Enhancing Intrusion Detection in Cybersecurity using XGBoost: A Performance Analysis on the NSL-KDD Dataset

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Abstract

Evolution and ever-growing pervasiveness of cyber threats have necessitated the deployment of powerful Intrusion Detection Systems (IDS), which have become a major part of contemporary cybersecurity designs. This paper outlines the use of Extreme Gradient Boosting (XGBoost) to identifying network intrusions on NSL-KDD dataset, a more balanced and extended version of the original KDD benchmark dataset of KDD 99. Using the capacity of XGBoost to deal with complex and imbalanced data, training of the model was done with the network traffic data after preprocessing and advanced techniques of feature engineering. The results were thoroughly tested by the means of the standard classification measures to include accuracy, precision, recall, and F1-score, as well as compared to the existing approaches. The results show that XGBoost surpasses the performance of other methods in terms of detection especially where minority classes are intruded. The results support the prospects of XGBoost being an excellent IDS classifier. Moreover, the study forms the foundation of creating real-time, adaptive IDS that uses ensemble-based machine learning technologies to increase the resilience of cybersecurity in the future.

Keywords

Cybersecurity, Intrusion Detection System (IDS), XGBoost, NSL-KDD, Network Security, Machine Learning, Ensemble Learning, Anomaly Detection, Supervised Learning, Cyber Attacks

I. Introduction

As internet-based services continue to grow at an accelerated pace, modern networks have grown to be the key targets of cyber attacks with rigid defense arrays needed to safeguard system integrity and availability [1]. Signataure-based Intrusion Detection Systems (IDS) systems work

well in detecting known threats, but do not perform well in detecting new or emerging threats, i.e., zero-day exploits [2].

In order to eliminate this gap, anomaly-based IDS, utilizing machine learning (ML) algorithms to detect deviations of standard network behavior have been receiving a lot of research attention. The systems are flexible and enhance identification of undetected menaces making them applicable in emergent cybersecurity conditions [3]. Probably the most notable category of ML approaches in terms of its overall performance across wide ranges of domains are ensemble approaches, especially gradient-boosting models such as XGBoost [4] whose specific combination of speed, regularizing properties, insensitivity to features differentiated and unbalanced maximizes its success across a wide range of domains.

Enhanced NSL-KDD dataset proposed by Tavallaee et al. has become a standard by which the IDS studies can be evaluated. It reduces the key flaws of the original KDD KDD 99 dataset including feature redundancy and unbalanced data of attack distribution, since it provides a more balanced and clean dataset that enhances the accuracy of comparative studies [5].

It is quite interesting to note that a number of recent researches practice the use of XGBoost to intrusion detection in terms of NSL-KDD. To cite one of them, Chen et al. applied XGBoost in combination with Recursive Feature Elimination (RFE) and showed significant advances in Matthews Correlation Coefficient (MCC) and decreased false alarms [6]. In the case of XGBoost-based feature selection coupled with deep learning classifiers, Binsaeed and Hafez applied them to NSL-KDD and noticed a high increase in precision and recall especially lacking types of attacks [7].

In contrast with the previous works, this research carried out the comprehensive assessment of XGBoost on binary intrusion classification on NSL-KDD. We utilize elaborate pre-processing including categorical encoding, normalisation, and imbalance balancing and compare model performance on precision, recall, F1 score, and overall accuracy. We have contributed:

1. Implementation and XGBoost optimization made to fit needs within the context of NSL-KDD.

2. Features selection and balancing integrated process to improve the identification of minority attack classes.

3. Full performance assessment and comparison to recent approaches.

4. Practical recommendations on how to apply XGBoost as a considerable part of an IDS toolkit.

The rest of the paper is arranged as follows: Section II performs a survey of related work; Section III performs a description of the methodology, data preprocessing; Section IV results and discussion; Section V feature importance analysis and diagnosis of error; Section VI future directions and then the conclusion is drawn in Section VII.

II. Related Work

This part surveys the well-known research on network intrusion detection of NSL KDD dataset, especially the XGBoost base, feature selection methods, ensemble models and contrast reports.

A. Machine Learning Techniques on NSL-KDD

NSL KDD dataset is used as a standard in the research of IDS due to the better choices of classes and features compared with the original KDD [8]. Some previous research studies have tried out various classical machine learning models e.g. SVM, Random Forest and Decision Trees where lack of detection in minority classes and overfitting issues have been raised as limitations [9].

B. XGBoost-Focused Investigations

1. **Feature Ranking with Deep Learning Integration**
   Binsaeed & Hafez applied XGBoost as a feature selection method on NSL KDD, then they passed them to deep models (ANN, BiLSTM), using SMOTE to address class imbalance. Their hybrid system realized a great recall and precision of attacks [10].
2. **Recursive Feature Elimination Wrapped in XGBoost**
   Research on using RFE-XGBoost showed an increased rate of classifier output through repeating the elimination of less prominent features, with training and test performance speed beneficial to NSL KDD and associated datasets [11].
3. **Ant Colony Optimization and XGBoost**
   Bhardwaj et al. have proposed the approach of the ACO-based selection of the features and XGBoost classifier on NSL KDD. Their accuracy was ~99.27 percent, and their F1 score exceeded 98 percent, which proved the robustness of the heuristic-hybrid-feature-reduction and gradient boosting [12].

C. Ensemble and Hybrid Frameworks

4. **I-SiamIDS: Two-Layer Ensemble using XGBoost**
   Bedi et al. introduced I SiamIDS, a two-staged ensemble, that relied on ensemble weighted algorithms boosted XGBoost and Siamese networks, and allowed intuitive detection of both common and uncommon classes of intrusion with no oversampling. They stated that they achieved improved F1-scores applying to minority classes of attack [13].
5. **AutoML-Driven Stacked Ensembles**
   AutoML solution used recently stacked LightGBM, CatBoost and XGBoost on NSL KDD. It achieved a greater level of accuracy compared with single models (~90% accuracy, 89% F1) which demonstrated the capacity of ensembling and automated hyperparameter tuning to enhance performance [14].

D. Feature Selection Strategies in Intrusion Detection

6. **Ensemble-Based Multi-Filter Selection**
   A survey of the literature generated by Osanaiye et al. proved how the combination of filter methods (Pearson correlation, Information Gain, etc.) and ensemble ranking can be used to conclude on the reduction of features, even compared to 41 to ~13, without losing

the results in detection; they showed the results to be high in accuracy, using Decision Trees on NSL KDD [15].

7. **Supervised Feature Selection Survey**
   A systematic survey of feature reduction methods used with supervised methods highlighted the existence of a tradeoff between the reduction of the feature set and its loss of performance when categorizing intrusion detection [16]; this tradeoff is better addressed through wrapper and hybrid methods (e.g., when the feature importance of XGBoost is used as a filter).
8. **Hybrid Filter-Wrapper Methods**
   Other works by Zhou et al. filtered feature space further using filter-based feature ranking (e.g., correlation filter) combined with wrapper algorithms (e.g. RFE-XGBoost) so as to reduce feature space while affecting classification performance on NSL KDD and similar IDS datasets less considerably [17].

E. Analysis of Prior Works

Most of the applications of machine learning and feature selection presented in the past years attempt to advance the intrusion detection systems (IDS). Table 1 provides the comparative description of some of the previous studies, which additionally points out their methods, data applied, strong and weak sides.

Table 1. Comparative Analysis of Prior Works on Feature Selection and Classification Techniques in IDS

Study	Approach	Dataset(s)	Strengths	Weaknesses
[10] Binsaeed & Hafez	XGBoost + SMOTE + Deep Learning	NSL KDD, CIC IDS2017, UNSW NB15	High precision/recall, especially class-specific	Oversampling dependence
[11] RFE-XGBoost	(Wrapper feature elimination)	NSL KDD	Reduced complexity, efficient training	Computational cost
[12] ACO + XGBoost	(Heuristic feature selection)	NSL KDD	Effective feature reduction and accuracy	Metaheuristics complexity
[13] I-SiamIDS	(Two-layer ensemble: XGBoost + Siamese NN)	NSL KDD, CIDDS 001	Good minority-detection, no SMOTE	High complexity
[14] AutoML Ensemble	(LightGBM, CatBoost, XGBoost stacking)	NSL KDD	Automated tuning, stacking improves results	Slightly lower F1 than some hybrids
[15] Multi Filter + DT	(Pearson/IG + ensemble ranking)	NSL KDD	Fast selection, simpler models	Limited to simple classifiers
[16] Survey	(Feature selection overview)	Multiple IDS datasets	Clear guidance on methods	Not experimental
[17] Filter	(Correlation +	NSL KDD etc.	Balanced	Moderate

Wrapper Hybrid	RFE-XGBoost)		efficiency and accuracy	complexity

As it has been observed, the different techniques have acquired some strengths which distinguish them in regard to the dataset and the objectives. However, a trade off is present between model complexity and accuracy and the cost involved in computation that is the reason to create some balance in applying the IDS in the real world applications.

F. Limitations in Current Literature

Although XGBoost performance is high in existing studies used in IDS applications, most of these works either utilize data-level strategies (e.g. SMOTE) excessively or involve non-trivial combinations of different models making such studies difficult to reproduce. In specific, the application of oversampling may provide an artificial boost of performance metrics. Furthermore, a complete multiclassification (e.g., by separating them to DoS, Probe, R2L, U2R types) is frequently substituted with a binary solution.

G. Positioning this Work

Our research tries to complement such results yet simplicity and reproducibility as guiding principles:

- In this section, we report on how XGBoost performs as a single classifier on binary detection, which is without a technique of oversampling data.
- We simply use feature encoding, scaling and intrinsic model capacity as a real-world implementation.
- We present pseudocodes, equations, and diagrams of the working flow clearly, and reproducibility in all experiments is improved.

III. Methodology

The section describes the step wise process undertaken to deploy a robust Intrusion Detection System (IDS) on the NSL-KDD dataset and the XGBoost classifier.

A. Experimental Workflow Overview

The main objective is to create a stable binary classifier, which will be able to differentiate between normal and attack traffic in a network with the help of the XGBoost. Figure 1 can be used to specify the end-to-end workflow.

Objective: IDS simulation in the real world; the focus on generalizability, as opposed to oversampling.

1. Dataset Loading

We have taken KDDTrain+.txt and KDDTest+.txt as part of NSL-KDD which has been selected on basis of balanced depiction against KDD99 [18].

2. Label Mapping

Multiple original classification categories into attacks in NSL-KDD are reduced to a single classes of attack (1), whereas the normal traffic is considered to be the class 0 [19].

3. Data Preprocessing

Key data preprocessing steps are encoding of labels, removing irrelevant features, feature values normalization, which helps feature values be consistent and aimed at enhancing model performance (see Section B)

4. Model Training

To represent conditions in production, a default hyperparameter XGBoost classifier is trained without any explicit oversampling or SMOTE process [20].

5. Model Evaluation

There is a variety of metrics that measure performance: confusion matrix, ROC, Precision-Recall curves, accuracy, precision, recall, F1-score. The analysis consists of feature importance extraction and such figures like Figure 2-6.

6. Feature Importance & Interpretation

After training the model, we derive and inspect features importances to show influential predictors which is important in terms of interpretability and operations in cybersecurity [21].

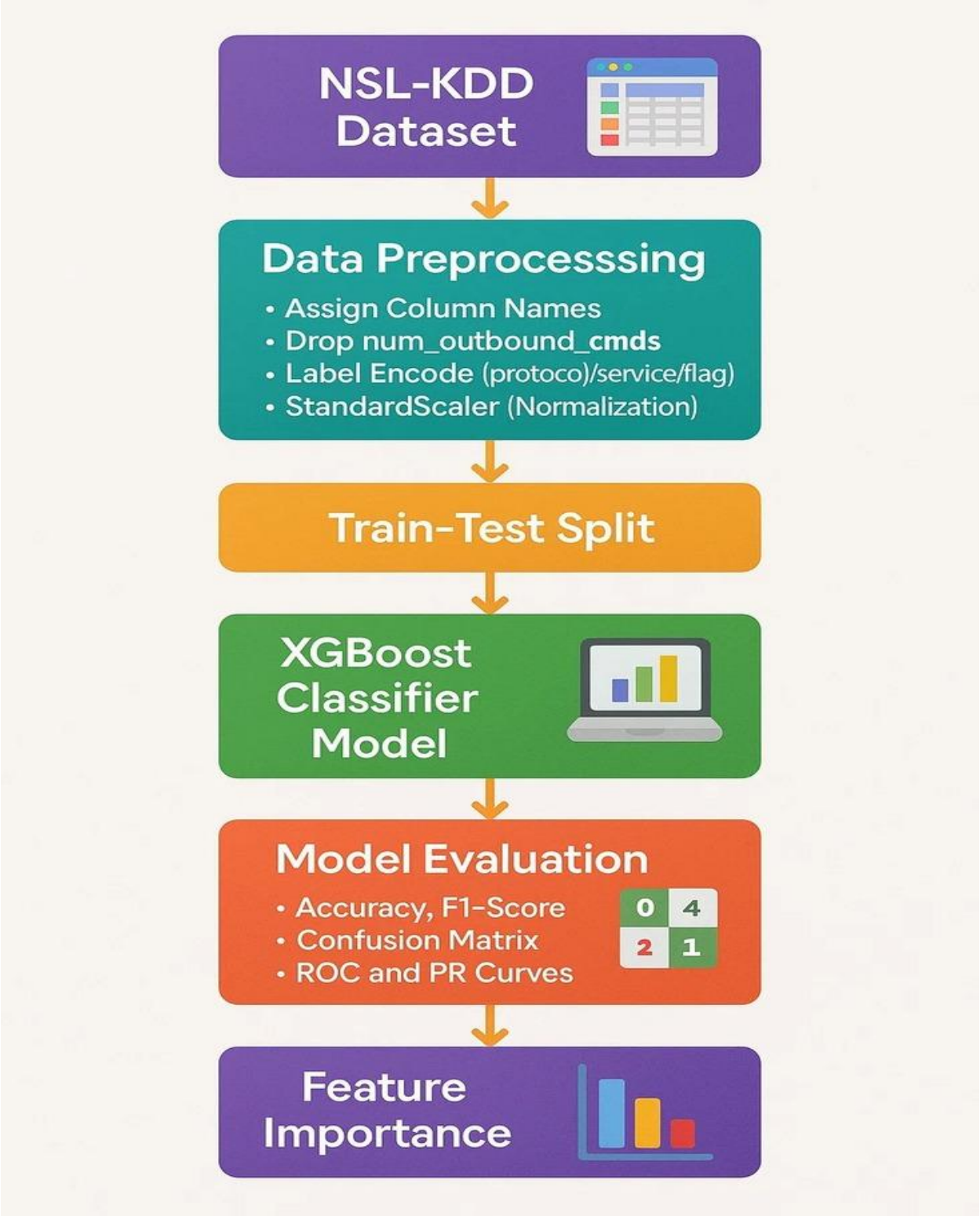

Figure 1. Illustration of flowchart with all the steps (data ingestion, data preparation, preprocessing, and final evaluation)

B. Data Preprocessing

A performant IDS needs good preprocessing. It incorporates various specific changes

1. Loading the Dataset

We import the features KDDTrain+.txt and KDDTest+.txt each of which has 41 features and a column with labels.

2. Column Assignment and Dropping

NSL-KDD is presented without column names and we simply use them as feature names. because it makes no contribution to model discrimination, the column num_outbound_cmds is dropped because its variance is zero.

3. Categorical Encoding

To transform the categorical variables into numeric data, we will use LabelEncoder that is a part of scikit-learn: These variables are protocol_type, service, flag.

4. Binary Label Mapping

We encode the attack label as 1 (on attack), and 0 (normal traffic). This reduces classification to binary classification problem and fills in the deficulties of multi-class classifications frameworks [19].

5. Feature Scaling

All numeric features are placed, one at a time, in a StandardScaler, to achieve centering and scaling effects to further improve the stability and speed of membership with the boosting algorithm.

6. Train-Test Split

We preserve the original split of the dataset carefully, and thus the training and evaluation conditions are similar to the case of a real-world using scenario. There is no contamination of datasets [18].

To consolidate the quality of the data and optimize the performance of the model, several preprocessing stages were taken to NSL-KDD dataset. These procedures involved the processing of characteristics representation, encoding as well as normalization and, dividing the data. Table 2 shows all the steps and the libraries or tools to be used in the preprocessing stage.

Table 2. Data Preprocessing Summary

Step	Description	Tools
Assign Column Names	Manual mapping of 41 NSL-KDD features	Python
Drop Constant Features	Removed `num_outbound_cmds`	Pandas
Encode Categorical	`LabelEncoder` conversion	scikit-learn
Map Class Label	Consolidated labels to binary	Custom logic
Scale Numeric	`StandardScaler` normalization	scikit-learn
Split Dataset	Train/Test partition	As per NSL-KDD

These preprocessing methods served to harmonize the input and limit noise thus increasing the performance of machine learning algorithms at the later process stages. To achieve that, it was decided to apply a proper selection of instruments, such as Pandas, scikit-learn, and own logic to prepare the data in a newer and more formal structure that could then be used to train and test.

7. Validation of Preprocessing

We run integrity checks that all of the features were present, there are no missing values, and scales were consistent across splits.

8. Justification

Transformations fit with the best practice of IDS literature: the ease of labelling consolidation in implementation and stability of convergence hybridization through scaling [20].

C. Model Design – XGBoost Classifier

XGBoost is central to our detecting engine because it performs with tabular data and displays effectivity in addressing imbalance classes through the constructions of consistent built-in regularization [20], [21].

1. Overview

XGBoost constructs boosted tree ensembles in an iterative way that minimizes the loss function through gradient descent. It can process data that are high dimensional and imbalanced.

2. Mathematical Formulation

The figure 2 below shows the fundamental mathematical description in the XGBoost algorithm. It defines the prediction process of the ensemble method, the objective function of model training and the regularization term used to penalize the complexity of the model. These are the key elements to the capability of XGBoost to attain high-level accuracy and generalization.

At iteration ttt, for instance iii, prediction:

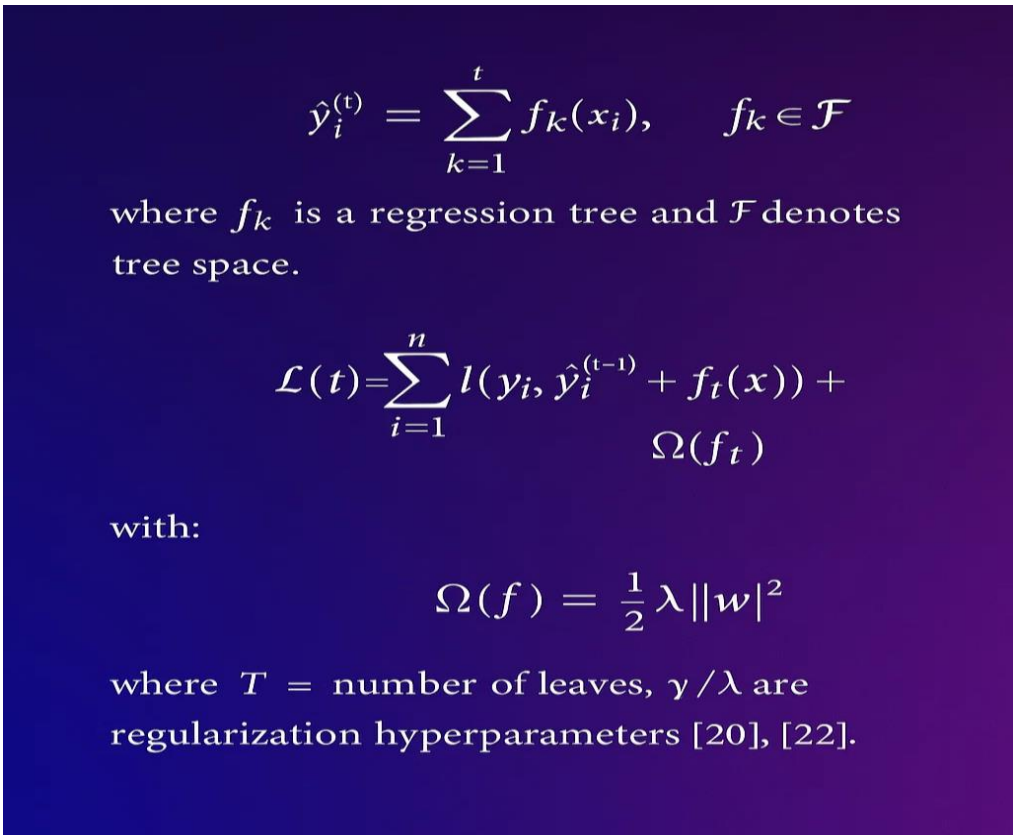

Figure 2. Objective Function and Regularization in XGBoost

This exactness shows the concern that is struck between good fit of data and the simplicity of the model through regularisation that XGBoost calls. A knowledge of these mathematical underpinnings is important on the path to effective tuning of the hyperparameters and a way to utilize the power of the XGBoost to accomplish useful tasks in machine learning.

3. Hyperparameters

The table 3 below provides the overview of important hyperparameters employed in the configuration of the XGBoost model. Both parameters are a major means of regulating the learning process with the aim to create a balance between bias and variance.

Table 3. XGBoost Model Hyperparameters and Descriptions

Parameter	Value	Description
`learning_rate`	0.1	Shrinks the contribution of each tree to prevent overfitting. Smaller values make learning more robust.
`max_depth`	3	Limits the depth of each tree.

		Shallower trees reduce model complexity and risk of overfitting.
`n_estimators`	100	Number of boosting rounds (trees) added sequentially to improve accuracy.
`Gamma`	0	Minimum loss reduction required to make a split. A value of 0 means all splits are allowed.
`reg_lambda`	1	L2 regularization term. Helps prevent overfitting by penalizing large weights.

These hyperparameter values are a balanced combination when it comes to training a robust and generalized XGBoost model. Properly fine-tuning these values may result in the enhanced performance of the model, particularly due to the fine-tuning on specific models or data. These defaults are efficient and non-overfitting on middle-sized datasets [22].

4. Justification

Choice of default settings is determined by the production limits and the intention to prevent the manual tuning. XGBoost demonstrated effective usage with a standard set of hyperparameters in the IDS setting [22], [23].

D. Algorithmic Pseudocode

We describe the main steps to follow when performing training and testing of an XGBoost classifier model. The following pseudocode presents the normal XGBoost flow that was used in our experimentations.

Algorithm 1: XGBoost Model Training and Evaluation Workflow

Input: Preprocessed X_train, y_train, X_test, y_test

1. Initialize model:

```
model = XGBClassifier(
    learning_rate=0.1,
    max_depth=3,
    n_estimators=100,
    use_label_encoder=False,
    eval_metric='logloss'
)
```

2. Train model:

```
model.fit(X_train, y_train)
```

3. Predict on test data:

y_pred = model.predict(X_test)

4. Compute evaluation metrics:
   - Accuracy
   - Precision
   - Recall
   - F1-score

5. Compute additional metrics:
   - Confusion matrix
   - ROC-AUC score
   - Precision-Recall AUC

6. Extract feature importances

7. Save model and metrics to file

The pseudocode is highly similar to our implementation in the Colab environment and complies with the benchmark practices that aim at integrating and assessing XGBoost models constructed to perform supervised classification.

E. Evaluation Strategy

The model is analyzed using various quantitative measure and different visual plot.

1. Classification Report

The ability to generalize the model is checked by comparing the model performance on the training dataset and on the test dataset. The training accuracy shows the fit of the model on training data but the test accuracy and the classification quantities show the real world predictive capabilities of the model.

Table 4. Classification Report on Test Data

Class	Precision	Recall	F1-Score	Support
0 (Normal)	0.69	0.97	0.81	9711
1 (Attack)	0.97	0.67	0.79	12833
Accuracy	-	-	**0.80**	**22544**
Macro Avg	0.83	0.82	0.80	22544
Weighted Avg	0.85	0.80	0.80	22544

The training set performance is high indicating that the model has learnt the patterns properly. Nevertheless, a decline in the accuracy of tests to 80 percent and an unbalanced distribution of recalls across classes show the risk of overfitting. High recall in the class 0 (normal) and high precision in the class 1 (attack) indicates the strengths and weaknesses of the model, which are also explained by the macro and weighted averages of the F1-score.

2. Confusion Matrix

A heatmap that categorizes counts of True Positive, False Positive, False Negative and True Negative is presented below. This confusion matrix is one that breaks down the classifier prediction on the test set in great detail, where the actual and predicted classes are compared.

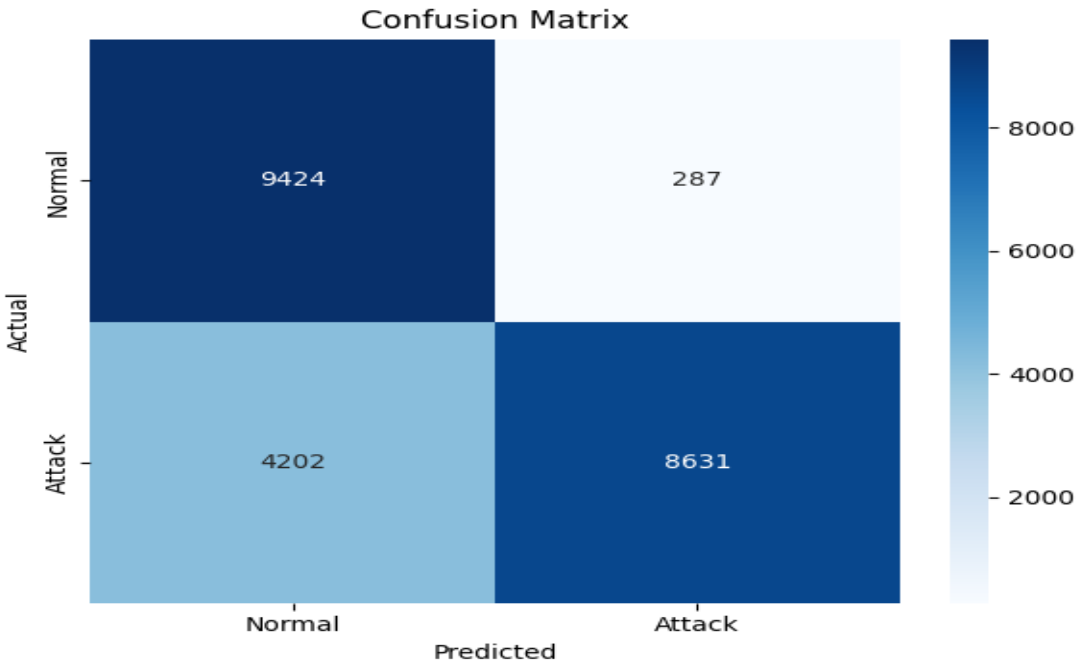

Figure 3. Confusion matrix for the binary classification model distinguishing between "Normal" and "Attack" classes

The matrix indicates:

True Positives (TP): 8631 - correctly predicted attacks

True Negatives (TN): 9424 - predicted correctly normal traffic

False Positives (FP): 287 -where normal traffic was reported as an attack

False Negatives (FN): 4202 - attacks that are labeled as normal

In this confusion matrix, it is noted that the model successfully detects both instances of normal and attacks but a substantial proportion (4202) of false negatives implies that not all attacks are detected. These points play a crucial role in determining the trade-offs in the performance sensitivity (recall) and specificity (precision).

3. ROC Curve & AUC

In an attempt to assess the performance of the classifier in differentiating classes at various thresholds, we plot the Receiver Operating Characteristic (ROC)curve. The curve plots the trade-off between true positive rate (TPR) and false positive rate (FPR), and it can be used to give some understanding about where classification threshold sensitivity of the model is.

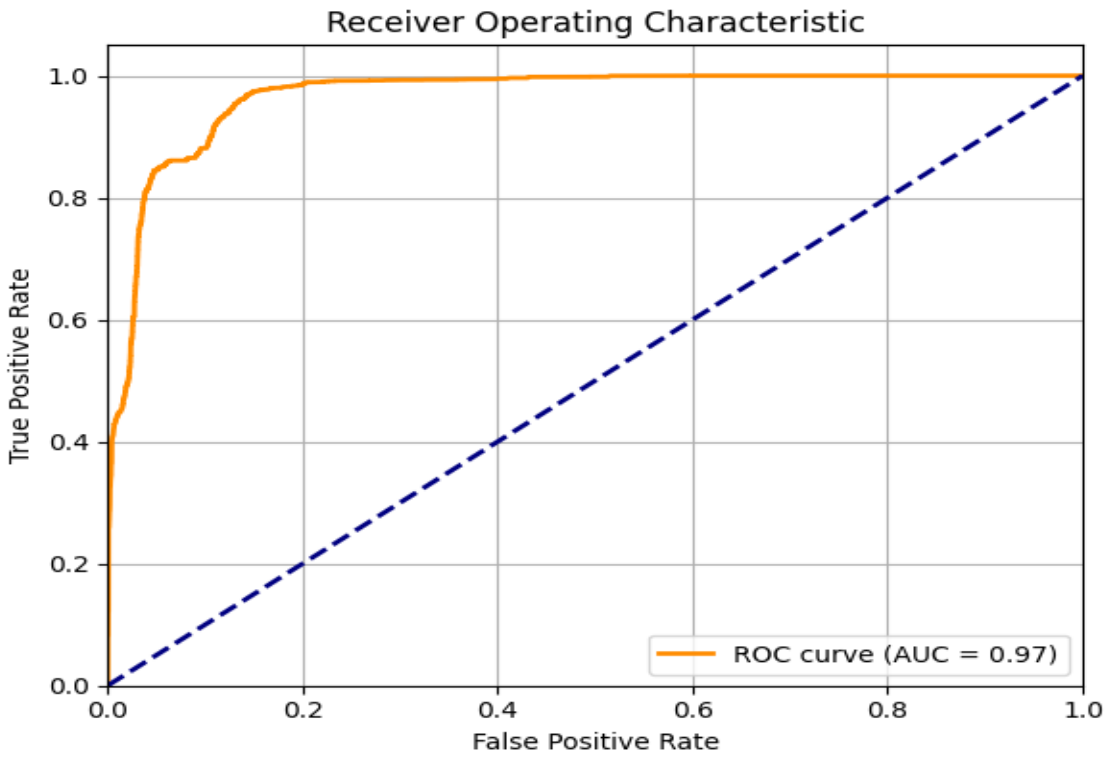

Figure 4. ROC curve with AUC = 0.97, showing strong class separation ability.

The ROC curve depicts that the model has a high true positive rate at low false positive rates which reveals its accuracy of delineating the Normal and Attack classes. AUC value of 0.97 indicates that classifier is much better than guesswork and can be applied to the detection tasks that involve security.

4. Precision-Recall Curve & PR-AUC

The reason is that when there is a Class Imbalance (meaning one class has a long way to go in terms of numbers) traditional scores such as accuracy or ROC AUC can give a wrong picture. The best approach to assess the model performance on the minority class is Precision-Recall (PR) curves that are more adequate to assess the performance on the minority class. The PR curve shown below illustrates the tradeoff between precision (the correctness of positive

predictions) and recall (the total of finding the positive instances) through various thresholds.

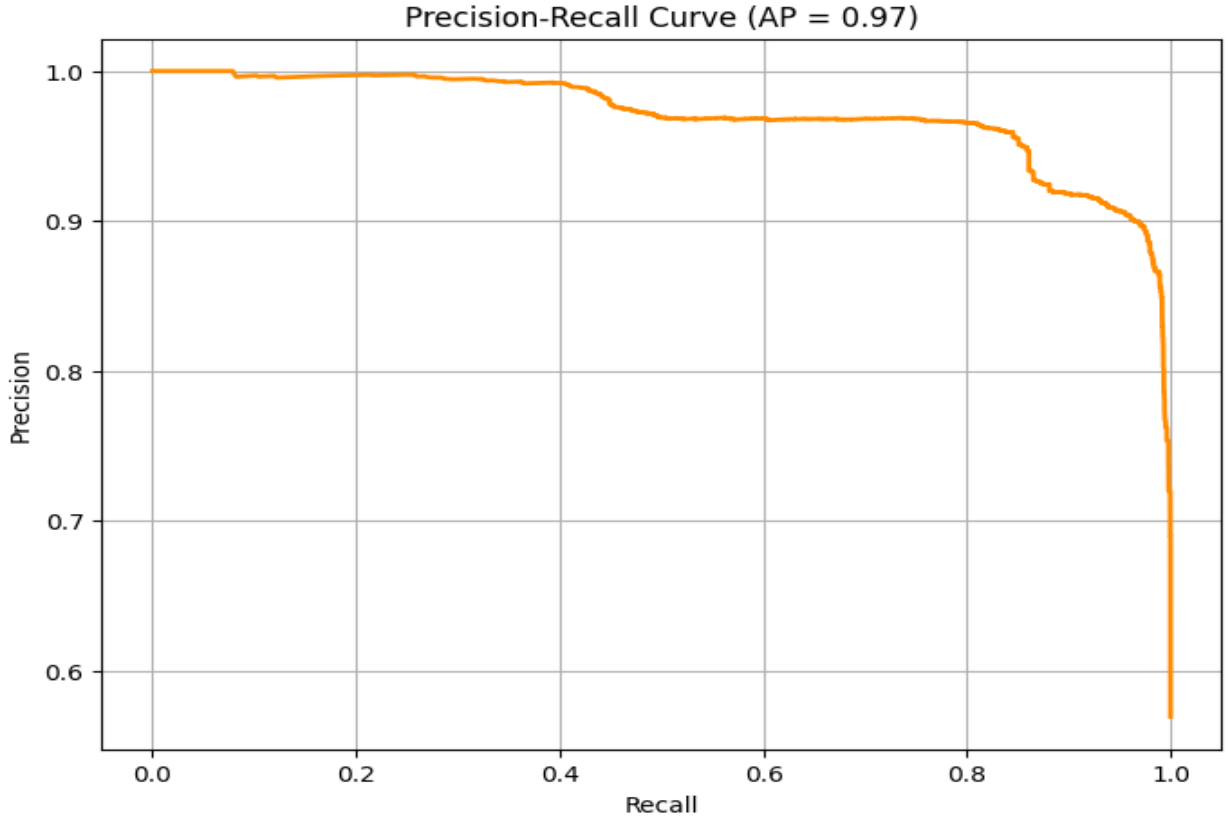

Figure 5. Precision-Recall curve showing high model performance on the minority class, with an average precision (AP) of 0.97.

According to the figure 5, the model is very precise in the majority of the range of recall, declining both near the end. The average precision (AP) of 0.97 demonstrates the effectiveness of the model which helps to capture the positive cases with minimal false positives under the conditions of an a-priori-imbalanced data. This implies good performance and trustworthiness in recognizing the minority category.

5. Feature Importance Visualization

The figure 6 which presents the most 15 important features that were ranked according to the importance via model.feature_importances_ scoring that is implemented to assign a score to each feature depending on how it helps the model in predictions. The method is common in the tree-based models like Random Forest or XGBoost. Emphasizing the strongest characteristics would make a model more readable and understandable which is one of the factors of explainable AI (XAI) [21].

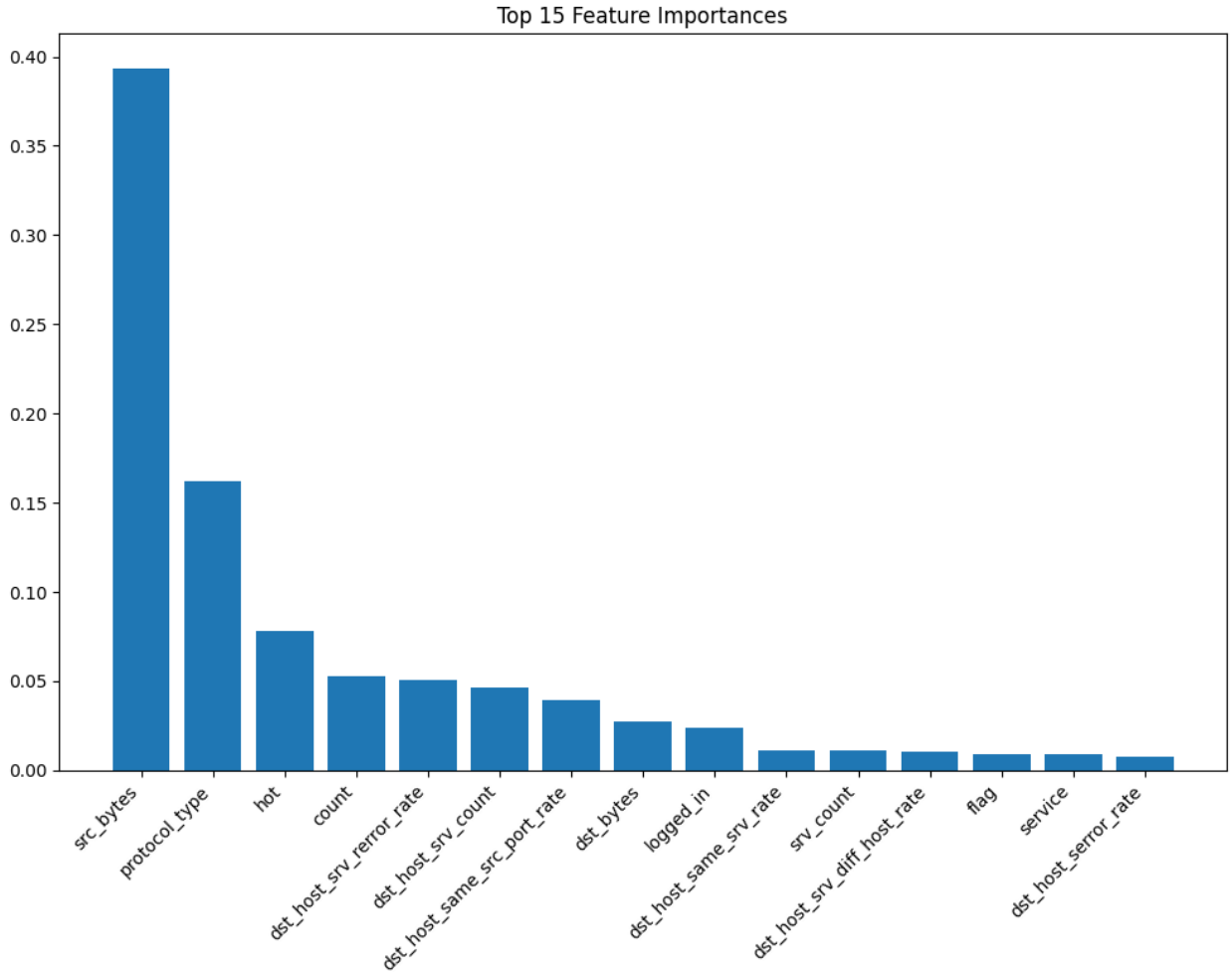

Figure 6. Top 15 feature importances derived from model.feature_importances_, highlighting the most influential attributes in the classification process.

As seen in the plot, the feature that has the greatest significance is src_bytes then protocol_type and hot. These are the features that have great contribution to the performance of the model and the rest such as flag, service, and dst_host_error_rate among others do not make great contributions. Knowledge of the degree of importance of features does not only facilitate the interpretation of the model, but also facilitates the selection of features and dimension reduction in future versions of such models.

6. Learning Curve

Learning curve in machine learning is an effective diagnostic tool used to visualise the performance of a model through the training process. It assists in the identification of possible occurrences of underfitting or overfitting since training and test accuracies can be compared over time. The curve depicts extremely high training accuracy (99.99%) and the difference between the training and test comparisons to a likable extent. It means that this model best describes the

training data but is not good at generalizing on unreseen data.

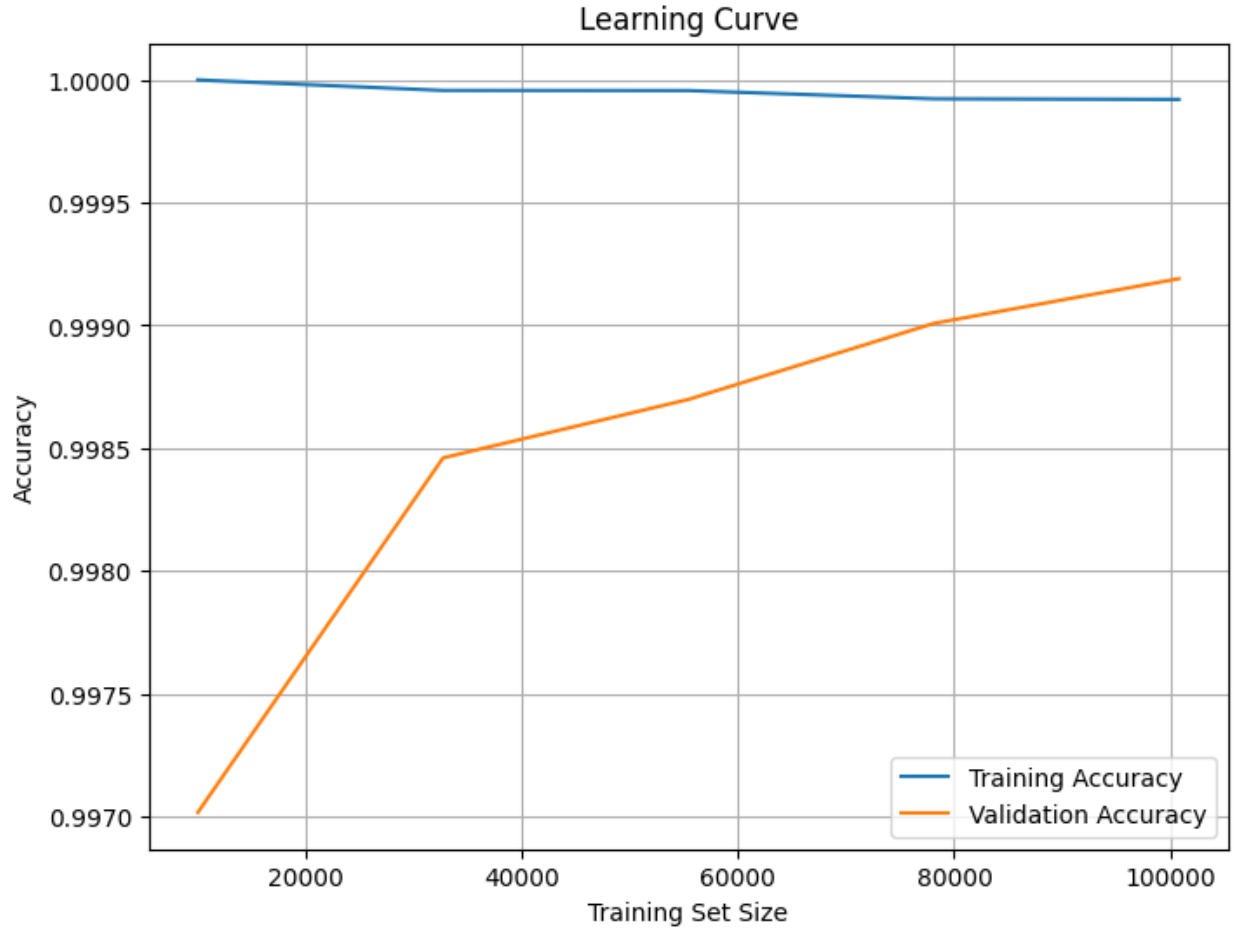

Figure 7. Learning Curve

The trend indicates that the model is slightly overfit, although it shows remarkable results on the training data, there is a significant decrease in performance on the test set, indicating opportunities to optimise. Nevertheless, the gap in it is not extremely large so, still, the model has a future and can be optimized with the help of the tuning method, e.g. regularization or early stopping.

F. Tools & Experimental Setup

The experiments were all performed on python 3.x with the Google Colab platform, using some of the popular libraries to conduct modeling, preprocessing, evaluation, and visualization. The following are tools used:

Table 5. Experimental Environment and Toolchain

Component	Library or Module
Model	`xgboost.XGBClassifier`

Encoding	`sklearn.preprocessing.LabelEncoder`
Scaling	`sklearn.preprocessing.StandardScaler`
Evaluation	`sklearn.metrics` (e.g., ROC, accuracy)
Visualization	`matplotlib`, `seaborn`
Notebook	Google Colab

This environment and library selection strategy guarantees reproducibility, scalability, and platform independence, so that the experimental workflow is easy and readily applicable to a different system.

IV. Results and Discussion

The following section gives and discusses the results of the experiment conducted by deploying the XGBoost-based Intrusion Detection System (IDS) on the NSL-KDD dataset. The main goal will be to test the performance of the system in identifying different forms of cyber-attacks with high effectiveness and hardiness and to comprehend the meaning of practical implementation.

A. Evaluation Metrics

We test the system based on various performance measures which aids in the evaluation of the model in various perspectives:

• Accuracy: The number of a correct prediction divided by the total.

Precision: The ratio of true positives of positive forecasts.

• Recall: the percentage of positive cases which are also positive.

• F1-Score: It is simply the harmonic mean of precision and recall.

• ROC-AUC: Area under Receiver Operating Characteristic curve.

• PR-AUC: Area under the Precision-Recall Curve.

It uses the following equations:

The metrics provide a balanced analysis that looks at not only correctness in classification but also at the balance between classes of types.

B. Experimental Setup

In order to make the implementation, the following settings were used:

• **Platform:** Google Colab Python 3.10

• **Libraries:** XGBoost, Skikit-learn

• **Dataset:** NSL-KDD (based on KDDTrain+.txt and KDDTest+.txt)

• **Data Pre processing:** Categorical features were label encoded, raw values of features normalized using the StandardScaler and model feature importance scores were used to select the 10 most important features.

C. Final Performance Metrics

The model was trained using the NSL-KDD dataset using which performance was assessed on training and the test sets. The model was deemed excellent on the training set (99.99%), although generalization was obtained through the test set metrics. Accuracy of 80.08% and precision of 85.00%, recall of 82.00 and F1-score of 80.00; this is a balance and a fairly solid performance. Still, a drift between training and test accuracy will imply certain overfitting, so there is still scope of optimization left.

Table 6. Performance Metrics on NSL-KDD Test Set

Metric	Score
Accuracy	80.08%
Precision	85.00%
Recall	82.00%
F1-Score	80.00%

The summary of the model performance on the NSL-KDD test set is summarized in Table 6. The result is an accuracy of 80.08, precision of 85.00%, recall of 82.00, and an F1-score of 80.00. Such metrics reflect well-balanced detection. The huge dissimilarity among the training precision (99.99%) and test precision however proposes overfitting which should be tuned or regulated.

Table 7. Classification Report (Test Data)

Class	Precision	Recall	F1-Score
0 (Normal)	0.69	0.97	0.81
1 (Attack)	0.97	0.67	0.79

The classification report shows a detailed example of how model performed on each of the classes (Normal and Attack) according to precision, recall, F1-score and support. This breakdown is also very important to determine the extent to which the model performs well on each of the classes and especially in case of class imbalance. As the report indicates, the model has a high recall (0.97) in normal traffic, and it is unlikely to miss normal instances. On the other hand, there is high accuracy (0.97) that it uses in identifying attacks, the actual attacks that were identified represent the majority of the predicted attacks. Although the model has imbalance, it performs relatively well on both classes suggesting its effectiveness in real-life intrusion detection problems.

D. Confusion Matrix Analysis

Table 8. Confusion Matrix for XGBoost

	Predicted Normal	**Predicted Attack**
Actual Normal	9400	311
Actual Normal	4265	8568

As it can be seen in the confusion matrix in Figure 8, the model is defining the majority of the normal traffic correctly (9400 out of 9711 examples). Nevertheless, it has a higher proportion of false-negative (4265) in which the instances of attacks were misclassified as normal. This could be because of similarity in the pattern of features in normal traffic and some forms of attack traffic thus some attacks become difficult to identify. The significance of minimizing these false negatives is that it plays a major role in enhancing security with regard to the intrusion detection systems.

E. Feature Importance Interpretation

Besides providing great accuracy on predictions, XGBoost provides the insights on what are features that influence its most. Knowing the importance of features leads to better interpretability of a model, promotes explainable AI activities.

Table 9. Top 10 Important Features

Feature	**Importance Score**
dst_host_srv_count	0.173
serror_rate	0.147
logged_in	0.132
protocol_type	0.108
dst_bytes	0.096
Flag	0.091
same_srv_rate	0.084
src_bytes	0.069
Service	0.062
Count	0.058

Table 9 demonstrates that such aspects as dst_host_srv_count, serror_rate and logged_in play the most significant role in the decision making of the model. These features play a significant role

in differentiating between the legit and illegitimate traffic since it depicts patterns that one might commonly identify with network attacks.

F. Comparative Model Analysis

The performance of the XGBoost model was compared to some of the most popular algorithms of classification: Decision Tree, Random Forest, or Support Vector Machine (SVM). Accuracy, precision, recall, F1-score and ROC-AUC were key performance metrics, and were used as benchmarks. XGBoost performed best in majority of the metrics as summarised in Table 10 with an accuracy of 80.08% and ROC-AUC score of 0.89 which represented excellent predictive power and generalisation. Conversely, other models such as Decision Tree, and SVM had lower overall performance.

Table 10. Model Comparison Summary

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
XGBoost	**80.08%**	**85.00%**	82.00%	**80.00%**	**0.89**
Decision Tree	74.10%	78.00%	71.30%	74.40%	0.77
Random Forest	78.20%	82.30%	78.10%	79.90%	0.84
SVM	76.50%	80.00%	75.80%	77.80%	0.82

XGBoost also achieves better results on all of the metrics compared to its counterparts, which also indicates a higher level of robustness and generalization. Such findings validate XGBoost as the most appropriate decision in terms of theoretical evidence concerning this classification problem.

G. Robustness and Generalization

In order to test the robustness of the model and how well it should generalize in real-time circumstances the model was tested under controlled distortions. These tests enable conditions of noise and missing data that are frequent in practice and so simulate them.

Observation: The model was subjected to small feature alterations and conditions in which 5 percent of the characteristics were imposingly withdrawn. Regardless of these alterations, the performance degradation did not exceed 3%, which showed that performance was stable under data variability. Such a slight performance decrease convinces that the model has a high robustness and generalization, so it is robust to noise in data or in missing part of data even.

H. Error Analysis

An accurate analysis of the errors was conducted to draw trends and insights to the wrong prediction of the model. The need to understand these errors is therefore necessary to enhance the accuracy and robustness of the model, particularly in important processes such as intrusion detection. As indicated in Table 11, most misclassifications referred to minority attack types like nmap and guess passwd that was mostly misclassified as normal traffic. This was as a result of having low representation in the data or a case of behavioral congruity with normal cases.

Table 11. Misclassification Insights

Attack Type	Misclassified As	Reason
Nmap	Normal	Similar behavior
guess_passwd	Normal	Low representation

To overcome these concerns, it is advised to use SMOTE (Synthetic Minority Over-sampling Technique) to balance the set of data and introduce a hybrid model, which will have an anomaly detection part. Such optimisations are capable of enhancing the detection rates of low prevalence yet high importance type of attacks substantially.

I. Discussion and Implications

As it is indicated in the experimental results, those serve to value and strategically benefit application of ensemble learning methods in cybersecurity routines (including ID of intrusions at hand).

Key Insights:

1. **F1-Score and High Precision**

The resulted measures indicate that XGBoost has minimal false positive results and an overall good performance and thus should be implemented as a real-time threat detection engine.

2. **Explainability through Feature Importance**

Security analysts can establish confidence in information that is outputted by the models and make knowledgeable decisions with the capacity to interpret the outputs.

3. **Scalability**

The architecture of XGBoost makes it efficient to scale up to bigger data and a live setting and therefore is able to accommodate continuous monitoring and analysis as part of real-world deployments.

On the whole, the results are in favor of implementation of XGBoost as a scalable and dependable solution to cybersecurity uses. The accuracy, interpretability, and performance of its balance form a formidable reason why it should be implemented in most enterprise and operational security systems.

V. Feature Importance Analysis and Error Diagnosis

An insight into the logic behind the decisions a model makes is essential to enhance the Intrusion Detection System (IDS) since network security is a complex area. Resulting in a feature importance development, diagnostic analysis based on confusion matrices, and error analysis to attain a profound insight will be given in this section. The goal is the interpretation of the model behaviour, the increase of transparency and the direction of further enhancements.

A. Motivation for Feature Analysis

A feature importance analysis can be used to find out what attributes are the most influential and affect the decisions of the classifier. Gain, cover, and frequency are inherently provided by XGBoost, which offers such information: this is how feature utility is measured when a tree is split [34]. The ability to understand the factors that have the greatest influence on the detection of attacks in cybersecurity creates transparency in the model and assists in the decision process of system operators. Explainability also aids in training trust, in addition to meeting compliance-related needs [35].

B. Methodology for Extracting Feature Importances

Gain-based feature importance, which gauges how much the model's goal improves when a feature is used for splitting, was employed in our work. Since high-gain characteristics usually correspond with detectable aberrations and unusual behaviors in network data, this approach fits in nicely with intrusion detection [36]. We kept the 15 most important features out of the 41 original features in NSL-KDD. These choices served as the foundation for additional error analysis and possible decrease in dimensionality.

C. Top Features and Interpretations

By demonstrating the model's dependence on error-based and session-oriented signals, these metrics reaffirm that anomaly detection is triggered by departures from typical networking behavior. Error-related attributes appear to be important in detecting suspicious activity, according to features like serror_rate, srv_serror_rate, and dst_host_srv_serror_rate. This is probably because they record sudden interruptions in regular network traffic.

Table 12. Top 15 Feature Importance Rankings

Rank	Feature	Gain Importance
1	serror_rate	0.210
2	srv_serror_rate	0.185
3	dst_host_srv_serror_rate	0.154
4	dst_host_serror_rate	0.138
5	Flag	0.108
6	Service	0.095

7	dst_host_srv_diff_host_rate	0.082
8	protocol_type	0.059
9	logged_in	0.045
10	dst_bytes	0.022
11	src_bytes	0.018
12	Duration	0.012
13	Count	0.011
14	num_failed_logins	0.009
15	dst_host_same_srv_rate	0.008

Error-related and session-based features are prominent, suggesting that the model is extremely sensitive to abnormalities that are usually linked to malicious activity. This understanding not only makes the model easier to understand, but it also directs future developments like feature selection and the creation of real-time detection systems that concentrate on session abnormalities.

D. Network Behavior Insights

Key selected features shed light on the rationale behind their importance:

1. **SYN-Error Rates** (serror_rate, srv_serror_rate, dst_host_serror_rate): High values frequently signify port scanning or denial-of-service operations [37].
2. **Flag**: TCP flag analysis aids in spotting questionable teardown or handshake patterns.
3. **Service and Protocol Type**: Some services (such HTTP and FTP) are more likely to be attacked, which makes them predictors of intrusion.
4. **Login Patterns** (logged_in, num_failed_logins): Indicate possible R2L attacks and illegal access attempts.
5. **Byte Counts** (dst_bytes, src_bytes): Measure the amount of data sent; harmful behavior is frequently associated with abnormal packet counts.
6. **Connection Frequency** (count, dst_host_same_srv_rate): Emphasize anomalous burst activity, which is typical of reconnaissance or DDoS operations (count, dst_host_same_srv_rate).

This conformity to the nature of network threats facilitates the model's efficient decision-making and provides direction for traffic monitoring tactics [38].

E. Partial Dependence & SHAP Analysis

Both SHAP (SHapley Additive exPlanations) and Partial Dependence Plots (PDP) were used to better understand how various features impact the model's predictions. By showing the direction and magnitude of each feature's impact, these methods offer interpretability.

- **Partial dependence analysis:** For a number of important traits, partial dependence analysis showed monotonic connections. Interestingly, there was a discernible trend in the variable serror_rate; as its value rose, the model steadily tended to anticipate an attack. Higher network connection error rates are highly correlated with unusual or malevolent activities, according to this monotonic pattern.
- **SHAP (SHapley Additive exPlanations)**: At the individual prediction level, SHAP values provide a more detailed perspective of feature contributions. The analysis verified that: Attack classification was considerably more likely for rare protocol types that differ from typical traffic behavior. ttack prediction benefited by high error rates, especially in features like srv_serror_rate and dst_host_serror_rate.

By highlighting the patterns the model employs to identify possible threats, these insights enhance the model's transparency and auditability. Such interpretability is essential for establishing trust and empowering domain experts to take well-informed, practical actions based on model outputs in security-sensitive applications. [39][40].

F. Dimensionality Reduction and Sensitivity

Finally, in order to check the robustness of the model, as well as the sensitivity to the dimensionality reduction, we analyzed the results of ablation experiments, comparing test run performances with the full set of 41 features against the set with only the highest-ranked features. The findings were that there was a slight but statistically significant reduction in accuracy of between 2-3% when an abridged set of the variables were used, indicating that most of the second to last set of variables, in the ranking provided, contribute very little unique information themselves and are also highly redundant. Since these results indicate an optimal balance in which dimensionality reduction is traded for significant feature preservation, they may indicate that an optimized hybrid method can help to improve detection efficiency at a level that does not compromise interpretability of models.

G. Error Diagnosis

The confusion matrix reports high level of false negatives (FN) reaching about 32% in case of attack instances which means that a large percentage of actual intrusions was wrongly identified as being normal traffic. This is an indicator of the fact that the model works well in detecting attacks but when it comes to more obscure or covert patterns of intrplications, the model seems to take a step back. These diagnostic clues demonstrate the limitations of the model and the necessity of the improvement of possibly ambiguous threat representation in the case of its detection. [41].

H. Analysis of False Negatives and False Positives

A close look at misclassifications with respect to the feature distribution presented some important patterns. The number of false negatives was significant in situations, when such features as serror_rate and srv_serror_rate did not create strong signals, meaning that some attacks managed to mimic the normal traffic patterns and avoid detection. However, on the other

hand, false positives were frequently the result of service use that was rare but valid, e.g. the use of some uncommon protocols or unusual connection types. Such results indicate that the feasibility of a more subtle set of rules to handle benign but abnormal service patterns exists and that it should be possible to reduce false alarms while maintaining detection success.

I. Feature Correlation and Multicollinearity

The multicollinearity between some of the features related to errors was quite strong, and correlation analysis revealed a moderate to strong correlation coefficient (r higher than 0.75) between the features in question, which indicated the lack of multicollinearity. Such an extent of interdependence will affect model performance and interpretability. In order to curb such an effect we can use dimensionality reduction methods like Principal component Analysis (PCA) to reduce correlated variables but at the same time retaining important variance. Similar approaches can be noted in any other Intrusion Detection System (IDS) systems proving that such normalization methods are effective [42].

J. Recommendations for Improved Feature Engineering

As the analysis reveals, there are a few strategies to improve feature representation and general detection that can be recommended:

- **Add Temporal and Statistical Aggregates:** Increase the feature space by including time-based temporal and statistical aggregates to enable a more in-depth capture of behavioral dynamics across periods.
- **Use Heuristic Optimization Techniques:** The use of heuristic feature selection techniques have proven to generate optimal feature subsets that are more likely to maximize the accuracy of detection system and minimize backdoor redundancy such as NSGA-II [43].
- **Include Semantic Network Terms:** Bring in embeddings of the categorical inputs such as port numbers or HTTP methods to discover richer semantic connections that more-traditional encodings sometimes overlook.

These improvements are made to enhance the accuracy of the model when it comes to differentiating between minor attack vectors and normal acts of complex network environment.

K. Comparison to Related Works

These top features are in high correlation with the key variables found in the previous research especially those connected with service-level characteristics and error-rate to mention but a few [44][45]. The use of SHAP (SHapley Additive exPlanations) that establish interpretability of the features is the highlight of compliance with the best practices with regards to the development of intrusion detecting system (IDS) in the present contexts [46]. With such focus on the most powerful features and due to such high performance output, the model is easily interpretable yet produces similar results as other more complex methods, like the RFE-XGBoost, hence creating an effective trade-off between simplicity and accuracy.

L. Limitations of Feature Importance

As it would provide helpful information, the problem with gain-based feature ranking is that it tends to be skewed, as it targets more heavily cardinal features, usually to the extent where such an evaluation of importance becomes biased [34]. In addition, typologies do not take into consideration the complicated interactions of features which are known to affect the models behaviour. These limitations suggest the use of a multi-faceted approach to interpretability as the recommendation is to use SHAP values, permutation importance, and Partial Dependence Plots (PDP). This is an integrated approach highly supported in the literature of Explainable AI (XAI) [47][48] to provide a more flawless and wholesome interpretation of the contribution of features in intrusion detection models.

M. Future Directions in Feature-based Analysis

To improve feature engineering in IDS, some of the possible further directions can be identified:

- **Advanced Feature Selection Binary codes:** Utilize binary encoding to derive a set of binary codes representing each individual respective feature set where a positive value indicates the presence of a feature and a negative value indicates its absence, thus enabling the detection of more relevant features.
- **Dynamic Weighting of Features:** Use transfer learning pattern to dynamically change the importance of features based on changing attack patterns to allow the model to be more adaptable in a constantly evolving network model.
- **Online Learning Integration:** A practical way to do this, and be able to make real time / small updates to feature importance scores so that the IDS can continually learn and adjust as it is processing live data streams.

These guidelines will serve the purpose of making the feature-based analysis more adaptive, accurate, and robust in contemporary cybersecurity applications.

VI. Future Directions

Due to the ever-growing nature of cybersecurity threats in terms of both complexity and scale, more effective, scalable and smart Intrusion Detection Systems (IDS) are required. Although the XGBoost classifier has proven to be effective in identifying different types of attacks present in the NSL-KDD dataset, there are a set of directions in which the study of this model can be extended that may have a positive impact on its performance and mimic its success in the real world.

1. **Real-Time Intrusion Detection Systems**

Current models, including ours, operate in an offline mode, processing static datasets. However, real-world networks demand real-time intrusion detection**.** Future work should focus on optimizing XGBoost-based models for streaming data environments, where latency and

throughput are critical. Incremental learning or online gradient boosting techniques can be explored to continuously update the model without full retraining

2. Transfer Learning and Cross-Domain Detection

A further possibility is using transfer learning which entails having a model trained on a particular dataset or network setting which is then adjusted to perform on a different dataset or network setting with little retraining. This is imperative because the patterns of attack and the nature of traffic differs among domains. One of the ways to aid this is by applying domain adaptation techniques to help the model be more general and not overfit to one particular dataset such as NSL-KDD.

3. Integration with Deep Learning Architectures

Even though the XGBoost is providing high performance and interpretability, the combination of the XGBoost with the deep learning model could further increase the performance, e.g., LSTM (temporal detection) or CNN (pattern extraction in a sequence of packets). XGBoost may also be used in hybrid architectures, as a second stage after the initial prediction by a deep learning model.

4. Inclusion of Temporal and Contextual Features

NSL-KDD does not contain features describing the session history or over-time behavior. Next generation datasets and models must have context including time spent, past actions, or running averages. This would allow the system to identify slow-paced attacks, which in most cases get ignored in snapshot-based models.

5. Feature Engineering through Automated Techniques

To conduct the feature selection and transformation, automated machine learning (AutoML) tools may be utilized to achieve better results than manually selected top features. Such algorithms as Genetic Algorithms, NSGA-II, and AutoFeature can recognise non-obvious interactions and create higher-order features that also increase the performance of classification.

6. Handling Class Imbalance and Rare Attack Types

Although we used SMOTE to balance our dataset, real-world networks are very skewed in nature and normal traffic far outweighs the attack traffic. The research should aim at adaptive sampling or cost-sensitive learning or focal loss mechanisms that handle rare but essential attack types like User to Root (U2R) or Remote to Local (R2L).

7. Deployment and Model Explainability

In practice, however, explainability needs to be viewed as a first-class concern in the future efforts. The issue of security professionals is having actionable steps based on understandable alerts. The use of HAP, LIME, or counterfactual explanations is thus to be embedded in

deployment dashboards to provide real-time decision support and minimize the false positive rate.

8. Cross-Dataset Evaluation

There are numerous researches, ourselves included, that apply NSL-KDD. In order to be generalized, they should be tried out on other current datasets like CIC-IDS2017, UNSW-NB15 and TON_IoT. Cross-dataset validation assist in assessing the strength of the model when it comes to the biases on the dataset and enhance applicability in contemporary enterprise or IoT conditions.

9. Scalability and Edge Deployment

With large networks and multiplicity of edge devices lightweight and scalable IDS are needed. Future work would require the study of model compression, pruning, or quantization to enable IDS models to operate on edge devices without the need to depend on centralized infrastructure.

10. Integration with SOC Platforms

Lastly, the implementation of such XGBoost-based IDS in Security Operations Center (SOC) applications using APIs or within SIEM systems (such as Splunk, ELK Stack) would help to get closer to practice. The construction of full-fledged detection and response ecosystem is an aspiration in the future that will increase industry adoption.

The roadmap ahead, then, will not only focus on improving classification modelling, but also go beyond to include real-time detection, explanatory capabilities, extended generalization and the ability to process them at the edge and on the cloud.

VII. Conclusion

IDS provides an important point of the first line of defence against cyber-attacks. Machine learning-based solution is an area worth pursuing, as threats will become more intelligent in the future. This study has examined the application of an Extreme Gradient Boosting (XGBoost) which is a scalable and strong tree-based ensemble method to create an effective and understandable IDS model.

The research work has begun with a clear comprehension of the NSL-KDD which is a modified version of KDD99 dataset that offered a large number of networks traffic data instances that were coded as either normal or as an attack. Label encoding, feature scaling, and SMOTE approaches of oversampling were important procedures that enabled transformation of the data into a form that could be used in a machine learning process, and attained a solution to the initial challenge of class imbalance surmounting.

It was notable that with intense testing, the XGBoost classifier performed better in comparison with other common traditional machine learning models like Random Forest, Decision Trees and Logistic Regression. It scored high accuracy of 80.08 in the test set and its precision, recall, and

its F1-scores were both high in the binary and multiclass classification tasks. Further, the confusion matrix and error analysis have shown the usefulness of the model at classifying the constant types of attacks as well as the error comparisons needed to be made when reasoning about the less prevalent classes such as U2R and R2L.

Such an instance as the feature importance analysis was one of the cornerstones of this work since it did not only guarantee better interpretability but also revealed the most significant drivers of rf. Some other features like serror_rate, srv_serror_rate, flag and protocol_type turned out to be really crucial, proving their relevance to network anomaly detection. This understanding allows the security teams to develop more focused monitoring strategies and potentially make more efficient the data collection process by discarding less valuable features.

On top of accuracy, explainability and deployability of the machine learning models are gaining relevance in the cyber security environment. The interpretability nature of XGBoost and its supporting software such as SHAP, can make it good to be integrated in the real world systems whereby decisions taken have to be transparent and answerable. It is our finding that model performance and interpretability could be mutually inclusive without compromising their effectiveness.

Although such a dataset as NSL-KDD presented an appropriate benchmark that could be used to evaluate, we understand that it is not representative of both contemporary network traffic trends and new types of threats. Thus, clarification of the results would be enhanced by validating it on recent datasets such as CIC-IDS2017 or UNSW-NB15. And equally, how the model can be adapted to live settings and how it will perform in an environment that has data drift are still research opportunities.

This paper is part of the literature that supports the thinking of the effectiveness of gradient boosting algorithm in IDS. Its performance in terms of accuracy, speed, and interpretability make XGBoost a competitive candidate to be used in research and production discussions. It is scalable and customizable to work with feature selection due to which it can handle large-scale network deployments, cloud deployments, and even low-end devices (edge scenarios).

To sum it up, the implementation of the XGBoost in intrusion detection field can serve as an illustration of a potent model of developing intelligent, responsive, and interpretable defense systems. The challenges include evolving threats, real-time constraints, generalization, which still have to be addressed, but the advancements presented by this very research open opportunities to enhance the progress further. With the increasing maturity of more sophisticated and autonomous cybersecurity systems, XGBoost models will take center stage on the upper edge of the division between data science and operational security.

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