A Review of Static Malware Detection for Android Apps Permission Based on Deep Learning

Hamida Lubuva

School of Information and Communication Engineering, University of Science and Technology Beijing, Beijing, China. hamidalubuva@gmail.com

Qiming Huang

School of Information and Communication Engineering, University of Science and Technology Beijing, Beijing, China.

qmhuangcn@163.com

Godfrey Charles Msonde School of Economics, Renmin University, Beijing, China, gmsonde@gmail.com

Published online: 31 October 2019

Abstract - In recent years, Android has been the main mobile operating system. The proliferation of apps powered not only by Android magnetized app developers, but also by malware developers with criminal intent to design and distribute malicious apps that can influence the ordinary activity of Android phones and tablets, steal private information and credentials, or even worse, lock the phone and ask for ransom. This study was carried out with a view of bring out clearly the review of previous researches carried regarding static analysis and pinpoint out what to be done in future. A systematic literature review which involves studying 56 research papers published in regard to static analysis. This review elaborate permissions misuse, reverse engineering and concept of static analysis in general. The outcomes of the review revealed that static analysis is widely used since it is not performed at run-time hence malicious applications cannot access to the device during analysis unlike dynamic analysis. During the review no single work done to the satisfaction curbing the existing and future evolving malwares. This study will help academicians to gain insight concerning static analysis without extensively perusing several articles to understand static malware analysis based on deep learning.

Index Terms – Static Analysis, Reverse Engineering, Permissions, Manifest File, APK File, Malicious Applications.

1. INTRODUCTION

With the rapid emergence of android as the principal operating system has led to the rise of malware applications built by hackers with a view of extracting both personal and sensitive user's data on the android device for malicious purposes [1], [2]. Static analysis has been a prime method used since the extraction of manifest file information is done

before the installation of the application unlike both dynamic and hybrid analysis [3].

The main aim of this study is to review previous work done on static malware of android apps. The subsequent sections depict the research done, citing the advantages and shortcomings. According to [4], discussed permission misuse by android apps using a static analysis tool of identification stating that it is possible to obtain all the manifest file permission. Despite the study, the paper did not mentioned or show the dataset used during the analysis and the procedure of getting readable contents of a minfest.xml file. Similarly, [5] studied system permission to show whether the application is over privilege but loopholes exists in the write-up since the author mentioned repacking of application files without executing on the device but there is no dataset and analysis performed based on static feature extraction.

According to [6], the authors proposed heuristic model and compared adagio, Drebin, ISCX and Mamadroid on a dataset and found their proposed model outpeforms the others. The only ad-hoc facing their framework is the proper selection of malware models to preserve great detection rate and apposite runtime performance as the method discovery analysis considerably depends on the malevolent applications used for model excavation. Likewise, [4], based the research on the SharedUserID by comparing the certificates of two applications if both have same features then the apps are likely to share same permissions using an android security tool. This was done in order to deduce whether one application misuse the permission of another application if granted access by the user. Althought the author did not provide the data used to test how the algorithm of proof of

concept was implemented using a security tool as dipicted in the work done by Karthick and Binu [7].

Conversely, [8] deliberated on malware for smart phones in overall. Though, the paper deliberates various categories of features very concisely and the authors did not cover all kinds of obtainable features. Accordingly, [9] explores numerous types of smart devices available for malicious applications, their effect on apps and related discovery approaches with a 99.8 percent accuracy detection rate. Nonetheless, they did not indicate what features they used in detection, bearing in mind that features have substantial influence on detection. In [10] the authors review diverse analysis procedures in smart devices illegal programs detection. The paper outline the examples of detection approaches along with their explanation.

The paper doesn't embrace what datasets used and valuation measures. Additionally, it does not illustrate all the latest works extensively. According to Peng et al.,[11], they scrutinize advancement of mobile malware, damages they cost and their proliferation model. Different operating systems are accounted for in the paper making it difficult to carefully review all available types. Conversely, we emphasize static malware detection for Android Apps Permit to mitigate how best the method is compared to dynamic, hybrid or metadata malware detection and prevention methods where the application is run on the user device without the user's knowledge of what is actually happening on the background.

The remainder of this paper is organized as follows. Section 2 offers background information on android and static analysis needed for paper repository by discussing definitions of static program analysis, model permission and techniques of analysis. Section 3 presents a summary of related work using static analysis presentations based on permissions from android apps. Section 4 addresses the description of android apps in reverse engineering. Section 5 outlines the debates and the paper is concluded.

2. BACKGROUND INFORMATION ON ANDROID AND STATIC ANALYSIS

In order to gain understanding of the purpose of this study, we review and give the reader the required preliminary information on android and static analysis. We explain the concept of static program analysis, permissions and analysis technique.

2.1. Concepts of Static Program Analysis

Static code analysis is also called static program analysis, which means that the application under test cannot be conducted dynamically and that it can detect bugs in an early stage before it is implemented [12]. The opposite of static code analysis is dynamic code analysis. In the latter, the program is executed and developers look for run-time errors as stated by [13].

According to Ghahrai [14], after coding and before performing unit tests, static analysis is performed. Static testing can be performed by a machine to "pass" the source code automatically and to detect non-compliance rules. A compiler that finds lexical, syntactic and even semantinal errors is the classic example.

Static software analysis usually includes an automated method that uses inputs the source code or object code of a program, analyses this code without it being executed, and produces results by analyzing its code structure, sequences of statements, and how variable values are interpreted via the divergent function calls. Static analysis ' primary benefit is that it can disclose mistakes (or vulnerabilities) that do not appear (or are not exploited) until long after the software is published to the public. There are different benefits/advantages of static analysis as follows; helps recognize prospective software quality problems before the software enters manufacturing during the development stage [15]. It identifies code regions that need to be re-factored / simplified [15].By concluding it for software to work and developers to comprehend their software, static code analysis is not only helpful but also essential. It simplifies the search process for bugs and mistakes by pointing to them correctly and helps to define problems.

2.2. Permissions

The resolution of a permission is to safeguard the privacy of an android user [16]. Not all permissions are dangerous some are useful to the developer to design security of an android device. Mobile apps must appeal for permission to access user's sensitive data for instance short messages and phone contacts, as well as particular system features for instance internet and camera. Reliant on the feature, the system might allow the permission spontaneously or might occassion the user to accept the request. A fundamental design of the android security design is that no mobile app, by default, has permission to accomplish any operations that would unfavorably impact other applications or the user. Android apps must adopt the least privilege to minimize damages [17]. Table 1 below depicts other previous studies in regard to android permission which are normally misused.

Android.	Usage	Exploitation
Permission		
<read write_<br="">EXTERNAL_ STORAGE></read>	Permit to read or write device's	Malicious app can read sensitive data of the user and write its
	external storage	malicious code on the device external storage.



<call_phone></call_phone>	Permits an app to induce a phone call without going via the interface of	Aid the user to record the voice of the user and use it for malicious purpose	device identifier, Voice Mail Box, Phone Number, SIM ID etc.malevolent activities using information gathered.
	the user dialer for		Table 1 List of Dangerous Android Permission [18]
	the user to		2.3. Analysis Technique
	authorize the call being engaged.		Control-flow analysis: Determining the order of execution of program statements or instructions. The control sequences are usually displayed as a control-flow graph (CFG). The CFG specifies all feasible routes of execution [19].
<receive_sms></receive_sms>	Permits an	Aid the malware	Important control flow constructs:
	app to observe the inbound SMS	to read, write and receive user's sensitive information to	Method calls: program analysis to define the function calls receiver – e.g., virtual functions, function pointers: abstract interpretation, type structures and restriction.
	messages, to record or	the malicious app developer.	Basic block: Maximum sequence of successive statements with one entry point, one exit point and no inner branches.
	implement processing on them.		Loops: An iteration block of codes till a specified state is achieved.
<set_process_limit></set_process_limit>	Permits an app to fix the determined number of app's processes that can be running but not required.	Overwhelming the device memory thus rendering to slowness in its normal operation	Data-flow analysis: Is a monitoring technique for how variables and values change through the flow of the program. It is a method for collecting data on the feasible set of values calculated at different points in a computer program. The control flow chart (CFG) of a program is used to determine those components of a program that could be propagated by a specific value allocated to a variable [20]. Compilers often use the data collected when optimizing a program for instance: x = c + d; x = 10 * 7;
<access_ wifi_<br="">STATE></access_>	Permits the app to access data about Wi- Fi network connected	Can aid the malware in hacking the Wi- Fi network and transmitting user information by utilizing this info.	It is easy for an optimizer to recognize that: a "useless" assignment is the first assignment tox, since the calculated value for x is never used (and thus the first statement can be removed from the program). At compile time, the expression $10 * 7$ can be calculated, simplifying the second assignment statement to $x = 70$; Points-to analysis: involves computing a static abstraction of all the data to which a pointer expression (or just a variable)
<read_ phone_<br="">STATE></read_>	Offers access to personal information of phone like IMSI/IMEI	Aids the developer of the malicious app to keep track of user's device and can include user's device in	 may point during runtime of the program [21]. 3. SUMMARY OF RELATED WORK BASED ON PERMISSIONS OF ANDROID APPS USING STATIC ANALYSIS Nearly 80 percent of the papers were based on static analysis
	INDI/INEL	user's device III	as illustrated by the study. There is a lot of job done in static

analysis as described Table 2, and more needs to be explored to get greater precision with a minimum amount of characteristics, as fewer characteristics decrease regression and classification training and testing time and provide quicker reaction [22].

There are different reviews which talked about static malware detection and their challenges. A framework for automatically analyzing permission use in Android apps was suggested and created. Permlyzer can analyze the use of permissions in Android apps accurately and thoroughly [23].Defines a strategy that uses system call log data to create a dataset [24]. This paper tackles the issue of android malware intrusion. Use Rotation Forest in this article to tackle the issue of android malware intrusion [25] .Table 2 provides a summary of the previous work based on static analysis.

Ref	Mechanis m	Malware Detection Rate/ Accuracy	Strengths	Weakness
[26]	Stowaway	Not Stated	The authors tested 950 applicatio ns and used stowaway tool to detect over- privilege android apps.	Despite using Stowaway , the tool is incapable of handling some multifacet ed reflective calls.
[27]	Stowaway/ StackOverf low	Not stated	This paper illustrated that the authors tested 10,000 apps and offered statistical models for envisagin g permissio n abuse and call for permissio	In this paper, Stowaway has been used together with Stack- Over- flow. But according to [26], is incapable of handling some complex reflective calls

[28]	Web-based app	Not stated	n document ation. They instituted that the popularity of a permissio n is sturdily related with its abuse, while other aspects such as effect and intrusion had little effect. The paper analyses 500000 apps for mobile device and the privileges they request using an algorithm of machine learning in order to rate the risk of an app for developer s and user to adopt.	The authors only mentione d that the apps were extracted and permissio n analyzed but no tool mentione d or software that helps the developer s or users to extract the APK file of an android app.
[29]	FAMOUS	99%	This paper proposes a predictive	The authors tested applicatio ns and



					1					
			forensic approach to detect suspicious android applicatio ns based on a trained model called Forensic Analysis of mobile devices using scoring (FAMOU S) which is intelligent to scan all the apps installed in the attached device and offer a	showed some suspicious APK file but they did not mentione d the dataset. They did not mentione d how many apps were tested to the devices attached to FAMOUS . The procedure of testing apps using FAMOUS was not shown		[31]	APK Auditor	88%	upsurges the flexibility of managing permissio n and advances the security and consistenc y of data in mobile devices. The authors analyzed 2,200 apps. The authors tested 8,762 apps and classified them as malicious	can be biased in the real world.
[30]	Permission	Not stated	descriptiv e report. 11,371 apps tested. In this	hence difficult for the developer s or users to attest the tool. The					or benign successful ly.	central server. The disadvant age to this method is that extra cost is incurred
[20]	Manageme nt App		scheme, end-users can avert malware behavior	method incurs extra performan ce cost.						in setting up the tool for analysis.
			from retrieving sensitive data and invoking sensitive API in real time. The explanatio n	Their proposed scheme was not tested on a real mobile device hence their results		[32]	RefinedDr oid	Not stated	In this paper the authors tested 727 apps to attest for fine- grained permissio n model which are	The tool deployed in this research is that it modifies the APK file of applicatio n during feature



[33]	APK Analyzer	Not stated	appropriat e for many standard apps. This tool allows the user to lower the privilege level of permissio n. The authors supplied the dataset of 576,174	extraction . This may lead to exaggerat ed outcomes. The authors did not test paid applicatio ns to				s based on Bayesian classificat ion intended to uncover unidentifi ed Android malware. The authors tested 2000 permissio n-based framewor k.	nt which might not be compared to authors using large samples in the experime nt to depict model performan ce.
			android apps while conductin g the experimen t for free android app and found there method to be better than those used by [34] which contains possible flaws that cause	determine effectiven ess of their methodol ogy.	[36]	DroidRay	Not stated	The authors tested 24,259 apps to show malware based on geographi cal spread. The model helps to curb new form in which malware spreads out.	Their model is not good enough since it did not mention the malware detection rate as compared to previous studies.
[35]	Java-based custom built APK analyzer	90%	In this paper the authors develop and examine proactive Machine Learning approache	The authors used a small sample size of malware apps in there experime	[37]	Weka tool	Not Stated	The authors used the machine based learning tool to test 200 apps to extract permissio ns in order to examine	The authors tested a small sample size and they authors did not classify the malwares whether



			whether they are malwares.	they are infosteal, Trojan among others.				The authors tested 11,215 apps and found 16	
[38]	SherlockD roid, (Alligator)	98.04%	The authors tested 102,156 apps using Alligator which is able to uncover unknown malware.	The authors failed to explore new clusters and learning scripts. The authors abscond introducin g weights on properties so that algorithm s such as	[40]	Woodpeck er	Not Stated	found 16 of them to be malwares. The author used their tool employin g inter- procedura l data flow analysis scheme to exhaustiv ely uncover possible	The authors did not provide the dataset to assist in future studies. They only stated they tested 13 permissio ns in
[39]	Apposcopy	Not stated	The authors	deviation do not deliberate each property with alike status In this scheme it				capability disclosure s where an unreliable app can acquire unlawful access to subtle	which 11 were leaked
			evaluated their tool on a mass of available Android applicatio ns and attest that it can efficiently and reliably to determine malware that fit to definite families.	is difficult to design any signature oriented scheme like Apposcop y since it can be defeated by obfuscatio n scheme such as real coding.	[41]	DroidAPI Miner	99%	data or restricted actions. In this paper, the authors purpose to alleviate malware installatio n via providing vigorous and frivolous classifiers . The authors	The authors in their experime nt realized a big false positives and negatives of 2.2% but they did not attest where the problem



					1			r		
			extensivel	occurred					malware	studies
			y carry	during					products	but
			out an	their					are	depicting
			analysis	analysis.					susceptibl	the
			to excerpt						e to	detection
			pertinent						common	rate to
			features						alterations	show best
			regarding						•	their
			malware							model is
			behavior							as
			netted at							compared
			API level							to other
			and							existing
			appraised							literature.
			different classifiers			[44]	CHEX	Not stated	The	This study
						[]	CHER	1 tot Stated	scholars	did not
			by the						presented	put into
			produced feature set						a method	considerat
			during the						to	ion the
			testing of						spontaneo	rate at
			3987						usly	which the
			apps.						discern	malicious
			apps.						entry	apps were
[42]	DNADroid	Not stated	The tool	The					points in	discovere
			adopted	authors					mobile	d to
			by authors	did not					app, as	support
			in this	mentione					well as	their
			study	d the					the new	study.
			showed a	malware					analysis	
			very low	detection					model and	
			false	rate in					attest that	
			positive	their					app	
			rate and	study.					splitting is	
			confirmed						effective	
			that all						and	
			141 apps						perfect	
			identified						way to	
			by						model	
			DNADroi						execution	
			d are						s of	
			indeed						manifold	
			replicas						entry	
			through						points and	
			visual or						expedite	
			behavioral						universal	
			confirmati						data-flow	
			on.						scrutiny.	
[43]	DroidCha	Not stated	The	The					The	
	meleon	1 of Stated	authors	authors					authors	
	mereon		found out	failed to					tested	
			that all the	strength					5486 real- world	
			anti-	their					world	
			antı-	their						



			apps.	
[45]	AndroSimi lar	94.4%	The authors were able to discover malicious apps vigorousl y using signature statistics in feature selection by deploying relationshi p digest hashing scheme.	In their approach the authors did not consider memory constrain in developin g a robust family signature to identify variants with family illustrativ e signatures
[46]	DroidBarri er		The authors achieved high reassuranc e by designing an verificatio n model that uses protected applicatio n IDs, preserved and secured by system runtime, to validate processes and put together their identity to genuine apps installed on the	In their work the authors not focus on validating inter- process communi cations and authorizin g admission to apps' assets.

			andı	roic	1.	
 	-	 -		-		

Table 2 Strength and Weaknesses of selected related work based on permissions of android apps using static analysis

4. REVERSE ENGINEERING OVERVIEW OF ANDROID APPLICATIONS

According to [47], Reverse engineering is the analysis of a subject system for classifying system components and their interrelationships, and for providing a specific or higher degree of perception image of a process. Reverse engineering is just the process of examining the code-to-code but not changing or replicating the source codes [22]. To perform inverse engineering .apk file needs to be decompiled which offers Dex and Android manifest file in an indecipherable format [48].

A number of arsenals are accessible for reverse engineering such as JD-GUI, DEX2JAR [49], APKTOOL [50], AXMLPRINTER2.JAR [51], ANDROGAURD[52] and CLASSYSHARK [53]. Figure 1 depicts APK file conversion steps to obtain the original source code of the manifest file, resources and the java codes.

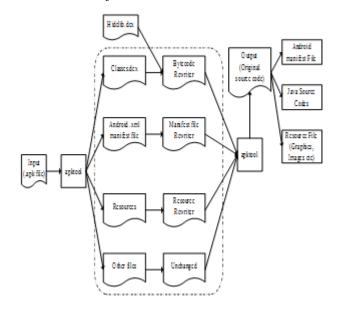


Figure 1 Reverse Engineering of APK File

In reverse engineering the APK file is extension is change from .apk to .zip and its contents extracted to obtain meta-inf, res, classes.dex, resources.arsc and the AndroidManifest.xml [54]. The contents are then extracted to a specified folder for analysis in the subsequent processes. The apktool.jar and the apktool.bat are utilized in a command prompt to obtain the manifest file and the java codes used as well as other resources as shown in Figure 1 which has been modified from the Pooja Singh et al. reference [55]. This process will enable



the user to study and analyze the permission model required by the application in order to install it unlike the dynamic analysis where the android application accessed the user's device for the user to know the permission [56].

5. DISCUSSION

In this paper, a review of about 48 articles were studied regarding to static analysis in Android malware detection based on manifest file which contain permissions a user must accept before installing the application. Most of the android applications are created by hackers in order to steal private information of a user on the device. Previous researched studied in this work reveals the android manifest.xml file contain information that an application intend to do. For instance several manifest files contain the READ CONTACT which reads and store all the personal contact of a user. These contacts will be used by the hackers for their ill intentions. In the internet several applications have been developed with productive names to perform a certain tasks but the android app does some different tasks like stealing photos and images from the user's phone. In this view it is important to analyze the APK android file before allowing it to access to the user device. Static analysis is the best feature as compared to dynamic, hybrid and metadata where the APK conversion is done before installing the file to the user's device. APK file cannot be studied without decompiling it to get the original source code. Since the manifest file contain the permission like WRITE_EXTERNAL_STORAGE, this permission will allow malware such as adware and other dangerous ones to be installed onto the user device and this will use the phone read access memory thus making the phone slow. Some of these adware are able to send and several SMS if the SEND SMS and RECEIVE_SMS permissions are enabled. In this study, static analysis is recommended as its plusses outperforms the other APK analysis features.

6. CONCLUSION

In this work, the use of static malware detection in android malware apps was thoroughly reviewed. A comparison of current job has been provided with regard to certain criteria. The review identified knowledge gaps in the current job, highlighting significant problems and opening problems that will guide future study initiatives. Analysis of static Android malware dominates the current job. Future work may consider reviewing other methods such as dynamic studies or the use of methods of hybrid assessment or deployment of metadata. Except in a few cases, sharing research datasets and tools among researchers lingered unaddressed. Hardening deep learning models against various assaults on adversaries and detecting, describing and measuring concept drift are essential in future job on malware detection for Android. In addition, scientists need to bear in mind the restriction of deep learning techniques such as absence of transparency and its nonautonomous model for building more effective models. Finally, the findings of this job can help encourage Android malware detection studies based on techniques of deep learning.

REFERENCES

- Z. Fang, W. Han, and Y. Li, "Permission based Android security: Issues and countermeasures," Comput. Secur., vol. 43, no. 0, pp. 205–218, 2014.
- [2] F. Tchakounté, "Permission-based malware detection mechanisms on android: analysis and perspectives," J. Comput. Sci., vol. 1, no. 2, pp. 63–77, 2014.
- [3] M. Egele, "A Survey on Automated Dynamic Malware Analysis Techniques and Tools Vienna University of Technology," ACM Comput. Surv. 44.2, vol. V, pp. 1–49, 2012.
- [4] S. Karthick and S. Binu, "Static analysis tool for identification of permission misuse by android applications," Int. J. Appl. Eng. Res., vol. 12, no. 24, pp. 15169–15178, 2017.
- [5] D. Geneiatakis, I. N. Fovino, I. Kounelis, and P. Stirparo, "A Permission verification approach for android mobile applications," Comput. Secur., vol. 49, pp. 192–205, 2015.
- [6] A. Skovoroda and D. Gamayunov, "Securing mobile devices: Malware mitigation methods," J. Wirel. Mob. Networks, Ubiquitous Comput. Dependable Appl., vol. 6, no. 2, pp. 78–97, 2015.
- [7] S. Karthick and S. Binu, "Android security issues and solutions," IEEE Int. Conf. Innov. Mech. Ind. Appl. ICIMIA 2017 - Proc., no. February, pp. 686–689, 2017.
- [8] G. Suarez-Tangil, J. E. Tapiador, P. Peris-Lopez, and A. Ribagorda, "Evolution, detection and analysis of malware for smart devices," IEEE Commun. Surv. Tutorials, vol. 16, no. 2, pp. 961–987, 2014.
- [9] M. La Polla, F. Martinelli, and D. Sgandurra, "A Survey on Security for Mobile Devices," IEEE Commun. Surv. Tutorials, vol. 15, no. 1, pp. 446–471, 2013.
- [10] S. Mohite and P. R. Sonar, "A survey on mobile malware: war without end," Int. J. Comput. Sci. Bus. Informatics, vol. 9, no. 1, pp. 23–35, 2014.
- [11] S. Peng, S. Yu, and A. Yang, "Smartphone Malware and Its Propagation Modeling: A Survey," IEEE Commun. Surv. Tutorials, vol. 16, no. 2, pp. 925–941, 2014.
- [12] M. Odusami, O. Abayomi-Alli, S. Misra, O. Shobayo, R. Damasevicius, and R. Maskeliunas, "Android Malware Detection: A Survey," Commun. Comput. Inf. Sci., vol. 942, no. 2, pp. 255–266, 2018.
- [13] N. DuPaul, "Static Analysis vs Dynamic Analysis | Veracode," VERACODE, 2019. [Online]. Available: https://www.veracode.com/blog/2013/12/static-testing-vs-dynamictesting. [Accessed: 25-Oct-2019].
- [14] A. Ghahrai, "Static Analysis vs Dynamic Analysis in Software Testing," Testing Excellence, 2018. [Online]. Available: https://www.testingexcellence.com/static-analysis-vs-dynamic-analysissoftware-testing/. [Accessed: 25-Oct-2019].
- [15] P. Anderson, "The use and limitations of hearing aids," J. Def. Softw. Eng., no. 6, pp. 19–21, 2008.
- [16] M. Derks, "Fair Privacy: Improving Usability of the Android Permission System," 2015.
- [17] J. Reardon et al., "50 Ways to Leak Your Data: An Exploration of Apps' Circumvention of the Android Permissions System," 28th USENIX Secur. Symp., pp. 603–620, 2019.
- [18] M. Sujithra and G. Padmavathi, "Enhanced Permission Based Malware Detection in Mobile Devices Using Optimized Random Forest Classifier with PSO-GA," Res. J. Appl. Sci. Eng. Technol., vol. 12, no. 7, pp. 732–741, 2016.
- [19] F. E. Allen, "Control flow analysis," Proc. a Symp. Compil. Optim., pp. 1–19, 1970.
- [20] K. D. Cooper and L. Torczon, "Chapter 9 Data-Flow Analysis," in Engineering Compiler, K. D. Cooper and L. B. T.-E. a C. (Second E. Torczon, Eds. Boston: Morgan Kaufmann, 2012, pp. 475–538.



- [21] L. Li et al., "Static analysis of android apps: A systematic literature review," Inf. Softw. Technol., vol. 88, pp. 67-95, 2017.
- S. R. Tiwari and R. U. Shukla, "An Android Malware Detection Technique Using Optimized Permission and API with PCA," Proc. 2nd Int. Conf. Intell. Comput. Control Syst. ICICCS 2018, no. Icirca, pp. 134-139, 2019.
- [23] W. Xu, F. Zhang, and S. Zhu, "Permlyzer: Analyzing permission usage in Android applications," 2013 IEEE 24th Int. Symp. Softw. Reliab. Eng. ISSRE 2013, pp. 400-410, 2013.
- [24] B. Sarma, N. Li, C. Gates, R. Potharaju, C. Nita-Rotaru, and I. Molloy, "Android permissions: A perspective combining risks and benefits," Proc. ACM Symp. Access Control Model. Technol. SACMAT, Jun. 2012
- [25] H. J. Zhu, Z. H. You, Z. X. Zhu, W. L. Shi, X. Chen, and L. Cheng, "DroidDet: Effective and robust detection of android malware using static analysis along with rotation forest model," Neurocomputing, vol. 272, pp. 638-646, 2018.
- [26] A. P. Felt, E. Chin, S. Hanna, D. Song, and D. Wagner, "Android permissions demystified," Proc. ACM Conf. Comput. Commun. Secur., pp. 627-636, 2011.
- [27] R. Stevens, J. Ganz, V. Filkov, P. Devanbu, and H. Chen, "Asking for (and about) permissions used by android apps," IEEE Int. Work. Conf. Min. Softw. Repos., pp. 31-40, 2013.
- [28] N. Gruschka, L. Lo Iacono, and J. Tolsdorf, "Classification of android app permissions: Tell me what app you are and i tell you what you are allowed to do," Eur. Conf. Inf. Warf. Secur. ECCWS, vol. 2018-June, no. June, pp. 181-189, 2018.
- [29] A. Kumar, K. S. Kuppusamy, and G. Aghila, "FAMOUS: Forensic Analysis of MObile devices Using Scoring of application permissions,' Futur. Gener. Comput. Syst., vol. 83, pp. 158-172, 2018.
- [30] S. Niu, R. Huang, W. Chen, and Y. Xue, "An Improved Permission Management Scheme of Android Application Based on Machine Learning," Secur. Commun. Networks, vol. 2018, pp. 1-12, 2018.
- [31] K. A. Talha, D. I. Alper, and C. Aydin, "APK Auditor: Permissionbased Android malware detection system," Digit. Investig., vol. 13, pp. 1-14.2015
- [32] J. Jeon et al., "Dr. android and Mr. hide: Fine-grained permissions in android applications," Proc. ACM Conf. Comput. Commun. Secur., pp. 3-14, 2012.
- [33] N. Munaiah et al., "Darwin: A static analysis dataset of malicious and benign android apps," WAMA 2016 - Proc. Int. Work. App Mark. Anal. co-located with FSE 2016, pp. 26-29, 2016.
- [34] T. K. Chawla and A. Kajala, "Transfiguring of an Android App Using Reverse Engineering," Int. J. Comput. Sci. Mob. Comput., vol. 3, no. 4, pp. 1204-1208, 2014.
- [35] S. Y. Yerima, S. Sezer, and G. McWilliams, "Analysis of Bayesian classification-based approaches for Android malware detection," IET Inf. Secur., vol. 8, no. 1, pp. 25–36, 2014. [36] M. Zheng, M. Sun, and J. C. . Lui, DroidRay: A Security Evaluation
- System for Customized Android Firmwares. 2014.
- [37] Z. Aung and W. Zaw, "Permission-Based Android Malware Detection," Int. J. Sci. Technol. Res., vol. 2, no. 3, pp. 228–234, 2013. [38] L. Apvrille, L. Apvrille, and A. S. Industries, "Pre-filtering Mobile
- Malware with Heuristic Techniques," GreHack 2013, Grenoble, Fr., no. June 2013, pp. 43-59, 2013.
- Y. Feng, S. Anand, I. Dillig, and A. Aiken, "Apposcopy: Semantics-[39] based detection of android malware through static analysis," Proc. ACM SIGSOFT Symp. Found. Softw. Eng., vol. 16-21-Nove, pp. 576-587, 2014.
- [40] M. Grace, Y. Zhou, Z. Wang, X. Jiang, and O. Drive, "Systematic Detection of Capability Leaks in Stock Android Smartphones," Ndss, 2012.
- [41] Y. Aafer, W. Du, and H. Yin, "DroidAPIMiner: Mining API-Level Features for Robust Malware Detection in Android BT - Security and Privacy in Communication Networks," 2013, pp. 86-103.

- [42] J. Crussell, C. Gibler, and H. Chen, "Attack of the Clones: Detecting Cloned Applications on Android Markets BT - Computer Security ESORICS 2012," 2012, pp. 37-54.
- [43] V. Rastogi, Y. Chen, and X. Jiang, "Catch Me If You Can: Evaluating Android Anti-Malware Against Transformation Attacks," IEEE Trans. Inf. Forensics Secur., vol. 9, no. 1, pp. 99-108, 2014.
- [44] L. Lu, Z. Li, Z. Wu, W. Lee, and G. Jiang, "CHEX: Statically Vetting Android Apps for Component Hijacking Vulnerabilities," in Proceedings of the 2012 ACM Conference on Computer and Communications Security, 2012, pp. 229-240.
- [45] P. Faruki, V. Ganmoor, V. Laxmi, M. S. Gaur, and A. Bharmal, "AndroSimilar: Robust Statistical Feature Signature for Android Malware Detection," in Proceedings of the 6th International Conference on Security of Information and Networks, 2013, pp. 152-159.
- [46] H. M. J. Almohri, D. (Daphne) Yao, and D. Kafura, "DroidBarrier: Know What is Executing on Your Android," in Proceedings of the 4th ACM Conference on Data and Application Security and Privacy, 2014, pp. 257-264.
- [47] E. J. Chikofsky and J. H. Cross, "Reverse Engineering and Design Recovery: A Taxonomy," pp. 13-17, 1990.
- [48] S. R. Tiwari and R. U. Shukla, "An Android Malware Detection Technique Based on Optimized Permissions and API," Proc. Int. Conf. Inven. Res. Comput. Appl. ICIRCA 2018, no. January, pp. 258-263, 2018.
- [49] H. A. Alatwi, "Android malware detection using category-based machine learning classifiers," 2016.
- [50] M.-Y. Su and K.-T. Fung, "Detection of android malware by static analysis on permissions and sensitive functions," in 2016 Eighth International Conference on Ubiquitous and Future Networks (ICUFN), 2016, pp. 873-875.
- [51] X. Li, J. Liu, Y. Huo, R. Zhang, and Y. Yao, "An Android malware detection method based on AndroidManifest file," in 2016 4th International Conference on Cloud Computing and Intelligence Systems (CCIS), 2016, pp. 239-243.
- [52] C. Liu, Z. Zhang, and S. Wang, "An Android Malware Detection Approach Using Bayesian Inference," in 2016 IEEE International Conference on Computer and Information Technology (CIT), 2016, pp. 476-483.
- [53] K. Wang, T. Song, and A. Liang, "Mmda: Metadata Based Malware Detection on Android," in 2016 12th International Conference on Computational Intelligence and Security (CIS), 2016, pp. 598-602.
- [54] S. Lachure, U. Pagrut, N. Jichkar, N. Khan, and J. Lachure, "Reverse Engineering APKS for Analysis," pp. 268-272, 2018.
- [55] P. Singh, P. Tiwari, and S. Singh, "Analysis of Malicious Behavior of Android Apps," Procedia Comput. Sci., vol. 79, pp. 215-220, 2016.
- [56] B. Bonné, S. T. Peddinti, I. Bilogrevic, N. Taft, S. Clara, and B. Bonné, "Exploring decision making with Android 's runtime permission dialogs using in-context surveys This paper is included in the Proceedings of the permission dialogs using in-context surveys," no. Soups, 2017.

Authors



Hamida Lubuva received her Bachelor Electronics and Communication Engineering in 2016 from the, St. Joseph University, Tanzania. She is currently pursuing Master Degree in Information and Communication Engineering at the University of Science and Technology Beijing. Her research areas include; Terminal Detection, Networking, Network security, Data Privacy.

Huang Qiming is an associate Professor and Master Tutor of Beijing University of Science and Technology, Huazhong University of Science and Technology, Postdoctoral Fellow, Department of Computer Science, Zhejiang University, Associate Research Fellow, School of Computer, Beijing



University of Posts and Telecommunications, Visiting Scholar, University of Hong Kong. At the Beijing University of Science and Technology, the School of Computing, the future of the Internet of Things, cloud computing encryption certification and authorization, block chain smart contracts, data privacy protection and deep learning based computer video classification, network intrusion detection direction of scientific research work, and committed to Applications in smart cities, industrial internet, health care information systems, and car networking. He has published more than 50 academic papers, and more than 20 papers have been included in SCI and EI. There are 1 collection of papers, 1 joint, and 4 textbooks. Teaching data structure and algorithm analysis, mobile Internet, communication network security foundation, computer network, software engineering, computer introduction and programming.



Godfrey Charles Msonde; received his Bachelor Degree of Science in Economics in 2012 from Mzumbe University, Tanzania. In 2019, He graduated Masters of National Economics from Renmin University of China, Beijing China. He is currently pursuing Master of International Public Policy at Wilfrid Laurier University, Canada. His research areas include Digital economy, development studies, Big Data, Smart Agriculture to Africa.