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Original Paper

A COMPARATIVE STUDY OF MACHINE LEARNING ALGORITHMS FOR INTRUSION DETECTION SYSTEMS

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ABSTRACT

Network environments must be safeguarded from a large number of cyber threats that are a real threat to most of the users. The development of ML techniques has brought about some noticeable improvements in the intrusion detection system (IDS) such as the ability to make better real-time analysis, adjust to newer concepts and provide a more accurate detection. This research involves the application of machine learning algorithms that use a comparative analysis to evaluate the performance of various IDS models. The research will discuss a range of machine learning techniques that are supervised and hybrid methods. We judge the models against time, precision, recall, etc., the main criterions in choosing the model. We find that while supervised machine learning models give high accuracy, using the Random Forests and SVM in a hybrid model improves the performance. Thus, the product is a hybrid model that combines the strengths of both approaches. For example, Random Forest can provide a strong feature representation but SVM can refine the decision boundary thus, lead to a more accurate and reliable classification model. Usually, this technique performs better than individual models or any single algorithm on its own.

KEYWORDS

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

1. INTRODUCTION

Cybersecurity defenses are now required to be strong enough to secure the networked systems in the digital era. Detection and prevention of any security breaches are tasks most important for intrusion detection systems, the so-called IDS. Conventional IDS solutions, which mainly base their operation on signature detection, have been struggling to cope with the rapidly growing variety of cybersecurity threats. As a result, the application of the machine learning techniques in IDS environment has moved into the central position hence to improve their efficiency has been the trend. Machine learning is contributing to the advanced development of IDS, which can help to be confident of the success of the pattern recognition activities and learn from the data. Through machine learning, IDS can take advantage of better detection rates, lowering the false positives and adapting to the new attacks. So, a result of the research and development activity done so far is the existence of many ML-based IDS models, which might each have certain strong and weak sides.

This work will analytically assess a few of the IDS models based on machine learning. We will investigate ensemble techniques such as RF and Gradient Boosting, as well as supervised machine learning techniques such as SVM and Decision Trees. We will also look at unsupervised learning methods, like clustering algorithms, which are extremely helpful in identifying previously unknown risks. We will compare three key performance metrics: detection rate, false alarm rate, and computing efficiency. In terms of the above measures, our aim is to point out how each of the machine learning approaches compares regarding intrusion detection performance. We will also discuss the applicability of these models in real-life network settings.

Cybersecurity is very important for businesses, governments, and individuals worldwide today. Along with them, threats to digital infrastructures are becoming more and more sophisticated and common. These infrastructures can be switched off and mitigated once an incident is recognized. However, in consideration of the dynamic behavior of cyber threats that have established a new pace of evolution through their adaptability, an importance is placed on the progress and development concerning technology in the field of Intrusion Detection Systems. Modern cyberattacks are very dynamic in nature. The dynamics of cyberattacks make the continued utilization of signature detection and rule-based systems quite difficult. Traditional systems are at major disadvantages because pattern-dependent and easily outsmarted by new and polymorphic threats are in quite a poor state. Therefore, the need for more adaptive and intelligent IDS solutions has never been greater. The increasing complexity and sophistication of cyber-attacks present significant challenges for traditional IDS. Traditional IDS have not been able to detect new and evolving threats because of their signature-based and rule-based nature. This necessity is a call for delivering IDSs that are more advanced, adaptive, and responsive. Many believe that solutions enhanced by machine learning will provide new opportunities for the detection and mitigation of intrusions. Using the most common machine learning algorithms, the IDS would learn

from historical data representing observatory behavior and thus automatically adapt new threats. Changing from static to dynamic threat detection can greatly enhance the performance and precision of IDS by lowering false positives and uncovering previously unknown attack paths.[1]

This paper is structured as follows: Section 2 gives an overview of the relevant literature on the topic of ML-based IDS. Section 3 describes the proposed methodology. Section 4 includes descriptions of the experimental set-up and evaluation metrics; Section 5 presents the experimental results with comments regarding performance among several models. Section 6 gives some directions for future research as the final conclusion of this paper. Through this analytical comparison, we wish to contribute to the body of knowledge on intrusion detection systems (IDS) and provide cybersecurity experts with a useful aid in upgrading their machine learning-based network protection strategies.

1.1 Motivation

The entire essence of this research work stems from the pressing necessity to systematically assess and compare the performance of various ML techniques under the IDS umbrella. While a very significant number of ML algorithms have been researched for intrusion detection, a comprehensive comparison of all techniques across various algorithms, datasets, and evaluation metrics is lacking.

This gap in literature provides an opportunity for substantial input concerning the advantages and disadvantages of various machine-learning-based techniques, which could direct further study and real-life applications. Moreover, because cyber threats continue to adapt, it is particularly important to characterize how different models behave under varying circumstances and attack methodologies. To achieve these objectives, this study will carry out a thorough comparative analysis that will identify the most promising machine learning approaches for intrusion detection, shed light on the practical significance of such techniques, and delineate avenues for future work.

The salient felt necessity of using machine learning to secure shadow-based IDS against deep cyber threats is what inspires this research study. This study aims to instruct on increasing cyberspace defenses against unceasingly changing offenses through presenting daunting analytical comparisons among various machine-learning algorithms.

1.2 Problem statement

The key objective of this research is to establish how different ML techniques in intrusion detection can be useful, which requires an in-depth comparison. The other hand of this process consists of locating different ML algorithms like ensemble techniques and supervised learning and testing them on a given dataset. The output of this exercise is the presentation of a comparative analysis which highlights the strengths and weaknesses of the various mathematical theories that the methods are grounded on and which could be useful in further research and application endeavors. The contribution of this research

is therefore claimed to fill in the gaps by exploring some of these ML based IDS in a comparative manner. This research is anticipated to provide concrete recommendations, offer some of the best solutions using the knowledge of machine learning in the area of intrusion detection and also set a foundation for other great strides to be made in this important area of cybernetics.

1.3 Objective

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

Provide Comparative Analysis: This would ensure that the comparative analysis is deep enough to show the strengths and weaknesses of each ML approach, using multiple benchmark datasets across diverse conditions and attack scenarios.

2. RELATED WORK

IDS is becoming the integral part of cyber security. They identify possibly malicious activity and suspicious activity on a network through the use of machine learning algorithms. The article discusses the overview of current research and developments related to machine learning in IDS using supervised, unsupervised, and deep learning methodologies. Major breakthroughs are made in IDS by using the techniques of ML. 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

Traditional IDS employs techniques that are based on anomaly or signatures. IDSs, such as Snort, identify known threats by matching the incoming data to a database of known patterns to the attack. Error-based intrusion detection systems, as the name suggests, set up a baseline of normal behavior and flag a departure from it as an opening of a breach. The early ML techniques tried to make improvements in the system by automatic detection and improved accuracy. Research works by Denning (1987) and Forrest et al. (1996) are found to be precursors in using ML in IDS, and their work proves that anomalies can be detected by using statistical and rule-based learning methods.

2.2 Supervised Learning in IDS

Supervised learning approaches include models trained on labelled datasets. Such approaches have been studied extensively, and in many studies, algorithms like DT, SVM, and NN have produced encouraging outcomes. For instance, Buczak and Guven (2016) 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, since the techniques depend on labelled training data, they very often fail to detect unknown threats. Training of a model by using a dataset with known output is called

a supervised learning exercise. This usually comprises identification between the benign and malignant activities in an IDS.

2.2.1 Random Forest and Decision Trees

We have seen a rise in such approaches. Accuracy as well as interpretability. Certain approaches in contemporary researches have attempted to. Augment Feature selection methods in order to enhance detection capabilities, Minimize the extent of the region and improve their detection precision. An example of such would be random forest, where it focuses on anomaly intrusion detection. In 2023, this paper incorporates random sampling to be able to provide a more favourable detection rate. Feature selection for forest based ecosystems using genetic algorithms.

2.2.2 Support Vector Machines (SVM)

Support vector machines. Has a good performance in classify in two classes problems. It's accepted for IDS. Kernel functions optimization problem solution. Example: "Enhanced Network Intrusion Detection". I deal with several aspects of SVM aiming at the optimization of parameters for instance (2019, 2022). This work describes a modified SVM model, which is reported to be more efficient ones. The accuracy of detection and speed of detection of this method is greater than the normal SVM.

2.3 Ensemble Methods

Ensemble approaches include using multiple learning algorithms to enhance performance. Many techniques, such as RF and GB, improve detection accuracy and also enhance robustness. For example, Al-Yaseen et al. (2017) have shown by using ensemble classifiers for intrusion detection, substantial improvements in the detection performance were derived compared to single algorithms.

2.4 Deep Learning Approaches

IDS has gained a lot from the latest advancements in deep learning. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have demonstrated impressive performance in handling complex and high-dimensional data. As noted by Yin et al. (2017), RNNs excel at identifying intrusions by analysing the temporal patterns found in network traffic data.

2.5 Comparative Studies

Studies comparing different ML methods for IDS are few but play a key role to find the best approaches. Ring et al. (2019) looked at various ML algorithms using the CICIDS2017 dataset. Yet, we lack in-depth reviews covering many algorithms, datasets, and performance measures, which shows why this research matters. New steps in deep learning have changed IDS a lot. Hasan et al. (2022) showed how well CNNs work for IDS by using their power to pull out features from network traffic data on their

own. Their work proved that CNNs could do better than old machine learning algorithms in spotting complex attack patterns because they can extract features so well [46]. In the same way, Wang et al. (2023) looked into using LSTM networks for time-series data in network intrusion detection. They pointed out that LSTMs are good at catching time-based patterns in network traffic, which is key to spot attack patterns and odd things that happen in order [47]. What they found showed that LSTMs could help spot tricky attacks that involve time-based sequences better. Wu et al. (2023) came up with a team learning approach that puts together multiple classifiers like RF, SVM, and DT. Their exploration stressed that ensemble styles make use of different classifiers' strengths to boost overall discovery effectiveness and cut down on false cons and negatives [48]. Combining colorful classifiers leads to a stronger IDS that can handle numerous types of attacks. Gupta et al. (2022) came up with a mixed model that blends deep literacy and old- academy machine literacy styles [49]. These mixed models show pledge to ameliorate IDS performance by tapping into the good points of multiple approaches. So, Zhang and the group as of 2023, study how to use encoder-decoder networks for the purpose of determining when events deviate from a norm, you know, to put it simply, detecting the abnormal. This is quite significant in the realm of fending off novel forms of breaches. What they found was quite interesting: these auto encoders can really pick up on data patterns and identify anomalies effectively. This ability makes them pretty handy for catching new or different threats that pop up [50].

On the other hand, Huang et al. (2023) checked out how clustering algorithms like DBSCAN and K-means could descry intrusions in big networks. Their study proved that clustering can group analogous attack patterns well helping to spot unseen attacks and make IDS more dependable overall [51]. Chen et al.(2022) gave a full review of advanced ways to pull out features. The results therefore demonstrate the significance of professed point birth ways in perfecting Intrusion Detection System (IDS) effectiveness. You see, they're suitable to offer characteristics that are n't just material but also incredibly distinctive. [52]. Here, Kumar et al. (2023) looked into using genetic algorithms to pick out the relevant features for IDS. Their study showed that these algorithms are pretty effective when it comes to reducing dimensionality and improving the efficiency of the models by pinpointing and keeping only the most informative features [53].

Next is this study by Singh and associates (2023). A comparison exploration was conducted with an emphasis on IDS performance criteria. In their study, they emphasized the significance of opting applicable criteria for these models. A paradigm for assessing IDS performance was indeed given by them, which considers a number of factors similar as the model's responsibility and discovery capabilities [54].

Now, Al-Hashmi et al. (2023) took a good look at recent datasets, including UNSW-NB15 and CICIDS. They made a note of how relevant these datasets are for today's IDS research. Their review stressed the

need for using updated datasets that genuinely reflect the current network conditions and the kinds of attack vectors we're seeing for accurate model evaluation [55]. Looking ahead, Zhang et al. (2024) considered the applicability of federated learning in distributed networks. Their research addressed several forms of data sharing and security problems. They emphasized how federated learning can enable collaborative model development at several nodes with the respective data remaining confidential and secure [56].

Lastly, Lee et al. (2023) looked into ways to make machine learning models in IDS more interpretable. They highlighted just how important it is for IDS decisions to be clear and understandable to users. This transparency is essential for building trust and aiding effective decision-making [57].

2.6 Current Gaps and Research Direction

Although there has been a lot of development, there are still a number of gaps in the literature: • Few relative analyses Due to the lack of a broad relative perspective, these research usually focus on specific ML approaches or a limited number of algorithms. Diversity of Datasets The variety of network features and attack scripts configured in real-world networks may not be fully represented by the few datasets utilized in many explorations.

• Measures of Evaluation Standardized evaluation criteria are necessary in order to provide meaningful comparisons between research. This paper provides a comprehensive logical assessment of various machine learning techniques, utilizing a variety of datasets and established evaluation criteria to provide a solid assessment of their efficacy in intrusion detection.

This relative analysis will contribute to relating the most promising ML approaches for IDS and guiding unborn exploration and practical executions An overview of the several ML models that are constantly applied to IDS is given in this section. These models fall into four orders deep literacy approaches, ensemble styles, supervised literacy, and unsupervised literacy. In each area, particular algorithms are bandied along with their uses, advantages, and disadvantages in relation to IDS.

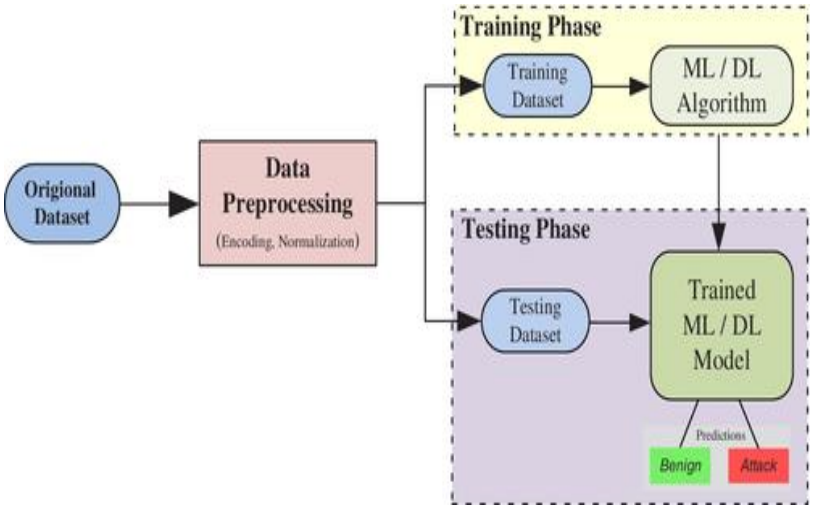

Fig.1. Machine Learning Model Training.

3. PROPOSED METHODOLOGY

Random Forest is an ensemble approach that combines several decision trees to provide a more reliable and accurate model. Because each tree is constructed using a random selection of features and data, overfitting is less likely to occur and speed is improved. As a flexible and robust machine learning algorithm, Random Forest leverages the combined power of these decision trees. Its ability to decrease overfitting and improve precision has made it a favorite choice in various machine learning and data analysis applications. While the supervised learning method SVM can be used for regression problems, it's mainly focused on classification tasks. To categorize data into separate classes, SVM searches for the best hyperplane in a high-dimensional space.

3.1 Proposed Model

In order to differentiate between normal and attack occurrences in a dataset, the suggested model is a hybrid classifier that combines the advantages of both algorithms: RF and SVM. Voting and stacking are two methods that can be used to create this combination.

This is a detailed tutorial on how to apply a hybrid RF and SVM algorithm for binary classification (attack vs. normal).

3.2 Preprocessing the Data

Make that the dataset has been cleaned, that features have been scaled if needed, and that it has been divided into training and test sets.

3.3 Implementing Hybrid Model

3.3.1 Voting

When voting, majority voting is used to aggregate the predictions from both RF and SVM (for classification).

Explanation

1. Loading and Preprocessing:
    - After loading the dataset, preprocess the data (scaling features), and segregate the features and target labels.
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.

3.4 Proposed hybrid Algorithm

Start

The size of the Input dataset for training is $N \times M$

The size of the Input dataset for testing is $N \times M$

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 Utilizing Table 1, determine the performance metrics.

Accurately identified information

Data that was incorrectly detected

Step 8: End

Explanation of Flow:

To begin with, the first step is determining from where to start. After this to load up the data which contains characters as well as their labels. To fit it, remove missing values and convert all characters correctly. The dataset should be split into 2 sets one for testing and another for training. Initialise Random Forest, SVM classifiers in-order to start base estimators but be careful with parameters. To define which combination of the base models you will use (voting or stacking) when adopting a hybrid scheme. Now you have to train the hybrid model, i.e. use this data (the training set) with the selected mode. Afterward, one should make predictions by applying the trained model to the test set, which will produce the desired outcomes. Assessing the model is imperative because it allows for an accurate evaluation of its performance and provides a comprehensive classification report. Ultimately, the process concludes with a finish, putting the procedure to rest.

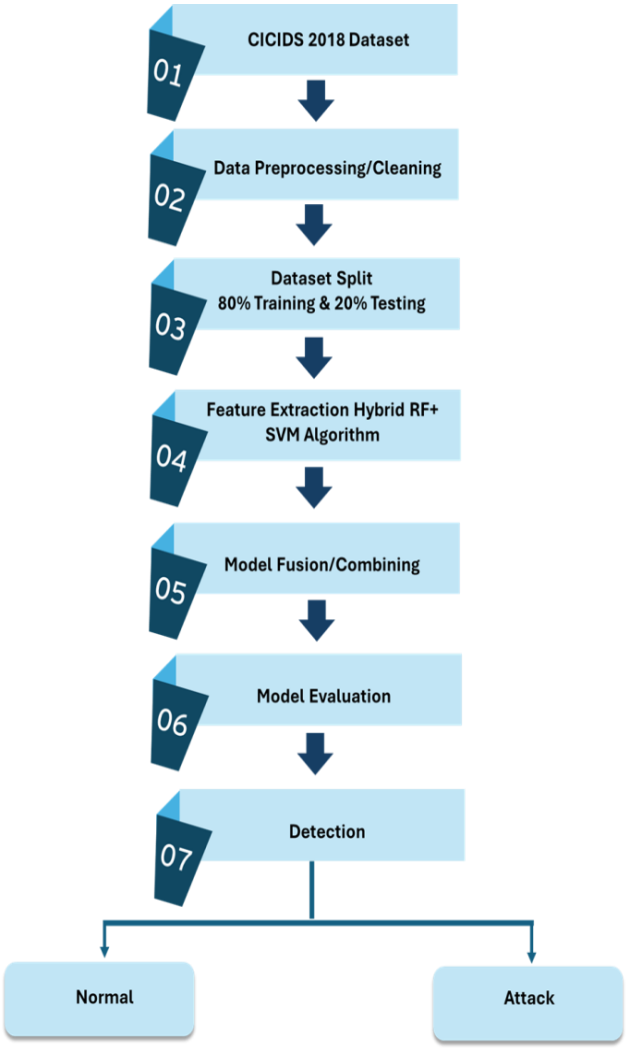

Fig.2. Proposed Model.

4. EXPERIMENTAL SETUP AND EVALUATION METRICS

This section describes the experimental setting that was used to assess how well different machine learning models performed for intrusion detection systems (IDS). It contains explanations of the datasets, preparation stages, model training and assessment protocols, and experiment outcomes.

4.1 Datasets

Several benchmark datasets were utilized to guarantee a thorough assessment, each of which represented a distinct facet of network traffic and intrusion scenarios:
The CICIDS2018 dataset is a recent collection of real-world traffic that includes thorough categorization for different kinds of attacks.
One noteworthy cybersecurity dataset is CICIDS 2018, or the Canadian Institute for Cybersecurity Intrusion Detection System 2018. For academics and practitioners looking to create and test intrusion detection systems, it is an invaluable resource because it includes data gathered from both typical traffic

scenarios and a range of network attacks. In addition to innocuous network activity, the dataset contains a variety of attack types, including denial-of-service and probing attacks. This enables thorough analysis and machine learning model training to improve cybersecurity defenses.

4.2 Data Preprocessing

A crucial step in ensuring the precision and consistency of the input data for machine learning models is data preprocessing:

• Data cleaning: correcting inaccurate data entries, eliminating duplication, and handling missing values.

Normalization is the process of scaling numerical characteristics to a common range in order to facilitate model training and improve convergence.

Finding and selecting relevant features is the first step in reducing dimensionality and enhancing model performance.

The process of coding categorical variables involves the use of methods such as one-hot encoding to produce numerical representations of category properties.

4.3 Model Training and Evaluation

The selected machine learning models were trained and evaluated using a consistent experimental methodology to ensure fair comparison.

• The evaluation of model generalization was made possible by dividing each dataset into training (80%) and testing (20%) parts, respectively.

• To reduce overfitting and ensure accurate performance estimates, K-fold cross-validation (K=5) was used.

• Hyperparameter tuning: Grid search and random search methods were used to identify each model's optimal hyperparameters.

The models' performance metrics.

Table 1. Selected Assets for portfolio.

Metric	Description	Formula
Accuracy	The proportion of correctly classified instances among all instances.	$\frac{TP + TN}{TP + TN + FP + FN}$
Precision	The proportion of true positive instances among the instances predicted as positive.	$\frac{TP}{TP + FP}$
Recall (Sensitivity)	The proportion of true positive instances among the actual positive instances.	$\frac{TP}{TP + FN}$
F1 Score	The harmonic mean of precision and recall, providing a balance between the two.	$2 * \frac{Precision * Recall}{Precision + Recall}$

Metric	Description	Formula
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 1. 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.

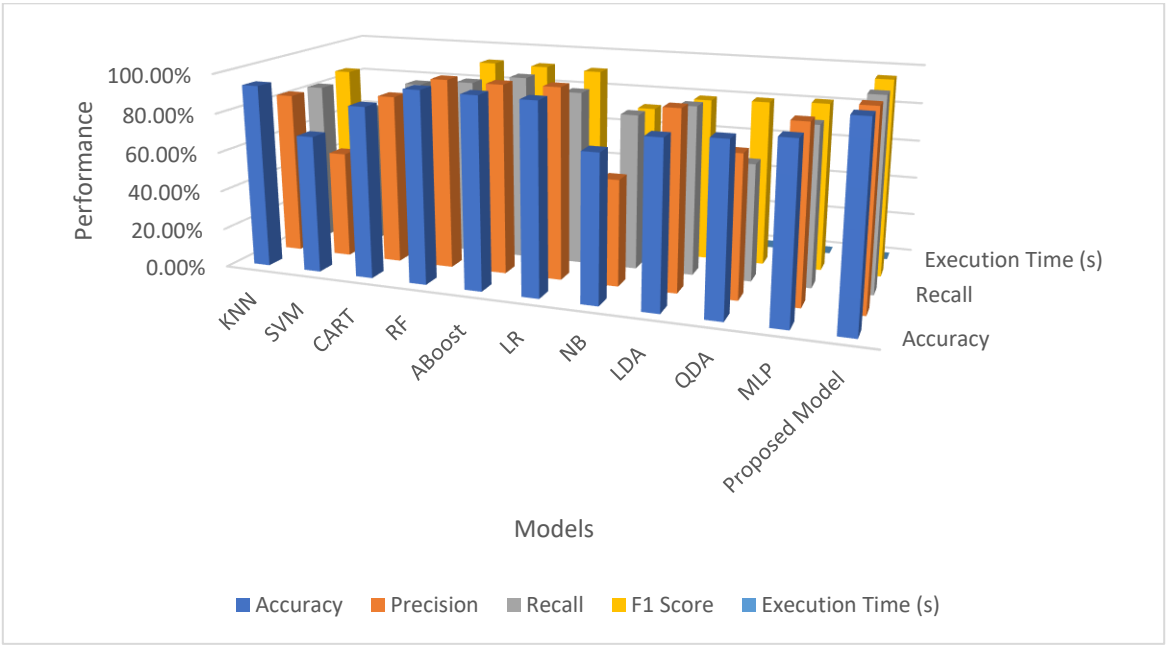

Fig.3. Performance comparison of Models.

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

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: The integration of various ML algorithms can be achieved through combinations of methods, such as using clustering methods or deep learning models, thus resulting in a better IDS performance.
2. This study will address the development of more elaborate security solutions by integrating ML-based IDS with a broad spectrum of cybersecurity frameworks and systems such as threat intelligence platforms (TIPs) and security information and project management (SIEMs) platforms. Our work denotes the implementation of machine learning mechanisms can enhance substantially the intelligence for Intrusion Detection Systems. By systematically demonstrating results from diverse machine learning models, we have hoped to provide key insights that point the way for further research and practical applications. The continued innovation and the enhancement of ML based IDS will be critical to maintaining cybersecurity defenses that are resilient, adaptive.

Authors Contributions (Compulsory)

All authors have equally contributed.

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