# Malware Detection in Android App Using Static and Dynamic Analysis

R.H.Sonawane<sup>1</sup>, P.K.Tate<sup>2</sup>, S.A.Shinde<sup>3</sup>, R.S.Bhole<sup>4</sup> Student of Computer Engineering <sup>1234</sup>Loknete Gopinathji Munde Institude of Engineering Education and Reseach, Nashik, India.

**Abstract:** Smartphones and mobile tablets are fast becoming necessary in daily life. Android has been the most popular mobile operating system since 2012. However, due to the open nature of Android, immeasurable malwares are hidden in a large number of kindly apps in Android markets that dangerously pressure Android security. Deep learning is a new area of machine learning research that has gained increasing detect in artificial intelligence. In this study, we propose to connect the features from the static analysis with features from dynamic analysis of Android apps and differentiate malware using deep learning techniques. We execute an Online deep-learning-based Android malware detection engine (DroidDetector) that can automatically identify whether an app is a malware or not. With thousands of Android apps, we systematically test DroidDetector and do an indepth analysis on the features that deep learning basically exploit to differentiate malware. The results show that deep learning is suitable for differenting Android malware and especially useful with the availability of more training data. DroidDetector can get 96.76% detection accuracy, which outperforms traditional machine learning techniques. An estimation of ten popular anti-virus softwares demonstrates the importance of advancing our capabilities in Android malware detection.

**Key Words:** Android security; malware detection; characterization; deep learning; association rules mining.

# **1. INTRODUCTION:**

Android harmfully surpassed a billion shipments of its devices in 2014 and has remain the No.1 mobile operating system since 2013, according to a just report from Gartner. Android markets, such as the Google Play Store and other mediator markets, play an important role in the fashion of Android devices. However, the openness of Android makes these markets hot targets for malware attacks and causes countless instances of malware being hidden behind a large number of benign apps that seriously blackmail users' security and privacy. Moreover, a report from McAfee Labs reveals that 3.73 million pieces of mobile malware were identified in 2013, increasing an astounding 197% from the end of 2012. accordingly, an urgent need arises to develop powerful solutions for Android malware detection. Unfortunately, the Android market presently has no such solution. Today, the main countermeasure to defense against malware on Android platforms is a risk communication mechanism that calls users about the permissions required before installing each app. This mechanism is rather ineffective as it presents permissions in a Malware Detection in Android App Using Static and Dynamic Analysis 115 complete fashion, thus requiring too much technical knowledge for a user to be able to separate malware from benign apps. Note that both a benign and a despiteful app may require the same permissions and are thus indistinguishable via this permission-based mechanism. In general, permission-based approaches are developed primarily for risk assessment rather than malware detection.

# 2. COMPARATIVE STUDY:

# DroidMiner: automatic Mining and classification of Fine-grained Malicious Behaviors in Android Applications.

Android app finding approaches rely on yourself selected detection heuristics, features, and models. In this paper, we explain a new, corresponding method, called DroidMiner, which uses static analysis to automatically mine malicious program reason from known Android malware, abstracts this reason into a sequence of threat modalities, and then seeks out these threat modality patterns in other unknown Android apps.

#### DREBIN : efficient and understandable Detection of Android Malware in Your Pocket

Malicious applications pose a threat to the security of the Android stage. The growing quantity and variety of these applications render predictable defenses largely unsuccessful and thus Android smartphones often stay unprotected from original malware. In this paper, we propose D REBIN, a lightweight method for finding of Android malware that allow identifying malicious applications openly on the smartphone. As the limited resources delay monitoring applications at run-time, D REBIN do a large static analysis, gather as many features of an application as possible. These features are fixed in a joint vector space, such that typical patterns problem-solving for malware can be automatically identified and used for explaining the decisions of our way.

#### Android Malware Detection Using Machine Learning Approach

we here Permission as well as String Based Anomaly Detection System for detecting Meaningful deviation in a mobile application's network behavior. The main goal of Proposed system is to protect mobile device users and avoid uncertainty of users. Identification of republished popular applications injected with a malicious code. More specifically, we attempt to detect a new type of mobile malware with self-updating capabilities that were newly found on the official Google Android Marketplace. Android applications are becoming increasingly because android phones are wide spread and steadily gaining popularity.

#### A Study of Android Malware finding methods and Machine Learning

Android OS is one of the widely used mobile Operating Systems. The amount of malicious applications and adware's are increasing constantly on par with the number of mobile devices. A great number of viable signature based tools are available on the market which prevent to an extent the access and distribution of malicious applications. Numerous researches have been conducted which declare that established signature based Finding system work well up to certain level and malware authors use numerous methods to avoid these tools.

#### An review Android Antimalware that identify Malicious Dynamic Code in Apps

Android is currently the most popular operating system and a significant number of

Smartphone's, tablet computers ship with Android. However, users feel their personal information at threat, facing a quickly increasing number of malware for Android which significantly exceeds that of other platforms. Antimalware's software guarantee to effectively protect against malware on Smartphone's and many products are accessible for free or at reasonable prices. We systematically analyze the security implications of the capability to load malicious dynamic code in Android apps. We assess an Android Antimalware software tool to identify try to load malicious code and from the study of many online applications we observed, that malicious code is loaded in an insecure way is a major issue. We also show how malware can use code-loading techniques to avoid detection by develop a theoretical weak point in current Android malware protection.

Paper	Paper	Paper	Paper	Paper	Paper	Paper	Paper	Paper	Paper	Paper
Paramet	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
er										
Paper	DroidMin	DREBI	Detecting	Android	A Study	А	Malware	An Assess	Detecting	HADM:
Name	er:	N:	APT	Malware	of	Machine	Detection	Android	Malicious	Hybrid
	Automate	Effectiv	Malware	Detection	Android	Learning	Techniqu	Antimalwa	Apps in	Analysis
	d Mining	e and	Infections	Using	Malware	Approach	es in	re	Official	for
	and	Explaina	Based	Machine	Detection	to	Android	that	and	Detection
	Characteri	ble	on	Learning	Techniqu	Android		Detects	Alternativ	of
	zation	Detectio	Malicious	Approch	es and	Malware		Malicious	e Android	Malware
	of Fine-	n	DNS and		Machine	Detection		Dynamic	Markets	
	grained	of	Traffic		Learning			code in		
	Malicious	Android	Analysis					apps.		
	Behaviors	Malware								
	in	in Your								
	Android	Pocket								

## **3. COMPARATIVE STUDY TABLE:**

- 2455-0620 Volume - 2, Issue - 10, Oct - 2016

	Applicati ons									
Author	Chao Yang,Phil lip Porras.	Daniel Arp, Hugo Gascon	Guodong Zhao, Lei Xu	Prof. Ganesh Bandal. Hemant Chavan, Amol Shivpure.	Balaji Baskaran and Anca Ralescu	Justin Sahs and Latifur Khan	Pallavi Kaushik, Amit Jain	Miss. Srushti Hatwar1, Prof. Chetan Shelke	Yajin Zhou, Zhi Wang, Wu Zhou, Xuxian Jiang	Lifan Xu Dongping Zhang Nuwan Jayasena John Cavazos
Domain Name	Mobile Security, Android Malware Analysis and Detection.	Mobile Security, Android Malware Analysis and Detectio n.	PT, malware infections , DNS, intrusion detection.	Android Security, Android System, Permissio n Detection.	Android malware, smartpho ne security	Computer Security, Data Mining, Support Vector Machines	Android, Dynamic Analysis, Machine learning, Malware, Malware detection, Static Analysis.	Antimalwa re, malicious code, malware, Android, Smartphon e	Mobile Security, Android Malware Analysis and Detection.	Computer Security, Data Mining, Support Vector Machines
Algorith m	1.DroidM iner's 2.Modalit y Generatio n	1. Self Organizi ng Map (SOM)	1.domain generatio n algorithm (DGA) 2.J48 decision tree algorithm	1. J48 (OR) C4.5 2. NAÏVE BAYES	1. ML algo- rithms. 2.J48 decision tree and 3.Random Forest algorithm s.	Weisfeile r-Lehman relabellin g, machine learning algorithm s	1.Leonid Batyuk et. 2. Sanz et 3. Enck et 4.clusteri ng algorithm	1. K- Means 2.Support Vector Machine (SVM)	1. clustering algorithm	1.Shortest Path Graph Kernel (SPGK) 2.Floyd- Washall 3.Support Vector Machine (SVM) 4.MKL algorithm
Plat- form	Android	Android	Android	Android	Android	Android	Android	Android	Android	Android
Techniq ues	1.machine learning technique s. 2.commo n code extraction technique s	1.machi ne learning techniqu es. 2.linearti me analysis and learning techniqu es	1.domain flux technique 2.malicio us DNS analysis technique s.	1.repacka ging, 2.update attack, 3. drive- by download	1.code obfuscati on technique. 2.static and dynamic technique s. 3.machine learning technique s	1.metamo rphic technique s	1.static and dynamic technique s	1.code- loading techniques	1.DroidRa nger.	1.dynami c analysis technique s. 2.static analysis, dynamic analysis, and hybrid technique s.
Attacks	1.confuse d deputy attacks. 2. collusion attacks	mimicry and poisonin g attacks	1.APT attacks 2.DDoS attacks	Update Attack	update attack	DDoS attacks	Update Attack	Code injection attacks	1. confused deputy attacks. 2. drive- by download attacks.	security attacks.
Issues	security issues	security issues	security issues	security issues	security issues	security issues	security issues	security issues, protection issues	security issues	security issues
Applicat ions	Android and Facebook applicatio ns.	maliciou s applicati ons from Android markets	malicious applicatio ns from Android markets	smartpho ne applicatio ns,securit y applicatio n.	malicious android appli- cations.	Android applicatio ns	Android applicatio ns	Android application s	smartpho ne applicatio ns	malicious applicatio ns from Android markets

INTERNATIONAL JOURNAL FOR INNOVATIVE RESEARCH IN MULTIDISCIPLINARY FIELD
--

ISSN - 2455-0620 Volume - 2, Issue - 10, Oct - 2016

oner is a new static analysisN combine spropose a framewor systemsurvey on framewor lead to potential against a combinemodel systemanalysis shows that the abilityn-based behaviorapro hyb hyb hyb hyb hyb hyb against a combinen-based systempro hyb hyb hyb hyb hyb hyb hyb against a combinemodel systemanalysis shows that the abilityn-based behaviorapro hyb h	
new static analysiscombine systemnovel systemframewor klead to potentialsystemwhich against a combineshows that the abilitybehaviora hyt handroidsystem thatconceptsIDnS placed at automaticclassifyin g Androidcounterac tingcollection tingfeatures featuresof Android footprintiing mai counteracautomatic ally mines maliciousstaticthe geressg Android updateting updatethe benignof staticload apps to loadng and classparasitic rom from a egmentsand weth malwarenetwork or normal applications unavailaband staticg Android apps to and analysisadditional basedbased met met mainiciousparasitic from a rom a enablesmalware infections applicatiothey are applicatiodiscussed. applicatioAndroid dy analysis and analysiscauses implemenmet met we heuristics-from a rom a enablesinfections infections applicatioapplicatio ility of a applicatioanalysis acusescauses implemenimplemen ted bothfrom a rom a enablesinfections infections applicatioapplicatio ility of a applicatiomachine acus acus acus acus andscusses infections applicatioinfections applicatioporter acus adiappint, acus acus acus acus acus andmachine <b< th=""><th>ose a</th></b<>	ose a
analysisssystemkforpotentialagainst acombinethe ability1AnsystemconceptsIDnSclassifyincounteraccollectionfeaturesof Androidfootprintimathatfromplaced atg Androidting theof 2081of bothapps tong andclassifyinautomaticstatictheapplicatioupdatebenignstaticloadheuristics-ionally minesanalysisnetworknsattackand 91analysisadditionalbasedmetparasiticmachinepoints tothey arediscussed.AndroiddynamicruntimeWe haveHACodelearning,detectmalwareTheapplicatioanalysiscausesimplemenWesegmentswhichmalwareor normalunavailabns.Forandmajorted bothevafrom aenablesinfectionsapplicatioility of aeachmachinesecurityschemesthemaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanofmaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanofmaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanofmalicious <td< th=""><th>id</th></td<>	id
systemconceptsIDnSclassifyincounteraccollectionfeaturesof Androidfootprintimathatfromplaced atg Androidting theof 2081of bothapps tong andclassifyinautomaticstatictheapplicatioupdatebenignstaticloadheuristics-ionally minesanalysisnetworknsattackand 91analysisadditionalbasedmetmaliciousandegresswhetherismaliciousandcode atfiltering.nanparasiticmachinepoints tothey arediscussed.AndroiddynamicruntimeWe haveHACodelearning,detectmalwareTheapplicatioanalysiscausesimplemenWesegmentswhichmalwareor normalunavailabns.Forandmajorted bothevafrom aenablesinfectionsapplicatioility of aeachmachinesecurityschemesthemaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanofmaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanofmaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanofmaliciousbetter<	oid
thatfromplaced atg Androidtingtheof2081ofbothapps tongandclarautomaticstatictheapplicatioupdatebenignstaticloadheuristics-ionally minesanalysisnetworknsattackand91analysisadditionalbasedmetmaliciousandegresswhetherismaliciousandcode atfiltering.nanparasiticmachinepoints tothey arediscussed.AndroiddynamicruntimeWe haveHACodelearning,detectmalwareTheapplicatioanalysiscausesimplemenWesegmentswhichmalwareor normalunavailabns.Forandmajorted bothevafrom aenablesinfectionsapplicatioility of aeachmachinesecurityschemesthemaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanofmaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanof	vare
automaticstatictheapplicatioupdatebenignstaticloadheuristics-ionally minesanalysisnetworknsattackand 91analysisadditionalbasedmemaliciousandegresswhetherismaliciousandcode atfiltering.namparasiticmachinepoints tothey arediscussed.AndroiddynamicruntimeWe haveHACodelearning,detectmalwareTheapplicatioanalysiscausesimplemenWesegmentswhichmalwareor normalunavailabns.Forandmajorted bothevafrom aenablesinfectionsapplicatioility of aeachmachinesecurityschemesthemaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanofmobilekeepcombinedthemalwareselected a.Allto showger andfeat	ificat
ally minesanalysisnetworknsattackand 91analysisadditionalbasedmemaliciousandegresswhetherismaliciousandcode atfiltering.nameparasiticmachinepoints tothey arediscussed.AndroiddynamicruntimeWe haveHACodelearning,detectmalwareTheapplicatioanalysiscausesimplemenWesegmentswhichmalwareor normalunavailabns.Forandmajorted bothevafrom aenablesinfectionsapplicatioility of aeachmachinesecurityschemesthecorpus ofittoinside thens.Tolargerdatapoint,learningissues. Weinformaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanofmobilekeepcombinedthemalwareselected a.Allto showger andfeat	
maliciousandegresswhetherismaliciousandcode atfiltering.narparasiticmachinepoints tothey arediscussed.AndroiddynamicruntimeWe haveHACodelearning,detectmalwareTheapplicatioanalysiscausesimplemenWesegmentswhichmalwareor normalunavailabns.Forandmajorted bothevafrom aenablesinfectionsapplicatioility of aeachmachinesecurityschemesthecorpus ofittoinside thens.Tolargerdatapoint,learningissues. Weinformaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanofmobilekeepcombinedthemalwareselected a.Allto showger andfeat	od
parasiticmachinepoints tothey arediscussed.AndroiddynamicruntimeWe haveHACodelearning,detectmalwareTheapplicatioanalysiscausesimplemenWesegmentswhichmalwareor normalunavailabns.Forandmajorted bothevafrom aenablesinfectionsapplicatioility of aeachmachinesecurityschemesthecorpus ofittoinside thens.Tolargerdatapoint,learningissues. Weinformaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanofmobilekeepcombinedthemalwareselected a.Allto showgerand	ed
Codelearning,detectmalwareTheapplicatioanalysiscausesimplemenWesegmentswhichmalwareor normalunavailabns.Forandmajorted bothevafrom aenablesinfectionsapplicatioility of aeachmachinesecurityschemesthecorpus ofittoinside thens.Tolargerdatapoint,learningissues. Weinformaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanofmobilekeepcombinedthemalwareselected a.Allto showger andfeat	M.
segmentswhichmalwareor normalunavailabns.Forandmajorted bothevafrom aenablesinfectionsapplicatioility of aeachmachinesecurityschemesthecorpus ofittoinside thens.Tolargerdatapoint,learningissues. Weinformaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanofmobilekeepcombinedthemalwareselected a.Allto showger andfeat	first
from aenablesinfectionsapplicatioility of aeachmachinesecurityschemesthecorpus ofittoinside thens.Tolargerdatapoint,learningissues. Weinformmaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanofmobilekeepcombinedthemalwareselected a.Allto showger andfeat	iate
corpus ofittoinside thens.Tolargerdatapoint,learningissues.weinformaliciousbetternetworkgenerateandroidwealgorithmwere ableDroidRanofmobilekeepcombinedthemalwareselected a.Allto showger andfeat	er-
malicious better network generate android we algorithm were able DroidRan of mobile keep combined the malware selected a . All to show ger and feat	ance
mobile keep combined the malware selected a . All to show ger and feat	16
	re
applicatio pace with DNS models, dataset random these that an the vec	)r
ns, and with traffic we have remains a subset of technique astonishing evaluation sets	and 4
then malware analysis. extracted great the s are ly large results of gra	1 sets
detects develop several problem training combined portion of successful gen	
n researce Our n features evoluatin application existing by from	10 and
of these out in realistic control of these evaluation approach obtain approach detecting stat	mio
and on available control on and m vulnerable miliarity for	rac
sequents demonst download proceeds performe accuracy to code anno col	cted
within rates the ed With a d k-fold in injection and from	cicu
other potential applicatio proper cross detecting due to uncoverin An	bio
previousl of this $\int respectively from dataset validation malicious download \sigma two apr$	catio
y approac android shared In samples and access zero-day is	cutio
unlabeled. h. where markets. among addition apps from malware	
mobile DREBI researcher to the unofficial in both	
apps. N s, a full sits official	
outperfo system kernel, and	
rms that learns we also unofficial	
related a new trained marketpla	
approac malware against ces	
hes and and share each demonstra	
identifie that individual te the	
s knowledg kernel feasibility	
maliciou e separately and	
s to all the . effectiven	
applicati mobile ess	
ons with devices, of our	
few so that approach.	
false they can	
alarms. protect	
themselve	
Irom	
1uuure atteaka	
auduks,	
developed	

## 4. CONCLUSION:

Deep learning is a new area of machine learning study. In this study, we extracted a total of 192 features from both static and dynamic analyses of Android apps and characterized malware using a DBN-based deep learning model. We designed DroidDetector and evaluated it with 20000 benign apps crawled from the Google Play Store and 1760 malwares collected from the well-known Contagio Community and Genome Project. The results show that using DroidDetector with a deep learning model can achieve a superior accuracy under different conditions, significantly outperforming traditional machine learning techniques. At present, DroidDetector has been deployed online for user testing. Moreover, we delved deeper into the features that deep learning exploits to characterize Android malware using association rule mining techniques. The evaluation of ten popular anti-virus softwares indicates that it is a matter of urgency to make changes in Android malware detection.

#### ACKNOWLEDGMENT:

It is my immense pleasure to work on this project **Malware Detection in Android App Using Static and Dynamic Analysis**. I would like to thank Dr. Arunkumar Dwivedi, Principal, LoGMIEER College of Engineering for giving me such an opportunity to develop practical knowledge about subject. I am also thankful to Prof K. V. Ugale, Head of Computer Engineering Department for his valuable encouragement at every phase of my seminar work and completion.

#### **REFERENCES:**

- 1. Y. Zhou, Q. Zhang, S. Zou, and X. Jiang. Riskranker: scalable and accurate zero-day android malware detection. In Proc. of the 10th MobiSys, 2012.
- 2. A. Reina, A. Fattori, and L. Cavallaro. A system call-centric analysis and stimulation technique to automatically reconstruct android malware behaviors. In Proc. of European Workshop on System Security (EUROSEC), April 2013.
- 3. Wen Liu. Mutiple classifier system based android malware detection. In Machine Learning and Cybernetics (ICMLC), 2013 International Conference on, volume 01, pages 57–62, July 2013. doi: 10.1109/ICMLC.2013.6890444.
- Mark A. Davenport, Richard G. Baraniuk, and Clayton D. Scott. Tuning support vector machines for minimax and neyman-pearson classification. IEEE Transactions on Pattern Analysis and Machine Intelligence, 32(10), 2010.
- 5. S. Zhao, X. Li, G. Xu, L. Zhang, and Z. Feng, "Attack tree based android malware detection with hybrid analysis," in Proceedings of the IEEE 13th International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom), 2014.
- L. Xie, X. Zhang, J.-P. Seifert, and S. Zhu. pBMDS: A Behavior-based Malware Detection System for Cellphone Devices. In Proceedings of the 3rd ACM conference on Wireless Network Security, WiSec '10, 2010.
- 7. S. Zhao, X. Li, G. Xu, L. Zhang, and Z. Feng, "Attack tree based android malware detection with hybrid analysis," in Proceedings of the IEEE 13th International Conference on Trust, Security and
- 8. Privacy in Computing and Communications (TrustCom), 2014.
- L. Xie, X. Zhang, J.-P. Seifert, and S. Zhu. pBMDS: A Behavior-based Malware Detection System for Cellphone Devices. In Proceedings of the 3rd ACM conference on Wireless Network Security, WiSec '10, 2010.
- 10. S. Zhao, X. Li, G. Xu, L. Zhang, and Z. Feng, "Attack tree based android malware detection with hybrid analysis," in Proceedings of the IEEE 13th International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom), 2014.
- 11. A. Mylonas, A. Kastania, and D. Gritzalis, Delegate the smartphone user? Security awareness in smartphone platforms, Computers & Security, vol. 34, pp. 47–66, 2013