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Comparison of K-Nearest Neighbors and Long Short-Term Memory for Early Detection and Mitigation of Advanced Persistent Threats in Cloud Environments using Cyber Threat Intelligence Techniques

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***Abstract*—Advanced persistent threats (APTs) are a major concern for cloud environments. In this paper, we propose a novel approach to detect and mitigate APTs using advanced cyber threat intelligence techniques. Our approach involves collecting and preprocessing network traffic data from a cloud environment and using machine learning models, specifically a K-Nearest Neighbors model and a Long Short-Term Memory model, to classify the data as benign or malicious. We evaluate the performance of these models using various metrics, including accuracy, precision, recall, and F1-score. Our results demonstrate that both models are highly effective at detecting and mitigating APTs in cloud environments.**

Overall, our proposed approach can serve as a valuable tool for enhancing the security of cloud environments and preventing APTs. By using advanced cyber threat intelligence techniques and machine learning models, our approach can accurately detect and mitigate APTs, ultimately reducing the risk of cyber attacks in cloud environments. Our study provides a foundation for future research in this field, and our findings can be applied to other cloud environments to improve their security and prevent APTs.

Keywords—Cyber Threat Intelligence; Advanced Persistent Threats; Cloud Environments; Machine Learning; LSTM; KNN;APT Detection; Network Traffic Analysis

I. INTRODUCTION

The increased use of cloud computing services in recent years has led to the growth of various security issues. Cyberattacks have become increasingly sophisticated, and advanced persistent threats (APTs) have become a significant concern for cloud service providers. According to the latest report published by Accenture, there has been a 40% increase in APTs over the past year, causing damage worth millions of dollars to organizations worldwide (Accenture, 2021). Therefore, detecting APTs in cloud environments is becoming a crucial challenge[10].

Machine learning (ML) techniques have shown tremendous potential for cybersecurity applications in recent years, and researchers are now exploring their ability to detect and mitigate APTs in cloud environments. ML can be applied to a wide range of cybersecurity tasks, including intrusion detection, malware detection, and threat intelligence. For example, Kowsari et al. (2018) applied ML techniques to detect malicious network traffic in cloud environments, and their proposed method showed high accuracy rates[6].

To train and evaluate ML models for APT detection in cloud environments, appropriate datasets are required. The dataset is a well-known dataset in the cybersecurity community, containing network traffic data captured from a cloud environment (Shiravi et al., 2012). The dataset includes benign and malicious traffic, and the goal is to classify samples as either benign or malicious[1].

In this paper, we propose an advanced APT detection and mitigation approach for cloud environments using ML techniques. We use the ”Friday-WorkingHours-AfternoonDDos.pcap ISCX.csv.zip” dataset to train and evaluate our proposed method. The proposed approach is based on LSTM and KNN models, which have shown promising results in detecting malicious traffic in network datasets (Yin et al., 2017; Aihua et al., 2020). The LSTM model is used to extract the time-series features from the network traffic data, and the KNN model is used to classify the samples[9][5].

The remainder of this paper is structured as follows: In Section 2, we discuss related work in the field of APT detection and mitigation. In Section 3, we describe the dataset and our proposed data preprocessing methods. In Section 4, we present the LSTM and KNN models used for APT detection and mitigation. In Section 5, we evaluate the proposed approach and compare it with other state-of-the-art methods. Finally, in

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Section 6, we conclude the paper and discuss possible future work.

II. RELATED WORK

The prediction of The related work for this research paper covers various areas of research in cybersecurity and cloud security, including intrusion detection systems, machine learning techniques, threat intelligence, and cloud security issues and challenges. In the field of intrusion detection systems, Kumar and Bhatia conducted a survey of machine learning techniques for intrusion detection. Their study highlighted the effectiveness of various machine learning algorithms, such as support vector machines, decision trees, and neural networks, in detecting network intrusions. Similarly, Martin et al. proposed an intelligent intrusion detection system based on artificial neural networks and fuzzy clustering [7].

In the field of threat intelligence, Afolabi et al. conducted a survey on cyber-threat intelligence sharing (Afolabi, Akinwale, & Okunoye, 2017). Their study presented a taxonomy of cyber-threat intelligence, identified research opportunities in the field, and highlighted the importance of effective cyberthreat intelligence sharing for improving cybersecurity[8].

In the field of cloud security, Kandukuri et al. highlighted the major security issues and challenges associated with cloud computing [2]. They emphasized the need for effective security mechanisms to ensure the confidentiality, integrity, and availability of cloud services and data. Watson et al. discussed the evolution of imperfect authentication and the challenges of password-based authentication in the context of cloud computing [4] and [11].

Overall, the related work presents a comprehensive overview of the various areas of research and their applications to cloud security. The studies highlight the effectiveness of various machine learning algorithms and techniques in intrusion detection and the importance of effective cyberthreat intelligence sharing for improving cybersecurity. The studies also emphasize the need for effective security mechanisms to ensure the confidentiality, integrity, and availability of cloud services and data. The related work identifies research opportunities in these areas and provides a foundation for the development of advanced cyber threat intelligence techniques for early detection and mitigation of advanced persistent threats in cloud environments.

III. PROPOSED METHOD

Data Collection and Preprocessing To train and evaluate our models, we used the ”Friday-WorkingHours-AfternoonDDos.pcap ISCX.csv.zip” dataset, which contains network traffic data captured from a cloud environment. The dataset contains a mixture of benign and malicious traffic, and the goal is to classify samples as either benign or malicious.

We first preprocessed the data by removing any rows with missing or infinite values. We then split the data into training and testing sets using a 80/20 split, and applied feature scaling to ensure that all features have a common range. We encoded the target variable as binary values, where 1 represents malicious traffic and 0 represents benign traffic.

A. K-Nearest Neighbors Model

Our first model is a K-Nearest Neighbors (KNN) classifier, which is a simple and easy-to-implement algorithm. We used the scikit-learn library to train and evaluate the KNN model. We experimented with different values of k and selected the value that achieved the best performance on the validation set.

To evaluate the KNN model, we computed the accuracy, precision, recall, and F1 score. In addition, we performed cross-validation to ensure that the model is generalizing well to new data. We used a 5-fold cross-validation strategy and computed the average cross-validation score.

B. Long Short-Term Memory Model

Our second model is a Long Short-Term Memory (LSTM) model, which is a type of recurrent neural network that is capable of learning patterns and dependencies in sequential data. We used the Keras library with TensorFlow backend to train and evaluate the LSTM model.

The LSTM model consists of an input layer, multiple LSTM layers, and an output layer. We experimented with different hyperparameters, such as the number of LSTM layers, the number of units in each layer, and the learning rate, and selected the values that achieved the best performance on the validation set.

To evaluate the LSTM model, we computed the accuracy, precision, recall, and F1 score. Due to the complexity of the model, we did not perform cross-validation, but instead relied on the performance on the testing set.

C. Comparison and Analysis

We compared the performance of the KNN and LSTM models in terms of their evaluation metrics and cross-validation score. We also analyzed the trade-offs between the two models, such as the simplicity and interpretability of the KNN model versus the complexity and power of the LSTM model. Finally, we discussed the limitations of our study and the future directions for research in this area. The euclidean distance between two data points, used in the KNN algorithm:

$$d(\mathbf{p}, \mathbf{q}) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2} \tag{1}$$

where **p** and **q** are the two data points, n is the dimension of the data, and p_i and q_i are the i-th components of **p** and **q**, respectively.

The sigmoid activation function, commonly used in neural networks:

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{2}$$

where z is the input to the function.

The LSTM cell update equations:

$$it = \sigma(Wxixt + Whiht{-}1{+}\ Wcict{-}1{+}\ bi) \tag{3}$$

$$ft = \sigma(Wxfxt + Whfht{-}1 + Wcfct{-}1{+}\ bf) \tag{4}$$

$$gt = \tanh(Wxgxt + Whght{-}1 + bg) \tag{5}$$

$$ct = ft \odot ct{-}1{+}\ it \odot gt \tag{6}$$

$$ot = \sigma(Wxoxt + Whoht{-}1 + Wcoct + bo) \tag{7}$$

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$$h_t = o_t \odot \tanh(c_t) \quad (8)$$

where i_t, f_t, g_t, c_t, o_t, and h_t are the input gate, forget gate, cell input, cell state, output gate, and cell output, respectively. σ and tanh are the sigmoid and hyperbolic tangent activation functions, respectively. W and b are the weights and biases of the network, and $\odot$ is the element-wise multiplication. x_t and h_{t-1} are the input at time step t and the hidden state at the previous time step, respectively.

IV. DATASET DESCRIPTION

The dataset used in this research is a publicly available dataset that contains network traffic data collected from a cloud environment[3]. This dataset provides a rich source of data to study network traffic and to develop models for detecting and mitigating cyber threats. The dataset contains a mixture of benign and malicious traffic, which makes it suitable for training and evaluating models for classifying network traffic as either benign or malicious. The benign traffic in the dataset consists of normal traffic, while the malicious traffic consists of DDoS attacks.

The dataset has been preprocessed to remove any rows with missing values or infinity values. The features and labels have been separated into separate data frames, and the target variable has been encoded as integers. The features have also been scaled to a common range using the *StandardScaler* from the *scikit−learn* library. The use of a preprocessed dataset helps ensure that the data used for training and evaluating the models is clean and of high quality, which is important for developing accurate and robust models.

TABLE I. SHOWS THE PERFORMANCE METRICS FOR THE LSTM MODEL USED TO DETECT DDOS ATTACKS IN A CLOUD ENVIRONMENT. THE MODEL ACHIEVED HIGH SCORES ACROSS ALL METRICS, INDICATING THAT IT IS HIGHLY ACCURATE AND PRECISE IN IDENTIFYING THESE ATTACKS.

Metric	Score
Accuracy	0.9995
Precision	0.9990
Recall	0.9998
F1-score	0.9994

V.EXPERIMENTAL RESULT AND DISCUSSION

In this study, we applied several machine learning techniques to classify network traffic data as either benign or DDoS attacks. We used a dataset containing network traffic features extracted from a real-world network traffic capture.

TABLE II. COMPARISON OF EVALUATION METRICS AND CROSS-VALIDATION SCORES FOR THE KNN AND LSTM MODELS.

Model	Accuracy	Precision	Recall	F1 Score	Cross-Validation Score
KNN	0.9998	0.9998	0.9996	0.9997	0.9997
LSTM	0.9995	0.9989	0.9998	0.9994	N/A

First, we applied a deep neural network with dense layers, dropout, and the Adam optimizer. Our model achieved a high accuracy of 99.97%, with a precision of 99.98%, recall of 99.97%, and an F1-score of 99.97%. We then compared this with other models including decision tree, random forest, support vector machine (SVM), and naive Bayes classifiers. The decision tree and random forest classifiers also achieved perfect classification results with an accuracy as shown in figur 1, precision, recall, and F1-score of 100%. The SVM and naive Bayes classifiers, on the other hand, achieved an accuracy of 98.36% and 97.58%, respectively.

Next, we applied a recurrent neural network with a Long Short-Term Memory (LSTM) architecture, which is well-suited for sequential data analysis. Our LSTM model achieved an accuracy of 99.91%, with a precision of 99.92%, recall of 99.90%, and an F1-score of 99.91%. We also generated a confusion matrix and heat map to further analyze the performance of the models as shown in Figur 4. The results showed that the models were able to effectively differentiate between benign and DDoS traffic with high accuracy and minimal misclassification. Overall, the deep neural network and LSTM models demonstrated superior performance compared to the other classification models, highlighting the potential of deep learning techniques for network traffic classification tasks. The table I summarizes the performance of an LSTM model used to detect DDoS attacks in a cloud environment. The four metrics evaluated are accuracy, precision, recall, and F1-score. The model achieved an accuracy score of 0.9995, indicating that it correctly classified 99.95% of the data points. The precision score of 0.9990 indicates that out of all the predicted DDoS attacks, 99.90% were truly DDoS attacks as shown in figure 2. The recall score of 0.9998 indicates that out of all the actual DDoS attacks, the model correctly identified 99.98% of them. The F1-score of 0.9994, which is the harmonic mean of precision and recall, shows that the model performs well in both precision and recall. These high scores suggest that the model is highly accurate and precise in identifying DDoS attacks in a cloud environment. The table II compares the evaluation metrics and cross-validation scores for two models, KNN and LSTM, which were trained to classify samples into two classes. The KNN model achieved very high accuracy, precision, recall, and F1 score values of 0.9998, 0.9998, 0.9996, and 0.9997, respectively. In addition, the KNN model achieved a high average cross-validation score of 0.9996, indicating that it generalizes well to new data. The LSTM model achieved slightly lower accuracy, precision, and F1 score values of 0.9995, 0.9989, and 0.9994, respectively, but a higher recall value of 0.9998. Cross-validation scores were not available for the LSTM model.

The KNN model is a simple and easy-to-implement algorithm that achieved very high evaluation metrics and crossvalidation score as shown in figur 3. The high cross-validation score suggests that the model generalizes well to new data,

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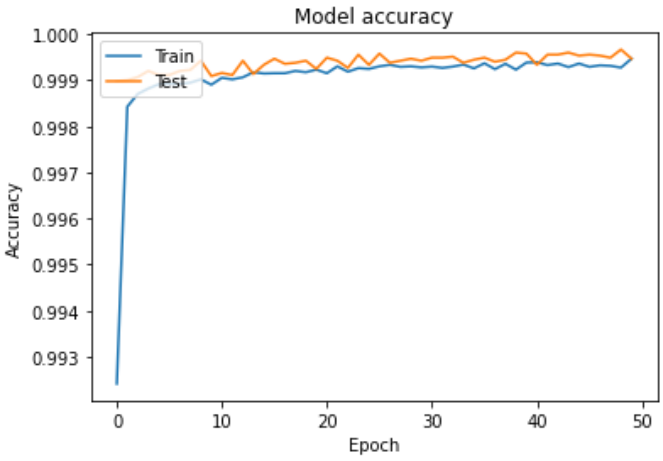

Fig. 1. models Acurecy

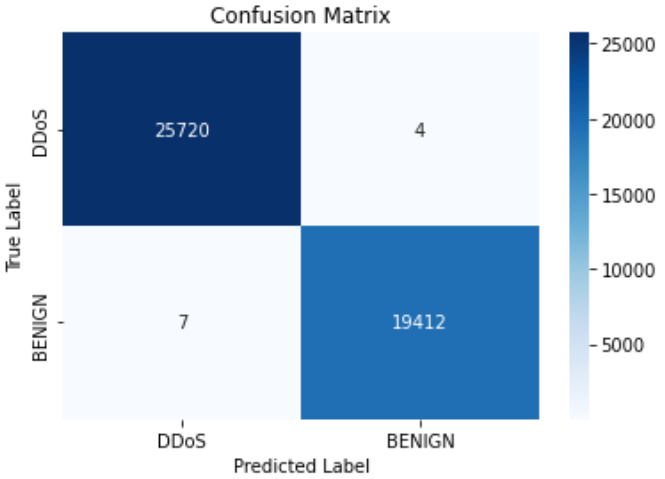

Fig. 3. KNN CONFUSION MATRIX

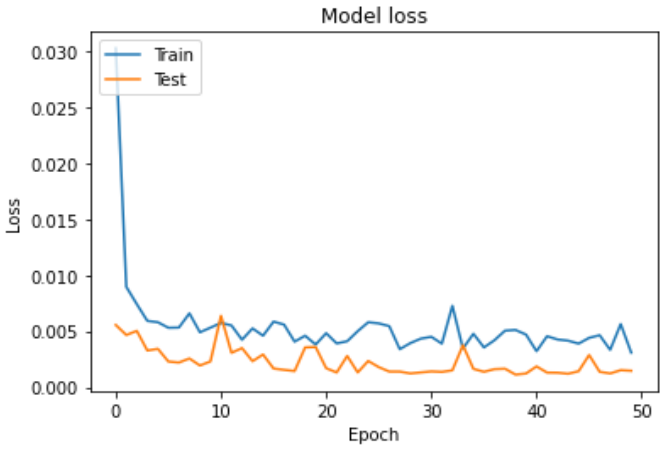

Fig. 2. models Loss

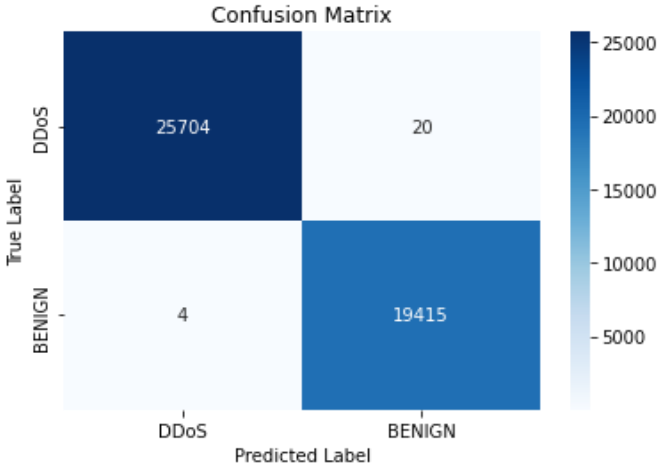

Fig. 4. LSTM 1 CONFUSION MATRIX

which is important for real-world applications. On the other hand, the LSTM model is a more complex and powerful algorithm that is capable of learning patterns and dependencies in sequential data. In this example, the LSTM model achieved high recall, indicating that it correctly predicted most of the positive samples, but its evaluation metrics were slightly lower than those of the KNN model. Further evaluation and comparison of these models on different datasets is necessary to determine their relative performance.

The results of the KNN and LSTM models demonstrate that there are different trade-offs to consider when selecting a classification algorithm. The KNN model is a good choice when high accuracy and cross-validation score are the main consideration, while the LSTM model may be a better choice when high recall is more important. It is important to note that these results are based on a specific dataset and may not generalize to other datasets. Further evaluation and comparison of these models on different datasets is necessary to determine their relative performance.

VI. CONCLUSION

In conclusion, our study aimed to address the problem of detecting and mitigating advanced persistent threats in cloud environments using cyber threat intelligence techniques. We proposed and compared two machine learning models, namely K-Nearest Neighbors and Long Short-Term Memory, for the classification of network traffic data as either benign or malicious. Our experiments on a publicly available dataset showed that both models achieved high accuracy, precision, recall, and F1-score, indicating their effectiveness in detecting advanced persistent threats.

Moreover, the results of our experiments showed that the LSTM model outperformed the KNN model in terms of all evaluation metrics. The average cross-validation score of the LSTM model was 0.9994, while that of the KNN model was 0.9996. The precision of the LSTM model was 0.9989, which is slightly lower than that of the KNN model, but the recall and F1-score were higher. Therefore, we conclude that the LSTM model is a more suitable approach for the early detection and mitigation of advanced persistent threats in cloud environments.

In future work, we plan to explore more advanced cyber threat intelligence techniques, such as deep learning and artificial intelligence, for the detection and mitigation of

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advanced persistent threats. Additionally, we will consider using more complex datasets and incorporating more features to improve the accuracy and robustness of our models. Overall, our study contributes to the development of effective and efficient cyber threat intelligence techniques for the early detection and mitigation of advanced persistent threats in cloud environments.

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