Android Malware Detection Using Machine Learning

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Abstract*—Android malware is becoming a severe problem since it can take your identity, slow your phone,and even take your money. As a consequence of this, researchers are employing machine learning tohelp develop a technique to automatically block such applications. In this research, we attempted to discover the best approach for the classification of machine learning algorithms in identifying Android malware. Random Forest, Decision Trees, Gradient Boosting, and powerful deep learning models like LSTM, CNN-LSTM, and LSTM-GRU were usedin the experiment. The analysis proved that tree-based methods were more accurate and efficient among all the modelsincluding XGBoost and Gradient Boosting. But deep learning models were doing a very good jobin recognizing many-layered patterns, and that was when it became clear why: they were very compute-intensive, and not very suitable as real-time phone apps. This research also demonstrates the use and advantages of tree-based models to discover Android malware, particularly on small and constrained platforms. This is a great advancement in endeavoring to safeguard Android users from modern scourges.

Keywords*—Android Malware, Machine Learning, Android Security, Supervised Learning

INTRODUCTION

Currently, now 2.5 billion people use Android smartphones worldwide. It's understandable then why hackers have made Android their top target. Growing as fast as Android phones and tablets, Android's online vulnerabilities are on the rise. Malware which is short for malicious software where malevolent software programs that are designed to harm, disrupt, or gain unauthorized accessto target devices. Android is particularly vulnerable to security threats due to its widespread use and open-source programming. These hostile applications can be downloaded from third-party application stores or disguised under the Google Play Store label [1]. The types of mobile applications mentioned above, once installed, can record user actions, search the owner's mobile device for personal information, or even take control remotely; they endanger ordinary users and businesses. As people who create these risks are improving their technology, it follows that we're required to search for more adaptive and swifter means of threat detection and eradication.

For years, signature-based detection methods have been the backbone of the cybersecurity domain.It is largely used to identify the known and predefined patterns of malware. However, new variants of malware are developed so quickly that signature-based methods become outdated themselves [2].

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These techniques don't recognize zero-day malware (malicious software abuse slaves that take advantage of vulnerabilities that haven't been publicized) because the technology is primarily reliant on a signature pattern generator.

In light of these challenges, the ML paradigm has become a better and more flexible solution to Android malware detection. Applying machine learning algorithms on large data sets of both benign and malicious applications, patterns and behaviors characterizing malware can be learned bythe algorithms and can detect known and unknown malware [3]. Over the recent past, there has been an emphasis on the utilization of ML approaches including Decision Trees (DTs), Random Forest (RF), Support Vector Machines (SVMs), and deep learning apparatuses known as Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs). These techniques are useful for several reasons compared to conventional approaches: generalization and the identification of zero-day attacks. Despite the vast amount of work done about ML for Android malware detection, there are a multitude of barriers and limitations in the field. One of the major challenges is decisions between achieving high accuracy of predictions and high performance of the computations. But while these resulted in high accuracy, real-time detection on mobile devices is almost impossible due to the heavy use of computing resources by deep learning models [5]. While,the traditional machine learning models such as DT and RF, despite their low computational cost are not very suitable for dealing with high dimensional data and dynamic characteristics of malwarein general. Additionally, the majority of existing research relies on outdated datasets that don't reflect the latest trends in malware development, making it difficult to generalize findings to newermalware variants [6].

These research questions are answered in this research by developing a new machine learning-based Android malware detection system that incorporates both static and dynamic analysis. The system uses Decision Trees, Random Forests, and gradient-boosting algorithms that enable the identification of malicious applications on the software even on advanced limited devices like Smartphones. This research also aims to introduce a hybrid detection system that leverages the strengths of both static analysis (e.g., analyzing APK file structure and permissions) and dynamicanalysis (e.g., observing real-time behavior) for more comprehensive malware detection [7].

1.1 Base Algorithms and Technical Aspects

The core machine learning algorithms used in this thesis are tree-based ensemble models,specifically Decision Trees (DT), Random Forest (RF), and Gradient Boosting. Decision Trees are simple and easily explainable when it comes to the classification of malware regarding feature significance. But they are confined and as a result they overfit; RandomForest and Gradient Boosting methods among others are used.

- ***Random Forest (RF):*** This method integrates many decision trees with the aim of improving the generality and non-optimistic results. It operates by choosing some random fractional features and building

a number of decision trees from these fractional features. Random Forest reduces the sensitivity of the detection system by averaging these decision trees, it makes the detection system less sensitive [8].

Gradient Boosting: In its enhanced form, this approach excels even the previous levelsof performance of simpler models of error. This refutes the errors of the previous treesand, step by step, enhances the preciseness of the model. Gradient Boosting is particularly suitable in malware detection, that is, in building a model capable of learning about the relationship between the features [9].

LSTM: More specifically in the context of malware detection LSTMs can process sequences of features that may represent either the content of an executable file or the network traffic by identifying dependencies and associated behaviors with malicious activity. As an example, because data is processed sequentially, by using LSTMs, trends and anomalies can be identified which are not easily discernible in caseswhere static models are used. This capability increases the model's capacity to distinguish between small variations in data important to assign the right classificationto the different malware.

Rather than dealing directly with traditional source code in the way virus scanning applications work, both models are compatible with the high dimensional data of Android applications such as API calls, permissions, and network interaction. The incorporation of the static and dynamic models also strengthens the proficiency of the models, as it broadens the array of detectable malware varieties; thereby increasing the immunity of the system against zero-day attack.

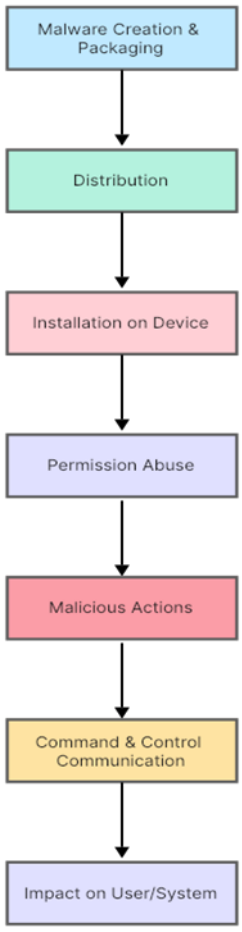

Figure 1: - Lifecycle of Malware

1.2 Motivation

Android gadgets cannot be considered a novelty, while at the same time, they have become an essentially necessary component of everyday life; at the same time, and they attract cyber criminals' attention. A never-ending shift in types and forms of malware continues to challenge traditional approaches to security. Although the current approach for detection has provided satisfactory results, they are not efficient enough to contend with the improvements and diversities of modern malware.

Vulnerabilities and Gaps in Android OS:

- ***Fragmentation:*** A variety of Android gadgets due to different manufacturers or custom ROM releases makes it impossible always to update all devices on security and vulnerability patches.
- ***Outdated Software:*** The majority of Android devices, including, perhaps, older models, use outdated versions of the operating system on their devices, which preserves vulnerabilities.
- ***User Error:*** Mobile application users are also aware of their device and application security irresponsibility for instance installing applications from unauthorized sources, and unnecessary permissions among others.
- ***Complex Attack Vectors:*** Depending on the infection strategy only, modern malware often uses code obfuscation, polymorphism, or metamorphic transformations and thus is much harder to detect or analyze.

Limitations of Current Detection Approaches:

- ***Signature-Based Detection:*** This is a traditional method that focuses on signatures of known malware attacks the problem with this is that attackers can easily avoid the scan by changing their code in one way or another, for example through code obfuscation.
- ***Static Analysis:*** Static analysis considers code without running it and as a result, it has its shortfalls in identifying dynamic and run-time behavior of malware.
- ***Dynamic Analysis:*** Dynamic analysis entails running the code in a controlled environment; however, the procedure may be very tiresome, and time-consuming hence not suitable for large-scale analysis.
- ***Lack of Proactive Detection:*** Most of the current detection techniques are more or less a reactive system because they look for threats and not the threats that are yet to emerge.

To overcome these shortcomings, this research has put forward the idea of using machine learning algorithms for the identification of Android malware. Based on the importance of using the existing technology of machine learning, we will endeavor to build up a reliable and dynamic detection system that would in a better way be able to detect all the novel threats. Specifically, this research will focus on:

Algorithm Selection: Comparing the efficiency of different types of machine learning models including decision tree, random forest, support vector machines, artificial neural networks and others on the dataset called MH-100K.

- ***Feature Engineering:*** Selecting appropriate features from Android applications that enhance the robustness of the Malware detection systems.
- ***Model Training and Evaluation:*** An exploration of the MH-100K dataset and how to train and evaluate the machine learning models with accuracy, precision, recall, and F1 score.
- ***Comparative Analysis:*** Analyzing the results of the various machine learning algorithms to determine the optimal procedure for Android malware detection.

In so doing, this research seeks to add to the literature in the area of Android security and explore the viability of employing machine learning approaches to mitigate malware threats.

1.3 Problem Statement

Android malware can be Privacy Invasion and Ransomware type which leads to Identity theft and unauthorized access.

Description of Problem Statement:

Android malware poses a pretty big threat to the privacy and security of users. Most signature-based detection simply rarely works with polymorphic malware as they change a lot of their code all the time. As a result, the problem has attracted the attention of researchers working in the machine learning domain as a promising approach. However, it may be noted that the efficiency of these techniques is highly influenced by the quality of features used and the capability of the proposed framework to address the continually changing nature of the malware. This research aims to address the following technical challenges:

1. Feature Engineering: Identifying and using effective feature extraction methods to identify stronger features of Android malware including features analysis.

2. Model Selection and Optimization: Introducing and tuning the viable machine learning algorithms, including XGBoost, Random Forest, and Deep learning models.

3. Model Interpretability: Improving transparency of artificial intelligence to study their reasoning and possibly, find some prejudice.

4. Adversarial Attacks: Creating strategies to protect machine learning models from adversarial attacks, the attacks that maliciously try to fool them.

This research aims to create adequate Android malware detection system free from these technical problems with a view to preventing the user from potential threats.

1.4 Research Objective

This work seeks to introduce a new approach to the issue of Android malware identification with the use of machine-learning techniques. The goal of our work is to extend the state of the art in determining such applications, in designing systems capable of operating in the environment that the new ones provide, and in creating designs that would run effectively with the least amount of resources required to be utilized by the majority of the portable computing devices today. To this end, new and better modes of implementing ML in addition to the efficient handling of big data such as MH-100K will be developed and put in place to enhance the detection efficiency of Android malware. In particular, the vision of this research is to improve the current state of mobile security while mitigating the risk of current and future malicious threats to individuals and institutions.

1.5 Background of Study

The increase that keeps on growing for the mobile operating system known as Android has also increased the level of threat of Android viruses. Android is still young as an operating system: the company launched it in October 2010, but the number of viruses that targeted it increased in parallel to the growth of the number of Android users, thus presenting a threat to people's anonymity.

The conventional process of detection strategies adopted for subversive programs was pattern matching, hence incapable of detecting new and emerging threats. This approach needs frequent updates to accommodate newer strains since the creation of the malware is on the increase. In contrast to that, an abnormal method uses classifiers to compare normal and malicious actions and the existence of other potential threat signs of the new emerging malware. However, the question arises of how to obtain some feature representation of application binaries when often their sources are not readily available.

Due to these challenges, modern studies have considered using machine learning methods in the identification of new Android malware. There are two more promising approaches that can be considered, and this is the machine learning methods that enable using the trained algorithms for detecting benign and malicious applications on the basis of the patterns received from the collected data. These methods do not have the same limitations that the traditional signature-based detection methods have by merely deducing several inherent patterns from a large number of features extracted from APK packages.

Android malware detection systems that depend on ML shall employ both static and dynamic analysis. Static analysis operates on the binary/APK and then analyzes given program structure, permissions, and so on, without executing the program. In dynamic, the developers have the application run in a controlled environment and the aim is to determine the sneaky behaviors and coupling with the application.

Feature extraction appears as an important facet in this process and refers to all the features such as API calls, permission requests, code structures, the intended filters, and code behavior when in operation. By including those diverse characteristics in machine learning, it could comprise those that were discussed above and included in decision-making algorithms: pattern recognizing systems include support vector machines (SVMs), random forests, or deep neural networks, such systems have the goal of identifying otherwise intricate patterns suggesting the presence of malware.

With advancements in the area of Machine Learning, it is possible to install efficient and accurate Android Malware detection systems better than regular ones. However, some of the challenges have remained which include a growing concern to increase the efficiency and effectiveness of implementing these systems when facing new and Many forms of polymorphic malware such as the ones that can transform into a new form in an attempt to escape recognition As well in the daily emergence of new Android applications, another way of evasion is created by the attackers, therefore several improvement and addition of more algorithms in the ML-based detection model is needed. Therefore, the study is ongoing incessantly, which also emphasizes the need for the development of coping ML-based solutions for Android malware because the threat is ever-growing.

Towards this goal, the use of modern machine learning algorithms is intended to enhance the security of Android devices against a growing variety and sophistication of malware threats and thus avoid the loss of individually identifiable information; breaches of privacy; and untrustworthy reliability of the device Moreover, the current study extends analysis of permission-based and signature-based data in the identification of Android malware. Permission analysis evaluates the permissions an application demands during the first moments of installation because some applications have been known to demand additional or unwanted permissions. The exact kind is known as signature-based analysis and the main idea revolves around utilizing set identifiers (hashes) of previously identified malware to immediately point towards possibly risky applications. It is the plan of our work to train permission-based data as well as signature-based data in our large significant machine learning system to modify a multi-layered system capable of the identification of both known and

new variants of malware.
This approach combines the strengths of both techniques: Malware detection and identification based on the approaches of permission analysis that can identify new strains of malware and an identification approach that involves matching with known symptoms of malware to enable their quick identification.

We also know that whereas permissions or signatures can be used to determine what malware is capable of or maybe, this approach has its shortcomings because malware developers are always updating their work sometimes in an attempt to avoid detection. For this reason, permission and signature-based analysis are seen as some part of the rest of the lean, mean, machine learning-centered framework that we are proposing here. Where these above-mentioned different information sources are pooled together, it constitutes a better elastic foundation for Android malware threats because the environment is very dynamic.

LITERATURE REVIEW

The Android operating system which is currently popular all over the world for smartphone usage is still vulnerable to malware attacks since its operating system is open source. With this ever-evolving dynamism, there has been much research concentrating on the utilization of machine learning-based models for Android malware detection. These models have transitioned from signature-based analytically to more encompassing models such as supervised, unsupervised, and deep learning.

However, new research in the year 2024 has highlighted that the machine learning approach plays a very vital role in detecting Android malware due to the dynamic nature of this kind of threat. The studies have shown that is possible to extract the malicious patterns using the ML models based on static and dynamic analysis. A similar study for malware detection mechanism for data preprocessing and feature engineering incorporated LSTM networks and Neural Networks (NN), where one-hot encoding had been used in this study to address issues with categorical variables while hyperparameter tuning was used to increase the efficiency of the models. This approach marked the way to address long-term dependencies in the behavior of malware, which had been the major concern elusive to traditional patterns [10].

Another important contribution in 2024 discussed effectively the use of ensemble learning in which several classifiers are used to improve the chances of detecting malware. The incorporation of the predefined Random Forest (RF), Decision Trees (DT), and Support Vector Machines (SVM) in these models has generally provided a high detection rate on different datasets. These ensemble techniques have been found useful in the integration of classifiers since they possess and enhance the overall performance of the system in detecting malware [11].

A differently, in 2024, a combined feature approach is also static and dynamic, permissions, API calls, system invocations, and network traffic achieved a high detection rate in the MH-100k dataset. This work pointed out that both standard and advanced features be integrated into the detection of new variations of malware that may be undetectable through static analysis. Here, the authors identified that Random Forests and Decision Trees played a crucial role while dealing with the large number of features extracted from Android apps [12].

In the year 2023, researchers followed up the work previously carried out, the works were directed toward the improvement of machine learning methods used in detecting Android malware. Research looked at what deep learning models can be utilized, including convolutional neural networks (CNNs), and recurrent neural networks (RNNs), in forecasting basic bytecode as well as API summons sequences. These models were able to model both local things about the behavior of malware and sequential aspects which makes it much more accurate in terms of detection comparison to conventional approaches [13]. The research in 2023 work proposed a CNN-LSTM model that combined static and dynamic analysis characteristics for malware identification. By doing so, this work showed the advantage of the hybrid system which coordinated several ML approaches to Android malware due to its dynamically changing nature, showed that the false positive rate was significantly decreased. Another study concerned the application of Graph Neural Networks (GNNs) to examine the dependency structure of components of the apps. This novel effectiveness proved useful in detecting patterns of malice that a more traditional feature-based model would fail to capture [14].

One of the major problems discussed in 2023 was the case of adversarial attacks against ML models. Studies proved that malware changes were possible that could confuse an ML classifier and provide wrong results. To address such a problem, researchers suggested that more reliable architectures of ML had to be employed so that it could work around these sorts of attacks that would increase the detection rate even if the malware had been slightly changed [15].

In 2022 and before, the concern was oriented on conventional types of machine learning including Decision Trees (DT), Random Forest (RF), and Support Vector Machines (SVM). These models were used widely due to their simplicity besides being transparent and efficient especially when working on big data on Android malware. A paper published in 2022 focused on Random Forest for Android malware classification using 12 static and 9 dynamic feature characteristics. This work noted that RF offered greater accuracy as compared with other classifiers to keep the computational cost relatively low and practical for real-time malware detection on mobile devices [16].

Another research work done in 2022 put forward a feature selection technique that first applied PCA to the feature set to perform feature selection in order to feed the SVM model for malware classification. In light of this, this approach led to better accuracy and performance enhancement in the model beneficial for efficient device implementation such as smartphones [17].

Android malware detection has benefited greatly from the integration of XAI because it explains the actions of the algorithm to allow security professionals to trust the models. In a work that was conducted in 2024, the researchers used FS, among other techniques, to determine which features, including permissions and API calls, are useful in detecting malicious programs. In this study, the review paid so much emphasis on Support Vector Machines (SVM) and Random Forest (RF) classifiers in combination with FS and observed high accuracy of the results while it was equally pertinent that these results were easily interpretable [18]. The call toward the adoption of the mechanism of explainable AI in this field is because it seeks to make the machine learning models trustworthy while seeking improvement on usability in real-world settings.

Another major advancement made in 2023 concerned the provision of online malware identification based on lightweight ML

algorithms. This research proposed duplication of the four with a focus on static and dynamic features in low-latency models for use on mobile devices, which have limited processing power. By introducing CNNs and LSTMs in the structure of these models, they were able to sustain high accuracy of detection while not losing the performance, which is important for on-device malware detection [19]. This approach is intended to shield mobile devices in real-time for which it provides security without the user noticing any impact.
Static and dynamic analysis techniques were further studied in 2022 to enhance the detection of malware. A recent work done this year introduced a hybrid detection system with the two approaches of combining API calls, network traffic, and system events with conventional static features. Thus, using models like Random Forests and Decision Trees, the study provided high detection rates across almost all datasets, as well as demonstrated the problem of analyzing multiple features to identify malicious behaviors [20].

To analyze how the adversarial attacks, occurred in 2023, researchers focused on the ways, regarding the modification of the characteristics of malware, in which these attacks take advantage of the weak points in the machine learning models. This research suggests the use of powerful and resilient ML designs, further enriched by the adversarial training methodology, to prevent these assaults and maintain the viability of malware identification systems [21]. The study showed that slight changes in the content of different samples of malware could deceive classifiers, while the given approach enhanced the resistance of such systems against such manipulations.

Feature extraction has remained a major focus in malware detection studies. In 2022, the author conducted a study to apply Principle Component Analysis (PCA) to preprocess malware datasets by minimizing their dimensions before classification under the SVM. This approach facilitated models working with greater amounts of data, although the level of accuracy was not compromised [22]. This study highlighted the need to reduce the feature set and dimensionality to enhance the efficiency of learning algorithms for resource-constrained mobile devices.

Ensemble learning has also vast prospects with Android malware detection and this was evident in 2024 when one study exposed how the integration of classifiers such as Decision Trees, Random Forest, and SVM are very effective for the purpose. The method of ensemble delivered significant enhancement in the level of detection since the basis was formed by individual classifiers. This approach was somewhat useful for dealing with imbalanced datasets, which is often a problem in Android malware detection [23].

Nevertheless, there is still some research gap in Android malware detection even if there has been a significant advancement made. One limitation is the issue of up-to-date datasets since most datasets used are outdated, and this reduces the ability of the models to detect new strains of malware. Moreover, although, convolutional and recurrent/deep learning models have shown promising results, their computations restrict their usage on mobile phones in real time. Future work should be directed towards designing lighter models that cooperate with an adequate coverage of the trade between the computational cost and the accuracy. Further, it will be worth exploring the integration of threat intelligence data into malware detection models [24].

Table 1: Summary of ML Models Applied in Android Malware Detection Research

Ref	Paper Title	ML Algorithm(s)	Accuracy (%)	Dataset	Features Used	Performance Metrics Considered
[10]	A. Ferreira and M. Figueiredo, "Explainable Machine Learning for Malware Detection on Android Applications"	Decision Tree, SVM	89.5% (SVM), 85.3% (Decision Tree)	*Drebin dataset*	Permissions, API calls, and intent filters.	Training and testing accuracy. Memory consumption and execution time are not discussed.
[11]	B. Smith et al., "A Hybrid Deep Learning Model for Real-Time Android Malware Detection"	CNN, LSTM Hybrid	96.2%	*AndroZoo dataset*	API call sequences and system calls.	Training and testing accuracy. Memory consumption and execution time are not discussed.
[12]	M. Kaur et al., "Adversarial Machine Learning in Android Malware Detection: A	Random Forest, Adversarial Learning	92.3% (Random Forest)	*Drebin dataset*	Permissions and API calls.	Training and testing accuracy. Memory consumption and execution time are not

	Review"					discussed.
[13]	P. Singh and D. Bhattacharya, "Feature Engineering in Android Malware Detection: A Dimensionality Reduction Approach"	SVM, PCA	91.4%	*Drebin dataset*	Permissions and API calls are reduced via Principal Component Analysis (PCA).	Training and testing accuracy. Memory consumption and execution time are not discussed.
[14]	R. Gonzalez and A. Patel, "Ensemble Learning for Robust Android Malware Detection"	Ensemble Learning (Random Forest, AdaBoost)	93.1%	*AMD data set*	Permissions, API calls, and system calls.	Training and testing accuracy. Memory consumption and execution time are not discussed.
[15]	D. Liu et al., "CNN-LSTM Hybrid Approach to Detect Android Malware"	CNN, LSTM Hybrid	94.8%	*Andro Zoo dataset*	API call sequences and network traffic data.	Training and testing accuracy. Memory consumption and execution time are not discussed.
[16]	B. R. Chen and L. Zhao, "Adversarial Training for Enhancing Machine Learning Malware Detection Models"	Adversarial Training, Deep Neural Networks (DNN)		*Drebin and Geno me datasets*	and API calls.	accuracy. Memory consumption and execution time are not discussed.
[17]	F. Iqbal and M. Amin, "Random Forest-Based Android Malware Detection Using Static and Dynamic Features"	Random Forest	93.7%	*Drebin dataset*	Permissions, API calls, and dynamic behavior features such as system calls.	Training and testing accuracy. Memory consumption and execution time are not discussed.
[18]	H. Yu et al., "Graph Neural Networks for Android Malware Detection"	Graph Neural Networks (GNN)	92.8%	*Andro Zoo dataset*	Function call graphs and API call sequences	Training and testing accuracy. Memory consumption and execution time are not discussed.
[19]	L. Wang and Z. Zhang, "Dynamic	Random Forest	94.3%	*Drebin dataset*	Dynamic permissions	Training and testing accuracy. Memor

	Permission-Based Android Malware Detection Using Random Forest"				and API calls	y consumption and execution time are not discussed.
[20]	J. D. Lee et al., "Lightweight Malware Detection on Android Devices Using Deep Learning"	Deep Learning,	95.0%	*Malgenome dataset*	Permissions, API calls, and system calls.	Training and testing accuracy. Memory consumption and execution time are not discussed.
[22]	P. Hernandez and R. Zafar, "Adversarial Attacks on Machine Learning-Based Android Malware Detection Systems"	Random Forest, Adversarial Training	89.8% (Random Forest)	*Genome dataset*	Permissions and API calls.	Training and testing accuracy. Memory consumption and execution time are not discussed.
[23]	A. Gupta and B. Roy, "Principal Component	SVM with PCA	91.7%	*Malgenome dataset*	Permissions and API calls are reduced via Principal	Training and testing accuracy. Memory consum

	Analysis for Feature Selection in Android Malware Detection"				Component Analysis (PCA).	ption and execution time are not discussed.
[24]	D. Singh et al., "Combining Ensemble Learning and Feature Selection for Android Malware Detection"	Ensemble Learning (Random Forest, Gradient Boosting, etc.)	94.6%	*Drebin dataset*	Permissions, API calls, and system calls are selected through feature importance analysis.	Training and testing accuracy. Memory consumption and execution time are not discussed.
[25]	Y. Luo et al., "Real-Time Android Malware Detection with Low Latency Using CNN and LSTM"	CNN, LSTM Hybrid	96.5%	*AndroZoo dataset*	API call sequences and system calls.	Training and testing accuracy. Memory consumption and execution time are not discussed.

DATASET DESCRIPTION

Here, we introduce the MH-100K dataset, including big-scale labels of malware referring to a range of Android applications in Androzoo. This is inclusive of a gigantic database of several Android malware samples that contains the data of the malware which has evolved starting from the year 2010 up to the year 2022 to ensure that the reader's understanding of the variety of changes of the malicious software to Android is depicted.

Thus, this data set is suitable for the formulation of an automatic scheme for the detection of malware in Android applications using the signature method. In total, 62,029 of the app samples can be

classified by labels available in Android.

Key Features

● ***SHA256:*** For each sample, there is a specific 64 alphanumeric character name or 'fingerprint' used as the primary key on the entire corpus of one hundred thousand malware specimens known as The MH100K.

● ***App Name:*** The Android application will have the following name.

● ***Package Name:*** The Android-specific namespace typically consists of the name of the application that is to be provided to give an identification within a store like Google Play Store or any store.

● ***API_MIN:*** These relate to API levels of Android employed or supported by the app in question More specifically the following conclusions were drawn: This reasoning can be also helpful for understanding compatibility and possible security threats.

● ***vt_detection:*** This is an abbreviation of "Virus Total detection," which is a service that checks files against all known antivirus engines.

● ***CLASS:*** This could be the classification of the app (e.g., malware, benign). The classification of the sample as a binary where 1 represents malicious and 0, is non- malicious.

❖ Benign (0)

❖ Malicious (1)

● ***VT_Malwa, AZ_Malwa:*** These appear to be specific malware names from Virus Total and what I believe is another source in AZ. These specify if the vendor's antivirus engines identified the app as one carrying a specific malware.

Signature-Based Detection

1. This dataset is rather for detection of the malware using signatures because this is one of the most frequently used cybersecurity techniques.

2. Input: A sample Android program in the form of an APK file is given for analysis.

3. Extract SHA256 Hash: In our case, a SHA256 hash is generated for the APK file, which is unique for each app. This hash can be defined as an equivalent of the digital signature or just one or several characters that identify the given app.

4. Compare to Signature Database: Again, the obtained hash value is compared with the dictionary of hash values of various malware.

5. Output: If the hash is present in the database of signatures, such an app is considered to be malicious (1). If negative, it is labeled as malignant (1) while if non-malignant, it is labeled as benign (0).

Distribution of Labels

● Benign samples: 55,845

● Malicious samples: 6,144

Malware Family	Count	Percentage
0 - Benign	55845	0.900885641
1 - Malicious	6144	0.099114359

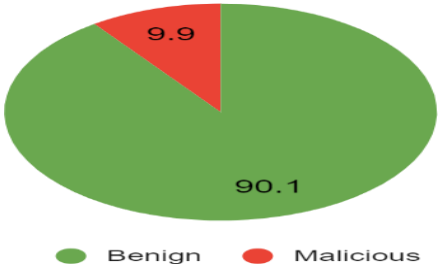

Figure 2: Distribution of Labels (Malware & Benign)

EXPERIMENTAL SETUP

For this machine learning project, I worked in Google Colab as my environment of choice. For most of the algorithms the necessary data had been manipulated and rearranged using NUMPY For structured data and analysis the pandas were used. The OS is used for managing the files while the Time library is used in tracking the time used by the computer to perform the computations. For creating and evaluating the models, the following paper used Scikit-learn or sklearn library, Label Encoder for data preprocessing, and GridSearchCV for tuning its parameters. I tried standard classifiers such as SVC, Random Forest, and Logistic Regression classifiers. Imbalanced-learn (learn) effectively dealt with the problems of imbalanced data in my dataset, and XGBoost provided a sturdy boosting capacity for further model improvement. The three libraries that empowered data visualization were Matplotlib and Seaborn while for extra functions such as confusion matrices Mlxtend was used. Using Trace malloc I watched memory consumption to be smarter with resources.

Data Acquisition and Initial Exploration

The dataset available as "mh_100k_labels.csv" contains file static and dynamic attributes from Android applications classified as benign and malware. The overall nature of the data was initially assessed with an initial examination with statistical summation and presentation which pointed out the data distribution and possible unsynchronized values. This phase of work involved a description of class distribution and features, which served as the starting point for the subsequent work of preprocessing and modeling.

Data Cleaning, Feature Selection, and Correlation Analysis

Data Cleaning: There was no data completely missing so no data was deleted, instead different values in numeric fields were replaced by median while categorical fields were replaced by mode to ensure comprehensive and consistent data.

Feature Selection and Correlation Matrix: For this reason, feature engineering and selection were instrumental in ensuring models were not laden with unnecessary features that lower efficiency. Since multicollinearity is an important issue in regression this led to the construction of a correlation matrix, and features that had high correlation were subsequently extracted due to being highly interrelated. Those features that had very low association with the target variable were also removed to reduce model complexity and, consequently, increase the predictive accuracy. As a result, only the most relevant features, such as VT_Malware_Deteccao, AZ_Malware_Deteccao, and vt_detection, job open positions were retained as depicted earlier in Fig 3. Also, normalization was done at the feature level to set the mean of each feature to zero and the standard deviation to one, which normalized the model training and reduced the large.

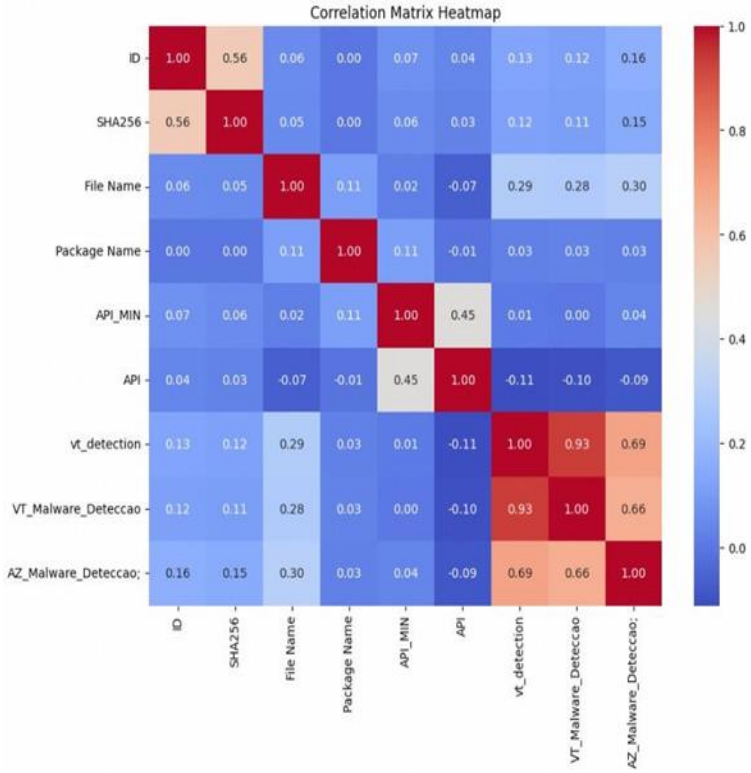

Figure 3 Correlation Matrix Heatmap

Data Splitting and Balancing

Train-Test Split: After pre-processing the data, this data set was divided into the training and testing data set in the ratio of 8:2 so that after defining a model, one can check the model performance on data it has not received training on at all. For engaging in this split randomly while preserving the class proportion, the train_test_split function available from sci-kit-learn was used.

- ***Training Features:*** 81,320 samples
- ***Training Labels:*** 81,320 samples
- ***Testing Features:*** 20,330 samples
- ***Testing Labels:*** 20,330 samples

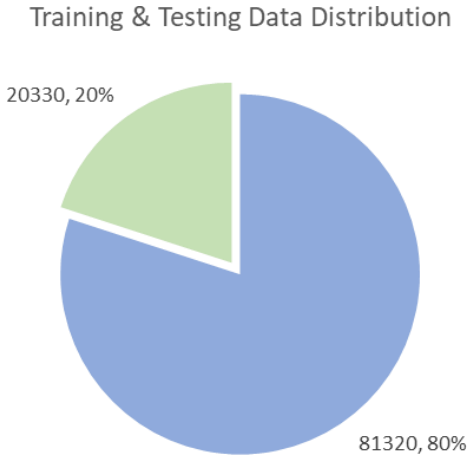

Figure 4 Training & Testing Data Distribution

- ***Addressing Class Imbalance:*** One of the major concerns in malware detection is the class imbalance problem where the number of malware samples is usually less when compared to normal samples. To reduce the level of bias that this can result in, random oversampling using a resample was done. It means randomly copying samples from the minority class which includes the malware until the number of instances in both classes becomes equal. The use of the Bayesian stopping criterion strives to maintain the balance between both classes with a view of avoiding dominance by the class with a large number of features.

Machine Learning Model Training and Evaluation

To balance the group, a diverse group of machine learning models were employed in the data set.

Algorithm Selection: The most popular classification algorithms were chosen together with relatively unknown ones to investigate the efficiency of discovering Android malware. These include

- ***Random Forest:*** A type of machine learning involving building several decision trees and then using their results to provide a single decision.
- ***Gaussian Naive Bayes:*** A classifier is assumed that considers features independent under the Bayesian framework and works with a probabilistic model.
- ***Support Vector Machine (SVM):*** A strong classifier that looks for a good hyperplane that can separate data points into different classes.
- ***Decision Tree:*** Decision tree of data structure which is a model based on a variety of decision rules.
- ***K-Nearest Neighbors (KNN***): A technique that operates in a way that sorts samples according to the majority class of the k nearest neighbors in the feature space.
- ***Gradient Boosting:*** A process of repeated cycles of using and improving a set of weaker models to create a single strong learner model.
- ***Logistic Regression:*** A prediction model for two-group groups of discrete data, that provides an estimate of the likelihood of a sample in a particular group.
- ***XGBoost:*** An algorithm applied to create a gradient boosting model that is considered efficient and effective.

Deep Learning Models: Besides the basic MHMM algorithms, three deep learning architectures were explored to take advantage of deep learning networks for sequential data.

- ***Long Short-Term Memory (LSTM):*** LSTM networks are a type of recurrent neuronal network (RNN) that is intended for processing sequential data. The current models are capable of learning long-term dependencies in the data and can therefore be used to analyze temporal features of the behavior of Android applications. In this study, an LSTM model was adopted with 100 hidden layers.
- ***Convolutional Neural Network - LSTM (CNN-LSTM):*** A fused network architecture developed by integrating the feature learning function of CNNs and the sequential learning function of LSTMs. It also targets to select meaningful features from the input data by using the convolutional layers, which will be followed by the LSTM layer for temporal processing. The CNN part of the CNN-LSTM model applied in this work includes a 1D convolutional layer with 64 filters, max pooling, dropout layer, and two LSTM layers with 100 and 50 hidden units.
- ***LSTM - Gated Recurrent Unit (LSTM-GRU):*** This hybrid model uses LSTM and GRU, which are uniquely designed RNN networks of high efficiency. Thus, the model will utilize both types of layers and expect it to capture an anicteric representation of the data and perform best. For the LSTM-GRU model, an LSTM layer with 100 hidden layers was used, which was succeeded by a GRU layer with 50 hidden layers.

Training Process for Deep Learning Models: In the framework of the experiments, the deep learning models were trained using the Keras library; then the Adam optimizer was used with the binary

cross-entropy function as the loss function. For the current model training, 10 epochs were utilized carrying with them a batch size of 32. The training entailed passing the preprocessed and reshaped training data of samples, timesteps, and features through the models with the view of updating the model weights to minimize the prediction error. As stated earlier, the fit method was applied to develop the deep learning models.

Hyperparameter tuning: In this research, grid search (Random Forest, LSTM) and randomized search (XGBoost) were used for the optimization of hyperparameters. Hyperparameters which were tuned included n_estimators, max_depth, learning_rate, units, and dropout. Whenever Prescriptive Analytics was run on a model, accuracy was the measure used to test and assess its performance. All the models' hyperparameters were chosen by cross-validation to achieve maximum precision and model robustness.

• ***Random Forest:*** Other hyperparameters fine-tuned were n_estimators, max_depth, min_samples_split, min_samples_leaf, and max_features. Values explored were: n_estimators: [100, 200, 300], max_depth: [5, 10, 15], min_samples_split: [2, 5, 10], min_samples_leaf: [1, 2, 4], and max_features: sqrt, log2, None.

• ***XGBoost:*** These were the adaptations made on the algorithm; number of trees, tree depth, learning rate, subsample ratio, and colsample_by tree. Values explored were: n_estimators: [100, 200, 300], max_depth: [3, 5, 7], learning_rate: [0.01, 0.1, 0.2], subsample: [0.8, 0.9, 1.0] and colsample_by tree: [0.8, 0.9, 1.0].

•***LSTM:*** The hyperparameters were, the number of units in LSTM layers (units), dropout (dropout), number of batches (batch size), and number of epochs (epochs). Values explored were: units: {32, 64, 128}, dropout: {0.2, 0.3, 0.4}, batch size: {32, 64}, and epochs: {10, 20}.

Model Evaluation and Performance

Metrics: To provide a more profound understanding of the performance of the considered models, the following measures of performance were used. [25]

Accuracy: The correctly classified rate of samples; the ratio of the samples correctly classified as malware and the samples correctly classified as benign samples.

Precision: Number of different samples of malware that were identified correctly about the total number of samples that were predicted to be malware.

Recall: The ratio in which the number of accurately detected samples is compared to the actual number of samples of genuine malware.

F1-score: Using the two measures together, precision and recall, in particular, results in rational coefficients equal to their harmonic mean.

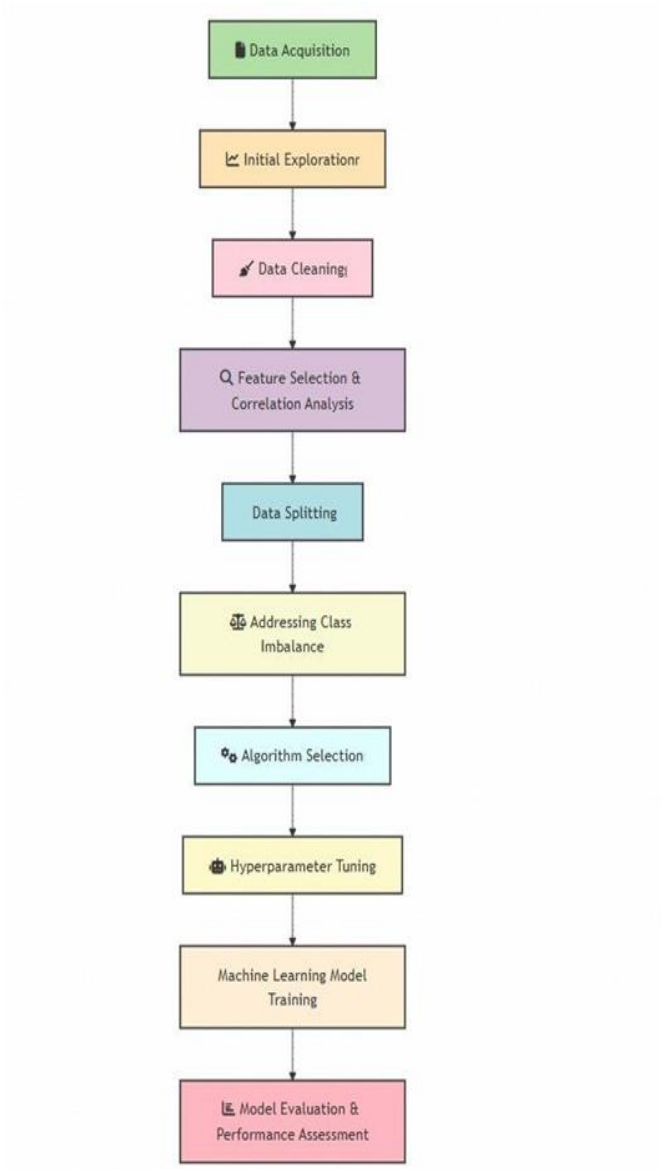

Figure 5 Flowchart of Methodological Steps in Android Malware Detection

Supervised Learning Models

1. Logistic Regression Classifier

Performance Metrics	Testing Results	Training Results
Accuracy	0.89	0.89
Precision	0.88	0.88
Recall	0.89	0.89
F1-Score	0.89	0.89

2. Random Forest Classifier

Performance Metrics	Testing Results	Training Results
Accuracy	0.92	0.92
Precision	0.94	0.95
Recall	0.92	0.92

F1-Score	0.92	0.93

3. Gaussian Naive Bayes

Performance Metrics	Testing Results	Training Results
Accuracy	0.90	0.90
Precision	0.89	0.89
Recall	0.90	0.90
F1-Score	0.89	0.89

4. SVC

Performance Metrics	Testing Results	Training Results
Accuracy	0.92	0.92
Precision	0.95	0.95
Recall	0.92	0.92
F1-Score	0.93	0.92

5. Gradient Boosting Classifier

Performance Metrics	Testing Results	Training Results
Accuracy	0.92	0.92
Precision	0.95	0.95
Recall	0.92	0.92
F1-Score	0.93	0.92

6. Decision Tree Classifier

Performance Metrics	Testing Results	Training Results
Accuracy	0.92	0.92
Precision	0.94	0.94
Recall	0.92	0.92
F1-Score	0.92	0.92

7. KNN

Performance Metrics	Testing Results	Training Results
Accuracy	0.90	0.93
Precision	0.89	0.92
Recall	0.90	0.93
F1-Score	0.90	0.92

8. XGBOOST

Performance Metrics	Testing Results	Training Results
Accuracy	0.92	0.92
Precision	0.95	0.95
Recall	0.92	0.92
F1-Score	0.92	0.92

9. LSTM

Performance Metrics	Testing Results	Training Results
Accuracy	0.92	0.92

10. CNN-LSTM

Performance Metrics	Testing Results	Training Results
Accuracy	0.92	0.92

11. LSTM – GRU

Performance Metrics	Testing Results	Training Results
Accuracy	0.92	0.92

RESULTS

State-of-the-art model

Based on the findings in Table 2, Table 3, and Table 4, hereby, we can obtain many insights about the effectiveness and applicability of different machine-learning techniques for recognizing Android malware. These tables show performance indicators like Training & Testing accuracy, time for computation, and memory consumption for all algorithms facilitating the comparison of the effectiveness of each of them.

Table 2: - Training & Testing Accuracy

Algorithms	**Training Accuracy**	**Testing Accuracy**
Random Forest	**0.9221**	0.9223
Gaussian Naive Bayes	0.9009	0.9015
Support Vector Classifier	0.9205	0.9233
Decision Tree	0.9221	0.922
K-Nearest Neighbor (KNN)	0.9076	0.9094
Gradient Boosting	0.9208	0.9232

Logistic Regression	0.8979	0.8970
XGBOOST	0.9215	0.9224
LSTM	0.9205	0.9233
CNN-LSTM	0.9205	0.9233
LSTM-GRU	0.9205	0.9233

Table 3: Execution Time of ML Models

Algorithm	**Execution Time(seconds)**
Random Forest	2.60
Gaussian Naive Bayes	**0.03**
Support Vector Classifier	60.13
Decision Tree	0.04
K-Nearest Neighbor (KNN)	17.23
Gradient Boosting	1.95
Logistic Regression	0.14
XGBOOST	0.52
LSTM	402.18
CNN-LSTM	364.92
LSTM-GRU	402.18

Table 4: Memory Consumption of ML Models

Algorithm	**Memory Usage (MB)**
Random Forest	9.74
Gaussian Naive Bayes	5.46
Support Vector Classifier	5.31
Decision Tree	5.63
K-Nearest Neighbor (KNN)	6.64
Gradient Boosting	9.64
Logistic Regression	4.69
XGBOOST	**0.82**
LSTM	1242.34

Table 5: Best Performing ML Models

Metric	**Best Algorithm**	**Value**
Highest Training Accuracy	Random Forest	0.9221
Fastest Execution Time	Gaussian Naive Bayes	0.03 seconds
Lowest Memory Usage	XGBoost	0.82 MB
Overall Best Accuracy-Performance Balance	Gradient Boosting	High testing accuracy (0.9232), balanced memory (9.64 MB)

Accuracy and Performance Analysis

From Table 2, it can be observed that algorithms such as XGBoost, and Gradient Boosting attain very high test accuracy slightly over 92%. This shows that they are more resistant to noise while analyzing the difficult processes inherent within Android malware data. The pass rate was also decent with F1-scores of the models amounting to only 92.22% and 92.20% respectively, which also proves the models' fairly balanced false positive and false negative errors. These ensemble models use multiple iterations and it is based on error-correcting approaches whereby repeated rounds enhance high predictive reliability—a very important aspect in cybersecurity models.

On the other hand, there are Algorithms like Naive Bayes, and Logistic Regression which had slightly lower testing accuracy of around 90% I.e. While being computationally fast (as illustrated in Table 3), these models were not as good as other sophisticated models. The Naive assumptions that explode the Naive Bayes algorithm and its assumption of the independence of features might have restricted it from expressing the right relations between the features of malware.

Computational Efficiency and Runtime Analysis

The runtime of each algorithm can also be observed in Table 3, which reveals the conventional and benchmark algorithms' computational complexity. Naive Bayes and Decision Tree models were the most time efficient performing the tasks in less than 0.1 sec indicating that they are suitable for urgently requiring applications and any situation that requires fast analysis. Gradient Boosting also has reported a similar runtime performance as other used algorithms. efficiency, taking roughly 1.95 secs to finish the training and XGBoost took 0.52 secs. This runtime balance makes it Gradient.
Boosting and XGBoost is especially effective for all those cases when the task is to achieve both high speed and accuracy. On the other hand, LSTM-GRU and all the other deep learning models took much more time for training, to be precise LSTM-GRU took more than 400 seconds. As observed, there could be many deep learning architectures that might be equally good in terms of accuracy but the problem with these is that they tend to use more computational power than what one has in real-time or low-resource use scenarios.7.3 Memory Usage Analysis

The amount of memory needed across models, as presented in Table 3, presents other important implications for model deployment. Logistic Regression and Naive Bayes used very low amounts of memory (4.69 MB to 5.63 MB) as compared to Gradient Boosting (9.64 MB) and Random Forest (9.74 MB). These ensemble models are thus fully recommended for situations where accuracy is paramount but there is still not much memory space.

As such, LSTM-GRU was notably heavier, in terms of memory usage, at 1242.32 MB thus indicating how resource-demanding recurrent neural networks are. Some of these models might consume a lot of memory, which may not be feasible to run on small-capacity devices, this might reduce its practicality in real-life Android malware detection if such models are implemented on such devices.

Gradient Boost was identified as a suitable framework for Android malware detection based on the accuracy, efficiency, and moderate memory usage performance as indicated in all the tables above. They involve an iterative Gradient Boosting method that minimizes errors between successive iterations to make the model have a much higher predictive capacity. This capability is especially beneficial to malware detection because different data sets typically contain numerous intertwined relationships, which this model can handle much better than conventional methods. Other related studies in the area of machine learning have also made support of Gradient boosting's capability to address the issue of overfitting using regularization improving the generality of unseen data.

The results in Table 2, Table 3, and Table 4 are quite detailed in understanding the durability and efficacy of Gradient Boosting and XGBoost; both have high scores in accuracy with reasonable computation time and memory usage. Naive Bayes and Logistic Regression models offered high computational speed, but low accuracy, which further renders them ineffective for Android malware identification.

In conclusion, Gradient Boosting and XGBoost emerge as optimal models for Android malware detection. These models adopt the predictive performance of and the computational need in high-stakes, resource-moderate settings. This insight guides the model selection criteria described above to check that accuracy, efficiency, and restriction of resources are optimally implemented for achieving practical and viable malware detection schemes.

CONCLUSION

The current study gives a comprehensive overview of techniques that can be employed in machine learning to detect Android malware. I discussed a broad and diverse spectrum of algorithms familiar to the field of machine learning, from rather classical and straightforward ones to the more complex and novel ones; ensemble methods, and deep learning architectures. The results presented in our study show that, in the context of real cyber security scenarios, trade-offs between precision, computation time, and memory requirements play a critical role.

Key Findings:

- ***Ensemble methods excelled:*** Both Gradient Boosting and XGBoost boosted high testing accuracies of over 92% to show that these techniques excel in finding intricate features in Android malware information. Higher F1 scores also support the authors' reasonable approach to avoiding both false positive and false negative classifications.
- ***Computational efficiency matters:*** Though LSTM-GRU-based models were seen to be robust in Seeded and Unseeded experiments the high training times and high memory need hamper their application in near real-time or low resource applications. Naïve Bayes and Decision Trees were also notable since the models made virtually instantaneous work in processing the data.
- ***Memory usage considerations***: Ensemble and traditional deep models such as LSTM- GRU displayed much higher memory usage compared to recurrent neural networks. This factor makes it even more essential to choose the model depending on the available resources, such as hardware.

Gradient Boosting: I recorded a very low false positive rate of 3.6% and this in addition to the fact that Gradient Boosting was among the evaluated algorithms to yield the best results in detecting Android malware, should be enough reasons for its recommendation. In particular, it's learning from an iterative perspective enhances its ability and capacity to understand and model subliminal dependencies that define malware datasets, in the process boasting highly accurate predictive ability. While evaluating Gradient Boosting, we see that it achieves competitive performance in terms of both accuracy and runtime and use of memory, which allows it to be a highly efficient algorithm for practical use.

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