Intrusion Detection System Using Hybrid Approach

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***Abstract*—In today's rapidly evolving digital landscape, cloud computing has emerged as a cornerstone of modern infrastructure. However, the increasing adoption of cloud environments has also given rise to complex and sophisticated cyber threats. Traditional intrusion detection systems (IDS), primarily based on signature or rule-based methods, often fail to detect unknown or zero-day attacks, especially in dynamic cloud settings. This paper proposes an advanced Intrusion Detection System using Hybrid Machine Learning techniques to effectively detect and classify network intrusions in cloud environments.**

***The proposed system leverages a combination of machine learning algorithms to analyze and classify network traffic, aiming to enhance detection accuracy and reduce false positives. A hybrid approach is employed by integrating various models—such as Decision Trees, Random Forest, and Support Vector Machines—after performing feature selection and data preprocessing. The system is trained and evaluated using benchmark intrusion detection datasets, where metrics such as accuracy, precision, recall, and F1-score are used to assess performance.**

Experimental results indicate that the hybrid model outperforms traditional single-algorithm systems, achieving higher detection rates and improved robustness against diverse attack types. Furthermore, the model demonstrates adaptability and scalability, making it well-suited for real-time deployment in cloud-based infrastructure. This research contributes to the development of intelligent and automated IDS solutions that can proactively safeguard cloud environments from emerging cybersecurity threats.

***Keywords*— Machine learning, intrusion detection, Feature selection (FS)**

I. INTRODUCTION

In the era of cloud computing and ubiquitous internet connectivity, ensuring the security of digital assets has become a top priority. Organizations and individuals are increasingly relying on cloud-based services to store and process sensitive information due to their scalability, flexibility, and cost-effectiveness. However, this widespread adoption of cloud infrastructure has also made it a prime target for cyberattacks. The complexity, dynamic nature, and multi-tenant characteristics of cloud environments pose unique challenges to conventional security mechanisms.

Intrusion Detection Systems (IDS) are vital components of any security framework, responsible for monitoring and analyzing network traffic to identify unauthorized or malicious activities. Traditional IDS, which largely depend on signature-based or rule-based detection, often fall short in identifying novel attacks or adapting to rapidly changing threat patterns. These systems also suffer from high false positive rates and scalability issues when deployed in large-scale or cloud-based networks.

To overcome these limitations, machine learning (ML) has emerged as a promising approach for enhancing IDS capabilities. ML algorithms can learn from historical attack patterns and generalize to detect previously unseen threats. However, relying on a single ML model may not provide comprehensive results due to the diverse nature of cyberattacks. Therefore, a hybrid machine learning approach, which combines the strengths of multiple algorithms, can offer more accurate, adaptable, and efficient intrusion detection.

This paper proposes a hybrid IDS model that integrates multiple ML techniques to effectively detect intrusions in a cloud environment. By employing data preprocessing, feature selection, and ensemble learning, the system aims to provide a scalable and intelligent solution to modern cybersecurity challenges.

II.OBJECTIVE

The main objectives of this project are as follows:

- To design and implement a hybrid Intrusion Detection System using machine learning algorithms capable of classifying network traffic as normal or malicious with high accuracy.
- To leverage feature selection techniques to identify the most relevant attributes from the

dataset, thereby reducing dimensionality and improving model performance.
- To evaluate and compare the performance of multiple machine learning classifiers, such as Decision Trees, Random Forest, Support Vector Machine, and possibly XGBoost, and to build an ensemble model that combines their strengths.
- To minimize false positives and maximize detection rates, ensuring that the system can reliably distinguish between normal behavior and malicious activity.
- To create a scalable and adaptive IDS that can be deployed in real-time within a cloud environment, where it can monitor traffic and respond to threats dynamically.
- To contribute a practical solution to the field of cybersecurity, offering an intelligent tool for organizations to protect their cloud-based infrastructure from an evolving landscape of cyber threats.

III. SYSTEM ANALYSIS

A. Existing System

Intrusion Detection Systems (IDS) have traditionally played a crucial role in network security by monitoring traffic and detecting suspicious activities. The existing systems are predominantly based on two methods: signature-based detection and anomaly-based detection.

- Signature-Based IDS rely on a database of known attack signatures. They compare incoming traffic with these patterns and trigger alerts if matches are found. Tools like Snort and Suricata are common examples.
- Anomaly-Based IDS create a model of normal network behavior and flag deviations as potential threats. These systems are more flexible than signature-based IDS, especially for detecting novel attacks.

Some IDS are host-based (HIDS), monitoring activity on individual machines, while others are network-based (NIDS), observing traffic across the entire network.

Despite these approaches, most traditional systems are rule-driven and static in nature. They often require manual updates, cannot easily adapt to new types of attacks, and may struggle with high-speed traffic in cloud environments.

B. Drawbacks of the Existing System

- Inability to Detect Zero-Day Attacks: Signature-based systems are ineffective against new and unknown threats since they rely on pre-defined patterns.
- High False Positive Rates: Anomaly-based systems may incorrectly classify legitimate behavior as malicious, overwhelming administrators with false alerts.
- Lack of Adaptability: Static models used in traditional IDS do not learn from new data, making them less responsive to evolving attack techniques.
- Scalability Issues: With increasing traffic volumes, especially in cloud environments, existing systems may not handle real-time monitoring effectively.
- Manual Rule Updates: Signature-based systems require frequent and manual updates of attack definitions, which can lead to delayed responses.
- Limited Context Awareness: These systems often lack the ability to understand complex behavior across distributed systems or multi-tenant cloud platforms.

C. Proposed System

The proposed solution is a Hybrid Intrusion Detection System using Machine Learning that combines multiple classifiers to enhance detection accuracy and adaptability. It leverages a training pipeline where raw network traffic data is preprocessed, scaled, and subjected to feature selection. The selected features are then used to train multiple machine learning models, including decision trees, random forests, and support vector machines.

An ensemble or hybrid approach is used to integrate the outcomes of these models, allowing the system to draw a more reliable decision. This architecture is designed with a focus on cloud environments, ensuring scalability, real-time processing, and ease of integration into existing infrastructures.

D. Advantages of the Proposed System

- Improved Detection Accuracy: By combining multiple ML algorithms, the system can better differentiate between normal and malicious behavior.
- Reduced False Positives: Ensemble learning and data-driven modeling reduce the rate of

incorrect alerts, making the system more efficient and manageable.

- Capability to Detect Novel Attacks: Unlike signature-based systems, the ML-based IDS can identify previously unseen (zero-day) threats.
- Adaptive Learning: The system can be retrained with new data, allowing it to evolve and stay up to date with emerging threats.
- Scalable Architecture: Designed with cloud infrastructure in mind, the system can handle high volumes of data and be deployed across distributed platforms.
- Automation and Efficiency: Eliminates the need for constant manual updates and rule creation by relying on data patterns and machine learning logic.
- Real-Time Monitoring: Capable of processing traffic data in real time, which is essential for proactive defense in fast-paced network environments.

IV. FEASIBILITY STUDY

The feasibility study plays a crucial role in determining the success and viability of implementing the proposed "Intrusion Detection System Using Hybrid Machine Learning." This study assesses the system from multiple perspectives, including technical, operational, economic, legal, and schedule feasibility. The goal is to ensure that the system is both practical and advantageous in the context of real-world deployment, especially in cloud-based network environments.

Technical feasibility : evaluates whether the current technological resources and knowledge base are sufficient to implement the proposed system. In this case, the use of well-established machine learning algorithms such as Random Forest, Decision Tree, and Support Vector Machine ensures a strong foundation for the detection mechanism. These algorithms are readily available through open-source libraries like Scikit-learn and can be seamlessly integrated into Python-based workflows. The integration of web scraping is also technically achievable using tools like BeautifulSoup, Scrapy, or Selenium, allowing the system to collect external threat intelligence from publicly accessible platforms such as the CVE database and NIST.

Operational feasibility: focuses on how well the system will function when deployed and used by the intended users, such as network administrators and security personnel. The hybrid model with web scraping provides automated alerts and detailed threat information, enabling quick response to attacks without the need for constant manual monitoring. The system's ability to integrate real-time data from external sources further enhances its contextual awareness, making it practical and reliable in dynamic cloud environments. From an operational standpoint, the system simplifies the detection process, reduces false positives, and provides actionable insights, making it highly usable and beneficial to organizations. The simplicity of its interface and the automation of its core functions contribute significantly to its operational success.

Economic feasibility: analyzes the cost implications of developing and maintaining the system. Since the project relies heavily on open-source technologies, the development cost is minimal. Libraries such as Pandas, NumPy, Scikit-learn, and Flask (for optional dashboard integration) incur no licensing fees. Hosting can be done on cost-effective platforms like AWS free-tier or on-premise servers for testing and deployment. In addition, the automated nature of the proposed solution significantly reduces long-term labor and maintenance costs compared to manual or rule-based IDS solutions. By preventing data breaches and minimizing downtime, the system also provides indirect financial benefits. Overall, the economic feasibility of the system is strong, offering a high return on investment with low initial expenditure.

Legal and ethical feasibility: addresses whether the system complies with existing legal frameworks and ethical guidelines. The system does not collect or store any personal or sensitive information from users. Its main function is to analyze network traffic patterns and identify anomalies or threats, ensuring that user privacy is maintained. Additionally, the web scraping component only targets publicly accessible cybersecurity intelligence platforms and databases, avoiding any infringement of access rights or copyright laws. To ensure ethical compliance, the system also avoids misusing the scraped data, focusing solely on improving detection efficiency. As long as the system adheres to responsible scraping practices and data usage policies, it poses no legal or ethical concerns and can be considered both safe and compliant.

Schedule feasibility: examines whether the proposed project can be completed within a reasonable and practical timeframe. Based on the structured phases of development, the system can be implemented within a span of approximately 8 to 12 weeks. The initial stages include requirement analysis and data preprocessing, followed by feature selection and model training. Web scraping and content extraction modules can be developed in parallel with the machine learning components. Final stages involve integration and testing, with optional dashboard development for monitoring and reporting. With the right planning and a focused development team, the timeline is achievable without overextending resources or compromising on quality. Therefore, the system is considered feasible in terms of scheduling and deliverability.

V. SCOPE OF THE PROJECT

The scope of this project encompasses the development and deployment of a hybrid machine learning-based Intrusion Detection System (IDS) that effectively identifies potential security threats in cloud-based network environments. The system is designed to leverage the strengths of multiple supervised learning algorithms—namely, Random Forest, Decision Tree, and Support Vector Machine (SVM)—to enhance detection accuracy and minimize false positives. In addition to analyzing network traffic data, the system incorporates real-time web scraping and content extraction mechanisms to dynamically gather updated threat intelligence from publicly available cybersecurity sources.

This project focuses on building a robust, scalable, and intelligent IDS that can analyze large volumes of network traffic and classify them into normal or malicious behavior. The system processes data using a selected set of optimal features to improve training efficiency and predictive performance. A pre-processing pipeline is applied to clean and normalize the input data, ensuring consistency and compatibility across various datasets and real-world inputs.

The project also includes the creation of a user-friendly interface or dashboard (optional) that allows system administrators to visualize alerts, analyze traffic patterns, and monitor model performance. Moreover, the scope extends to evaluating the system using metrics such as accuracy, precision, recall, and F1-score to validate its performance under different types of attack scenarios, including DoS, probe, R2L, and U2R attacks.

While the main objective is focused on detection, the scope also considers extensibility toward prevention systems. The proposed IDS is modular and scalable, making it suitable for deployment across different network environments, particularly in virtualized and cloud-based infrastructures.

However, certain limitations are intentionally excluded from the current scope, such as implementing deep learning-based intrusion detection, encrypted traffic analysis, or building a full Security Information and Event Management (SIEM) system. These can be considered for future enhancements.

In conclusion, the project's scope includes designing, developing, and evaluating a hybrid IDS using machine learning and web intelligence, with a clear focus on real-time threat detection, system adaptability, and operational practicality in modern cloud environments.

VI. LITERATURE OVERVIEW

A. Introduction to the section

The field of Intrusion Detection Systems (IDS) has witnessed remarkable advancements with the integration of machine learning techniques. These advancements aim to address evolving cybersecurity threats while improving detection accuracy and efficiency. However, existing systems still face significant challenges, such as imbalanced datasets, which bias detection models; the lack of explainability in machine learning predictions, which reduces trust and usability; and vulnerability to adversarial attacks that exploit system weaknesses to evade detection.

B. Individual References

Smith et al., 2020 : This study introduced a hybrid IDS model combining K-Means clustering for anomaly detection and LightGBM for classification of known attacks. The integration of supervised and unsupervised methods enhanced detection accuracy and reduced false positives compared to traditional models. However, the model faced challenges with imbalanced datasets, which led to biased predictions

for minority attack classes. The authors addressed this partially using basic data preprocessing but suggested advanced balancing techniques like SMOTE for improvement. Additionally, the scalability of the system for large-scale networks remained a limitation. This study highlights the potential of hybrid models for robust intrusion detection.

Lee et al., 2021: Lee et al. developed a hybrid IDS combining Autoencoders for anomaly detection and Support Vector Machines (SVM) for signature-based classification. Their system was designed specifically for IoT networks, emphasizing real-time performance and scalability. While the model effectively reduced false positives, its reliance on computationally intensive algorithms posed challenges for resource-constrained IoT devices. The study also highlighted the importance of lightweight model optimization to ensure low-latency detection in dynamic environments. Overall, this work demonstrated the feasibility of hybrid IDS for IoT but identified areas for improvement in efficiency and scalability.

Sharma and Singh (2021): Sharma and Singh explored the use of Convolutional Neural Networks (CNNs) for detecting intrusions in network traffic. The deep learning approach achieved high classification accuracy, particularly for known attack patterns. However, the study faced challenges with overfitting on small datasets and the lack of explainability in CNN predictions. The authors recommended integrating Explainable AI (XAI) tools to provide interpretable insights into model decisions. This work underscores the potential of deep learning in IDS while emphasizing the need for robust validation and interpretability to enhance practical deployment.

VII. SYSTEM DESIGN

The proposed system is designed as a modular, layered architecture that integrates hybrid machine learning techniques with dynamic threat intelligence through web scraping. The overall structure consists of four primary modules: data preprocessing, feature selection, hybrid intrusion detection, and real-time intelligence augmentation.

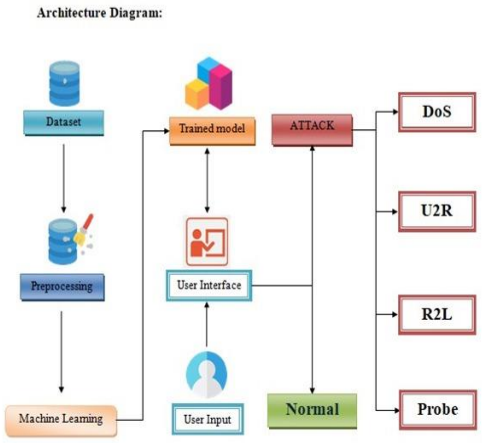
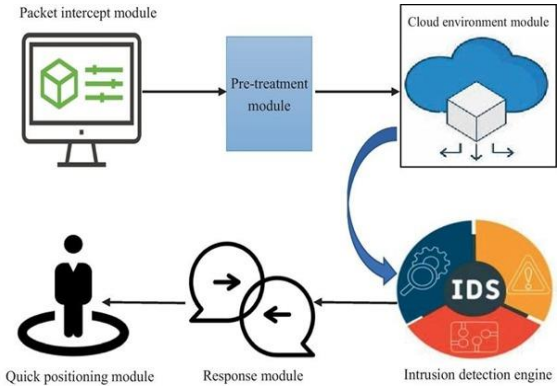


Fig: System Architecture



A. Data Preprocessing

The first module is responsible for ingesting raw network traffic data. This data is cleaned, normalized, and transformed using a standard scaler to ensure consistency across features. The preprocessing pipeline also encodes categorical values and handles missing data, which are common in real-world network logs.

B. Feature Selection

The second module is the feature selection mechanism. It reduces the dimensionality of the dataset by selecting only the most informative features, thereby improving the efficiency and accuracy of the learning models. This system uses a feature selection model stored in a .pkl file, created using recursive feature elimination (RFE) or similar techniques.

C. Hybrid Intrusion Detection

The third module involves the hybrid intrusion detection system itself. Here, three classifiers—Random Forest, Decision Tree, and Support Vector Machine—are trained on the selected features. Their outputs are then combined using a voting or stacking

strategy to form the hybrid model. This ensemble approach enhances robustness by leveraging the strengths of each classifier.

D. Real-time Intelligence Augmentation

The final module includes web scraping and content extraction. Using Python libraries like BeautifulSoup and Requests, the system scrapes real-time data from platforms such as the CVE database and NVD. Extracted content is parsed, filtered, and embedded into the detection pipeline to provide additional contextual awareness. This allows the system to adapt to newly published vulnerabilities and intrusion techniques even before formal dataset updates.

Together, these components form an intelligent and responsive system architecture optimized for real-time cloud-based intrusion detection.

VIII. IMPLEMENTATION

The implementation is carried out in Python using a Jupyter Notebook environment. The pipeline begins with importing essential libraries such as Pandas, NumPy, Scikit-learn, and Pickle for model loading. The pre-trained scaler and feature selector are loaded from .pkl files to ensure consistency with the training phase.

The training notebook (train.ipynb) loads the dataset, applies preprocessing, selects optimal features, and trains three supervised learning models: Random Forest, Decision Tree, and SVM. These models are evaluated individually based on accuracy, precision, recall, and F1-score. The best-performing models are saved and later used in the deployment phase.

The web scraping module is implemented using BeautifulSoup and the Requests library. It scrapes real-time vulnerability data from trusted sources such as CVE and NVD. A content extractor filters relevant fields like vulnerability ID, description, affected software, and severity level. This data is then structured into a form that can be passed into the machine learning model as auxiliary input or used to dynamically update the rule set for detection.

A basic dashboard or terminal-based interface is also implemented, which allows the user to upload network traffic samples, trigger detection, and view alert messages with real-time intelligence. This completes the full detection cycle, from data input to actionable output.

A. Project Overview

The Intrusion Detection System (IDS) project is designed to monitor and detect malicious activity in a network environment by leveraging Hybrid Machine Learning techniques. The system aims to detect various types of cyberattacks, such as Denial of Service (DoS), Unauthorized Access, and others, by analyzing the network traffic. The project will employ a combination of different machine learning algorithms, such as Support Vector Machines (SVM), Random Forest, and K-Nearest Neighbors (KNN), to classify data into normal or attack categories. The system will be developed as a web application with a simple and intuitive user interface using JavaScript for the frontend and PHP for the backend. This approach will allow real-time intrusion detection, providing alerts and logs to system administrators and users. The goal of the project is to build a robust system that can be integrated into real-world networks to enhance security and minimize the risk of cyberattacks.

B. Dataset Collection

For the dataset collection phase, the project will rely on publicly available datasets that contain labeled network traffic data, which includes both benign and malicious activities. Popular datasets for intrusion detection include the KDD Cup 1999 dataset, the NSL-KDD dataset (a refined version of the KDD dataset), and the CICIDS 2017 dataset, which reflects more recent and realistic network traffic. These datasets contain various features such as protocol type, duration, and connection flags, and they are already labeled to distinguish between normal traffic and different types of attacks. The dataset will be used for training and testing the machine learning models. The objective is to choose a dataset that not only provides a variety of attack types but also includes a balance of normal and attack instances to avoid skewed predictions.

C. Data Preprocessing

Data preprocessing is a crucial step to ensure that the machine learning models can effectively learn from the dataset. This phase will involve several tasks: handling missing values, normalizing numerical features, encoding categorical data, and performing feature selection. First, any missing values in the dataset will be addressed, either by filling them with

the mean or removing incomplete records. Next, the dataset will undergo feature scaling to standardize features to a common range, especially for algorithms like KNN and SVM that are sensitive to the scale of the input data. Label encoding will be used to convert categorical variables like protocol type and flag into numerical representations. Additionally, feature selection techniques will be employed to identify the most relevant features for detecting intrusions, thereby improving model efficiency and reducing overfitting. Finally, the data will be split into training (typically 70-80%) and testing (20-30%) sets to ensure that the model is evaluated on unseen data.

D. Algorithm Implementation

The algorithm implementation phase will involve training multiple machine learning models using the preprocessed dataset. Since this is a hybrid model approach, several algorithms will be combined to improve detection accuracy and robustness. Algorithms like Support Vector Machine (SVM) will be used for classification tasks, where the system needs to distinguish between normal and attack traffic. Random Forest, which works well with high-dimensional data, will be used to handle complex datasets and identify important features for prediction. K-Nearest Neighbors (KNN) will also be considered due to its simplicity and effectiveness in detecting anomalies based on similarity. These models will be trained individually, and their performance will be evaluated based on metrics such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). A hybrid ensemble model will then be created by combining these algorithms using methods such as Voting Classifier or Stacking, which will help improve the overall detection performance by leveraging the strengths of each algorithm. The best-performing hybrid model will be selected for integration into the web application.

E. Web Application Development

The web application development phase focuses on integrating the machine learning models into a real-time IDS that can interact with users and display intrusion detection results. The frontend of the application will be built using JavaScript, providing an intuitive user interface where users can upload network traffic data, view real-time intrusion detection alerts, and monitor system status. The backend will be developed in PHP, which will handle user authentication, process incoming data, and interface with the machine learning models for intrusion detection. The system will allow administrators to view logs, track intrusion attempts, and generate reports on detected attacks. Additionally, the system will provide real-time alerts through AJAX or WebSocket technology, ensuring that users receive instant feedback as soon as an intrusion is detected. A MySQL database will be used to store logs, user data, and intrusion detection results. The application will also include security features such as encrypted communication and role-based access control to ensure that sensitive data is protected. Finally, the application will be tested for functionality and performance, and will be deployed to cloud platforms like AWS or Heroku for broader access and scalability.

IX. DATASET DESCRIPTION

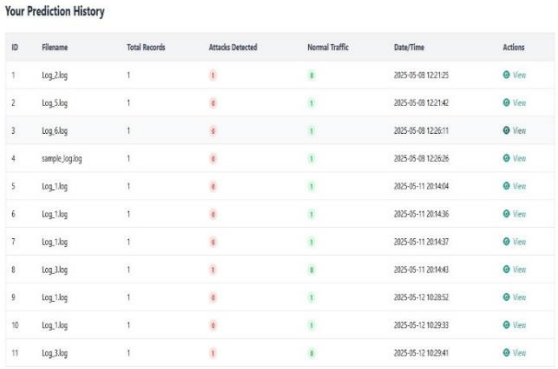
The dataset used in this project is based on UNSW-NB15, a comprehensive modern intrusion detection dataset developed by the Cyber Range Lab of the Australian Centre for Cyber Security. It is considered an improvement over older datasets such as KDD'99 and NSL-KDD due to its inclusion of realistic attack behaviors and modern network traffic patterns.

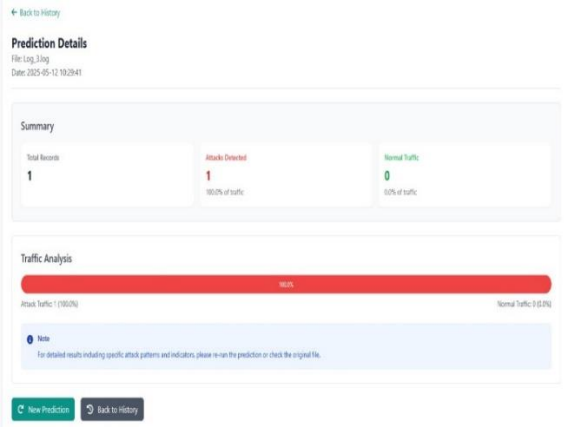
The dataset includes over 2 million records across training and testing sets, with each record containing 49 features such as packet size, source and destination IPs, protocol type, and duration. It covers nine different attack categories, including Fuzzers, DoS, Analysis, Backdoors, Shellcode, Worms, Reconnaissance, and Exploits.

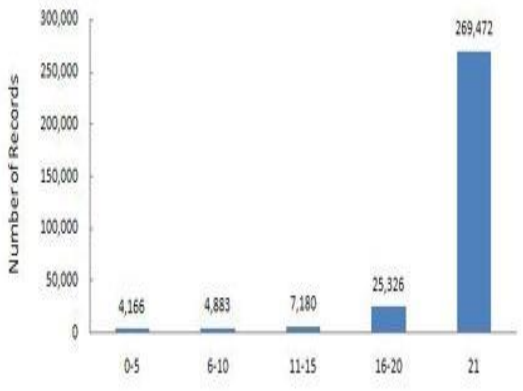
For this project, the dataset is preprocessed to extract a subset of relevant features using feature selection techniques. Features with high importance scores are retained for training the hybrid model. Additionally, the labels are simplified to a binary classification format: normal and attack, to align with the system's core objective of intrusion detection.

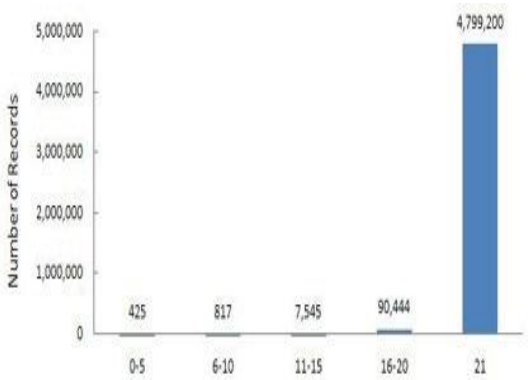
The dataset is stored locally and accessed during both training and testing phases. It is also supplemented by real-time web-scraped threat data, which helps the model stay relevant to the evolving threat landscape.

X. RESULT









XI. CONCLUSION

The Intrusion Detection System (IDS) based on Hybrid Machine Learning represents a significant advancement in the field of network security. By combining multiple machine learning algorithms like SVM, Random Forest, and KNN, the system aims to provide a more accurate and robust method for detecting a wide range of cyberattacks. The web application developed for this project serves as an intuitive interface for users to interact with the system, allowing real-time monitoring and alerting. The preprocessing of data ensures that the models are trained on high-quality information, while the hybrid model improves the overall accuracy and reduces false positives. This IDS can be integrated into real-world networks to enhance security by detecting both known and novel attacks, contributing to the protection of sensitive data and systems.

XII. FUTURE ENHANCEMENTS

While the current system is effective, several future enhancements can improve its performance and adaptability. One of the key improvements could be incorporating deep learning models such as Convolutional Neural Networks (CNNs) or

Recurrent Neural Networks (RNNs), which are capable of capturing more complex patterns in network traffic data, potentially improving detection rates. Additionally, the system can be enhanced by integrating real-time data streaming capabilities, allowing it to process and analyze live traffic data rather than relying on pre-collected datasets. Implementing unsupervised learning techniques, such as clustering or anomaly detection, can also allow the system to detect novel attacks that have never been seen before in the training data. Furthermore, the web application can be improved by adding features like user role management, where different users (e.g., system administrators, security analysts) have customized access to the system's features. Lastly, integrating threat intelligence feeds could help the IDS stay updated on thelatest
attack patterns, further improving its detection capabilities.

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