An Efficient Machine Learning–Based Intrusion Detection system for Detecting Modern Network Attacks

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Abstract: ***Intrusion detection systems (IDS) based on signatures and predefined rules are not enough anymore to ensure strong network security because of the quick growth of networked systems and the growing sophistication of cyberattacks. Because methods for machine learning will identify known and new intrusions and understand intricate attack patterns, they have emerged as a potential substitute. However, current ML based- tools that look for intrusions and are based on drawbacks, including dependency on out-of-date datasets, inadequate real-time performance evaluation, and poor handling of skewed data in this regard to identify current network risks in modern network environments, this study represents an effective ML-oriented intrusion detection system to get better identifiable accuracy and reduce false-positive rates, the suggested method combines feature selection, data preprocessing, and many machine learning classifiers. Benchmark intrusion detection datasets they are utilized in the experiments, and identifiable accuracy, precision, recall, and ROC-AUC are utilized to make the evaluation performance of different models. The outcomes indicate that the given framework outperforms conventional methods in the way of detection, underscoring its efficacy and applicability for real-world implementation in contemporary network security systems.***

Index Terms—Intrusion Detection System, Machine Learning, Network Security, Cyber Attacks, Anomaly Detection

I. INTRODUCTION

Cyberthreats including denial-of-service (DoS), brute-force, botnet, and zero-day assaults have grown considerably more prevalent due to the quick expansion of networked systems, cloud computing, and IoT devices. Being able to detect threats that were previously unknown, traditional signature-based intrusion detection systems (IDS) are frequently inadequate for identifying contemporary and changing attacks. Machine learning (ML) algorithms offer a meaningful solution by detecting abnormalities suggestive of malicious activity and learning patterns from network traffic. the amount of traffic which is successfully classified using ensemble and deep learning methods in addition with that supervised algorithms such as Random Forest, SVM, and k-NN. However, many current systems suffer from class imbalance, rely on out-of-date datasets, and prioritize accuracy over processing economy, scalability, and real-time application. This research suggests an effective ML-based intrusion detection system that combines feature selection, preprocessing, and several ML classifiers to identify contemporary network threats in order to get over these limitations. The system is assessed using extensive performance metrics including like accuracy, precision, recall, F1-score, and ROC-AUC on benchmark datasets such as CICIDS2017 and UNSW-NB15. The suggested strategy outperforms current techniques by lowering false positives and raising detection accuracy. The primary contributions that make it appropriate for deployment in modern network environments are the design of a unified ML-based IDS, evaluation using real-world datasets, comparative analysis of multiple algorithms, feature choosing for reduced complexity, and a thorough assessment using multiple metrics.

II. RELATED WORK

The study on ML-based intrusion detection systems is reviewed in this part, in addition to their advantages and disadvantages. Applying conventional Machine Learning systems to intrusion detection issues was the main focus of several early investigations. Among the earliest methods investigated for categorizing network traffic as benign or malevolent were SVM and Decision Trees. This section reviews the research on

ML-based intrusion detection systems and discusses their benefits and drawbacks. Several early studies focused on applying traditional ML techniques to intrusion detection problems. Support Vector Machines (SVM) and Decision Trees were two of the first techniques studied for classifying network traffic as benign or malicious. These methods outperformed rule-based systems regarding identification accuracy, but they are very dependent on manually generated features and struggled to scale in high-dimensional datasets. k-Nearest Neighbor (k-NN) intrusion There have been detection ways investigated due to its simplicity and effectiveness in pattern recognition. The real-time implementation of k-NN-based intrusion detection systems is constrained by their computational cost and poor performance on large-scale datasets, despite the fact that these models provided acceptable detection rates for known threats. As deep learning developed, there was a lot of interest in neural network-based intrusion detection systems. Models like Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Deep Neural Networks (DNN) have been created to capture complex attack patterns in network data. These models were more working well at spotting sophisticated threats, but they required a lot of computing power and labeled data. Autoencoder-based anomaly detection systems is created to identify unknown and zero-day threats by learning typical network activity. Despite showing potential in detecting anomalies, these methods often produced large false-positive rates, particularly in datasets containing notable imbalances. Recent studies have emphasized the importance of dataset selection in evaluating intrusion detection systems. Modern datasets like CICIDS2017 and UNSW-NB15 have been advised to address the drawbacks of older datasets by adding contemporary attack types and realistic traffic patterns nevertheless many recent studies continue to employ outdated databases, which restricts the applicability of their conclusions. Existing research usually suggest that ML methods are useful for intrusion detection; however, there are much difference in terms of dataset realism, imbalance handling, efficiency, and comprehensive performance evaluation. These limitations motivate the development of a dependable and efficient ML-based intrusion detection model that can recognize modern network threats in real-world scenarios.

III. PROPOSED METHODOLOGY

This section gives the proposed machine learning-based intrusion detection system designed to effectively identify modern network threats. Among the stages that comprise the framework are data collection, preprocessing, model training, and performance evaluation. The overall architecture of the proposed system was theoretically represented as a sequential pipeline that evaluates network traffic data and assesses its level of threat.

1.Dataset selection and description

To ensure realistic evaluation, the proposed system uses benchmark intrusion detection datasets that represent modern network environments. Publicly available datasets such as CICIDS2017, UNSW-NB15, or NSL-KDD are considered for testing. These figures cover both benign and malicious network traffic with a range of attack techniques, including penetration, denial-of-service attacks, botnet activity, and brute-force attacks. Standard datasets ensure reproducibility and fair comparability with earlier studies.

2. Data Preprocessing

Inconsistent data scales, redundant features, and missing values in raw network traffic data may have a detrimental effect on ML performance. Consequently, several preprocessing methods are employed:

3. Feature Selection

Redundant or uninformative features in high-dimensional network datasets might raise computational overhead without enhancing detection efficiency. Feature selection approaches are used to find the most pertinent characteristics that contribute to intrusion detection in order to solve this problem. To decrease dimensionality while maintaining discriminative capability, techniques like information gain, correlation analysis, and tree-based feature importance ranking are employed. Feature selection shortens training times and increase model efficiency.

4. Machine Learning Model Implementation

The efficacy of several supervised machine learning(ML) systems in intrusion detection is assessed. Among the chosen models are:

- Random Forest (RF)

- Support Vector Machine (SVM)
- k-Nearest Neighbors (k-NN)
- Gradient Boosting / XGBoost

5. Framework for Intrusion Detection The proposed intrusion detection architecture combines preprocessing, feature selection, and classification into a single system. Incoming network traffic data is initially examined to extract relevant properties before being fed into trained machine learning systems for classification. The framework is made to detect both known and unknown attacks by spotting complex patterns in network traffic data.

6. Performance Evaluation
the performance of the shared framework is evaluated using widely accepted metrics, including:

- Accuracy
- Precision
- Recall
- F1-score
- Receiver Operating Characteristic – Area Under Curve (ROC-AUC)

7. Experimental Setup
Training and testing subsets of the dataset are separated in order to evaluate model generalization. Cross-validation techniques are involved to confirm fair and exact results. Every experiment is conducted in the same computer environment to guarantee uniformity and equity in comparison.

8. Framework Advantages The suggested approach highlights:

- Effective identification of contemporary network threats
- decreased chances of erroneous positives
- Enhanced generality across many sorts of attacks
- Usefulness in actual network environments

IV EXPERIMENTAL SETUP AND RESULTS

The experiments were performed to make evaluation to give the performance of the said machine learning–based intrusion detection framework. The setup details are listed below.

- Datasets:
  - CICIDS2017 – contains modern network attacks including DoS, Brute Force, Botnet, and Web attacks
  - UNSW-NB15 – captures real-world network traffic with multiple attack categories
- Data Preprocessing:
  - Missing values removed
  - Categorical features encoded
  - Features normalized using Min-Max scaling
- Feature Selection:
  - Top 20 relevant features selected using tree-based feature importance
- Machine Learning Models Implemented:
  - Random Forest (RF)
  - Support Vector Machine (SVM)
  - k-Nearest Neighbors (k-NN)
  - XGBoost
- Evaluation Metrics:
  - Accuracy, Precision, Recall, F1-Score, ROC-AUC
- Experimental Environment:
  - Hardware: Intel i7 CPU, 16GB RAM
  - Software: Python 3.10, scikit-learn, XGBoost, Jupyter Notebook

The dataset which is divided into 70% training and 30% testing, and 5-fold cross-validation was applied to ensure robustness of results

V. RESULTS

Model	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-Score (%)*	*ROC-AUC (%)*
Random Forest	*98.5*	*97.8*	*98.1*	*97.9*	*99.0*
SVM	*96.2*	*95.6*	*95.2*	*95.4*	*97.0*
k-NN	*94.1*	*93.5*	*92.8*	*93.1*	*95.2*
XGBoost	*98.8*	*98.3*	*98.5*	*98.4*	*99.2*

VI CONCLUSION AND FUTURE WORK

1. CONCLUSION
This paper presented an efficient machine learning-based intrusion detection framework is for detecting modern network threats. The proposed method combines feature selection, data preprocessing, and multiple ML classifiers to modified detection accuracy while lowering false positives. Experiments on

benchmark datasets like CICIDS2017 and UNSW-NB15 show that ensemble models, particularly XGBoost and Random Forest, perform better than conventional classifiers In relation to accuracy, and precision, recall, and ROC-AUC. The results validate the effectiveness and robustness of the proposed framework in real-world network environments. By addressing significant flaws in present intrusion detection systems, such as outdated datasets, class imbalance, and insufficient evaluation metrics, the framework provides a practical and adaptable better solution for modern cybersecurity concerns.

2. FUTURE WORK

Even with the positive results, there are yet, some methods to make the proposed framework better: integration with real-time network monitoring tools to evaluate system performance in situations involving real-time network traffic. Integrating hybrid ML techniques with deep learning to develop the detection of intricate assaults such as zero-day and multi-stage attacks. To ensure that the models can tolerate purposefully constructed inputs meant to evade discovery, adversarial robustness is examined. Optimization to ensure efficient deployment without compromising detection accuracy in resource-constrained environments, such as Internet of Things networks. Expansion of Selection of features and dimensionality reduction methods to boost computing efficiency and generalization potential. The application of these developments in future work will enhance the framework's practical applicability and support the ongoing development of intelligent intrusion detection systems.

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