Interpretable Android Malware Detection based on Dynamic Analysis

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Keywords: Malware, Dynamic Analysis, Android, Security.

Abstract: Android has emerged as the dominant operating system for smart devices, which has consequently led to the proliferation of Android malware. In response to this, different analysis methods have been suggested for the identification of Android malware. In this paper, we focus on so-called dynamic analysis, in which we run applications and monitor their behaviour at run-time rather analyzing the source code and resources (which is called static analysis). One approach to dynamic analysis is to use machine learning methods to identify malware; essentially we run a large set of applications that may or may not be malware, and we learn how to tell them apart. While this approach has been successfully applied, both academic and industrial stakeholders exhibit a stronger interest in comprehending the rationale behind the classification of apps as malicious. This falls under the domain of interpretable machine learning, with a specific focus on the research field of mobile malware detection. To fill this gap, we propose an explainable ML-based dynamic analysis framework for Android malware. Our approach provides explanations for the classification results by indicating the features that are contributing the most to the detection result. The quality of explanations are assessed using stability metrics.

1 INTRODUCTION

Mobile malware poses substantial security risks, impacting both individuals and enterprises by exploiting valuable data stored on mobile devices. Android, holding a 72% market share (Statista, 2023), is a prime target due to its open nature. Cyberattacks, such as mobile banking threats (Kapersky, 2023), underscore this vulnerability despite efforts by Google and OEMs (original equipment manufacturers)(Kovacs, ByEduard, 2023). Traditional signature-based detection methods struggle due to evolving threats, prompting interest in adaptive methods and machine learning solutions, especially for zero-day malware (Cai, 2020; Rafael Fedler and Kulicke, 2013).

Dynamic analysis is an important technique in the field of Android malware detection. This approach involves running potentially malicious Android applications in a controlled environment to monitor their behavior in real-time. By observing how an app interacts with the device, network, and other applications, security analysts can uncover hidden malicious activities that may not be evident through static analysis alone. Dynamic analysis provides valuable insights into an app's run-time behavior, enabling the detection of malware that exhibits polymorphic or obfuscated characteristics.

There is a great deal of research on Android malware detection through dynamic analysis, much of which is based on using machine learning (ML) techniques (Yan and Yan, 2018). While ML models show promise in detecting malicious apps, their underlying selection processes are often complex, making it challenging to explain why an app has been classified as malicious. This lack of transparency hinders the ability to understand the key features or behaviors that triggered the classification result, which is crucial for both security analysts and app developers. Moreover, the absence of explainability makes it difficult to identify false positives and false negatives, potentially damaging the reputation of legitimate apps and allowing some malicious ones to remain undetected. Researchers are actively working on methods to enhance the interpretability of ML models, as it's not only about making accurate predictions but also about providing insights into why certain decisions are made, thereby improving the overall effectiveness and trustworthiness of ML-based systems. While there are some existing works using explainable ML methods in static analysis of Android malware detection (Fan et al., 2020; Wu et al., 2021), similar methods have not been employed extensively for dynamic analysis. Moreover, some of the existing

research studies on dynamic analysis rely on inaccessible or outdated tools. A notable trend is the scarcity of open-source initiatives or comprehensive instructions, hindering result reproduction and validation.

In this paper, we present an explainable ML-based approach to dynamic analysis for Android malware detection. Our goal is not only to apply ML techniques to automatically detect Android malware, but also to provide explanations for the results. First, since existing tools often do not provide source code or current data, we start by replicating a standard approach to dynamic analysis for Android malware detection. Additionally, existing studies often do not provide a clear list or justification for the features analyzed. As an example, the approach in (Tam et al., 2015) states that 141 dynamic characteristics were used for analysis. However, the exact list of features is not included. This not only makes it hard to reproduce the work, but it makes it hard to really understand why particular features were selected. Therefore, in our work, we take a different approach. We focus on explicitly specifying the features and parameters that we select and share them with the readers. In the end, our goal is to develop a tool that uses these features to identify malware. But we do not want our tool to be a black-box that flags malware without justification. Instead, we identify the most important features that resulted in the classification of an app as malware.

The main contributions of this paper are summarized as follows:

- We present a clear methodology for producing a tool for dynamic malware analysis. The list of apps used, the feature extraction and selection, and developed ML models (for which we also addressed the class imbalance issues to improve the results) are open-source and publicly available to the research community on GitHub [1]. This will facilitate the reproducibility of our research.
- We employ an explanation technique for interpreting the predictions made by our ML models and evaluate its effectiveness. In this way, we can identify the features that are contributing the most to detection of an app as malware as well as evaluating the quality of explanations. To the best of our knowledge, this study is the first work attempting to provide a systematic approach to use explainable ML methods for dynamic analysis of Android malware.
- We have created datasets of traces for recent Android apps (goodware and malware), which is well-suited for dynamic analysis. Also, using our open-source scripts, researchers can generate new datasets in an easy and seamless manner.

[1]Link to our GitHub repository will be provided after receiving the review to facilitate the double-blind paper evaluation method

2 BACKGROUND AND RELATED WORK

2.1 Preliminaries

There are two main approaches to Android malware detection and analysis: static analysis and dynamic analysis. The *static analysis* approach involves analyzing the code and resources of an app without executing it. The idea is to look at aspects such as API calls or permissions, and then identify patterns that have previously been observed in existing malware. This is useful for identifying known malware, and for flagging suspicious code or patterns. Significantly, static analysis does not require any real or simulated execution of code on a device. One problem with static analysis is that it is generally unable to detect new malicious behaviour that happens at runtime (Yan and Yan, 2018). It is also not effective in identifying malicious deformation techniques such as java reflection and dynamic code loading (Pan et al., 2020). Hence, a comprehensive approach to malware analysis can not be based solely on static methods.

Dynamic analysis refers to the approach where the behaviour of an application is monitored while it is executed in a controlled environment. In this manner, we can monitor things like system calls, network traffic, user interactions and inter-process communication. One advantage of this approach is that it can identify zero-day attacks that have not previously been observed. Moreover, it can identify malware that has been deliberately written to evade static analysis(Yan and Yan, 2018). There are drawbacks to the dynamic approach. First of all, this can be resource and time consuming. Moreover, simulating a wide range of application behaviours is a serious challenge; it may not be possible to capture all behaviours. While we may like to perform dynamic analysis using an emulator, it turns out that malware developers can use evasion techniques and anti-emulation techniques to avoid detection in a controlled environment (Liu et al., 2022a). Finally, dynamic analysis has difficulty handling polymorphic malware and malware with encrypted traffic. Compared with static analysis, there are fewer studies on dynamic analysis and it needs further investigation by the research community. Therefore, in this paper, our focus is on *dynamic analysis* for Android malware detection. Note that a hybrid approach can take advantage of both static

and dynamic analysis by using static analysis to identify potential malware and then running the app in a controlled environment to gain insights about the runtime behavior of an app.

2.2 Interpretable Machine Learning for Dynamic Analysis

There are many studies that have used ML methods (including deep learning) for dynamic analysis of Android malware. However, researchers have raised concerns regarding the over-optimistic classification results produced by various ML-based malware detection techniques (Arp et al., 2022; Pendlebury et al., 2019). Furthermore, the approaches to Android malware detection mainly rely on black-box models. Consequently, security analysts frequently found themselves questioning the reliability of predictions from such highly accurate ML-based malware detection models and pondering the suitability of model selection before deployment. In response to these issues, several studies introduced methods aimed at explaining the predictions made by ML-based malware detection models. Examples of such studies for static analysis are (Fan et al., 2020; Wu et al., 2021; Liu et al., 2022b). While there are studies that attempt at providing explanations for dynamic analysis such as (De Lorenzo et al., 2020), none of the existing ones have investigated using eXplainable Artificial Intelligence techniques(XAI) (Dwivedi et al., 2023) for interpreting the results of classification for dynamic analysis.

2.3 Using System Calls for ML-based Dynamic Analysis

In the following, we give a brief summary of the main recent studies that employed system calls as their only set of features or along with other features. We refer interested readers to (Yan and Yan, 2018; Liu et al., 2022a; Razgallah et al., 2021) for more comprehensive surveys of dynamic analysis for Android malware detection.

SpyDroid, which is proposed in (Iqbal and Zulkernine, 2018), is an Android malware dynamic analysis framework that utilizes multiple malware detectors (each of them focusing on certain set of features). It provides real-time monitoring of Android apps on user devices. SpyDroid supports monitoring CPU and memory usage as well as kernel system calls. Random Forest (RF) is used as the ML technique for malware detection and it is shown that an ensemble of sub-detectors greatly enhances the detection rate. The authors in (Zhang et al., 2022), propose Android malware detection system (AMDS), which relied on system calls. The system call traces are processed using N-gram analysis. Then, Decision Trees (DT), K-Nearest Neighbors (KNN), Naive Bayes (NB), Support Vector Machines (SVMs), RF, and Multi-layer Perceptron (MLP) ML models are used for malware detection. The experimental findings illustrate that AMDS exhibits the ability to detect threats at an early stage with high accuracy. TwinDroid(Asma Razagallah, 2022) is a dataset of 1000 system call traces for Android apps. TwinDroid also incorporates an automated pipeline for generating traces, giving users the capability to create new traces. An early version of TwinDroid is used in (Razgallah and Khoury, 2021) for Android malware detection by using n-grams as well as Term Frequency–Inverse Document Frequency (TF–IDF) weight vector of system calls and ML classification methods.

MALINE (Dimjašević et al., 2016) is an open-source tool using dynamic Android malware detection methods based on tracking system calls. System call frequency and system call dependency are employed for indicating malicious behaviour. Using such features, the performance of SVMs, RF, LASSO, and ridge regression classifiers are assessed. Moreover, the effectiveness of choosing simple features (e.g., frequency of system calls) was demonstrated. Another recent study, (Mahdavifar et al., 2020), detects malware families based on different categories of system calls and applying a semi-supervised deep learning method. The proposed techniques outperforms classifiers such as RF and SVM as well as a supervised deep neural network. Sequences of system calls are used in Deep4MalDroid (Hou et al., 2016) to construct a weighted directed graph, which is then given to a deep learning framework for malware detection. DroidScribe (Dash et al., 2016) provides a framework for malware family classification. It utilizes (Tam et al., 2015) as its dynamic analysis component to capture system calls information. Then, it employs Conformal Prediction with SVM to perform the classification.

3 METHODOLOGY

In this section, we explain our approach for developing an Android malware detection system based on dynamic analysis using interpretable machine learning.

3.1 Data Collection and Pre-processing

We used the *AndroZoo* dataset (Allix et al., 2016) for obtaining our goodware and part of our malware. *AndroZoo* is commonly used by research community for Android malware detection and analysis. Note that *AndroZoo* does not explicitly label apps as malware. Instead, it provides the number of antiviruses from *VirusTotal* (VirusTotal, 2023) that flagged the app as malware. Particularly, there is a property for an app called *vt_detection* in *AndroZoo*. A non-zero value for this property means that one or more antivirus tools have flagged this app as malware; otherwise, the app is considered to be goodware (*vt_detection*=0). To collect our malware samples, we chose the apps such that their *vt_detection* is more than 4 (to have more confidence in their label). A similar approach has been employed in (Pendlebury et al., 2019). Moreover, we also downloaded malware from *VirusShare* (VirusShare, 2023), which is a repository of malware samples.

The quality of the dataset is of crucial importance for Android malware ML-based detection. If the dataset is not up-to-date or not representative of the population under study, the conclusions may be invalid. Therefore, while selecting the apps, we considered addressing issues including realistic class ratio and temporal inconsistency.

3.1.1 Realistic Class Ratio and Addressing Class Imbalance

To have realistic settings, the class ratio between benign and malware classes at test time is chosen similar to the one at deployment time. In the Android app domain, malware is the minority class. Similar to (Pendlebury et al., 2019; Miranda et al., 2022), we used the average overall ratio of 10% Android malware in our test samples to represent the real-world scenario. Moreover, we addressed the dataset imbalance issue by using class weights and undersampling techniques. More details are provided in Section 4.

3.1.2 Addressing Temporal Inconsistency

Temporal inconsistency (i.e., when malware and benign apps are selected randomly from different time periods)(Miranda et al., 2022; Cavallaro et al., 2023) unrealistically improves the performance of the ML-based malware detection approaches. Additionally, explanations of ML-based Android malware detection suggest that the models can accurately predict malware by relying on temporal-related features rather than the actual characteristics of malicious and benign behaviors (Liu et al., 2022b). To prevent temporal inconsistency, we chose both malware and goodware from the same timeframe, i.e., 2022.

3.2 Feature Selection

There are different features that may be included in developing a dynamic analysis solution. Many of the primary studies on dynamic analysis selected features associated with system calls and dynamic activities such as network access and memory dump to capture malicious behavior (Razgallah et al., 2021; Liu et al., 2022a; Saneeha Khalid, 2022). Among such features, system calls are the mainstream and have been favored by the research community for dynamic analysis of Android malware. In contrast to API calls, Linux kernel system calls are independent from the Android Operating System (OS) version, rendering them more robust against strategies employed by malware to evade detection. Therefore, in this paper, we focus primarily on the analysis of *system calls*

All apps interact with the platform where they are executed by requesting services through a number of available system calls. These calls define an interface that allow apps to read/write files, send/receive data through the network, read data from a sensor, make a phone call, etc. Legitimate apps can be characterized by the way they use such an interface, which facilitates the identification of malicious components inserted into a seemingly harmless app and, more generally, other forms of malware. For any system call, there are many possible ways it can be analyzed for potential malicious intent.

- **File Access Patterns**: Investigating the files that the application is trying to access using these calls. We look for patterns that might be indicative of malicious intent, such as accessing sensitive system files, personal user data, or configuration files.
- **Unusual File Locations**: Paying attention to file paths that are typically not accessed by well-behaved applications. Trying to access files outside of its designated storage or data directories might be an indication that an app could be attempting to breach security boundaries.
- **Frequency and Repetition**: High-frequency or repetitive use of the system calls to specific files might be suspicious. If an application is repeatedly accessing the same file rapidly, it could indicate that it's attempting to exfiltrate data.
- **Permission Violations**: If the application is making calls to files that it shouldn't have access to, based on its permissions, it could be trying to ex-

ploit vulnerabilities and access sensitive information.

- **Network Behavior**: Correlating the system calls with the application's network behavior. If it is accessing files and then sending them over the network, it might be exfiltrating data.

Examples of applications that exhibit such behaviors include Psiphon, Boulders, and Currency Pro. These applications have been found to contain a malware variant named *daam* which is designed to surreptitiously extract data from the user's mobile device(Spadafora, Anthony, 2023a). The stolen data is then transmitted to a command-and-control server, which is operated by malicious actors. These applications display patterns of network behavior, as evidenced by the data transmission occurring over the network. Additionally, they consistently attempt to access files and directories beyond their designated locations. Another illustrative case is the app named Flashlight Plus. This particular app requests an extensive array of permissions, indicating a potential attempt to exploit vulnerabilities and gain access to sensitive information. It also downloads a remote configuration by executing an HTTP request after one opens the app (exhibiting unusual Network behaviour). Additionally, it even registers a Firebase Cloud Messaging (FCM) listener to receive push messages to commit ad fraud on users' devices (Spadafora, Anthony, 2023b) (indicating permission violations and unusual file access locations).

3.3 Feature Extraction Process

We explored a variety of tools to collect system calls produced by running an Android app in an emulator. We mainly used the following tools:

- **adb** (ADB, 2023): Android Debug Bridge (adb) is a command-line tool for Android that enables us to communicate with a device or emulator and perform different actions such as installing and debugging apps, transferring files, and accessing device shells.
- **Android Emulator** (Android Studio, 2023): The Android Emulator emulates Android devices on your computer, allowing you to assess your application across a diverse range of devices and Android API versions, eliminating the necessity for possessing each physical device. It's a valuable tool for efficient app development and testing. Thus, all of our tests were carried out on this emulator.
- **strace** (strace, 2023): This is a Linux command-line utility which enables us to monitor and record system calls and signals generated by an app during its execution.
- **Monkey** (monkey, 2023): *Monkey* is a command line tool for testing Android applications. It simulates random user interactions for stress testing and for uncovering potential issues. We found that most of the existing works for dynamic analysis employed *Monkey* in some form. It allows us to automate testing of random user interactions, quickly perform a high volume of tests, and test across various device configurations.

We developed a Python script to extract system calls. The script performs the following tasks in order:

1. Installing an Android app from the input repository using adb.
2. Launching the app using *Monkey*.
3. Retrieving the process ID (PID) of the app as well as its child PIDs.
4. Monitoring the process and capturing the system calls using *strace* (the PIDs were attached to *strace*).
5. Simulating user interactions on the application using *Monkey* for 300 seconds, which is in line with existing studies such as (Iqbal and Zulkernine, 2018; Cai et al., 2018).
6. Stopping the *strace* process and moving the *strace* output file to the output repository.
7. Uninstalling the app.

Figure 1 provides an example of a trace from our logs. The highlighted line in Figure 1 indicates a call to the *recvfrom* system call. The arguments are:

- 55: File descriptor for the socket.
- 0xb9201088: Destination buffer address.
- 1228: Maximum number of bytes to receive.
- 64: Flags (additional options for the call).
- 0: Source address (ignored in this case).
- 0: Source address length (ignored in this case).

The return value here is -1, indicating an error, and the error code is EAGAIN (i.e., resource is temporarily unavailable). This often happens when the socket is set to non-blocking mode, and no data is available for reading at the moment.

We have examined all of the traces from our tests and we focus on extracting following information:

1. **System call name**: The *system call name* refers to the specific system call that was invoked during the execution of an application. System calls

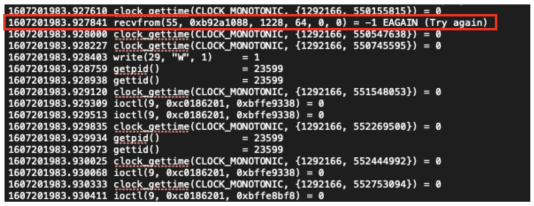


Figure 1: Trace Log

are fundamental operations that the application performs to interact with the underlying operating system. Certain system calls might be indicative of malicious behavior, such as trying to access sensitive data or performing unauthorized action. For example, if we observe an app making repeated *open* or *read* system calls to access system files or sensitive user data without any legitimate reason, it could indicate that it is attempting to exfiltrate user information.

2. **System call frequency**: The *system call frequency* tracks how often a particular system call is invoked within the execution of the application. Unusual or high frequencies of certain system calls might indicate that it is performing some action excessively, which could be an indication of malicious activity. For example, an application making an unusually high number of *sendto* or *connect* system calls might suggest that it is trying to establish unauthorized network connections or potentially sending out spam messages.

By examining these features collectively, we can establish patterns and anomalies that might indicate the presence of malicious behavior. It's important to note that while these features can provide valuable insights, they should be considered in conjunction with other dynamic analysis techniques, such as network traffic analysis, as well as static analysis techniques to build a comprehensive understanding of an application's behavior. *We identified a list of distinctive system calls used in all the strace logs for malware and goodware. For each system call, its frequency is included in our feature vector.*

3.4 Classification Models and Explanation Method

3.4.1 ML Classifiers

We have opted to employ Random Forest (RF) (Breiman, 2001) and eXtreme Gradient Boost (XGBoost) (Chen et al., 2015), as our classification methods. Both of these methods are considered as ensemble learning techniques. Such techniques combine the predictions of multiple ML models.

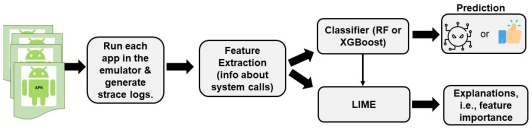


Figure 2: Proposed framework.

RF have been widely used for both static and dynamic analysis of Android malware (Razgallah et al., 2021) and it demonstrated superior performance. Random forest employs an ensemble of decision trees to classify an app as malware or benign by aggregating the majority vote. Moreover, XGBoost is a fast and efficient boosting algorithm that has built-in regularization to prevent overfitting. XGBoost has been used in some of the recent publications for dynamic analysis such as (Ananya et al., 2020; Karbab and Debbabi, 2019). Finally, tree-based and boosting algorithms have shown promise in their performance while working with imbalanced datasets.

3.4.2 Explanation Method

To interpret the prediction results from the above classifiers, we employed Local Interpretable Model-agnostic Explanations (LIME) (Ribeiro et al., 2016), which is a widely used approach in various other fields (Belle and Papantonis, 2021). Apart from its model-agnostic nature and the ability to offer localized interpretability, LIME is favored for its simple implementation and lower computational overhead when compared to similar techniques in the field of eXplainable Artificial Intelligence (XAI) (Dwivedi et al., 2023). Moreover, LIME has been used for explaining the ML-based predictions for static analysis of Android malware (Fan et al., 2020). It was shown that LIME outperforms other explanation methods with respect to stability, robustness, and effectiveness of its explanations as well as run-time overhead for large datasets. LIME operates by altering specific feature values within a single data sample and then monitors the resulting impact on the output, essentially acquiring the classification label of the modified sample. Once predictions are created for a collection of perturbed input samples, LIME proceeds to approximate the decision boundary and calculate the weights that denote the significance of individual features. It should be noted that LIME is a post hoc explainable method, i.e., it is applied to a model after training. Figure 2 shows our proposed framework.

Table 1: Parameter values for RF classifier.

Parameter Description	Values
Number of trees	[50, 100, 200, 500]
Maximum tree depth	[None, 10, 16, 20, 30]
The minimum number of samples required to split an internal node	[2, 5, 10, 20]

Table 2: Parameter values for XGBoost classifier.

Parameter Description	Values
Number of gradient boosted trees	[50, 100, 200, 500]
Maximum tree depth	[3, 6, 9, 12]
Boosting learning rate	[0.001, 0.01, 0.1, 0.3]
Subsample ratio of the training instance	[0.5, 0.8, 1.0]
Subsample ratio of columns when constructing each tree	[0.5, 0.8, 1.0]

Table 3: Scenarios.

Scenario	No. Goodware	No. Malware
S1-10	2430	270
S2-15	2295	405
S3-20	2160	540

Table 4: Model performance evaluation metrics and their computed values for the first three scenarios.

Scenario	Classifier	Precision	Recall	F1-Score
S1-10	RF	1	0.33	0.5
S1-10	XGBoost	0.79	0.50	0.61
S2-15	RF	0.93	0.47	0.62
S2-15	XGBoost	0.81	0.57	0.67
S3-20	RF	0.89	0.53	0.67
S3-20	XGBoost	0.78	0.60	0.68

4 PERFORMANCE EVALUATION AND ANALYSIS OF RESULTS

4.1 Experimental Setup

We carried out our experiments on a Tensorbook with Ubuntu 22.04 OS, Intel Core i7-processor (14 cores), NVIDIA RTX 3070 Ti GPU, and 32 GB memory (DDR5-4800). We randomly chose 2,798 benign apps *AndroZoo* and 624 malware from *AndroZoo* and *VirusShare*. The Android emulator was used to emulate a Pixel 6 (API 31) device. Moreover, 146 unique system calls were identified by analyzing the traces for benign apps and malware; these have been incorporated in our feature vector. Finally, the classification algorithms are implemented using Scikit-Learn ML library (scikit-learn, 2023). Table 1 and Table 2 show the assigned hyperparameter values in our experiments for RF classifier and XGBoost classifier, respectively.

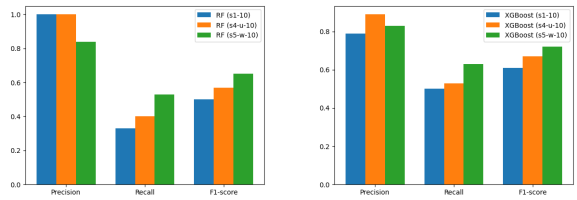
4.2 Performance Evaluation

We used the grid searching method with 10-fold cross validation for hyperparameter tuning. Since our dataset is imbalanced, having high accuracy does not necessarily mean high detection rate for our positive class (i.e., malware). Therefore, we have looked into other metrics which are better representatives for the performance of our classifiers as follows.

In our first set of experiments, we examined three scenarios, each maintaining a consistent 10% malware ratio during testing, while the training data contained 10% (S1-10), 15% (S2-15), and 20% (S3-20) malware in these respective scenarios. Table 3 shows the distribution of goodware and malware in the training sets of our scenarios. Note that although maintaining a realistic class ratio during training can reduce the overall error rate, different ratios can be employed to adjust the decision boundary, thereby balancing the trade-off between false positives and false negatives (and subsequently affect precision and recall). Table 4 summarizes the obtained values of performance metrics from the three scenarios. If we look at the recall values of the malware class, XGBoost has a higher value in all three scenarios. Therefore, XGBoost performs better than RF in terms of detecting malware (i.e., it correctly identifies malware with higher probability). It is evident from the three scenarios that When the ratio of malware in the training set goes up, the decision boundary moves towards the goodware class, i.e., the recall is increased for malware but the precision is reduced. Therefore, if our objective is to improve malware detection (i.e., recall), we can increase the malware ratio in the training set. Overall, XGBoost has a better performance compared with RF classifier due to its higher F1-score. Also, we can see the increase in F1-score when we increase the malware ratio (having a more balanced dataset) in s2-15 and s3-20 compared with s1-10 scenario. This results from the fact that the F1-score is a measure of harmonic mean of precision and recall. So, the closer the values of precision and recall are to each other, the better (higher) the F1-score will be.

Addressing class imbalance using undersampling: In this scenario (named s4-u-10), we applied Tomek links under-sampling technique (Haibo and Yunqian, 2013) to our training set. Tomek links consist of pairs of closely located instances belonging to different classes. Tomek links are present when two samples are each other's nearest neighbors. By eliminating the majority class instances in each pair, the separation between the two classes is widened, thus facilitating the classification process. Figure 3 shows the results of this scenario for different classifiers and in comparison with s1-10 (as our base scenario). Figure 3a displays 21%, and 14% improvement in recall and F1-score, respectively for the RF classifier. Moreover, Figure 3b illustrates 12.6% , 6%, and 9.8% improvement in precision, recall and F1-score, respectively for the XGBoost classifier.

Addressing class imbalance using class weights: In this scenario, named s5-w-10, we used



(a) (b)

Figure 3: Performance comparison of s1-10 scenario with scenarios addressing class imbalance.

class weights to address the class imbalance problem. By assigning higher weights to the minority class (i.e., malware class), the model is enabled to give more importance to malware samples during training and mitigate the bias towards the majority class (i.e., benign class). The class weights are inversely proportional to their frequency of occurrence in the dataset. Figure 3 illustrates the performance of the classifiers when adding the class weights. In Figure 3a, we observe 60% and 30% improvement in recall and F1-score, respectively for the RF classifier. Similarly, figure 3b shows 26% and 18% improvement in recall and F1-score, respectively for the XGBoost classifier. It should be noted that adding class weights is only effective (i.e., the improvement in the metrics is noticeable) if the dataset is highly imbalanced (i.e., ratio of 10% or less for malware in our experiments).

Considering the two techniques that we used for addressing the class imbalance and improving the performance of models, class weight shows more promise in terms of improving metrics when making a comparison with Tomek links technique (s4-u-10). Particularly, when adding class weights, the amount of increase in F1-score is 16% for the RF classifier and 8.2% for the XGBoost classifier compared with the Tomek links scenario (s4-u-10). A drawback to under-sampling is that we have eliminated information that may be valuable; however, in a large dataset, this may become less of a concern as the number of removed benign samples is much lower than the total number of such samples.

4.3 Analysis of LIME Explanations

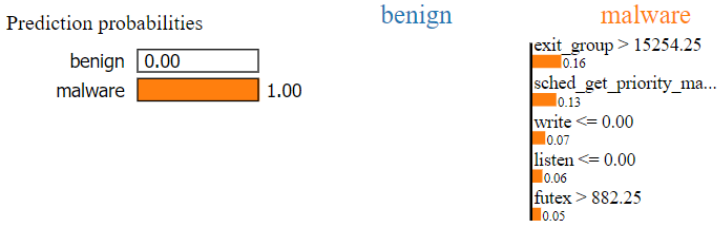
So far, our focus has been on analyzing the performance of our classifiers and mitigating the class imbalance issue for dynamic analysis. We do not have any information about the contributions of different features (i.e., the frequency of system calls) to the predictions made by our classifiers. In other words there is an important question to answer *"Why is an Android App classified as malware by our ML models?"*. To provide some insights for the prediction results, we have utilized the LIME explainable technique. Furthermore, we focus on XGBoost classifier results with class weights (scenario s5-w-10) since it outperforms the RF classifier.

Table 5: Top system calls and their presence in true positives.

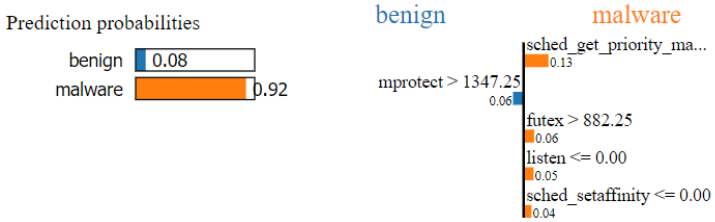
System call	Presence in true positives
exit_group	66%
sched_get_priority_max	46%
sched_getscheduler	33%
futex	26%

We analyzed the true positives (15 samples) for our testing set, which includes a total of 300 Android apps out of which 30 apps are malware. As we mentioned earlier, LIME provides local explainability, i.e., it indicates the most contributing features to the prediction result for a test instance. We configure LIME to show the top five features for a prediction in our experiments. Figure 4 shows output examples of applying LIME to three test instances. By looking at prediction probabilities, Figure 4a shows that the XGBoost classifier is 100% confident that com.jiccos.jicco is malware. Similarly, the confidence of the classifier is 92% and 99% when detecting malware in Figure 4b and Figure 4c. Moreover, the top five system calls (based on their frequencies) are shown in Figure 4. For instance, the most important system calls (based on their frequencies) to the prediction in Figure 4a are *exit_group*, *sched_get_priority_max*, *futex*, *write*, and *listen* with weights of 0.16, 0.13, 0.05, 0.07, and 0.06, respectively. Note that the descriptions of system calls can be found in (syscalls(2) — Linux manual page, 2023). Additionally, the explanation provides the reasons why the model make this prediction as follows:
$exit\_group > 15254.25$
$sched\_get\_priority\_max = 34$
$futex > 882.25$
$write = 0$
$listen = 0$
Table 5 displays the top four system calls that are present in most of the true positives based on the output of LIME.

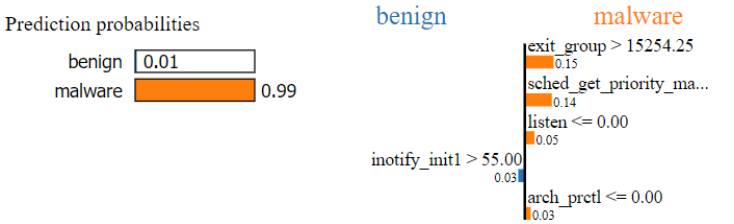
Explanation Quality: One important aspect of explanations to consider is their stability, i.e., the changes in explanations when utilizing the explainable method (in our case LIME) multiple times under the same conditions. We use two stability metrics, which were defined in (Visani et al., 2022) for LIME, namely Variables Stability Index (VSI) and Coefficients Stability Index (CSI). High VSI values ensure that the variables (features) obtained in various LIME instances are consistently identical. Conversely, low values indicate unreliable explanations, as different



(a) APK package name: com.jiccos.jicco



(b) APK package name: com.wGuitarProTabs



(c) APK package name: com.hmsqw.customer

Figure 4: Examples of LIME explanations for three true positives in the testing set.

LIME calls may yield entirely different variables to explain the same machine learning decision. Regarding CSI, high values guarantee the reliability of LIME coefficients for each feature. Conversely, low values advise practitioners to exercise caution: for a given feature, the initial LIME call may yield a specific coefficient value, but subsequent calls are likely to produce different values. As the coefficient represents the impact of the feature on the ML model decision, obtaining different values corresponds to significantly distinct explanations. Table 6 shows the computed stability metrics for LIME explanations of our true positives. The average of VSI values is 90.6% with standard deviation of 5% whereas the average of CSI values is 97.6% with standard deviation of 3.8%. Therefore, in our experiments for malware detection LIME results are more stable w.r.t. to CSI rather than VSI.

Limitations of our approach: It should be noted that system calls are inherently low-level and lack the extensive information found in the more semantically enriched Android APIs. Therefore, mapping them directly to the malware's behavior is a challenging task. A dataset that mapped high-level Android APIs to different representations of low-level system call traces was created in (Nisi et al., 2019). But the dataset is not accessible and we could not use it to map the system calls to API calls and subsequently relate them to an app's behavior. Moreover, we examined the reports from *VirusTotal* for some of our malware in the testing set but the features listed are mainly related to static analysis of those apps. One can gain some insights regarding the malware's behavior by extracting more information from the traces (e.g., the parameters and their values for a system call) and then manually analyze them (which is a time-consuming task).

4.4 Threats to Validity

Android app crashes: In dynamic analysis of Android APKs, the failure to generate logs for the apps can be attributed to multiple factors. A common issue arises when the package name is not recognized, resulting in the inability to retrieve the process ID. Furthermore, the *"INSTALL_FAILED_NO_MATCHING_ABIS"* error suggests an architecture mismatch, where the APK contains native libraries incompatible with the device's CPU architecture (Note that the emulator is mimicking the architecture of a physical device.). Such in-

Table 6: Stability metric values for LIME explanations of true positives.

APK Package Name	VSI	CSI
com.jiccos.jicco	100%	96.8%
bdeffdiheil.fihjcifeeem.bgabacdiebn	92.4%	100%
com.sector.s.one	88%	99.6%
com.lomolsoft.dict.vedict	96%	98.6%
com.auyou.eqy	85.3%	97.1%
plus.H55AD811E	89.3%	98.8%
com.kfx008.youershizi	86.6%	99.1%
com.wGuitarProTabs	98.5%	84%
com.edifier.edifierconnect	92.4%	99.6%
com.yoyohn.weishangzuotu	96%	99.1%
com.jtjsb.storyteller	86.2%	99.4%
com.lomolsoft.language.learnmarathi	85.3%	96.1%
com.bastion.bd	88.4%	97.3%
com.wish.defaultcallservice	90.6%	100%
com.hmsqw.customer	84%	99.6%

compatibilities prevent the APK from installing and running, hence no logs can be produced. Additionally, the absence of activities to run, indicated by *"No activities found to run, monkey aborted"* error message, could signify malformed APKs or an APK designed for a different Android version than the analysis environment. This leads to a failure in launching the app and capturing logs. The aforementioned issues collectively disrupt the log generation process, which is critical for understanding the behaviour of the APKs under scrutiny. Moreover, it was shown in (Alzaylaee et al., 2017) that to enhance the efficiency of the analysis, using a physical phone as the environment to run the apps is superior because a significantly higher number of apps experience crashes when being analyzed on an emulator.

Anti-emulator techniques incorporated in the apps: Emulation is frequently employed for dynamic analysis of (unknown) malware due to its ability to track run-time behavior. To circumvent detection by dynamic analysis, some attackers incorporate their malware with anti-emulation techniques. Thus, such malware have the potential to identify their presence within an emulator and adjust their behaviors accordingly. Nonetheless, this is not the only application of anti-emulation techniques. Legitimate software providers are also investing considerable efforts in preventing their products from operating within an emulated execution environment. The primary reasons for this are protecting their intellectual property from emulation-assisted reverse-engineering and preventing piracy of utilizing the application without purchasing the actual hardware product (Jang et al., 2019). Emulator detection makes it difficult for the reverse engineers to run the app on an emulated device. So, they would require to modify the app code to remove the emulator checks or run the app on a physical device. This would make large-scale app analysis more challenging and time-consuming.

Random testing of the apps: Since our approach relies on random testing, there's a possibility that we could overlook elusive behaviors, potentially impacting our capability to identify certain apps as malicious. More specifically, although using *Monkey* is the a standard approach for simulating and testing user interactions with the Android apps for dynamic analysis, it may miss specific use cases and it is not ideal for testing precise user flows. Using user-guided tools such as (SwiftHand2, 2023) or ARES (Romdhana et al., 2022) may be more beneficial and increase the reliability of the tests.

5 CONCLUSION AND FUTURE WORK

In this paper, we presented an interpretable ML-based dynamic analysis approach for Android malware detection. We focused on extracting the frequency of system calls as features to train our ML models. We applied an explainable method, called LIME, to the prediction results of the ML models to indicate the most contributing features to each prediction. Finally, we evaluated the stability of LIME explanations for true positives of our model. This is an early attempt at providing explainability for dynamic analysis of Android malware. For facilitating the reproducibility of our research, all the codes and data are publicly accessible.

There are many directions for future work. First, one could develop an enhanced user interaction simulator, rather than simply relying on the random interactions generated by *Monkey*. This could involve using testing frameworks that allow you to script specific user flows, ensuring that the application's critical functionalities are thoroughly tested. By simulating actual user interactions, you can uncover usability issues, identify edge cases, and provide more realistic test scenarios. A more accurate simulation of user behavior could provide a more useful model for malware analysis. Second, using larger datasets and deep learning models would enhance the performance of our ML-based analysis provided that the data is of high quality (e.g., temporal inconsistency and class imbalance are properly addressed). This prevents the research work from having over-optimistic results as it is the case for some existing studies. Third, using other interpretable ML techniques and comparing their explanation quality with LIME as well as applying explainable techniques to malware family classification are promising areas that need further exploration. Finally, investigating the performance of an

interpretable hybrid approach (combining the static analysis and dynamic analysis and using explanation methods) is another avenue for further research. This would result in enhancing the performance of the ML model and subsequently may increase the reliability and quality of the explanations.

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