

Machine Learning Models for UNSW-NB15 Dataset

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Abstract—Network security is an increasingly critical concern in the digital age, with organizations facing a multitude of cyber threats. In response to this challenge, the development of robust Intrusion Detection Systems (IDS) has become imperative. This paper presents a comprehensive study on the application of machine learning techniques to enhance network security, with a focus on the evaluation and comparison of Random Forest, Artificial Neural Network (ANN), and XGBoost models. This project explores the UNSW-NB15 dataset, a well-established benchmark in the field of network security, which includes various network-based attacks and normal traffic data. The machine learning models are applied to this dataset to detect and classify potential network intrusions, encompassing diverse attack categories, such as denial-of-service (DoS) attacks, port scans, and web application vulnerabilities. The research encompasses model development, training, and evaluation using appropriate metrics. The models' performance is assessed in terms of accuracy, precision, recall, F1-score, and computational efficiency. Additionally, the study provides insights into feature engineering and selection techniques to improve model performance. The findings of this research offer a comprehensive comparison of the three machine learning models' effectiveness in detecting network intrusions, shedding light on their strengths and weaknesses. This analysis is invaluable for both the academic community and the cybersecurity industry, providing guidance on the selection and deployment of appropriate IDS solutions.

Index Terms—Network Security, Intrusion Detection System, Machine Learning

I. INTRODUCTION

In today's interconnected world, the security of computer networks is of paramount importance. The proliferation of digital communication and data exchange has brought about a corresponding increase in cyber threats (see Fig.1), making network security a critical concern for individuals, businesses, and governments alike. The need for robust Intrusion Detection Systems (IDS) has never been more pressing, as these systems play a pivotal role in safeguarding network infrastructures against a wide array of malicious activities.

Network intrusion detection involves the continuous monitoring of network traffic to identify and respond to unauthorized and potentially harmful activities. Traditional rule-based IDS solutions have limitations in adapting to the evolving landscape of cyber threats. As a result, there has been a growing interest in harnessing the power of machine learning to enhance the efficacy of intrusion detection.

This research paper presents a comprehensive study on the application of machine learning techniques in the domain of

network security. Specifically, it focuses on the evaluation and comparison of three widely employed machine learning models: Random Forest, Artificial Neural Network (ANN), and Long Short-Term Memory Recurrent Neural Network (LSTM-RNN). The objective is to assess the ability of these models to detect and classify network intrusions using the well-established UNSW-NB15 dataset, which captures various network-based attacks and normal network traffic.

The motivation behind this research is twofold. Firstly, it addresses the growing need for advanced IDS solutions that can effectively identify and respond to an ever-expanding range of cyber threats. Secondly, it seeks to provide valuable insights into the strengths and weaknesses of machine learning-based approaches for network intrusion detection. By comparing these three models, this study aims to offer guidance to the academic community and industry practitioners regarding the selection and deployment of suitable IDS solutions.

In the subsequent sections of this paper, we delve into the methodologies employed for model development, the features selected for analysis, the experimental setup, and the results obtained through extensive evaluation. The findings are expected to contribute to the ongoing discourse on network security and facilitate informed decisions in the quest to fortify network defenses.

II. RELATED WORK & BACKGROUND STUDIES

In the ever-evolving landscape of network security, Network Intrusion Detection Systems (NIDS) serve as essential guardians against emerging cyber threats. These systems vigilantly monitor network traffic, promptly identifying and responding to anomalies or malicious activities to ensure the resilience of digital infrastructures. Over time, from early rule-based methods to contemporary machine learning-driven approaches, the evolution of NIDS underscores the continuous pursuit of adaptability and efficacy. Early work by Denning [14] laid the groundwork for anomaly-based detection, and ongoing research explores advanced machine learning models and newer datasets, such as UNSW-NB15 [1], [9], to propel the capabilities of NIDS.

Wilton et al. [7] propose new algorithms for learning from positive and unlabeled data (PU learning) using random forests. They introduce a novel perspective of decision tree learning as recursive greedy risk minimization and extend it to the PU setting.

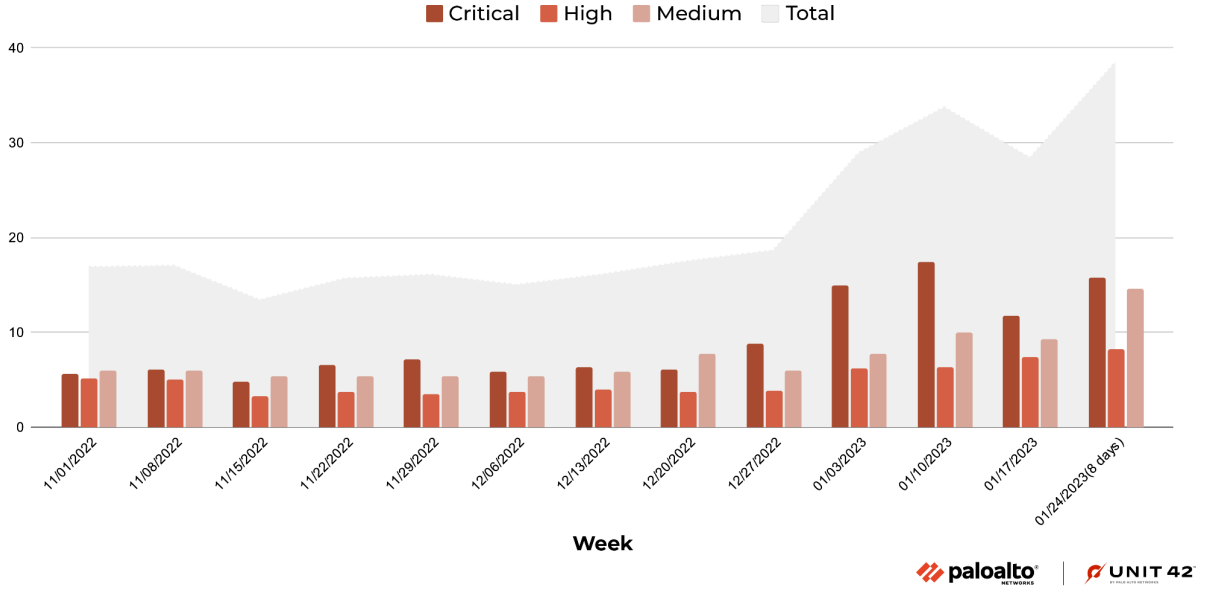


Fig. 1. Growth of Network Attacks. [6]

Hartl et al. [8] propose a recurrent neural network (RNN) based intrusion detection system (IDS) for network data, and evaluate its adversarial robustness, explainability, and defense methods. They show that RNNs can achieve high accuracy and detect attacks before the flow terminates, but also that they are vulnerable to adversarial attacks that manipulate packet length and Interarrival time. They introduce the Adversarial Robustness Score (ARS) as a new metric to quantify the IDS's resistance to such attacks, and demonstrate that it can be improved by adversarial training. They also apply and extend several feature importance and explainability methods to understand how the RNN makes its decisions, and reveal the influence of different features, packets, and values on the classification outcome.

Bhamare et al. [10] discuss the security issues in cloud computing and the limitations of supervised machine learning (ML) techniques for intrusion detection systems (IDS). They trained and tested four ML algorithms -J48, SVM, Naïve Bayes, and Logistic Regression using two different datasets UNSW for training and ISOT [15] for testing obtained from simulated cloud environments. The authors found that the ML models perform well with the same dataset but poorly with a different dataset, indicating a lack of robustness and applicability to real scenarios. They suggest exploring unsupervised ML and anomaly detection techniques for cloud security.

Siliveriy et al. [11] propose a model for multi-attack classification to improve intrusion detection performance using deep learning approaches, such as RNN, LSTM-RNN, and DNN. The authors use three deep learning models to self-learn the features and classify the network data into different attack types, such as DoS, Probe, R2L, U2R, and Normal2. The models are trained and tested on three benchmark datasets: KDD'99, NSL-KDD, and UNSW-NB1534. The authors compare the

results of their models with existing shallow and deep learning methods in terms of accuracy, detection rate, false alarm rate, and other metrics. They show that their models outperform the existing methods, especially in detecting low-frequency attacks like R2L and U2R.

Sinha et al. [13] propose a deep learning model that combines a 1-D convolutional neural network (CNN) and a bidirectional long short-term memory (BiLSTM) network to detect network intrusions from time-series data. The authors use a 1-D CNN layer to learn the spatial features of the network data, followed by max pooling, batch normalization, and reshape layers. The authors use two BiLSTM layers to learn the temporal features of the network data from both forward and backward directions, followed by dropout and dense layers.

III. DESCRIPTION OF PROPOSED FRAMEWORK

This section explains how we create machine-learning and neural network models for the UNSW-NB15 dataset. This section provides a detailed overview of the procedures involved in both training and assessing the models' performance. To give a clearer picture, let's delve into the specifics.

A. Data Preprocessing

- **Loading Data :** The dataset is available in csv file format with mostly numeric columns.
- **Feature Extraction :** To capture essential characteristics, 40 columns were chosen. Columns for transportation and application layer protocols and the state of the connection were dropped.
- **Encoding Non-integer columns :** The attack classes were encoded from 0 to 9 to be feed to different machine learning and neural network models.

- **Feature scaling and Standardization :** The features were mostly right-skewed. So, log transformation is applied to decrease the skewness. Then, standardization is applied to all the columns.

IV. EXPERIMENTAL RESULTS

V. CONCLUSION

Based on our analysis and evaluation of the network attack detection model using the UNSW-NB15 dataset, specifically employing a Convolutional Neural Network (CNN) architecture with 40 selected columns, we can draw the following conclusions: The CNN model we implemented demonstrates promising performance in accurately categorizing network attacks and normal network traffic. It achieves commendable levels of accuracy, precision, recall, and F1-score, highlighting its proficiency in recognizing instances of malicious activities. The selected features, including various network-related attributes, prove valuable in distinguishing between network attacks and benign network behavior. These features play a pivotal role in enabling the model to make precise classifications. The interpretability of the CNN model is a noteworthy aspect of our analysis. It provides insights into the significance of different features in the classification process, contributing to a better understanding of the characteristics of network attacks. Unlike the paper's approach, we did not reduce the feature set, utilizing all 40 columns for our analysis. Despite the success of the CNN model, there is still room for improvement in future work. Further refining the model's design and fine-tuning its parameters hold the potential to enhance its effectiveness in detecting network attacks. Experimentation with alternative network structures, exploration of dropout rates, or investigation into advanced methods such as recurrent neural networks (RNNs) or transformers could be beneficial.

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