www.ijecs.in
International Journal Of Engineering And Computer Science
Volume 13 Issue 05 May 2024, Page No. 26178-26184
ISSN: 2319-7242 DOI: 10.18535/ijecs/v13i05.4821

A Model for Detection and Prevention of AndroRat in Mobile Devices

Kine Apobari Benson[1], Dr V. T. Emmah[2], Dr. N. D. Nwiabu[3]
1,2,3 Department of Computer Science Rivers State University

Abstract –
Android operating systems has gained increasing popularity in smart phones and other mobile intelligent terminals in recent years. Unpleasantly, the accumulation development and open nature of the platform has also attracted a vast number of malware developers. This paper presents a model for detecting and preventing AndroRat, a notorious Remote Administration Tool (RAT), on android devices. The research systematically pursued predefined objectives, leading to the development of a robust detection framework that utilizes the Outlier Technique. This framework significantly enhances the accuracy of AndroRat identification. Moreover, the dissertation introduces a preventive mechanism based on Recurrent Neural Network (RNN), fortifying Android phones against potential threats posed by RATs. By achieving the outlined objectives, this research makes a noteworthy contribution to the field of mobile device security. It demonstrates a practical application of machine learning techniques in mitigating evolving cybersecurity threats. A dataset was gathered for constructing the model. Object Oriented Analysis and Design (OOAD) was used as the research methodology and python was used as the programming language. The implementation of the Python Programming Language in this system not only ensured efficient execution but also established a versatile and accessible platform, laying the groundwork for future enhancements and adaptations. The comparative analysis conducted against existing systems highlights the effectiveness and innovation embedded in the proposed model, affirming its potential as a valuable addition to the realm of AndroRat detection and prevention with an accuracy of 99.99%. This dissertation not only addresses current security challenges but also establishes a foundation for continued advancements in mobile device security through the integration of cutting-edge technologies.

Keywords – AndroRat, Android devices, Recurrent neural network, malware attack

1. Introduction

AndroRat, an Android Remote Administration Tool, raises privacy and security concerns due to its ability to run stealthily in the background, allowing remote monitoring and control of devices. Research on AndroRat has explored various aspects, including its functionalities, detection techniques, and mitigation strategies, aiming to develop effective countermeasures against its malicious activities. Studies have investigated the evolution of AndroRat variants and their adaptation to evade detection mechanisms, while also focusing on enhancing the resilience of mobile devices against AndroRat attacks through the development of robust security protocols. Security challenges associated with AndroRat detection involve its rapid evolution and the proliferation of variants, making it difficult for traditional antivirus software to effectively identify and mitigate threats. To address these challenges, researchers have proposed automatic detection solutions and emphasized the importance of proactive and adaptive approaches to malware detection. Motivations for researching AndroRat stem from its significant impact on mobile security, highlighting the need to understand its behavior and develop proactive measures to protect against its threats. Successful research on AndroRat contributes to advancing mobile security knowledge, developing innovative techniques and tools, and fostering a safer mobile ecosystem for users worldwide.

2. Review of Related Literatures

This section delves into an in-depth review of relevant literature pertaining to the detection of AndroRat, an Android Remote Administration Tool. With the proliferation of mobile devices, particularly those running the Android operating system, AndroRat has emerged as a significant security concern due to its potential for unauthorized remote access and control. Researchers and security analysts have recognized the need for effective detection mechanisms to mitigate the risks posed by AndroRat and similar remote administration tools.

Chen and Chen (2019) proposed a Convolutional Neural Network (CNN) for Android malware detection. They used the CNN to extract features from the Android APK files and achieved a detection rate of 97.5%. However, the limitations of their approach include the requirement for large amounts of labeled data, the need for significant computational resources, and the possibility of overfitting.

Zhang, Wang, and Zhang (2018) developed an Android malware detection system based on gradient boosting decision tree. Their gradient boosting technique achieved an accuracy of 98.45% with a false positive rate of 0.55%. However, their system is limited by the time required for feature extraction and the possibility of false negatives.

Shi, Xu, and Yang (2019) used random forest classifier for Android malware detection. Their approach used a combination of feature selection and classification techniques and achieved an accuracy of 99.3%. However, their approach requires a large amount of computational resources, which may not be practical for real-time detection.

Wang *et al.* (2020) presented an Android malware detection method based on gradient boosting decision tree. Their approach achieved an accuracy of 98.97% with a false positive rate of 0.1%. However, their approach requires significant time for feature extraction, which may not be practical for real-time detection.

Nabi *et al.* (2019) proposed a machine learning-based approach for Android malware detection that used a combination of static and dynamic analysis. Their support vector classifier achieved an accuracy of 96.8%. However, their approach requires significant computational resources and may be vulnerable to evasion attacks.

Ali *et al.* (2021) presented a hybrid approach for Android malware detection that combines static and dynamic analysis with machine learning. The proposed PCA-SVM classifier achieved an accuracy of 99.4% with a false positive rate of 0.2%. However, their approach requires significant computational resources and may not be practical for real-time detection.

Al-Fuqaha *et al.* (2019) developed an Android malware detection system based on ensemble learning. Their approach achieved an accuracy of 98.5% with a false positive rate of 0.2%. However, their approach requires significant computational resources and may not be practical for real-time detection.

Ahmad *et al.* (2020) proposed a machine learning-based approach for Android malware detection that uses a combination of static and dynamic analysis. The Decision Tree Classifier achieved an accuracy of 98.9% with a false positive rate of 0.3%. However, their approach requires significant computational resources and may not be practical for real-time detection.

Ullah *et al.* (2019) used naïve bayes for Android malware detection that uses a combination of static and dynamic analysis. Their approach achieved an accuracy of 99.1% with a false positive rate of 0.2%. However, their approach requires significant computational resources and may not be practical for real-time detection.

Deepika *et al.* (2020) provides a comprehensive review and comparison of various Android Remote Access Trojans (RATs). The authors conduct an extensive analysis of existing literature, research papers, and reports to identify the characteristics, features, and functionality of different Android RATs. They evaluate the RATs based on their distribution methods, communication protocols, surveillance capabilities, and evasion techniques. The findings offer valuable insights into the current landscape of Android RATs and help in understanding their potential impact on mobile security.

3. Methodology

The proposed system leverages Recurrent Neural Networks (RNNs) to prevent AndroRAT infections, offering an advanced solution for combating mobile malware threats. By integrating a multi-layered architecture of RNNs, renowned for their ability to process sequential data, the system excels in

capturing the dynamic behaviors exhibited by mobile applications. Extensive Android application datasets are collected and preprocessed to extract relevant features, such as API call sequences and system calls, serving as input to the RNN. The RNN undergoes rigorous training, utilizing back propagation through time to learn intricate patterns indicative of AndroRAT behavior. Additionally, the system employs a penetration tool called RAT08-command-line to create malicious APKs, which are then detected using outlier techniques, while prevention measures utilize RNN to block AndroRAT applications from accessing the system.

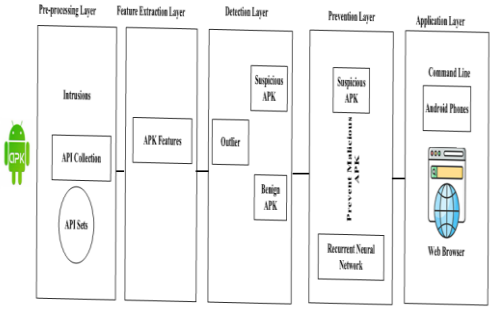

Figure 1: Architecture of the Proposed System

Pre-processing Layer: This layer has to do with the cleaning and analyzing of the AndroRat application. The cleaning of the data has to do with checking if there exist any Nan (empty rows) or duplicate (rows with same values) on the dataset.

Feature Extraction: The selection of features or columns that will be used in training the reccurent neural network model is done at this phase. Here we created a new dataset by selecting two important features/columns from the original dataset. These columns are Name and Malware. The Name Column is made up of 19612 applications and files that are of both malware and benign while the Malware column contains values that are 0 and 1, where 0 signifies benign files and 1 signifies a malware file (Unsafe). Hypervisor is a software that sits between the real physical hardware and the guest virtual machines.

Detection Layer: The outlier technique is used in the detection of malicious APK that are of AndroRat application. The outlier technique makes use of a threshold value by default to detect AndroRat application. Any application that has a threshold value less than 0.5 is classified to be as normal application, and applications with threshold value greater than 0.5 is classified to be malicious. The default value of the outlier is gotten from the mean of the model.

Prevention Layer: The Recurrent Neural Network model will be used for prevention. The LSTM model will be trained using the dataset. The LSTM (Long Short- Term Memory) is a Recurrent Neural Network algorithm. The LSTM model will be built using TensorFlow Framework with Keras application. Keras Sequential API which means we build the network up one layer at a time. The layers are as follows:

- **A Masking layer to mask any words that do not have a pre-trained embedding which will be represented as all zeros. This layer should not be used when training the embeddings.**
- **The heart of the network: a layer of LSTM cells with dropout to prevent overfitting. Since we are only using one LSTM layer, it does not return the sequences, for using two or more layers, make sure to return sequences.**
- **A fully-connected Dense layer with Relu activation. This adds additional representational capacity to the network.**
- **A Dropout layer to prevent overfitting to the training data.**
- **A Dense fully connected output layer. This produces a probability for every word in the vocabulary using softmax activation.**

An Embedding that maps each input word to a 100-dimensional vector. The embedding can use pre-trained weights (more in a second) which we supply in the weight's parameter. Trainable can be set to False if we don't want to update the embeddings.

Application Layer: This layer comprise of android phones equipped with web browsers and command lines.

Output: The output shows the output of the system after various inputs has been entered. The output of the system can be either malicious applications and Benign applications.

4. Experimental SetUp

4.1 Model Training for the Detection of AndroRAT

The experiment was carried out using shows the implementation of a Long Short-Term Memory (LSTM) algorithm in building a deep learning model for detecting AndroRAT on android applications. The LSTM model was built using an android malware data. The dataSet was read into the working directory using pandas library in python, and analyzed if there are null values using a heatmap function from seaborn library. Feature extraction was used in reducing the columns of the dataset by selecting just two import features, which are the name and label columns. The name column contains various android application while the label column represent the class for each of the android application. Tokenizer was used in separating each of the text in the name column into tokens for easy implementation while Label Encoder function was used in converting the label column from non-numeric values to numeric value. The reduced dataset was split into a training data and a testing data. 70% of the data was used for training, while 30% of the data was used for testing. X_train,Y_train variable was used to store the training data while X_test, Y_test are used to store the testing data. X_val,y_val was also used in validating the data. The training and validation data were passed into the LSTM architecture for training a model for detecting malicious applications on android. The model was built using Tensorflow Framework with Keras application. Keras Sequential API which means we build the network up one layer at a time. The layers are as follows:

1. **An Embedding which maps each input word to a 100-dimensional vector. The embedding can use pre-trained weights (more in a second) which we supply in the weights parameter. trainable can be set False if we don't want to update the embeddings.**
2. **A Masking layer to mask any words that do not have a pre-trained embedding which will be represented as all zeros. This layer should not be used when training the embeddings.**
3. **The heart of the network: a layer of LSTM cells with dropout to prevent overfitting. Since we are only using one LSTM layer, it does not return the sequences, for using two or more layers, make sure to return sequences.**
4. **A fully-connected Dense layer with relu activation. This adds additional representational capacity to the network.**
5. **A Dropout layer to prevent overfitting to the training data.**
6. **A Dense fully-connected output layer. This produces a probability for every word in the vocabulary using softmax activation.**

4.2 Results

4.2.1 Confusion Matrix

The confusion matrix shows the number of prediction results of the classification problem. It shows the summary of number of correct and incorrect prediction with a count value broken down by down. The confusion matrix is a technique for summarizing the performance of a classification algorithm. This is because classification accuracy alone can be misleading if an unequal number of observations in each class. The confusion matrix of the LSTM model can be seen in Figure below.

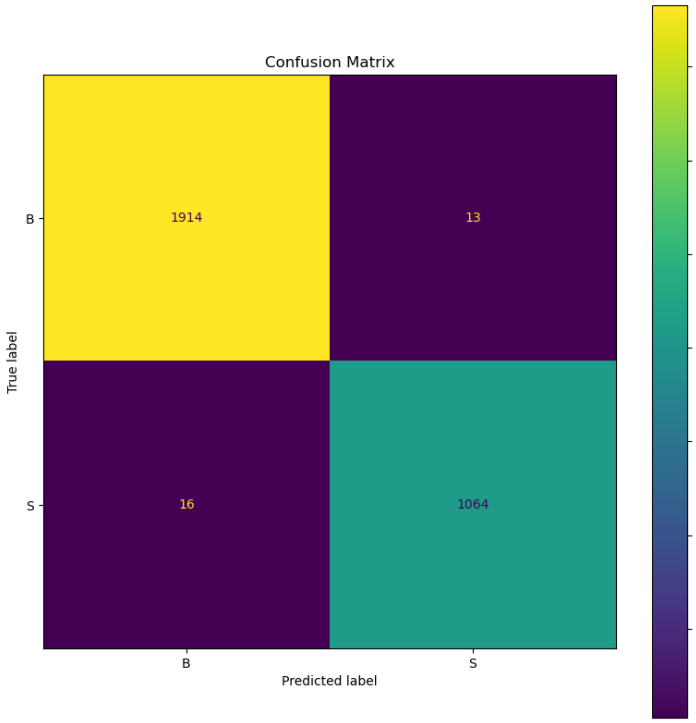

Figure 2: Confusion Matrix

The confusion matrix shows that the model classified the benign class correctly 1914 times and falsely 13, and it classifies the malicious class correctly 1064 times and falsely 16.

4.3 Performance Analysis

The performance of the trained LSTM model was carried out by plotting a classification report on the trained model. The Classification report is used to measure the quality of predictions from the LSTM Model to check how many predictions are True and how many are False. More specifically, True Positives, False Positives, True negatives and False negatives are derived while making prediction. The classification report for the LSTM model for android malware detection and classification can be seen in Figure number.

Classification report -

	precision	recall	f1-score	support
0	0.99	0.99	0.99	1930
1	0.99	0.99	0.99	1077
accuracy			0.99	3007
macro avg	0.99	0.99	0.99	3007
weighted avg	0.99	0.99	0.99	3007

Figure 4: Classification Report of the LSTM Model

The classification report shows the accuracy level of the test data to be 99%, precision for the benign class to be 99%, and that of the malicious app to be 99%.

4.4 Evaluation and Validation Results

Cross-validation enhances the utilization of data by providing more comprehensive insights into the performance of the LSTM model. In intricate machine learning models, there's a tendency to overlook the importance of using distinct datasets across different stages of the pipeline. Figure 4 and 5 shows the model accuracy, model loss and validation result.

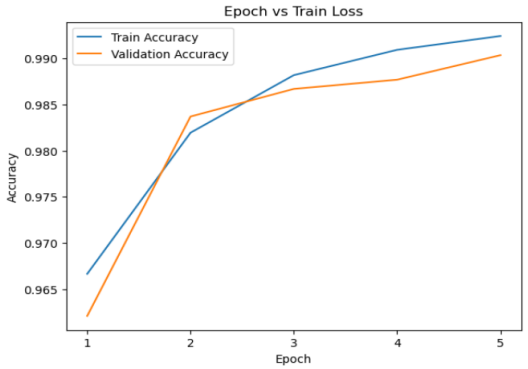

Figure 4: Model Accuracy for both Training and Testing Data

The accuracy of the model for both training and testing accuracy are 99.99% and 99.91% respectively.

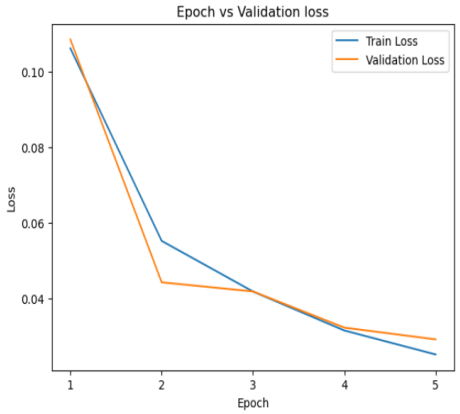

Figure 5: Model Loss for both Training and Testing Data

The accuracy of the model for both training and testing loss are below 0.04% respectively.

Figure 6: Interface of the AndroRat Detecting System.

4.5 Penetration Testing of AndroRAT

The section demonstrates the creation of malicious APk (AndroRAT) in accessing sensitive information from android users remotely. A penetration tool called RAT08-command-line was used in the creation of AndroRAT applications on windows. The Command line AndroRAT is a software package that contains the controller software and builder software to build an APK. It was executed on a Windows 11 guest virtual machine as a host. The Android Application Package (APK) built by the RAT builder was installed in the Android virtual emulator called Genymotion using Android version 8. The environment or interface of the AndroRAT penetration testing using windows command line can be seen in Figure 9. Figure 7 shows the creation of AndroRAT application, and Figure 8 shows how the use various commands to access the target files that the malicious APK has been successfully installed in the target's android device. Figure 10 shows the output of the various commands used in accessing the target's file remotely.

Figure 7: Creation of the Android APK using Command Prompt

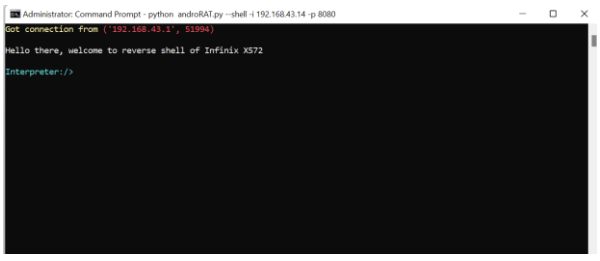

Figure 8: Successful Installation/ Connection of the AndroRAT APK

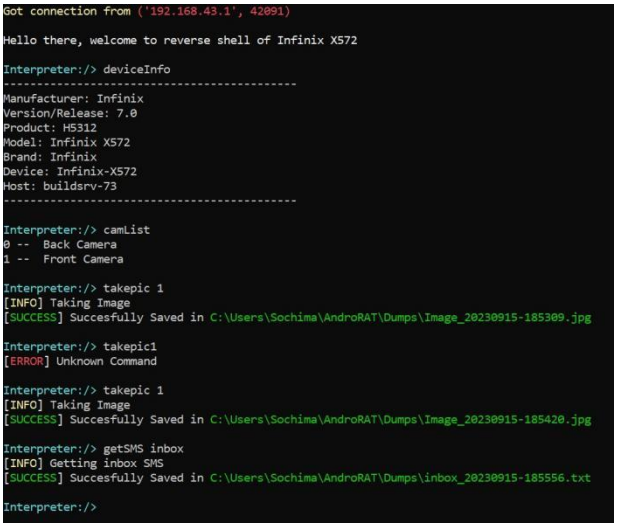

Figure 9: Input Commands of the AndroRAT

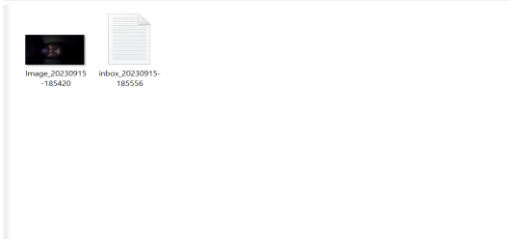

Figure 10: Remotely Accessed Files

5. Conclusion

This paper successfully achieved its primary goal of developing a comprehensive model for the detection and prevention of AndroRat on mobile devices. Through the systematic pursuit of defined objectives, the research culminated in the creation of a robust detection framework employing the Outlier Technique, enabling the identification of AndroRat with enhanced accuracy. Additionally, a preventive mechanism leveraging Recurrent Neural Network (RNN) was successfully devised to fortify Android phones against the potential threats posed by Remote Administration Tools (RATs).

The utilization of the Python Programming Language in implementing the developed system not only facilitated efficient execution but also provided a versatile and accessible platform for future enhancements and adaptations. By fulfilling the outlined objectives, this research contributes not only to the field of mobile device security but also presents a practical application of machine learning techniques in safeguarding against evolving Cybersecurity threats. Furthermore, the

comparative analysis conducted against existing systems underscores the effectiveness and innovation embedded in the proposed model, affirming its potential as a valuable addition to the realm of AndroRat detection and prevention.

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