SIGNIFICANT PERMISSION PREDICTION FOR MACHINE LEARNING BASED MALWARE DETECTION

[1]A. Anusha, [2]J. Tejaashwini Goud, [3]B. Madhumitha, [4]B. Bhavana

[1]Assisstant Professor, Department of Computer Science and Engineering, CMR Technical Campus, Medchal, Hyderabad, India.

[2,3,4]Student, Department of Computer Science and Engineering, CMR Technical Campus, Medchal, Hyderabad, India.

Abstract

Malware has always been a problem in regards to any technological advances in the software world. Thus, it is to be expected that smart phones and other mobile devices are facing the same issues. In this paper, a practical and effective anomaly based malware detection framework is proposed with an emphasis on Android mobile computing platform. A dataset consisting of both benign and malicious applications (apps) were installed on an Android device to analyze the behavioural patterns. We first generate the system metrics (feature vector) from each app by executing it in a controlled environment. Then, a variety of machine learning algorithms: Ada Boost, Gradient Boost, Gaussian Naive Bayes, Random Forest, and Decision Tree are used to classify the app as benign or malware. Each algorithm is assessed using various performance criteria to identify which ones are more suitable to detect malicious software. The results suggest that Random Forest and Decision Tree provide the best outcomes thus making them the most effective techniques for malware detection.

Keywords: -Benign, Malicious, Ada Boost, Gradient Boost, Gaussian Naive Bayes, Random Forest, Decision Tree

1. INTRODUCTION

Malware has had a tremendous impact on the world as we know it. The rising number of computer security incidents since 1988 suggests that malware is an epidemic. Surfing the World Wide Web with all anti-virus and firewall protection disabled for a day should convince any reader of the widespread and malicious nature of malware. The detection of malware is an area of major concern not only to the research community but also to the general public. Techniques researchers develop for malware detection are realized through the implementation of malware detectors. Malware is short form of malicious software. The term “Malware” is commonly used now-a-days to refer a variety of forms of intrusive software such as viruses, worms, spyware, trojan horses etc., The common function of malware is that they are specifically designed to damage, disrupt, steal, and some other illegitimate actions. Malware can infect any computing machines and the prevention of the malware have been well studied for personal computers. As the current generation uses smartphone more, the chances of malware intrusion is more compared to previous generation. Users download files like apk’s from untrusted third parties which may include many malware executable files. They get downloaded along with the users downloaded file and get executed in the background of our mobile device. So, our solutions for finding malware in the mobile platform is less compared to finding malwares in Personal Computers.

2. LITERATURE SURVEY

2.1 Input Validation Techniques

Input validation based attacks occur due to lack of inspection or insufficient inspection on the input provided by the clients. The two most common input validation based attacks are SQL injection attacks and Cross site scripting attacks.

2.1.1 SQL Injection Attacks

SQL Injection Attacks SQL language being a very rich language, paves the way for a number of attacks. The first real existence of SQL injection was explored in 1998 in a magazine Phrack . In this magazine an article on implementing attacks using SQL injection was explained by Rain Forest Puppy (RFP). An extensive study on the SQL injection attack and its classification was provided by Halfond et al., This work classified SQL injection attack based on the type of user input, namely Injection through cookies, injection through server variables and second order injections. The attack was also categorized based on the goal of the attacker, namely identifying injectable parameters, performing database finger-printing, determining database schema, extracting data, adding or modifying data, performing denial of service, evading detection, bypassing authentication, executing remote commands, performing privilege escalation. Dynamic analysis is done during runtime of a web application. The input given by the user is extracted and is combined with the code of the application to check if there is an intended attack. Dynamic analysis unearths most of the real time attacks at the cost of response time, and thereby affecting the performance of the server. This system monitored Java-based applications and detected SQL injection attacks in real time. The proposed detection technique was based on the assumption that injected SQL commands had differences in their structure with regard to the expected SQL commands that were built by the scripts of the web application.

2.1.2 Cross-Site Scripting Attacks

Certain works provide client side solutions for CrossSite Scripting attacks where a change in the browser code or a fire wall set up is recommended. The disadvantages of these works are that client/user involvement is needed and the clients need to have technical knowledge for implementing these solutions. Peter et al., implemented a system named Secure Web Application protocol (SWAP), that uses proxy layer and provides a server-side solution to detect and prevent XSS attack. It also uses a modified browser that detects script content that is included by the user. Noxes is a client side solution for XSS attacks. It creates a personal firewall on the client side and checks every outgoing request and incoming response. It uses both manual and automatically generated rules to prevent XSS attacks on the client side.

2.2 Vulnerability Detection in Smartphone Applications

Recent researches carried out in the field of Smartphone security have concentrated mostly on Android operating system (OS). The security issues in Android are a concern owing to the fact that it is open source and developing of android application is very easy. Adrienne Porter felt et al., surveyed and classified mobile malwares based on their behavior. Some of the commonly noted behaviors were, collecting user information, sending premium-rate Short messaging Service (SMS), malware written for amusement, for credential theft, search engine fraud and ransom. Different defensive mechanisms that were available against these malwares were discussed and evaluated. Threats have been classified as physical threats, application-based threats, network-based threats, web-based threats, and mobile vulnerabilities by Jalaluddin Khan et al,.They presented a survey on already existing privacy threats and defensive mechanisms. Biometric authentication was suggested as a defensive mechanism for these attacks. Alexios Mylonas et al.,classified users based on their trust and awareness on web applications. They provided a database guideline for trusted repository, license and agreement, poor security checks, pirated applications and the users' perception. Another type of attack called the android scraping was reported by Ken Munro et al., Android scraping is the unauthorized extraction of information from Smartphones. Various methods for scraping data were discussed, namely.

2.2.1 Behavioral Analysis

Jacob et al., conducted a survey of different reasoning techniques used by behavioral detectors. They classified these detectors into main families, namely stimulation based detectors and formal detectors depending on their data collection and data interpretation mechanisms. Timothy K. Buennemeyer et al., in their work introduced capabilities developed for Battery-Sensing Intrusion protection system (BSIPS) that raised an alert when an abnormal current change occurred. They developed a Correlation Intrusion Detection Engine (CIDE) that provides power profiling for mobile devices and a correlated view of B-SIPS and Snort alerts. The B-SIPS client was designed with customizable features to accommodate varying user skill levels. Users with advanced computer skills could configure the application to provide more refined detection and alert information. The basic users could effectively operate the system with default settings.

2.2.2 Signature Based Analysis

Griffin et al., used signature-based method that depended on the identifying unique signatures that defined the malware. This work used string signatures, each of which was a contiguous byte sequence that potentially could match many variants of a malware family. A similar work had been proposed by Yu Feng et al.,. A system named Apposcopy, which used a semantics-based approach to identify a prevalent class of Android malware that stole private information, was developed. It used a high level language for specifying signatures of malware families and performed static analysis to decide if an application was benign or malicious. G.Suarez-Tangil et al., introduced a system called dendroid based on text mining and information retrieval. This system automatically classified malicious applications as families based on common code structure. For 31 family classification this system used vector space model. This also provided relationship among families and their evolution from common ancestors. If an unknown application was installed, the system would automatically identify its family and assign this application to that family. The limitation of these systems was that it can be applied only to known malicious code.

3. SYSTEM ANALYSIS

Existing System

In this existing system, But the main point is now days malware writers have techniques such as polymorphism which can fool these pattern-based methods very easily. But there is a different approach that can try that is malware detection behavior-based techniques. This approach is very different than pattern based as here check behavior and collect its information by executing it and that information we will use inorder to detect malware or not. In general, most of the time we can observe that new malware's that arise on a regular basis are just a little changed version of older malware using some clever techniques. So, this should be clear by now that techniques based on behaviour of malware are a great choice in order classify or detect malware.

Limitations

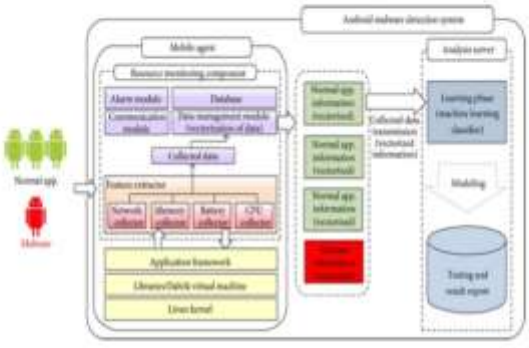
- Efficiency levels are very low

Proposed System

For each newly collected unknown Android app, it will be first parsed through the unzipper and decompiles to get the smali codes, then its API calls will be extracted from the smali codes, and the relationships among these API calls will be further analysed. Based on the extracted features and using the constructed classification model, this app will be labelled as either benign or malicious. Classification is the only technique used to categorize the given app as malicious or the genuine one.

Advantages

- Prediction levels are very high.
- Apk has predictable content. Application behaviour can be learned by simply reading the file.
- Checks are safe.


Android malware detection system
Mobile agent
Resource monitoring component
Alarm module
Database
Communication module
Data management module (vectorization of data)
Collected data
Feature extractor
Network collector
Memory collector
Battery collector
CPU collector
Application framework
Libraries/Dalvik virtual machine
Linux kernel
Normal app
Malware
Normal app information (vectorized)
Normal app information (vectorized)
Normal app information (vectorized)
Collected data transmission (vectorized information)
Analysis server
Learning phase (machine learning classifier)
Modeling
Testing and result report

System Architecture

4. MODULES AND DESCRIPTION

User The user opens the software and then runs it. The user waits for the system to generate the result.

System

The system gets trained with the dataset of benign and malware and then takes the input from the user. The system verifies the input and process the result based on the matched attributes with the particular dataset.

Admin

The admin adds any new field in the dataset and makes the system help in getting trained with the dataset. He adds new attributes to the dataset if they are not present in the dataset. When the user runs the Software and if that malware is not present in the dataset the admin trains the system with that new word into the dataset and then the system displays the result. The admin also provides the security to the system and manage to rebuild the system if the system is crashed.

5. IMPLEMENTATION

Data Collection

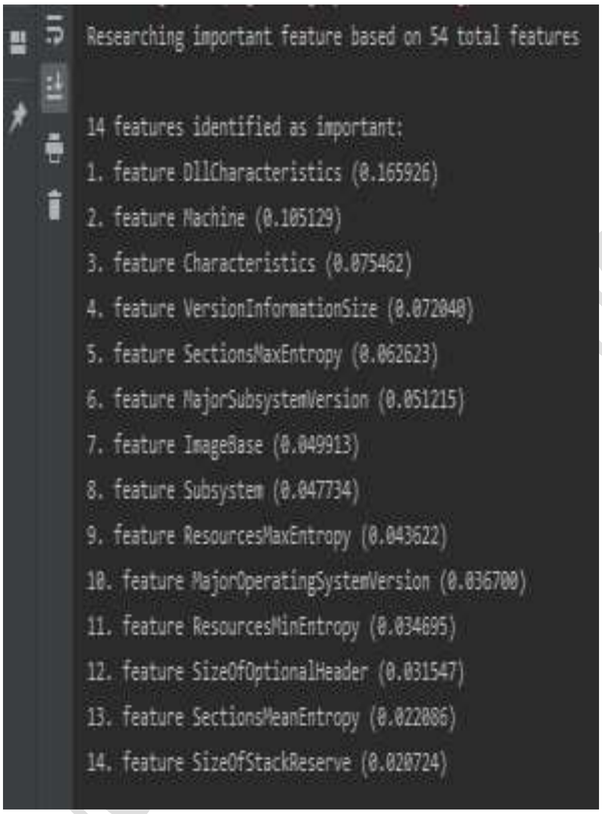
In our project we have used a dataset which is obtained from the Kaggle. It contains all the features for an app being malicious to predict whether the given app is benign or not. All the features represent the app as malicious or benign based on many values present in the dataset. There are many datasets present in Kaggle, Github and other repositories which are used not only Malware classification but also in Genre Classification etc., As we wanted to use for Malware and Benign Classification, this dataset is very helpful and shows high accuracy in finding or in prediction of Malware.

Data Description

Our dataset contains many features which are used to categorize the malware and benign apps. There are a total of 54 features which help in classification of them. But the main features which our project extracted for the Classification is 13. Some of the features are: Subsystem, DllCharacteristics, SizeofOptionalHeader, ResourcesMaxEntropy, SectionsMaxEntropy, MajorSubsystemversion, SizeofStackReserve, ajorOperatingSystemVersion etc.,

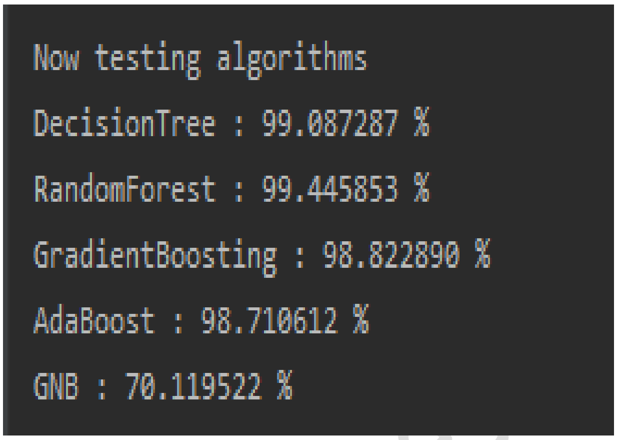
Outputs are represented in the form of percentages of accuracy values of each Classification Algorithm. The final accuracy shows how best the Algorithm is in terms of prediction.

6. EXPERIMENTAL RESULTS



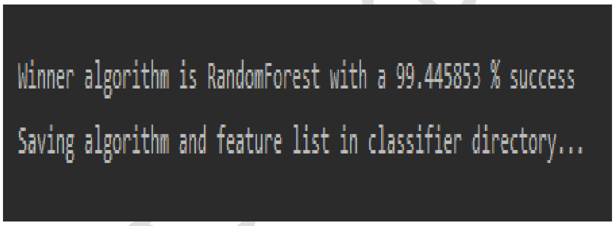
```
Researching important feature based on 54 total features

14 features identified as important:
1. feature DllCharacteristics (0.165926)
2. feature Machine (0.105129)
3. feature Characteristics (0.075462)
4. feature VersionInformationSize (0.072040)
5. feature SectionsMaxEntropy (0.062623)
6. feature MajorSubsystemVersion (0.051215)
7. feature ImageBase (0.049913)
8. feature Subsystem (0.047734)
9. feature ResourcesMaxEntropy (0.043622)
10. feature MajorOperatingSystemVersion (0.036700)
11. feature ResourcesMinEntropy (0.034695)
12. feature SizeOfOptionalHeader (0.031547)
13. feature SectionsMeanEntropy (0.022086)
14. feature SizeOfStackReserve (0.020724)
```

Fig: 1. Features



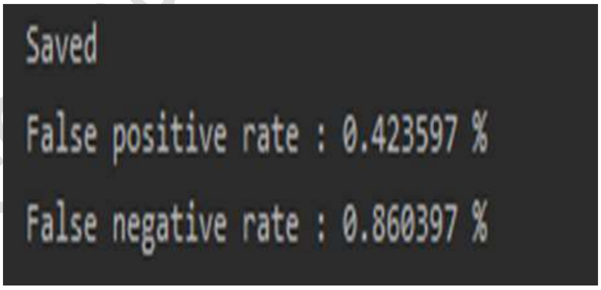
```
Now testing algorithms
DecisionTree : 99.087287 %
RandomForest : 99.445853 %
GradientBoosting : 98.822890 %
AdaBoost : 98.710612 %
GNB : 70.119522 %
```

Fig: 2. Algorithms



```
Winner algorithm is RandomForest with a 99.445853 % success
Saving algorithm and feature list in classifier directory...
```

Fig: 3. Winner Algorithm



```
Saved
False positive rate : 0.423597 %
False negative rate : 0.860397 %
```

Fig: 4. False Rates

7. CONCLUSION

We can predict that it is possible to reduce the number of malware by being analysed for mobile malware detection, while maintaining high effectiveness and accuracy. This technique has been designed to extract not only significant permission detection analysis, but also many other modes for creation of malware through a systematic approach.

8. FUTURE ENHANCEMENT

As we know the same malware doesn’t continue to be long time. New forms malware and its intrusion is possible in the days ahead. So, we would like to modify the following in our project.

- Increase the size of the training set.
- To use Algorithms which gives more accuracy if any new kind of malware evolves.
- Implement unique techniques to control the malware.

Vol 11, Issue 5,May/2020
ISSN NO:0377-9254

9. REFERNCES

[1] IDC, "Smartphone os market share, 2017 q1." [Online]. Available: https://www.idc.com/promo/smartphone-market-share/os

[2] Statista, "Cumulative number of apps downloaded from the google play as of may 2016." [Online]. Available: https://www.statista.com/ statistics/281106/number-of-android-app-downloads-from-google-play/

[3] G. Kelly, "Report: 97% of mobile malware is on android. this is the easy way you stay safe," in Forbes Tech, 2014.

[4] G. DATA, "8,400 new android malware samples every day." [Online]. Available: https://www.gdatasoftware.com/blog/2017/ 04/29712-8-400-new-android-malware-samples-every-day

[5] Symantec, "Latest intelligence for march 2016," in Symantec Official Blog, 2016.

[6] M. Grace, Y. Zhou, Q. Zhang, S. Zou, and X. Jiang, "Riskranker: scalable and accurate zero-day android malware detection," in Proceedings of the 10th international conference on Mobile systems, applications, and services. ACM, 2012, pp. 281–294.

[7] A. P. Felt, E. Chin, S. Hanna, D. Song, and D. Wagner, "Android permissions demystified," in Proceedings of the 18th ACM conference on Computer and communications security. ACM, 2011, pp. 627–638.

[8] W. Enck, P. Gilbert, S. Han, V. Tendulkar, B.-G. Chun, L. P. Cox, J. Jung, P. McDaniel, and A. N. Sheth, "Taintdroid: an informationflow tracking system for realtime privacy monitoring on smartphones," ACM Transactions on Computer Systems (TOCS), vol. 32, no. 2, p. 5, 2014.

[9] D. Arp, M. Spreitzenbarth, M. Hubner, H. Gascon, K. Rieck, and ¨ C. Siemens, "Drebin: Effective and explainable detection of android malware in your pocket," in Proceedings of the Annual Symposium on Network and Distributed System Security (NDSS), 2014.

[10] C. Yang, Z. Xu, G. Gu, V. Yegneswaran, and P. Porras, "Droidminer: Automated mining and characterization of fine-grained malicious behaviors in android applications," in European Symposium on Research in Computer Security. Springer, 2014, pp. 163–182.

10. Bibliography

1. H. He and E. A. Garcia, "Learning from imbalanced data," IEEE Transactions on Knowledge and Data Engineering, vol. 21, no. 9, pp. 1263–1284, Sept 2009.

2. R. Agrawal, R. Srikant et al., "Fast algorithms for mining association rules," in Proc. 20th int. conf. very large data bases, VLDB, vol. 1215, 1994, pp. 487–499.

3. M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The weka data mining software: an update," ACM SIGKDD explorations newsletter, vol. 11, no. 1, pp. 10–18, 2009.

4. C.-Y. Huang, Y.-T. Tsai, and C.-H. Hsu, "Performance evaluation on permission-based detection for android malware," in Advances in Intelligent Systems and Applications-Volume 2. Springer, 2013, pp. 111–120.

5. A. Jindal, A. Dua, K. Kaur, M. Singh, N. Kumar, and S. Mishra, "Decision tree and svm-based data analytics for theft detection in smart grid," IEEE Transactions on Industrial Informatics, vol. 12, no. 3, pp. 1005–1016, 2016.