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# Android Malware Detection using App permissions

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**Abstract:** With the growth in the android market, there is a significant increase of apps with malicious activities. According to ZDNet, 10-24% of apps over the Play store couldbe malicious applications. Over the layer, these apps look similar to any other standard app, but they impact the user system in harmful ways. The current methodologies to detect malwares are resource heavy as well as exhaustive, yet fail to compete with the pace of new malwares. So, We tried to approach this Problem using Machine Learning Techniquesand developed a model to predict an Application for potential Malware risk.

**Keywords:** Android Permissions, Malware Detection, Random Forest, Machine Learning

## 1. INTRODUCTION

Despite the growing malwares, there is still not an effective method to detect malware applications. Withthe progressive scope of Machine Learning in various domains, we believe the issue of detecting Malware can be solved using Machine Learning techniques. Our project aimsat a detailed and systematic study of malware detection using machine learning techniques, and further creating an efficient ML model which could classify the apps into benign(0)and malware(1) depending on the requested app permissions.

TABLE VII: Summary of app distribution.

| | Installs | | Installer | | | | | Children | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Vector | All | Unw. | All | Unw. | Plat. | Pkg. | Sig. | Pkg. | Sig. | VDR | RVDR |
| Playstore | 87.2% | 67.5% | 10 | 3 | 0 | 2 | 9 | 1.2M | 816K | 0.6% | 1.0 |
| Alt-market | 5.7% | 10.4% | 102 | 31 | 15 | 87 | 67 | 128K | 77K | 3.2% | 5.3 |
| Backup | 2.0% | 4.8% | 49 | 2 | 24 | 31 | 39 | 528K | 355K | 0.9% | 1.5 |
| Pkginstaller | 0.7% | 10.5% | 79 | 5 | 25 | 11 | 74 | 197K | 127K | 2.4% | 4.0 |
| Bloatware | 0.4% | 6.0% | 54 | 2 | 28 | 37 | 41 | 2.1K | 1.3K | 1.2% | 2.0 |
| PPI | 0.2% | 0.1% | 21 | 0 | 2 | 20 | 11 | 1.5K | 1.3K | 0.3% | 0.5 |
| Fileshare | <0.1% | <0.1% | 13 | 3 | 4 | 13 | 11 | 8.8K | 7.4K | 1.3% | 2.1 |
| Themes | <0.1% | <0.1% | 2 | 0 | 2 | 2 | 2 | 634 | 14 | 0.3% | 0.5 |
| Browser | <0.1% | <0.1% | 47 | 4 | 3 | 40 | 38 | 4.8K | 3.3K | 3.8% | 6.3 |
| MDM | <0.1% | <0.1% | 7 | 1 | 1 | 7 | 6 | 766 | 489 | 0.3% | 0.5 |
| Filemanager | <0.1% | <0.1% | 58 | 11 | 9 | 32 | 43 | 6.6K | 4.7K | 2.6% | 4.3 |
| IM | <0.1% | <0.1% | 13 | 2 | 0 | 10 | 11 | 2K | 1.2K | 2.9% | 4.8 |
| Other | <0.1% | 0.3% | 151 | 68 | 28 | 125 | 98 | 9.1K | 5.3K | 3.9% | 6.5 |
| Unclassified | 3.7% | <0.1% | 3.5K | 2.4K | 386 | 3.3K | 814 | 91K | 16K | <0.1% | 0.1 |
| All | 100.0% | 100.0% | 4.2K | 2.5K | 79 | 3.6K | 1.0K | 1.6M | 992K | 1.6% | 2.6 |

This study Proposes

- Examining and Evaluating Android metadata and Permissions as Malware Predictors
- Presenting a machine learning malware detection strategy that depend on openly available metadata information.
- Analyzing such a model and determining its utility as a first-stage malware filter for Android malware detection

## 2. LITERATURE REVIEW

**Paper 1:**

In the paper titled Dynamic Permissions based Android Malware Detection using Machine Learning Techniques [1], the authors talk about various Machine Learning techniques which could be used for Malware Detection in Android apps usingpermissions. The study has been conducted on an appreciable sample size of 11,000 apps with close to an equal number of benign and malicious apps. All the used terminologies are defined properly and well explained. The used methodology has been also well described which empowers others to perform the study themselves. Adequate use of graphs and tables to present vital facts/figures whenever necessary, makes it easier to follow

  

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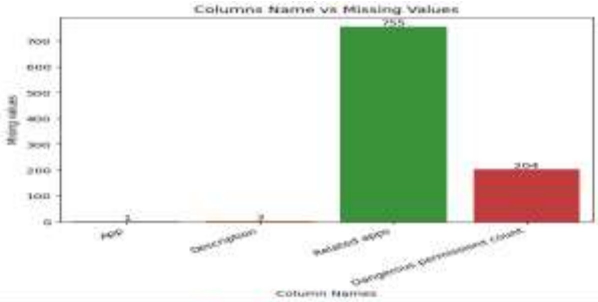
through the steps of study. Though the author demonstrates the performances of Machine Learning techniques, they don't compare between the feasibility, practicality and performance of pre-existing classical techniques and new ML techniques. Further, the study also fails to deliver why one ML technique outperforms the other. Another criticism against the paper is its lack of reasoning on why the app permissions stand out to be such a good measure for classifying benign and malicious applications.

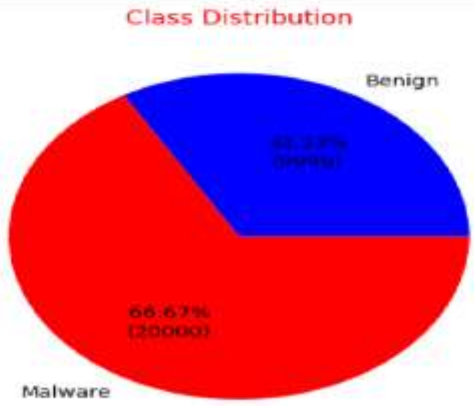
**Paper 2:**
In the paper titled Machine Learning for Android Malware Detection Using Permission and API Calls [2] authors start by laying out the different techniques used in circulation of Malware and current Malware detection techniques to fight against them. They then point out why such solutions like traditional Signature based approaches are not good enough. Moving further into the premise an emphasis on why application permission acts as a great tool for Malware Detection is made by presenting Android Application structure in much detail. Though the methodology explained is decent, exact details of technologies used are not provided, which raises an eye on the credibility. The paper provides 3 Machine Learning methods using which experiments were done over some 2510 apps containing 1260 malwares. The paper lacks many important aspects like description of used techniques and also fails to analyze their performances. Future prospects and the ways the study can be extended are not talked upon.

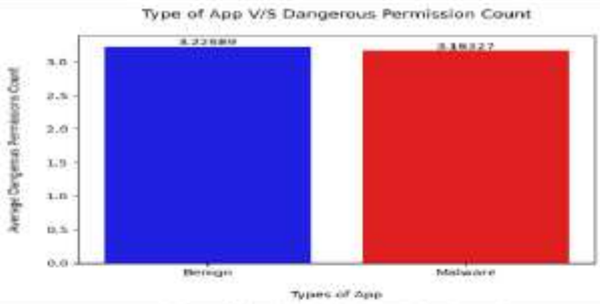
## 3. DATASET DESCRIPTION

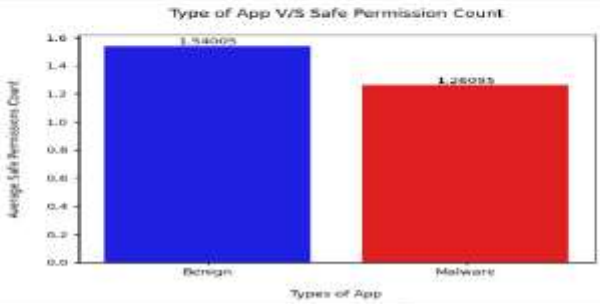
**Details:**
Dataset has been taken from kaggle
Data contains the details of the permission of around 30k app
There are 183 features in the dataset like Dangerous Permis-sions Count, Default : Access DRM content, Default : Moveapplication resource, etc.
There is one target class(binary- 0/1) named - 'Class', indi- cating Benign(0) and Malware(1) applications.
There are 29,999 records with 20,000 malwares and 9,999 benign apps.

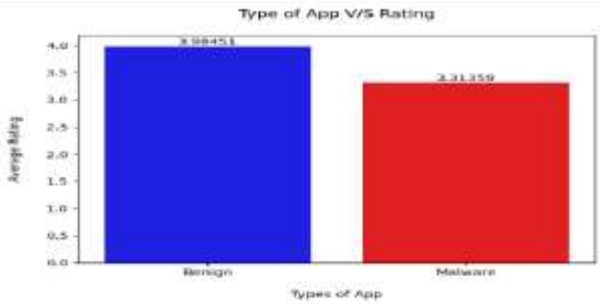
**Preprocessing, Visualization and Analysis:** Data is read from a csv file into a dataframe for easy use. Attributes required are seperated out from dataset. Several plots are built to better un- derstand/analyse the data. Date is checked for null/missing values and are therefore replaced by the mean of the column. Data is then analysed on the basis of the distribution of Malware and Benign applications in various settings and several plots were made to vi- sualise the results. Plotting and visualization are done by Matplotlib and Seaborn. Removed other data having information other than permissions. Mapped application names to index to easily retrieve the information.



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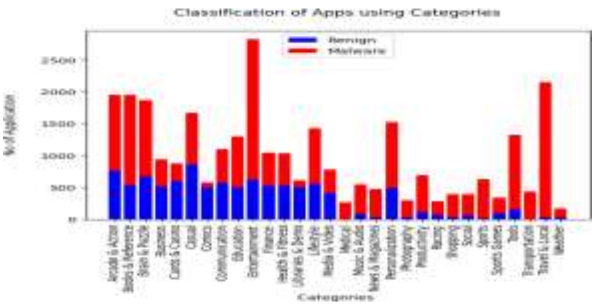
**Plots:**




| Classifier Algorithm | Optimal parameters | Precision | Accuracy | Recall | ROC_AUC |
|---|---|---|---|---|---|
| Logistic Regression | test_size=0.2, random_state=42 | 0.66828208 55614974 | 0.66783333 33333333 | 0.99800349 38857 | 0.50100877 15289011 |
| Gaussian NB | Default | 0.96171171 17117117 | 0.53716666 66666667 | 0.31969054 15522835 | 0.64705048 90400655 |
| Decision Tree | Criterion=Gini, max_depth=10, max_leaf_nodes=10 | 0.73061586 17634028 | 0.67916666 66666667 | 0.82305964 56201648 | 0.60646208 57303031 |

## 4. METHODOLOGY

After Preprocessing the data, data is split into testing and train-ing sets on a 8:2 ratio. Complete Sampling over the Dataset, however the outcome doesn't appears as expected at the end. Gong with the sampling, different classifiers are used, like logistic regression, decision trees, and NaiveBayes. However, the outcomes are unsatisfactory.
However, after observing the Dataset, we observed that there are multiple multivariate data tables, therefore we must apply PCA to each and every Dataset. Variance Percentage is plotted after using the PCA.As a result, we decided to use the inverse transform. It is totally up to us to implement the classifiers to the provided dataset. First, we applied Random Forest, which resulted in a significant improvement in the accuracies. After that, we used the Boosting approach to increase their prediction accuracy. We used the boosting strategy on an unsampled dataset and on one after selecting Re- liable features, and the results show that the model is improving. At last, we applied SVM and MLP to the resulting dataset and obtained our best results. When we compare the results obtained after feature selection and boosting, we can see that we have progressed and obtained the final accuracy.

## 5. RESULTS AND ANALYSIS

**Model Trained on the UnSampled Data**

| Decision Tree (Criterion=Gini ,max_depth=10,max_leaf_nodes=10) | |
|---|---|
| Precision | 0.7306158617634028 |
| Accuracy | 0.6791666666666667 |
| Recall | 0.8230596456201648 |
| Roc_Auc | 0.6064620857303031 |

| Logistic Regression (Default) | |
|---|---|
| Precision | 0.6682820855614974 |
| Accuracy | 0.6678333333333333 |
| Recall | 0.9980034938857 |
| Roc_Auc | 0.5010087715289011 |

| GaussianNB (Default) | |
|---|---|
| Precision | 0.9617117117117117 |
| Accuracy | 0.5371666666666667 |
| Recall | 0.3196905415522835 |
| Roc_Auc | 0.6470504890400655 |

**Overall**
In Tabulation that, Order of Accuracy is:
**Decision Tree > Logistic Regression > Gaussian Naive Bayes**

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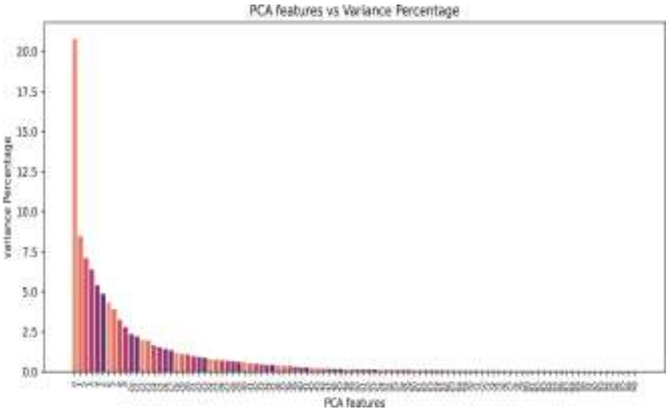
This were the results before we had done sampling and under-sampling.




| Logistic | Optimal Parameter | Accuracy | Recall | ROC |
|---|---|---|---|---|
| SVM | default | Training Accuracy 0.85 Test Accuracy 0.85 | 0.94 | 0.80 |
| Random Forest | n_estimators=200, n_jobs = -1 | Training Accuracy 0.87 Test Accuracy 0.86 | 0.93 | 0.81 |
| MLP | random_state = 42, max_iter = 300 | Training Accuracy 0.85 Test Accuracy 0.85 | 0.95 | 0.80 |

By looking at the result we can say that Random Forest perform best among all the classifiers with Accuracy of 86%. In Tabulation , Order of Accuracy is as follow: **Random Forest** > **MLP** > **SVM**

## 6. CONCLUSION

Learning-

Different ways to visualize the data for better understandingof features. Machine Learning models involving Naive Bayes, Logistic Regression and Decision Tree to model the problem. How to work on platforms like Kaggle and Google Colab. Team work and collective decisions.

## REFERENCES

[1] A. Mahindru and P. Singh, “Dynamic permissions based an-droid malware detection using machine learning techniques,” in Proceedings of the 10th innovations in software engineer- ing conference, pp. 202–210, 2017. 1