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Android Malware Detection Using Category-Based Machine Learning Classifiers

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Abstract

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by Huda Ali Alatwi

Android malware growth has been increasing dramatically along with increasing the diversity and complicity of their developing techniques. Machine learning techniques are the current methods to model patterns of static features and dynamic behaviors of Android malware. Whereas the accuracy rates of the machine learning classifiers increase with increasing the quality of the features, we relate between the apps' features and the features that are needed to deliver its category's functionality. Differently, our classification approach defines legitimate static features for benign apps under a specific category as opposite to identifying malicious patterns. We utilize the features of the top rated apps in a specific category to train a malware detection classifier for that given category. Android apps stores organize apps into different categories, for instance, 26 categories on Google Play Store. Each category has its distinct functionalities which means the apps under a specific category are similar in their static and dynamic features. In general, benign apps under a certain category tend to share a common set of features. On the contrary, malicious apps tend to request abnormal features, less or more than what is common for the category that they belong to. This study proposes category-based machine learning classifiers to enhance the performance of classification models at detecting malicious apps under a certain category. The intensive machine learning experiments proved that category-based classifiers report a remarkable higher average performance compared to non-category based.

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Chapter 1

Preface

1.1 Introduction

According to International Data Corporation (IDC), Android OS is the most popular smartphone platform with 82.2% of the market share of smartphones, while 13.9% for iOS apple in the second quarter of 2015 [3]. Statistically speaking, it is also the first targeted platform by malware authors seeking to take the control over millions of Android smartphones over the world. Due to the popularity of Android's smartphones, its apps' security is a serious issue concerning 80% of smartphones users.

Android is an open source development environment that offers a rich SDK that enables developers to deploy their own apps and distribute them through Android apps centers. Android's popularity is a result of being an open source, third-party distribution centers, a rich SDK, and the popularity of Java as a programing language. Importantly, due to this open environment, malaware authors can develop malicious apps that abuse the features that the platform offers or pack a legitimate app with a piece of malicious code; besides, exploiting vulnerabilities in the platform, hardware, or other installed apps to lunch malicious behaviors. Mainly, malware authors seek access confidential data of a device's user, monetary benefits via premium SMS, or joining the device to a botnet. Even legitimate apps introduce the risk of privacy-invading; Mcafee reported in Q1 2014 that 82% of Android apps track user's and 80% gather location data.

Research studies in the Android malware detection field work in three approaches static, dynamic or hybrid. In static analysis, malware is disassembled into a source code from where specific features are extracted. In dynamic analysis, malware is monitored at run-time in a virtual environment. In the both approaches, machine learning algorithms have been used to build classification models by training classifiers with datasets of mlaware features that collected from static or dynamic analysis. The learned classification models are then used to detect malicious apps and classify them into their families.

In this study, we approach the problem differently by utilizing the features of benign apps for malware detection. We relate between the features that the app requests and the common features for its category. Android apps stores organize apps into different categories; for example, Google play store organizes apps in 26 categories such as: "Health & Fitness", "News & Magazine", "Books & References", "Music & Audio", etc. Each category has its distinct functionalities which means the apps under a certain category share similar features. One group of these features are the permissions; permissions are the privileges that enable apps to access the system's resources to perform their functions. Each built-in permission is responsible for providing the capabilities to execute a particular process. Apps belong to a specific category deliver the same functionality as a result they require a common combination of permissions. For instance, apps under "Communication" category commonly request `READ_CONTACTS` but it is uncommon if it is requested by apps under "News & Magazines". In general, benign apps under a certain category tend to have a common set of features: permissions, intents filters, hardware components, broadcast receivers, APIs, etc. On the contrary, malicious apps tend to request abnormal features, less or more than what is common for the category that they belong to. Repeatedly from that point of view, this study proposes category-based machine learning classifiers to enhance the performance of classification models at detecting malicious apps under a certain category. .

1.2 Motivations

Android malware growth has been increasing dramatically along with increasing of the diversity and complicity of their developing techniques. According to F-Secure, a computer security company, Android had the biggest share of smartphone malware by 97% in 2014 [9]. Android global market share of smartphone industry is 78% which represents the biggest share among other smartphone platforms [3]. Statically speaking, Android apps' security concerns one billion of active users over the world [8]. Due to the openness of Android environment, there is a remarkable increase in the number of published Android apps. According to the statistics (staista), the number of available apps to download in Google play stores was around 1,500,000 in 2014 [2].

Static analysis can report a high accuracy rate in detection malware; and it is relatively cheap compared to dynamic analysis in terms of effort, time, and computational resources. Machine learning algorithms are the current methods for detecting malware on Android. In the both approaches, static and dynamic, they are used to model patterns of static features and dynamic behaviors of malware. Mostly, the researches focus on training supervised machine learning classifiers to detect, classify the malware to a known malware family, or using semi-supervised learning to discover a new one. In fact, machine learning techniques can report remarkable accuracy rates at detecting malicious apps depending on the quality of the features that used for training the classifiers e.g how specific they are. Whereas the accuracy rates of the classifiers increase with increasing the quality of the features, we relate between the apps' features and the features that are needed to deliver its category's functionality to detect malicious patterns. In other words, we train a malware detection classifier for each category, separately.

1.3 Scope

This study is a static analysis that uses the features that can be extracted from the source codes of the apps' .apk files. We parsed three group of features from each apps in our datasets: permissions, broadcast receivers, and APIs. Whereas we propose category-based classifiers to improve the performance of the classification models at detecting malicious apps under a certain category, we worked on two categories on the Google Play Store "Music & Audio" and "Personalization". We built three datasets of apps features: apps from all categories (`allCateg`), apps from "Music & Audio" category (`musicCateg`), and apps from "Personalization" category (`personaCateg`); in each dataset the benign apps were downloaded from the top rated apps on the Google Play Store while malicious apps from virushare. For each dataset, we trained three machine learning classifiers: Support Vector Machines, RandomForest, and AdaBootsM. We tested the classifiers with two datasets of apps from "Music & Audio" and "Personalization" categories. By evaluating the performance of the classifiers, the category-based classifiers reported a higher performance by 3.5-4.5% compared to non-category based.

1.4 Contribution

Mostly, research studies in Android malware detection focus on identifying the features of malicious apps by using machine learning techniques to recognize and model the malicious patterns of static features and dynamic behaviors of malware. Up to our knowledge, no researches have worked on relating between the apps' features and the features of benign to distinguish benign form malicious ones in the same category. Differently, our classification approach defines legitimate static features for benign apps under a specific category as opposite to identifying malicious patterns. We utilize the features of the top rated apps in a specific category to define a profile of the common sets of features for that category. In other words, to detect whether or not the app posses the characteristics of benign, we relate between the app's features and the features that are needed to deliver its category's functionalities. Android stores organize apps into different categories; 26 categories on the Google Play Store, for example. In each category, the apps deliver a similar functionality as a result the they tend to request a common set of features like same permissions, APIs, hardware components, broadcast receivers, intents filters,..etc. On the contrary, malicious apps tend to have abnormal features, less or more than what is common for the category that they belong to. Whereas the accuracy rates of the classifiers increase with increasing the quality of the features, we propose category-based classifiers to enhance the performance of machine learning algorithms at detecting malicious apps under a given category.

1.5 Thesis Structure

The structure of this thesis is organized in six chapters. Chapter 2 shows a brief background about Android OS which includes architecture, security features, application components, permissions model, and permissions protection levels. Chapter 3 presents related work has been done in static and dynamic malware detection in Android environment. Chapter 4 shows the implementation of this study which covers the framework, used tools, datasets, extracting features, selecting features using features selection algorithms, and training machine learning classifiers. Chapter 5 demonstrates the results, the significant findings, and performance evaluation of the classifiers. Chapter 6 concludes the study work, emphasizes our findings, and suggests further potentials for future work for our proposed approach in this study.

Chapter 2

Background

Android is an open-source operating system for mobile phones, tablets, TVs, cars, embedded and wearable devices. It was built based on Linux kernel, developed by Google and released on September 23, 2008 . As a result of the open environment of Android, many companies and manufacturers uses it as a platform for their products. Besides, this environment allows companies to customize the Android system to fit with their devices needs. Android offers a friendly development environment through a variety of tools: Android SDK, Android NDK, Android Debug Bridge (ADB), and Android Developer Tools (Eclipse). Android Software Development Kit (SDK) is updated with every release of a new version of Android; it provides comprehensive packages of Java framework classes, libraries, and debuggers for programmers. Also, the SDK offers Android Emulator which enables developers to run and test their apps on different virtual devices that run different versions of Android OS. Secondly, Android Native Development Kit (NDK) is a set of libraries written in C, C++, and other languages can be loaded into Java code through System.loadLibrary call. Android Debug Bridge (ADB) is a command line tool in a client-server form that consists of three components: client, server, and daemon. The client runs on the development machine where the daemon runs in the background on each emulator or device instance and the server manages communication between the client and the daemon. ADB enables developers to test their apps for bugs by connecting the device running the software to a PC and using terminal commands. Finally, Eclipse is the official Integrated Development Environment (IDE) to develop Android apps. It provides many features through GUI or command lines; it allows programmers to develop their apps with different programming languages: JAVA is widely used for Android apps, C, C++. Google Play Store is the official distribution center for Android Apps which are developed by Google or third-parties. It allows Android users to browse, install, and update the apps. Over 50 billion apps were downloaded by Android users from Google Play Store in 2013 . Unsurprisingly, the open development environment of Android encourages the developers and even the attackers to deploy their own applications. Android markets follow specific procedures that aim to detect and remove malicious apps. For instance, Google Play Store uses a tool called Bouncer that scans the uploaded apps and applies security measurements before publishing. The Google Bouncer is a dynamic analysis technique that tests apps by running them in virtual environments to monitor automatically the app's behavior. Even with the security measurements that Google takes, the attackers find their ways to pass their malicious apps through the scanning system by using hiding techniques such as encryption and heuristic evasion. Security researchers from Columbia University have exploited vulnerabilities in Google's Bouncer system. The vulnerabilities allow the attackers to pass the malware apps to the Android market [6]. The team found that the examined dynamic and static analysis tools were vulnerable to repackaged and heuristic evasion based malware. Indeed, Android malware detection is a significant issue for security researchers; also, it is a serious challenge for Android users' privacy. The following sections briefly cover basics of Android OS which include its architecture, security features, apps components, permissions model and permission protection levels.

2.1 Android Architecture

As can be seen in the Figure 2.1, the Android stack consists of four layers that manage the whole system starting from hardware sensors to the user's high-level apps. Each layer provides specific services and groups of programs that run similar functions. The first layer, the Linux Kernel layer is the most important layer and located at the bottom; it represents the heart of Android system. It provides the OS services and manages the hardware's functions such as memory, power, drivers, network stack, security settings, shared libraries and hardware abstraction. The second layer, the native library layer, provides native libraries which are a set of instructions that manage data processing. The native layer provides the open source libraries, such as surface manager, media framework, SQLite, Webkit, OpenGL—ES, FreeType, and SSL. In short, those libraries do the following jobs: Surface manager library is for composing windows on the screen; media framework library is for processing input and output of video and audio data; SQLite library is for database operations; Webkit is for supporting web browsers; OpenGL—ES is for supporting high performance 2D and 3D graphics; FreeType is for fonts support; SSL library is for providing services of SSL and TLS protocols. This layer also provides the Android runtime libraries which include the core libraries and the Dalvik VM. The Core libraries are a group of Java core libraries for developing Android apps. The Dalvik VM is the virtual environment for sandboxing the apps where they are isolated and run separately in a way for securing and optimizing resources' uses. The third layer, the Application Framework Layer, includes the Android APIs. The APIs are classes and interfaces for Android apps' development. This layer interacts with the running apps and manages the basic functions on the device. The most important programs in this layer are activity manager, content provider, telephony manager, location manager, and resources manager. Each manager is responsible for managing a specific function. For example, the the activity manager controls life cycle of the apps. The content provider manages sharing data between the apps. The telephony manager provides sevices regarding voice calls. The resources manager regulates resources that are needed for running the apps. Finally, the Application Layer which is the topmost layer where the phone's functions are provided to the end-user. The application layer provide functionalities that include making calls, managing contacts, sending messages, and browsing web. In this layer, Android provides a set of core applications, such as email client, calendar, browser, maps, contacts, SMS program, gallery, and etc.

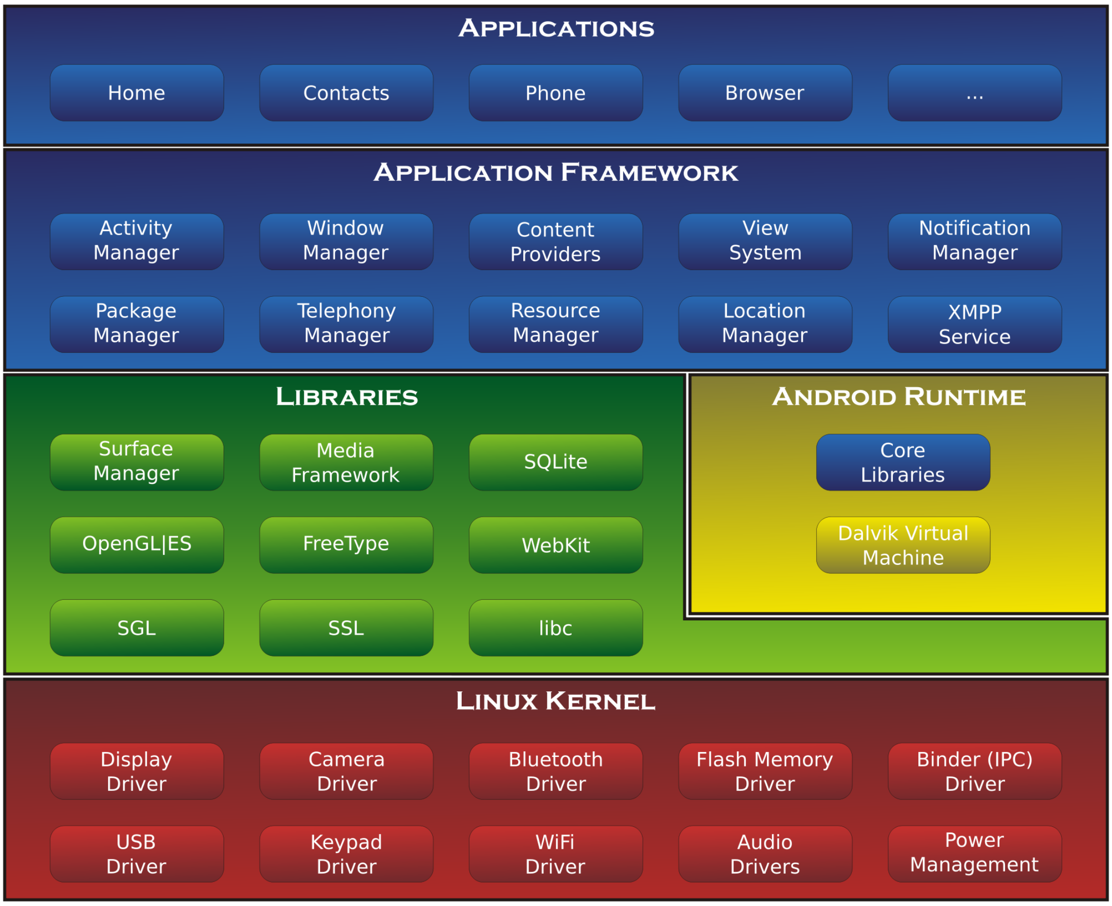


Figure 2.1: Android's Stack Structure

2.2 Android Application Components

In the development phase, an Android application consists of two folders and one file: Class, Resources and AndroidManifest.xml, respectively. The Class folder contains the apps' source codes; the Resources folder contains the app's multimedia; AndroidManifest.xml is the app's configuration file that lists essential information about the app for the Android system. The information that is listed in the AndroidManifest.xml file is as follows: Java package name, the app's components, hosted processes, permissions, instrumentation classes, and other libraries. During the compiling phase, tboth folders and the AndroidManifest.xml file are bundled together to generate the executable file of the application in .apk format. The structure of Android application consists of four components: Activity, Service, BroadCastReceiver, and ContentProvider [4]. All those components are defined by the app's developer in the AndroidManifest.xml file.

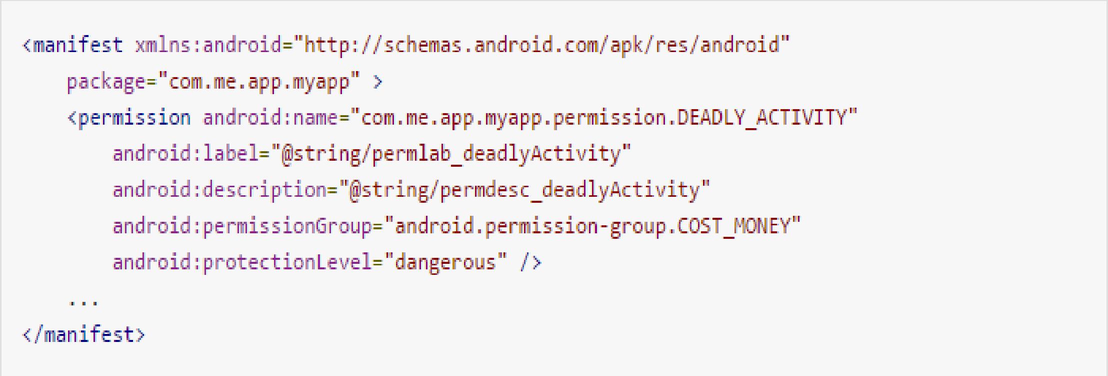
- Activity: defines the user interface is triggered by the user when he interacts with app's interface components such as: buttons, menus, icons, checkboxes, etc.
- Service: defines the background processes such as downloading a file or playing music after closing the app UI. Any component can start a service by calling one of the two methods:
  - StartService(): The service continues running till explicitly stopped.
  - BinService(): The service is bound to the component. It continues running as long as the component is running and stops when the component stops.
- BroadCastReceiver: used by the app as a mailbox to receive and respond to the broadcast messages (intent) of other apps or the system, such as the message is sent by the system when the battery reaches a low limit.
- ContentProvider: used to store the app's data and to share it with other apps; it provides database functions of inserting, deleting, and querying.

2.3 Android Security Features

Android security aims to protect user's data and phones' hardware. system, and software. The main foundations of the Android's security are the following: relying on Linux kernel, applications sandboxing, applications signing, and application-defined and user-granted permissions. The Linux kernel is commonly trusted to be used in highly sensitive-security environments. Due to its open environment, Linux security is constantly enhanced by security specialists, developers who fix and patch security bugs, and attackers who find vulnerabilities to be exploited. It also offers the ability to remove the unnecessary and insecure parts from the kernel. The apps sandboxing feature isolates the apps' processes and data from others under a unique UID. In the kernel, Android gives each app a distinct Linux user ID at installation time. In other words, each app has a constant unique UID for whole the duration of its life. The same app may have a different UID on other devices what matters is that two different apps cannot be assigned with one UID. Because each app has its own UID, they cannot run in the same process instead they need to run separately under its UID. That isolates the running process to secure apps from each other. Also, the data of any app is stored under its UID and is inaccessible by the other apps. The application signing feature, requires that any apps' .apk file must be signed by the developer's certificate to identify the app's author. This feature enables the apps to share one UID if they were signed by the same certificate. It also allows the system to grant or deny the signature-level permissions; the system grants the signature-level permissions to the requested app, if it is signed with the same certificate of other apps that declared the permissions. Finally, the permission model that is adopted by Android protects the phone's resources and functions be making them accessible only to the apps that are granted with the appropriate privileges. By default, no apps have permissions to handle the phone's hardware, software, functions and data. The apps' developers need to declare required permissions for the app's functionality. At installation time, the users need to grant requested permissions otherwise the installation is terminated by the system. The next section illustrates the Android permission model in more detail.

2.4 Android Permission Model

The permissions model is the main security concept that Android security relies on. Android runs applications separately in sandboxes. Each app is run in an isolated environment where it has no access to the system's resources. The permissions must be given to the app to be able to access and use system resources that are required for its functionality. All the permissions that must be declared in the AndroidManifest.xml file by the developer in the development phase. These permissions also must be granted by the system or the user at the installation time; once they are granted they could not be changed unless the application is uninstalled by the user. The permissions can be declared in one or more <permission>tags in the AndroidManifest.xml file; they also must be defined with required and optional attributes. The <label>and <description>attributes are the strings that are displayed to the user at installation time. These attributes must be clearly defined to help the user in understanding the privileges that the permission indicates. The <permissionGroup>attribute is optional and used by the system to display the category of the permission to the user. The <protection-Level>attribute is required to identify the security level of the permission; it defines the criticality of the app privileges. The figure below shows the DEADLY_ACTIVITY permission along with its attributes.



```
<manifest xmlns:android="http://schemas.android.com/apk/res/android"
    package="com.me.app.myapp" >
    <permission android:name="com.me.app.myapp.permission.DEADLY_ACTIVITY"
        android:label="@string/permlab_deadlyActivity"
        android:description="@string/permdesc_deadlyActivity"
        android:permissionGroup="android.permission-group.COST_MONEY"
        android:protectionLevel="dangerous" />
    ...
</manifest>
```

Figure 2.2: AndroidManifest.xml file

The permissions model uses the two <uses-permission>and <permission>tags to govern apps' access to the system resources and other app's data, respectively. The <uses-permission>tag defines the permissions that the app needs to access specific data, hardware, software and other system resources. On the other hand, the <permission>tag defines the permissions that other apps need to have access to the app's data and components. In other words, it defines how the app's components can be accessible by the other apps.

2.5 Android Permission Protection Level

Android has more than 130 built-in permissions; it also allows developers to declare new permissions for their apps called dynamic permissions. The built-in permissions are classified into four security levels: normal, dangerous, signature, and signature or system.

- "normal": a low risk permission that enables the app to access to the least critical system resources; it is automatically granted by the system without notifying the user.
- "dangerous": a high risk permission that enables the app to access the user's private data and the phone's hardware, system and software. The dangerous permission is shown on the screen at installation time to the user who is responsible

for granting this kind of permission. The user has to grant the requested permissions under his understanding and acceptance of the consequences, otherwise the installation process is terminated by the system.

- "signature": a permission granted by the system only if the app requests a permission that is declared by another app and both apps are signed with the same certificate. This permission is granted automatically by the system without notifying the user if tboth apps have the same certificate.
- "signtureorsystem": a permission granted by the system only if the apps are in the Android system image or signed with the same certificate of the app that declared the permission. This permission is granted automatically by the system without notifying the user.

2.6 Android Malware

The table below briefly lists most common Android malware types and its characteristics

Type	**Definition**	**Example**
Trojan	Masquerades as a benign app to hide its maliciousness identity. It offers useful functionalities to the user but performs malicious activities in the background without knowledge of the user.	FakeNetFlix, Zsone, Zitmo, Spitmo, Fakeplayer, Android.Foney,
Backdoor	Enables remote access to the system and bypasses system's authentication mechanism. It usually exploits vulnerabilities in the system to take root's privileges; it has ability to itself and remain undetected.	Basebridge, KMin, Obad.
Worm	Copies and spreads itself over a network's node without need to be launched by a system's user.	Android.Obad.OS
Bot	Enables an attacker to remotely control the device from a server called Bot-master. The attacker commands the system other infected ones to launch an attack such as: DDoS.	Geinimi, Beanbot, Anserverbot,
Spyware	Sends user's data such as: contacts, messages, location, and other confidential data to a remote server. and activities on the device and collects	Nickyspy, GPSSpy.
Adware	Sends personalized advertisements based on a user's collected data such as location.	Plankton
Ransomware	Locks the system to make it inaccessible until some ransom is paid by the user.	FakeDefender

Table 2.1: Android Malware Families

Chapter 3

Related Work

In this chapter, we survey some research studies in detection malware in Android environment. There are mainly two approaches are used to detect malware: static analysis and dynamic analysis. Static analysis technique examines the app's source code without executing it to detect malicious patterns; the executable app is disassembled to the source code files from where many features are extracted such as: permissions, hardware components, broadcast receivers, APIs, intents, data flow, control flow, etc. On the other hand, dynamic analysis examines the app in a run time environment and monitors the app's dynamic behavior and the system's responses; dynamic features are monitored like network connections, system calls, resources' usage, etc. Commonly, in both approaches, the data is collected to train machine learning classifiers to build a separation modeling between benign and malicious characteristics of the apps. The following sections show in details some research studies have been conducted in the both approaches.

3.1 Static Analysis

(Seo, Gupta, Sallam, Bertino, & Yim, 2014) proposed (DroidAnalyzer) that uses permissions, dangerous APIs and keywords associated with malicious behaviors to detect potential malicious scripts in Android apps [26]. Lists of common malicious APIs and keywords were collected by static analysis from a large dataset of Android malware. These lists are used in the algorithm of DroidAnalyzer which depends on keywords searching technique. The lists define suspicious keywords are used in malicious actions such as root exploiting, leakage user private data, cost money through sending SMS or calling premium numbers. Malware from different families were analyzed to build up those lists of malicious and suspicious keywords, API, and commands. For instance, the monetization malware usually contain sendsms() and ocalContentResolver2.delete()

APIs. In case of spyware, that gather user's SMS, they contain APIs such as getMessageBody(), getOriginatingAddress(), getDateTimeinstance(). The tool mainly takes the app's disassembled code as an input and infers the risky APIs and their suspicion level as an output. The tool scans the apps' code for matches with the lists; then, it reports 4 suspicion levels: R, RS, S and C. The level R indicates surely rooting or root exploit app. The level RS indicates a suspicious as rooting app or for rooted phones. The level S indicates a suspicious malware without rooting exploit. The level C indicates a safe app without suspicious APIs nor keywords.

(Arp, Spreitzenbarth, Hubner, Gascon, & Rieck, 2014) proposed (DERBIN) a lightweight static analysis framework that extracts a set of features from the app's AndroidManifest.xml (hardware components, requested permissions, App components, and filtered intents) and disassembled code (restricted API calls, used permissions, restricted API calls, network addresses) to generate a joint vector space [11]. Support Vector Machines (SVM) was applied on the dataset to learn a separation between the two-classes of apps (benign and malicious). The system was tested with 123,453 benign and 5,560 malware; it reported successfully 94% of the malware with a false positive rate of 1%. The system also gives explanations to the user with identifying the suspicious properties and the malicious patterns of the detected malware in meaningful descriptions.

(Wu, Mao, Wei, Lee, & Wu, 2012) proposed (Droidmat) that detects malware through analyzing AndroidManifest.xml and tracing systems calls [29]. Droidmat depends on static analysis of the apps' permissions, components, intent messages, and API calls. In the first, Droidmat extracts different features from the apps' AndroidManifest.xml such as: permissions and intention messages. Then, it marks the app's components: activity, service, and receiver as initial points to trace the API calls that are related to the permissions. The features were collected are: permissions, components (activity, receiver, and service), intents, and usage of the API calls with what kind of components. Next, it applies K-means algorithm to model malware while the number of clusters are determined by singular value decomposition (SVD).

(Sanz, Santos, Laorden, Ugarte-Pedrero, & Bringas, 2012) proposed a machine learning method for automatic Android apps categorization and malware detection [25]. The method analyzes different sets of the apps' features are extracted from the AndroidManifest.xml file, the source code files (the frequency of occurrence of the printable strings), and Android market (permissions, rating, and number of ratings).The machine learning algorithms were applied: Decision Trees (DT), K-Nearest Neighbour (KNN), Bayesian Networks (BN), Random Forest (RF) and Support Vector Machines (SVM). For the results, BN was reported as the best classifier while RF as the second, and DT as the worst.

(Sahs, & Khan, 2012) built up a system uses the extracted permissions and the control flow graphs from benign apps to train one-class Support Vector Machines (SVM) classifier [22]. The classifier was trained to give always positive for the trained data and a negative for the tested data that is adequately different from the trained ones. The team used kernels over binary vectors, strings, sets of features, non-standard permissions, and apps. The Bit-vector classifies apps based on the requested permissions; it was able to report all the malware but also reported falsely half of benginin as malicious. The string kernel reported mostly all the sample as malware. On the other hand, the graph kernel had a higher false positive rate (benign classified as malware) than true negative (malware classified as benign) rate.

(Vidas, Christin, & Cranor, 2011) proposed Permission Check Tool to assist Android developers in declaring the least privilege permissions that are required for the app's functionality [28] . The tool automatically analyzes the app's code and derives the minimum set of permissions that are needed to be run.

(Fuchs, Chaudhuri, & Foster, 2009) proposed (SCandroid) that analyzes data flow in Java codes of Android apps by using a modular that traces data movement across the app's components [18]. The idea of SCandroid is based on the common structure of basic components that the apps follow and intercommunication between them.

(Enck, Ongtang, & McDaniel, 2009) proposed (Kirin) that applies a set of predefined security rules at installation time to detect any match between the app and templates of malicious patterns [15]. Kirin declares a specific combination of permissions could be dangerous and used to launch malicious actions. The system consists of three components: installer, security service, and database of security rules. The installer extracts the security configuration from the app's AndroidManifest.xml file. Next, the security service applies the security rules against the extracted configuration; if there is a match then the app fails in passing validation process; in this case, the system provides two choices either terminating the installation or providing the results of analyzing the risk of granting the required permissions to the user to make his decision. On the drawbacks side, Kirin functions only at installation time and doesn't provide any support at runtime. Also, it is limited to the available information in the package's AndroidManifest.xml file.

3.2 Dynamic Analysis

(Shabtai, Kanonov, Elovici, Glezer, & Weiss, 2012) proposed Artificial Neural Networks (ANNs)-based system to detect unknown Android malware through analyzing the apps' permissions and system calls [27]. Two types of ANN were used: Feedforward Neural Networks (FNN) and Recurrent Neural Networks (RNNs). The Feedforward Neural Networks were used for training the model with the requested permissions to build distinguishable patterns between goodware and malware. The Recurrent Neural Networks (RNNs) were used for training the model with the system calls of the benign apps' execution behaviors.

(Zhou, Wang, Zhou, & Jiang, 2011) proposed (DroidRanger) to detect known and unknown malware using two approaches: permission-based and heuristics-based [31]. DroidRanger basically consists of two engines: footprint-based and heuristic-based. The footprint-based detection engine uses permission-based filtering and behavioral footprint matching to detect known malware. While, the heuristic-based engine is used to detect zero-day malware. The permission-based filtering filters out the apps that do not request malicious permissions that are essential for malware's functionality. After that, the behavioral footprint matching tries to matches between the app and other malware's behaviors could be found in the AndroidManifest.xml, byte code, APIs, and structural layout of the application. On the other hand, the heuristics-based filtering monitors automatically specific malicious actions such as: dynamic loading for a new code or native Linux system calls; it also analyzes the logged system calls to detect malicious behaviors.

(Ongtang, McLaughlin, Enck, & McDaniel, 2009) proposed Secure Application Interaction (SAINT), an infrastructure to control granting the permissions to the app at the install-time [15]. Also, SAINT controls how the app uses the permissions at run-time for interaction with other interfaces of other apps, PKI, and the Android system. The SAINT was proposed as an extended policy infrastructure for the Android's policies. SAINT works by applying three groups of policies: install-time policy, run-time policy, and administrative policy. At installation time, SAINT's installer extracts the requested permissions from the app's AndroidManifest.xml; then, it inquiries the AppPolicy provider for each permission to match it with a set of predefined rules. Then, the AppPolicy returns the decision of proceeding the installation or terminating it. The SAINT's install-time policy consists of three components: label, owner, and conditions; the label declares the permission to be granted; the owner declares the app that requests the permission; the conditions are a set of checks are applied on the app's attributes. At run-time, SAINT allows IPCs between the apps when both the caller and the callee are passed the checking process by AppPolicy provider: if the conditions of IPC are not satisfied, it is blocked otherwise the IPC is directed to the Android permission checks which allows IPC to continue based on the Android's policy. SAINT applies two types of policies at run-time: access policy and expose policy. The access policy governs applying the security measurements on the caller that initiates the IPC and the IPC. While, the expose policy governs applying the security measurements on the callee which receives the IPC. SAINT's architecture consists of three components: installer, mediator, and AppPolicy Provider. The SAINT's installer is a modified version of the Android's installer that parses the package to extract its configurations to be examined by the run-time policy. The SAINT's policy is implemented in xml format to match with the app's AndroidManifest.xml: the installer matches between the app' configurations and its corresponding permission-granting policy that are retrieved from the AppPolicy provider: if there is no conflict the app's installation is processed, otherwise it is terminated. The SAINT's mediator enforces the runtime policy and governs interaction between the components such as: starting a new activity, accessing content providers, binding components to services and receiving broadcast intents. The AppPolicy Provider is a SQLite database where the install-time and run-time policies are stored; the AppPolicy Provider's datbase is stored in the system directory/data/system.

Many tools of dynamic detection use various techniques and features to detect malicious apps; Virusmeter measures high power consumption [21], pB-MDS uses a user's inputs and system calls [30], Crowdroid applies k-means on vectors of the system's calls [13], AntiMalDroid applies SVM algorithm on vectors of logged behavior sequences [31]. AppInspector and TaintDroid track the flow of sensitive data between third-party apps [14]. A host-based malware system monitors: CPU consumption, number of sent packets through the Wi-Fi, number of running processes, Keyboard/Touch-screen pressing and Application startup [27].

Chapter 4

Design & Methodology

In this chapter, we discuss the methodology of this study which covers the framework, the apps sample, reverse engineering the apps, extracting and preprocessing features, selecting the best subset of features using features selection algorithms, and building the classification models.

This study lays out detection Android malware as a machine learning problem. As a result, the work flow of this study can be basically divided into two distinct phases: training phase and classification phase. In the **training phase**, a set of features (Permissions, Broadcast Receivers, API Classes) are parsed from the source codes of a large sample of malware and benign apps; the extracted features are represented in a binary vector format; the features then are filtered with using attribute selection algorithms to end up with the best subset of the most significant and relevant features that define the characteristics of goodness or maliciousness of the apps; three machine learning algorithms (Support Vector Machines, Random Forests, and Adaboost) are trained with the datasets to build classification models. In the **classification phase**, the same set of features are extracted from a sample of benign and malware to be tested and classified by the learned models from the training phase.

This study as mentioned before aims to enhance the performance of machine learning classifiers by relating between apps' features and the category that they belong to. Good applications under a specific category tend to have a common set of features while the malicious apps tend to have abnormal, less, or more features compared to the good apps in the same category. To achieve the goal of this study, we use machine learning algorithms to train and build three groups of classification models: `(allCateg)`, `(musicCateg)`, and `(personaCateg)`. The `(allCateg)` classifiers are trained with the features of the top rated apps on Google Play Store and malware from all categories. The `(musicCateg)` classifiers are trained with the features of the top rated apps on

Google Play Store and malware from ”Music & Audio” category. The (`personaCateg`) classifiers are trained with the features of the top rated apps on Google Play Store and malware from ”Personalization” category.

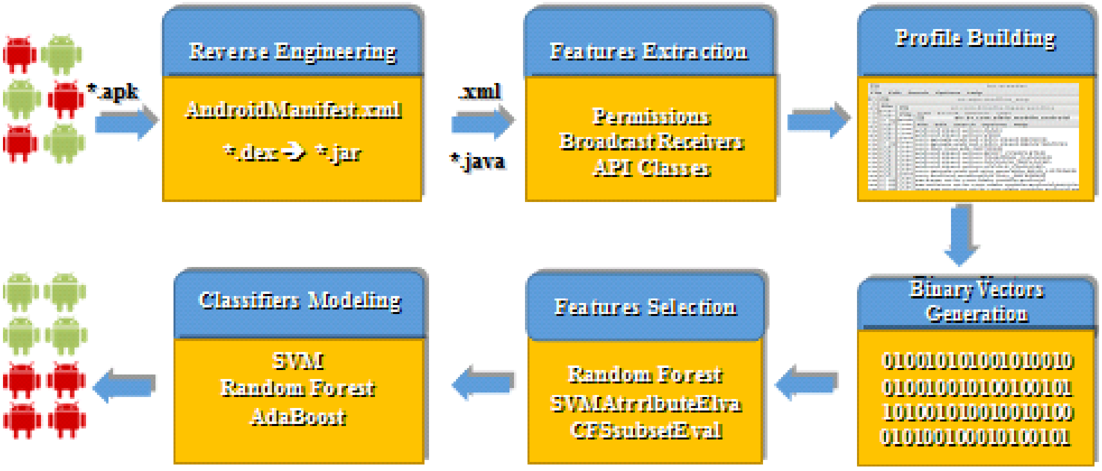


FIGURE 4.1: The framwork of the study

The framework of this study, as shown in the above figure, consists of six components. The first component is a module to reverse engineer the apk files into source code in forms of AndroidManiFest.xml and java classes. The second component is a module to parse three group of features: permissions, broadcast receivers, and APIs. The third module is to transform the extracted features from each app into a binary vector that can be applicable for machine learning algorithms; each app is represented as a single instance with binary vector of features and a class label indicates whether the app is benign or malicious. The last component is modeling the classifiers by training three machine learning algorithms: Support Vector machines, Random Forests and Adaboost with the binary vectors of the apps in our sample. The learned models are used to detect whether a given app is malicious or benign. The next follow sections explain in details the implementation of this study which cover the datasets, the used tools, the features of our main interest, and the machine learning algorithms.

4.1 Data Collection

For the first part of the study which is building classification models for apps from all categories, we train the models with features of 4063 malicious apps and the top 1000 rated apps from all the 26 categories on Google Play Store.

The second part of our study mainly focuses on relating between the app’s features and a common set of features for the category that belongs to. In this study, we chose to work on two categories of apps: “Music and Audio” and ”Personalization”. The

	All Categories	Music & Audio	Personalization
Benign	1000	854	732
Malware	4063	1336	942
Total	5063	1990	1674

Table 4.1: Datasets allCateg, musicCateg, personaCateg

data is collected from each dataset, separately to train two groups of malware detection classifiers one for music apps and the another one for personalization apps. The `(musicCateg)` dataset contains 855 apps from the top rated apps from “Music & Audio” category on the Google Play store and 1136 malicious apps from the same category. The `(personaCateg)` dataset contains 732 apps from the top rated apps from “Personalization” category on the Google Play store and 942 malicious apps from the same category, as well.

Category	Description	Sub-Categories
Music & Audio	Apps enable the user to play audio files, musical instruments, or listen to radio	Radio, Tuners, chords & scores, Live music & event tickets, Karaoke, singing & lyrics, Guitar, Audio & podcasts.
Personalization	Apps enable the user to customize the device or enjoy some of its features.	Home screen customization, Emojis, themes, smileys, Live wallpapers, Ringtone makers, Weather widgets.

Table 4.2: Categories’ Descriptions

4.2 Reverse Engineering

The apps’ ”apk” files were decompiled into their source codes from where specific group of features were parsed into a corresponding profile for each app. This process was automated by scripting and integrating multiple reverse engineering tools in **Santoku**, a customized Linux system for mobile security, to transform the .apk files into source codes in formats of **AndroidMainfest.xml** and **.java** files. The table below shows the tools were used in the Reverse Engineering phase.

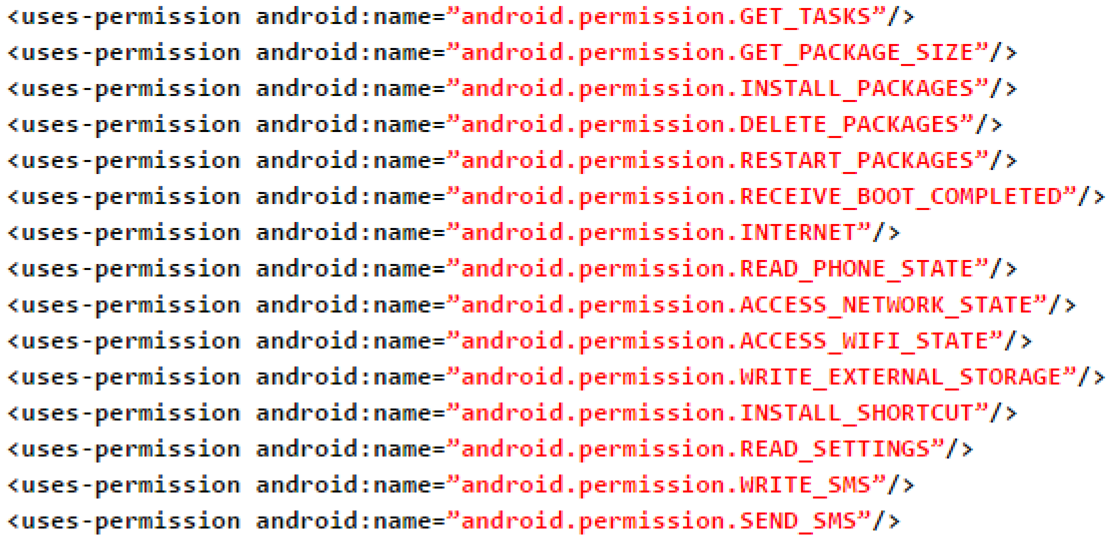
Tool	Use
APKTool	Decodes .apk files into nearly the original forms (.xml, .png, .dex).
dex2jar	Converts .dex files into .jar files.
jd	Converts .jar files into .java files.

Table 4.3: Reverse Engineering Tools

4.3 Features Parsing

Malware detection using data mining techniques require feeding machine learning algorithms with a dataset of instances and variables to learn patterns and build classification models. The features (**Permissions, Broadcast Receivers, APIs**) are parsed from the source codes by a python module; the extracted features are used to construct a binary vector for each app in our sample. If a specific feature, like `READ_PHONE_STATE` permission, is requested by the app, it represented by 1 in its binary vector while it is represented by 0 if it is not requested. The next sections explain the investigated features.

4.3.1 Permissions



```
<uses-permission android:name=”android.permission.GET_TASKS”/>
<uses-permission android:name=”android.permission.GET_PACKAGE_SIZE”/>
<uses-permission android:name=”android.permission.INSTALL_PACKAGES”/>
<uses-permission android:name=”android.permission.DELETE_PACKAGES”/>
<uses-permission android:name=”android.permission.RESTART_PACKAGES”/>
<uses-permission android:name=”android.permission.RECEIVE_BOOT_COMPLETED”/>
<uses-permission android:name=”android.permission.INTERNET”/>
<uses-permission android:name=”android.permission.READ_PHONE_STATE”/>
<uses-permission android:name=”android.permission.ACCESS_NETWORK_STATE”/>
<uses-permission android:name=”android.permission.ACCESS_WIFI_STATE”/>
<uses-permission android:name=”android.permission.WRITE_EXTERNAL_STORAGE”/>
<uses-permission android:name=”android.permission.INSTALL_SHORTCUT”/>
<uses-permission android:name=”android.permission.READ_SETTINGS”/>
<uses-permission android:name=”android.permission.WRITE_SMS”/>
<uses-permission android:name=”android.permission.SEND_SMS”/>
```

Figure 4.2: Permissions Requested by Malware

The Android system runs apps in sandboxes on the virtual environment(Davik VM) where apps are isolated from direct interfering with the system's resources and other apps'. Android regulates apps access to the resources of hardware, OS, and other installed apps through the Permissions model; the apps need to be granted with the appropriate permissions to perform any kind of privileged processes on the system. The app's developer needs to declare the required permissions for the app in the AndroidManifest.xml file; and the user needs at installation time to grant the requested permissions to proceed installation or otherwise the installation process is terminated.

The permissions are the most important and common features that have been used in detecting malware in the Android environment. We here also considered them as long as other groups of static features. Many studies in the field have worked on building models of permissions that are requested by malicious apps to define sets of permissions that if they are granted that enable apps to launch malicious activities. In our study, we relate between the permissions that are requested by an app and a common set of permissions for the category that the app belongs to by training classification models with the permissions of the top rated apps in the same category. Undoubtedly, that the functionalities of a specific category require a set of permissions while if the app requests uncommon or overprivileged permissions compared to the benign apps in the same category that can indicate a malicious intention.

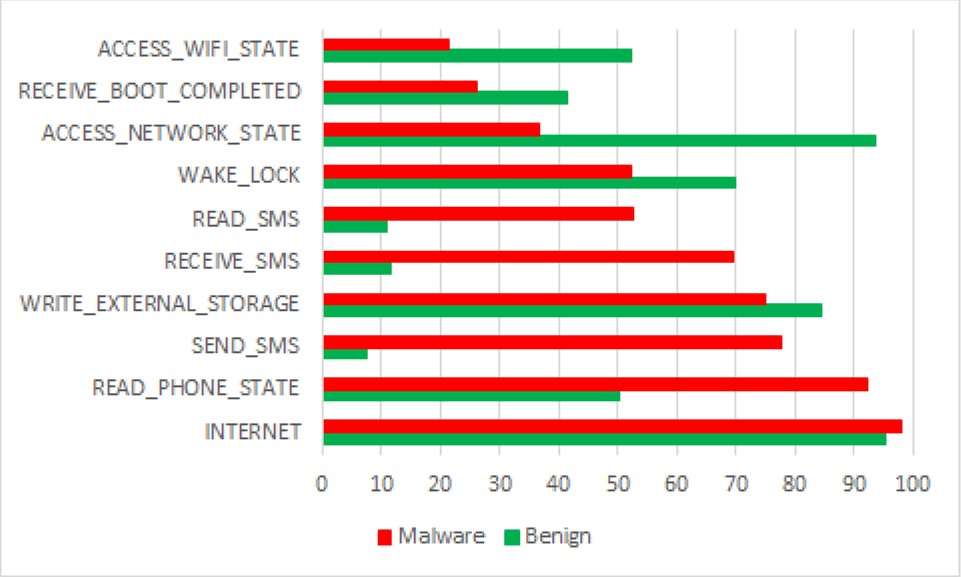


FIGURE 4.3: Top 10 Requested Permissions in ”allCateg” Dataset

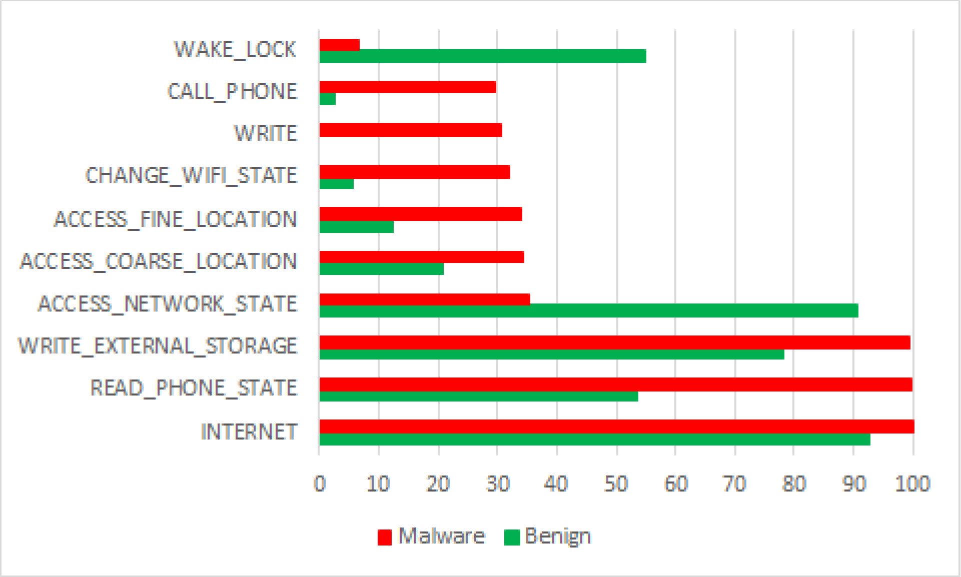


FIGURE 4.4: Top 10 Requested Permissions in ”msicCateg” Dataset

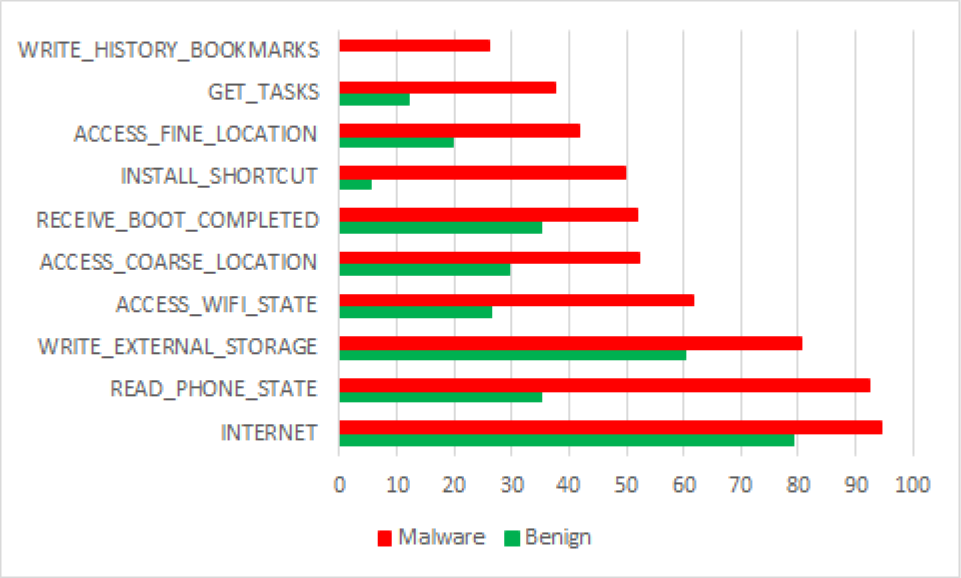


FIGURE 4.5: Top 10 Requested Permissions in ”personaCateg” Dataset

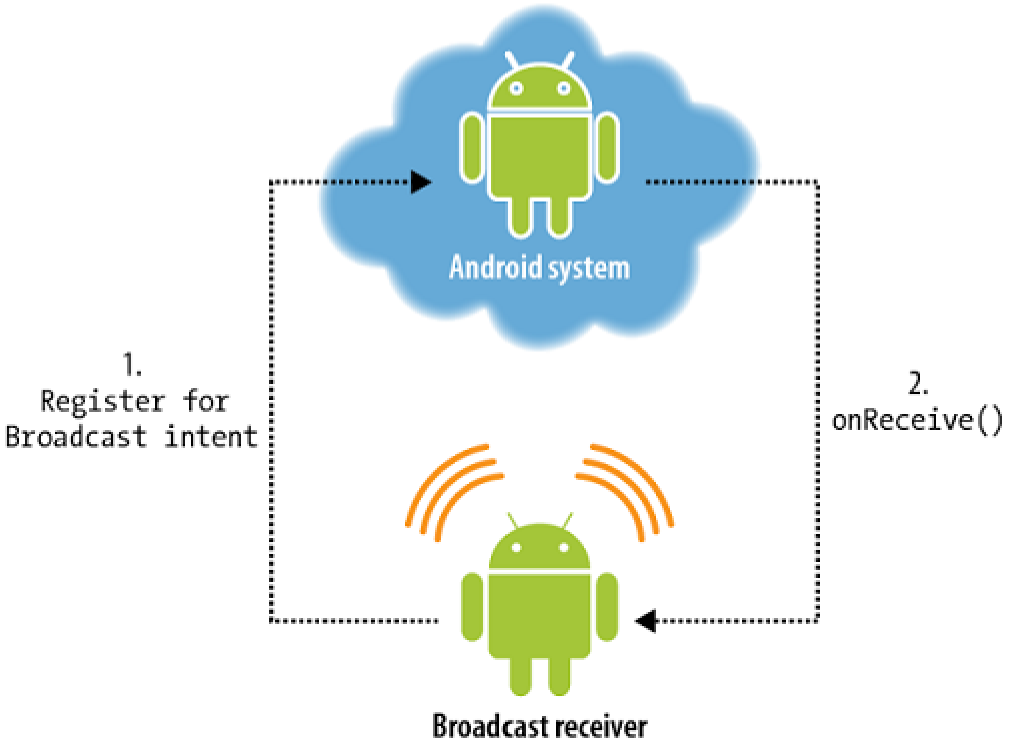
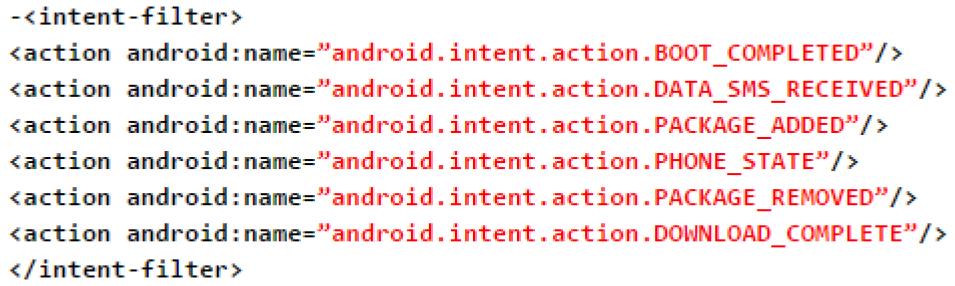


FIGURE 4.6: Broadcasts Mechanism in Android

4.3.2 Broadcast Receivers

Android allows apps to interact with the system and other apps by sending and listening to broadcasts that are sent across the system and the installed apps. Android announces systems events in broadcast messages that can be received by other apps that listen to specific kind of events such as (`BOOT_COMPLETED`, `SMS_RECEIVED`, CONNECTIVITY_CHANGE, etc...). Apps also can send broadcasts to other apps to trigger some actions such as an app needs to open a web page so any installed web browser can response. Broadcast receivers can be registered statically in the AndroidManifest.xml file or dynamically in the code. In our study, we mainly focus on the broadcast receivers that listen to the Android system events. We relate between the app's broadcast receivers and the Android broadcast events that the top rated apps in the same category they listen to.



```
-<intent-filter>
<action android:name=”android.intent.action.BOOT_COMPLETED”/>
<action android:name=”android.intent.action.DATA_SMS_RECEIVED”/>
<action android:name=”android.intent.action.PACKAGE_ADDED”/>
<action android:name=”android.intent.action.PHONE_STATE”/>
<action android:name=”android.intent.action.PACKAGE_REMOVED”/>
<action android:name=”android.intent.action.DOWNLOAD_COMPLETE”/>
</intent-filter>
```

FIGURE 4.7: Broadcasts Receivers requested by malicious apps

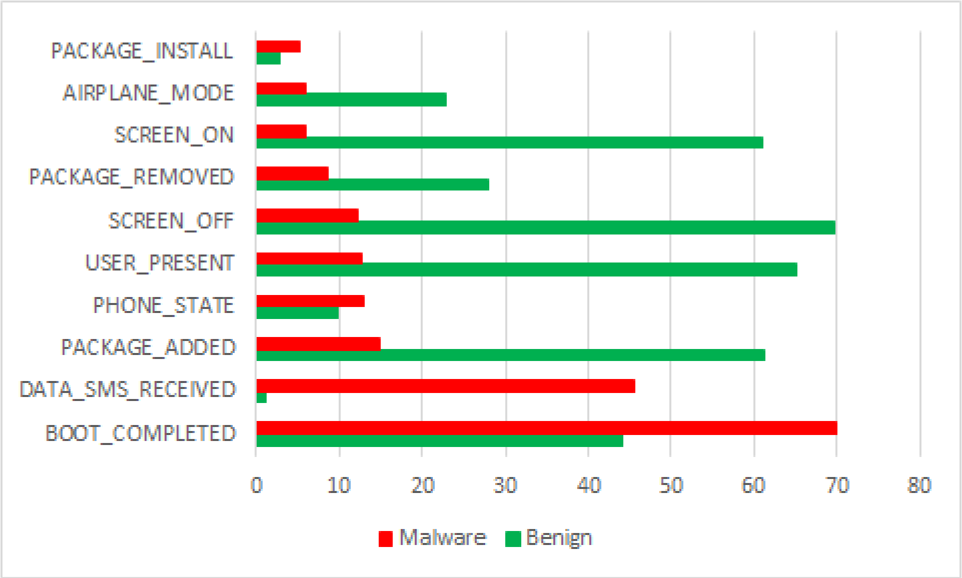


FIGURE 4.8: Top 10 Broadcast Receivers in ”allCateg” Dataset

4.3.3 APIs Classes

APIs are classes and interferes that enable apps to interact and lunch functionalities of the underlying Android system. Android platform provides a hierarchical structure of classes based on the targeted version of the Android system which specified by the API level. The framework API level 23 provides a core set of 232 packages and hundreds of classes and interfaces. We use the APIs as features to identify the processes that the app wants to execute; malicious apps call sensitive APIs that enable lunching malicious

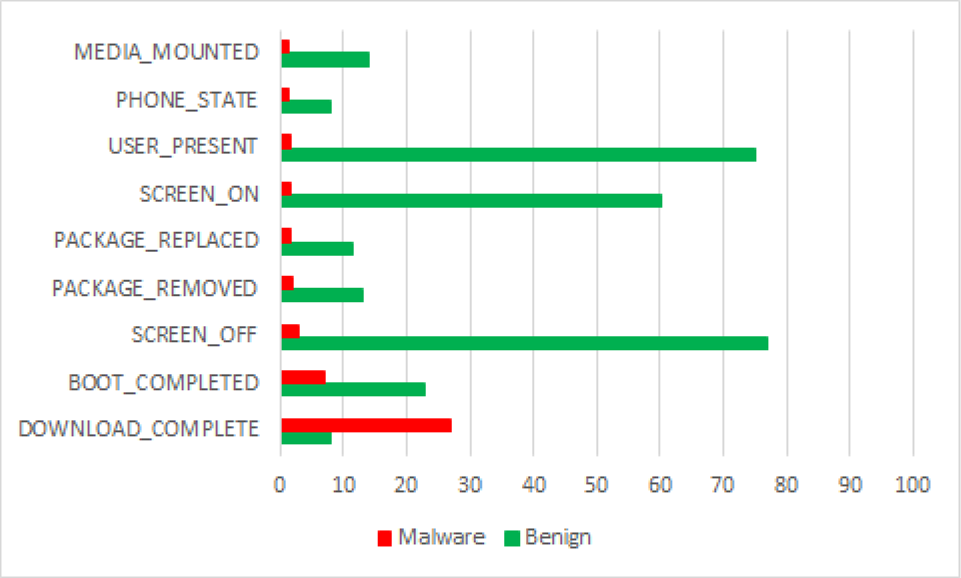
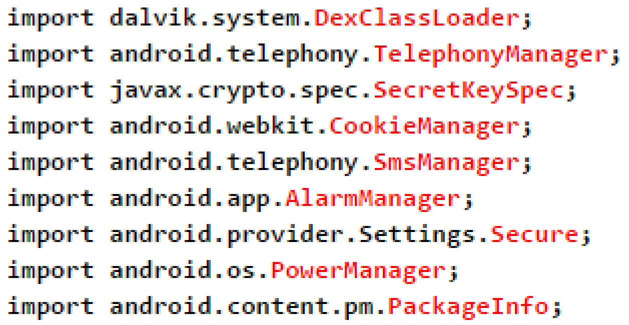


FIGURE 4.9: Top 10 Broadcast Receivers in ”musicCateg” Dataset

activities such as loading external jar files by calling `loadClass()` or collecting device’s info by calling `getDeviceId()`. Apps are under a certain category call a certain set of APIs that are needed for providing the category’s functionalities. We relate between the APIs requested by the app’s and the common set of APIs that requested by the benign apps in the same category.



```
import dalvik.system.DexClassLoader;
import android.telephony.TelephonyManager;
import javax.crypto.spec.SecretKeySpec;
import android.webkit.CookieManager;
import android.telephony.SmsManager;
import android.app.AlarmManager;
import android.provider.Settings.Secure;
import android.os.PowerManager;
import android.content.pm.PackageInfo;
```

FIGURE 4.10: APIs requested by malicious apps

4.4 Binary Vector Generation

Each app in the sample was represented as a single instance with binary vector of features and a class label indicates whether the app is benign or malicious. The figure 4.14 shows the instances of the dataset; if the feature is present in the app it is represented by 1, if it is not present in the app, it is represented by 0.

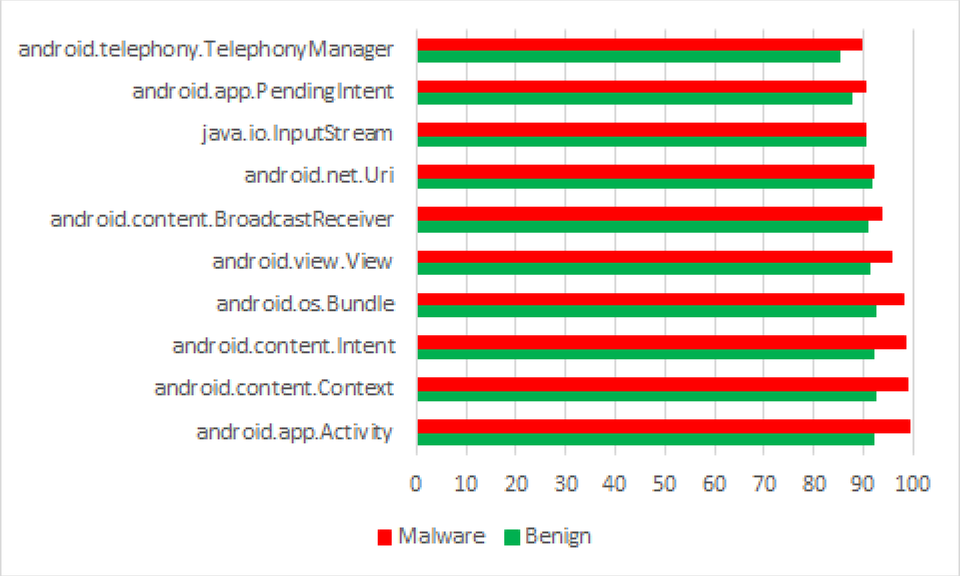


FIGURE 4.11: Top 10 Requested APIs in "allCateg" Dataset

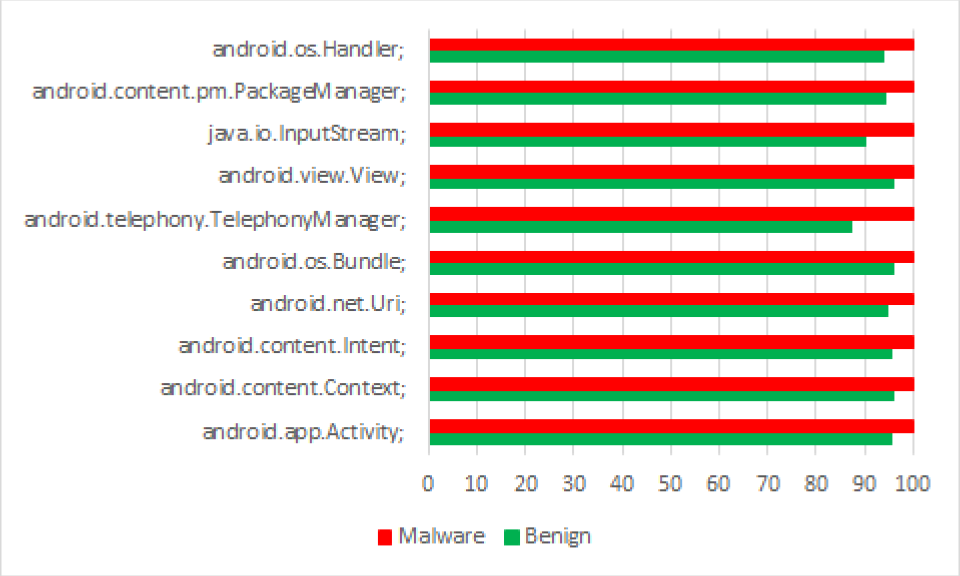


FIGURE 4.12: Top 10 Requested APIs in "musicCateg" Dataset

4.5 Features Selection

This step aims to reduce the high-dimensional of the variables space in the datasets by identifying subsets of features that are the best predictors for the class labels. Generally, features selection enhances the generalization of the learned models by reducing overfitting, increases the classification accuracy, and reduces the training and classification times, produces simplified interpreted models. Typically, features selection techniques are divided into three main approaches: filters, wrappers, and embedded. Wrappers firstly search the variables space for subsets of features and then they evaluate the selected features by applying the machine learning algorithms. Filters use statistical

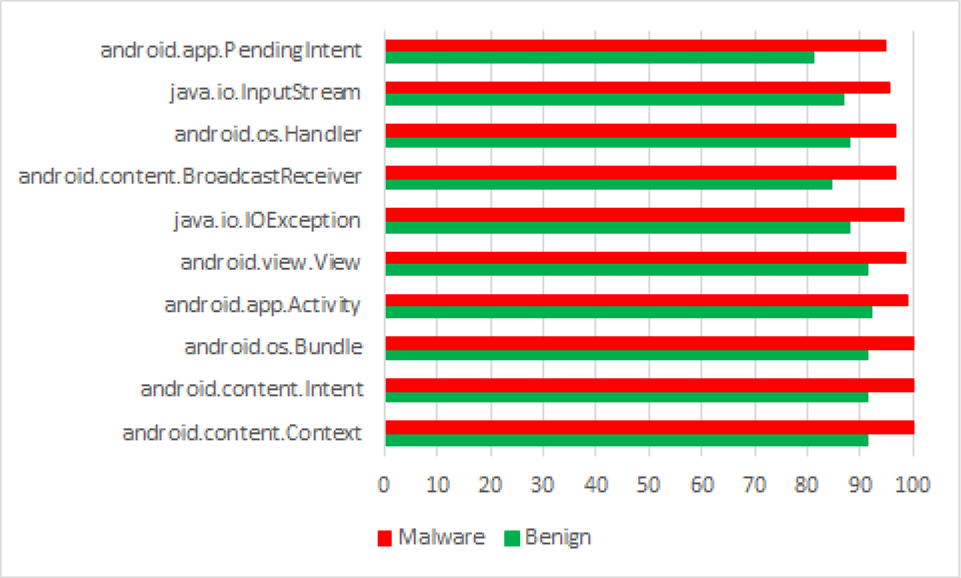


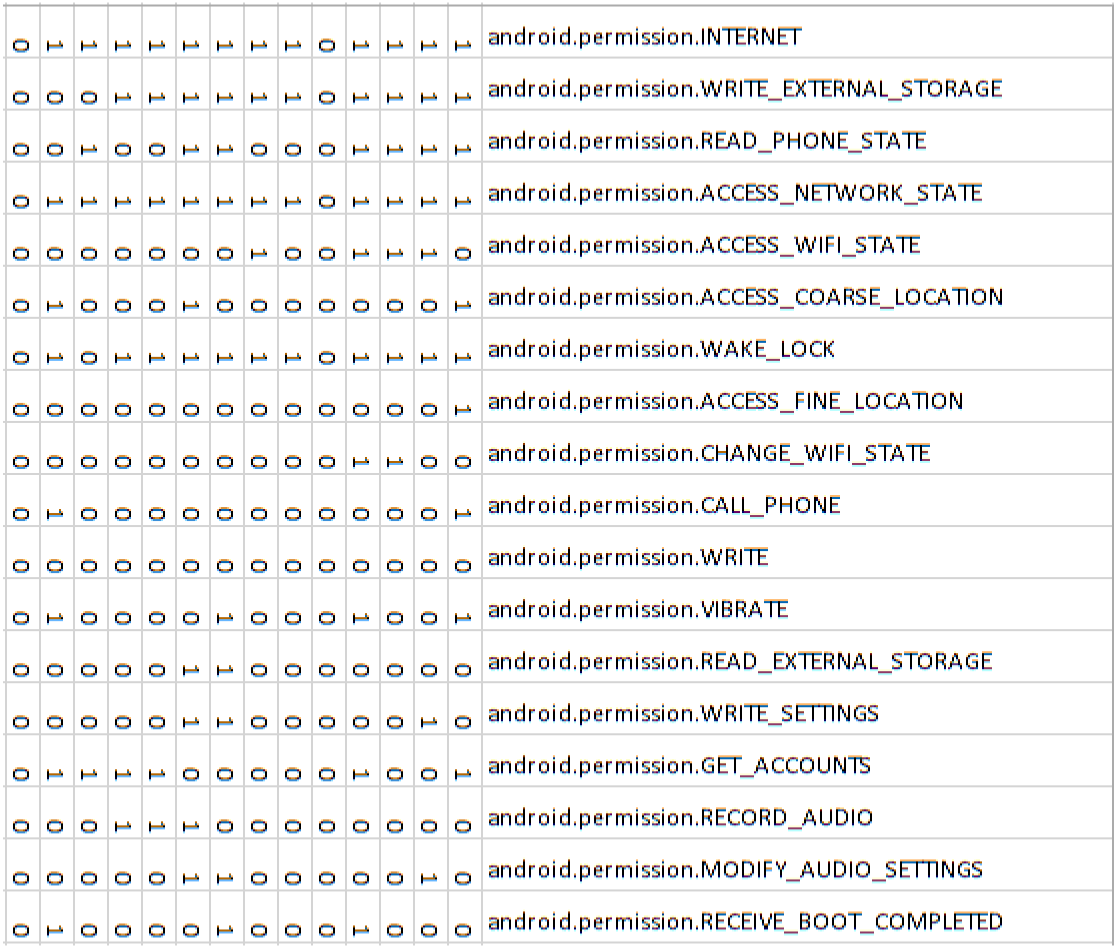
Figure 4.13: Top 10 Requested APIs in "personaCateg" Dataset

analysis to rank each feature based on the statistical properties of the dataset; the features then kept or filtered out based on their score; the drawback of this technique that features are selected without involving the machine learning algorithm in the process of selecting the features. Embedded techniques selects and builds learned models at the same time, one example of this technique is Random Forests algorithm.

Before applying features selection algorithms, we cleaned the datasets; the features are provided by the **Android** platform were the most important for our consideration in filtering out or keeping a certain set of features for applying the features selection algorithms. For each machine learning algorithm, we used different features selection algorithm.

Groups of Features	All Categories	Music & Audio	Personalization
Permissions	142	57	56
Broadcast Receivers	136	84	92
APIs Classes	2497	2284	1767

Table 4.4: Numbers of Selected Features



0	1	1	1	1	1	1	1	1	0	1	1	1	1	android.permission.INTERNET
0	0	0	1	1	1	1	1	1	0	1	1	1	1	android.permission.WRITE_EXTERNAL_STORAGE
0	0	1	0	0	1	1	0	0	0	1	1	1	1	android.permission.READ_PHONE_STATE
0	1	1	1	1	1	1	1	1	0	1	1	1	1	android.permission.ACCESS_NETWORK_STATE
0	0	0	0	0	0	0	1	0	0	1	1	1	0	android.permission.ACCESS_WIFI_STATE
0	1	0	0	0	1	0	0	0	0	0	0	0	1	android.permission.ACCESS_COARSE_LOCATION
0	1	0	1	1	1	1	1	1	0	1	1	1	1	android.permission.WAKE_LOCK
0	0	0	0	0	0	0	0	0	0	0	0	0	1	android.permission.ACCESS_FINE_LOCATION
0	0	0	0	0	0	0	0	0	0	1	1	0	0	android.permission.CHANGE_WIFI_STATE
0	1	0	0	0	0	0	0	0	0	0	0	0	1	android.permission.CALL_PHONE
0	0	0	0	0	0	0	0	0	0	0	0	0	0	android.permission.WRITE
0	1	0	0	0	0	1	0	0	0	1	0	0	1	android.permission.VIBRATE
0	0	0	0	0	1	1	0	0	0	0	0	0	0	android.permission.READ_EXTERNAL_STORAGE
0	0	0	0	0	1	1	0	0	0	0	0	1	0	android.permission.WRITE_SETTINGS
0	1	1	1	1	0	0	0	0	0	1	0	0	1	android.permission.GET_ACCOUNTS
0	0	0	1	1	1	0	0	0	0	0	0	0	0	android.permission.RECORD_AUDIO
0	0	0	0	0	1	1	0	0	0	0	0	1	0	android.permission.MODIFY_AUDIO_SETTINGS
0	1	0	0	0	0	1	0	0	0	1	0	0	0	android.permission.RECEIVE_BOOT_COMPLETED

FIGURE 4.14: Apps' Binary Vectors

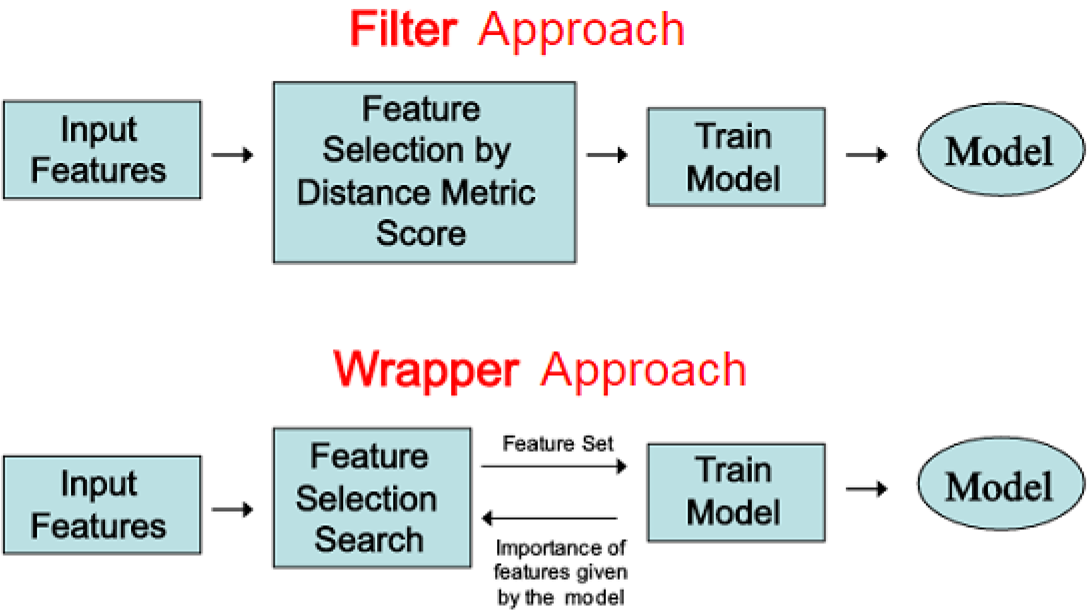


FIGURE 4.15: Features Selection Approaches

4.6 Classification Models

4.6.1 AdaBoost

Adaboost, short for ”adaptive Boosting”, is an ensemble technique and a metaheuristic machine learning algorithm. It is used conjointly with other machine learning algorithms to boost their performance. The algorithm sequentially builds a model based on the errors of previous models by learning a simple classifier and focusing on getting the misclassified data points to be classified correctly in the next round. Weak classifiers like decision trees are used to explore the data points and train a model for the easy to be predicted points, Adaboost then works to get the misclassified data points to be classified correctly by giving them higher weights. The errors of the early experts indicate the hard to be predicated data points. Adaboost improves weak learners and converts them from simple into complex classifiers. Adaboost is prone to overfitting because of its sensitivity to noisy data, but in some problems it can be less susceptible to overfitting compared to other classifiers. It is an efficient classifier for very high dimensional variables space problems; it selects the predictors features and discards the irreverent ones which increases the accuracy of the learned model.

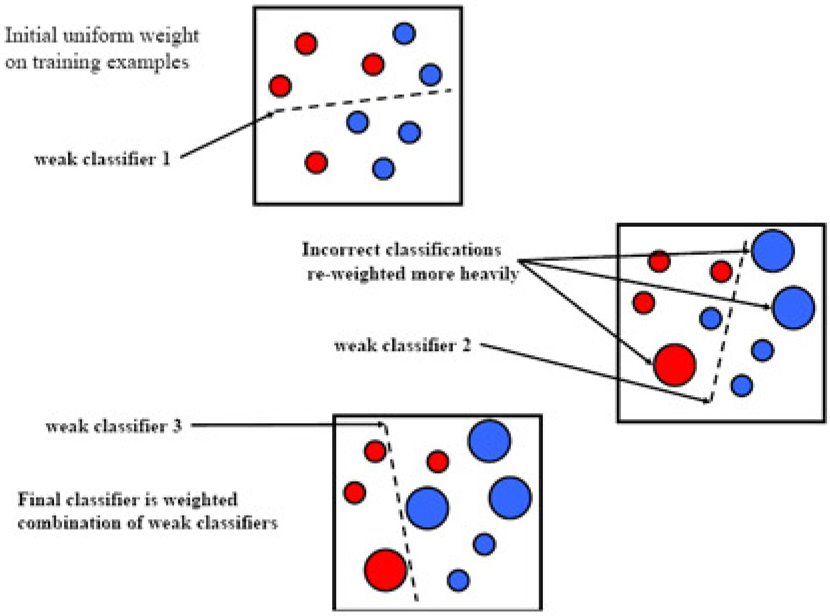


Figure 4.16: AdaBoost

4.6.2 Support Vector Machines

Support Vector Machines (SVM) and also called Support Vector Networks (SVN) are supervised machine learning methods to analyze, detect and match patterns of data for classification and regression purposes. SVM is a non-probabilistic binary linear classifier that assigns training data into one category or more. It also can be used efficiently for nonlinear classification problems using Kernel Trick. Kernel Trick is a class of SVM algorithms that maps the input features into a very high dimensional output space in a simple and cheaper computational way. SVM is a representation of training data as points in the space that conglomerate based on their category in form of groups that are separated by a clear distinct gap called a hyperplane. In the training phase, SVM builds up a model of patterns from the training data which is used as a space for classification phase. In the classification phase, the new input points are mapped into the trained space and categorized based on which side of the gap they fall on. In the figure below a straight line separates between two classes, the new data are mapped into the space if they up the line will be categorized into otherwise into. Hyperplane is a subspace less by one dimension than its ambient space; it is 2-dimensions in 3D space, and a 1-dimension in 2D space. SVM forms a hyperplane or set of hyperplanes for data classification and regression. For more confidence and less generalization error, the hyperplane must be selected by functional margin that makes the distance between the nearest training data points in any class as much larger as possible. We selected SVM because its resistance to over-fitting even in the very high dimensional variables space like our datasets. SVM is the best choice for binary classification problems like ours.

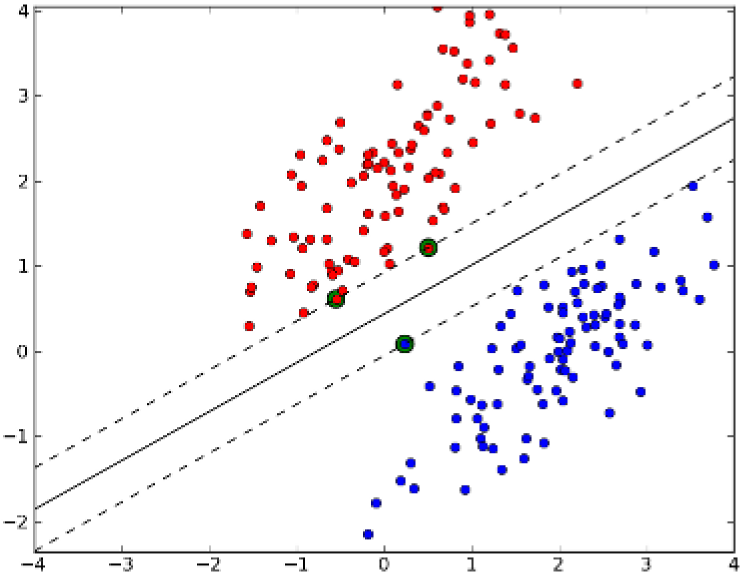


FIGURE 4.17: Support Vector Machines

4.6.3 Random Forest

Random forest is an ensemble algorithm that constructs a collection of decorrelated decision trees. The algorithm uses bagging technique to sample the randomly the instances and features, and then learns a decision tree classifier for each subset of the data. The algorithm grows number of classification trees, for a new input vector to be classified the algorithm puts the input vector down in each classification tree. Each tree gives a prediction class for the input vector, the algorithm decides the class label based on the majority of the votes from all the decisions trees. Random Forests by selecting repeatedly a random subset of features and data, they increase the generalization of the classification models and decrease over-fitting. So, compared to other algorithms, they build high accurate, robust and reliable classification models. They also work efficiently with very large instances and high dimensional features spaces. They learn models and select the best features at the same time; they estimate the importance of the features at training time, in each round the algorithm dominates the most important features that can split the data points into classes to be the root and in the highest levels of the tree while the least important become the leaves of the tree.

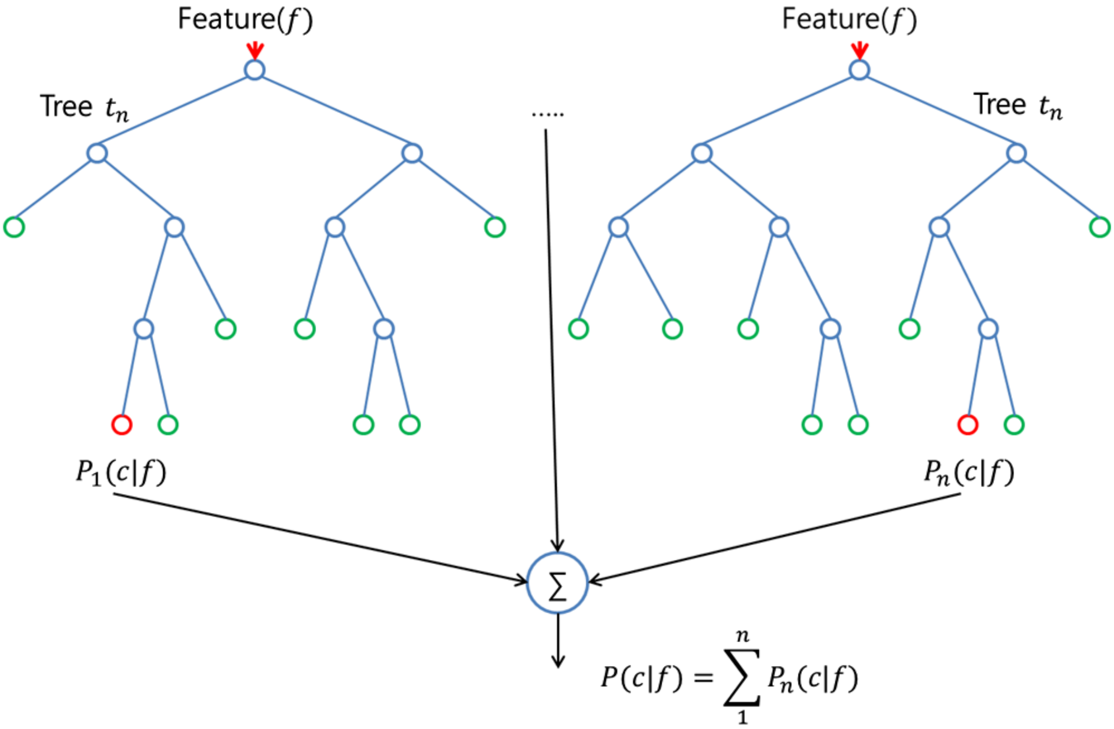


FIGURE 4.18: Random Forests

Chapter 5

Experiments & Analysis Results

In this chapter, we discuss the results of the experiments, evaluate the performance of the classification models, and demonstrate our findings. The first section explains the terminology of the metrics that we used in measuring the performance of the classifiers. The second section shows the results of testing three datasets: apps from all categories with `allCateg` classifiers, apps from "Music & Audio" category with `allCateg` and `musicCateg` classifers, respectively and apps from "Personalization" category with `allCateg` and `personaCateg` classifiers, as well. In the last section, we compare the performance of the non-category and the category-based classifiers at detecting malicious and benign apps from the two categories: "Music & Audio" and "Personalization".

This study aims to improve the performance of the classification models by enhancing the quality of the selected features for training the classifiers. Each category has a distinct functionality from another one; benign apps under a certain category have a common set of features; in contrast, malicious apps tend to request abnormal, less, or more features compared to benign apps in the same category. To detect malicious apps, we relate between the apps' features and the features that are needed to deliver the category's functionality that the app belongs to. To achieve this goal, we prepared three datasets that contain binary vectors of benign and malicious features of: apps from all categories `(allCateg)`, apps from "Music & Audio" category `(musicCateg)`, and apps from "Personalization" category `(personaCateg)`. In the training phase, for each dataset, we built three classification models using: Support Vector Machines, Random Forests, and adaBoost. The classifiers were trained with three groups of features: permissions, broadcast receivers, and APIs. In the testing phase, to validate our approach, music apps were tested with `allCateg` and `musicCateg` classifers, respectively and personalization apps were tested with `allCateg` and `personaCateg` classifiers, as well. The experiments were repeated 50 times and in each round all the three datasets were shuffled randomly where 70% of the dataset was used for training and 30% for testing.

5.1 Experiments' Environment

Due to the large number of the datasets' instances and its high-dimensional features space that require powerful computational resources for applying variety of machine learning algorithms, we did carry out our experiments on a virtual machine on AWS with the characteristics that are shown in the table below.

vCPUs	2 vCPUs, 2.5 GHz, Intel Xeon Family
Memory	16 GiB
OS	Ubuntu
Data Mining Tool	Rstudio

Table 5.1: Experiments' Environment

5.2 Experiments' Settings

For the three datasets: `allCateg`, `musicCateg` and `personaCateg`, 70% of the dataset was used for training the classifier, and 30% used was for testing. The datasets were randomly shuffled in each round of the 50 iterations that we used to average the performance of the classifiers. The R code of implementing the experiments is shown in the Appendix A.

5.3 Evaluation Measurements

In order to evaluate the performance of the classification models, we used the metrics as the following:

- **Accuracy:** The proportion of the total number of the apps that are correctly classified whether as benign or malicious.
$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn}$$
- **Precision:** The proportion of the actual malicious apps are correctly classified to the total of all apps that are classified as malicious.
$$\text{Precision} = \frac{tp}{tp + fp}$$

- **Recall:** The proportion of the malicious apps that are classified correctly to the total number of the malicious that are classified correctly as malicious or incorrectly as benign.
$$\text{Recall} = \frac{tp}{tp + fn}$$
- **F-Measure:** The harmonic mean of precision and recall. This value tells how much the model is discriminative.
$$\text{F-Measure} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$
- **ROC Area:** The probability that a given malicious app will be correctly classified as malicious is higher than classified as benign. This metric is calculated by combining **FPR** and **TPR**. Generally, the higher the ROC value is, the higher accurate predictions that the classification model gives.

- **Confusion Matrix:** shows the number of the apps that are classified correctly (the prediction class value matches the actual class value) or incorrectly (the prediction class value doesn't match the actual class value). In our experiment, the malicious apps are labeled as positive while the benign apps as negative. The matrix confusion shows the detection results in 4 terms:
  - **True Positive (TP):** The number of the malicious apps that are correctly classified as malicious.
  - **False Negative (FN):** The number of the malicious apps that are incorrectly classified as not malicious (benign)
  - **True Negative (TN):** The number of the benign apps that are correctly classified as not malicious (benign).
  - **False Positive (FP)**: The number of the benign apps that are incorrectly classified as malicious.

	Predicated as (Malicuios)	**Predicated as (Benign)**
Actual (Malicious)	True Positive	False Negative
Actual (Benign)	False Positive	True Negative

Table 5.2: Confusion Matrix

The next sections show the average performance of 50 iterations of testing the learned classifiers. In each round, the datasets were randomly shuffled: 70% for training and 30% for testing the classifier.

5.4 Testing Apps from all categories with allCateg Classifiers

Metric	allCateg-SVM	allCateg-RF	allCateg-AdaBoost
Accuracy	0.9903	0.9881	0.9743
Precision	0.9799	0.9967	0.9762
F-Measure	0.9707	0.9631	0.9179
Recall	0.9671	0.9318	0.8674
FPR	0.0039	0.0005	0.0043
TPR	0.9671	0.9318	0.8674
FNR	0.0382	0.0681	0.1325
TNR	0.9960	0.9994	0.9956
Specificity	0.9960	0.9994	0.9956
Sensitivity	0.9617	0.9318	0.8674

Table 5.3: Testing all categories app with allCateg classifiers

Table 5.3 shows the average performance of testing a random dataset of apps from all categories over 50 iterations with three classifiers: Support Vector Machines, Random Forests, and Adaboost.

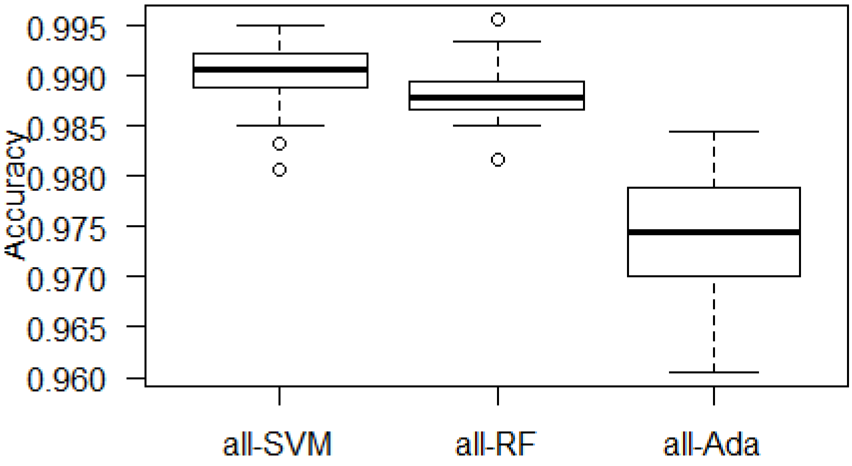


Figure 5.1: Accuracy of allCateg Classifiers

Figure 5.1 shows the variation of the classifiers' accuracy over 50 iterations of shuffling the dataset randomly for training and testing. As can be seen, the `allCateg-SVM` classifier reports the highest average accuracy, `allCateg-RF` as the second, and lastly `allCateg-Ada`. The classifiers report average accuracy as following: 0.9903, 0.9881, 0.9743 for SVM, RF, and Ada, respectively.

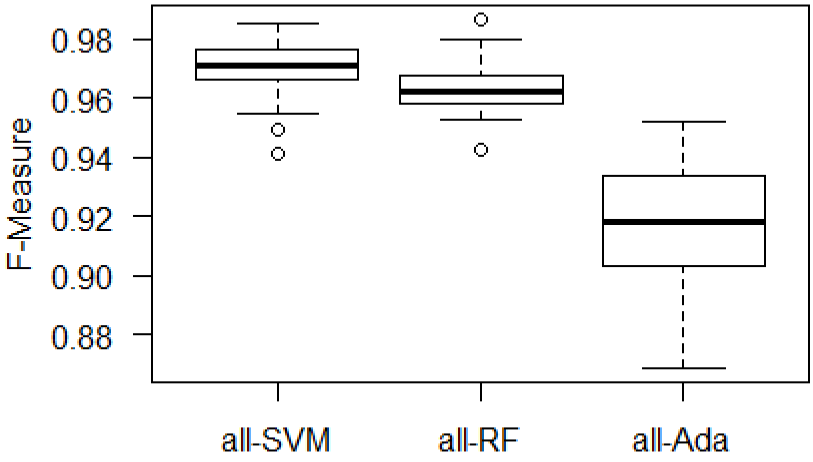


FIGURE 5.2: Fmeasure allCateg Classifiers

Figure 5.2 shows the variation of the classifiers' F-Measure over 50 iterations of shuffling the dataset randomly for training and testing. As can be seen, the `allCateg-SVM` classifier reports the highest average F-Measure, `allCateg-RF` as the second, and lastly `allCateg-Ada`. The classifiers report average F-Measure as following: 0.9707, 0.9631, 0.9179 for SVM, RF, and Ada, respectively.

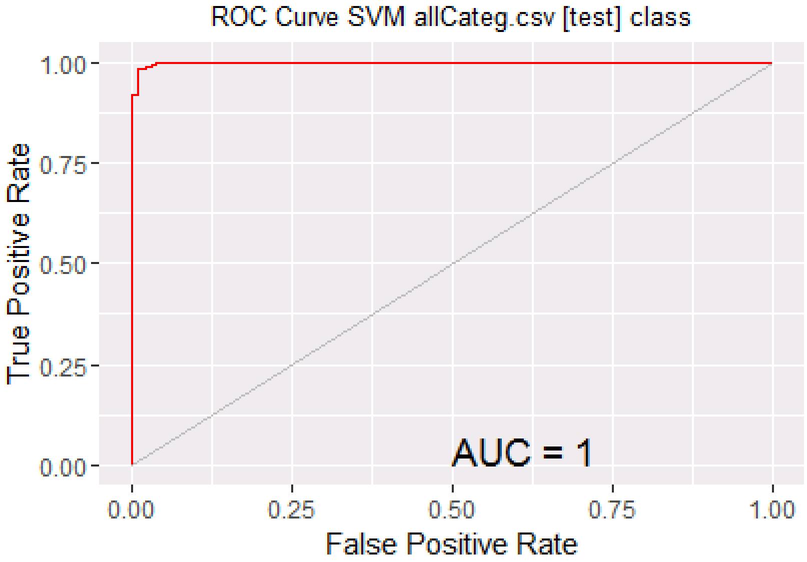


FIGURE 5.3: ROC curve for Testing all categories apps with allCateg-SVM classifier

Figure 5.3 shows that the Area under the ROC curve for the `allCateg-SVM` model on allCateg.csv [test] is 0.9989.

5.5 Testing Music Apps with musicCateg & allCateg Classifiers

5.5.1 Support Vectors Machine

Metric	musicCateg-SVM	allCateg-SVM
Accuracy	0.9872	0.9458
Precision	0.9777	1
F-Measure	0.9886	0.9547
Recall	0.9999	0.9134
FPR	0.0286	0
TPR	0.9999	0.9134
FNR	0.0002	0.0865
TNR	0.9713	1
Specificity	0.9713	1
Sensitivity	0.9999	0.9134

TABLE 5.4: Testing music apps with musicCateg & allCateg SVM classifers

5.5.2 RandomForest

Metric	musicCateg-RF	allCateg-RF
Accuracy	0.9899	0.9754
Precision	0.9855	0.9994
F-Measure	0.9911	0.9789
Recall	0.9968	0.9593
FPR	0.0187	0.0008
TPR	0.9968	0.9593
FNR	0.0031	0.0406
TNR	0.9812	0.9991
Specificity	0.9812	0.9991
Sensitivity	0.9968	0.9593

TABLE 5.5: Testing music apps with musicCateg & allCateg RF classifiers

5.5.3 AdaBoost

Metric	musicCateg-ada	allCateg-ada
Accuracy	0.9925	0.9852
Precision	0.9895	0.9997
F-Measure	0.9933	0.9872
Recall	0.9972	0.9751
FPR	0.0136	0.0003
TPR	0.9972	0.9751
FNR	0.0027	0.0248
TNR	0.9863	0.9996
Specificity	0.9863	0.9996
Sensitivity	0.9972	0.9751

TABLE 5.6: Testing music apps with musicCateg & allCateg adaBoost classifiers

5.6 Evaluating Performance of musicCateg & allCateg Classifiers

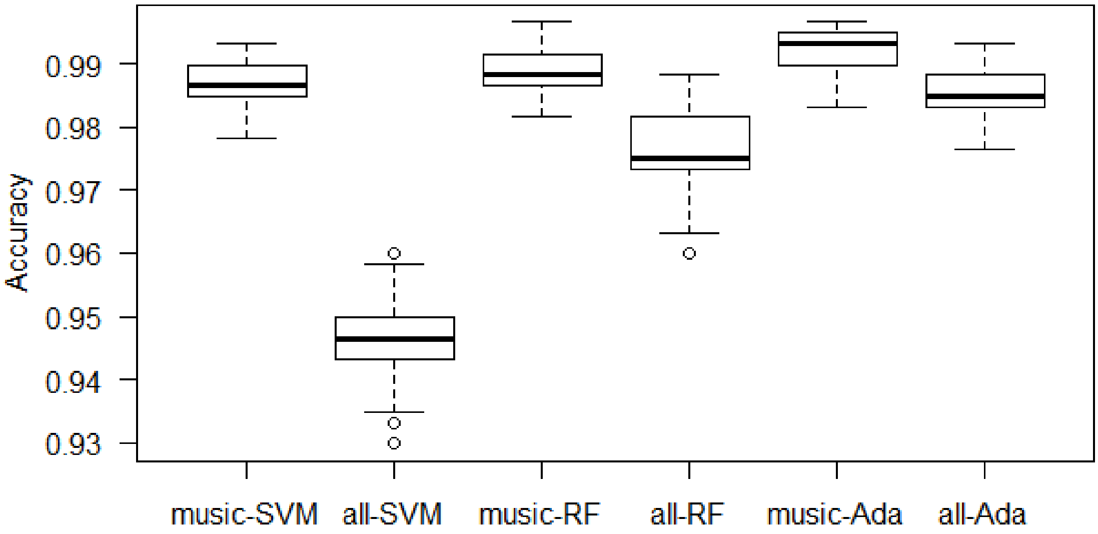


FIGURE 5.4: Accuracy of "musicCateg" &"allCateg" Classifiers

Figure 5.4 shows the variation of the classifiers' accuracy over 50 iterations of shuffling the datasets randomly for training and testing. As can be seen, the `musicCateg` classifiers report average accuracy higher than `allCateg` classifiers at detecting malicious and benign apps in "Music & Audio" Category. The `musicCateg` classifiers report average accuracy 0.9872, 0.9891, and 0.9934 for SVM, RF, and Ada, respectively. While the `allCateg` classifiers report average accuracy as following: 0.9458, 0.9795, and 0.9852.

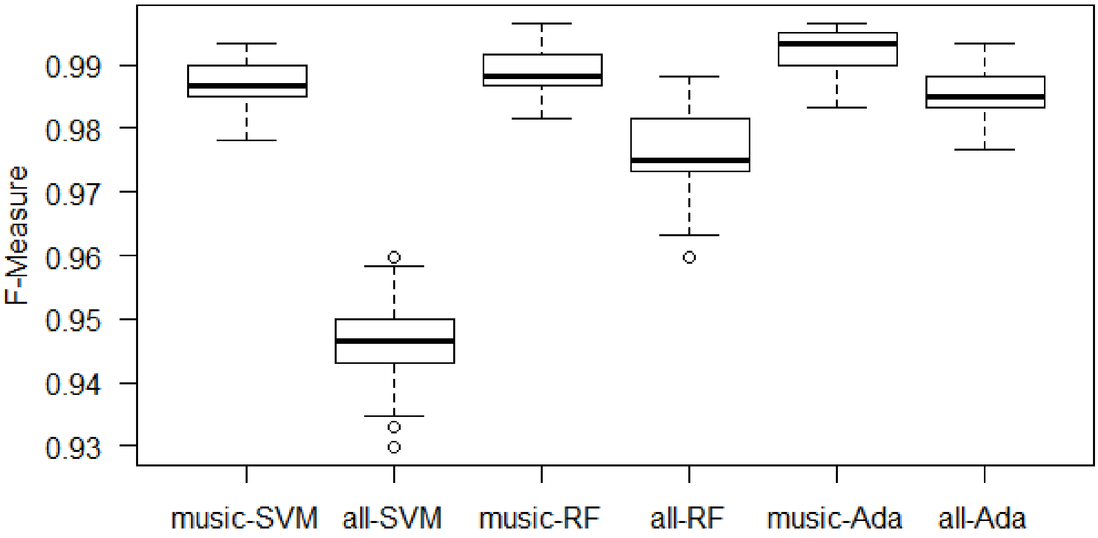


FIGURE 5.5: Fmeasure of musicCateg & allCateg Classifiers

Figure 5.5 shows the variation of the classifiers' F-Measure over 50 iterations. As can be seen, the `musicCateg` classifiers report average F-Measure higher than `allCateg` classifiers. The `musicCateg` classifiers report average F-measure 0.9886, 0.9904, and 0.9925 for SVM, RF, and Ada, respectively. While `allCateg` classifiers report average accuracy as following: 0.9547, 0.9761, and 0.9872.

The boxplots of accuracy and f-measure of the classifiers in Figure 5.5 and Figure 5.4 show noticeable differences in the average performance of category-based ”musicCateg” and non-Category based ”allCateg” classifiers at detecting malicious music apps. Notably, Support Vector Machines reports huge variations in accuracy and f-measure between ”musicCateg” and ”allCateg”.

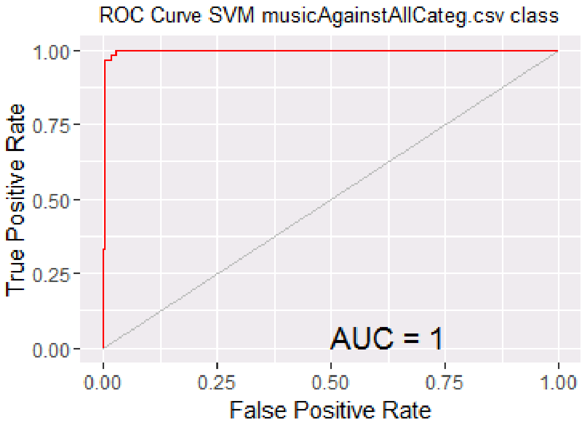


FIGURE 5.6: ROC curve for Testing music apps with allCateg-SVM classifier

Figure 5.6 shows that the area under the ROC curve for the ksvm model on musicAgainstAllCateg.csv is 0.9968.

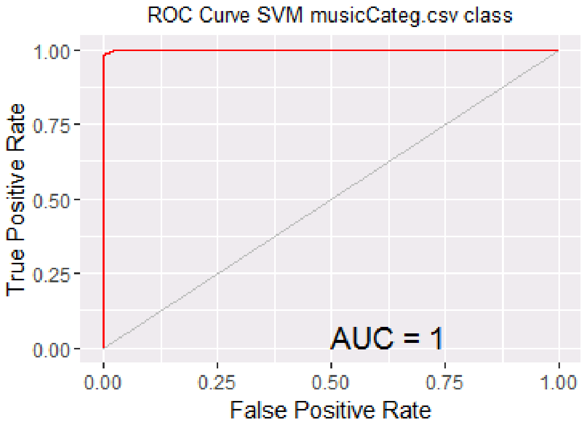
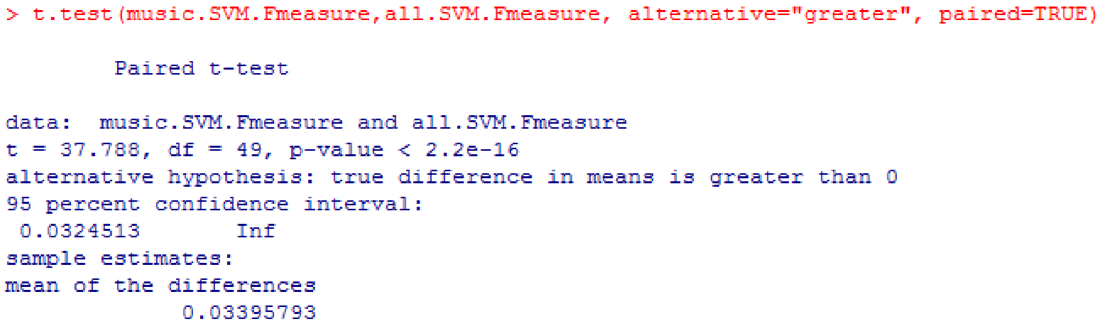


FIGURE 5.7: ROC curve for Testing music apps with allCateg-SVM classifier

Figure 5.7 shows that the area under the ROC curve for the ksvm model on musicCateg.csv is 0.9997 which bigger than the AUC of testing music apps with the allCateg-SVM classifier.



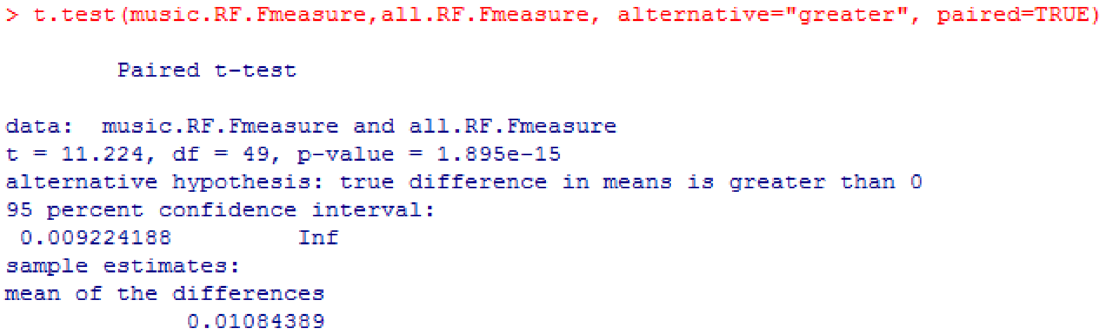
```
> t.test(music.SVM.Fmeasure,all.SVM.Fmeasure, alternative="greater", paired=TRUE)

        Paired t-test

data:  music.SVM.Fmeasure and all.SVM.Fmeasure
t = 37.788, df = 49, p-value < 2.2e-16
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 0.0324513       Inf
sample estimates:
mean of the differences
             0.03395793
```

Figure 5.8: t.test of F-measure of musicCateg-SVM & allCateg-SVM classifiers

Figure 5.8 shows that T.test function produces 3.39% a mean of the differences which indicates that musicCateg-SVM outperforms allCateg-SVM at detecting malicious apps in "Music & Audio" category.



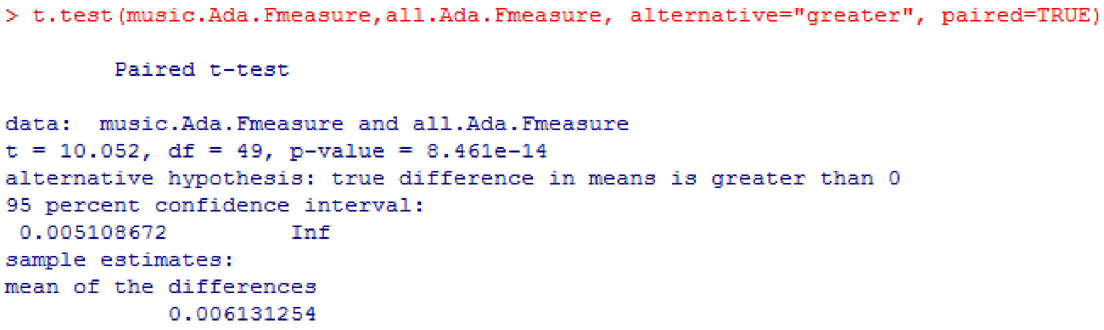
```
> t.test(music.RF.Fmeasure,all.RF.Fmeasure, alternative="greater", paired=TRUE)

        Paired t-test

data:  music.RF.Fmeasure and all.RF.Fmeasure
t = 11.224, df = 49, p-value = 1.895e-15
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 0.009224188         Inf
sample estimates:
mean of the differences
             0.01084389
```

Figure 5.9: t.test of F-measure of musicCateg-RF & allCateg-RF classifiers

Figure 5.9 shows that T.test function produces 1.08% a mean of the differences between musicCateg-RF and allCateg-RF.



```
> t.test(music.Ada.Fmeasure,all.Ada.Fmeasure, alternative="greater", paired=TRUE)

        Paired t-test

data:  music.Ada.Fmeasure and all.Ada.Fmeasure
t = 10.052, df = 49, p-value = 8.461e-14
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 0.005108672         Inf
sample estimates:
mean of the differences
            0.006131254
```

Figure 5.10: t.test of F-measure of musicCateg-Ada & allCateg-Ada classifiers

Figure 5.10 shows that T.test function produces 0.61% a mean of the differences between musicCateg-Ada and allCateg-Ada.

5.6.1 Proving Outperformance of Category-based Classifier "music-Categ"

Null Hypothesis: There are no significance differences between the classifiers' performance of category-based `musicCateg` and non-category `allCateg` at detecting malicious and benign in "Music & Audio" category.

Alternative Hypothesis: There are significance differences between the classifiers' performance of category-based `musicCateg` and non-category `allCateg` at detecting malicious and benign in "Music & Audio" category.

$\mathbf{H}_0 : \mu^{Fmeasure}_{musicCateg} \leq \mu^{Fmeasure}_{allCateg}$

$\mathbf{H}_a : \mu^{Fmeasure}_{musicCateg} > \mu^{Fmeasure}_{allCateg}$

50 replication of calculations of F-measures under both conditions on the same replicate of dataset.

Hence: the use of a Paired t.test and from the boxplots in Figure 5.5, our assumption gaussianity is clearly plausible.

Empirically: $\mu^{Fmeasure}_{musicCateg} - \mu^{Fmeasure}_{allCateg} = 3.4\%$

Informally, $\mu^{Fmeasure}_{musicCateg} > \mu^{Fmeasure}_{allCateg}$

Theoretical by inference:

$p - value \simeq 0$ rejects H_0, concludes $H_a : \mu^{Fmeasure}_{musicCateg} > \mu^{Fmeasure}_{allCateg}$

$\mu^{Fmeasure}_{musicCateg} - \mu^{Fmeasure}_{allCateg} \epsilon \, [3.25, \ \infty]$

$\text{LB}_{95\%}(\mu^{Fmeasure}_{musicCateg} - \mu^{Fmeasure}_{allCateg}) = 3.25\%$

5.7 Testing Personalization Apps with personaCateg & allCateg Classifiers

5.7.1 Support Vector Machines

Metric	personaCateg-SVM	allCateg-SVM
Accuracy	0.9855	0.8947
Precision	0.9833	1
F-Measure	0.9736	0.9318
Recall	0.9651	0.8726
FPR	0.0006	0
TPR	0.9651	0.8726
FNR	0.0348	0.1273
TNR	0.9934	1
Specificity	0.9934	1
Sensitivity	0.9651	0.8726

Table 5.7: Testing personalization apps with personaCateg & allCateg SVM classifiers

5.7.2 RandomForest

Metric	personaCateg-RF	allCateg-RF
Accuracy	0.9424	0.8749
Precision	0.9552	08642
F-Measure	0.9603	0.9190
Recall	0.9661	0.9845
FPR	0.1188	0.4072
TPR	0.9661	0.9845
FNR	0.0338	0.0157
TNR	0.8811	0.5927
Specificity	0.8811	0.5927
Sensitivity	0.9661	0.9845

Table 5.8: Testing personalization apps with personaCateg & allCateg RF classifiers

5.7.3 AdaBoost

Metric	personaCateg-Ada	allCateg-Ada
Accuracy	0.9597	0.9424
Precision	0.9904	0.9552
F-Measure	0.9726	0.9603
Recall	0.9559	0.9845
FPR	0.0257	0.1188
TPR	0.9559	0.9552
FNR	0.0440	0.0338
TNR	0.9742	0.8811
Specificity	0.9742	0.8811
Sensitivity	0.9559	0.9845

Table 5.9: Testing personalization apps with personaCateg & allCateg Ada classifiers

5.8 Evaluating Performance of personaCateg & allCateg Classifiers

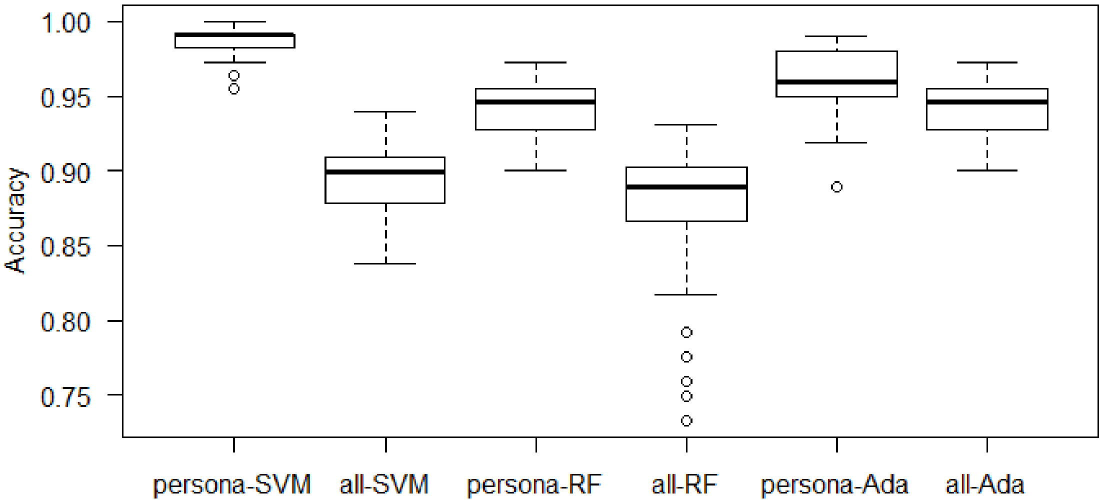


FIGURE 5.11: Accuracy of "personaCateg" &"allCateg" Classifiers

Figure 5.11 shows the variation of the classifiers' accuracy over 50 iterations. As can be seen, the `personaCateg` classifiers report average accuracy higher than `allCateg` classifiers at detecting malicious or reporting benign apps in "Personalization" category. The `personaCateg` classifiers report average accuracy as following: 0.9855, 0.9424, 0.9597 for Support Vector Machines, Random Forests, and Adaboost, respectively. While `allCateg` classifiers report average of accuracy as following: 0.8947, 0.8749 and 0.9924.

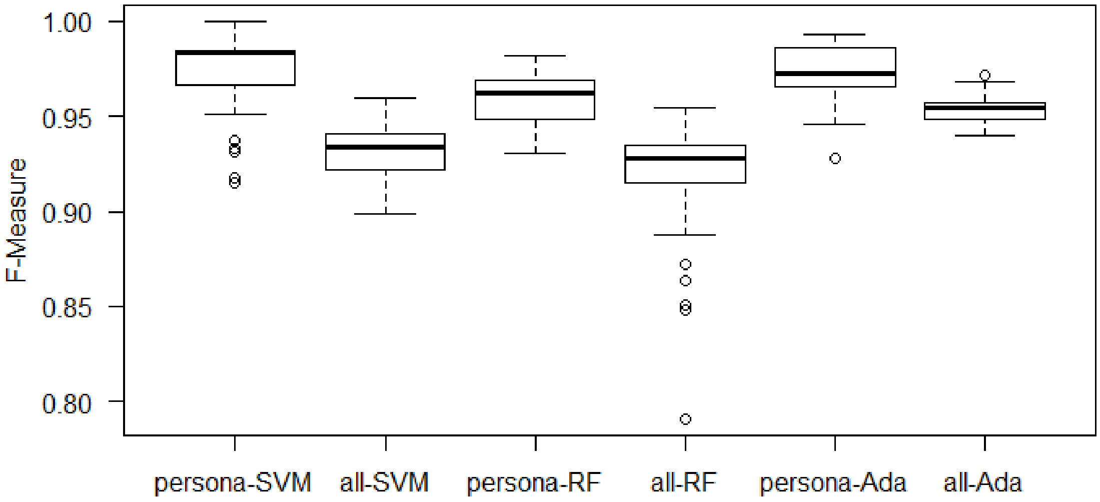


FIGURE 5.12: Fmeasure of "personaCateg" &"allCateg" Classifiers

Figure 5.12 shows the variation of the classifiers' accuracy over 50 iterations. As can be seen, the `personaCateg` classifiers report average fmeasure higher than `allCateg` classifiers. The `personaCateg` classifiers report average fmeasure as following: 0.9736, 0.9603, 0.9726 for Support Vector Machines, Random Forests, and Adaboost, respectively. While `allCateg` classifiers report average of fmeasure as following: 0.9318, 0.9190 and 0.9603.

The boxplots of accuracy and f-measure of the classifiers in Figure 5.11 and Figure 5.12 show noticeable differences in the average performance of category-based ”personaCateg” and non-Category based ”allCateg” classifiers at detecting malicious music apps. Notably, Support Vector Machines reports huge variations in accuracy and f-measure between ”musicCateg” and ”allCateg”.

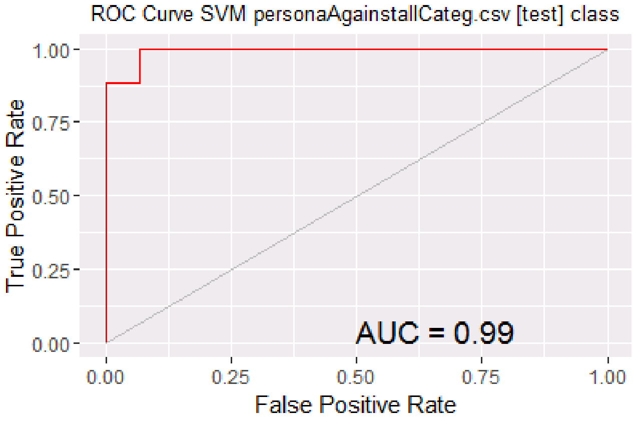


FIGURE 5.13: ROC curve for Testing personalization apps with allCateg-SVM classifier

Figure 5.13 shows that the area under the ROC curve for the ksvm model on personaAgainstallCateg.csv is 0.9924

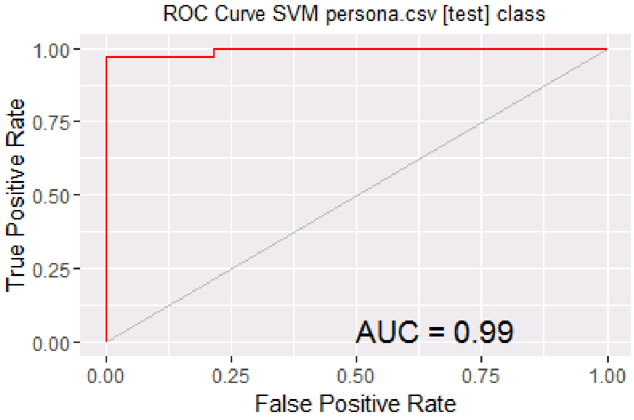
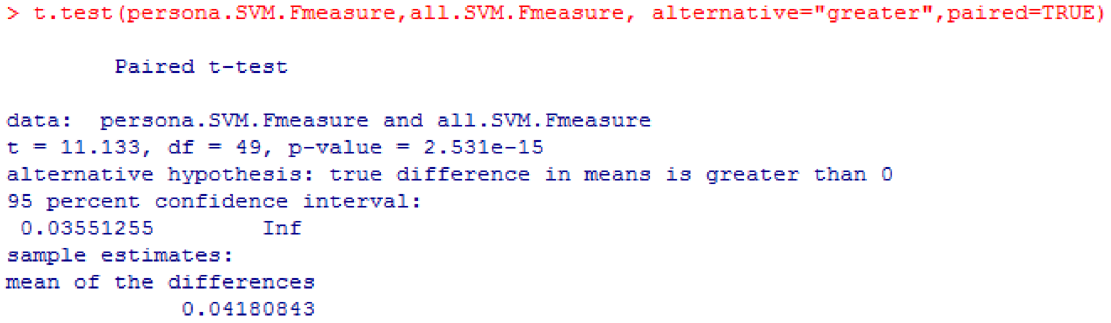


FIGURE 5.14: ROC curve for Testing personalization apps with personaCateg-SVM classifier

Figure 5.14 shows that the area under the ROC curve for the ksvm model on musicCateg.csv is 0.9940 which bigger than the AUC of testing personalization apps with the allCateg-SVM classifier.



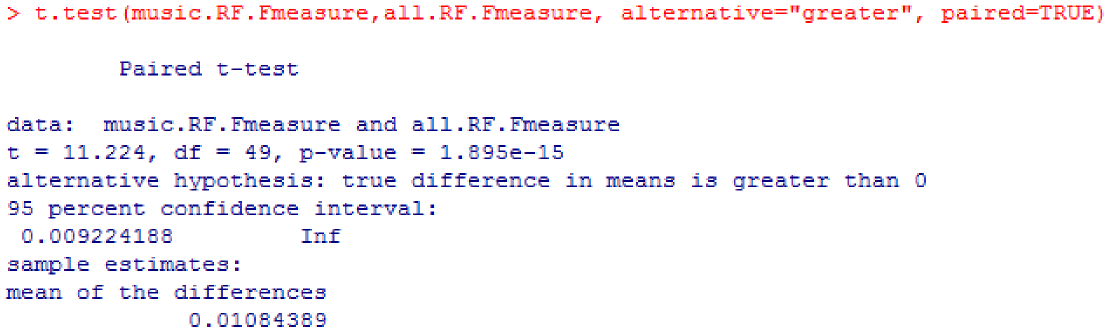
```
> t.test(persona.SVM.Fmeasure,all.SVM.Fmeasure, alternative="greater",paired=TRUE)

        Paired t-test

data:  persona.SVM.Fmeasure and all.SVM.Fmeasure
t = 11.133, df = 49, p-value = 2.531e-15
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 0.03551255        Inf
sample estimates:
mean of the differences
             0.04180843
```

Figure 5.15: t.test of F-measure of personaCateg-SVM & allCateg-SVM classifiers

Figure 5.15 shows that T.test function produces 4.18% a mean of the differences which indicates that personaCateg-SVM outperforms allCateg-SVM at detecting malicious apps in ”Personalization” category.



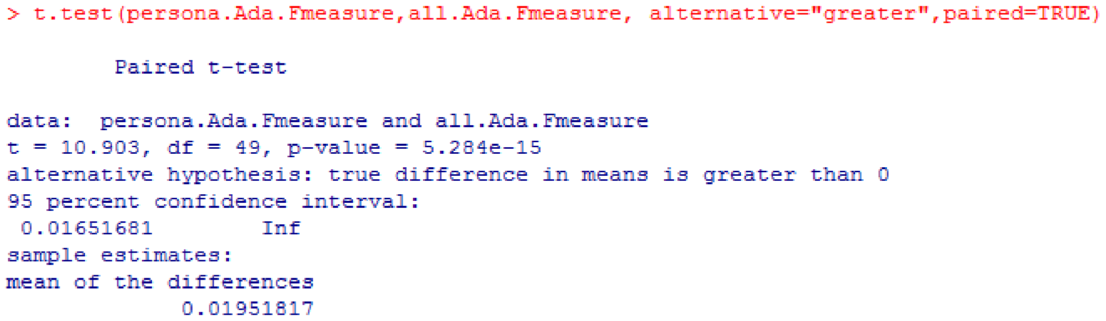
```
> t.test(music.RF.Fmeasure,all.RF.Fmeasure, alternative="greater", paired=TRUE)

        Paired t-test

data:  music.RF.Fmeasure and all.RF.Fmeasure
t = 11.224, df = 49, p-value = 1.895e-15
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 0.009224188         Inf
sample estimates:
mean of the differences
             0.01084389
```

Figure 5.16: t.test of F-measure of personaCateg-RF & allCateg-RF classifiers

Figure 5.16 shows that T.test function produces 1.08% a mean of the differences between personaCateg-RF and allCateg-RF.



```
> t.test(persona.Ada.Fmeasure,all.Ada.Fmeasure, alternative="greater",paired=TRUE)

        Paired t-test

data:  persona.Ada.Fmeasure and all.Ada.Fmeasure
t = 10.903, df = 49, p-value = 5.284e-15
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 0.01651681        Inf
sample estimates:
mean of the differences
             0.01951817
```

Figure 5.17: t.test of F-measure of personaCateg-Ada & allCateg-Ada classifiers

Figure 5.17 shows that T.test function produces 1.95% a mean of the differences between personaCateg-Ada and allCateg-Ada.

5.8.1 Proving Outperformance of Category-based Classifier "personaCateg"

Null Hypothesis: There are no significance differences between the classifiers' performance of category-based `personaCateg` and non-category `allCateg` at detecting malicious and benign under "Personalization" category.

Alternative Hypothesis: There are significance differences between the classifiers' performance of category-based `personaCateg` and non-category `allCateg` at detecting malicious and benign under "Persoalization" category.

$\mathbf{H}_0 : \mu^{Fmeasure}_{personaCateg} \leq \mu^{Fmeasure}_{allCateg}$

$\mathbf{H}_a : \mu^{Fmeasure}_{personaCateg} > \mu^{Fmeasure}_{allCateg}$

50 replication of calculations of F-measures under both conditions on the same replicate of dataset.

Hence: the use of a Paired t.test and from the boxplots in Figure 5.12, our assumption gaussianity is clearly plausible.

Empirically: $\mu^{Fmeasure}_{personaCateg} - \mu^{Fmeasure}_{allCateg} = 4.18\%$

Informally, $\mu^{Fmeasure}_{personaCateg} > \mu^{Fmeasure}_{allCateg}$

Theoretical by inference:

$p - value \simeq 0$ rejects H_0, concludes $H_a : \mu^{Fmeasure}_{personaCateg} > \mu^{Fmeasure}_{allCateg}$

$\mu^{Fmeasure}_{personaCateg} - \mu^{Fmeasure}_{allCateg} \epsilon\, [3.55,\ \infty]$

$\text{LB}_{95\%}(\mu^{Fmeasure}_{personaCateg} - \mu^{Fmeasure}_{allCateg}) = 3.55\%$

Chapter 6

Conclusion

In our study, we propose category-based machine learning classifiers to improve the performance of the classification models. In static analysis of Android malware, machine learning algorithms have been used to train classifiers with features of malicious apps to build models that capable of detecting malicious patterns. Differently, our classification approach defines legitimate static features for benign apps as opposite to identifying malicious patterns. We utilize the features of the top rated apps in a specific category to define a profile of the common sets of features for that category. In other words, to detect whether or not the app posses the characteristics of benign, we relate between the app's features and the features that are needed to deliver the category's functionality that the app belongs to. Android stores organize apps into different categories; 26 categories on the Google Play Store, for example. In each category, the apps deliver a similar functionality as a result the they tend to request a common set of features like same permissions, APIs, hardware components, broadcast receivers, intents filters, etc. On the contrary, malicious apps tend to have abnormal features, less or more than what is common for the category that they belong to. Malicious apps can be identified by comparing between the features they request to the features that are requested by benign apps in the same category. For example, malicious apps, compared to the benign apps in the same category, tend to request over-privileged permissions, listen to specific events that broadcast by the Android system, or using unneeded APIs for the app's category functionality that can be used to lunch malicious behaviors.

We compare the performance of category-based and non-category based classifiers at detecting malicious apps under a specific category. To achieve this comparison, we built three datasets of apps' features: apps from all categories (`allCateg`), apps from "Music & Audio" category (`musicCateg`), and apps from "Personalization" category (`personaCateg`). For each dataset, we trained three machine learning classifiers:

Support Vector Machines, Random Forests, and AdaBoost; the classifiers were trained with three group of features: permissions, broadcast receivers, and APIs. For testing, apps from "Music & Audio" category were tested with `(musicCateg)` and `(allCateg)` classifiers, respectively; and apps from "Personalization" category were tested with `personaCateg` and `allCateg` classifiers, as well. The category-based classifiers reported a higher performance compared to the non-category based at detecting malicious and benign in the two categories of our study: "Music & Audio" and "Personalization".

Our future work will consider three aspects. First, including other static features such as: functions calls in building the classification models to get a better understanding of the processes that apps may lunch in a way to increase the detection accuracy of the classifiers. Second, implementing the proposed solution on a large-scale level by building profile models for other categories and sub categories. Third, testing the feasibility of integrating our solution with dynamic detection techniques by profiling dynamic features for each category; dynamic features like system calls, network connections, resources' usage, and etc.

Appendix A

Building Classification Models in -R-

```
library(e1071)
library(randomForest)
library(adabag)
library(ROCR)
####################################################
# Measures of goodness in binary classification
####################################################
measures <- function(label, response)
{
n<-length(label)

confmat     <- table(label, response)
Accuracy    <- sum(diag(confmat))/n
FPR         <- confmat[1,2]/rowSums(confmat)[1]
TPR         <- confmat[2,2]/rowSums(confmat)[2]
FNR         <- confmat[2,1]/rowSums(confmat)[2]
TNR         <- confmat[1,1]/rowSums(confmat)[1]
Precision   <- confmat[2,2]/colSums(confmat)[2]
Recall      <- TPR
Specificity <- TNR
Sensitivity <- TPR
F.measure   <- 2*(Precision*Recall)/(Precision+Recall)

measured<-list(Accuracy=Accuracy,
Precision = Precision,
F.measure = F.measure,
Recall=Recall,
FPR=FPR, TPR = TPR,
FNR=FNR, TNR = TNR,
Specificity=Specificity,
Sensitivity=Sensitivity)

return(measured)
```

```
}

##################################################
##### reading the data
##################################################
allcategories <- read.csv("allCateg.csv")
music_allcategories <- read.csv("musicgainstAllCateg.csv")
names(music_allcategories) <- names(allcategories)
music <- read.csv("musicCateg.csv")

#get the ids for all categories data
benA <- which(allcategories$class=='benign')
malA <- which(allcategories$class=='malicious')

#get the ids for music all categories data
benB <- which(music_allcategories$class=='benign')
malB <- which(music_allcategories$class=='malicious')


met.svm.music <- matrix(0,50,10,byrow=T)
met.svm.all <- matrix(0,50,10,byrow=T)
met.rf.music <- matrix(0,50,10,byrow=T)
met.rf.all <- matrix(0,50,10,byrow=T)
met.ada.music <- matrix(0,50,10,byrow=T)
met.ada.all <- matrix(0,50,10,byrow=T)

for(i in 1:50){

#sampling rows for data with all categories
trainA <- allcategories[c(sample(benA,length(benA)*0.7,replace = F),
sample(malA,length(malA)*0.7,replace = F)),]

#sampling rows for data with music all categories
s <- c(sample(benB,length(benB)*0.7,replace = F),sample(malB,length(malB)*0.7,replace = F))
trainB <- music_allcategories[s,]

# stack music all categories and all categories for training
train <- as.data.frame(rbind(trainA,trainB))

# select in music the same ids from music all categories
trainC <- music[s,]

# built the test data
test_musicallcategories <- music_allcategories[-s,]
test_music <- music[-s,]

##################################################
# train SVM
##################################################
svm.music <- svm(class~.,data=trainC,scale=F)
svm.allcategories <- svm(class~.,data=train,scale=F)

# getting the predictions
pred.svm.music <- predict(svm.music,test_music)
pred.svm.allcategories <- predict(svm.allcategories,test_musicallcategories)
```

```
#finding the metrics
met.svm.music[i,] <- unlist(measures(pred.svm.music,test_music$class))
met.svm.all[i,] <- unlist(measures(pred.svm.allcategories,test_musicallcategories$class))

###################################################
#train random forest
###################################################

rf.music <- randomForest(class˜.,data=trainC,ntree=100)
rf.allcategories <- randomForest(class˜.,data=train,ntree=100)

# getting the predictions
pred.rf.music <- predict(rf.music,test_music)
pred.rf.allcategories <- predict(rf.allcategories,test_musicallcategories)

#finding the metrics
met.rf.music[i,] <- unlist(measures(pred.rf.music,test_music$class))
met.rf.all[i,] <- unlist(measures(pred.rf.allcategories,test_musicallcategories$class))

###################################################
#train adaBoosted trees
###################################################

adaB.music <- boosting(class˜.,data=trainC, mfinal = 100)
adaB.allcategories <- boosting(class˜.,data=train, mfinal = 100)

# getting the predictions
pred.ada.music <- predict(adaB.music,test_music)
pred.ada.allcategories <- predict(adaB.allcategories,test_musicallcategories)

#finding the metrics
met.ada.music[i,] <- unlist(measures(pred.ada.music$class,test_music$class))
met.ada.all[i,] <- unlist(measures(pred.ada.allcategories$class,
test_musicallcategories$class))

}
###################################################
#column names: Accuracy,Precision,F.measure,Recall,FPR,TPR,FNR,TNR,Specificity,Sensitivity
# Accuracy boxplots
boxplot(met.svm.all[,1],met.svm.music[,1])
boxplot(met.rf.all[,1],met.rf.music[,1])
boxplot(met.ada.all[,1],met.ada.music[,1])

# F.measure boxplots
boxplot(met.svm.music[,1],met.svm.all[,1], names = c("musicCateg","allCateg"),
col = c("blue","orange"))
boxplot(met.rf.music[,1],met.rf.all[,1], names = c("musicCateg","allCateg"),
col = c("blue","orange"))
boxplot(met.ada.music[,1],met.ada.all[,1], names = c("musicCateg","allCateg"),
col = c("blue","orange"))

# average of the columns
avg.metr.svm.music <- apply(met.svm.music,2,mean)
avg.metr.svm.all <- apply(met.svm.all,2,mean)
avg.metr.rf.music <- apply(met.rf.music,2,mean)
avg.metr.rf.all <- apply(met.rf.all,2,mean)
avg.metr.ada.music <- apply(met.ada.music,2,mean)
avg.metr.ada.all <- apply(met.ada.all,2,mean)

allmetric.avg <-rbind(avg.metr.svm.music,avg.metr.svm.all,avg.metr.rf.music,
avg.metr.rf.all,avg.metr.ada.music, avg.metr.ada.all)

# saving the avgs to a file
write.table(allmetric.avg,"avg.csv",row.names=F)
```

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