

# Supervised Learning Technique to Reveal Malwares in Android Device

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**Abstract:** Mobile phone industry is growing at rapid speed. These mobile phones are running on different platform such as JAVA, Android, IOS, Symbian and others. Out of all these platforms Android covers maximum share amount Smartphone platform. Android platform supports millions of applications that can be downloaded from various repositories such as Google Play. These applications are installed and used. The applications present in these repository may be malicious which lead to security problems using these applications. In this paper an effective approach has been proposed for detection of the malicious application based on the permission groups. In proposed work, binary classification of applications are carried out into two labels i.e. Benign and malicious one. In this developed approach the distinguished features are evaluated and filtered out using feature evaluation techniques such as Information gain, Gain ratio, Gini Index, Chi-square test. Finally based on the features evaluated the classification is done using supervised machine learning techniques.

**Keywords—**malicious, android, classification, Naïve Bayes

## I. INTRODUCTION

The rapid growth of smartphone has led to a renaissance in mobile application services. Android and iPhone operating system (IOS) are the most common platform for Smartphone. These platforms are having their own market from where required applications can be downloaded. Any application can be downloaded from the App Store (iPhone) or Android Market (Google Android), both of which provide point and click access for hundreds and thousands of users to commercial or free applications.

With an estimated market share of 70% to 80%, Android has become the most popular operating system for Smartphone and tablets. Expecting a shipment of 1 billion Android devices in 2017 and with over 50 billion total app downloads since the first Android phone was released in 2008, cyber criminals naturally expanded their vicious activities towards Google's mobile platform. With the increase demand and vast usage, the security of Android mobile themselves and their application services have become increasingly important issue for mobile owners.

## II. LITERATURE REVIEW

The open nature of the Android system has certain benefits and drawbacks. As Android source code is available open it becomes very easy for attacker to develop malware which can harm any Android device. In this section the work done in the direction of malicious application detection is discussed. For analysing malware different type of techniques has been proposed, but on broader scale these techniques are categorized as:

- Static analysis
- Dynamic analysis
- Hybrid analysis.

Android Malware Forensics: Reconstruction of Malicious Events et.al Juanru Li, DawuGu, YuhaoLuo proposed a systematic procedure for Android malware forensic analysis and malicious events reconstruction. This paper discusses about how to defeat anti-forensics code. How to combine existing tools and techniques to help analysis.

Permission-Based Android Malware Detection [10] et.al Zarni Aung, Win it describes the process of extracting features from the Android .apk files. In this paper a new dataset has been created from extracted features of Android applications in order to develop Android malware detection framework.

Mobile-Sandbox: Having Deeper Look into Android Application et.al Michael Spreitzen Barth proposed a Mobile-Sandbox, system which is designed to automatically analyse Android applications in two novel ways. It combines static and dynamic analysis, i.e., results of static analysis are used to guide dynamic analysis extend coverage of executed code. It uses specific techniques to log calls to native (i.e., \non-Java") APIs.

## III. PROPOSED METHOD

The process for identification of malicious Android application consists of step wise approach and steps are divided further into different sub-tasks includes as shown in Figure 1.

- a) Data extraction
- b) Features extraction
- c) Features evaluation
- d) Classification techniques

### A. Data extraction:

In this step the different types of APK files are extracted from different repositories. These APK files are special type of compressed files which includes source code, manifest.xml and other resources as required by the application. In this step the APK files are downloaded from Google Play[], sharevirus[] for benign and malicious application.

### B. Feature extraction:

It is the most crucial step for the whole process as classification depends on which features are extracted. In our proposed work permission regarding each application are considered as the features as most of the malicious applications use some common type of permission pattern which is quite different from the benign applications. The APK file is unzipped and permissions regarding that application are extracted from the manifest.xml file. For this purpose we develop a XML parser which extracts all the permissions for every application and dataset is built.

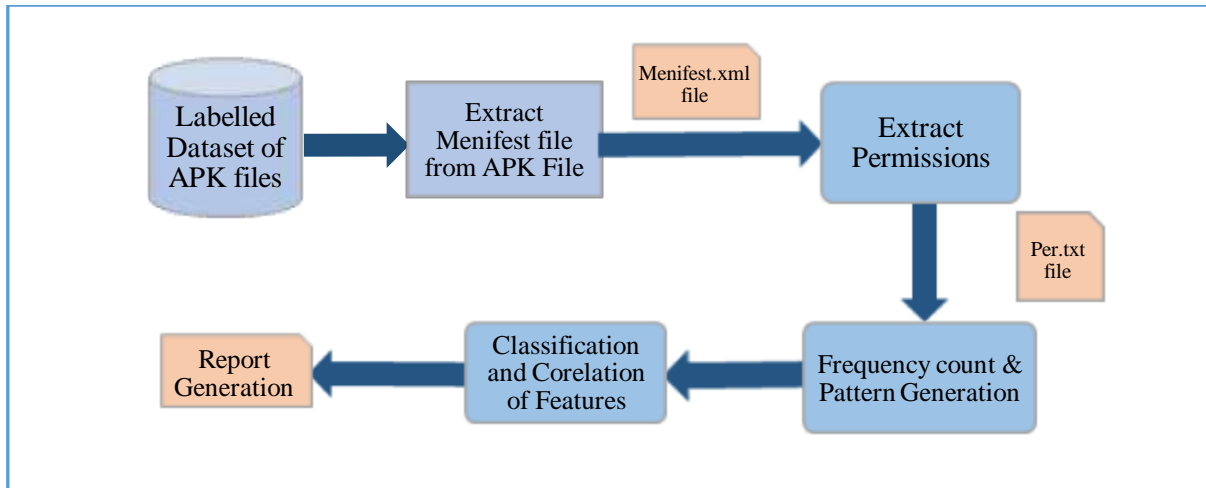


Figure 1: Android Malware Detection System

C. Feature evaluation:

The extracted features includes similar and distinguish features for type of application i.e malicious and benign. In order to get better classification result and accuracy there is a need of filter down this features set.

Feature evaluation step find the correlation and calculated amount of information per feature. The features which has no information value are pruned from the dataset and new refined dataset is made. Moreover this reduced feature set reduce the overburden and provide optimizing result classification.

In the proposed work recursive feature evaluation technique and cross correlation methods are used for feature evaluation. The feature evaluation methods are implemented with the help of R statistical language.

D. Classification Technique:

Classification techniques are machine learning techniques in which algorithm is first trained with the help of available dataset and then it is tested in terms of correctly classification rate. These classification techniques includes Naïve bayes, decision tree, Support vector machine and others.

Naïve Bayes classification technique based on the probabilistic approach i.e. Bayes rule. Naïve Bayes is quite hood in malicious filtering domain as there are many equally important features for different class of attributes. It is quite fast learning technique with one pass of counting over the data; testing linear in the number of attributes, and document collection size. Naive bayes classification is based on following values:

- i. **Prior probability:** The probability that an event will reflect established beliefs about the event before the arrival of new evidence or information. Prior probabilities are the original probabilities of an outcome, which will be updated with new information to create posterior probabilities.
- ii. **Posterior probability:** The revised probability of an event occurring after taking into consideration new information. Posterior probability is normally calculated by updating the prior probability by using Bayes' theorem. In statistical terms, the posterior probability is the probability of event 'A' occurring given that event B has occurred.

iii. **Bayesian probability:** This is based on prior and posterior probability of the events.

iv. **Independent events probability:** The probability of two independent events is defined by the product of their individual probability.

$$P(A \wedge B) = P(A) \times P(B) \dots \dots \dots (1)$$

v. **Conditional Probability:** The probability value which depends on the sequence of two events.

$$P(A|B) = \frac{P(A \wedge B)}{P(B)} \dots \dots \dots (2)$$

And

$$P(B|A) = \frac{P(A \wedge B)}{P(A)} \dots \dots \dots (3)$$

From equation 2 and 3,  $P(A \wedge B) = P(B|A).P(A)$ .

In R language the Naïve bayes technique is implemented.

IV. EXPERIMENTAL SETUP AND RESULT ANALYSIS

For the classification purpose R studio[13] version 0.99.484 and Java runtime version 1.8.0\_31-b13 with system configuration as Intel I-5 processor 3<sup>rd</sup> generation with 8 GB of RAM memory is used. R studio provide a developing environment for R language. R language is a collection of machine learning algorithms for data mining tasks. The classification algorithms can either be applied using R library, packages and interfaces. R languages contains packages for data pre-processing, classification, regression, clustering, association rules, and visualization. R is open source software issued under the GNU General Public License.

In experimental setup, dataset of malicious and benign android applications randomly divided into almost 10 sets for cross validation i.e. Dataset = {D<sub>1</sub>, D<sub>2</sub>, D<sub>3</sub>, D<sub>4</sub>, D<sub>5</sub>, D<sub>6</sub>, D<sub>7</sub>, D<sub>8</sub>, D<sub>9</sub>, D<sub>10</sub>}. All the sets are mutually exclusive. Out of these 10 sets 9 sets at each iteration are used for training purpose i.e. E<sub>training</sub> and remaining set is used for testing i.e. E<sub>testing</sub>. This process is repeated 10 times. At each iteration i.e.:

Accuracy is defined as the percentage of correctly classified result. In this dissertation accuracy is defined by the correctly classification of the permissions in their respective class i.e. Benign and malware and obtained accuracy is shown in Figure 2.

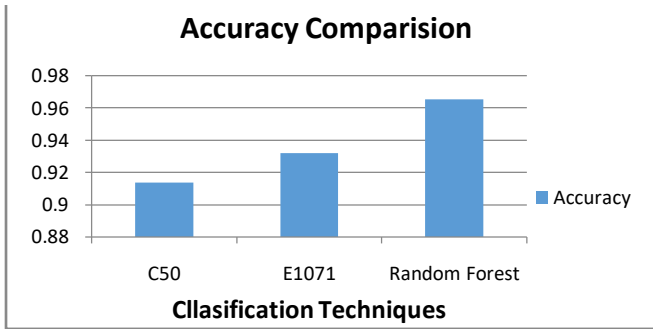


Figure 2: Accuracy comparison of classification techniques for proposed work

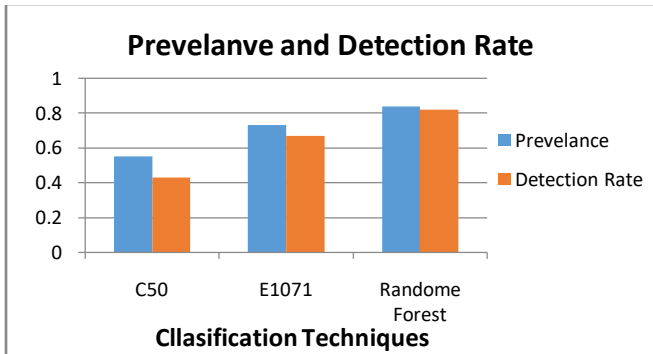


Figure 3: Comparison based on Prevalance and Detection rate

In this work the average detection rate for all the classes is 0.8217 for the proposed method as shown in Figure 3.

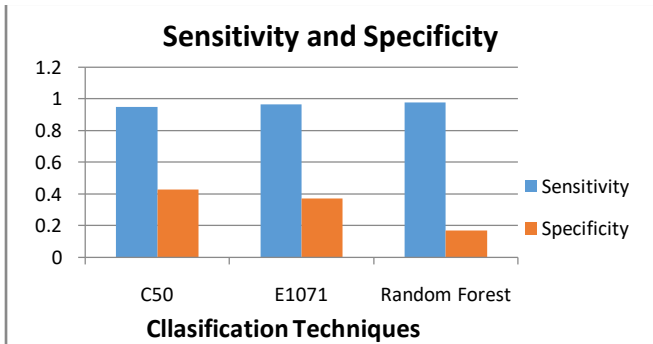


Figure 4: Comparison based on Specificity and Sensitivity

The F1-score in the base paper is .9577, which is calculated for last test performed in 5-fold method. Whereas, in proposed work the F1-Score calculated is .9793 as shown in Figure 5.

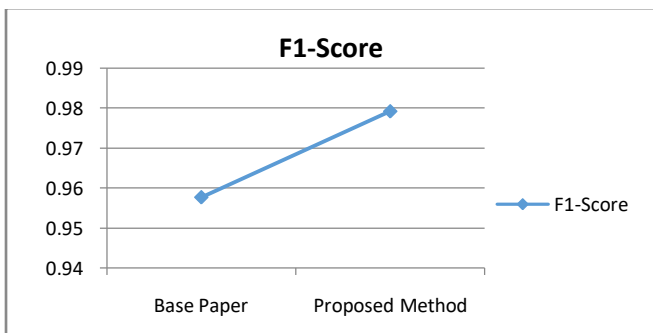


Figure 5: Comparison of F1-Score for Proposed Method

V. CONCLUSION AND FUTURE WORK:

Malicious application are one the main barrier of today’s mobile security infrastructure. Malicious application is a collective term coined for all those application which are either themselves or support other application for various attacks. Some of the common android mobile based attacks are data leak, password theft, malware and others.

The work presented includes the comparison of different feature evaluation and classification techniques under android application scenario. The comparison of features evaluation is done in order to identify the minimum and optimize set of feature vector.

In classification, random forest updateable comes out with best result for multi class classification as compared to Decision tree (C50), Naïve bayes (E1071) and Random Forest. In this work different classification techniques has been applied on the basis of results and accuracy the classification result of Random forest method is fairly good with classification accuracy as 98.31%. The absolute mean error is 0.0635.

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