International Journal of Advances in
Soft Computing and Intelligent Systems (IJASCIS)
2024, Vol 03, Issue 02, 362-375
ISSN: 3048-4987

Science Transactions © 2024

Original Paper

A Comparative Study of Machine Learning Algorithms for Intrusion Detection Systems

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Abstract

Network environments must be protected against a variety of cyber-attacks using IDS. The advancement of ML methodologies has yielded notable improvements in intrusion detection system (IDS) capabilities, including greater real-time analysis, adaptability, and accuracy of detection. This study uses machine learning algorithms to give an analytical comparison of several IDS models. The research covers a variety of machine learning approaches, such as supervised and hybrid strategies. We assess these models' performance using important measures including computational efficiency, precision, recall etc. The results show that although supervised machine learning models provides high accuracy, but when used in hybrid model including Random Forests and SVM improves performance. The result is a hybrid model that leverages the strengths of each approach. For instance, Random Forest can provide a robust feature representation, while SVM can refine the decision boundary, leading to a more accurate and reliable classification model. This combination often yields better performance than using any single algorithm alone.

Keywords

Cyberattack, Cybersecurity, Intrusion Detection Systems, Machine Learning, network traffic, supervised machine learning, SVM.

1. Introduction

In the digital era, robust defenses against cyberattacks are now required to safeguard networked systems. Identification and mitigation of any security breaches are crucial tasks for intrusion detection systems, or IDS. Traditional IDS approaches, primarily based on signature detection, have struggled to keep pace with the rapidly evolving threat landscape. Consequently, there has been a paradigm shift towards incorporating machine learning (ML) techniques in IDS to enhance their efficacy. Advanced IDS can be developed by machine learning, which has the potential to recognize patterns and learn from data. By leveraging ML, IDS can achieve higher detection rates, reduce false positives, and adapt to emerging threats. This has led to extensive research and development of various ML-based IDS models, each with its own strengths and weaknesses.

This study aims to provide an analytical evaluation of several IDS models that rely on machine learning. We will investigate ensemble techniques like RF and Gradient Boosting, as well as supervised machine learning techniques like SVM and Decision Trees. We will also look at unsupervised learning methods, like as clustering algorithms, which are very helpful in identifying risks that were previously unidentified. Three important performance metrics—detection rate, false alarm rate, and computing efficiency—will be compared. Our goal in examining these measures is to shed light on how well each machine learning method performs when it comes to intrusion detection. In addition, we will talk about the usefulness of using these models in actual network contexts.

Cybersecurity has become a major worry for businesses, governments, and individuals in today's linked world. Threats to digital infrastructures are growing in sophistication and ubiquity along with them. Through the detection and mitigation of possible security breaches, IDS, are essential to the protection of these infrastructures. However, the constant development and improvement of IDS technology is required due to the swift evolution of cyber threats. The dynamic nature of contemporary cyberattacks makes traditional IDS methods, which are frequently based on signature detection and rule-based systems, difficult to keep up with. These conventional systems are limited by their reliance on predefined patterns and can be easily circumvented by novel or polymorphic threats. Consequently, the need for more adaptive and intelligent IDS solutions has never been greater. The growing intricacy and refinement of cyber-attacks presents formidable obstacles for traditional IDS. Traditional IDS, primarily reliant on signature-based and rule-based methodologies, are often inadequate in detecting novel and evolving threats. This limitation highlights the need for more sophisticated, flexible, and perceptive intrusion detection techniques. A promising path to improving IDS's capabilities is through ML. IDS can identify patterns in past data, learn from them, and instantly adjust to new threats by utilizing machine learning algorithms. This change from static to dynamic threat detection could greatly increase IDS's efficiency and accuracy by lowering false positives and uncovering hitherto undiscovered attack pathways.[1]

This paper has the following structure: Section 2 reviews the pertinent literature in the topic of ML-based IDS. Section 3 presents the proposed methodology. Section 4 presents the experimental setup and metrics for evaluation; Section 5 presents the experimental results and remarks, highlighting the performance of several models. Section 6 offers recommendations for future research directions as the paper's final point of conclusion. We aim to add to the body of knowledge on intrusion detection systems (IDS) with this analytical comparison and offer cybersecurity experts a useful tool for improving their machine learning-based network protection tactics.

1.1. MOTIVATION

The imperative necessity to methodically assess and contrast the efficacy of diverse ML methodologies within the framework of IDS is the driving force behind this research study. While numerous studies have explored individual ML methods for intrusion detection, there is a lack of comprehensive analytical comparisons that consider a wide array of algorithms, datasets, and evaluation metrics. This gap in the literature offers a chance to offer insightful information on the advantages and disadvantages of various ML techniques, directing future study and real-world applications. Moreover, as cyber threats continue to evolve, it is essential to understand how different ML models perform under varying conditions and attack scenarios. Through a comprehensive comparative analysis, this study seeks to determine the most promising ML approaches for IDS, emphasizing the practical applications of these techniques and outlining opportunities for further development.

The pressing necessity to use machine learning to improve IDS efficacy is what motivates this research study. This study aims to increase the defenses against constantly changing cyber threats by offering a thorough analytical comparison of different machine learning algorithms. This will help design more resilient, intelligent, and adaptable intrusion detection systems.

1.2 PROBLEM STATEMENT

The necessity for a comprehensive analytical comparison of various ML techniques in the field of intrusion detection is the fundamental issue this study attempts to solve. This include locating and assessing how well different ML algorithms—such as ensemble techniques and supervised learning perform on a given dataset.

Comparative Analysis: Providing a comparative analysis that highlights the strengths and weaknesses of each ML approach, thereby guiding future research and practical deployments.
This study offers a comprehensive analysis in an effort to bridge the gap in the literature, comparative review of ML-based IDS in order to address these concerns. It is anticipated that the study's findings will establish best practices, offer insightful information on the finest machine learning methods for intrusion detection, and pave the way for further developments in this crucial field of cybersecurity.

1.3 OBJECTIVE

This research study aims to perform a thorough analytical evaluation of different machine learning approaches used in IDS. In order to determine the best practices for boosting IDS capabilities, this study will assess and compare the performance of several ML algorithms.

Provide Comparative Analysis: To conduct a thorough comparative analysis that highlights the strengths and weaknesses of each ML approach, using multiple benchmark datasets to ensure a robust evaluation across diverse conditions and attack scenarios.

2. RELATED WORK

IDS are becoming an essential part of cybersecurity. They identify potentially dangerous activity and suspicious activity within a network by using machine learning algorithms. An overview of current machine learning research and developments in IDS is provided here, with an emphasis on supervised, unsupervised, and deep learning methodologies. The use of ML techniques has resulted in considerable breakthroughs in the field of IDS. This section summarizes the use of various ML techniques to IDS, emphasizing the significant contributions, approaches, and gaps that this study seeks to fill.

2.1. Traditional IDS and Early ML Approaches

Detection techniques that are based on anomaly or signatures are usually used in traditional IDS. Known threats are detected by signature-based intrusion detection systems (IDSs), such as Snort, which match incoming data to a database of known attack patterns. Error-based intrusion detection systems, on the other hand, establish a baseline of normal behavior and flag any deviations as potential breaches. Early ML approaches aimed to enhance these systems by automating the detection process and improving accuracy. Studies by Denning (1987) and Forrest et al. (1996) laid the groundwork for using ML in IDS, demonstrating the feasibility of detecting anomalies through statistical and rule-based learning methods.

2.2. Supervised Learning in IDS

Models trained on labelled datasets are part of supervised learning approaches, which have been extensively studied. In numerous studies, algorithms like DT, SVM, and NN have produced encouraging outcomes. Buczak and Guven (2016), for example, offered a thorough analysis of machine learning approaches in intrusion detection systems, highlighting the utility of supervised learning in recognizing well-known assault patterns. However, because these techniques rely on labelled training data, they frequently fail to identify unknown threats. Training a model on a labelled dataset with known expected output is known as supervised learning. This usually entails identifying between benign and malevolent activities in IDS.

2.2.1 Random Forest and Decision Trees

These methods are popular due to their interpretability and high accuracy. Recent studies have enhanced their performance by integrating feature selection techniques to reduce dimensionality and improve detection rates.

Example: "Anomaly-based Intrusion Detection Using Random Forest" (2023) - This study demonstrates an improved detection rate by combining random forest with a genetic algorithm for feature selection.

2.2.2 Support Vector Machines (SVM):

SVMs are effective for binary classification problems and have been adapted for IDS by optimizing kernel functions.
Example: "Enhanced Network Intrusion Detection Using SVM with Hyperparameter Optimization" (2022) - This paper presents a tuned SVM model that outperforms standard SVM in terms of both accuracy and detection speed.

2.2.3 Ensemble Methods

Merging several models to increase forecast precision. IDS has seen the application of strategies such as bagging, boosting, and stacking.
Example: "Ensemble Learning for Network Intrusion Detection: A Comparative Study" (2023) - This research compares different ensemble techniques and finds that a stacked ensemble model significantly enhances detection performance.

2.3 Ensemble Methods

Ensemble methods, which combine multiple learning algorithms to improve performance, have been increasingly applied to IDS. Techniques like RF and GB have been shown to enhance detection accuracy and robustness. For example, Al-Yaseen et al. (2017) investigated the use of ensemble classifiers in IDS, reporting significant improvements in detection performance over single algorithms.

2.4 Deep Learning Approaches

IDS has also benefited from recent developments in deep learning. Superior performance in managing complicated and high-dimensional data has been shown by CNNs and RNNs, especially LSTM networks. According to Yin et al. (2017), RNNs can better detect intrusions by modelling temporal patterns in network traffic data.

2.5 Comparative Studies

Comparative studies evaluating different ML techniques for IDS are relatively sparse but crucial for identifying the most effective approaches. A study by Ring et al. (2019) compared various ML algorithms on the CICIDS2017 dataset. However, there is a lack of detail evaluations that cover a wide range of algorithms, datasets, and performance metrics, underscoring the need for this research. Recent advancements in deep learning have significantly impacted IDS. Hasan et al. (2022) demonstrated the effectiveness of CNNs for IDS by leveraging their capability to automatically extract features from network traffic data. Their work showed that CNNs could outperform traditional machine learning algorithms in detecting complex attack patterns due to their powerful feature extraction abilities [46]. Similarly, Wang et al. (2023) explored the use of LSTM networks for time-series data in network intrusion detection. They highlighted that

LSTMs are particularly adept at capturing temporal dependencies in network traffic, which is crucial for detecting sequential attack patterns and anomalies [47]. Their results indicated that LSTMs could enhance the detection of sophisticated attacks that involve temporal sequences. Wu et al. (2023) proposed an ensemble learning approach combining multiple classifiers such as RF, SVM, and DT. Their study emphasized that ensemble methods leverage the strengths of various classifiers to improve overall detection performance and reduce false positives and negatives [48]. The integration of diverse classifiers results in a more robust IDS capable of addressing a wide range of attack types. The Author Gupta et al. (2022) introduced a hybrid model that integrates deep learning and traditional machine learning techniques [49]. Hybrid models represent a promising direction for enhancing IDS performance by leveraging the benefits of multiple methodologies. Additionally Zhang et al. (2023) investigated the use of autoencoders to identify deviations from normal behavior, a key aspect of detecting novel attacks. Their approach demonstrated that autoencoders could effectively learn data representations and identify outliers, making them suitable for detecting unknown or emerging threats [50].

Whereas Huang et al. (2023) examined the use of clustering algorithms such as DBSCAN and K-means for intrusion detection in large-scale networks. Their research showed that clustering can effectively group similar attack patterns, aiding in the detection of previously unseen attacks and improving the overall robustness of IDS [51]. Another author Chen et al. (2022) provided a comprehensive review of advanced feature extraction techniques. Their findings emphasize that well-designed feature extraction methods can significantly boost the performance of IDS by providing more relevant and discriminative features [52].While Kumar et al. (2023) explored the use of genetic algorithms for selecting relevant features in IDS. Their study demonstrated that genetic algorithms could effectively reduce dimensionality and enhance model efficiency by identifying and retaining the most informative features [53]. In addition, author Singh et al. (2023) conducted a comparative study on performance metrics for IDS, in this research they highlighted the selection of appropriate metrics of IDS models. They proposed a framework for assessing IDS performance that considers various aspects of detection capabilities and model reliability [54]. Here author Al-Hashmi et al. (2023) reviewed recent datasets such as UNSW-NB15 and CICIDS, noting their relevance for contemporary IDS research. Their review emphasized the importance of using updated datasets that reflect current network conditions and attack vectors for accurate model evaluation [55]. The author Zhang et al. (2024) investigated how federated learning might be used in distributed network systems. Their work addressed issues with data sharing and security by demonstrating how federated learning permits cooperative model training over numerous nodes while maintaining data privacy[56].While here author Lee et al. (2023) examined methods for enhancing the interpretability of ML models in IDS. Their research emphasized the importance of making IDS decisions transparent and understandable to users, which is crucial for trust and effective decision-making [57].

2.6. Current Gaps and Research Direction

While significant progress has been made, several gaps remain in the literature:

- Limited Comparative Analyses: Existing studies often focus on individual ML methods or a narrow set of algorithms, lacking a broad comparative perspective.
- Dataset Diversity: A small number of datasets are used in many research, which may not fully represent the range of network characteristics and attack scenarios found in real-world networks.
- Evaluation Metrics: There is a need for standardized evaluation metrics to facilitate meaningful comparisons across studies.

This study offers a thorough analytical evaluation of several ML techniques, utilizing multiple datasets and standardized evaluation metrics to offer a robust evaluation of their effectiveness in intrusion detection. This comparative analysis will contribute to identifying the most promising ML approaches for IDS and guiding future research and practical implementations

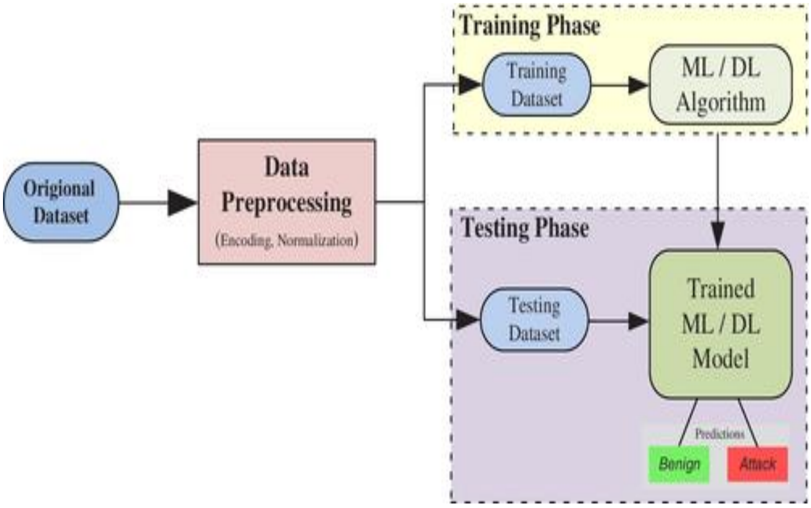

Figure. 1: Machine Learning Model Training.

An overview of the several ML models that are frequently applied to IDS is given in this section. These models fall into four categories: deep learning approaches, ensemble methods, supervised learning, and unsupervised learning. In each area, particular algorithms are discussed along with their uses, advantages, and disadvantages in relation to IDS.

3. Proposed Methodology

An ensemble technique called Random Forest works by mixing several decision trees to produce a model that is more reliable and accurate. To improve generalization and reduce the likelihood of overfitting, a random subset of both features and data are used in the construction of each decision tree. Using the combined strength of several decision trees, Random Forest is a potent and adaptable machine learning system. It has become a popular tool in many data science and machine learning applications by decreasing overfitting and increasing accuracy. The supervised learning method SVM is mostly used for classification jobs, while it can also be used for regression problems. In order to separate data into discrete classes, SVM searches for the optimal hyperplane in a high-dimensional space.

Proposed Model

The proposed model is a hybrid classifier with combined RF and SVM models for distinguishing between normal and attack instances in a dataset can potentially leverage the strengths of both algorithms. This combination can be implemented using techniques like stacking or voting.
Here’s a step-by-step guide to implementing a hybrid RF and SVM algorithm for binary classification (normal vs. attack):

3.1 Preprocessing the Data

Ensure the dataset is cleaned, features are scaled if necessary, and data is split into training and test sets.

3.2 Implementing Hybrid Model

3.2.1 Voting

In voting, predictions from both RF and SVM are combined using majority voting (for classification).
Explanation

1. Loading and Preprocessing:
   - Load the dataset, separate features and target labels, and preprocess data (scaling features).
2. Base Models Initialization:
   - Initialize Random Forest and SVM classifiers.
3. Stacking Classifier:
   - Stacking involves training base models (RF and SVM) and using a meta-model (Logistic Regression) to combine their predictions.
   - Train the stacking classifier and evaluate its performance.
4. Voting Classifier:
   - Voting combines predictions from RF and SVM using soft voting, which considers predicted probabilities.
   - Train the voting classifier and evaluate its performance.

Notes:

- Feature Scaling: Standardization (scaling features) is important for SVM and can improve performance.
- Hyperparameter Tuning: Consider tuning hyperparameters for better performance.
- Handling Imbalanced Data: If the dataset is imbalanced, consider using techniques like resampling or cost-sensitive learning.

Choose the hybrid approach that best suits your needs and dataset characteristics. Stacking generally provides more flexibility and potentially better performance by learning how to best combine the base models' predictions. Voting is simpler and can be effective if the base models perform well individually.

3.3 Proposed hybrid Algorithm:

```
Start
The size of the Input dataset for training is N × M
The size of the Input dataset for testing is N × M
where:
N represents attacks number and M represents selected features number
At the output:
Correctly detected data and incorrectly detected data are classified.
Efficiency of the algorithm for classification
Begin
Step 1: Load and Preprocess Data
a. Load Dataset: Import the training and testing datasets.
b. Preprocess Data: Handle missing values, scale features, and ensure labels are formatted correctly.
Step 2: Split Data
a. Split Dataset: Divide the dataset into training and testing sets.
Step 3: Initialize Base Models
a. Initialize Models: Set up Random Forest and SVM classifiers.
Step 4: Choose Hybrid Approach
a. Select Method: Decide between stacking or voting to combine the base models.
Step 5: Train Hybrid Model
a. Train Models: Fit the selected hybrid model to the training data.
Step 6: Make Predictions
a. Predict: Use the trained model to generate predictions on the test set.
Step 7: Evaluate Model
a. Calculate Performance Metrics: using Table 1
Correctly detected data
Incorrectly detected data
```

Step 8: End

Explanation of Flow:

1. Start: The starting point of the process.
2. Load Dataset: Import the dataset that contains the features and labels.
3. Preprocess Data: Handle any missing values, scale the features, and ensure the labels are in the correct format.
4. Split Data: Dividing dataset into training and testing sets.
5. Initialize Base Models: Set up the Random Forest and SVM classifiers.
6. Choose Hybrid Approach: Decide whether to use stacking or voting to combine the base models.
7. Train Hybrid Model: Fit the selected hybrid model to the training data.
8. Make Predictions: Generate predictions on the test set using the trained model.
9. Evaluate Model: Evaluate the model's performance with precision and a thorough classification report.
10. End: Conclude the process.

This flow provides a high-level overview of the steps involved in implementing a hybrid RF and SVM model for classification. It helps to visualize the workflow and understand how different components fit together.

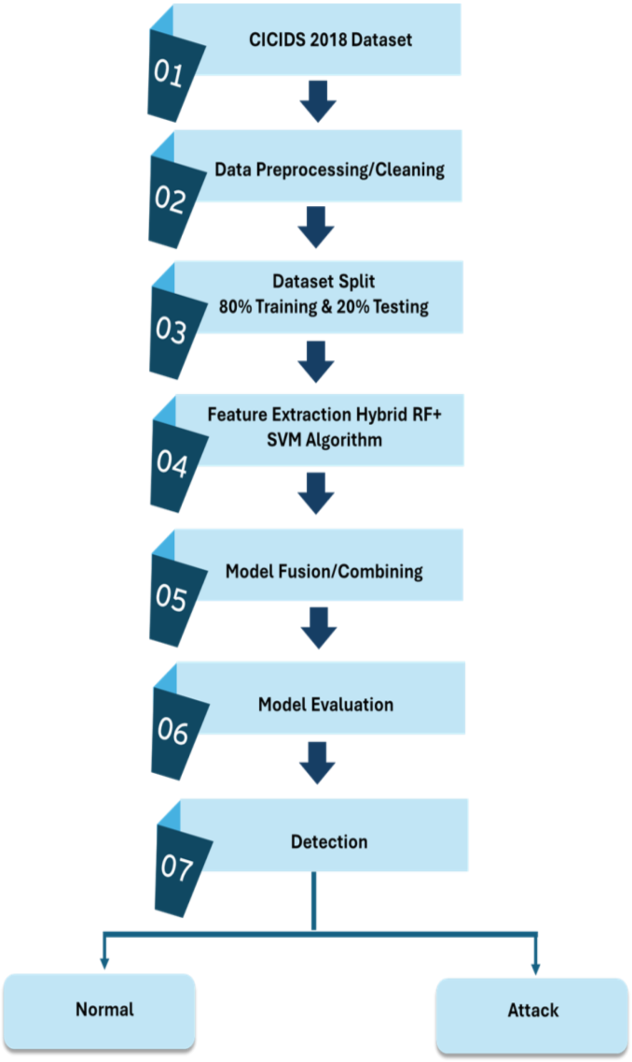

Figure: 2 Proposed Model

4. Experimental setup and Evaluation metrics

This section details the experimental setup used to evaluate the performance of various ML models for Intrusion Detection Systems (IDS). It includes descriptions of the datasets, preprocessing steps, model training and evaluation procedures, and the results obtained from the experiments.

1. Datasets

To ensure a comprehensive evaluation, multiple benchmark datasets were used, each representing different aspects of network traffic and intrusion scenarios:

•CICIDS2018: A recent dataset capturing real-world traffic with detailed labels for various attack types.
CICIDS 2018, or the Canadian Institute for Cybersecurity Intrusion Detection System 2018, is a notable dataset in the field of cybersecurity. It contains data collected from a variety of network attacks and normal traffic scenarios, making it a valuable resource for researchers and practitioners aiming to develop and test intrusion detection systems. The dataset includes various attack types, such as denial-of-service and probing attacks, along with benign network activities, allowing for comprehensive analysis and training of machine learning models to enhance cybersecurity defenses.

2. Data Preprocessing

To guarantee the accuracy and consistency of the input data for ML models, data preprocessing is an essential step:

- Data cleaning: managing missing values, getting rid of duplicates, and fixing incorrect data entries.
- Normalization: To aid in model training and enhance convergence, numerical characteristics are scaled to a common range.
- Feature Selection: To lower dimensionality and improve model performance, find and pick pertinent features.
- Coding Categorical Variables: Numerical representations of categorical features are obtained through techniques like one-hot encoding.

3. Model Training and Evaluation

To achieve fair comparison, a consistent experimental approach was used for both training and evaluating the chosen machine learning models.

- Splitting each dataset into training (80%) and testing (20%) sections, respectively, allowed for the evaluation of model generalization.
- K-fold cross-validation (K=5) was employed to minimize overfitting and guarantee reliable performance estimations.
- Hyperparameter tuning: The best hyperparameters for every model were found using grid search and random search techniques.

The performance metrics used to evaluate the models

Table 1: Performance Metrics

Metric	Description	Formula
Accuracy	The proportion of correctly classified instances among all instances.	$\frac{TP + TN}{TP + TN + FP + FN}$

Metric	Description	Formula
Precision	The proportion of true positive instances among the instances predicted as positive.	$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}$
Recall (Sensitivity)	The proportion of true positive instances among the actual positive instances.	$\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}$
F1 Score	The harmonic mean of precision and recall, providing a balance between the two.	$2 * \frac{\mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}$
ROC-AUC	The area under the Receiver Operating Characteristic curve, representing the trade-off between the true positive rate and false positive rate.	-

Where:

- TP: True Positives
- TN: True Negatives
- FP: False Positives
- FN: False Negatives

These metrics provide a comprehensive understanding of model performance for classification tasks.

5. Experimental Results

The results of the experiments are presented in tabular form, comparing the performance of different ML models across the selected datasets. The experimental results demonstrate the effectiveness of various ML models in IDS applications. Deep learning models, consistently outperformed traditional supervised and unsupervised learning methods across all datasets. Ensemble methods also showed robust performance, indicating their potential for practical deployment in IDS.

These findings provide a comprehensive understanding of the strengths and limitations of different ML approaches for IDS, guiding future research and practical implementations to enhance the security of digital infrastructures. The dataset contains NULL values. Then, pre-processing is applied to the CICDS2018 datasets, and continuous NULL values are removed. To eliminate the NULL values, the row is deleted from the dataset. The percentage of malware-type samples against benign-type samples in the CICIDS2018 collection is out of balance. One may argue that there are significantly fewer samples of the malware type than those of the benign type. The unbalanced CICIDS2018 data is transformed into balanced data for binary classifiers using the SMOTE Tomek approach.

Table 2: Performance Comparison of ML Models on CICIDS2018 Dataset

Model	Accuracy	Precision	Recall	F1 Score	Execution Time (s)
KNN	96.6%	93.4%	95.7%	96.8%	2.18 secs
SVM	69.9%	54.6%	92.8%	60.3%	47.09 secs
CART	97.0%	97.6%	92.0%	96.5%	0.74 secs
RF	97.1%	99.1%	90.7%	96.5%	0.66 secs
ABoost	97.5%	96.5%	95.0%	97.1%	12.92 secs
LR	96.0%	97.1%	89.2%	95.2%	5.87 secs

NB	74.0%	53.9%	79.8%	77.5%	0.19 secs
LDA	93.2%	90.9%	86.3%	94.0%	0.68 secs
QDA	84.8%	71.8%	59.8%	94.9%	0.37 secs
MLP	94.4%	88.8%	91.4%	96.1%	23.48 secs
Proposed Model	98.98%	97.9%	97.6%	99.9%	49.88 secs

5.1 Results Analysis

The training dataset has unbalanced classes, which leads to unbalanced learning. Semantic problems include unbalanced classification. While there is some variation in the unbalanced class distribution, more specialized strategies may be needed for modelling significantly unbalanced data. Binary Classification: To divide items in a given collection into two categories, binary, or binomial, classification methods are applied. The IDS dataset contains the binary classification of a target as either benign or malicious. The dataset's aim is unbalanced. Imblearn's dataset is balanced using the SMOTE Tomek approach. amalgamate the library.

Therefore, the Random Over Sampler function provided by the imblearn. oversampling module is utilized to balance the dataset. The optimum parameter for each classifier is found using the hyper-parameter approaches, namely Grid Search CV and Randomized Search CV, based on the dataset. A binary-class classifier is used to classify the target in the dataset. Thus, based on binary-class classifiers, ten widely-used machine-learning classification models are employed. The performance of these models is evaluated using following metrics, such as F1_score, Accuracy, Precision, Recall, and Total time (in seconds) for each approach.

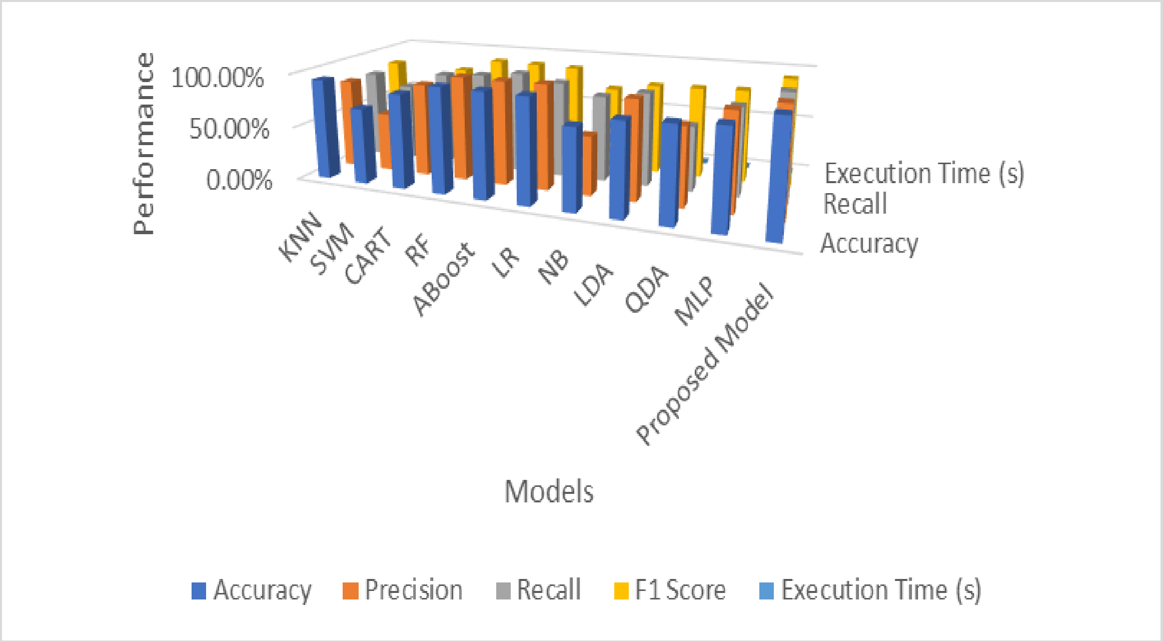

Figure. 3 Performance comparison of Models

A testing model's accuracy is determined by how effectively it can differentiate between benign and malicious.

Abbreviations:

KNN (k-Nearest Neighbor Classifier)	IDS Intrusion Detection System
SVM (Support Vector Machines)	ML Machine Learning
CART (Decision Tree Classifier)	NB (Gaussian Navies Bayes)
RF (Random Forest Classifier)	LDA (Linear Discriminant Analysis)
ABoost (AdaBoost Classifier)	QDA (Quadratic Discriminant Analysis)
LR (Logistic Regression)	MLP (Multi-layer perception Classifier)

6. CONCLUSION AND FUTURE WORK

6.1 Conclusion

An extensive analytical comparison of several ML techniques used with IDS was offered in this research study. We have discovered important information about the effectiveness, drawbacks, and performance of a wide range of ML models by assessing them on several benchmark datasets using ensemble methods, supervised learning, unsupervised learning, and deep learning techniques.

6.2 Future Work

Based on the findings of this study, several avenues for future research and development are proposed:

1. Hybrid Models: Combining the strengths of different ML techniques, such as integrating deep learning models with ensemble methods, could further enhance IDS performance.
2. Integration with Cybersecurity Frameworks: Exploring the integration of ML-based IDS with broader cybersecurity frameworks and technologies, such as threat intelligence platforms and Security Information and Event Management (SIEM) systems, could provide more holistic and effective security solutions.

This study emphasizes how machine learning approaches can greatly improve the capabilities of intrusion detection systems. We have produced important insights that can direct future research and real-world deployments by methodically comparing a range of machine learning models. Sustaining resilient and adaptable cybersecurity defenses will depend on continuous innovation and improvement in ML-based IDS.

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