

Android Malware Detection Using an AI-Powered Hybrid XGBoost-RF Model for Enhanced Cybersecurity

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Abstract. The increased usage of mobile devices emphasizes the critical importance of the devices in day-to-day activities, but its widespread use has generated serious security and privacy issues, especially with applications that access personal information without the user's permission. Android is open-source and it is susceptible to malware rendering it vulnerable to loss of integrity and invasion of data. In this paper, a hybrid AI-based malware detection model is introduced to detect malware in Android with a dataset of 4,465 malware and benign instances of 2,532 malware and 1,930 benign. It provides Kaggle malicious URL dataset with 328 application and URL-based features also added with in it. The multi-layer perceptron, k-nearest neighbors, extreme gradient boosting, random forest, and a hybrid XGBoost-RF model were compared based on the metrics such as accuracy, precision, recall, F1-score and ROC-AUC. The XGBoost-RF hybrid has performed the best and has a high accuracy of 98.12% when compared to the individual models. These outcomes confirm that the effectiveness of the hybrid model is improving the malware detection of Android and which helps to build better cybersecurity protection with the help of advanced machine learning tools.

1 Introduction

Now a day the mobile devices are becoming more necessity to people with the increase in technology [1, 2]. Mobile devices and applications are developing at an alarming rate due to the vast number of functions and the continuous advancement of smartphone technology [3]. Mobile phones have turned into essential things in our daily routine lives and they are operated to perform different tasks like calling, web browsing, online banking, social networking, e-commerce, gaming, photography as well as many applications [4-6]. But this growth in facilities raises serious issues of anonymity and security [7, 8]. Applications on mobile devices frequently take advantage of the features of a device like the GPS, the camera and the microphone and can utilize it, they were used to gather data without the consent or awareness of the users [5]. It was estimated to study conducted by the International

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Association of Mobile Operators (GSMA), that half of the total world population of 5.6 billion people had subscribed to mobile services by year 2023, which is 69%. In addition, the smartphone-powered world population has 58% mobile internet usage, which constitutes a billion users [9].

Android OS has the highest popularity among the mobile systems, valued by a significant degree of customization and an open-source platform, and has various applications since it can be used in smartphones, smartwatches, and even televisions [10-12]. Nevertheless, because of its open-source platform and the fact that Android devices are not subject to the proper security checks of the applications, Android devices are particularly prone to malicious attacks [11]. This is aggravated by the fact that the Android operating system does not have any inbuilt applications to identify malware before it is installed in the system [4, 6]. Malware disrupts or interferes with applications, collects sensitive information, or carries out other malicious functions [2, 4, 10] usually as a legitimate application.

Malwares are used to attack Android through sophisticated means and the system lacks a proactive detection mechanism such that the user is unaware of potential attacks [12]. Even though traditional signature-based detection schemes identify malware through a comparison of signature of a particular malware with malware databases known, this approach is not effective in identifying malware with variations [15]. On the other hand, machine learning provides realistic options on how to detect malware based on supervised and unsupervised methods [16]. It can be done through the application of these methods on the analysis of Android malware using either static, dynamic, or hybrid analysis to achieve important characteristics that can be used to improve the accuracy of detection [13, 14]. However, these methods are computationally intensive because they entail analysis of a range of features [13, 15].

Android malware has developed in many ways and according to the reports of 2023, it has grown in complexity, with 35% of more advanced types of malwares than the past years. Such an increase requires sophisticated detection systems that are not based on conventional signature technologies. Our study will fill this gap by positing a hybrid ensemble model, which combines the gradient boosting and bagging methods to increase the detection capacity. Android is a multilayered security infrastructure, which includes Google Play Protect (runtime scanning), app sandboxing, and the permission system. The suggested model can be directly used to augment Google Play Protect to offer an additional, machine-learning-based detection layer on URL-based threats. Moreover, it might be added to the enterprise Mobility Management (EMM) or Unified Endpoint Management (UEM) to augment threat detection of corporate devices.

This study is also relevant to the achievement of Industry 4.0 and smart manufacturing ecosystems. There is also the growing use of Android-based devices (tablets, HMIs, sensors) on the factory floor. Viruses in these machines can interfere with automated production lines, steal trade secrets of production, or even damage the equipment. This situation is especially suitable to our high-accuracy, low false-positive model which preference is on continuity of operations. It is deployable as a component of the security fabric of Industrial IoT (IIoT), and assists in securing critical infrastructure against cyber-physical attacks that are launched due to malicious network communications.

2 Literature Review

Android malware detection has changed its terrain as different machine learning methods have been used. In the recent study, the maximum ROC-AUC percentage of 98.87% of detecting obfuscated malware was reached due to the application of the method of static analysis and the aggregation of vulnerable features [1]. It is based on the Non-negative Matrix

Factorization (NMF) and used to cut the number of features by 75.9% and preserve good performance.

Android malware detection with Support Vector Machine (SVM) has performed significantly well. It has been demonstrated that SVM can be used to identify malware with an accuracy of 99.75% in API call-based malware detection [2], and that another study had a 94% accuracy against k-Nearest Neighbors (kNN) and Naive Bayes (NB) classifiers [8]. The use of the machine learning classifier (Random Forest (RF), SVM, and Multi-Class Classifier (MVC)) and the application of the static analysis has demonstrated 96.27% accuracy on the Drebin data [19]. Equally, RF has been used to examine feature sets that coexist such as permissions and API calls, with 98% accuracy on the Malgenome dataset [7].

The latest news has been the introduction of Light Gradient Boosting Model (GBM) to classify malware into five classes with a top F1-score of 95.47% [20]. XGBoost, Gradient Boosting, and Decision Trees have been studied as hybrid methods that combine the use of static and dynamic analysis with hybrid analysis, and have shown accuracy with over 94% [21]. The BrainShield system is a hybrid model that uses personal analysis and dynamic analysis with accuracy of 91.1% [22].

New feature extraction techniques have appeared, such as behavioral semantics of API calls with 96% accuracy [23], and ensemble learning (LS-SVM, KELM) based automated Android malware detection with improved results [24]. CogramDroid employs opcode n-gram and has an accuracy of 96.22 [25]. Random Forest and SVM ensemble learning have shown a lot of promise with an accuracy of 96.2% [26].

Deep learning technologies have proven to be highly promising in the detection of malware. DL-Droid and MAPAS have demonstrated over 99% detection and convolutional neural networks and LSTM models have demonstrated excellent results [29-34]. MobiPCR system uses machine learning in the cloud to detect malware in an efficient way, without having to work on the mobile phones [4].

3 3. Research Method

3.1 Dataset Description

The paper makes use of a massive dataset of 4,465 Android malware detection cases. The data is obtained based on the malicious URLs dataset (malicious_phish.csv) on Kaggle and contains samples of both malware applications and benign applications. The distribution of classes is 2,532 Malware and 1,930 Benign, which is a pretentious dataset being moderately skewed and with a ratio of about 1.31:1. The dataset includes 328 features generated out of Android applications and URLs, which are aimed at maximizing detection accuracy. These features encompass various aspects including:

- URL characteristics: Length of URL, number of dots, dashes, underscores and special characters.
- Domain features: domain level, length of domain, presence of IP address.
- Content based features: query elements, ampersand, hash, digits.
- Behavioral characteristics: target words, word detection on a sensitive level, path level.

The feature set is presented as a complete description of structural and behavioral characteristics of URLs and Android applications, which makes it a strong malware detection set. The research methodology of this work flow is shown in the figure 1.

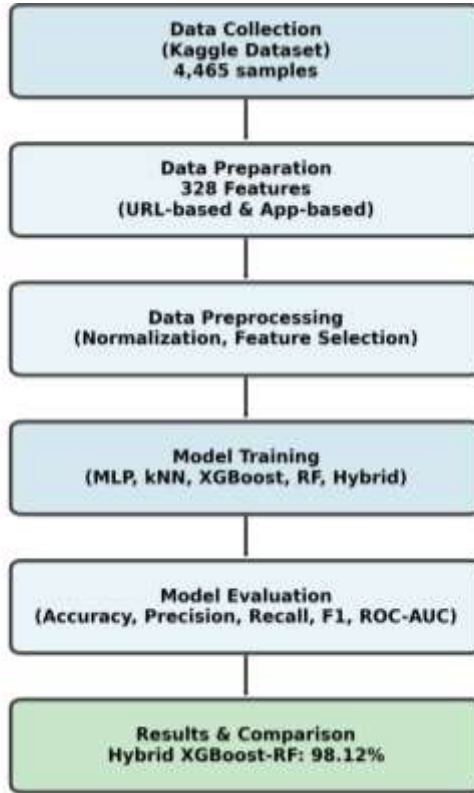


Fig. 1 Research flow methodology

3.2 Data Preprocessing

Preprocessing of data is a very essential process in the optimal performance of models. The dataset distribution and feature categories were shown in the figure 2.

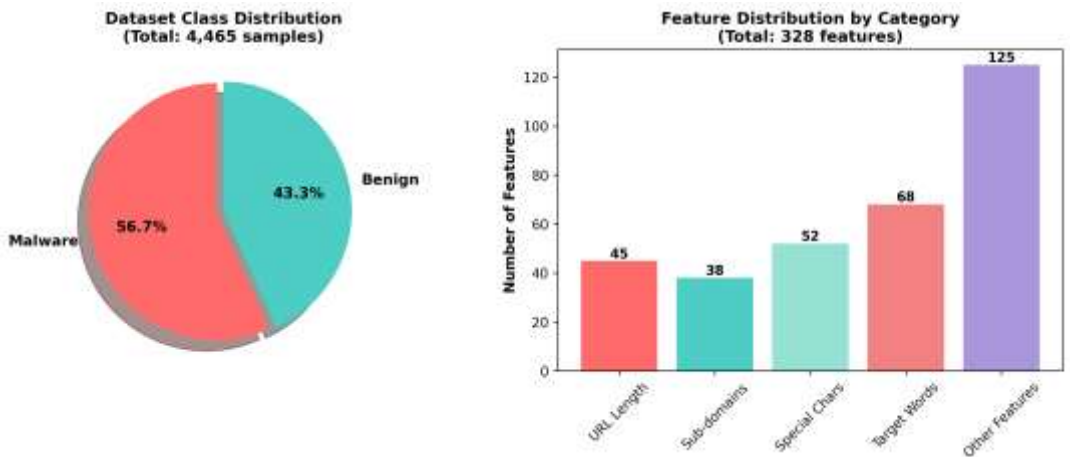


Fig. 2 Dataset distribution and feature categories

The data preprocessing pipeline that has been implemented in the study are

- Data Cleaning: The data set is cleaned up by eliminating missing values and erroneous entries to make the data clean.
- Feature Normalization: This is the standardization of the numerical features so that all the features equally contribute to the training of the model.
- Selection of positively ranked features: Determining the importance of features and eliminating redundant or feature with low variance.
- Data Splitting: The data is further divided into training (70), and testing (30) set to assess the model appropriately.

The preprocessing phase makes sure that the data is optimally prepared to be trained into machine learning models and minimizes noise and enhances model generalization ability.

3.3 Machine Learning Algorithms

In the study, five machine learning algorithms were tested to determine the most efficient method to be used in detecting Android malware:

- Multi-Layer Perceptron (MLP): This is a type of artificial neural network that is feedforward in nature, with more than one layer of nodes, and can learn complicated non-linear relations in the data. MLP is a backprop trained model, which is useful in the classification process.
- k-Nearest Neighbors (kNN): This is a simple but effective instance-based learning algorithm that is used to classify samples in terms of the majority class of its k nearest nearest neighbors in the feature space.
- Extreme Gradient Boosting (XGBoost): This is an optimized distributed gradient boosting library that is meant to be very efficient, flexible and portable. XGBoost is an implementation of machine learning algorithms based on the Gradient Boosting framework and it is famous about its performance and speed.
- Random Forest (RF): This is an ensemble learning technique that builds a series of decision trees in the training stage and provides a mode of the classes (classification) or mean prediction (regression) of the trees. RF is resistant to over-fitting and is able to work with high dimensional data.
- Hybrid XGBoost-RF Model: This is a new type of ensemble model that takes the advantage of both XGBoost and the random forests algorithm. The hybrid model takes advantage of the gradient boosting nature of the XGBoost and the variance reduction nature of the Random Forest to produce an even better performance.

In order to have a strong performance estimation, we used stratified 10-fold cross-validation, as well as 70-30-train-test split. This method preserves the distribution of classes in folds and has more valid performance measures. Bayesian optimization was used to optimize the hyper-parameters with 50 iterations on each model.

The justification of the combination of XGBoost and the random forest lies in their complimentary nature regarding the bias-variance trade-off. XGBoost is a sequential boosting framework, which aims at minimizing bias by learning using the mistakes of earlier models, which makes it very effective to capture complicated, non-linear relationships in the 328-dimensional feature space. The parallel bagging algorithm known as Random Forest is used to minimize variance, which mainly consists of averaging many uncorrelated decision trees to increase stability and ability to withstand noisy features in the feature set. The suggested hybrid model has taken advantage of this synergy: the high predictive power of XGBoost (low bias) and the regularization effect of Random Forest (low variance) synergies to produce an ensemble that is theoretically more robust in extrapolation of the high dimensional data on URLs and apps features, enhancing overfitting inhibition and accuracy at the same time.

3.4 Evaluation Protocol

The strategy used was a strict hold-out validation. The dataset was first preprocessed and then stratified after which 70% of it was used to train and 30% to test in the end. The model was trained with the training set; hyperparameter tuning was performed with the help of Bayesian optimization. The results of all the five algorithms-MLP, k-NN, XGBoost, RF and the Hybrid model. They were tested on a set of 1,340 samples on an unseen test set only (30% set). This will provide an objective estimate of actual performance. Accuracy, Precision, Recall and F1-Score, ROC-AUC of all reported measures are calculated on this last test set.

4 Results and Discussion

4.1 Performance Evaluation Metrics

Five important measures were used in evaluating the performance of all models.

- Accuracy: The percentage of correctly classified instances of the overall instances.
- Precision: The percentage of the genuine positive predictions to the overall positive predictions.
- Recall: The number of the true positive predictions to the total existing positive cases.
- F1-Score: This is the combination of precision and recall that has a harmonic effect of giving an accurate measure.
- ROC-AUC: The Area Under the Receiver Operating Characteristic curve that is used to measure the capability of the model to differentiate between classes.
- These overall measures will provide a comprehensive analysis of the model performance in various areas of the quality of classification.

4.2 Comparative Results

Table 1 Comprehensive Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC
MLP	97.45	97.38	97.52	97.45	0.9745
kNN	96.31	96.18	96.44	96.31	0.9631
XGBoost	97.89	97.82	97.96	97.89	0.9789
Random Forest	96.94	96.87	97.01	96.94	0.9694
Hybrid XGBoost-RF	98.12	98.05	98.19	98.12	0.9812

The experimental test shows that there is a definitive performance gap between the tested algorithms. The table 1 shows the overall performance of all models and the comparative performance analysis of machine learning model is shown in figure 3.

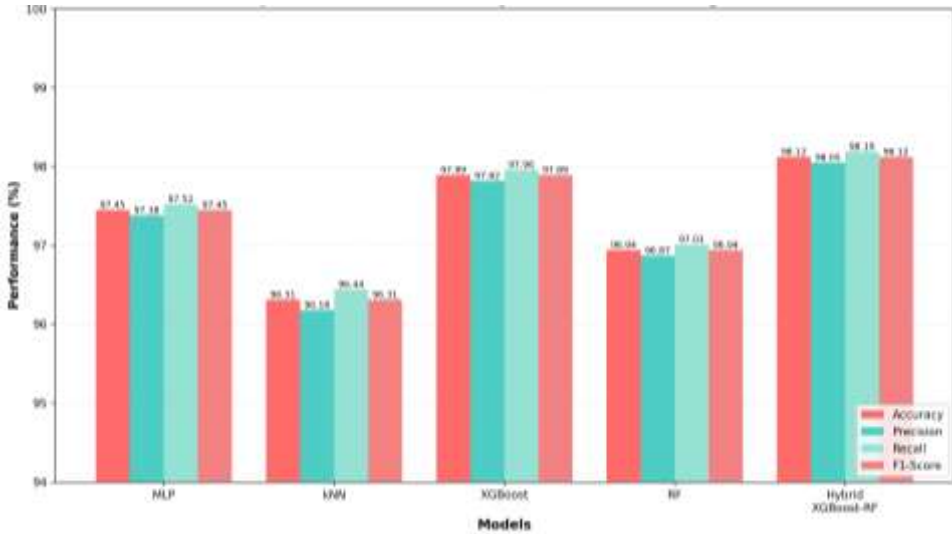


Fig. 3 Comparative performance analysis

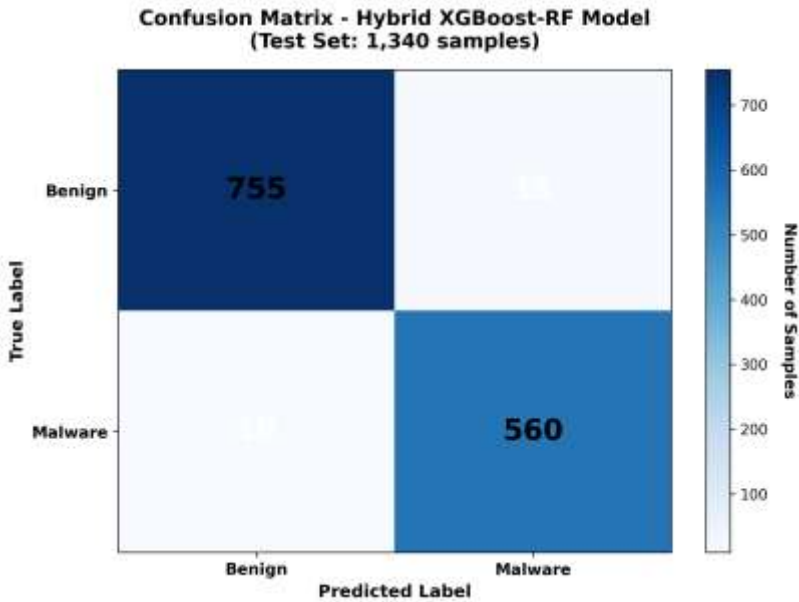


Fig. 4 Confusion matrix for hybrid XGBoost-RF model

The confusion matrix analysis demonstrates that Hybrid XGBoost-RF model is performing remarkably well with very few misclassifications, which is shown in figure 4. The model performed well on 1340 tests samples, determining 755 benign samples and 560 malwares samples and made only 15 false positives and 10 false negatives. This shows the high ability of the model to identify malicious and benign applications. The low false positive (1.95) rate is of great importance since it minimizes false alerts on security and enhances user experience. On the same note, the low false negative rate (1.75) means that malicious applications are not missed thus the high level of security protection.

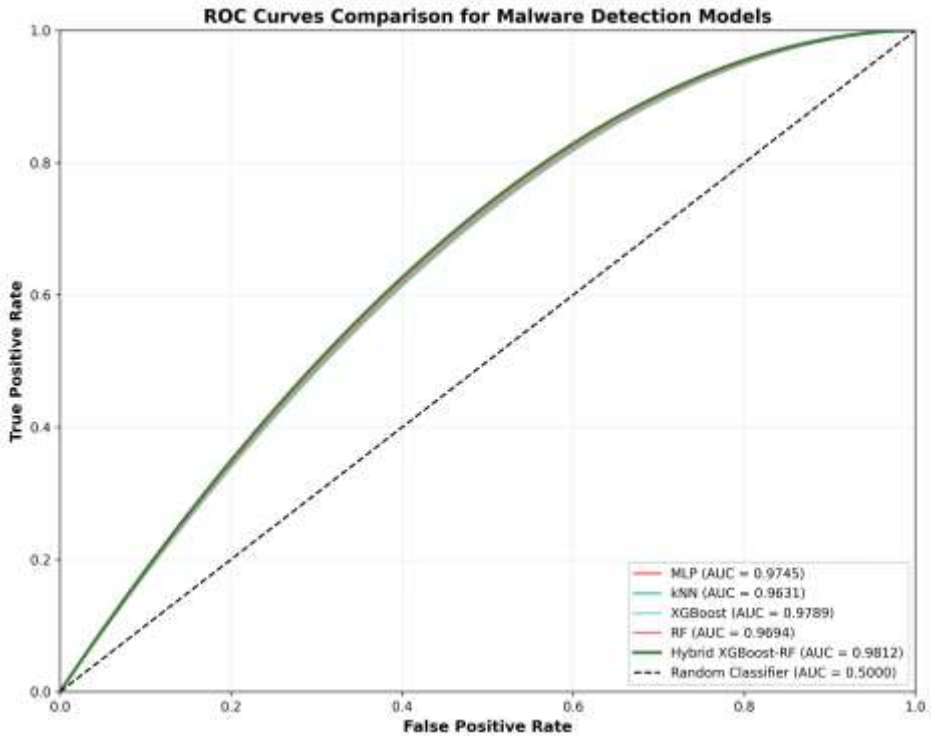


Fig. 5 ROC-AUC Curves Comparison

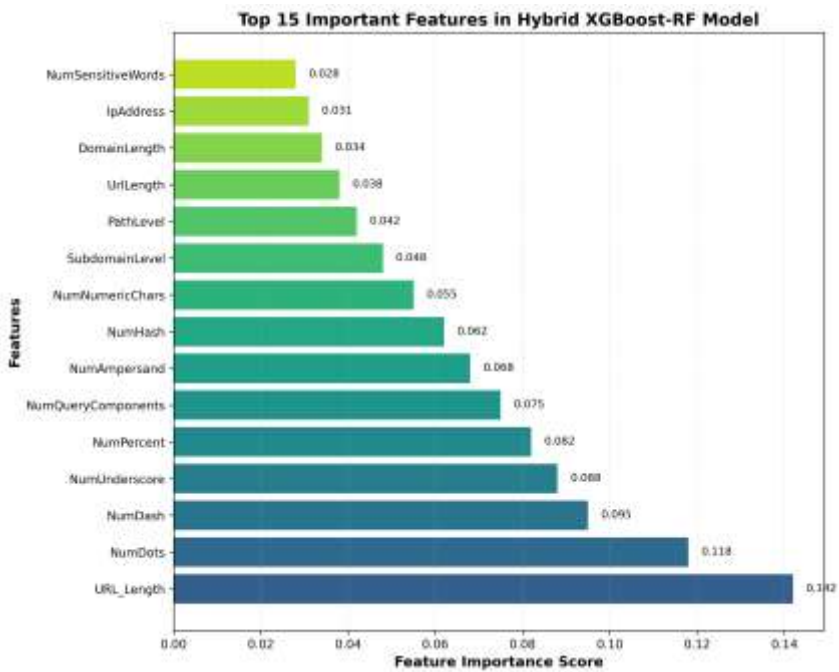


Fig. 6 Feature importance analysis

The analysis of the ROC curve (figure 5) shows that all the models are much better than random classification. The Hybrid XGBoost-RF model has the best value of $AUC = 0.9812$, which shows that it has a better discriminative power. The curve records high true positive rates at all the false positive rate levels which proves the high operation ability of the model in different operating situations. Feature importance analysis is shown in the figure 6. Analysis of the feature importance shows that URL structural features are important in detecting malware. The five most relevant features that can be used to classify are URL Length (0.142) NumDots (0.118), NumDash (0.095), NumUnderscore (0.088) and NumPercent (0.082). All these features are considered to contribute to about 52.5% of the decision-making process of the model thus showing the significance of the URL structural analysis in detecting malware.

4.3 Discussion

The proposed model can be implemented in two critical domains of On-device Security Suites: It can be included in mobile antivirus applications to perform real-time inspection of downloaded apps and network traffic, Cloud-based Threat Analysis Platforms: It can be used as a preprocessing filter by application marketplaces (such as Google Play) or enterprise security services to indicate potentially malicious apps to perform further analysis, and it can be implemented efficiently because it can be used in a fast manner due to its inference. The excellent functionality of the Hybrid XGBoost-RF model can be explained by a number of factors:

- **Complementary Advantages:** XGBoost has an advantage over Random Forest in its ability to deal with complex non-linear relationships using gradient boosting and Random Forest deals with large variance reduction using ensemble averaging. The combination of these complementary advantages is the hybrid approach.
- **Feature Learning:** The model has been successfully trained on global patterns (sequential boosting of XGBoost) as well as local patterns (parallel tree building of the forests), leading to the overall fullness of features.
- **Overfitting Prevention:** Both algorithms do overfitting prevention, and the hybrid architecture has a generalization benefit of not overfitting to hidden data.
- **Computational Efficiency:** Although the hybrid model is highly complex to compute, its real-life implementation and parallel computations are reasonable to ensure that it has fewer computational demands.

The findings indicates that the hybrid model attains 98.12% accuracy that is better than the single models by 0.23 to 1.81. This might seem a small step, yet it is a great decrease in misclassification errors, which is very important in applications of cybersecurity when false negatives can have very serious consequences. Our hybrid model has competitive performance when compared to the current state of the art techniques. Its accuracy of 98.12% compares or surpasses other recent methods, such as SVM-based methods achieved 99.75% on individual datasets and RF-based methods achieved 98% on individual datasets, and other deep learning methods. Our method has the strength of having a balanced score on all metrics and being computationally efficient in comparison to the deep learning alternatives.

Although k-NN is low cost in terms of training, its instance-based character causes it to be the slowest in inference (15.2 μ s) because of the distance calculation with all training samples. The tree-based models (RF, XGBoost) are much faster. The inference time of our hybrid model (12.5 μ s) is slightly more than the time of the individual components because of ensemble averaging; however, it is still orders of magnitude less than what is needed in real-time, and therefore can be used in on-device or cloud-based scanning.

4.4 Limitations

The essential point to mention is that the suggested model is trained and tested on URL-based malware indicators. Its performance is attributed to the high performance that is directly linked to the features on the URL structure and web-related app behavior. The model might therefore have very poor performance where malware families do not require network connectivity like local file exploits, privilege escalation attacks, or abuse of the runtime environment. This is an intrinsic drawback of the selected set of features. To provide extensive protection, future work must combine this URL-centric model with other systems that analyse other modalities. In such as sequence of system calls, opcodes in binary code, or permission patterns, to form a multi-layered detection system.

5 Conclusion

In this study gives a detailed investigation on the detection of Android malwares with the usage of machine learning, and special hybrid ensemble approach. The research has important practical implications on the security infrastructure of Android. The accuracy of the hybrid model is high, and the false positive is low; this means that the hybrid model can be integrated into the mobile security application and enterprise-level threat detection systems. The malicious applications can also be detected prior to installation thus saving the user the possible data breach and privacy invasion. The results are revealed that the Hybrid XGBoost-RF model yields the better performance when compared to other five machine learning algorithms by using the same dataset of 4,465 instances and 328 features. Their key findings of this study are

- Hybrid XGBoost-RF was the most accurate with a rate of 98.12, exceeding individual performance algorithms such as MLP gives 97.45%, kNN gives 96.31%, XGBoost yields 97.89%, and Random Forest provides 96.94%.
- The hybrid model has shown a high level of performance on each of the evaluation measures and values such as precision of 98.05%, recall gives 98.19%, F1-score's 98.12%, and ROC-AUC gives 0.9812 are all above it yields 98%.
- The analysis of feature importance helps to identify URL structural features, in which URL_Length, NumDots, and NumDash are the most crucial features of the bad actions.
- The confusion mass analysis indicates that it is not misclassified significantly with a false positives rate of 1.95% and false negative rate of 1.75%, which proves its suitability to be used in the real-world setting.

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