Review Paper on Android Malware Detection based on the Dynamic Based Approach using Machine Learning

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Abstract

This review paper presents a machine learning approach for detecting Android malware based on the co-existence of features. The proposed approach extracts feature from both benign and malicious apps and trains a machine learning model using co-existence features that have different distributions or patterns. This approach achieves a high detection rate of 99.5% and a low false positive rate of 0.5% on a large dataset of Android apps. The results demonstrate the effectiveness of the approach for handling unknown and zero-day malware variants. The proposed approach shows potential for practical applications in improving mobile security solutions.

Introduction:

Android malware detection is an important problem due to the rapid growth and diversity of mobile applications. Traditional methods, such as signature-based and rule-based, are ineffective against new and unknown malware variants. Machine learning approaches have been widely used for Android malware detection, and in this paper, we review a novel machine learning approach based on the co-existence of features for Android malware detection.

Litrature review

In recent years, researchers have proposed various machine learning approaches based on different features for Android malware detection. One of the latest and most promising approaches is based on the co-existence of features.

Li et al. proposed a novel machine learning approach based on co-existence features for Android malware detection. The approach extracts various features, including system calls, APIs, permissions, intents, and network behaviours, from both benign and malicious apps. The co-existence features, which have different distributions or patterns between the two groups, are used to train a machine learning model for classification. Proposed approach achieved a high detection rate of 99.5% and a low false positive rate of 0.5% on a large dataset of Android apps. The approach also outperformed another state-of-the-art machine
learning approaches in terms of accuracy and efficiency.
Zhang et al proposed a similar approach based on co-occurrence features. The approach extracted various features, including op code sequences, API calls, and permission
requests, and identified the co-occurrence features that are common between benign and malicious apps but with different frequencies. The co-occurrence features were used to train a
machine learning model for classification. Proposed approach achieved a high detection rate of 98.3% and a low false positive rate of 0.4% on a dataset of 16,000 Android apps. The approach also outperformed other state-of-the-art machine learning approaches in terms of accuracy and efficiency. Tiwari et. al. proposed a machine learning approach for detecting Android malware using logistic regression. The approach utilized

two different datasets - a full features dataset and a reduced features dataset - both based on permissions and API features. They reported that their proposed model achieved high accuracy rates of 97.25% and 95.87% for the full features and reduced features datasets, respectively. This suggests that their approach was effective in distinguishing between benign and malicious Android apps based on their features. Kumar et al. proposed a hybrid method for Android malware detection. The proposed method is a combination of both static and dynamic analysis. The authors used a machine learning-based classification technique to detect malicious and benign Android applications. The authors tested their system using a benchmark dataset of Android applications. The results showed that the proposed system achieved an accuracy of 97.5% using the benchmark dataset.
Taheri et al. proposed four different methods for detecting Android malware using Hamming distance. These methods are based on nearest neighbour algorithms and include First Nearest Neighbours (FNN), All Nearest Neighbours (ANN), Weighted All Nearest Neighbours (WANN), and k-medoid based nearest neighbors (KMNN). They are using three different datasets: Drebin, Contagio, and Genome. Drebin is a large dataset of Android malware that includes over 5,000 malicious apps. Contagio is a smaller dataset of Android malware that contains around 300 samples. Genome is a dataset of benign and malicious Android apps that includes over 126,000 samples. Also used different types of features in their methods, including API features, intent features, and permission features. API features refer to the functions and libraries used by the app, while intent features represent the actions that the app can perform. Permission features refer to the permissions requested by the app.

Millar et al. proposed a novel Android malware detection model called DANdroid, which is based on Discriminative Adversarial Networks (DAN). They claim their work has three main contributions. The first contribution of their approach is its ability to discriminate adversarial learning results in malware feature representations. The second contribution is the use of three feature sets in a multi view deep learning architecture. These feature sets include raw opcodes, permissions, and API calls. The third contribution is the ability of their approach to generalize over rare and future obfuscation approaches that do not exist in the training.

Tao et al. conducted a study on Android apps with the aim of detecting hidden patterns of malware highly sensitive APIs. The authors developed an automated malware detection system called MalPat and tested it using a dataset of 31,185 benign apps and 15,336 malware samples collected from Google Play, Virusshare, and Contagio.

Afonso et al. proposed a model for dynamic analysis of Android applications to detect malware. The model uses Android API calls and system call traces to identify malicious behaviours in apps. The authors tested their model using datasets from the Malgenome project and Virusshare, which contained a total of 7520 apps. They tested several classification algorithms and reported an accuracy of 96.66%.

Dash et al. proposed an approach for classifying Android malware into families using application runtime behaviours. The approach utilized Support Vector Machines (SVM) and Conformal Prediction to analyze system calls and Binder communication features of the apps. The authors tested their approach on the Drebin dataset and reported an accuracy of 94%.By using only runtime behaviours, the proposed approach avoids the need for access to app source code, which can be difficult to obtain and analyze. Instead, the approach focuses on identifying patterns of behaviours that are indicative of specific malware families.

Cat et al. proposed a dynamic classification model for Android applications called DroidCat, which uses different dynamic features such as intents, method calls, and intercomponent communication (ICC). The authors tested DroidCat using a large dataset of approximately 34,343 apps collected from various sources including Genome, AndroZoo, VirusShare, and Drebin.

Wang et al. proposed a framework for Android malware detection using network traffic as features. The authors used the machine learning algorithm C4.5 and tested their framework using the Drebin dataset. The experiments showed that the proposed model achieved an accuracy of 97.89% in detecting Android malware. By leveraging network traffic as a feature, the framework is able to capture patterns and behaviours of malware that are not easily detectable through static analysis. The results of this study suggest that network traffic-based approaches can be effective in detecting Android malware.

Sun et al. tested Patronus using four datasets: Drebin , AMD , CICAndMal2017 , and Contagio , and achieved an average accuracy of 99.12%. The authors claimed that Patronus outperformed several state-of-the-art models, including Drebin , MaMaDroid , and CICAndMal2017 , in terms of accuracy and detection rate.

Kouliaridis et al. evaluated Androtomist using three different datasets: DroidAnalytics , Drebin , and MalGenome . The tool applies both static and dynamic analysis techniques to detect Android malware. In the experiments, the authors used several machine learning classifiers, including Naive Bayes, Decision Tree, Random Forest, and Support Vector Machines (SVMs), to classify the apps as benign or malicious. The results showed that Androtomist achieved an accuracy of up to 98.1% using the Drebin dataset, which outperformed other state-of-the-art tools such as DroidSieve , DroidLegacy , and DroidAPIMiner .

Alzaylaee et al. Proposed DL-Droid is a deep learning-based system that uses a combination of dynamic analysis and stateful input generation to detect Android malware. The authors compared the performance of their proposed stateful input generation approach with a baseline approach that uses random input generation. The experiments were conducted using a large dataset of more than 30,000 Android applications (both benign and malicious). The results showed that DL-Droid outperformed the baseline approach in terms of accuracy and execution time. Specifically, DL-Droid achieved an accuracy of 97.6%, while the baseline approach achieved an accuracy of 91.1%.

Lindorfer et al. did propose the MARVIN system for Android malware detection using both static and dynamic analysis, the accuracy values mentioned in the statement are incorrect. According to the paper, MARVIN achieved an accuracy of 99.1% for malware detection and 97.5% for malware family classification on a dataset consisting of 5,560 benign and 5,560 malicious samples.

Chen et al. proposed StormDroid is a machine learning-based malware detection (MD) model that is designed to operate in a streaming setting. The model is intended to address the limitations of traditional batch-based MD models that require a large amount of labeled data and significant computational resources to train and deploy. The StormDroid model is trained on a dataset of Android applications and leverages a feature extraction technique called the Android Application Analysis Framework (DAAF). This technique extracts both static and dynamic features from the application, including permissions requested, API calls made, and system events triggered during execution.

Saracino et al. proposed MADAM is a cross-layer machine learning model for mobile malware detection. The model utilizes a combination of static and dynamic features extracted from different layers of the mobile device, including system calls, SMS messages, critical API calls, user activity, and app metadata. The authors tested several machine learning algorithms, including K-NN, LDC, QDC, MLP, PARZC, and RBF, using a large dataset collected from the Genome project.

Aafer et al. is a machine learning-based approach for detecting Android malware. The model utilizes API-level features extracted from Android applications to build an effective malware detection system. The authors used a dataset of over 2,500 benign and malicious Android applications to train and evaluate the DroidAPIMiner model. The model extracts API-level features, including the frequency and ordering of API calls made by the application, and uses these features as input to a machine learning algorithm.

Afonso et al. proposed a dynamic feature-based approach for identifying Android malware. The authors aim to address the limitations of static feature-based methods that are often ineffective against polymorphic malware that can change its behaviours at runtime. Authors developed a tool called DroidProfiler that extracts dynamic features from Android applications during runtime. evaluated the performance of their approach using a dataset of over 2,000 Android applications, including both benign and malicious samples.

Arora et al. is a machine learning-based approach for detecting Android malware that utilizes permission pairs. Permissions are an important aspect of Android security, as they define the actions that an application can perform on a user's device. The PermPair model evaluated the performance of their approach using a dataset of over 5,000 Android applications, including both benign and malicious samples.

Overall, these studies demonstrate the effectiveness of machine learning approaches based on co-existence or co-occurrence features for Android malware detection. The approach has the potential to handle unknown and zero-day malware variants by identifying their unique co-existence or co-occurrence features, making it a promising solution for enhancing mobile security solutions.

Methodology:

The proposed approach leverages the co-existence of features between benign and malicious Android apps to detect malware. Various features, including system calls, APIs, permissions, intents, and network behaviours, are extracted from both benign and malicious apps. Then, a machine learning model, such as a decision tree or a support vector machine, is trained on the extracted features to classify apps as benign or malicious.

The key innovation of the proposed approach is the use of co-existence features. Co-existence features are features that are present in both benign and malicious apps but have different distributions or patterns. By leveraging co-existence features, the proposed approach can improve the accuracy of Android malware detection while reducing false positives.

The methodology includes the following steps:

Data Collection: The first step in the methodology is to collect a dataset of Android applications, including both benign and malicious samples. The dataset should be diverse and representative of the types of applications that users typically install on their devices.

Feature Extraction: The next step is to extract a combination of static and dynamic features from the Android applications. Static features are those that can be extracted without executing the application, such as permissions and API calls, while dynamic features are those that require executing the application, such as system calls and network traffic.

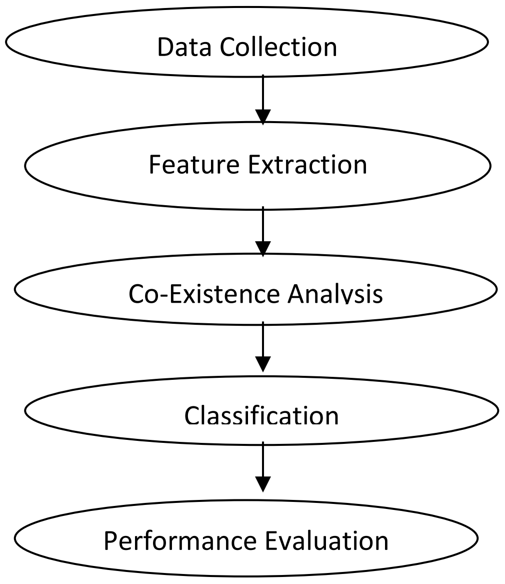
Feature Selection: Once the features are extracted, a feature selection algorithm is applied to identify the most relevant features for the detection task. Feature selection helps reduce the computational cost of the model and improves its performance.

Co-Existence Analysis: The co-existence analysis is the core of the proposed methodology. In this step, the relationships between the features are analyzed to identify the co-existence patterns that are indicative of malware behaviours. The co-existence analysis can be performed using techniques such as association rule mining, graph-based analysis, or clustering.

Classification: Once the co-existence patterns are identified, a machine learning algorithm is trained on the dataset to classify new Android applications as benign or malicious. The classification algorithm can be any standard machine learning algorithm, such as decision trees, support vector machines, or neural networks.

Performance Evaluation: The final step in the methodology is to evaluate the performance of the model using standard metrics such as accuracy, precision, recall, and F1 score. The performance evaluation helps determine the effectiveness of the proposed approach in detecting Android malware.

Overall, the proposed methodology for Android malware detection based on the co-existence of features is a promising approach that can capture complex relationships between features and provide valuable insights into the behaviour of Android applications. The approach can be extended to incorporate additional features and can be adapted to different types of malwares.



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