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# Designing IDS to Analyze Malicious Attacks using Machine Learning

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Abstract: This study presents a novel approach to enhance network security through the design and implementation of an Intrusion Detection System (IDS) employing machine learning (ML) techniques. The primary aim is to address current challenges in real-time threat detection by seamlessly integrating ML models, including Logistic Regression, Random Forest, and XGBoost. The research tackles drawbacks in existing systems, emphasizing the struggle with real-time threat detection, the complexity of ML integration. The working model classifies incoming requests as normal or intrusions, categorizing the latter into DDoS, R2L, U2R, or Probing attacks. Leveraging insights from four referenced papers, this study builds on efficient activation functions, optimized feature selection, and empirical analyses of ML models for adaptive network intrusion detection. Results showcase promising comparisons between ML algorithms which include Logistic Regression, Random Forest, XG Boost. Keywords: Intrusion Detection System, Machine Learning

### I. INTRODUCTION

In the dynamic internet landscape, the surge in network security challenges is evident alongside technological advancements. Ensuring the security of internet applications is crucial as our reliance on them grows. Among defense mechanisms, the Intrusion Detection System (IDS) plays a pivotal role, akin to a fortress guarding against threats.

Operating as a server-side protection system, an IDS continuously analyzes network activities, much like a sentinel, to detect and thwart attacks. Categorized as Host-Based Intrusion Detection System (HIDS) and Network-Based Intrusion Detection System (NIDS), these systems offer retrospective and real-time analysis, respectively.

While traditional methods like feature matching and machine learning are prevalent, the emergence of machine learning algorithms has revolutionized intrusion detection, offering superior accuracy and self-learning capabilities. This paper focuses on a network-based IDS design based traditional IDS dataset, integrating machine learning for enhanced accuracy and real-time defense. This paper further more compares various machine learning models to provide accurate and precise values using various parameters for training and testing. This helps to achieve a model having high accuracy to detect intrusion in the system.

The proposed system features a modular development approach, enabling easy expansion and development of functionalities. This ensures high-precision intelligent defense, balancing overall operating efficiency. This report details the system architecture, implementation methods, and CNN integration, heralding a new era of intrusion detection powered by advanced deep learning techniques.

Sr.	Paper Title and Year	Author	Key Findings and Results
No			
1.	Design And implementation of IDS	Shihao Wang*, Zhefan Chen, Jin Chen,	This paper implements networkbased
	Using Deep Learning (2023 IEEE	Peiwen Zhu	intrusion detection systems with
	3rd International Conference on		convolutional neural networks, enabling
	Electronic Technology,		efficient coordination and highprecision
	Communication and Information)		defense. The system collects and
			processes traffic data for real-time
			intrusion detection using efficient
			activation functions and optimizers

#### II. LITERATURE REVIEW



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2.	An Optimized Network Intrusion	LIU Dongdong, DOU Hongtao, HAN	This paper introduces a featurebased
	Detection Mode (2022 IEEE 5th	Bo,NIU Lei	network intrusion detection model,
	Advanced Information Management,		highlighting its effectiveness with the
	Communicates, Electronic and		KDD CUP99 dataset, where it
	Automation Control Conference)		outperforms other models in terms of
			detection rates and false alarmsThis
			paper presents an optimized network
			intrusion detection model using feature
			selection, showing improved
			performance compared to other models.
			However, further research is required to
			assess its scalability and real-world
			applicability
3.	Empirical Analysis of Machine	Dr. Aranga Arivarasan, Mr. S. P.	This paper empirically analyzes
	Learning Models towards Adaptive	Senthilkumar	machine learning models for adaptive
	Network Intrusion Detection		network intrusion detection,
	Systems (2022 4th International		investigating their effectiveness in
	Conference on Smart Systems and		detecting network intrusions. The
	Inventive Technology)		research shows that machine learning
			models effectively detect network
			intrusions using tools like TensorFlow
			and scikit-learn for analysis and
			evaluation.
4.	Intrusion detection system analysis	Rupak Dutta, Nirupama B.K,	This research employs machine
	using ML (2022 IEEE 2nd Mysore	Niranjanamurthy	learning for efficient invader detection,
	Sub Section International		evaluating models within the context of
	Conference)		Intrusion Detection Systems (IDS),
			encompassing both Host-based (HIDS)
			and Network-based (NIDS)
			classifications. Among the four
			algorithms, KNeighborsClassifier
			performed best with an accuracy score
			of 0.867, making it a reliable choice for
			future research or implementations

## III. SYSTEM ARCHITECTURE

The project's modeling and analysis encompass several key components, beginning with data collection and preprocessing. A diverse dataset of network traffic data is collected and then subjected to rigorous preprocessing, including cleaning, normalization, and feature engineering, to enhance its quality and relevance.

Next, three machine learning (ML) models—Logistic Regression, Random Forest, and XGBoost—are developed for intrusion detection. These models are trained on the preprocessed dataset to distinguish between normal network activity and various types of attacks, such as DDoS, R2L, U2R, and Probing to provide accuracy and precision.

In real-time intrusion detection, incoming network requests are analyzed by the ML models for classification. The models determine whether a request constitutes normal activity or falls into one of the predefined attack categories which will further detect intrusion. This real-time analysis allows for immediate identification and response to potential security threats.

This will help to notify the administrator of the intrusion and direct to take protective measures towards the attack.



This comprehensive approach to modeling and analysis integrates machine learning with IDS, enabling effective and efficient intrusion detection in complex network environments.





#### IV. PROPOSED METHODOLOGY

To achieve the objectives outlined in our research, we employed a systematic methodology, integrating machine learning (ML) with the Intrusion Detection System (IDS). The following steps delineate the key components of our approach:

- Dataset Selection and Preprocessing: We utilized a diverse dataset containing network traffic data to train and evaluate our ML models. Data preprocessing involved cleaning, normalization, and feature engineering to enhance the quality and relevance of the input data.
- 2) Training and Testing: Using NSL-KDD datasets for training and testing the various considered machine learning models for identifying the attacks. This step will help in predicting the accuracy of the models and considering which model to be used in the IDS which will provide better and optimized output.
- 3) *Machine Learning Model Development:* Three ML models—Logistic Regression, Random Forest, and XGBoost—were implemented for intrusion detection. The models were trained on labeled data, distinguishing between normal network activity and four types of attacks: DDoS, R2L, U2R, and Probing.
- 4) *Integration with IDS:* We seamlessly integrated the developed ML models with the IDS to enable real-time intrusion detection. The integration involved the creation of interfaces to facilitate communication and data exchange between the ML models and IDS.
- 5) *Evaluation Framework:* We established a comprehensive evaluation framework to assess the performance of our IDS. Metrics such as accuracy, precision, recall, and F1 score were used to quantify the effectiveness of the ML models in detecting and classifying intrusions.
- 6) Validation and Comparison: The performance of our system was validated through rigorous testing using both simulated and real-orld scenarios. Comparative analyses were conducted against existing IDS solutions and traditional methods to gauge the efficacy of our approach. By meticulously executing these steps, our methodology aimed to create a robust IDS that not only leverages ML for enhanced threat detection but also seamlessly integrates with existing infrastructure while providing an intuitive visualization.

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#### V. RESULT ANALYSIS

Two techniques data scientists can use to balance datasets are Oversampling and Undersampling Oversampling is appropriate when data scientists do not have enough information. One class is abundant, or the majority, and the other is rare, or the minority. In oversampling, the scientist increases the number of rare events. The scientist uses some type of technique to create artificial events. One technique to create artificial events is synthetic minority oversampling technique (SMOTE).

Undersampling is appropriate when there is plenty of data for an accurate analysis. The data scientist uses all of the rare events but reduces the number of abundant events to create two equally sized classes. Typically, scientists randomly delete events in the majority class new to end up with the same number of events as the minority class. Undersampling is a technique to balance uneven datasets by keeping all of the data in the minority class and decreasing the size of the majority class. It is one of several techniques data scientists can use to extract more accurate information from originally imbalanced datasets.

Random oversampling involves randomly duplicating examples from the minority class and adding them to the training dataset. Examples from the training dataset are selected randomly with replacement. This means that examples from the minority class can be chosen and added to the new "more balanced" training dataset multiple times; they are selected from the original training dataset, added to the new training dataset, and then returned or "replaced" in the original dataset, allowing them to be selected again.

SMOTET omek is somewhere upsampling and downsampling. SMOTETomek is a hybrid method which is a mixture of the above two methods, it uses an under-sampling method (Tomek) with an oversampling method (SMOTE). This is present within imblearn.combine module.

Lastly, by going through the analysis of the types of attacks considered i.e. Probe, U2R, R2L and DDoS. DDoS attack has the most dominance over the other attacks in the training and the testing phase.

Model	Train Log Loss	Test Log Loss	Misclassified Points
Logistic Regression without over sampling or under sampling	0.2623	0.9640	25.0793
Random Forest without over sampling or under sampling	0.0162	0.4468	13.1851
XGBOOST without over sampling or under sampling	0.0206	0.3990	8.6721
Logistic Regression with under sampling	1.0356	2.3678	35.3235
Random Forest with under sampling	0.1186	1.5287	61.4075
XGBOOST with under sampling	0.1616	1.6396	62.5891
Logistic Regression with over sampling using RandomOverSampler	1.3815	1.3819	25.0741
Random Forest with over sampling using RandomOverSampler	0.0106	0.6264	14.7363
XGBOOST with over sampling using RandomOverSampler	0.0377	0.6415	12.3470
Logistic Regression with over sampling using SMOTETomek	1.3823	1.3802	25.0689
Random Forest with over sampling using SMOTETomek	0.0207	0.4894	11.7692
XGBOOST with over sampling using SMOTETomek	0.0361	0.7281	10.5980

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	VI. IMPLEMENTATIONS		
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	NIDS		Login SignUp
			<b>9</b>
	NETWORK INTRUSION DETECTION SYSTEM		
	This is a software application to detect network intrusion by monitoring a network or system for malicious activity and predicts		
	whether it is Normal or Abnormal(attacked with intrusion classes like DOS/PROBE/R2L/U2R).		
	Login		
	Email address		
	sample@gmail.com		
	We'll never share your email with anyone else.		
	Password		
	Submit		
	DS X +	~	~ - ª ×
<- →		W	
	NIDS		logout
	Choose File for Prediction		
	Browse outputs.txt		
	Predict		
	Intrusion:		
	Yes		
	Predicted Attack Class:		
	DOS		

#### VII. CONCLUSION

By seamlessly integrating machine learning (ML) techniques, including Logistic Regression, Random Forest, and XGBoost, with the Intrusion Detection System (IDS), we have successfully addressed longstanding challenges in real-time threat detection. Predicted the Intrusion-based signal using a combination of different classification algorithms. Also used some over-sampling and under-sampling techniques to make changes in the data.

The data were imbalanced, so the Recall score/Sensitivity score will be the most effective performance metric to evaluate the best model for binary classification and log loss score for multi-class classification. So based on the best recall score, finally chosen the Random forest algorithm on the over-sampled data for binary classification part and XGBOOST algorithm on the raw data for multi-class classification part. Comparative analyses against IDS solutions underline the competitive advantage of our ML-driven approach, showcasing its robust performance and adaptability across diverse network environments However, the system is currently weak against malicious attacks against artificial intelligence systems.

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