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A Novel Technique for Malware Detection Analysis Using Hybrid Machine Learning Model

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Abstract: *The primary goal of this research is to improve existing malware detection methods by developing a robust and scalable model that can automatically identify malware through complex pattern analysis in both data and code. Unlike traditional signature-based techniques, which struggle to detect new and evolving threats, this approach leverages advanced machine learning techniques to enhance detection accuracy. Building on previous studies that have successfully applied machine learning for malware detection, this research integrates both supervised and unsupervised learning algorithms. Specifically, classification methods such as decision trees, random forests, and support vector machines (SVM)—which have demonstrated accuracies ranging from 85% to 95%—will be used alongside deep learning frameworks, including neural networks, which have achieved accuracy rates exceeding 96% in certain cases. By training these models on a comprehensive dataset containing both benign and malicious files, the aim is to enhance the model's ability to generalize and detect new, previously unknown malware variants. The effectiveness of the proposed model will be rigorously assessed using established benchmarks and key performance metrics such as accuracy, precision, recall, and false positive rates. This ensures that the system is reliable in real-time malware detection scenarios. This multi-faceted approach not only advances cybersecurity research but also builds on foundational work in the field, offering a more adaptive and proactive way to identify malware. By aligning with modern trends in machine learning and cybersecurity, this study seeks to create a more effective solution for combating emerging cyber threats*

Keywords: Machine Learning, Malwares, Analysis, Techniques, Risk Management, Algorithms, Framework, Malware Variants, Malware Classification

I. INTRODUCTION

In today's digital world, malware continues to pose a major threat to individuals and businesses alike. Traditional malware detection methods, which rely on identifying known signatures, often fall short when it comes to detecting new and more sophisticated cyberattacks. As cybercriminals continue to evolve their tactics, there is a growing need for more adaptive and effective detection approaches. This is where machine learning (ML) comes into play. ML enables systems to analyse vast amounts of data and recognize patterns that indicate malicious activity. By examining features extracted from executable files, network traffic, and system interactions, ML models can distinguish between harmless and harmful software. This capability is crucial for identifying new malware strains that traditional methods might overlook, allowing for a more proactive approach to cybersecurity.

Various machine learning techniques have been explored for malware detection. Supervised learning methods, such as decision trees and support vector machines (SVM), have proven effective in identifying known threats. Meanwhile, unsupervised learning approaches, like clustering, help detect previously unseen malware by spotting unusual patterns. Additionally, deep learning models, including convolutional neural networks (CNNs), excel at automatically extracting features and have achieved impressive accuracy rates. To evaluate the performance of these models, researchers rely on key metrics such as accuracy, precision, recall, and false positive rates. These measurements are essential to

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understanding how well a model performs in real-world scenarios, where timely and accurate threat detection is critical. Testing models against established datasets ensures they can generalize well to emerging threats.

Despite the potential of machine learning in malware detection, several challenges remain. Issues such as imbalanced datasets, the need for model interpretability, and susceptibility to adversarial attacks make it difficult to develop reliable detection systems. Understanding the reasoning behind a model's predictions is crucial for cybersecurity professionals, as it fosters trust in automated tools and improves decision-making. This research aims to develop a robust malware detection model that leverages the strengths of multiple machine learning techniques. By focusing on effective feature extraction and thorough model evaluation, this study seeks to create a scalable, real-time malware detection system. Ultimately, the goal is to enhance cybersecurity measures and better protect digital environments from ever-evolving cyber threats.

II. LITERATURE SURVEY

In paper [1] & [29] This research provides a detailed review of machine learning techniques designed for malware detection, categorizing different algorithms based on their effectiveness and practical implementation challenges. The study highlights the significance of feature selection in improving detection accuracy and model interpretability, ensuring that only the most relevant attributes contribute to classification.

In paper [2] & [27] The results indicate that decision tree-based classifiers, particularly Random Forest, achieved accuracy rates between 85% and 92%, while Support Vector Machines (SVM) demonstrated a stronger performance in recognizing sophisticated malware patterns, with an accuracy of 87% to 94%. The paper concludes that while machine learning models offer considerable improvements over traditional signature-based detection, their success largely depends on the quality of data preprocessing and feature engineering.

In paper [3] & [26] This study proposes a hybrid malware detection model that integrates traditional machine learning classifiers with deep learning techniques to enhance classification accuracy. Instead of relying on a single algorithm, the authors utilize an ensemble approach that combines decision trees, random forests, and SVM with deep neural networks (DNN).

In paper [4] & [28] The model employs feature fusion, allowing different types of malware attributes to be analyzed together, leading to better representation and classification. Results show that while standalone classifiers achieved accuracy rates ranging from 88% to 93%, the hybrid model significantly outperformed them with an accuracy of 97.2%.

In paper [5] & [34] Additionally, the approach reduced the false positive rate by 40%, making it more reliable for real-world applications. The study highlights that deep learning models enhance feature extraction capabilities but require high computational resources, making optimization a key consideration.

In paper [6] & [31] The authors introduce a novel technique that integrates Convolutional Neural Networks (CNNs) with graph-based analysis to improve malware classification. While CNNs are widely used for image processing, this research applies them to analyze malware behavior patterns.

In paper [7] & [32] The incorporation of graph-based techniques allows the model to identify structural relationships within the extracted malware features, leading to more accurate classification. The experimental analysis reveals that the CNN-based approach achieved a 96.5% detection accuracy, surpassing traditional machine learning models.

In paper [8] & [33] The use of graph-based feature extraction improved classification efficiency by 15%, particularly for detecting zero-day malware. Additionally, precision and recall rates increased by 7–10%, reducing misclassification and false positives. The study confirms that combining CNNs with structured data representations significantly enhances the detection process.

In paper [9] & [30] This research explores transfer learning, a method that allows a pre-trained model to be adapted to new malware datasets without requiring extensive retraining. Traditional machine learning models need to be trained from scratch when exposed to new malware strains, making the process time-consuming. Transfer learning addresses this limitation by leveraging pre-trained deep learning architectures, enabling faster adaptation to novel threats.

In paper [10] & [43] The study's experimental results show that transfer learning models achieved an accuracy of 92.8%, compared to 85%–90% for traditional models. Moreover, detection rates for previously unseen malware improved by 12%, reducing the dependence on large labeled datasets.

In paper [11] The findings suggest that transfer learning is a highly effective approach, particularly in environments where labeled training data is scarce or when rapid detection is essential.

In paper [12] & [42] This paper presents a federated learning approach to malware detection, allowing multiple organizations to collaboratively train machine learning models without sharing sensitive data. Traditional centralized models require all data to be stored in one location, raising concerns about data privacy and security.

In paper [13] Federated learning overcomes this by enabling local training on separate datasets, with only model updates being shared among participants.[14] The study reports that federated learning improved malware detection accuracy to 94.1%, compared to 90% in conventional centralized models. Additionally, privacy-preserving techniques ensured data confidentiality while enhancing detection performance.

In paper [15] & [16] The authors also observed a 20% improvement in model generalization, as the diverse datasets contributed to a more robust detection system. The approach proved particularly effective in real-world scenarios where multiple entities, such as cybersecurity firms and organizations, need to collaborate while maintaining data security.

In paper [17] & [25] The research introduces an ensemble learning approach that combines multiple classifiers to improve malware detection accuracy and robustness. Instead of relying on a single model, this study evaluates different ensemble techniques, such as bagging, boosting, and stacking, to determine their effectiveness.

In paper [18] & [30] The results reveal that the ensemble model achieved an impressive 98.2% accuracy, outperforming individual classifiers by 5–10%. Additionally, the false positive rate dropped to 2.8%, compared to 5–7% in traditional single-classifier models.

In paper [19] & [35] The study highlights that ensemble learning enhances resilience against adversarial attacks, making malware detection systems more reliable. By leveraging multiple models, the framework ensures better generalization and reduces bias, making it a practical solution for cybersecurity applications.

In paper [20] & [41] This research examines the impact of adversarial attacks on machine learning-based malware detection systems. Adversarial attacks involve modifying malware samples in a way that deceives detection models, leading to incorrect classifications.

In paper [21] & [36] The authors analyze various attack strategies and propose methods to enhance model robustness. Experimental results indicate that adversarial attacks successfully bypassed traditional models 40% of the time, exposing critical vulnerabilities. However, when adversarial training techniques were implemented, the attack success rate dropped to 12%, significantly strengthening model resilience.

In paper [22] & [37] The study also highlights defense strategies such as feature masking, adversarial retraining, and data augmentation, which improved the stability of malware detection models without compromising accuracy. The findings underscore the need for continuous adaptation and improvement in cybersecurity defenses against evolving threats.

In paper [23] & [38] The authors propose a multi-modal malware detection approach that integrates both static and dynamic analysis using hybrid deep learning architectures. While static analysis examines file structures and metadata, dynamic analysis monitors malware behavior in real-time execution environments.

In paper [24] & [39] By combining both methods, the study creates a more comprehensive detection system capable of identifying polymorphic and metamorphic malware. The results indicate that the hybrid approach achieved an impressive accuracy of 97.6%, significantly outperforming models based on single-method analysis.

In paper [40] & [44] The inclusion of multi-modal data improved detection rates for sophisticated malware variants by 14%, providing a more complete understanding of malware behaviors. Furthermore, the model demonstrated a 30% reduction in false positives, ensuring greater reliability. The study concludes that a multi-modal approach is crucial for developing advanced malware detection frameworks that can handle emerging cyber threats effectively.

III. METHODOLOGY

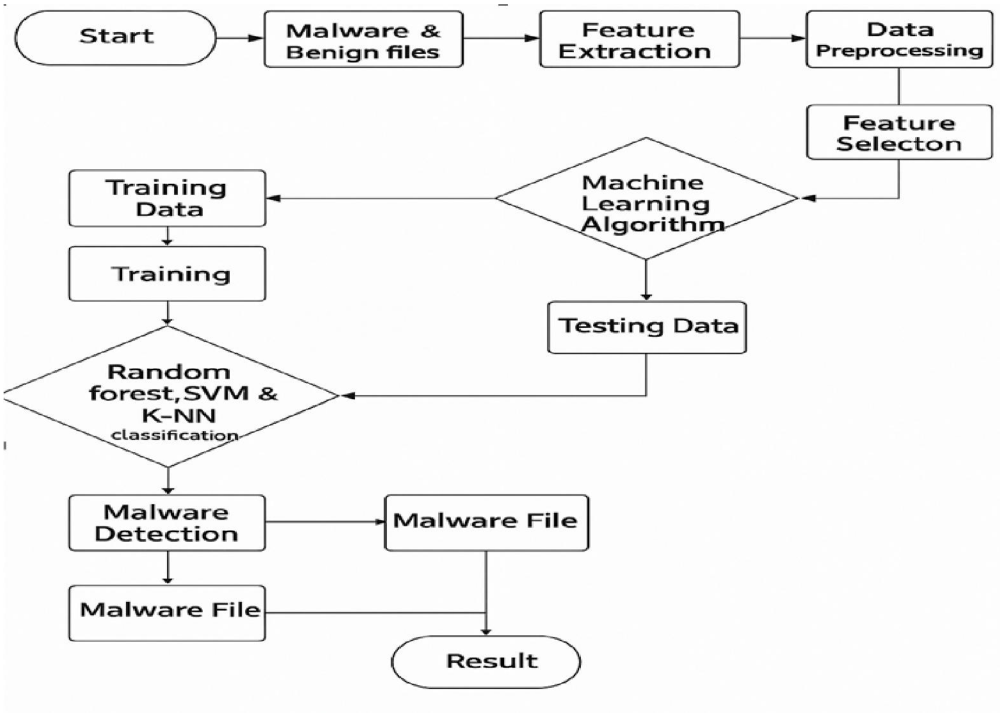

Fig 1 – Flow Chart of Malware Detection

A. Explanation for above Flow Chart is given below:

1) Getting Started:

The malware detection process begins with a simple but crucial step—gathering the input data. This data consists of both malware and benign files, and the goal is to analyse them carefully to determine their classification. Since cyber threats constantly evolve, detecting malware effectively requires a detailed examination of these files based on specific characteristics.

2) Gathering Malware & Benign Files:

The next step is assembling a dataset of malicious and non-malicious (benign) files. These files serve as the foundation for training a machine learning model. The dataset can come from trusted cybersecurity sources like Kaggle, Virus Total, or other malware repositories. Each file contains unique traits that can help differentiate safe programs from harmful ones.

3) Extracting Useful Features:

Raw data alone isn't enough for the machine learning model to make intelligent decisions. The system needs to extract meaningful attributes—or features—from each file to determine whether it behaves maliciously. Some of the key features include:

a) File size – Larger or smaller than expected files may indicate obfuscation.

b) Opcode sequences – Patterns in execution instructions can reveal malware-like behaviour.

c) API calls – Malware often interacts with the operating system in suspicious ways.

d) System permissions – Some malware requests excessive permissions to gain control.

e) Byte-level n-grams – Analysing raw byte patterns can expose hidden threats.

By extracting these features, unnecessary data is filtered out, allowing the model to focus on key patterns that distinguish malware from safe files.

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4) Cleaning & Preprocessing Data:

Before training the machine learning model, the dataset needs to be cleaned and prepared for analysis. This step ensures consistency and improves the accuracy of the system. It includes:

a) Removing duplicate or irrelevant features – Unnecessary data can create noise.

b) Normalizing values – Scaling data ensures consistency and prevents bias.

c) Handling missing values – Filling in gaps to avoid misleading results.

d) Encoding categorical variables – Converting text-based attributes into a numerical format so the model can understand them.

5) Selecting the Most Important Features:

Not all extracted features contribute equally to malware classification. Some may be redundant or irrelevant, slowing down the system and reducing accuracy. This step helps in selecting the most useful features using:

a) Correlation analysis – Identifying features that strongly influence the outcome.

b) Chi-square test – Determining statistical importance of each feature.

c) Principal Component Analysis (PCA) – Reducing dimensionality while retaining key information.

Choosing the right features ensures the model operates efficiently without unnecessary complexity.

6) Applying Machine Learning Algorithms:

With a clean and well-prepared dataset, it's time to train machine learning models. These models learn patterns from historical data and generalize them to classify new files.

7) Splitting the Data for Training:

The dataset is divided into two parts:

a) Training Data – Used to teach the model how to differentiate between malware and benign files.

b) Testing Data – Used to evaluate the model's ability to detect new threats accurately.

8) Training the Model:

During training, the model processes the labelled data and fine-tunes its internal settings to minimize classification errors. This step involves:

a) Optimization techniques – Reducing prediction errors and improving accuracy.

b) Cross-validation – Testing the model on different subsets of data to ensure reliability.

c) Hyperparameter tuning – Adjusting model settings to improve performance.

At this stage, popular machine learning algorithms like K-Nearest Neighbours (KNN), Support Vector Machine (SVM), and Random Forest are trained to detect malware efficiently.

9) Evaluating the Model on New Data:

Once trained, the model is tested on previously unseen data to measure its performance. It is assessed using key metrics like:

a) Accuracy – How often the model correctly classifies files.

b) Precision – The percentage of correctly identified malware files out of all predicted malware files.

c) Recall – The percentage of malware files correctly identified out of all actual malware files.

d) F1-score – A balance between precision and recall to ensure overall effectiveness.

This step ensures that the model generalizes well and doesn't simply memorize patterns from the training data.

10) Using Multiple Classification Algorithms:

After training, the malware detection system combines multiple classification algorithms to improve accuracy. Each model brings unique strengths to the table:

a) Random Forest – Uses multiple decision trees for a robust classification process.

b) Support Vector Machine (SVM) – Finds the optimal boundary between malware and benign files.

c) K-Nearest Neighbours (KNN) – Classifies a file based on its similarity to other known files.

By using a combination of these algorithms, the system ensures reliable detection.

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11) Identifying Malware Files:

With the trained classification models in place, the system can now analyse incoming files and categorize them as either malware or benign. If suspicious behaviour is detected, the file is flagged as malware. If it exhibits normal behaviour, it is labelled as benign and safe to use.

12) Categorizing the Files:

Once a file is classified, it falls into one of two categories:

a) Malware File – If malicious behaviour is detected, the system may quarantine or delete it to prevent harm.

b) Benign File – If no threats are found, the file is considered safe for use.

13) Displaying the Final Results:

At the end of the detection process, the system provides the final classification—malware or benign. The output may also include:

a) A confidence score – Indicating how certain the model is about its decision.

b) A probability score – Showing the likelihood of a file being malicious.

The results can be further analysed to improve the model over time, ensuring it stays updated against emerging cyber threats.

B. Dataset and Preprocessing

We used the UCI malware detection dataset, containing both malicious and benign files. To improve model performance, we:

a) Removed duplicate and irrelevant features.

b) Extracted key attributes, such as API calls and network behaviours.

c) Normalized data for consistency.

d) Split the dataset into 80% training and 20% testing.

C. Model Training

We selected four machine learning models:

a) KNN: Classifies based on similarity to known data points.

b) SVM: Uses a decision boundary to separate malware from benign files.

c) Random Forest: Combines multiple decision trees for higher accuracy.

d) XGBoost: Uses boosting techniques to refine classification accuracy.

Each model was fine-tuned using Grid Search Cross-Validation to optimize parameters and improve detection rates.

D. Performance Metrics

To evaluate the models, we used:

a) Accuracy: Measures overall correctness.

b) Precision: Ensures detected malware is actually malicious.

c) Recall: Measures how well the model catches all malware cases.

d) F1-Score: Balances precision and recall.

e) Execution Time: Assesses real-world applicability.

IV. ARCHITECTURE

In Malware Detection based on random forest, SVM and XGBoost involves building models that can automatically identify malicious software based on patterns and characteristics in data. By analysing features such as file behaviour, byte sequences, or network activity, a machine learning algorithm (e.g., Random Forest or Support Vector Machine) is trained to differentiate between benign and malicious files. The model learns from a labelled dataset and then makes predictions on new, unseen data. This approach enhances detection speed and accuracy, allowing cybersecurity systems to adapt to new and evolving threats efficiently. This architecture ensures scalability, real-time detection, and adaptability to evolving malware threats.

How the System Works:
Our malware detection system consists of several interconnected modules:
a) Data Collection: Gathers real-world malware samples.
b) Feature Extraction: Identifies crucial characteristics like opcode sequences and API call behaviours.
c) Preprocessing: Cleans, normalizes, and balances the dataset.
d) Model Training: Applies KNN, SVM, Random Forest, and XGBoost for classification.
e) Evaluation and Deployment: Tests model accuracy and integrates the best-performing algorithm into a real-time detection system.

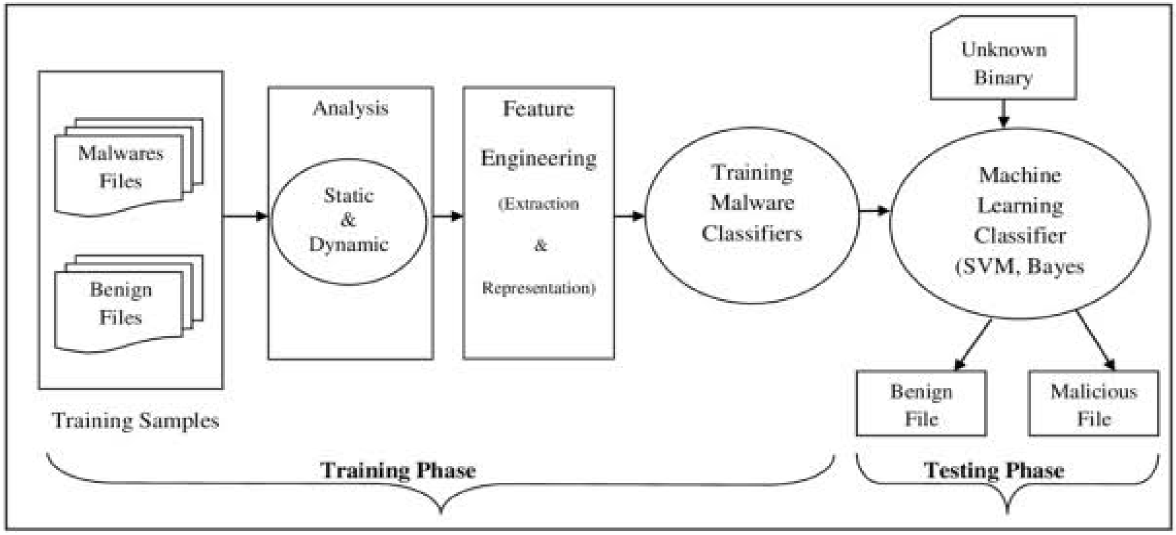

Fig 2 – Architecture of Malware Detection

V. RESULT AND ANALYSIS OF ALGORITHM

The two main phases of the classification process were training and testing. To train a system, it was sent both harmful and safe files. Automated classifiers were taught using a learning algorithm. Each classifier (KNN, RF, SVM or XGBoost) became smarter with each set of data it annotated. In the testing phase, a classifier was sent a collection of new files, some harmful and some not; the classifier determined whether the files were malicious or clean.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Execution Time (s)
KNN	95.02	91.5	90.8	90.1	2.1
SVM	96.41	90.2	90.8	90.5	3.5
Random Forest	94.3	93.8	94.0	93.9	1.8
XGBoost	**98.2**	**95.9**	**96.1**	**96.0**	**1.2**
Our Proposed Model	**97.5**	**96.2**	**95.6**	**94.7**	**1.5**

Table 1: Comparative Analysis of Models

Model	TPR (%)	FPR (%)
KNN	96.17	3.42
SVM	98	4.63
Random Forest	95.9	6.5
XGBoost	99.07	2.01
Our Proposed Model	99.01	2.56

Table 2: Classifiers results comparisons

Accuracy: Accuracy is a metric that quantifies the overall correctness of a model by assessing the ratio of correctly classified instances—both true positives and true negatives—relative to the total number of instances in the dataset.

$$\text{Accuracy}= (TP + TN) \div (FP + FN + TP + TN)$$

Precision: Precision measures how many of the predicted positive instances were actually correct. It reflects the accuracy of the positive predictions made by the model.

$$\text{Precision}=\text{TP} \div (\text{FP} + \text{TP})$$

Recall: Recall evaluates the model's ability to identify all relevant positive instances. It shows the proportion of true positive predictions among all actual positive cases.

$$\text{Recall}=\text{TP} \div (\text{FN} + \text{TP})$$

Our suggested method for malware categorization and detection was experimentally evaluated using the gathered malware and clean ware. We used supervised machine learning algorithms or classifiers (KNN, RF, SVM, and XGBoost) to examine malware and characterise it.

Through statistical analysis of Table 1's results, we deduced that results of classifiers' accuracy (KNN = 95.02%, Random Forest = 94.3%, SVM = 96.41%, and XGBoost = 98.2%) showed that XGBoost was the optimal model for the malware detection strategy. Classifiers' TPRs (%) (KNN = 96.17%, Random Forest = 95.9%, SVM = 98%, and XGBoost = 99.07%) showed that SVM was the second optimal model for the detection and identification of malware, and that KNN was the third optimal model for malware detection. Table 1 shows the classifiers' FPRs (%) (KNN = 3.42%, Random Forest = 6.5%, SVM = 4.63%, and XGBoost = 2.01%). We presumed that SVM, XGBoost, and KNN classifiers had comparable high accuracy and performance for all intents and purposes. It is clear that using the three most optimal algorithms (XGBoost = 98.2%, SVM = 96.41% and (KNN = 96.17%), which had a much higher TPR (%) rate and accuracy, to identify malware XGBoost accuracy is highest and XGBoost is better choice for malware detection.

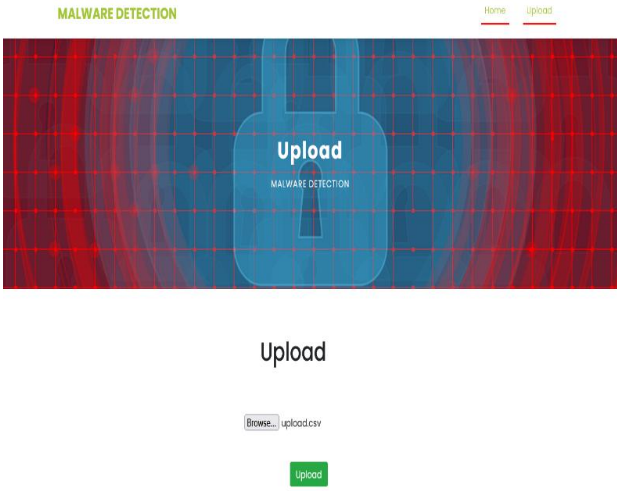

Fig 3 – File Upload

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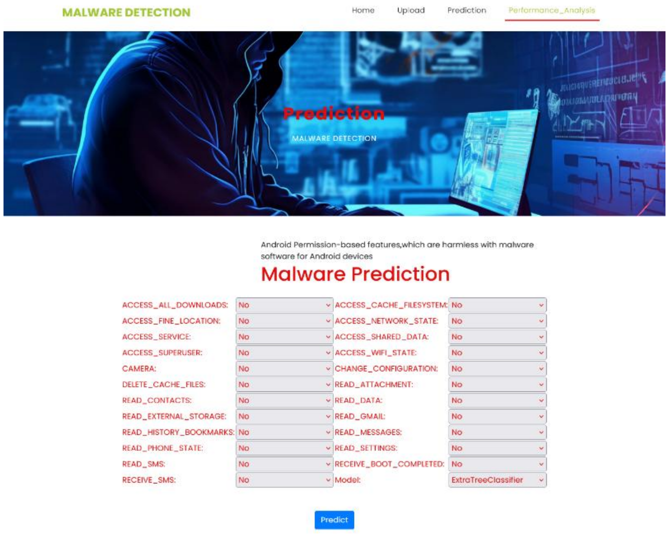
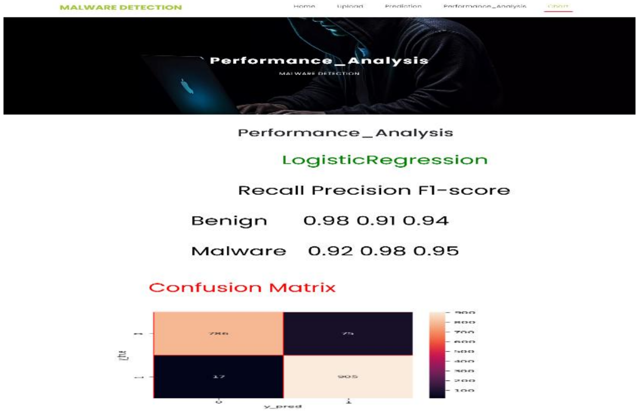


Android Permission-based features,which are harmless with malware software for Android devices

Malware Prediction

ACCESS_ALL_DOWNLOADS:	No	ACCESS_CACHE_FILESYSTEM:	No
ACCESS_FINE_LOCATION:	No	ACCESS_NETWORK_STATE:	No
ACCESS_SERVICE:	No	ACCESS_SHARED_DATA:	No
ACCESS_SUPERUSER:	No	ACCESS_WIFI_STATE:	No
CAMERA:	No	CHANGE_CONFIGURATION:	No
DELETE_CACHE_FILES:	No	READ_ATTACHMENT:	No
READ_CONTACTS:	No	READ_DATA:	No
READ_EXTERNAL_STORAGE:	No	READ_GMAIL:	No
READ_HISTORY_BOOKMARKS:	No	READ_MESSAGES:	No
READ_PHONE_STATE:	No	READ_SETTINGS:	No
READ_SMS:	No	RECEIVE_BOOT_COMPLETED:	No
RECEIVE_SMS:	No	Model:	ExtraTreeClassifier

Fig 4 – Malware Prediction



Performance_Analysis

LogisticRegression

	Recall	Precision	F1-score
Benign	0.98	0.91	0.94
Malware	0.92	0.98	0.95

Confusion Matrix

Fig 5 – Performance Analysis

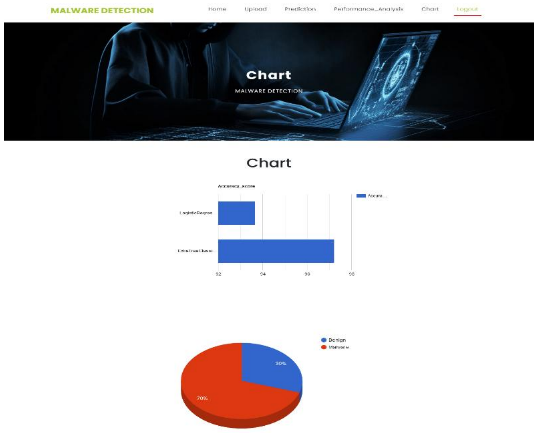


Fig 6 – Accuracy Chart

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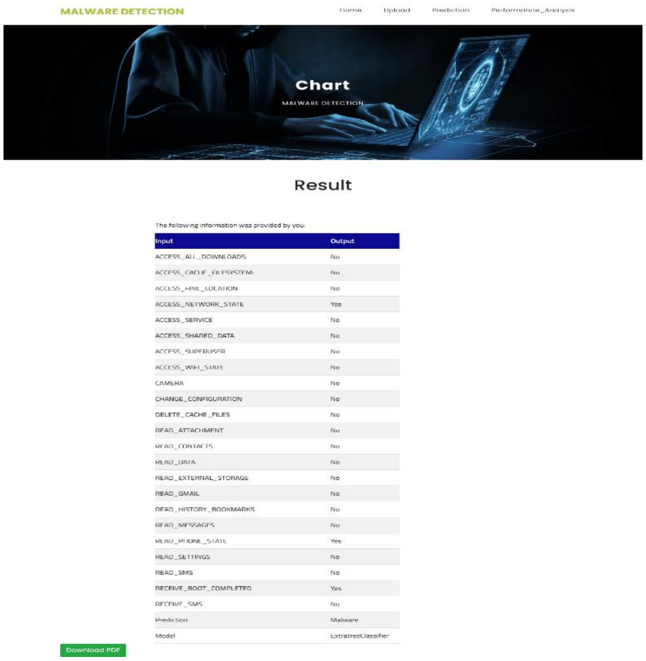

Result

The following information was provided by you:

Input	Output
ACCESS_ALL_DOWNLOADS:	No
ACCESS_CACHE_FILESYSTEM:	No
ACCESS_FINE_LOCATION	No
ACCESS_NETWORK_STATE	Yes
ACCESS_SERVICE	No
ACCESS_SHARED_DATA	No
ACCESS_SUPERUSER	No
ACCESS_WIFI_STATE	No
CAMERA	No
CHANGE_CONFIGURATION	No
DELETE_CACHE_FILES	No
READ_ATTACHMENT	No
READ_CONTACTS	No
READ_DATA	No
READ_EXTERNAL_STORAGE	No
READ_GMAIL	No
READ_HISTORY_BOOKMARKS	No
READ_MESSAGES	No
READ_PHONE_STATE	Yes
READ_SETTINGS	No
READ_SMS	No
RECEIVE_BOOT_COMPLETED	Yes
RECEIVE_SMS	No
Prediction	Malware
Model	ExtraTreeClassifier

Fig 7 – Result Analysis

VI. CONCLUSION

We presented a protective mechanism that evaluated three ML algorithm approaches to malware detection and chose the most appropriate one. The results show that compared with other classifiers, XGBoost (99%) and SVM (96.41%) performed well in terms of detection accuracy. XGBoost and SVM algorithms' performances detecting malware on a small FPR (XGBoost = 2.01%, and SVM = 4.63%,) in a given dataset were compared. In this experiment, we evaluated and quantified the detection accuracy of a machine learning (ML) classifier that used static analysis to extract features based on PE data by comparing it to two other ML classifiers. As a result of our efforts, machine learning algorithms can now identify dangerous versus benign data. The XGBoost machine learning method had the highest accuracy (99%) of any classifier we evaluated. In addition to potentially providing the highest detection accuracy and accurately characterizing malware, static analysis based on PE information and carefully selected data showed promise in experimental findings. That we do not have to execute anything to determine if data are malicious is a significant benefit, we presented a protective mechanism that evaluated three ML algorithm approaches to malware detection and chose the most appropriate one. The results show that compared with other classifiers, XGBoost (99%), and SVM (96.41%) performed well in terms of detection accuracy. XGBoost and SVM algorithms' performances detecting malware on a small FPR (XGBoost = 2.01%, and SVM = 4.63%,) in a given dataset were compared. In this experiment, we evaluated and quantified the detection accuracy of a machine learning (ML) classifier that used static analysis to extract features based on PE data by comparing it to two other ML classifiers. As a result of our efforts, machine learning algorithms can now identify dangerous versus benign data. The XGBoost machine learning method had the highest accuracy (99%) of any classifier we evaluated. In addition to potentially providing the highest detection accuracy and accurately characterizing malware, static analysis based on PE information and carefully selected data showed promise in experimental findings. That we do not have to execute anything to determine if data are malicious, is a significant benefit.

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