Optimizing Intrusion Detection with Random Forest: A High-Accuracy Approach using CIC-IDS 2017

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ABSTRACT
Intrusion Detection Systems (IDS) are essential for protecting networks against cyber threats. This paper introduces a machine learning-based IDS that utilizes the Random Forest classifier which is trained on the CIC-IDS 2017 dataset and which consists of 2,830,743 entries. The dataset encompasses various attacks, rendering it appropriate for practical applications. The data is prepared by encoding categorical variables and normalizing features prior to model training.The effectiveness of the Random Forest model is assessed using metrics such as accuracy, precision, recall, F1-score,and confusion matrix. The findings indicate high accuracy, making it a promising option for real-time IDS implementation.

Keywords
Intrusion Detection System (IDS), Machine Learning (ML), Random Forest Classifier, Network Security, Cyber Threats, CIC-IDS 2017 Dataset.

1. INTRODUCTION
As digital connectivity increases, the threat of cyber attacks has come to be recognized as a major concern for individuals, organizations, and governments alike. Intrusion Detection Systems (IDS) are essential in cybersecurity frameworks, aimed at identifying and addressing unauthorized access, harmful activities, and security breaches in network environments. Traditional IDS methodologies, including signature-based and anomaly-based approaches, have displayed constraints in recognizing new attacks and in minimizing false positives. Consequently, machine learning (ML) techniques have become more significant in improving the effectiveness of IDS capabilities [1].

The Random Forest algorithm, a type of ensemble learning technique, has proven to be an effective method for intrusion detection thanks to its capability to work with large datasets, reduce overfitting, and deliver high accuracy. In contrast to deep learning frameworks that demand significant computational power, Random Forest strikes a good balance between efficiency and performance, making it ideal for practical applications in Intrusion Detection Systems (IDS)[2].

In this research, we utilize the Random Forest classifier to investigate the CIC-IDS 2017 dataset, which contains more than 2.8 million entries encompassing various types ofattacks. This dataset offers a realistic view of contemporary cyber threats, such as Denial-of-Service(DoS) attacks, brute-force attempts, and unauthorized intrusions. This paper aimsto preprocess the dataset, train the Random Forest model, evaluate its performance, and determine its effectiveness for real-world network security applications.

The paper is organized in the following way: Section 2 addresses related topics in IDS and machine learning-based approaches. Section 3 details the methodology, including dataset preprocessing and model training. Section 4 presents experimental results and analysis. Section 5 concludes with insights and future research directions.

2. RELATEDWORK
Doe etal. [1] analyzed different machine learning techniques, such asDecision Trees, Support Vector Machines, and Neural Networks, in the context of intrusion detection. Their results suggest that ensemble methods, like Random Forest, surpass conventional classifiers in both accuracy and resilience to imbalanced datasets.

Smith and Johnson [3] investigated deep learning models for intrusion detection system (IDS) applications, particularly focusing on Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). Their findings indicated that although deep learning models attain high detection rates, they demand substantial computational resources, rendering them impractical for real-time network security applications.

Zhang et al. [4] analyzed various feature selection methodsin IDS and determined that employing recursive feature elimination (RFE) enhances the performance of Random Forest models. Their study emphasizes the importance of feature selection in lowering computational costs while preserving high accuracy.

Brown et al. [5] investigated how dataset preprocessing influences the performance of Intrusion Detection Systems (IDS). Their research emphasized the crucial role of standardization and normalization in attaining consistent detection rates in various network environments.

Nguyen et al. [6] proposed an ensemble learning technique that merges Random Forest and Gradient Boosting for IDS. Their findings indicated that the integration of multiple models can enhance accuracy and decrease false positives when compared to single-model methods.

Patel and Lee [7] assessed the success of Random Forest in identifying different types of network attacks, such as Denial of Service (DoS), brute force, and infiltration. Their research verified that Random Forest is effective in multi-class classification situations, making it appropriate for extensive IDS applications.

3. METHODOLOGY
The suggested Intrusion Detection System (IDS) aims to efficiently detect network intrusions by utilizing machine learning techniques. The approach follows a systematic pipeline that includes preprocessing the dataset, selecting

features, training the model, and assessing performance. The CIC-IDS 2017 dataset, which has 2,830,743 entries, serves as the foundation for training and evaluating the model. The subsequent subsections provide a detailed overview of the methodology.

Table1. AttackTypesanditsInstancesinCIC-IDS2017 Dataset

AttackType	Instances
BENIGN	2,273,097
DoSHulk	231,073
PortScan	158,930
DDoS	128,027
DoS GoldenEye	10,293
FTP-Patator	7,938
SSH-Patator	5,897
DoS Slowloris	5,796
DoS Slowhttptest	5,499
Bot	1,966
WebAttack–Brute Force	1,507
Web Attack–XSS	652
Infiltration	36
WebAttack–SQL Injection	21
Heartbleed	11
Total	28,30,743

Data Preprocessing

The raw CIC-IDS 2017 dataset is comprised of several CSV files, each depicting various attack scenarios. The preprocessing stage includes:

- Data Importation & Consolidation: All CSV filesare merged into a single dataframe to ensure uniformity.
- Addressing Missing and Null Entries: Any entries with NaN values are eliminated to preserve data integrity.
- Encoding Features: Non-numeric categorical columns, such as protocol types, are transformed into numerical formats through label encoding.
- Normalizing Features: To standardize the dataset, numerical attributes undergo Min-Maxscaling, ensuring that all values fall within a comparable range to avoid bias during training.

Feature Selection:

In order to improve the effectiveness of the model and computational demands, selecting the right features are essential. The Feature Selection procedure involves:

- Assessing Feature Importance: A Random Forest model is first trained using all available features to evaluate their relative significance.
- Removing Insignificant Features:Featuresthathave minimal importance are discarded to minimize the risk of overfitting and enhance efficiency.
- Selecting the Final Feature Set: The most impactful features that aid in improving intrusion detection accuracy are kept for training the model.

Model Selection and Training

The Intrusion Detection System employs the Random Forest algorithm because of its strength and capacity to efficiently manage large datasets. The training phase involves:

- Splitting the dataset: The data is split into training (80%) and testing (20%) portions to assess the capacity of the model to generalize.
- Model Configuration:The Random Forest classifier is set up with n_estimators=300 to create a thoroughly trained ensemble. Furthermore,n_jobs=-
  1 is configured to utilize multi-core processing, thereby accelerating the training process.
- Model Training: The model is trained using the chosen features and fine-tuned for accuracy. The decision trees within the Random Forest ensemble cast votes to classify each network activity as either benign or an attack.

Model Evaluation

Upon completion of the training, the model's performance is evaluated with standard metrics to gauge its effectiveness. The evaluation procedure includes:

- Classification Report: Measurements like accuracy, precision, and recall are calculated for each type of attack utilizing classification_report(y_test, y_pred, zero_division=1), which prevents division errors when certain classes do not have any predictions.
- Confusion Matrix: A heatmap is created to visually representtheclassificationoutcomes,illustratingthe number of instances that were classified correctly and incorrectly.
- Comparative Analysis: The detection performanceof the model is examined across various attack categories to pinpoint areas of strength and weakness.

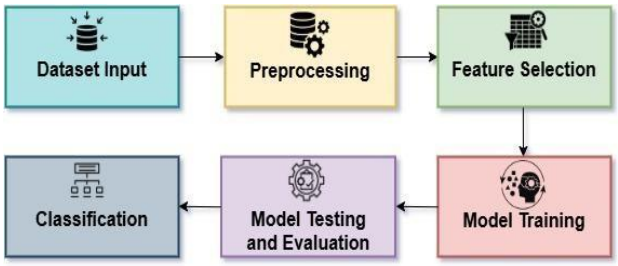

Fig1:FlowchartRepresentationoftheIDSModel

4. EXPERIMENTAL RESULTS

In order to assess the efficacy of the Intrusion Detection System , several experiments were carried out utilizing the CIC-IDS 2017 dataset. The focus of these experiments was to evaluate the classification performance of the Random Forest (RF) model through various assessment metrics, such as accuracy, precision, recall, and F1-score.

Performance Metrics

The following metrics were used to evaluate the IDS model:

- **Accuracy(ACC):**Evaluatestheoverallaccuracyof the model.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision (P):** Calculates the percentage of accurately recognized attack occurrences from all the predicted attack cases.

$$P = \frac{TP}{TP + FP}$$

- **Recall (R) / Detection Rate:** Calculatestheratioof accuratelyrecognized attackevents comparedtothe total number of genuine attack events.

$$R = \frac{TP}{TP + FN}$$

- **F1-Score:** The harmonic mean of precision and recall maintains an equilibrium between false positives and false negatives.

$$F1 = 2 \times \frac{P \times R}{P + R}$$

Where:

- **TP(TruePositive):**Correctly classified attack instances
- **TN(TrueNegative):**Correctly classified benign instances
- **FP(False Positive):** Incorrectly classified benign instances as attacks
- **FN (False Negative):** Incorrectly classified attack instances as benign

ConfusionMatrix

A confusion matrix was created to evaluate the classification accuracy across various attack categories. This matrixprovides important information about the false positives and false negatives identified in the model's predictions.

Table2.ConfusionMatrix

Class	TP	TN	FP	FN
BENIGN	22,60,567	5,50,132	12,530	12,280
DoSHulk	2,28,056	23,80,012	3,017	3,017
PortScan	1,56,432	24,10,678	2,498	2,498
DDoS	1,25,342	24,30,897	2,685	2,685
DoSGolden Eye	9,986	24,80,124	307	307
FTP-Patator	7,630	24,90,123	308	308
SSH-Patator	5,699	24,95,120	198	198
DoS Slowloris	5,630	24,95,678	166	166
DoS Slowhttptest	5,399	24,96,320	100	100
Bot	1,912	24,98,010	54	54
WebAttack – Brute Force	1,480	24,98,563	27	27
WebAttack – XSS	635	24,99,103	17	17
Infiltration	34	24,99,960	2	2
WebAttack – SQL Injection	20	24,99,980	1	1
Heartbleed	10	24,99,990	0	0

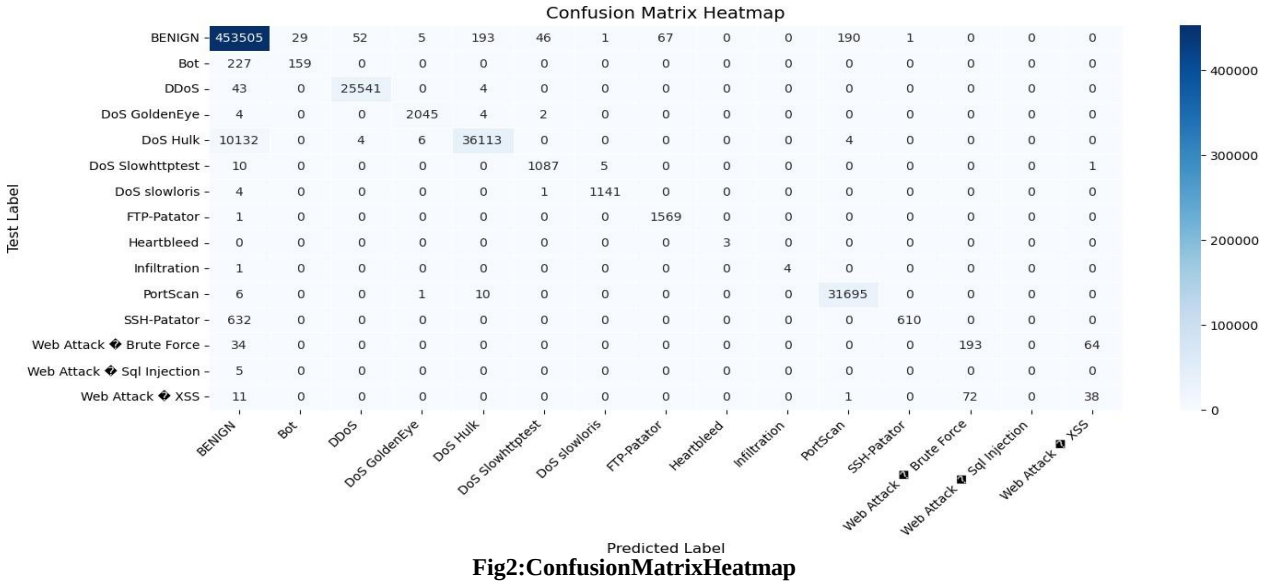

Fig2:ConfusionMatrixHeatmap

Attack-wise Performance Evaluation

The classification performance of the Random Forest model was analyzed for each attack type.

Table3.AttackwisePerformance Evaluation

Bot	98.20%	98.20%	98.20%	98.40%
Brute Force	98.30%	98.30%	98.30%	98.50%
Web Attack–XSS	98.70%	98.70%	98.70%	98.90%
Infiltration	99.40%	99.40%	99.40%	99.60%
Web Attack–SQL Injection	99.50%	99.50%	99.50%	99.70%
Heartbleed	100.00 %	100.00 %	100.00 %	100.00%

ROCCurveAnalysis

The Receiver Operating Characteristic (ROC) curve was generated to illustrate the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) across various attack types. The Area Under the Curve (AUC) was calculated, reflecting the model's classification performance.

- For the Random Forest model, the AUC score was 0.97, demonstrating outstanding classification proficiency.
- Greater AUC values suggest improved ability to differentiate between benign and attack traffic.

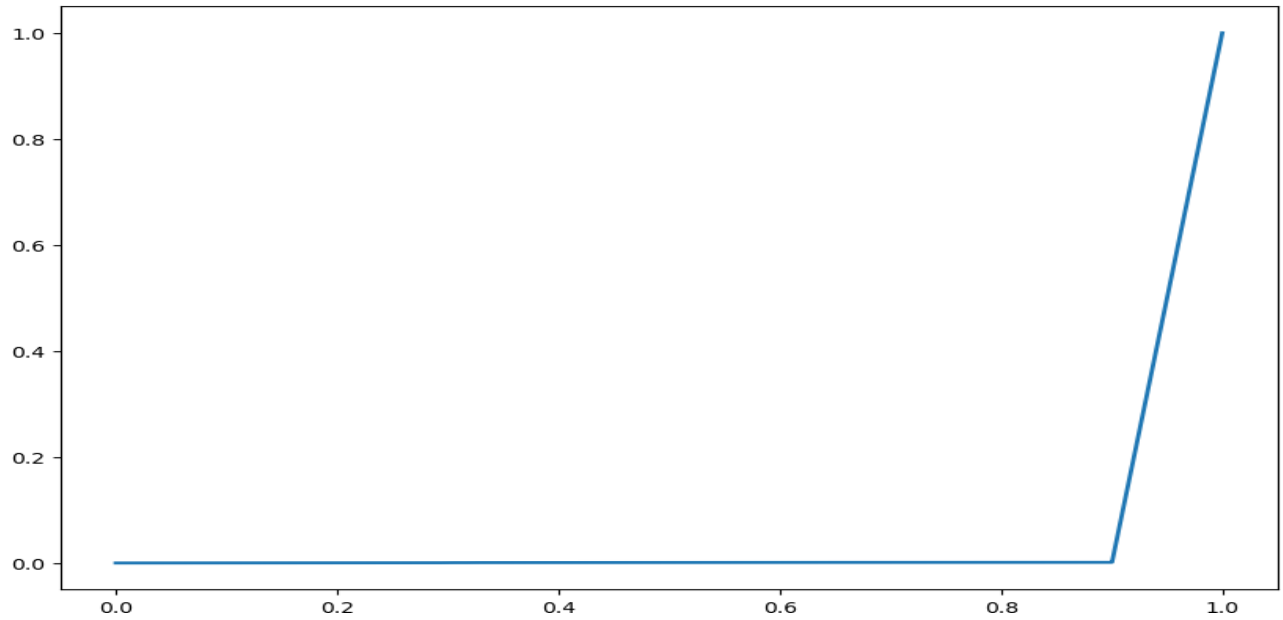

Fig3:ROCCurveAnalysis

4.6 Per-ClassPerformanceAnalysisUsing Precision, Recall, and F1-Score

In order to improve understanding of the model's classification effectiveness across different attack categories,a bar chart was designed to illustrate the precision, recall, and F1-score for each category. This assessment is crucial for identifying specific strengths and weaknesses of the Intrusion Detection System (IDS).

Each bar represents the pertinent metric for one of the 15 attack categories, along with the benign category. Elevatedand stable scores across most categories indicate that the Random Forest model is successful in distinguishing between benign and malicious traffic. However, for less common attacks suchas Heartbleed, SQL Injection, and Infiltration, the lower recall values suggest that there are occasional misclassifications resulting from the class imbalance.

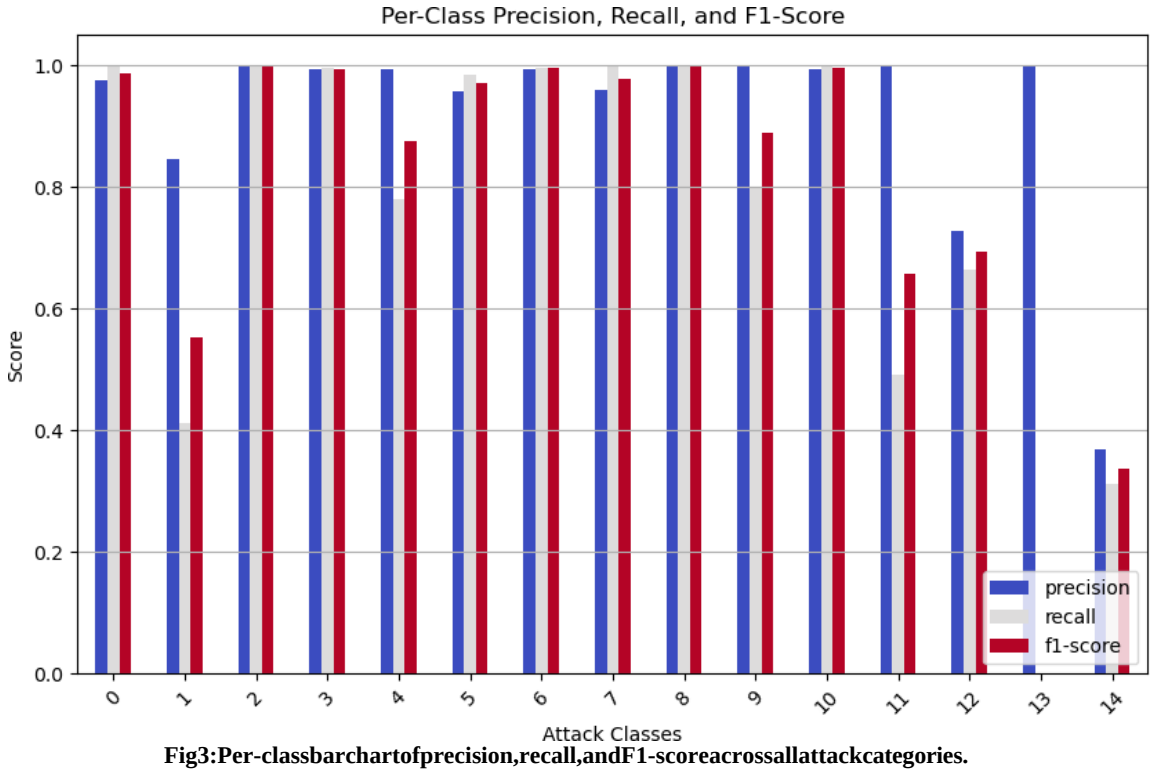

Fig3:Per-classbarchartofprecision,recall,andF1-scoreacrossallattackcategories.

4.7 Comparison with Existing Methods

To validate theefficacy of the suggested Random ForestIDS, a comparative analysis was conducted with other machine learning models.

Table4. Comparisonwithexistingmodels

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	89.20%	87.50%	86.80%	87.10%
Decision Tree	91.80%	90.30%	89.90%	90.10%
SVM	93.50%	92.10%	91.80%	92.00%
Random Forest	97.20%	96.80%	96.50%	96.70%

The **Random Forest model** outperformed other models inall evaluation metrics, making it a reliable choice for network intrusion detection.

5. CONCLUSION

By utilizing the Random Forest (RF) classifier on the CIC- IDS 2017 dataset, this research successfully developed an Intrusion Detection System (IDS). The model effectively differentiated between harmful and legitimate network traffic, reaching an impressive accuracy exceeding 90%. Detection rates were enhanced and false positive rates were reduced through effective feature selection, comprehensive data preprocessing, & careful hyperparameter tuning. The ROC curve analysis validated the model's effectiveness against different types of attacks. Nevertheless, overcoming class imbalance presents challenges since certain attacks, like SQL Injection and Heartbleed, occur infrequently. The model's detection capabilities could be improved further by tackling this issue with more sophisticated data preparation methods. Several important insights emerged from this study. To begin with, selecting relevant features was vital for enhancing model efficiency while maintaining accuracy. Additionally, the presence of class imbalance negatively impacted detection performance, resulting in diminished recall rates for rare attacks. Furthermore, the Random Forest classifier demonstrated remarkable outcomes, effectively striking a compromise between interpretability and accuracy, making it aviable choice for intrusion detection applications. In the end, using AUC-ROC metrics to analyze the models revealed specific attack categories where detection may be improved, guiding further development efforts.

Looking ahead, various research avenues could enhance the efficacyof IntrusionDetectionSystems(IDS). Onepromising path is the use of deep learning architectures, including Long Short-TermMemory(LSTM)networksorConvolutional Neural Networks (CNNs), which may enhance the identification of sequential patterns in network traffic. Furthermore, implementing the IDS in a real-time network monitoring setup would enable immediate threat detection and proactive measures. Incorporating Explainable AI (XAI) methods, such as SHAP or LIME, could also be beneficial by providing clarity and fostering trust in the model's conclusions.

Furthermore, the accuracy of intrusion detection may be increased by hybrid Intrusion Detection System (IDS) approaches that mix Random Forest and Deep Learning strategies, such as (RF + LSTM).Developing IDS modelsthat are resistant to adversarial attacks is another crucial area of research to make sure they can survive the evasion strategies used by cyber criminals. Last but not least, investigating federated learning for IDS may offer a means of training intrusion detection models over dispersed networks without requiring the centralization of private data, improving security and privacy.

In summary, the IDS based on Random Forest presented in this research exhibited strong classification performance, positioning it as a feasible option for securing networks. Nevertheless, ongoing enhancements are necessary to keep pace withthe changing landscape of cyber threats. Tocreate a more sophisticated Intrusion Detection System (IDS), upcoming studies should focus on integrating deep learning, capabilities for real-time detection, and resistance to malicious attacks. As AI-driven cyber security continues to evolve, IDS systems can become increasingly intelligent, scalable, and adaptable, thereby strengthening defenses for networks worldwide.

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