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A Unified Approach for Network Intrusion Detection using Ensemble Machine Learning Classifier using Support Vector Machine and Naive Bayes

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Abstract: The Internet and communication areas are developing at a rapid pace, which has increased network size and data demand. Consequently, this surge has given rise to numerous new attacks, posing significant challenges for network security, which are notoriously difficult to pinpoint accurately. Reviewing existing literature reveals that intruders employ sophisticated intelligence and tactics to create these threats, making their monitoring and detection quite challenging. This underscores the critical importance of network data security over the open web. Hence, it becomes imperative to develop a security mechanism that can effectively monitor network traffic to identify and detect these threats.One such potent security measure discovered to tackle these challenges is an Intrusion Detection System (IDS). Many IDS techniques leverage various Machine Learning (ML) algorithms to safeguard data against a range of network attacks. In the past, ML methods have typically centered on creating a solitary model for intrusion detection. Yet, it is widely acknowledged that no individual machine learning algorithm can effectively manage all forms of network attacks. Hence, this study primarily emphasizes the proposal of an ensemble classifier merging the strengths of the Support Vector Machine (SVM) and Naive Bayes (NB) algorithms. This strategy aims to bolster the efficiency of network intrusion detection through meticulous monitoring of network traffic data.

Keywords: *Support Vector Machine (SVM), Naive Bayes (NB), Network Intrusion Detection, Network Security, Ensemble Learning Classifier, Ensemble Voting Technique.*

1. Introduction

The Internet acts as a global network infrastructure that facilitates the swift and efficient transfer of data among interconnected devices worldwide, enabling communication, information sharing, and collaboration across vast distances. Due to its open nature and increased vulnerability, the Internet becomes a prime channel for intruders to launch new and more sophisticated attacks [1,2]. Machine Learning (ML) classifiers are more powerfuland detect anymalicious function accurately [3,4]. The primary objective of an Intrusion Detection System (IDS) in this context is to detect network attacks [5]. This research work is primarily focused on detecting a wide range of network attacks such as “Denial of Service (DoS)”, “User-to-Root” (U2R), “Root-to-Local” (R2L), and “Probing” attacks. To detect more attacks, it is necessary to build an effective classifier for theaccurate prediction of these attacks. Thus, this research proposes an ensemble-based machine classifier combining “Support Vector Machine” and “Naive Bayes”. Furthermore, the results of this research are compared with those obtained from conventional machine learning classifiers. Examining the efficacy and efficiency of the suggested method in managing various network attack situations is the goal of this research investigation.

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2. Related ML Classifiers for Threat Detection and Identification

2.1. Support Vector Machine (SVM)

Among the supervised learning techniques that are most frequently used for tasks involving regression and classification is SVM. [6,7]. SVM is adept at solving linear classifications through the use of hyperplanes and addressing non-linear classification challenges with kernel tricks. This method is applicable to both binary and multiclass classification scenarios[8]. For linear data, classes are separated by an optimal boundary called a hyperplane. The data is separated into two groups by this hyperplane, and the data points that are next to it are referred to as support vectors. The position of the hyperplane is influenced by these support vectors, which has an impact on prediction accuracy. SVM aims to find

a hyperplane that maximizes the margin space, leading to high prediction accuracy with low computational requirements [9]. However, for complex and non-separable data, creating an optimal hyperplane becomes inefficient. This calls for higher-dimensional (3D) separation, achieved by introducing a third dimension (z1) using a kernel function [22]. The kernel function transforms non-linearly separable data into linearly separable data. The kernel function must satisfy the rule as given inequation2.1:

$$z1=y1 + y2 \quad (2.1)$$

Then the higher-order dimensionality (3D) is converted to 2 D space with z1=1.This process change the kernel function rule (Equation2.1) as given inequation 2.2

$$y1 + y2 = 1 \quad (2.2)$$

which is the equation of a circle, and the figure given below (2.1) shows the best hyperplane.

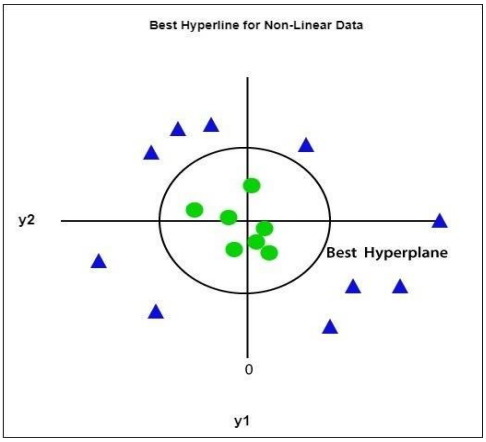

Fig 2.1 Best Hyperlinefor Non-Linear Data

SVM employs two methods for multiclass classification: the One-Vs-One (OVO) approach and the One-Vs-All (OVA) approach [9]. In the OVO method, multiple SVMs handle sub problems by treating each pair of classes as a binary classification task. This way, SVM conducts binary classification for each pair and aggregates predictions to generate the final result. The objective is to identify the best hyperplane to divide each pair of classes. Subsequently, all predictions are aggregated to generate the final prediction. On the other hand, the One-Vs-All approach trains multiple SVMs using a dataset with all class labels. Each SVM focuses on one specific class. After training all SVMs, predictions for the test data are made by combining predictions from all SVM models [21]. Here, the hyperplane separates points into two groups: one group consists of points from a specific class, while the other includes points from all other classes. The following figure [2.2] shows a model of multiclass classification.

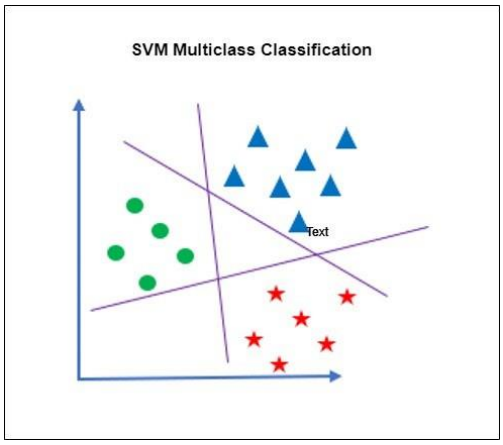

Fig 2.2 SVM Multiclass Classification

2.2. Naive Bayes

The "Naive Bayes" algorithm is an approach to supervised learning that applies the Bayes Theorem (BT) under the "naive" presumption that, given the value of the class variable, all pairs of features will be conditionally independent. [10, 11]. The NB classifier proves to be an effective probabilistic classifier,

predicting the probability of each class by analyzing the frequency and combination of values within the provided dataset. It operates under the assumption that all features are independent of each other. The BT provides conditional occurrence of event M, given that event N has occurred. The conditional probability of NB is given in equation 2.3.

$$Pb(M|N) = \frac{(Pb(N|M) * Pb(M))}{Pb(N)} \quad \textbf{(2.3)}$$

Where,

Pb(M|N): Posterior occurrence of a class.

Pb(M): Prior occurrence. It is the overall occurrence of M

Pb(N|M): relative occurrence. Given that M belongs to a class, it is the conditional occurrence of each N. A class is regarded as relative occurrence if its prediction is the highest. By filtering records from the training dataset, this is known.

Pb(N): occurrence of Evidence. This is referred to as from the training sub-sets by filtering records

NB classifiers perform well in a variety of real-world applications, including spam filtering and document classification. They can predict the required parameters with very little training data. Comparing NB classifiers to more intricate techniques, they frequently show remarkable speed. The NB classifier is used in IDS) to model the probable occurrence of threats. Certain features hold more significant influence in determining whether data received from a source is likely to contain a threat [12,13]. For instance, when a packet enters the network, details such as the packet's class, its hypothesis, its flow within the network, and the initial probability of threat occurrence are all learned from the probabilities within the given network environment.

3. Ensemble Classification

Ensemble learning is recognized for its superior predictive performance achieved through the selection of base classifiers and the application of a voting technique to determine the best prediction among them [14]. Consequently, the prediction rate surpasses that of a single classifier model. This enhancement is attained by mitigating the variance component of prediction errors through the introduction of bias, within the context of the bias-variance trade-off principle. The Intrusion Detection System (IDS) utilizes both homogeneous and heterogeneous ensemble models [15, 16] for the detection and classification of network threats, employing voting technique.

Three main voting techniques are used in ensemble learning: Simple Average, Majority Voting, and Weighted Average Voting [17,18]. In Simple Average Voting, predictions from all base classifiers are aggregated by the ensemble classifier. In Majority Voting (also referred to as "Hard Voting"), the ensemble classifier evaluates the predictions from each base classifier and assigns final predictions based on the classes with the highest votes across all base classifiers. Conversely, the Weighted Average Voting method (also termed "Soft Voting"), assigns equal weightage to each class. Using this method, the ensemble classifier receives predictions from all base classifiers and uses an average function to calculate the prediction value based on the weights supplied to each class. This results in the final prediction.

4. Proposed Ensemble Classification of SVM-NB

The primary objective of this research phase was to detect four major attack categories: DoS, U2R, R2L, and probing. A proposed ensemble classifier was developed to efficiently detect these attacks by combining SVM and NB. This integration falls under the heterogeneous pattern, with the proposed SVM-NB ensemble classifier constructed using stacking. The aim of SVM is to optimize margin space by identifying and utilizing the best hyperplane to effectively separate data. Taking into account the speed of the Naive Bayes classifier and the accuracy of the SVM classifier, a novel ensemble model is proposed using both SVM and NB.

Data Pre-Processing

The KDD99 dataset is widely utilized in the field of Intrusion Detection systems, comprising 41 labeled features that represent network traffic details. Instances in the dataset are categorized as normal or attack, with attacks further subdivided into four major categories: DoS, U2R, R2L, and probing. For this research investigation, 10,000 instances (Normal – 4370 and Attack – 5630) were analyzed.Prior to initiating the classification process, it is crucial to undergo the initial cleaning phase of the dataset. Many machine learning classifiers operate with numerical values, thus requiring the conversion of categorical values to numerical format. Within the dataset, attributes such as “protocol_type”, “service”, and “flag” are initially in categorical form and are subsequently transformed into numerical representations.

Feature Selection

Datasets may contain insignificant or redundant features, resulting in increased computational costs and potential slowdowns during classification. To address this issue, an efficient feature selection technique is employed. This process involves filtering the optimal features from the entire set, thereby enhancing the classifier's performance. In the current research proposal, the Firefly algorithm is

utilized to create an optimal subset of features, selecting 30 out of a total of 41 features.

Training and Testing Dataset

In machine learning classification, the classifier predicts output classes using two datasets: training and testing. The input dataset is split into these subsets. The training set helps develop the classifier by learning prediction rules from the samples. Then, the testing set evaluates and validates the model's accuracy. The model makes predictions based on the rules learned from the training samples.For this research phase, a benchmark IDS dataset is chosen to train and test the classifier, ensuring effective modeling and improved accuracy. The dataset is shuffled randomly and split into training and testing subsets, with an 80% to 20% train-test ratio used.

Architecture of Proposed Ensemble SVM-NB Classification

The proposed research model is constructed using the stacking ensemble model because the base classifiers SVM and NB are of different types. The process of the ensemble model unfolds in two stages:i) Modeling the base classifiers, and ii) Making predictions using the ensemble voting technique.

In the first stage of modeling, the base classifiers are trained using a preprocessed training dataset. Both classifiers are provided with the same set of training instances. Employing supervised learning techniques, the base classifiers learn the prediction rules from the training dataset. Each base classifier generates predictions (or votes) for every instance in the dataset. The accuracy of the model is evaluated by testing them using a test dataset following the successful modeling and training of the base classifiers.

In the second stage, the prediction outcomes of both base classifiers are inputted into a new model referred to as Ensemble SVM-NB. Theensemble classifier combines these predictions and employs the weighted average voting technique to determine the highest voted class. By aggregating the predictions of all classes, the final prediction yielded by the ensemble model is more accurate than that of a single classifier.The figure[4.1] given below shows the modeling of ensemble classification of SVM-NB for threat detection and classification.

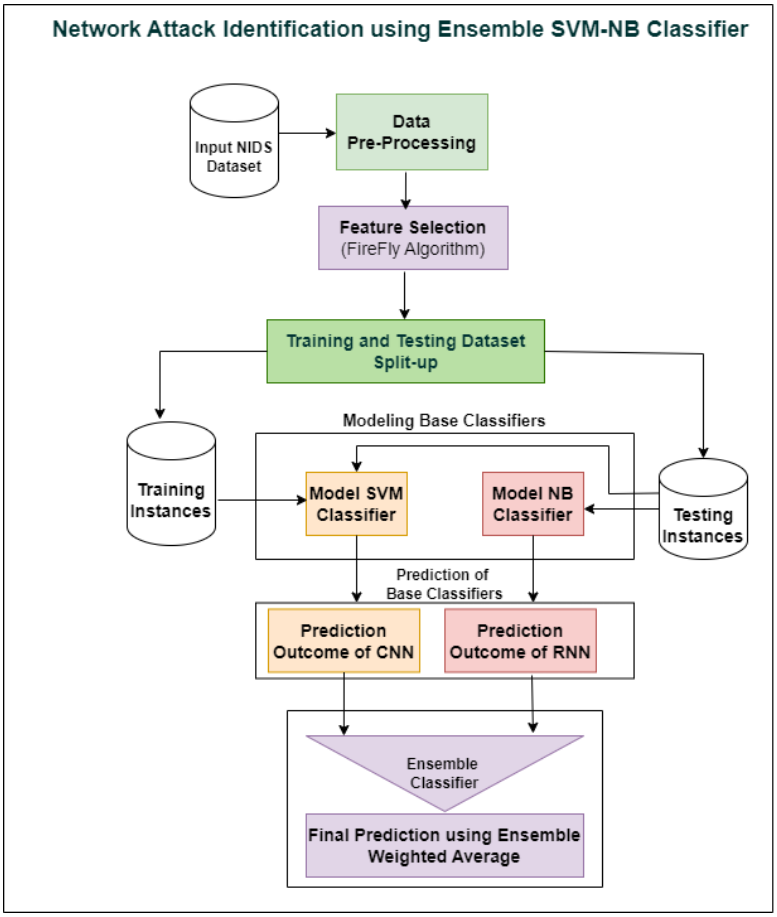

Fig 4.1 Proposed Ensemble Classifier of SVM-NB for Threat Detection and Identification

Algorithm 4.1 explains various steps takes place in Ensemble-Based SVM-NB model building for Threat detection.

5. Performance Evaluation

Algorithm 4.1: Ensemble-Based SVM-NB Model Building for Threat Detection

Step 1: Select the data set file (KDD-IDS).

Step 2: Select the features using Firefly feature selection algorithm.

Step 3: Split data set into a Train-Test dataset.

Step4: Train SVM and Naïve Bayes Classifier with the training dataset.//Base classifiers

Step5: Find the probability of threat and non-threat occurrence

5.1. Find the optimal hyper-plane and apply kernel function to classify the data using SVM.

5.2. Find probabilistic prediction using the NB classifier.

Step 6: Test base classifiers using the test dataset.

Step 7: Find prediction outcome for SVM and NB and pass it to the newensemble classifier.

Step 8: Apply weighted average voting technique to find the highest voting of each class and make the final prediction.

Step 9: Classify threat and non-threat

The classification performance indicates how accurately the classifier predicts and categorizes classes, making it a pivotal step in the classification process[19,20]. In this context, the effectiveness of the ensemble classifier is assessed through the utilization of the confusion matrix. In addition, several crucial performance measures like "F1 Score," "Accuracy," "Precision," and "Recall" are calculated to assess how effective the suggested ensemble classifier is.

Confusion Matrix

One of the best and simplest methods for assessing the classification model's performance is to use the confusion matrix. Four potential tabular prediction combinations are provided in this table. The potential forecasts are Instances that are accurately assigned to a positive class are referred to as True Positives (TP). Instances that are incorrectly assigned to a negative class are known as false positives (FP). True Negative (TN): Examples that are appropriately categorized as belonging to a negative class. False Negative (FN): Examples that are incorrectly assigned to a class that is positive.

Accuracy: The ratio of correctly determined occurrences to all instances.

Precision: The proportion of successfully categorized positive items among all positive algorithms.

Sensitivity: Another term for sensitivity is recall. It is the percentage of positives that are accurately classified as such is measured. It provides us with the likelihood of accurately selecting a positive class from the subset of positive classes.

F1 Score: The F-measure is another name for the F1 score. It can be applied as a lone indicator of test performance for the positive class.

In this research, the performance of the proposed classifier by using the metrics “Accuracy”, “Precision”, “Recall”, and “F1 Score”.The given below table (5.1) and figure (5.1) shows the overall performance comparison of the proposed Ensemble Classifier of SVM-NB with conventional classifiers SVM, NB and Hybrid Classifier of SVM-NB in tabular format and graphical format respectively.

Table 5.1 Performance Evaluation of NB, SVM, Hybrid SVM-NB and EnsembleSVM-NB

Classifier	Accuracy	Precision	Recall	F1Score
Naïve Bayes	0.9	0.82	0.89	0.83
Support Vector Machine	0.91	0.87	0.92	0.87
Ensemble Classifier of SVM-NB	0.935	0.928	0.94	0.93

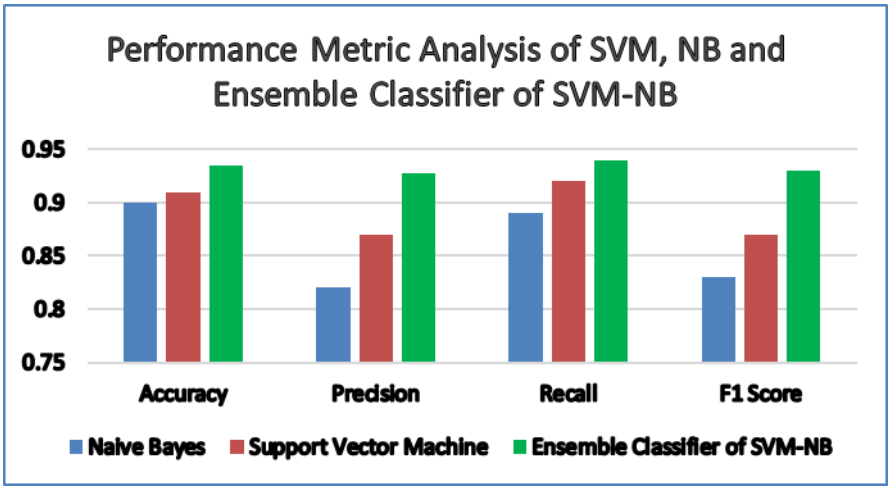

Fig 5.1 Performance Analysis Comparison of Ensemble SVM-NB and Existing Classifiers

6. Conclusion and Future Scope for Further Research

This research employs the ensemble-based machine learning classifier SVM-NB, which is implemented and tested using MATLAB. To ensure precise prediction, the dataset undergoes random shuffling, with 80% of instances allocated for training the base classifiers. The ensemble classifier generates predictions using the weighted voting technique. The performance evaluation of the proposed classifier is conducted on the remaining 20% of the testing dataset.Through the assessment of metrics such as accuracy, precision, recall, and F1 score, the performance of the proposed classifier is quantified and juxtaposed against other classifiers like SVM andNB. Experimental results indicate that the ensemble model yields a more accurate prediction outcome (0.935) compared to SVM (0.91) and NB (0.9).

In this research, signature-based intrusion detection is proposed and investigated and the research outcome proves that the proposed classifier effectively detects network threats. But it isnot enough. In the future, more novel attacks may be created by the attacker to break the network security and illegally access the resources. So, an AI-based automatic detection techniquecanbedevelopedtohandlebothsignature-basedandanomaly-basedattacks.

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