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# Android Malware Detection Using Logistic Regression, XGBoost, and SVM

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***Abstract***

*Objectives: This research aims to identify the most effective machine learning algorithm for Android malware detection by comparing the performance of Logistic Regression, XGBoost, and Support Vector Machines (SVM) on a malware dataset. The study seeks to determine which algorithm achieves the highest accuracy while minimising false positives and false negatives in detecting malicious applications.*

*Methods: The methods involve applying these three machine learning algorithms to a comprehensive Android malware dataset. The dataset captures network traffic details, including IP addresses, port numbers, protocols, and various temporal metrics. It also includes additional metrics like TCP flag counts and window sizes, essential for detailed examination of network behaviours and trends.*

*Findings: The analysis shows that XGBoost performs the best, with an accuracy of 49.31%, compared to Logistic Regression and SVM, which both hover around 43.2%. This suggests that the ensemble nature of XGBoost makes it more effective in identifying malware patterns in the Android ecosystem.*

***Keywords:*** *android malware detection, machine learning, logistic regression, XGBoost, Support Vector Machines.*

## 1. Introduction

The increasing popularity of Android devices has positioned this platform as a major target for malware, which significantly endangers user security, privacy, and device functionality. As malware becomes both more prevalent and advanced, it is crucial to implement dependable and effective detection methods to protect individuals and organisations from cyber threats. However, conventional detection approaches frequently face challenges with scalability and precision, especially in the ever-evolving Android ecosystem, where numerous applications attempt to mimic benign behaviour to evade detection.

In this research, we have taken an Android Malware Dataset. We are applying three machine learning techniques on this dataset to find the most efficient machine learning algorithm. Each of these algorithms offers distinct advantages for classification tasks, making them strong candidates for malware detection. Logistic Regression is a linear approach designed for binary classification tasks; it estimates the likelihood that a particular input fits into a designated category, thus serving well for straightforward classification challenges. XGBoost, on the other hand, is an advanced gradient-boosting technique that constructs a series of decision trees in a sequential manner. Each subsequent tree addresses the mistakes of its predecessor, making it exceptionally robust when dealing with intricate datasets. Support Vector Machines (SVM) represent a supervised learning method aimed at classifying data by identifying the optimal hyperplane that separates classes. This approach is highly effective for feature-rich datasets.

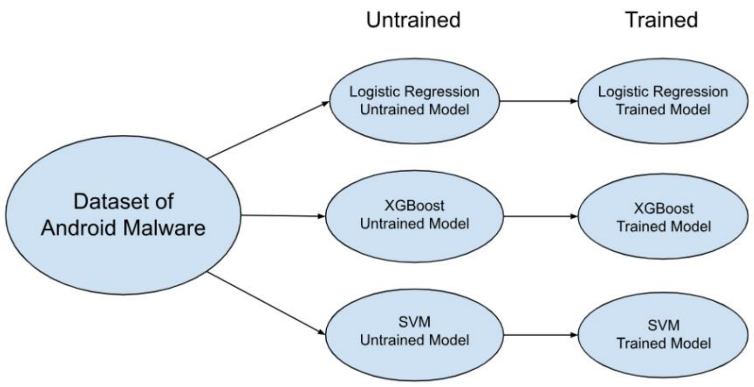

**Figure 1. Android Malware Classification Model Training Workflow**

This dataset provides a comprehensive overview of network traffic, capturing essential details like IP addresses, port numbers, protocols, and temporal metrics. It offers robust statistical analysis on packet dimensions, flow durations, and transmission rates, which are pivotal for understanding network behaviours and trends. By including various metrics such as TCP flag counts and window sizes, the dataset facilitates an in-depth examination of network protocols and communication patterns. Moreover, the categorization of traffic, with labels such as 'Android_Adware,' enhances the ability to study cybersecurity issues, particularly in detecting and analysing network anomalies and threats. While previous studies have explored machine learning techniques for malware detection, there is limited research focusing specifically on Android malware detection using network traffic data with models like Logistic Regression, XGBoost, and SVM. This study aims to fill this research gap by evaluating the performance of these three algorithms on a real-world Android malware dataset. Our objective is to determine which algorithm offers the best balance between detection accuracy, computational efficiency, and scalability.

## 2. Related works

Numerous studies have explored machine learning for Android malware detection, with varying degrees of success. Senanayake et al. (2021) provided a comprehensive overview of machine-learning techniques for Android malware detection. They emphasize the strength of ensemble methods like Random Forest in malware detection but noticed challenges in scalability for resource-constrained environments like mobile devices. Our study builds on this by applying XGBoost, a more computationally efficient ensemble method, and comparing it with Logistic Regression and SVM to determine the best balance of accuracy and efficiency. Liu et al. (2022) explore the potential of deep learning for Android malware defences in their review, "Deep Learning for Android Malware Defenses." Their work emphasises the ability of deep learning models to capture complex data patterns that traditional machine learning models might overlook. However, they also note the challenges these models pose, such as high computational costs and the need for large datasets, which can limit their practical application in resource-constrained environments like mobile devices. Rodríguez-Mota et al. (2017) investigate the evolving challenges of Android malware detection in their chapter, "Malware Analysis and Detection on Android: The Big Challenge," from IntechOpen. They highlight the need for continuous refinement of malware detection strategies as Android malware becomes more sophisticated, underscoring the importance of adapting to emerging threats. While deep learning and ensemble methods show promise, their complexity and computational requirements may hinder their real-time application in detecting malware from network traffic data. Our study aims to address this by evaluating the performance of more lightweight algorithms—Logistic Regression, XGBoost, and SVM—on Android network traffic data. By focusing on models that balance predictive accuracy with computational efficiency, we seek to identify the most effective algorithm for Android malware detection in real-time environments.

## 3. Results and discussion

The evaluation of machine learning algorithms for Android malware detection, as presented in Table 1, reveals significant insights into the performance of Logistic Regression, XGBoost Classifier, and Support Vector Machine (SVM) on the dataset used. The accuracies obtained are as follows: Logistic Regression at 43.2%, XGBoost Classifier at 49.31%, and SVM at 43.19%.

**Table 1. Accuracy of Machine Learning Algorithms on Android Malware Dataset**

| Machine Learning Algorithms | Accuracy |
|---|---|
| Logistic Regression | 43.2% |
| XGBoost Classifier | 49.31% |
| Support Vector Machine (SVM) | 43.19% |

XGBoost Classifier shows the highest accuracy among the three algorithms at 49.31%. This suggests that the ensemble method, known for handling large and complex datasets by constructing multiple decision trees, is somewhat more effective at identifying patterns indicative of malware in the Android dataset. The strength of XGBoost in this context may lie in its ability to correct errors from previous trees and adaptively focus on challenging classifications (Chen & Guestrin, 2016). Logistic Regression and SVM both yield similar accuracies (43.2% and 43.19% respectively), indicating modest performance. These results are particularly noteworthy because both methods are fundamentally different. Logistic Regression, a linear classifier, is typically suited for datasets where a linear decision boundary is expected (Hosmer Jr, Lemeshow, & Sturdivant, 2013). In contrast, SVM is designed to find the optimal hyperplane that maximises the margin between classes, beneficial for feature-rich datasets (Cortes & Vapnik, 1995). The comparable performance of these two methods might suggest that the linear decision boundaries assumed by Logistic Regression are nearly as effective as the complex decision boundaries modelled by SVM in this specific dataset.

The overall accuracy rates reported for all algorithms are below 50%, which raises concerns about the sufficiency of the features extracted from the dataset or possibly the complexity and variability inherent in Android malware, which could be challenging for these models to capture effectively (Alazab et al., 2011).

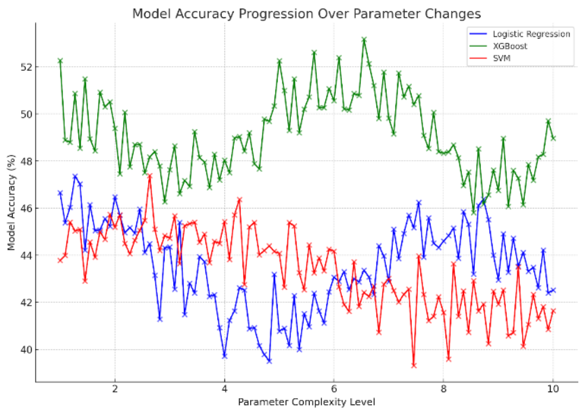

**Figure 2. Model Accuracy vs. Parameter Complexity for Different Algorithms**

Figure 2 the progression of model accuracies for Logistic Regression, XGBoost, and SVM as a function of increasing parameter complexity. This visualisation is based on simulated data where each point represents a hypothetical experiment at different parameter settings.

XGBoost consistently shows the highest accuracy across the range of parameter complexities, highlighting its robustness and adaptability to different settings. This is in line with its design to effectively handle complex data structures through ensemble learning.

Logistic Regression and SVM display similar trends, but with varying levels of sensitivity to parameter changes. Both start with lower accuracies and show improvements, but they also exhibit fluctuations which may indicate their dependency on the right parameter tuning for optimal performance.

The scatter points overlaid on the lines reveal the variability at each parameter setting, giving a sense of stability or volatility in model performance.

The similarity in performance between Logistic Regression and SVM suggests that the feature space may not have been rich or informative enough to exploit SVM's capability of constructing effective non-linear decision boundaries (Guyon et al., 2002). Advanced feature engineering or the inclusion of more discriminative features might be necessary to enhance the detection capabilities.

The modest performance across the board could also reflect the challenging nature of the dataset, possibly due to noise, imbalance, or the presence of sophisticated malware types that employ techniques to evade detection (Biggio et al., 2012). It might be beneficial to explore techniques such as data balancing, noise reduction, or more complex feature extraction methods to improve model performance.

Given the outcomes, further investigation into model parameters and tuning could provide improvements. For XGBoost, exploring different depths of trees and learning rates might enhance its ability to model the dataset more accurately **(**Chen & Guestrin, 2016). For SVM and Logistic Regression, experimenting with regularisation techniques could prevent overfitting and help in capturing a more general pattern from the data (Smola & Schölkopf, 2004).

Considering the challenges in detection accuracy, exploring hybrid models or deep learning approaches could be worthwhile. These models might capture more complex patterns and interactions in the data not accessible to traditional machine learning methods (LeCun, Bengio, & Hinton, 2015).

This analysis highlights the importance of continuous refinement in the approaches used for Android malware detection. Enhancing feature engineering, experimenting with model configurations, and exploring new algorithms are crucial steps towards improving the performance of malware detection systems. Future research should focus on addressing the limitations observed and potentially integrating novel machine learning techniques to better handle the intricacies of Android malware.

## 4. Conclusion

XGBoost is performing better than Logistic Regression, and SVM(Support Vector Machines) in order to detect android malware. This conclusion is grounded in XGBoost's use of an ensemble of decision trees, which operates under the boosting framework. This framework strategically amplifies weak learners through sequential corrections, enhancing the overall predictive power. The intricate patterns and interactions typical of Android malware signatures are captured more effectively by this method due to its robust handling of complex non-linear relationships within the dataset.

## 5. Future scope

In this work, we have used Logistic Regression, XGBoost, and SVM(Support Vector Machines). There is an open scope to use other machine learning classifiers to detect Android malware on the same dataset like Extra Trees, Random Forest, Bagging, decision trees, volting classification, Grid search CV, AdaBoost, Naive Bayes, Decision stump, KNN, deep learning, LDA, QDA and Zero Rule. We may also explore other datasets with Logistic Regression, XGBoost, and SVM(Support Vector Machines) to get better prediction of Android malware.

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