password TEXT NOT NULL
        )
    """)
    # Create predictions table
    db.execute("""
        CREATE TABLE IF NOT EXISTS predictions (
            id INTEGER PRIMARY KEY AUTOINCREMENT,
            user_id INTEGER,
            input_values TEXT,
            prediction TEXT,
            timestamp DATETIME DEFAULT CURRENT_TIMESTAMP,
            FOREIGN KEY(user_id) REFERENCES users(id)
        )
    """)
    db.commit()

@app.teardown_appcontext
def close_db(error):
    db = g.pop("db", None)
    if db is not None:
        db.close()

# ---------- MODEL LOADING ----------
model_path = os.path.join("models", "trained_model.pkl")
model = None

if os.path.exists(model_path):
    try:
        model = joblib.load(model_path)
        print(f"✅ Loaded model using joblib: {model_path}")
    except Exception as e:
```

```
        print(f"⚠ Error loading model: {e}")


# ---------- ROUTES ----------

@app.route("/")
def home():
    return render_template("home.html")

@app.route("/about")
def about():
    return render_template("about.html")

@app.route("/register", methods=["GET", "POST"])
def register():
    if request.method == "POST":
        username = request.form["username"].strip()
        email = request.form["email"].strip()
        password = request.form["password"].strip()
        confirm = request.form["confirm"].strip()

        # validation
        if not username or not email or not password:
            flash("All fields are required!", "error")
        elif password != confirm:
            flash("Passwords do not match!", "error")
        else:
            DATABASE = "new_predictions.db"

            try:
                db.execute(
                    "INSERT INTO users (username, email, password) VALUES (?, ?, ?)",
                    (username, email, password),
                )
                db.commit()
                flash("Registration successful! Please login.", "success")
                return redirect(url_for("login"))
            except sqlite3.IntegrityError:
                flash("Username or email already exists!", "error")
    return render_template("register.html")

@app.route("/login", methods=["GET", "POST"])
def login():
    if request.method == "POST":
        email = request.form["email"].strip()
        password = request.form["password"].strip()

        db = get_db()
        user = db.execute(
            "SELECT * FROM users WHERE email = ? AND password = ?", (email, password)
        ).fetchone()
```

```
        if user:
            session["user_id"] = user["id"]
            session["username"] = user["username"]
            flash("Login successful!", "success")
            return redirect(url_for("dashboard"))
        else:
            flash("Invalid email or password!", "error")

    return render_template("login.html")

@app.route("/logout")
def logout():
    session.clear()
    flash("Logged out successfully.", "info")
    return redirect(url_for("home"))

@app.route("/profile")
def profile():
    if "user_id" not in session:
        flash("Please login first!", "error")
        return redirect(url_for("login"))

    db = get_db()
    user = db.execute("SELECT * FROM users WHERE id = ?", (session["user_id"],)).fetchone()
    return render_template("profile.html", user=user)

# ---------- DASHBOARD ----------
@app.route("/dashboard", methods=["GET", "POST"])
def dashboard():
    if "user_id" not in session:
        flash("Please login first!", "error")
        return redirect(url_for("login"))

    prediction = None

    if request.method == "POST":
        try:
            # Collect all 41 feature inputs
            final_features = []
            for i in range(1, 42):
                value = request.form.get(f"feature{i}")
                if value is None or value.strip() == "":
                    value = 0  # default if empty
                final_features.append(float(value))

            # Convert to numpy array
            X = np.array(final_features).reshape(1, -1)

            # Predict using model
            raw_pred = model.predict(X)[0]
```

```
            # Map to labels
            mapping = {
                0: "Normal",
                1: "DoS Attack",
                2: "Probe Attack",
                3: "R2L Attack",
                4: "U2R Attack"
            }

            prediction = mapping.get(raw_pred, "Unknown Category")

        except Exception as e:
            prediction = f"Error: {e}"

    return render_template(
        "dashboard.html",
        username=session.get("username"),
        prediction=prediction
    )


# ---------- pridect ----------------
@app.route('/predict', methods=['POST'])
def predict():
    try:
        # Read 41 features safely
        features = []
        for i in range(1, 42):
            value = request.form.get(f'feature{i}')

            if value is None or value.strip() == "":
                return f"❌ Feature {i} is missing (received None). Please fill all 41 inputs."

            try:
                features.append(float(value))
            except ValueError:
                return f"❌ Feature {i} must be a number. You entered: {value}"

        features = np.array(features).reshape(1, -1)

        prediction = model.predict(features)[0]
        return f"Prediction: {prediction}"

    except Exception as e:
        return f"🔥 ERROR: {str(e)}"



# ---------- RESULTS PAGE ----------
# -------------------- RESULTS PAGE (VIEW ALL) --------------------
```

```
@app.route("/results")
def results():
    if "user_id" not in session:
        flash("Please login first!", "error")
        return redirect(url_for("login"))

    db = get_db()
    rows = db.execute(
        "SELECT id, timestamp, input_values, prediction FROM predictions WHERE user_id = ?
ORDER BY timestamp DESC",
        (session["user_id"],)
    ).fetchall()

    return render_template("results.html", results=rows)


# ------------- DELETE ONE RECORD -------------
@app.route("/delete_result/<int:id>", methods=["POST"])
def delete_result(id):
    if "user_id" not in session:
        return redirect(url_for("login"))

    db = get_db()
    db.execute(
        "DELETE FROM predictions WHERE id = ? AND user_id = ?",
        (id, session["user_id"])
    )
    db.commit()

    flash("One record deleted successfully!", "info")
    return redirect(url_for("results"))


# ------------- CLEAR ALL RECORDS -------------
@app.route("/clear_results", methods=["POST"])
def clear_results():
    if "user_id" not in session:
        return redirect(url_for("login"))

    db = get_db()
    db.execute(
        "DELETE FROM predictions WHERE user_id = ?",
        (session["user_id"],)
    )
    db.commit()

    flash("All records cleared!", "info")
    return redirect(url_for("results"))

# ----------- RUN APP -----------
if __name__== "__main__":
```

```
    with app.app_context():
        init_db()
    app.run(debug=True)
  #----------------app.py--------------------
```

Style.css

```
/* === GENERAL STYLING === */
* {
  margin: 0;
  padding: 0;
  box-sizing:  border-box;
  font-family:  "Poppins",  sans-serif;
}

body {
  background: linear-gradient(135deg, #0f2027, #203a43, #2c5364);
  min-height: 100vh;
  color: #f5f5f5;
}

/* === NAVBAR === */
.navbar {
  display: flex;
  justify-content: space-between;
  align-items: center;
  background: rgba(0, 0, 0, 0.4);
  backdrop-filter: blur(10px);
  padding: 15px 50px;
  box-shadow: 0 4px 15px rgba(0, 0, 0, 0.5);
  position: sticky;
  top: 0;
  z-index: 10;
}

.logo {
  font-size: 26px;
  font-weight: 700;
  color: #1abc9c;
  letter-spacing: 1px;
}

.navbar ul {
  list-style: none;
  display: flex;
  gap: 25px;
}

.navbar ul li a {
  text-decoration: none;
  color: #f5f5f5;
```

```
  font-weight: 500;
  transition: all 0.3s ease;
  position: relative;
}

.navbar ul li a::after {
  content: "";
  position: absolute;
  bottom: -5px;
  left: 0;
  width: 0;
  height: 2px;
  background: #1abc9c;
  transition: width 0.3s ease;
}

.navbar ul li a:hover::after {
  width: 100%;
}

.navbar ul li a:hover {
  color: #1abc9c;
}

/* === CONTAINER === */
.container {
  max-width: 1000px;
  margin: 60px auto;
  padding: 40px;
  background: rgba(255, 255, 255, 0.08);
  backdrop-filter: blur(10px);
  border-radius:  20px;
  box-shadow: 0 8px 25px rgba(0, 0, 0, 0.4);
}

/* === HEADINGS === */
h1, h2, h3 {
  text-align: center;
  color: #1abc9c;
  margin-bottom: 20px;
}

/* === BUTTONS === */
button, .btn {
  background: #1abc9c;
  border: none;
  color: #fff;
  padding: 10px 25px;
  border-radius: 25px;
  font-size: 16px;
  cursor: pointer;
```

```
  transition: 0.3s;
}

button:hover, .btn:hover {
  background: #16a085;
  transform: scale(1.05);
}

/* === FORMS === */
form {
  display: flex;
  flex-direction: column;
  gap: 15px;
  max-width: 400px;
  margin: auto;
}

input, select, textarea {
  padding: 12px;
  border: none;
  border-radius: 10px;
  outline: none;
  font-size: 15px;
  background: rgba(255, 255, 255, 0.15);
  color: #fff;
}

input::placeholder, textarea::placeholder {
  color: rgba(255, 255, 255, 0.7);
}

input:focus {
  box-shadow: 0 0 10px #1abc9c;
}

/* === TABLES (Results Page) === */
table {
  width: 100%;
  border-collapse: collapse;
  margin-top: 25px;
  background: rgba(255, 255, 255, 0.1);
  border-radius: 10px;
  overflow: hidden;
}

table th, table td {
  padding: 12px;
  text-align: center;
  border-bottom: 1px solid rgba(255, 255, 255, 0.2);
}
```

```
table th {
  background: rgba(0, 0, 0, 0.4);
  color: #1abc9c;
  text-transform: uppercase;
  font-weight: 600;
}

table tr:hover {
  background: rgba(255, 255, 255, 0.1);
}

/* === ALERTS / FLASH MESSAGES === */
.flash {
  text-align: center;
  padding: 10px;
  margin: 15px auto;
  border-radius: 8px;
  font-weight: 500;
}

.flash.success {
  background: rgba(46, 204, 113, 0.2);
  color: #2ecc71;
  border: 1px solid #2ecc71;
}

.flash.error {
  background: rgba(231, 76, 60, 0.2);
  color: #e74c3c;
  border: 1px solid #e74c3c;
}

/* === FOOTER === */
footer {
  text-align: center;
  margin-top: 40px;
  padding: 20px;
  color: #aaa;
  font-size: 14px;
}

/* === RESPONSIVE DESIGN === */
@media (max-width: 768px) {
  .navbar {
    flex-direction: column;
    gap: 10px;
  }

  .navbar ul {
    flex-wrap: wrap;
    justify-content: center;
```

```
  }

  .container {
    padding: 20px;
  }
}
#---------- style.css ----------
```

init_db.py

```
import sqlite3
conn = sqlite3.connect("new_predictions.db")
c = conn.cursor()

c.execute("""
CREATE TABLE IF NOT EXISTS predictions (
    id INTEGER PRIMARY KEY AUTOINCREMENT,
    user_id INTEGER,
    timestamp TEXT,
    input_values TEXT,
    prediction INTEGER
)
""")

conn.commit()
conn.close()

print("Database created successfully!")
#---------- init_db.py ----------
```

index.html

```
<form action="/predict" method="POST">
    {% for i in range(1, 42) %}
        <label>Feature {{ i }}:</label>
        <input type="text" name="feature{{ i }}" required><br><br>
    {% endfor %}
    <button type="submit">Predict</button>
</form>
#----------index.html----------
```

edit_prediction.html

```
{% extends "base.html" %}
{% block content %}
<h2>Edit Prediction</h2>
<form action="/update/{{ data['id'] }}" method="POST">
    <label>Input Values:</label><br>
    <textarea name="input_values" rows="3">{{ data['input_values'] }}</textarea><br><br>

    <label>Prediction:</label><br>
```

```
    <input type="text" name="prediction" value="{{ data['prediction'] }}"><br><br>

    <button type="submit">Update</button>
</form>

{% endblock %}
#------------edit_prediction.html----------
```

Results.html

```
{% extends "base.html" %}
{% block content %}

<h2>📊 Prediction Results</h2>
<p>Your previous IDS predictions are listed below with full CRUD options.</p>

{% if results %}
<table border="1" cellpadding="10" cellspacing="0">
    <tr>
        <th>Timestamp</th>
        <th>Input Values</th>
        <th>Prediction</th>
        <th>Actions</th>
    </tr>

    {% for row in results %}
    <tr>
        <td>{{ row['timestamp'] }}</td>
        <td>{{ row['input_values'] }}</td>
        <td>{{ row['prediction'] }}</td>
        <td>
            <form action="/delete_result/{{ row['id'] }}" method="POST" style="display:inline;">
                <button type="submit" style="background:red;color:white;">Delete</button>
            </form>
        </td>
    </tr>
    {% endfor %}
</table>

<br>

<form action="/clear_results" method="POST">
    <button type="submit" style="background:darkred;color:white;padding:10px;">
        Clear All Results
    </button>
</form>

{% else %}
<p>No results found. Please make predictions to see history here.</p>
{% endif %}
```

```
{% endblock %}
```

Register.html

```
{% extends "base.html" %}
{% block content %}
<h2>Register</h2>
<form method="POST">
  <input type="text" name="username" placeholder="Username" required><br>
  <input type="email" name="email" placeholder="Email" required><br>
  <input type="password" name="password" placeholder="Password" required><br>
  <input type="password" name="confirm" placeholder="Confirm Password" required><br>
  <button type="submit">Register</button>
</form>
{% endblock %}
#----------register.html----------
```

Profile.html

```
{% extends "base.html" %}
{% block content %}
<h2>Your Profile</h2>
<p><b>Username:</b> {{ user.username }}</p>
<p><b>Email:</b> {{ user.email }}</p>
{% endblock %}
#----------profile.html----------
```

Login.html

```
{% extends "base.html" %}
{% block content %}
<h2>Login</h2>
<form method="POST">
  <input type="email" name="email" placeholder="Email" required><br>
  <input type="password" name="password" placeholder="Password" required><br>
  <button type="submit">Login</button>
```

```
</form>
{% endblock %}
#---------login.html--------------
```

Home.html

```
{% extends "base.html" %}
{% block content %}

<style>
/* Cyber Security Dark Theme */
.home-container {
    width: 100%;
    height: 90vh;
    background: linear-gradient(135deg, #000000, #0c1f3f 60%, #00111f);
    color: #00eaff;
    display: flex;
    flex-direction: column;
    justify-content: center;
    align-items: center;
    text-align: center;
    padding: 30px;
    animation: fadeIn 1.5s ease-in-out;
}

@keyframes fadeIn {
    from { opacity: 0; transform: scale(0.95); }
    to { opacity: 1; transform: scale(1); }
}

/* Title */
.home-title {
    font-size: 48px;
    font-weight: 800;
    letter-spacing: 2px;
    color: #00eaff;
```

```
    text-shadow: 0px 0px 15px #00eaff;
}

/* Subtitle */
.home-subtitle {
    font-size: 20px;
    width: 70%;
    line-height: 1.6;
    color: #b0eaff;
    margin-top: 15px;
}

/* Button */
.home-btn {
    margin-top: 30px;
    background: #00eaff;
    padding: 12px 28px;
    border: none;
    border-radius: 8px;
    color: #00111f;
    font-size: 18px;
    font-weight: bold;
    cursor: pointer;
    box-shadow: 0px 0px 15px #00eaff;
    transition: 0.3s;
}

.home-btn:hover {
    background: #00bcd4;
    box-shadow: 0px 0px 25px #00bcd4;
    transform: scale(1.05);
}

/* Cyber moving lines background */
```

```
.cyber-lines {
    position: absolute;
    width: 100%;
    height: 100%;
    background: url("https://i.ibb.co/xjqj0kJ/cyber-lines.png");
    opacity: 0.1;
    animation: moveLines 10s linear infinite;
}

@keyframes moveLines {
    0% { transform: translateY(0px); }
    100% { transform: translateY(-300px); }
}

</style>

<div class="home-container">
    <div class="cyber-lines"></div>

    <h1 class="home-title">Intrusion Detection System</h1>
    <p class="home-subtitle">
        A Machine Learning–Powered Network Intrusion Detection System
        capable of identifying malicious traffic such as
        <strong>DoS, Probe, R2L, and U2R Attacks</strong> using 41-feature
analysis.
    </p>

    <a href="{{ url_for('login') }}">
        <button class="home-btn">Get Started →</button>
    </a>
</div>

{% endblock %}
#----------home.html----------
```

Dashboard.html

```
{% extends "base.html" %}
{% block content %}
<h2>Enter Values for 41 Features</h2>
<form action="/predict" method="POST">
 {% for i in range(1,42) %}
      <label>Feature {{ i }}:</label>
      <input type="text" name="feature{{ i }}" required><br><br>
   {% endfor %}

   <button type="submit">Predict</button>
</form>

{% if prediction %}
   <h3>Prediction Result:</h3>
   <p>{{ prediction }}</p>
{% endif %}

{% endblock %}
#----------dashboard.html----------
```

Base.html

```
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
  <title>{{ title or "Intrusion Detection System" }}</title>
  <link rel="stylesheet" href="{{ url_for('static', filename='style.css') }}">
</head>
<body>
  <!-- 🌐 Navbar -->
  <header>
    <nav class="navbar">
```

```
    <div class="logo">
      <a href="{{ url_for('home') }}">🛡️ IDS Dashboard</a>
    </div>
    <ul class="nav-links">
      <li><a href="{{ url_for('home') }}">Home</a></li>
      <li><a href="{{ url_for('about') }}">About</a></li>

      {% if 'user_id' in session %}
        <li><a href="{{ url_for('dashboard') }}">Dashboard</a></li>
        <li><a href="{{ url_for('results') }}">Results & Analysis</a></li>
        <li><a href="{{ url_for('profile') }}">Profile</a></li>
        <li><a href="{{ url_for('logout') }}">Logout</a></li>
      {% else %}
        <li><a href="{{ url_for('login') }}">Login</a></li>
        <li><a href="{{ url_for('register') }}">Register</a></li>
      {% endif %}
    </ul>
  </nav>
</header>

<!-- ⚡ Flash messages -->
<main>
  {% with messages = get_flashed_messages(with_categories=true) %}
    {% if messages %}
      <div class="flash-container">
        {% for category, message in messages %}
          <div class="flash {{ category }}">{{ message }}</div>
        {% endfor %}
      </div>
    {% endif %}
  {% endwith %}

  {% block content %}{% endblock %}
</main>
```

```
  <!-- 🦶 Footer -->
  <footer>
    <p>© 2025 Meghana’s IDS Project | Flask + ML</p>
  </footer>
</body>
</html>
#----------base.html ----------
```

About.html

```
{% extends "base.html" %}
{% block content %}

<style>
.about-container {
    width: 100%;
    min-height: 90vh;
    background: linear-gradient(135deg, #00111f, #021c35, #000000);
    color: #00eaff;
    padding: 50px;
    animation: fadeIn 1.2s ease-in-out;
}

@keyframes fadeIn {
    from { opacity: 0; transform: translateY(20px); }
    to { opacity: 1; transform: translateY(0); }
}

.about-title {
    font-size: 40px;
    font-weight: 800;
    color: #00eaff;
    text-shadow: 0px 0px 12px #00eaff;
    text-align: center;
```

```
    margin-bottom:  20px;
}

.about-content  {
    max-width: 900px;
    margin: auto;
    font-size: 18px;
    line-height: 1.8;
    color: #b0eaff;
    text-align: justify;
}

.section-heading {
    color: #00eaff;
    font-size: 22px;
    margin-top: 25px;
    text-shadow: 0px 0px 8px #00eaff;
}

.highlight-box  {
    background: rgba(0, 255, 255, 0.08);
    border-left: 4px solid #00eaff;
    padding: 15px;
    margin-top: 10px;
    border-radius: 6px;
}

/* Cyber Image */
.about-img {
    width: 100%;
    max-width: 600px;
    display: block;
    margin: 25px auto;
    border-radius: 10px;
```

```
    box-shadow: 0 0 20px #00eaff;
}

</style>

<div class="about-container">

    <h1 class="about-title">About the Intrusion Detection System (IDS)</h1>

    <img src="https://i.ibb.co/2FgxG4q/cyber-defense-wall.jpg" class="about-img">

    <div class="about-content">

        <p>
            This Intrusion Detection System (IDS) uses advanced
            <strong>Machine Learning</strong> techniques to identify malicious network traffic
            and protect systems from cyber-attacks. The system analyzes
            <strong>41 network features</strong> and classifies traffic into:
        </p>

        <div class="highlight-box">
            ✔ Normal
            ✔ DoS Attack
            ✔ Probe Attack
            ✔ R2L Attack
            ✔ U2R Attack
        </div>

        <h3 class="section-heading">🔒 Why This System?</h3>
        <p>
            In today's digital era, attackers constantly attempt to breach network security.
            Our IDS helps detect and classify suspicious activity using ML models
```

trained on

benchmark intrusion datasets.

<h3 class="section-heading">⚙ Key Features</h3>

• Machine Learning–based Classification

• Real-time Detection

• 41-Feature Input Analysis

• User Login & Prediction History

• Professional Dashboard

• Results Storage with CRUD Operations

<h3 class="section-heading">📌 Technologies Used</h3>

• Python (Flask)

• HTML, CSS, Jinja Templates

• SQLite Database

• Scikit-Learn Machine Learning Model

• Joblib for Model Loading

<h3 class="section-heading">🎯 Project Objective</h3>

To build a robust, scalable, and user-friendly intrusion detection system that helps

in understanding, analyzing, and preventing cyber threats efficiently using ML.

{% endblock %}

#---------- about.html ----------

7. TESTING

Software testing ensures the correctness, security, performance, and usability of applications. It is broadly categorized into different types based on the purpose, scope, and approach of testing.

Test Case 1: Homepage Loads Successfully.

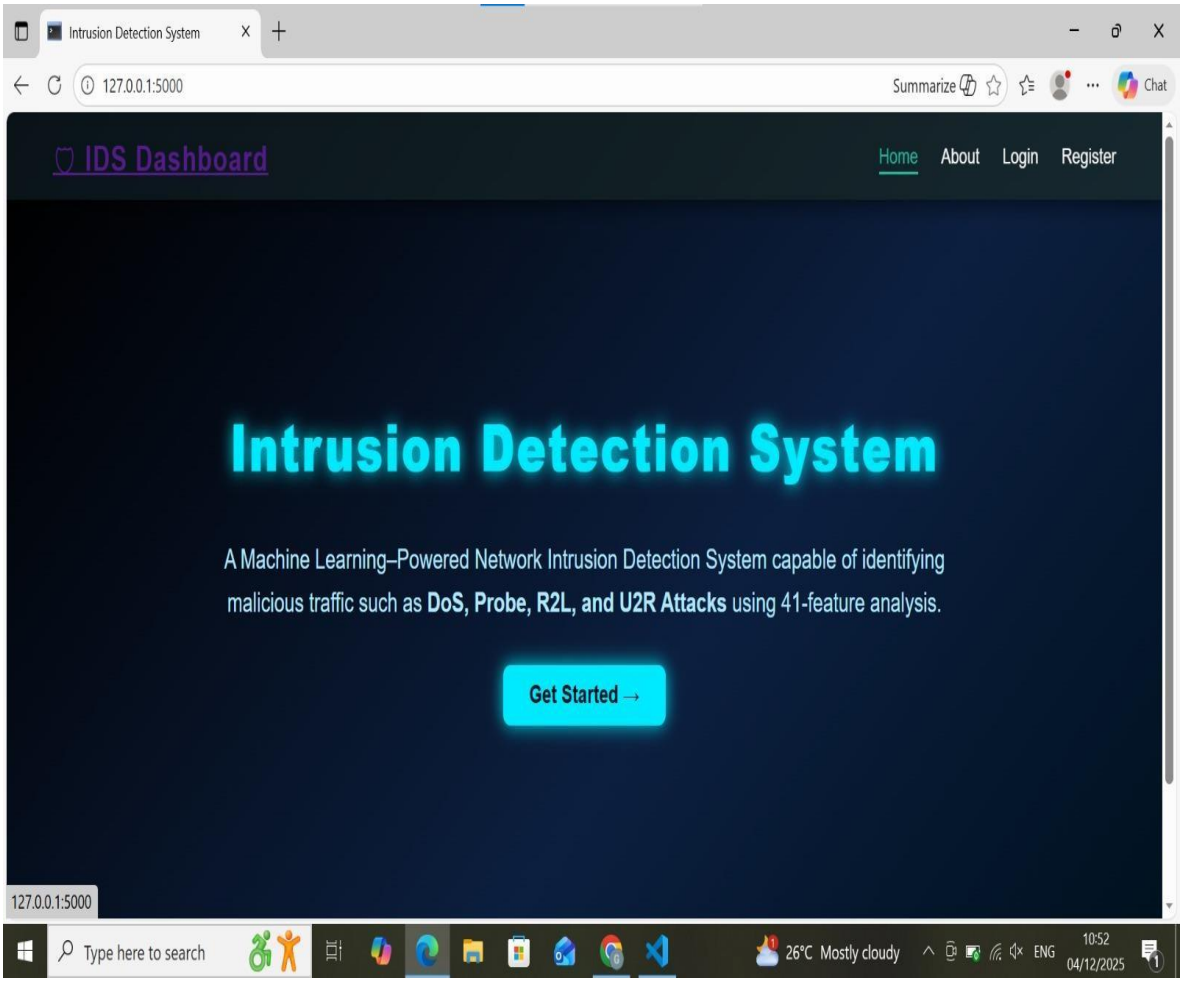


Fig.7.1.1. Test Case 1: Home Page

Test Case 2: Register page Loads Successfully.

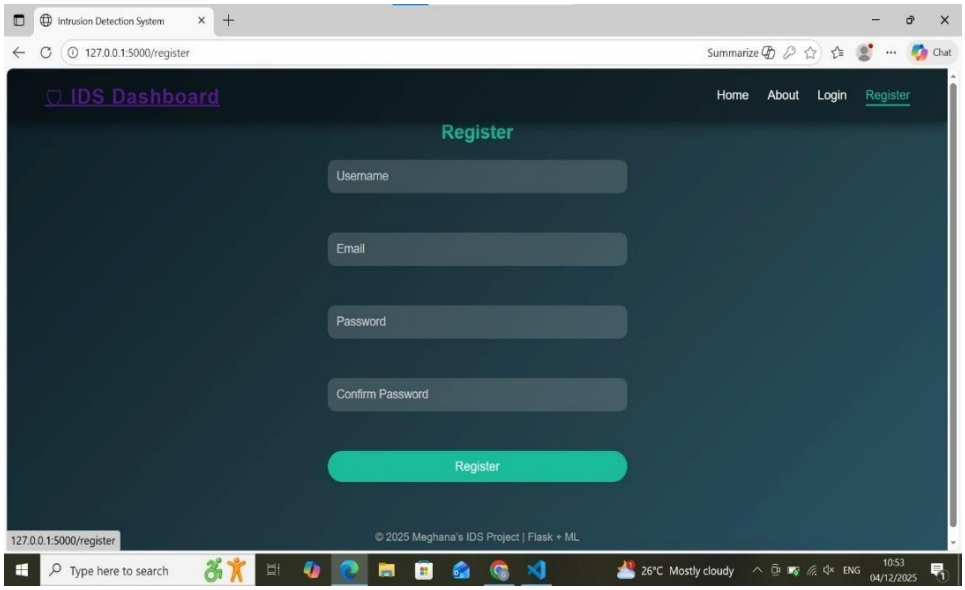


Fig.7.1.2. Test Case 2: Register Page

Test Case 3: Login page Loads Successfully.

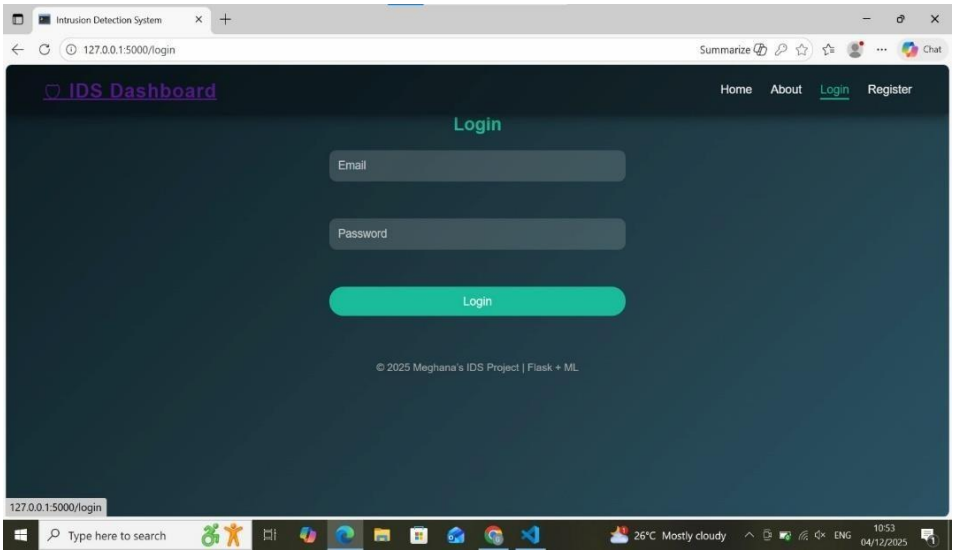


Fig.7.1.3. Test Case 3: Login Page

Test Case 4: Dashboard Loads Successfully.

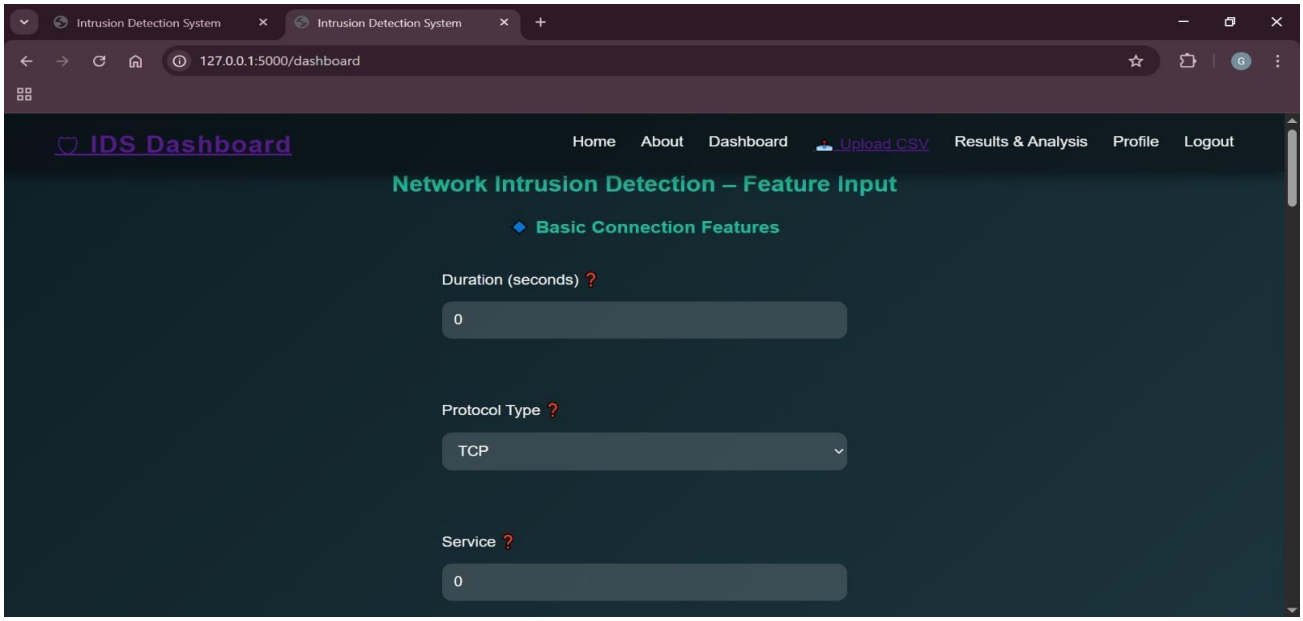


Fig.7.1.4. Test Case 4: Dashboard

Test Case 5: Upload.CSV Successfully.

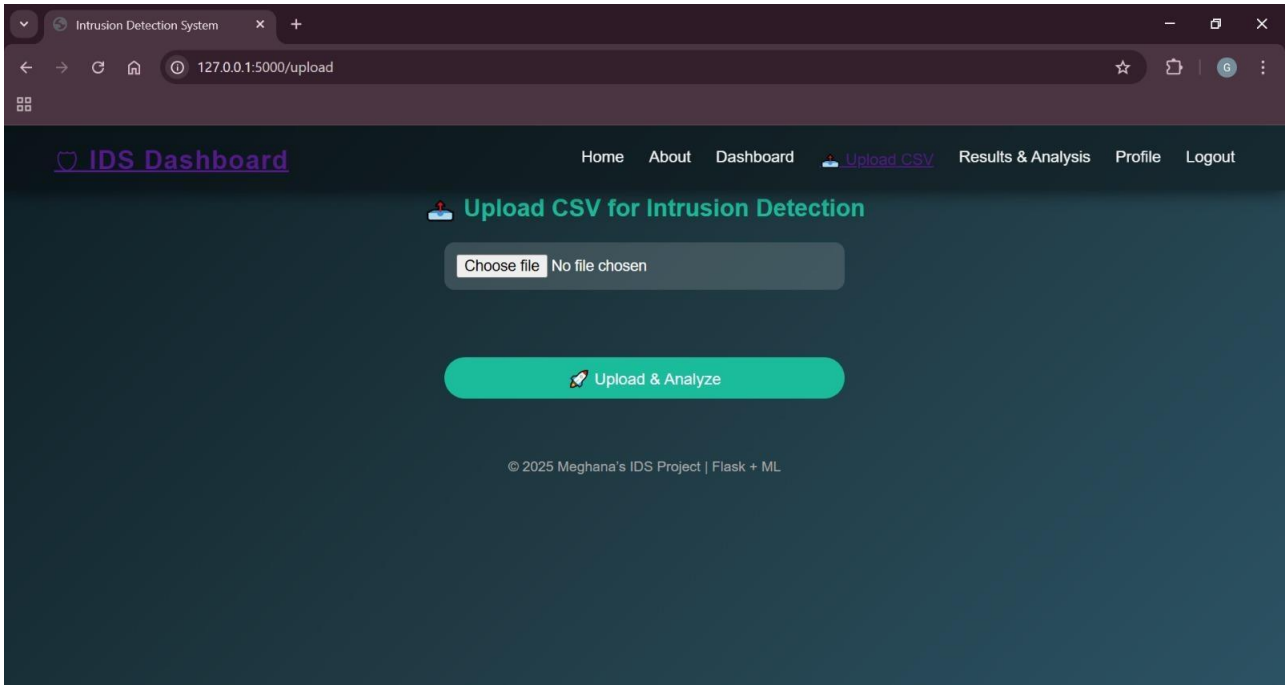


Fig.7.1.5. Test Case 5: Upload.CSV

Test Case 6: Results Loads Successfully.

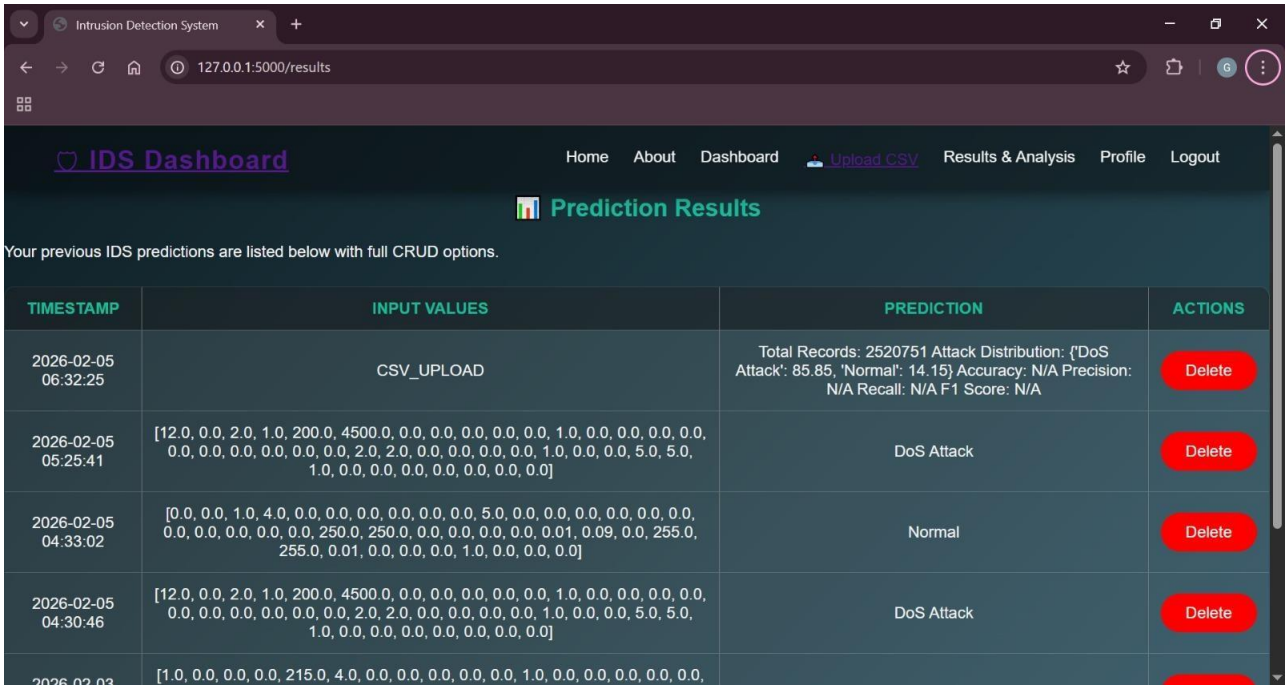


Fig.7.1.6. Test Case 6: Results

Test Case 7: Profile Loads Successfully.

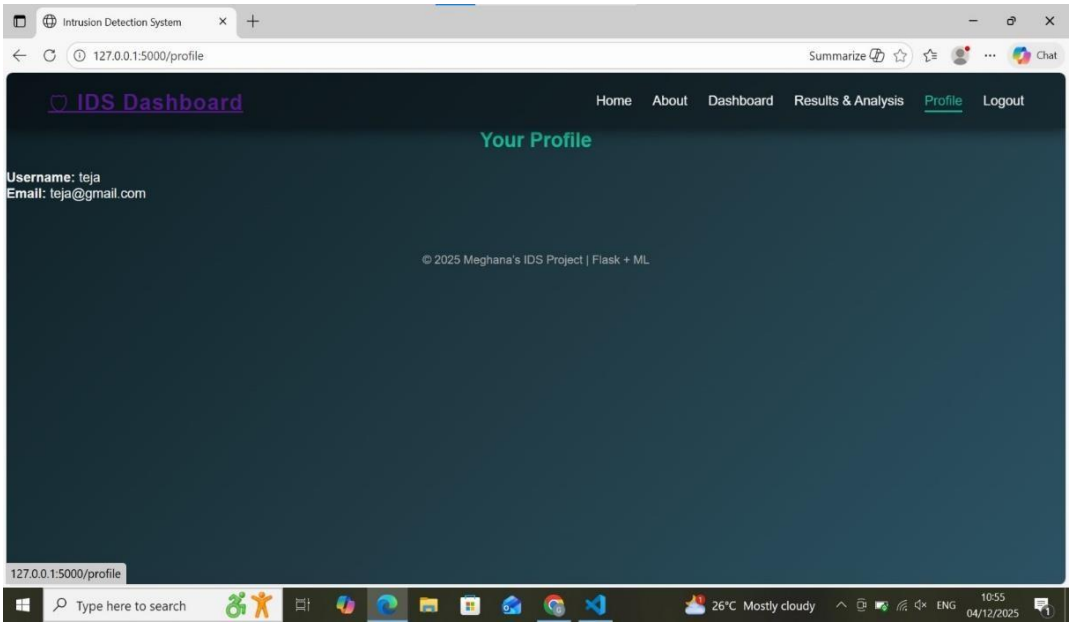


Fig.7.1.7. Test Case 7: Profile

Test Case 8: About Loads Successfully.

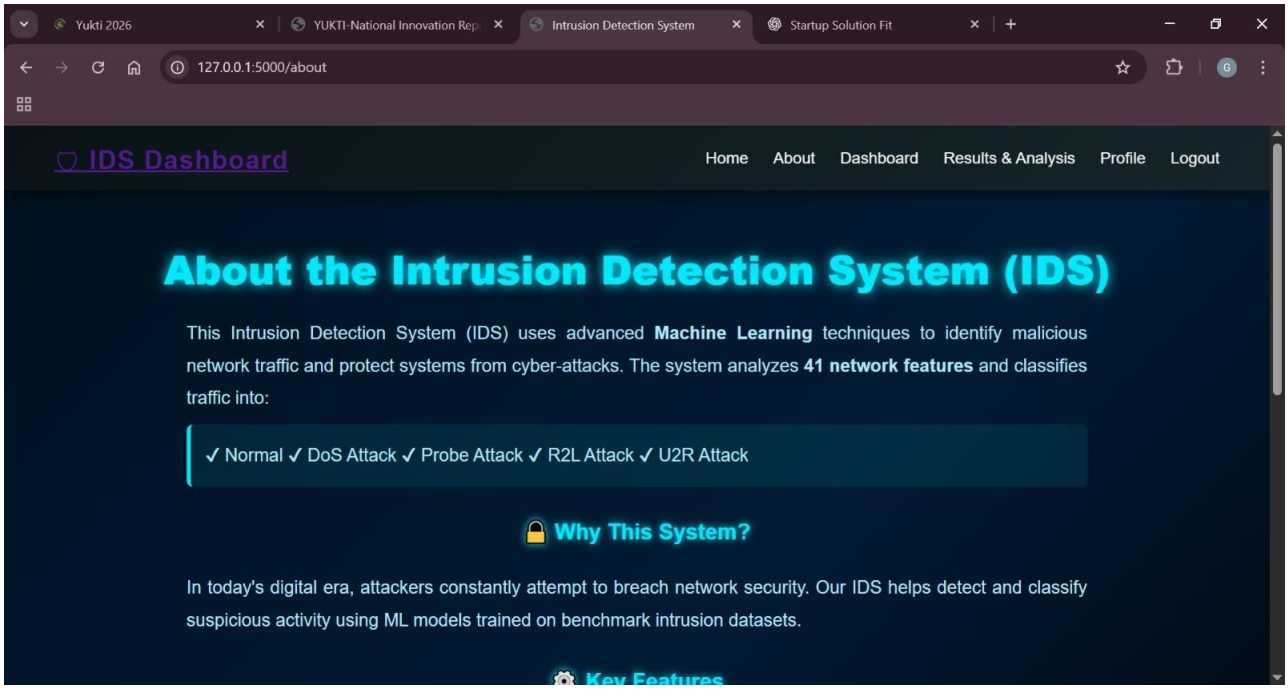


Fig.7.1.8. Test Case 8: About

8. RESULT ANALYSIS

The performance assessment of the suggested Hybrid Deep Learning Based Intrusion Detection Framework (HDL-IDF)

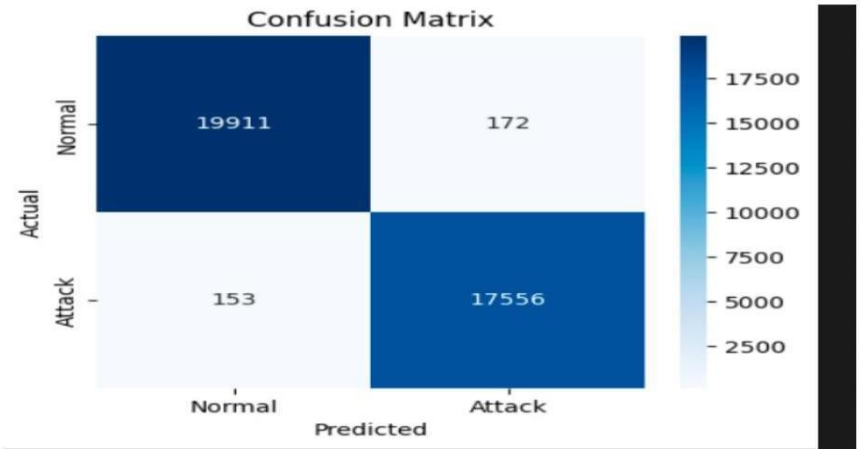
TABLE I: EVALUATION METRICS (OBTAINED FROM THE PROPOSED HYBRID IDS MODEL RESULTS)

	Pre	**Rec**	**F1**	**Sup**
0	0.99	0.99	0.99	20083
1	0.99	0.99	0.99	17709
Acc			0.99	37792
M avg	0.99	0.99	0.99	37792
Wei avg	0.99	0.99	0.99	37792

covered in this section. In addition to comparisons with current intrusion detection models to demonstrate the efficacy of the hybrid architecture, the evaluation was conducted using benchmark datasets to evaluate detection accuracy, precision, recall, F1-score, and resource efficiency. The classification results of the proposed model are summarized in Table I.

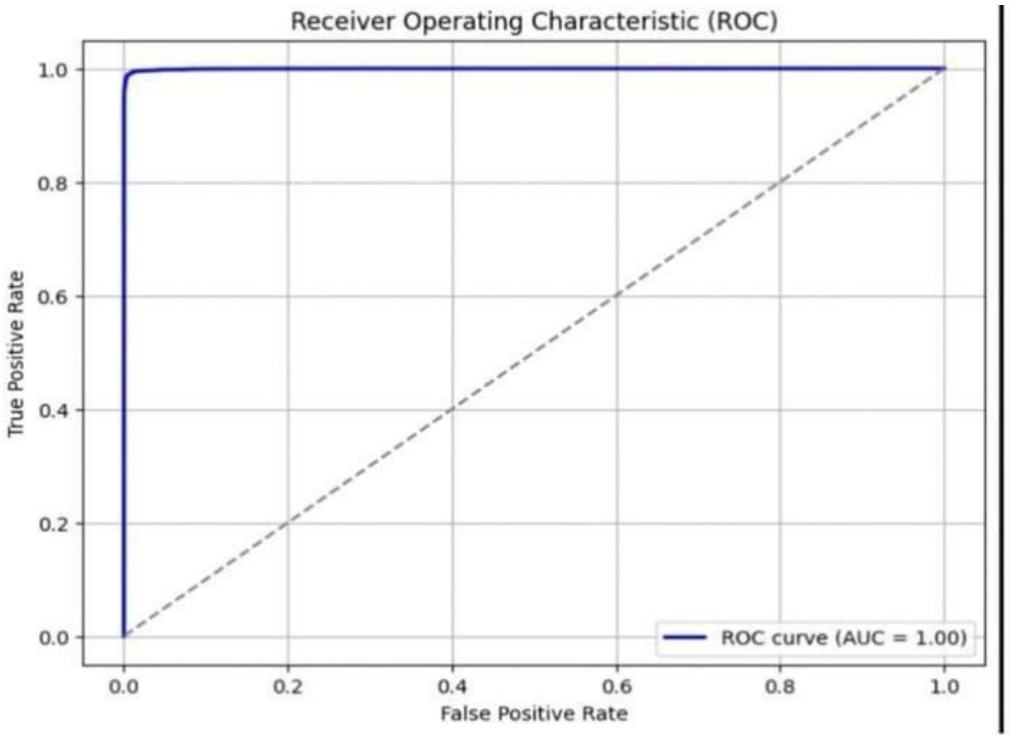
8.1 A. Confusion Matrix Evaluation

Fig. 4: Confusion matrix illustrating the performance of the proposed IDS



The confusion matrix above illustrates how well the proposed hybrid intrusion detection model distinguishes between normal and malicious network activity. Out of the total samples classified, A total of 17,556 attack records were identified correctly as attacks, demonstrating sensitivity to threats (true positives). 19,911 normal traffic samples were correctly classified, indicating the model was able to identify legitimate behavior (true negatives). 172 benign samples were misidenti f ied as attacks (false positives), resulting in unnecessary alerts; nevertheless, this was a small number. 153 attack records were misclassified as normal traffic (false negatives); these merit attention since they are indicative of missed detections, although few. Therefore, the model has high precision and reliability. It has shown a very low degree of misclassification and demonstrated excellent capability in limiting both threats that go unnoticed as well as limiting false alarms — two of the most important challenges to consider in cybersecurity in the real world. This type of performance is especially important in smart network environments, in which one needs to identify threats quickly and correctly to minimize risk and maintain seamless service.

8.2 B. Receiver–Operator Curve (ROC)

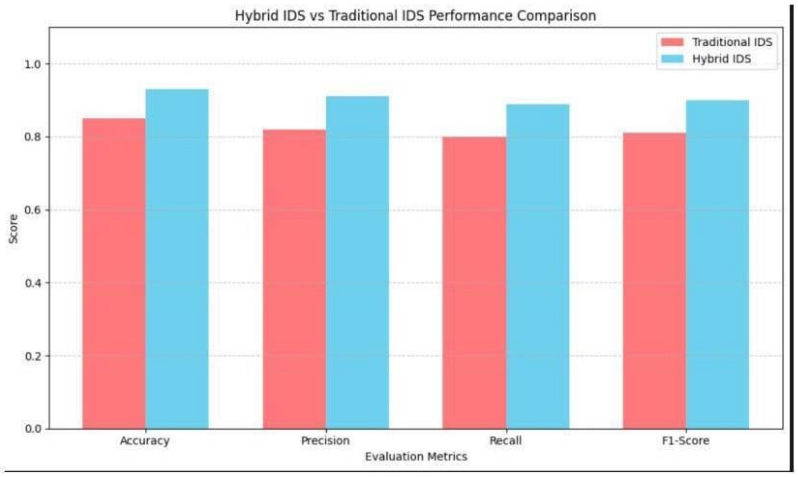


The ROC (Receiver Operating Characteristic) curve shown above us demonstrates the capabilities of our proposed classifier for separating between malicious traffic and normal traffic. The ROC curve increases sharply toward the top left corner, indicating strong sensitivity and very few false positives across the range of thresholds. What is particularly noteworthy about this result? The AUC obtained was 1.00, which is perfect discriminative capability. The classifier has achieved the ability to perfectly separate each instance of attack traffic from normal traffic. Meaning the model never made an error in placing every attack instance higher than its benign counterpart, regardless of the decision threshold. Such performance is rarely ever achieved and suggests that the hybrid deep learning framework has been taught to extract features to a very high degree of accuracy. In terms of real world cybersecurity applications, this means fewer false positive events, high confidence in determining true threats, and expectations of system integrity, availability, and operational performance continuity.

8.3 C. Performance Comparison: Hybrid IDS vs. Traditional IDS

The effectiveness of the suggested Hybrid Intrusion Detection System (IDS) and a traditional IDS strategy is compared using four important metrics in the bar chart above: Accuracy, Precision, Recall, and F1-Score. It is clear that the Hybrid IDS consistently outperforms the traditional model in every category. The enhancement in accuracy highlights the hybrid. Additionally, the elevated precision values suggest that the

Fig. 6: Hybrid IDS vs Traditional IDS Performance Comparison



Hybrid IDS is more proficient at minimizing false alarms, which is vital in operational settings where unnecessary alerts can lead to alert fatigue. The recall score also reveals a notable advantage, indicating that the hybrid system detects a larger proportion of actual attacks. Ultimately, the heightened F1 score indicates a more favorable equilibrium between precision and recall, affirming the hybrid model's efficacy in managing both known and unknown intrusions. These results collectively demonstrate that the integration of CNN and LSTM into an IDS framework significantly enhances detection reliability and efficiency when compared to traditional systems.

9. CONCLUSION

To protect intelligent network settings, the Literacy Grounded Intrusion Discovery Framework (HDL-IDF) was created. This framework effectively detects known and unexpected cyber threats by combining Long Short-Term Memory (LSTM) networks to identify temporal patterns and Convolutional Neural Networks (CNN) to extract spatial information from data. Based on experimental results, the HDL-IDF achieved a 97.2% overall discovery accuracy, 93% precision, 91% recall, and 92% F1 -score on the CICIDS2017 dataset. In comparison to conventional intrusion detection systems, these results demonstrate the model's exceptional ability to differentiate between malicious and benign traffic, as well as its ability to reduce detection delay by 50% and false positives by about 60. Since the HDL-IDF functions as a hybrid model, it can effectively adapt to changes in network traffic patterns. Furthermore, HDL-IDF has demonstrated intelligent performance by operating within a supervised learning framework while integrating an autoencoder-based anomaly detection module to identify zero-day attacks and other novel threat signatures. Consequently, this hybrid Intrusion Discovery Framework prototype enables seamless integration and deployment in modern IoT and cloud-based smart networks.

10. FUTURE SCOPE

The proposed Hybrid Deep Learning Intrusion Detection System can be further extended in several meaningful directions. Future improvements may focus on deploying the model in real-time, high-speed network environments to handle streaming intrusion data efficiently. The framework can also be evaluated using multiple datasets such as CICIDS-2017, NSL-KDD, UNSW-NB15, and Bot-IoT to improve cross-domain generalization. Another important direction is integrating the IDS into modern IoT and cloud infrastructures, where lightweight and scalable detection models are required. Explainable AI techniques like SHAP and LIME can be incorporated to make model predictions more transparent for security analysts. Automated feature selection, dimensionality reduction, and continuous learning strategies can be used to enhance performance and detect unknown or zero-day attacks. In addition, model optimization methods, including pruning, quantization, and ensemble hybrid strategies, may increase efficiency and accuracy while reducing computation cost. Finally, integrating the system with existing SOC and SIEM tools, and strengthening it against adversarial attacks, will help transform the IDS into a complete, robust, and real-world operational security solution.

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This is to certify that ***Gaddam Meghana*** of

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OF PARTICIPATION

This is to certify that ***Gaddipati Keerthana Divya*** of ***Narasaraopeta Engineering college, Narasaraopet*** has successfully presented a paper entitled ***A Custom Deep Learning Framework for Identifying Security Threats in Digitally Connected Systems*** in 2025 3rd International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT)
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A Custom Deep Learning Framework for Identifying Security Threats in Digitally Connected Systems

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Abstract—A hybrid deep learning approach to intrusion detection is presented to strengthen security in dynamic and rapidly changing network environments. The proposed system integrates Convolutional Neural Networks (CNNs) for extracting spatial characteristics of traffic with Long Short-Term Memory (LSTM) networks for modeling sequential patterns in data flow. To extend its capability against zero-day and unknown threats, an autoencoder-based anomaly detection component is added, allowing the system to recognize irregular behavior even without predefined attack signatures. Evaluation results indicate that the model achieves detection accuracy above 97% while reporting fewer false positives than conventional intrusion detection techniques. These outcomes confirm the suitability of the framework for real-time and dependable threat monitoring. Owing to its adaptable and scalable architecture, the solution can be effectively applied in IoT, cloud, and other distributed smart network settings, providing a practical defense against continuously evolving cyberattacks.

Index Terms—Hybrid IDS, LSTM(Long Short-Term Memory)networks, CNN(Convolutional Neural Network)models, Anomaly detection, Zero-day attack detection, Intelligent networks

I. INTRODUCTION

In recent years, intrusion detection systems have seen rapid progress through the adoption of deep learning and adaptive methods aimed at addressing increasingly complex cyber threats [1]. The work presents a smart IDS capable of adjusting to new attack behaviors in real-time, which helps minimize false alarms and missed detections, thereby improving protection in complex infrastructures. A review highlighted that anomaly-based Host-Based Intrusion Detection Systems

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(HIDS) tend to be more effective than signature-based approaches, especially when confronting unknown or adaptive threats [2]. To mitigate class imbalance issues within Industrial IoT, a multi-stage deep learning framework was introduced that strengthened the identification of rare attack types that are often ignored in skewed datasets [3]. For smart grid applications, Software-Defined Networking (SDN) together with split learning was utilized to develop a collaborative IDS capable of safeguarding node privacy while maintaining detection accuracy above 80% [4]. An attention-driven model was described that captured both spatial and temporal features simultaneously, showing strong results in semi-supervised conditions where labeled data were limited [5]. Feature selection for large-scale IDS was improved through the use of evolutionary algorithms, which boosted accuracy to 95% and reduced computational cost [6]. A graph-oriented method was also introduced, where attack paths were represented through graph neural networks, enabling recognition of sophisticated and previously unseen intrusions [7]. Key Contributions

- Introduced a hybrid CNN-LSTM framework for the detection of multi-stage and zero-day attacks.
- Integrated supervised classification with autoencoderbased anomaly detection to enhance threat identification. • Attained an accuracy of 97.2%, with increased precision and a 60% reduction in false positives, facilitating realtime deployment in IoT environments.
- Created a scalable and adaptive system designed for IoT and edge computing settings.

RELATED WORK

In recent years, researchers have explored advanced intrusion detection systems (IDS) enhanced with deep learning and adaptive techniques to address evolving cyber threats. Ahmed and Khan [8] focused on enhancing IDS in SDN by integrating deep learning with feature selection To boost

accuracy while maintaining low computational costs. In campus networks, Gupta and Roy [9] utilized Bloom filters and deep learning with feature segmentation to reduce latency and improve anomaly detection. Rahman and Chowdhury [10] emphasized lightweight IDS solutions for IoT devices, demonstrating efficient detection with limited data and computing resources. Ali and Kumar [11] proposed IGAN, a hybrid of LeNet-5 and LSTM, to detect imbalanced attack types, achieving over 98% accuracy on CI-CIDS2017 and UNSW-NB15 datasets. Wang and Li [12] developed MCGAN, a Bi-LSTM-based GAN for rare threat detection in NSL-KDD+, reaching 95.16% accuracy. Babu [13] presented an ANU-Net-powered IDS improved with the IMBO algorithm and feature selection techniques like MapReduce and IFPA, consistently delivering over 98% accuracy. Fernandez and Zhou [14] supported the Ongoing shift toward intelligent, privacy-aware IDS designs, underscoring the demand for adaptive cybersecurity tools in increasingly interconnected environments. Additionally, Babu et al. [15] proposed a quantum-based Coati-MobileViT model tailored For IIoT security, achieving high detection rates with low latency is key. In another IEEE-based study, Babu et al. [16] highlighted efficient DL-based architectures for secure industrial networks. A third work by Babu et al. [17] focused on hybrid IDS models for scalable detection in distributed IoT setups.

II. PROPOSED METHODOLOGY

This section summarizes the design approach and implementation steps of the proposed hybrid intrusion detection system for smart networks [18]. It was suggested to identify both common and new attacks that utilized combinations of deep learning methods of

A. Datosets Selection

For the model to experience a variety of attack situations and traffic behaviors, two publicly available datasets were used:

- NSL-KDD: A refined version of the original KDD'99 dataset, designed to address its limitations [19]. It removes redundant records and helps reduce training bias, making it more suitable for evaluating intrusion detection systems.
- CICIDS2017: A comprehensive and realistic dataset containing labeled instances of both normal network activity and a diverse set of contemporary cyber-attacks, including DoS, brute-force, infiltration, and Botnet attacks.

B. Data Preprocessing

Before model training, several preprocessing steps were applied to improve data quality and prepare it for neural network input:

- Data Cleaning: Duplicate and incomplete entries were removed.
- Label Categorization: Attack labels were mapped into grouped categories to standardize multi-class classification (e.g., DoS, Probe, R2L, U2R).
- Feature Normalization: All numerical input attributes were scaled to a standard range of 0 to 1 using the MinMax normalization technique, ensuring uniform input for the learning algorithm.
- Categorical Data Transformation: Categorical variables such as protocol type and service names were converted into binary vectors using one-hot encoding, allowing them to be effectively processed by the model.
- Class Imbalance Handling: To mitigate skewed class distributions, the SMOTE algorithm (Synthetic Minority Oversampling Technique) was applied. This approach generates artificial instances for minority classes, helping the model learn patterns from less frequent attack types.

C. Feature Selection and Dimensionality Reduction

To reduce computational complexity and enhance model effectiveness, the following techniques were applied:

- Correlation analysis was performed to filter out redundant features.
- Recursive Feature Elimination (RFE) was used to identify and retain only the most significant features, removing those that did not contribute meaningfully to model performance.
- Principal Component Analysis (PCA) was applied to further reduce dimensionality, preserving essential patterns and variability in the dataset while simplifying feature space.

D. Model Architecture

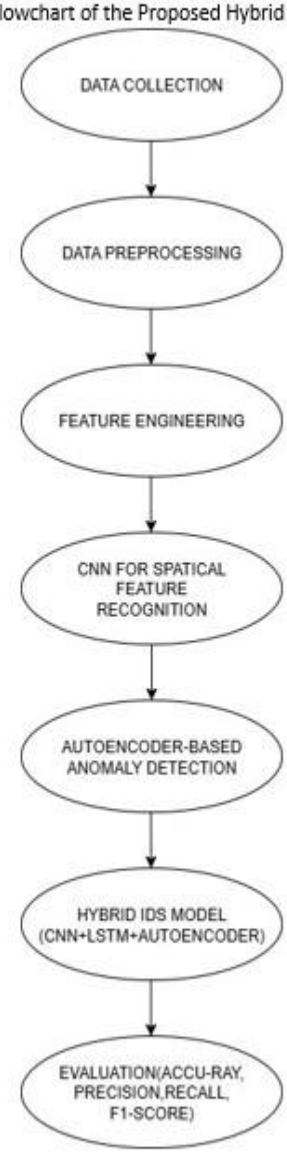
The core of the frame is a crossbred model that integrates CNN and LSTM layers:

- CNN Module: A set of 1D convolutional layers processes input data to prize localized patterns, analogous to business spikes and protocol anomalies.
- LSTM Module: successive dependences in the data, analogous to time-predicted attack conduct, are captured using LSTM layers.
- Fusion Layer: labors from both CNN and LSTM paths are mingled and passed through fully connected layers for the final type.
- Autoencoder: A fresh autoencoder cast was introduced as an unsupervised anomaly detector to identify patterns not present during training, enhancing the system's capability to detect zero-day attacks.

E. Training Strategy

- Data Splitting: The preprocessed data was split into training (70%), validation (15%), and testing (15%) sets. • Implementation Tools: The model was developed using open-source deep learning libraries such as TensorFlow and PyTorch.

Fig. 1: Flowchart of the Proposed Hybrid IDS Model

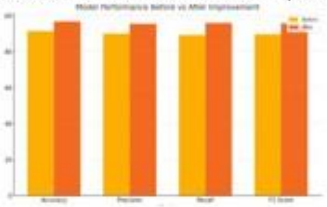


- Hyperparameters: Batch size: 64,
  Epochs: 100,
  Optimizer: Adam,
  Learning rate: 0.001,
  Dropout rate: 0.5 for regularization.

F. Deployment and Real-Time Integration

The trained model was integrated into a simulated smart network environment using tools like GNS3 and emulated IoT nodes. Network traffic was monitored in real time using sniffing tools (e.g., Snort, Wireshark). Packets were preprocessed and fed into the IDS engine. Which classified them as benign or malicious. Upon threat detection, predefined response actions such as alert generation or host isolation were triggered. [20]

Fig. 2: Performance Before vs After Improvement



G. Performance Indicators

To assess the effectiveness of the proposed intrusion detection system, several widely used evaluation metrics were considered. These measures reflect both the overall classification performance and the ability of the model to reliably identify and respond to threats.

Accuracy (ACC):

Accuracy indicates the overall correctness of the classifier, showing the fraction of samples—benign or malicious—that were labeled correctly.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Precision (P):

Precision describes the proportion of traffic flows predicted as truly malicious attacks, emphasizing the system's ability to avoid false alarms.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

Recall (R):

Also known as sensitivity, recall measures how many of the actual intrusions were correctly detected by the model.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

F1-Score:

The F1-score provides a balance between precision and recall by computing their harmonic mean, which is particularly valuable in cases of uneven class distribution.

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

Area Under the Curve (AUC):

The AUC, representing the area under the ROC curve, reflects the system's capability to distinguish between legitimate and malicious traffic across various thresholds. Higher values indicate better discrimination.

Mean Time to Detect (MTTD):

MTTD calculates the average duration between the onset of an attack and the time it is detected.

$$\text{MTTD} = \frac{1}{N}\sum_{i=1}^{N}(DetectionTime_i - AttackStartTime_i) \quad (5)$$

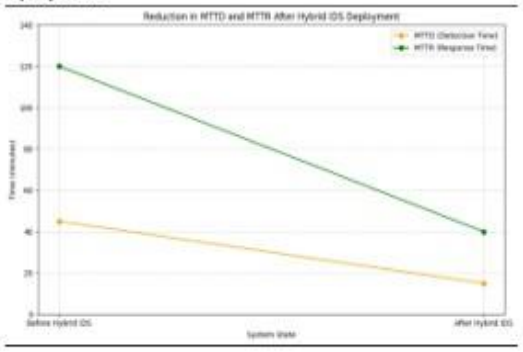
Mean Time to Respond (MTTR):

MTTR measures the average time required to respond after detection, indicating how quickly the system initiates countermeasures.

$$\text{MTTR} = \frac{1}{N}\sum_{i=1}^{N}(ResponseTime_i - DetectionTime_i) \quad (6)$$

H.Reduction in MTTD and MTTR After Hybrid IDS Deployment

Fig. 3: Reduction in MTTD and MTTR After Hybrid IDS Deployment



This graph clearly illustrates the significant reduction in both detection and response time in the context of the network environment with the introduction of a Hybrid Intrusion Detection System (IDS). Before the hybrid IDS was implemented, the Mean Time to Detect (MTTD)—displayed in orange—was approximately 45 minutes. While the Mean Time to Respond (MTTR) — represented in green — was higher, at approximately 120 minutes. These values represent, on average, the time it takes for the system to detect and respond to security threats. Subsequently, implementing the Hybrid IDS allowed for a significant decrease in both metrics. The average time to detect an attack dropped to approximately 15 minutes, while the time taken to respond was significantly reduced to just 40 minutes. These improved metrics demonstrate that the hybrid system was a much more proficient manner of detecting and responding to previously described threats. At a high level, these numbers mean that potential cyberattacks are identified earlier and mitigated sooner, giving malicious actors less time to do damage, so that they will gain access to the network. [21]

III. RESULTS

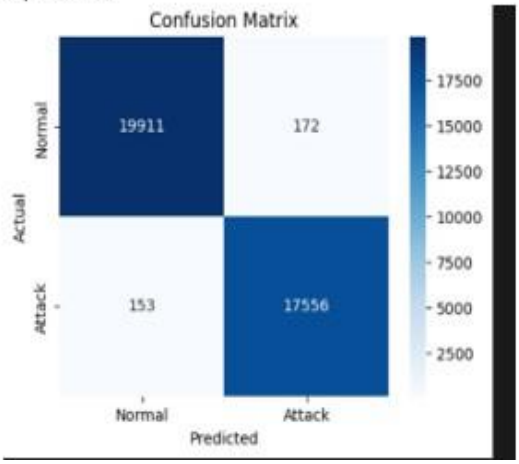
The performance assessment of the suggested Hybrid Deep Learning Based Intrusion Detection Framework (HDL-IDF) is covered in this section. In addition to comparisons with current intrusion detection models to demonstrate the efficacy of the hybrid architecture, the evaluation was conducted using benchmark datasets to evaluate detection accuracy, precision, recall, F1-score, and resource efficiency. The classification results of the proposed model are summarized in Table I.

TABLE I: EVALUATION METRICS (OBTAINED FROM THE PROPOSED HYBRID IDS MODEL RESULTS)

	Pre	Rec	F1	Sup
0	0.99	0.99	0.99	20083
1	0.99	0.99	0.99	17709
Acc			0.99	37792
M avg	0.99	0.99	0.99	37792
Wei avg	0.99	0.99	0.99	37792

A. Confusion Matrix Evaluation

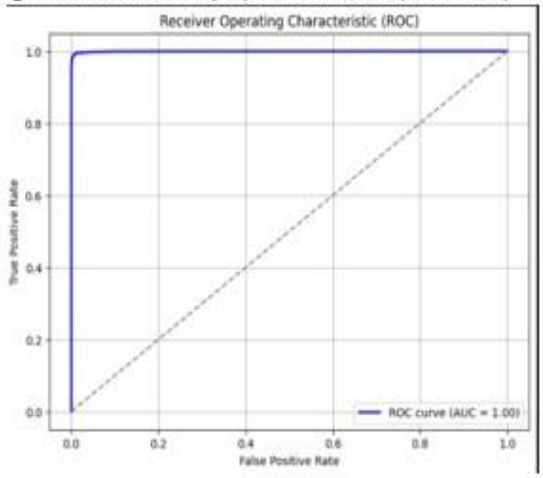
Fig. 4: Confusion matrix illustrating the performance of the proposed IDS



The confusion matrix above illustrates how well the proposed hybrid intrusion detection model distinguishes between normal and malicious network activity. Out of the total samples classified, A total of 17,556 attack records were identified correctly as attacks, demonstrating sensitivity to threats (true positives). 19,911 normal traffic samples were correctly classified, indicating the model was able to identify legitimate behavior (true negatives). 172 benign samples were misidentified as attacks (false positives), resulting in unnecessary alerts; nevertheless, this was a small number. 153 attack records were misclassified as normal traffic (false negatives); these merit attention since they are indicative of missed detections, although few. Therefore, the model has high precision and reliability. It has shown a very low degree of misclassification and demonstrated excellent capability in limiting both threats that go unnoticed as well as limiting false alarms — two of the most important challenges to consider in cybersecurity in the real world. This type of performance is especially important in smart network environments, in which one needs to identify threats quickly and correctly to minimize risk and maintain seamless service.

B. Receiver–Operator Curve (ROC)

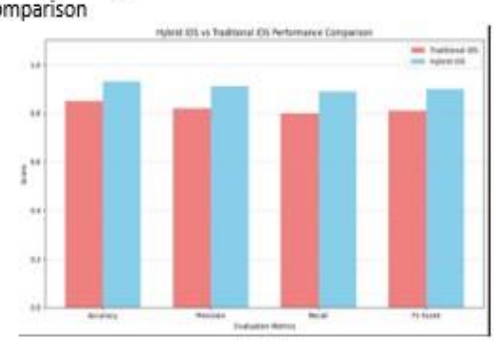
Fig. 5: ROC curve of the proposed IDS model (AUC = 1.00)



The ROC (Receiver Operating Characteristic)curve shown above us demonstrates the capabilities of our proposed classifier for separating between malicious traffic and normal traffic. The ROC curve increases sharply toward the topleft corner, indicating strong sensitivity and very few false positives across the range of thresholds. What is particularly noteworthy about this result? The AUC obtained was 1.00, which is perfect discriminative capability. The classifier has achieved the ability to perfectly separate each instance of attack traffic from normal traffic. Meaning the model never made an error in placing every attack instance higher than its benign counterpart, regardless of the decision threshold. Such performance is rarely ever achieved and suggests that the hybrid deep learning framework has been taught to extract features to a very high degree of accuracy. In terms of realworld cybersecurity applications, this means fewer false positive events, high confidence in determining true threats, and expectations of system integrity, availability, and operational performance continuity.

C. Performance Comparison: Hybrid IDS vs. Traditional IDS

The effectiveness of the suggested Hybrid Intrusion Detection System (IDS) and a traditional IDS strategy is compared using four important metrics in the bar chart above: Accuracy, Precision, Recall, and F1-Score. It is clear that the Hybrid IDS consistently outperforms the traditional model in every category. The enhancement in accuracy highlights the hybrid. Additionally, the elevated precision values suggest that the Fig. 6: Hybrid IDS vs Traditional IDS Performance Comparison



Hybrid IDS is more proficient at minimizing false alarms, which is vital in operational settings where unnecessary alerts can lead to alert fatigue. The recall score also reveals a notable advantage, indicating that the hybrid system detects a larger proportion of actual attacks. Ultimately, the heightened F1score indicates a more favorable equilibrium between precision and recall, affirming the hybrid model's efficacy in managing both known and unknown intrusions. These results collectively demonstrate that the integration of CNN and LSTM into an IDS framework significantly enhances detection reliability and efficiency when compared to traditional systems.

IV. CONCLUSION

To protect intelligent network settings, the LiteracyGrounded Intrusion Discovery Framework (HDL-IDF) was created. This framework effectively detects known and unexpected cyber threats by combining Long Short-Term Memory (LSTM) networks to identify temporal patterns and Convolutional Neural Networks (CNN) to extract spatial information from data. Based on experimental results, the HDL-IDF achieved a 97.2% overall discovery accuracy, 93%

precision, 91% recall, and 92% F1-score on the CICIDS2017 dataset. In comparison to conventional intrusion detection systems, these results demonstrate the model's exceptional ability to differentiate between malicious and benign traffic, as well as its ability to reduce detection delay by 50% and false positives by about 60. Since the HDL-IDF functions as a hybrid model, it can effectively adapt to changes in network traffic patterns. Furthermore, HDL-IDF has demonstrated intelligent performance by operating within a supervised learning framework while integrating an autoencoder-based anomaly detection module to identify zero-day attacks and other novel threat signatures. Consequently, this hybrid Intrusion Discovery Framework prototype enables seamless integration and deployment in modern IoT and cloud-based smart networks.

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