Android Malware Detection using Feature Ranking of Permissions

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January 24, 2022

Abstract

We investigate the use of Android permissions as the vehicle to allow for quick and effective differentiation between benign and malware apps. To this end, we extract all Android permissions, eliminating those that have zero impact, and apply two feature ranking algorithms namely Chi-Square test and Fisher’s Exact test to rank and additionally filter them, resulting in a comparatively small set of relevant permissions. Then we use Decision Tree, Support Vector Machine, and Random Forest Classifier algorithms to detect malware apps. Our analysis indicates that this approach can result in better accuracy and F-score value than other reported approaches. In particular, when random forest is used as the classifier with the combination of Fisher’s Exact test, we achieve 99.34% in accuracy and 92.17% in F-score with the false positive rate of 0.56% for the dataset in question, with results improving to 99.82% in accuracy and 95.28% in F-score with the false positive rate as low as 0.05% when only malware from three most popular malware families are considered.

1 Introduction

In our increasingly connected society, number of mobile devices and mobile apps continue to increase, providing numerous services for personal and business use. Because of huge market share and open source features, the Android platform is the main target of hackers. Report [1] reveals that 97% of mobile malware are on Android and about 8.5 million new Android malware samples have been discovered in the first quarter of 2018 which represents a 12% increase from the first quarter of 2017 [2].

However, malware detection is a challenging task as mobile devices are more vulnerable to malware attacks due to limited computational resources. Antivirus solutions are generally used in desktop computers where they track the application data in real time using the latest malware signature files downloaded from antivirus databases, but this is not feasible in mobile devices and does not scale well because of significant computational overhead [3].

Many approaches have been used to detect malware but they are not always effective. For example, DroidScribe [4] is a dynamic malware detection approach based on feature sets that include IP addresses and ports used, network traffic size, file types, method names, and the like. They classify malware using inter-process communication with the combination of support vector machine-based classifier. DroidScope [5] is another dynamic malware detection approach that monitors the behavior of apps at run time and reconstructs OS-level semantics and Java-level semantics.

In this work, we focus on using permissions which are declared in Android manifest file and can be extracted easily. This manifest file contains the structure and meta data of Android app. In addition to running each app in separate application sandbox which isolates app’s data from other apps, Android uses its permission system to enforce additional limitations on their apps. An app can perform a specific operation only if it has requested and subsequently obtained the appropriate permission. Android permissions are normally grouped into three categories, namely normal permissions, dangerous permissions and signature permissions [6].

• Normal permissions are those that pose little or no risk to the user’s privacy; they are automatically granted by the operating system.

• Dangerous permissions pose higher risk to the user’s privacy and these permissions must be explicitly granted by the user.

• Signature permissions are granted by the system and can be accessed by those apps only which have the same certificate as the apps that define the permission. Most often, signature permissions are used by apps installed by the mobile operator.

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To perform specific tasks on Android devices such as accessing WiFi, sending SMS, reading SMS, accessing camera etc., each app has to explicitly ask the user to grant the permissions during installation or these permissions may be requested before using the app. End user grant the permission and continue with the installation or deny the permission and cancel the installation process. Effectiveness of Android permission system is primarily dependent upon the end user who is responsible for granting the permissions to the apps, which is likely the weakest link in Android security mechanism. This is the main reason why efficient and effective malware detection for Android apps is a crucial component of the Android ecosystem.

Permissions extracted from manifest file can be used as the basis for cost-effective malware detection and avoid high cost of time and computation. Our dataset is based on Drebin dataset which contains data on nearly 120,000 app samples, including both benign and malware apps. However, a large number of available features makes straightforward application infeasible, and an effective approach is necessary to reduce the number of features.

To this end, we apply two feature ranking algorithms (Chi-Square test and Fisher’s Exact test) and automatically extract effective permissions which have strong association with the class variable and rank the permissions based on their p-values. Then, we apply three machine learning algorithms, namely decision tree, random forest and support vector machine, to categorize apps into benign and malware. We find that random forest achieves the higher accuracy rate of 99.34% for the entire Drebin app dataset and 99.82% for the portion of the Drebin dataset which contains malware apps from three most common malware families only, in addition to all the benign apps. These results indicate that our approach is better than other existing approaches based on permissions only.

The main contributions of this paper are twofold:

- We created feature sets of Android permissions, removed unnecessary permissions with zero impact and applied two permission ranking algorithms Chi-Square Test and Fisher’s Exact Test to reduce the dimensionality of the dataset without loss of information content.
- We employed three classification algorithms namely decision tree, random forest and support vector machine to evaluate the effectiveness of ranked permissions. The experimental results show that random forest can achieve an accuracy rate which is better than that of other reported approaches.

This paper is organized as follows. Section introduces the related work. Section describes our approach. Experimental results are given in Section and compared with existing methods in Section. Section concludes this paper.

2 Related Work

Numerous authors have applied machine learning algorithms on Android permissions to detect malware apps. Risks incurred by individual permissions as well as by combinations of permissions has been analyzed in, where feature ranking methods such as mutual information, correlation coefficient and t-test were employed to rank permissions based on their risk. They also use sequential forward selection and principal component analysis to identify subsets of risky permissions and evaluate the effectiveness of model using decision tree, random forest and support vector machine. Zhang et al. exploited function call graph vectorization to extract information that allowed files to be identified as malicious.

Drebin performs static analysis of Android apps and identify malicious apps directly on smartphone. It gathers as many features of an app from manifest file and disassembled code such as hardware components, requested permissions, used permissions, app components, filtered intents, restricted API calls, suspicious API calls, network addresses. It embeds them in a joint vector space such that typical patterns indicative for malware can be automatically identified and used for explaining the decision. However, using large number of features increases the complexity of the algorithm and hence increases the computational overhead. Drebin performs binary classification using a linear support vector machine that determines a hyperplane and separates benign and malware apps with maximal margin.

In our previous work, we have used kernel density estimation, a non-parametric method for estimating probability distribution from data, to examine Android permission patterns and calculate the moments of permissions distribution. While examining dangerous permissions, we found that benign apps have lower mean, higher coefficient of variance, higher skewness and higher kurtosis than malware apps.

Aung and Zaw proposed a framework to gather permissions from manifest files of 500 Android APK files and develop a machine learning-based malware detection system to detect Android malware. Their system monitors permission-based features and events extracted from Android apps and analyses these features by using classification algorithms to distinguish between benign and malware apps.
A number of Android apps, some 175 malware and 796 benign ones, have been analyzed in [12]. App permissions have been extracted from manifest file and API calls from classes.dex file, and stored in a feature set. They selected 19 relevant API calls using information gain [13] and compared the results using machine learning classifiers.

Two main aspects of permission-based Android malware detection: feature selection methods and classification algorithms have been analyzed in [14]. They investigated four different feature selection methods such as Gain Ratio Attribute Evaluator, Relief Attribute Evaluator, Control Flow Subset Evaluator and Consistency Subset Evaluator with machine learning classifiers. Using these feature selection methods, they selected 97 features that could represent the whole dataset. Their experiments show that random forest and J48 decision tree classifiers achieve the highest performance of all feature selection methods used.

Forensic analysis tool FAMOUS (forensic analysis of mobile devices using scoring of application permissions) was developed for the detection of Android malware based on static analysis [15]. This tool will scan all the installed apps of Android device and provide an explanatory report. Their best performing model uses weighted score feature set to achieve classification based on app permissions.

An innovative malware detection framework for Android has looked into more than 29,000 benign and malware apps in the period 2010 to 2019 to identify the most significant permissions [16]. The authors evaluated eight ML algorithms and founds that the Random Forest classifier based model performed best.

We note that all of the different machine learning algorithms used did not achieve high accuracy, with best results ranging from 91.75% to at most 94.84% which is not too high [11, 12, 14, 15]. In addition, none of the above approaches can learn effective feature interaction, which shows the improvement of the performance of learning models. This observation has motivated us to find a better approach for malware detection using app permissions.

### 3 Our Approach: Relevant permission-based malware detection system

For our malware detection system, we used Drebin [3] dataset which contains data for a total of 114,298 benign apps and 5510 malware apps. Malware apps used in this dataset are classified into 169 malware categories. The list of features used by each app includes hardware components (GPS, Camera, Touchscreen etc.), permissions, API calls, network addresses and others.

From this dataset, we considered only app permissions and created two datasets: one with all the apps and another with all benign apps and malware apps from top three malware families only. The malware in this set include samples from FakeInstaller, DroidKungFu, and Opfake families with 925, 666, and 612 malware samples, respectively, with a total of 2203 samples or about 40% of all malware apps. As shown in Table 1 our first dataset contains 119,808 apps and second dataset contains 116,501 apps.

### Table 1: Datasets used in our experiments.

| dataset  | total apps | benign apps | malware apps | description                  |
|----------|------------|-------------|--------------|------------------------------|
| Dataset1 | 119808     | 114298      | 5510         | All benign and all malware   |
| Dataset2 | 116501     | 114298      | 2203         | All benign and top three malware families only |

Our detection system proceeds in several steps. First, we remove irrelevant permissions from the feature set. Then, we rank the features using feature selection methods, namely Chi-Square test and Fisher’s Exact test. In the final step, we apply classification algorithms, namely, Decision Tree, Support Vector Machine and Random Forest to classify apps into benign and malware ones.

#### 3.1 Remove irrelevant permissions

An app can execute a specific operation only if it has required permissions. We created a feature set that contains total of 94 permissions, out of which 37 are normal, 28 are dangerous, and 29 are signature permissions. While analyzing Drebin dataset, we found that 45 of those permissions that were never used in any benign or malware app in the dataset such as ADD_VOICEMAIL, BIND_CARRIER_SERVICES, BIND_TEXTSERVICE etc. We removed these permissions and kept the remaining 49 relevant ones.

#### 3.2 Feature Selection

Our next step is to find permissions which have strong association with class variable named AppCategory in dataset1 and dataset2. AppCategory is a class variable that categorizes an app as benign or malware. Individual permission is used to...
predict the AppCategory based on their p-value and it leads to remove the unrelated permissions. Focusing on most relevant permissions aims to reduce the dimensionality of the dataset without loss of accuracy, and also to subsequently improve the training speed of the detection algorithms. We used two feature ranking methods (Chi-Square test and Fisher’s Exact test) in our approach.

- Chi-Square test [17] is a statistical hypothesis test used to determine the correlation between individual permissions and the AppCategory. In Chi-Square test, we are ranking permissions based on their p-values and rejecting the null hypothesis, when the p-value of permission feature is less than or equal to 0.05. The threshold value of 0.05 is usually set to reject the null hypothesis. The null hypothesis is that individual permissions and the AppCategory are independent and the correlation with a p-value lower than the given threshold value is statistically significant. Smaller p-value indicates stronger evidence against the null hypothesis, so the null hypothesis can be rejected.

- Fisher’s Exact test [18] is another statistical method used to determine the association between two categorical variables. Just like Chi-Square test, Fisher’s Exact test evaluates the null hypothesis of independence. As in the previous case, we reject the null hypothesis when the p-value of permission features is less than or equal to 0.05. It is worth noting that Fisher’s test is one of the exact tests because the significance of deviation from the null hypothesis such as p-value can be calculated exactly, rather than relying on an approximation [19].

Table 2 shows the reduced set of permissions (with their p-values) obtained by applying feature ranking algorithms on dataset1 and dataset2. For dataset1, Chi-Square test and Fisher’s Exact test identify the same number of permissions (47) whose p-values less than or equal to 0.05; for dataset2, Chi-Square test has 39 permissions whose p-values less than or equal to 0.05 while Fisher’s Exact test has 2 additional permission (READ_SYNC_STATS and REORDER_TASKS) for a total of 41 permissions.

3.3 Machine Learning based Classification Algorithms

We employed three supervised machine learning-based classification algorithms, namely, decision tree, random forest, and support vector machine, to classify benign and malware apps.

- Decision Tree is used in prediction problems where the outcome belongs to one out of a limited set of categories [20]. It is based on divide and conquer strategy to build a suitable tree from a given learning set which contains a set of labeled instances. In our case, nodes of the decision tree are permissions and leaves are the established class labels. Decision trees are built as a set of rules during learning process. These rules are then used to predict the classes of test observations. Decision trees predict by evaluating which class is the most common among the training data within the partition rather than taking average in each partition [21].

- Support Vector Machine [22] is a supervised machine learning algorithm used for binary classification. In SVM, each observation is plotted as a point in N-dimensional space and finds the hyper plane that separates the N-dimensional space into two classes. Here N represents the number of permissions or features. Given the labeled training data, SVM estimates an optimal hyperplane which classifies new samples.

- Random Forest [23] is an ensemble learning method for classification that constructs a large number of individual decision trees at the time of training or, in other words, makes a forest of decision trees. It is an ensemble learning method because it combines a number of decision trees into one predictive model where it reduces the overfitting by averaging the result. Each decision tree predicts the app category (benign or malware) and the app category with the most votes becomes the final prediction of the algorithm. Like other ensemble learning algorithms, random forest often surpasses a single tree in terms of accuracy of class.

4 Results and Evaluation

4.1 Experimental Setup

All experiments were conducted on a PC with Intel Core i7-9700 running at 4.7GHz with 32GB RAM memory, using RStudio version 1.25033 software [24].
Table 2: Permissions and their p-values after applying Chi-Square Test and Fisher’s Exact Test on dataset1 and dataset2.

| Permission                          | p-values from Chi-Square test | p-values from Fisher’s Exact Test |
|-------------------------------------|-------------------------------|----------------------------------|
| dataset1                            | dataset2                      | dataset1                         | dataset2 |
| ACCESS_COARSE_LOCATION              | 1.68E-37                      | N/A                              | 1.07E-35  |
| ACCESS_FINE_LOCATION                | 9.86E-26                      | 4.90E-03                         | 1.11E-24  |
| ACCESS_LOCATION_EXTRA_COMMANDS     | 0                             | 5.42E-120                        | 2.83E-201 |
| ACCESS_NETWORK_STATE                | 1.67E-57                      | N/A                              | 6.11E-59  |
| ACCESS_WIFI_STATE                  | 0                             | 4.20E-176                        | 0         |
| BATTERY_STATS                       | 1.58E-08                      | N/A                              | 3.64E-07  |
| BIND_WALLPAPER                      | 5.47E-03                      | N/A                              | 8.50E-03  |
| BLUEETOOTH                          | 1.06E-76                      | N/A                              | 1.39E-50  |
| BLUETOOTH_ADMIN                     | 2.08E-84                      | 4.44E-03                         | 6.72E-53  |
| CALL_PHONE                          | 2.90E-17                      | 8.91E-26                         | 4.96E-16  |
| CAMERA                              | 4.72E-20                      | 3.49E-31                         | 4.62E-23  |
| CHANGE_NETWORK_STATE                | 5.79E-201                     | 5.25E-108                        | 1.18E-122 |
| CHANGE_WIFI_MULTICAST_STATE        | 6.05E-03                      | 4.88E-02                         | 1.29E-03  |
| CLEAR_APP_CACHE                     | 3.36E-48                      | N/A                              | 9.95E-29  |
| DISABLE_KEYGUARD                   | 1.90E-299                     | 1.71E-04                         | 7.87E-171 |
| EXPAND_STATUS_BAR                  | 1.20E-46                      | 1.14E-02                         | 1.37E-28  |
| GET_ACCOUNTS                        | 6.37E-89                      | 3.57E-12                         | 2.77E-66  |
| GET_PACKAGE_SIZE                   | 1.35E-58                      | N/A                              | 1.97E-34  |
| INSTALL_PACKAGES                   | 0                             | 0                                | 0         |
| INTERNET                            | 1.68E-57                      | 4.54E-25                         | 2.74E-73  |
| KILL_BACKGROUND_PROCESSES          | 1.95E-42                      | 6.63E-05                         | 6.60E-30  |
| MODIFY_AUDIO_SETTINGS               | 7.97E-04                      | 1.97E-05                         | 4.55E-04  |
| PROCESS_OUTGOING_CALLS             | 5.41E-115                     | 6.26E-03                         | 8.10E-70  |
| READCALENDAR                        | 1.40E-11                      | 2.81E-13                         | 4.90E-14  |
| READ_CONTACTS                      | 0                             | 3.08E-21                         | 1.94E-231 |
| READ_EXTERNAL_STORAGE              | 2.46E-115                     | 0                                | 4.58E-77  |
| READ_LOGS                           | 7.31E-117                     | 6.12E-06                         | 1.81E-85  |
| READ_PHONE_STATE                   | 0                             | 0                                | 0         |
| READ_SMS                            | 0                             | 0                                | 0         |
| READ_SYNC_SETTINGS                  | 0.34E-03                      | 1.77E-02                         | 9.93E-03  |
| RECEIVE_BOOT_COMPLETED              | 4.34E-03                      | N/A                              | 4.13E-04  |
| RECEIVE_SMS                         | 0                             | 0                                | 0         |
| RECEIVE_MMS                         | 3.98E-203                     | N/A                              | 2.97E-97  |
| RECEIVE_MMS                         | 0                             | 0                                | 0         |
| RECEIVE_MMS                         | 3.98E-203                     | N/A                              | 2.97E-97  |
| RECEIVE_WAP_PUSH                    | 0                             | 5.98E-152                        | 2.89E-133 |
| RECORD/AUDIO                        | 6.63E-04                      | 1.27E-06                         | 4.14E-04  |
| REORDER_TASKS                       | 0                             | N/A                              | 3.64E-02  |
| SEND_SMS                            | 0                             | 0                                | 0         |
| SET_WALLPAPER                       | 2.26E-23                      | 2.67E-21                         | 7.80E-21  |
| SET_WALLPAPER_HINTS                 | 1.62E-32                      | 1.09E-02                         | 2.66E-21  |
| SYSTEM_ALERT_WINDOW                 | 6.19E-52                      | 1.20E-39                         | 2.10E-48  |
| VIBRATE                             | 0                             | 6.29E-77                         | 0         |
| WAKE_LOCK                           | 5.95E-07                      | 7.58E-13                         | 7.26E-08  |
| WRITECALENDAR                       | 1.70E-121                     | 2.24E-17                         | 1.25E-88  |
| WRITE_EXTERNAL_STORAGE              | 0                             | 1.91E-192                        | 0         |
| WRITE_SETTINGS                      | 2.01E-128                     | 6.99E-19                         | 4.13E-97  |
| WRITE_SYNC_SETTINGS                 | 3.33E-02                      | 2.03E-02                         | 3.08E-02  |
All experiments were conducted with four sets of features, shown in Table 3. The raw dataset that contains all permissions (feature set 1) is used for reference. After the removal of irrelevant permissions from the datasets we conducted experiments on second feature set which contains remaining 49 permissions. Finally, we apply feature ranking algorithms such as Chi-Square test and Fisher’s Exact test to create third and fourth feature set which contains permissions whose p-value is less than or equal to 0.05.

### 4.2 Evaluation Metrics

In this section, we present evaluation metrics used in our experiments. Since our goal is to identify malware apps, the basic measures are as follows:

- **True Positives (TP)** are malware apps that are correctly classified as malware.
- **True Negatives (TN)** are benign apps that are correctly classified as benign.
- **False positives (FP)** are benign apps that are incorrectly classified as malware.
- **False negatives (FN)** are malware apps that are incorrectly classified as benign.

Furthermore, we are using the following derived evaluation metrics namely accuracy rate, false positive rate, false negative rate, true positive rate, true negative rate, precision and F-score for calculating the effectiveness of chosen classifiers.

True positive rate (also referred to as recall) is the proportion of malware apps correctly classified. Given the number of true positive and false negative, true positive rate can be obtained as

\[
TPR = \frac{TP}{TP + FN} \tag{1}
\]

True negative rate is the proportion of benign apps correctly classified; it can be obtained as

\[
TNR = \frac{TN}{TN + FP} \tag{2}
\]

False positive rate is the proportion of benign apps that are incorrectly classified as malware; it can be obtained as

\[
FPR = \frac{FP}{FP + TN} \tag{3}
\]

False negative rate is the rate of malware apps that are incorrectly classified as benign apps. Given the number of false negative and true positive, FNR can be obtained as

\[
FNR = \frac{FN}{FN + TP} \tag{4}
\]

Accuracy is the rate of correctly predicted malware samples and benign samples out of all samples in the dataset and can be obtained as

\[
ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}
\]
Precision is the accuracy of malware apps correctly classified; it is also referred to as positive predictive rate. It can be obtained as

\[ \text{Precision} = \frac{TP}{TP + FP} \]  

Finally, F-Score is a weighted average of recall and precision. Closer the value of F-Score to 100%, better the classification is performed. As we have precision and recall values, F-score can be obtained as

\[ F\text{-Score} = \frac{(1 + \alpha^2) \times (\text{Precision} \times \text{Recall})}{(\alpha^2 \times \text{Precision} + \text{Recall})} \]  

where \( \alpha \) indicates the relative weight assigned to precision as opposed to recall. We are using \( \alpha=1 \), which indicates that equal weight is assigned to both precision and recall.

4.3 Results and Analysis

In all experiments, we divided our dataset into training set and testing set, with 70% of the data used for training classifier and the remaining 30% used for testing. We also logged the processing time of all the classifiers. Processing time includes CPU time (user time, system time) and elapsed time that the classifiers spend to predict the app category. CPU time is the combination of user time and system time, where user time is the amount of time spent for predicting the app category and system time is the amount of time spent by the kernel or the operating system on behalf of predicting the app category. Elapsed time is the wall clock time to predict the app category. User time, system time and elapsed time are measured in seconds.

4.3.1 Decision Tree Classifier

Decision tree experiments were conducted on two datasets with four feature sets. If we compare the decision tree experiments in Table 4, experiments with Chi-Square and Fisher’s Exact test-filtered dataset1 have better F-Score values (68.77%) for dataset1 than the same dataset but with no filtering and with relevant features only where F-scores are 62.23% and 64.11%, respectively.

| dataset | feature count (filtering) | ACC   | FPR  | FNR  | TPR  | TNR  | Precision | F-Score |
|---------|---------------------------|-------|------|------|------|------|-----------|---------|
| dataset1| 94 (none)                 | 98.77 | 0.93 | 23.61| 76.39| 99.07| 52.50     | 62.23   |
|         | 49 (relevant only)        | 98.86 | 0.83 | 23.61| 76.39| 99.17| 55.22     | 64.11   |
| dataset2| 94 (none)                 | 98.99 | 0.79 | 20.20| 79.8 | 99.21| 52.49     | 63.32   |
|         | 49 (relevant only)        | 99.01 | 0.78 | 20.20| 79.8 | 99.22| 52.88     | 63.60   |
| dataset1| 47 (Chi-Square)           | 99.08 | 0.62 | 23.61| 76.39| 99.38| 62.53     | 68.77   |
|         | 47 (Fisher’s Exact)       | 99.08 | 0.62 | 23.61| 76.39| 99.38| 62.53     | 68.77   |
| dataset2| 39 (Chi-Square)           | 99.33 | 0.26 | 24.30| 75.70| 99.74| 83.45     | 79.39   |
|         | 41 (Fisher’s Exact)       | 99.38 | 0.20 | 24.30| 75.70| 99.80| 86.88     | 80.90   |

The same observation holds for dataset2 with F-Score values of 79.39% and 80.90% for the two filtered feature sets in Table 4 as compared to F-Score values of 63.32% and 63.60% obtained for dataset2 with no filtering and with relevant features only. Note that Chi-Square and Fisher’s Exact feature sets both lead to the same results in Table 4 for dataset1 due to the identical feature set, as per Table 2.

Regarding computation time shown in Table 5, filtering using Fisher’s Exact test and subsequent classification with Decision Tree take the least processing time, but the difference is not very large.

4.3.2 Support Vector Machine classifier

A total of 16 experiments were conducted for SVM: eight experiments were conducted before tuning the parameters, which is done using the default SVM parameters in R [25]; the other eight were conducted after tuning the parameters in which case SVM parameters cost and gamma have been set at the optimized level obtained through the tune [26] function in R. Gamma parameter defines how far the impact of a single training example reaches, with small and large values of gamma corresponding to a Gaussian function with large and small variance, respectively. Cost parameter controls the impact of each individual support vector and controls the training errors.
Table 5: Computation times (in seconds) for Decision Tree classifier.

| data set | feature count (filtering) | user | system | elapsed |
|----------|---------------------------|------|--------|---------|
| dataset1 | 94 (none)                 | 1.27 | 0.08   | 1.35    |
|          | 49 (relevant only)        | 0.69 | 0.01   | 0.70    |
| dataset2 | 94 (none)                 | 1.38 | 0.10   | 1.47    |
|          | 49 (relevant only)        | 0.80 | 0.01   | 0.81    |
| dataset1 | 47 (Chi-Square)           | 0.74 | 0.00   | 0.74    |
|          | 47 (Fisher’s Exact)       | 0.69 | 0.00   | 0.69    |
| dataset2 | 39 (Chi-Square)           | 0.64 | 0.02   | 0.65    |
|          | 41 (Fisher’s Exact)       | 0.58 | 0.03   | 0.61    |

After tuning the SVM parameters, we observe an improvement in evaluation metrics values, Table 6, that F-Score for dataset1 with 94 permissions has the value of 65.51% before tuning the parameters, but after tuning F-Score value significantly increase to 88.42%. Same is true with other SVM experiments.

Table 6: Experimental results for Support Vector Machine classifier. All results given in percent.

| dataset  | feature count (filtering) | tuning | ACC   | FPR   | FNR   | TPR   | TNR   | Precision | F-Score |
|----------|---------------------------|--------|-------|-------|-------|-------|-------|-----------|---------|
| dataset1 | 94 (none)                 | before | 97.88 | 1.79  | 15.59 | 84.41 | 98.21 | 53.53     | 65.51   |
|          |                            | after  | 98.98 | 0.72  | 7.92  | 92.08 | 99.28 | 85.05     | 88.42   |
|          | 49 (relevant only)        | before | 98.19 | 1.53  | 12.48 | 87.52 | 98.47 | 60.49     | 71.53   |
|          |                            | after  | 99.13 | 0.56  | 7.93  | 92.07 | 99.44 | 87.99     | 89.99   |
| dataset2 | 94 (none)                 | before | 99.25 | 0.55  | 13.41 | 86.59 | 99.45 | 71.54     | 78.35   |
|          |                            | after  | 99.62 | 0.28  | 5.79  | 94.21 | 99.72 | 86.85     | 90.38   |
|          | 49 (relevant only)        | before | 99.64 | 0.22  | 7.85  | 92.15 | 99.78 | 88.47     | 90.27   |
|          |                            | after  | 99.66 | 0.24  | 5.71  | 94.29 | 99.76 | 88.51     | 91.30   |
| dataset1 | 47 (Chi-Square/Fisher’s Exact) | before | 98.49 | 1.29  | 7.35  | 92.65 | 98.71 | 72.96     | 81.63   |
|          |                            | after  | 99.27 | 0.42  | 7.76  | 92.24 | 99.58 | 90.66     | 91.44   |
| dataset2 | 39 (Chi-Square) / 41 (Fisher’s Exact) | before | 99.72 | 0.14  | 8.06  | 91.94 | 99.86 | 92.51     | 92.22   |
|          |                            | after  | 99.77 | 0.05  | 8.92  | 91.08 | 99.95 | 97.16     | 94.02   |

We can also observe in Table 6 that, after tuning the parameters, SVM with Chi-Square and Fisher’s Exact feature sets gives the best results among SVM experiments. In particular, it obtains the best F-Score value of 91.44% for dataset1, and 94.02% for dataset2. However, the computation time for SVM classifier, as shown in Fig. 7, is much higher than that of its Decision Tree counterpart.

4.3.3 Random Forest Experiments

Random Forest experiments were conducted on two datasets with four feature sets. As seen from Table 9, Random Forest with Chi-Square feature sets and Random Forest with Fisher’s Exact feature sets give the best results among all classifiers. As can be see, F-score values for dataset1 and dataset2 with Chi-Square filtering are 92.03% and 95.05%, respectively, with the corresponding accuracy rates of 99.35% and 99.81%, respectively. When Fisher’s Exact test is used, accuracy rate and F-score are slightly higher at 99.34% and 92.17%, respectively, for dataset1, and 99.34% and 99.82%, respectively, for dataset2. While accuracy values are virtually identical for both Chi-Square and Fisher’s Exact test filtering, the latter gives higher values for the F-score. Accuracy is marginally better for dataset1 with Chi-Square filtering on account of slightly better false positive rate, true negative rate and precision rate.

As shown in Tables 4, 6, and 8, the value of F-score increases with all classifiers when we filter permissions, first by removing the irrelevant ones and then by ranking the remaining ones and retaining those with p-value below 0.05 using either Chi-Square or Fisher’s Exact tests. In fact, the value of F-score reach to the maximum in all the classifiers.

In the above experiments, Decision Tree is giving the worst results in terms of accuracy and F-score, while Random Forest is giving the best results. If the malware is from the top three malware family then Random Forest with Fisher’s Exact feature set has the best F-Score of 95.28% among all the classifiers. Even if the malware is not from the top three malware family then still Random Forest with Fisher’s Exact feature set gives the best F-Score of 92.17%. If we compare the computational
Table 7: Computation time (in seconds) for Support Vector Machine classifier.

| dataset | feature count (filtering) | tuning | user | system | elapsed |
|---------|---------------------------|--------|------|--------|---------|
| dataset1 | 94 (none) | before | 40.45 | 0.03 | 40.48 |
|         | | after | 35.91 | 0.10 | 36.01 |
|         | 49 (relevant only) | before | 37.99 | 0.09 | 38.30 |
|         | | after | 33.76 | 0.02 | 33.78 |
| dataset2 | 94 (none) | before | 38.19 | 0.09 | 38.30 |
|         | | after | 33.76 | 0.02 | 33.78 |
|         | 49 (relevant only) | before | 36.55 | 0.13 | 36.69 |
|         | | after | 31.09 | 0.08 | 31.15 |

Table 8: Experimental results for Random Forest classifier. All results given in percent.

| dataset | feature count (filtering) | ACC | FPR | FNR | TPR | TNR | Precision | F-Score |
|---------|---------------------------|-----|-----|-----|-----|-----|-----------|---------|
| dataset1 | 94 (none) | 98.60 | 1.25 | 5.62 | 94.38 | 98.75 | 74.02 | 82.97 |
|         | 49 (relevant only) | 98.89 | 0.88 | 6.64 | 93.36 | 99.12 | 81.71 | 87.15 |
| dataset2 | 94 (none) | 99.60 | 0.33 | 4.45 | 95.55 | 99.67 | 82.79 | 88.71 |
|         | 49 (relevant only) | 99.74 | 0.18 | 4.97 | 95.03 | 99.82 | 90.94 | 92.94 |
| dataset1 | 47 (Chi-Square) | 99.35 | 0.40 | 6.71 | 93.29 | 99.60 | 90.80 | 92.03 |
| dataset2 | 39 (Chi-Square) | 99.81 | 0.03 | 8.30 | 91.70 | 99.97 | 98.65 | 95.05 |
| dataset1 | 47 (Fisher’s Exact) | 99.34 | 0.56 | 3.16 | 96.84 | 99.44 | 87.93 | 92.17 |
| dataset2 | 41 (Fisher’s Exact) | 99.82 | 0.05 | 6.66 | 93.34 | 99.95 | 97.30 | 95.28 |

Table 9: Computation time (in seconds) for Random Forest classifier.

| dataset | feature count (filtering) | user | system | elapsed |
|---------|---------------------------|------|--------|---------|
| dataset1 | 94 (none) | 2.44 | 0.06 | 2.50 |
|         | 49 (relevant only) | 2.30 | 0.03 | 2.33 |
| dataset2 | 94 (none) | 1.91 | 0.01 | 1.93 |
|         | 49 (relevant only) | 1.36 | 0.01 | 1.38 |
| dataset1 | 47 (Chi-Square) | 1.87 | 0.01 | 1.89 |
| dataset2 | 39 (Chi-Square) | 1.17 | 0.02 | 1.19 |
| dataset1 | 47 (Fisher’s Exact) | 1.98 | 0.03 | 2.02 |
| dataset2 | 41 (Fisher’s Exact) | 2.51 | 0.04 | 2.59 |

performance of all classifiers, then Decision Tree is giving the best results and have processing time under 1.50 seconds, but it is not good in accuracy and F-score. While Random Forest has processing time under 2.60 seconds, which is also considered to be good result because Random Forest operate by constructing a multitude of decision trees and Random Forest also has the best accuracy rate and F-score value among other classifiers.
5 Comparison with existing methods

We evaluate our results by comparing them with the existing methods and we find that some approaches do not work well in detecting Android malware. There are many tools which depend on signatures [6] and look for patterns and if specific pattern is not matched, then the technique will not be able to detect that specific type of malware. There are also some approaches which focus on risky permissions only and ignore the normal permissions, and hence does not correctly classify the benign and malware apps. There are few approaches who apply their algorithms on small dataset and may lead to incorrect classification results.

Our approach is more efficient than Drebin [3] in terms of accuracy because when we combine permissions with feature ranking algorithms, we are able to detect malware with an accuracy rate of 99.34% for dataset1 and 99.82% for dataset2 using Fisher’s Exact algorithm and random forest classifier while Drebin has the accuracy rate of 93.90% for full dataset and 95.90% for Malgenome dataset.

Different ranking algorithms were used in [8] but they only use the high-risk permissions using sequential forward selection and principal component analysis approaches, and ignore the low risk permissions. Contrary to that, we focus on all permissions, regardless of whether they are categorized as normal permissions, dangerous permissions or signature permissions, and retain only the relevant ones. The best F-score value reported in [8] is about 91% with the false positive rate of 0.60% while our best F-score value is 92.17% for dataset1 and 95.28% for dataset2 with the false positive rate of 0.56% and 0.05% respectively. Their target was to detect the malware abuse by extracting high risk permissions, but our approach is to develop a framework that can detect both benign apps and malware apps.

A combination of app permissions and source code-based analysis was reported in [27]. They used different machine learning classifiers such as C4.5 decision tree, random forest, SVM etc. With the combination of classifiers, they achieved a best F-score value of 95.6% using source code-based analysis, which is slightly better than our best F-score value 95.28%. But they did the experiments on small dataset, they only used 387 apps for permissions-based analysis and 368 apps for source code-based analysis. While our dataset contains a large number of apps, which contains a total of 119,808 apps, 114,298 are benign apps and 5510 are malware apps and the detection of Android malware from large number of apps is a challenging task.

We also compare our results with APK Auditor [28], which is a permission-based Android malware detection tool and consists of three main parts, namely signature database, an Android client, and central server which communicates between end user and signature database. APK Auditor classifies apps based on permissions and stores the extracted information of apps in a signature database. However, they have a rather low accuracy rate of 88% as opposed to our accuracy rate of 99.34% for dataset1 and 99.82% for dataset2. Their detection rate is low because they are using a total of 145 permissions including irrelevant permissions; our detection approach is based on the most relevant features and is thus able to achieve a higher accuracy rate.

The best results were achieved with Random Forest Classifier reported in [16] which reported accuracy of 97%, but that approach does not involve feature interaction which is addressed in our model.

Despite the accuracy rate higher than other approaches, we also experience a false negative rate of 6.66% for dataset2 and recall rate of 93.34%. In future, our aim is to improve these numbers with the combination of other features such as API calls, method calls etc.

6 Conclusion and Future Work

Permission system is one of the security procedures used by the Android operating system. Our target was to develop an approach based on the Android permission system for the detection of Android malware. Our proposed approach utilized machine learning classifiers, which were trained with the proposed features sets. Unnecessary feature sets were removed from the datasets and then ranked using Chi-Square test and Fisher’s Exact test feature ranking algorithms. These feature sets were ranked based on their p-values. Different experiments were conducted on four feature sets and we concluded that the permissions interactions based on Chi-Square and Fisher’s Exact are the most effective in detecting malware apps. If the malware app is from the top three malware family, our approach produces the best results. Even if the malware app is not from the top three malware family, still our approach is better than many existing approaches. Comparison with the state-of-the-art approaches are also done in this paper. Our experimental results validate our approach for malware detection, which can effectively detect malware with more accuracy and higher F-Score compared to existing approaches. The experiment results show that our approach combined with Fisher’s Exact and random forest algorithm has a high accuracy rate and F-score value. For future research, our aim is to increase the precision rate and recall rate, and hence increase F-score value with the combination of permissions and other features such as API calls and methods calls, among others.
7 Acknowledgments

Research presented here was in part supported through Canada’s National Science and Engineering Research Council (NSERC) Discovery Grants.

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