ANDROID MALWARE DETECTION USING MACHINE LEARNING

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering

by

KAKUMANU GEETHA MADHAV (Reg.No - 40110519)
GUTTAPALEM SAMITHA (Reg.No – 40110423)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

SCHOOL OF COMPUTING

SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)
CATEGORY -1 UNIVERSITY BY UGC
Accredited with Grade “A++” by NAAC I 12B Status by UGC I Approved by AICTE
JEPPIAAR NAGAR, RAJIV GANDHISALAI,
CHENNAI - 600119

APRIL - 2024

SATHYABAMA
INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)
CATEGORY-I UNIVERSITY BY UGC
Accredited "A++" Grade by NAAC | 12B Status by UGC | Approved by AICTE
www.sathyabama.ac.in

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **KAKUMANU GEETHA MADHAV(40110519) and GUTTAPALEM SAMITHA(40110423)** who carried out the Project work entitled **"Android Malware Detection Using Machine Learning"**under my supervision from November 2023 to April 2024.

Internal Guide

Ms. MANJU C NAIR M.E(PhD.)

Head of the Department

Dr. L. LAKSHMANAN, M.E., Ph.D.

Submitted for Viva voice Examination held on_____

Internal Examiner **External Examiner**

DECLARATION

I, **GUTTAPALEM SAMITHA (Reg.No– 40110423),** hereby declare that the Project Report entitled **"Android Malware Detection Using Machine Learning"** done by me under the guidance of **Ms. MANJU C NAIR M.E(PhD.)** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in **Computer Science and Engineering**.

DATE: 12.04.2024

PLACE:CHENNAI **SIGNATURE OF THE CANDIDATE**

ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to **Board of Management of SATHYABAMA INSTITUTE OF SCIENCE AND TECHNOLOGY** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

I convey my thanks to **Dr. T.Sasikala M.E., Ph. D**, **Dean**, School of Computing, **Dr. L. Lakshmanan M.E., Ph.D.,** Head of the Department of Computer Science and Engineering for providing me necessary support and details at the right time during the progressive reviews.

I would like to express my sincere and deep sense of gratitude to my Project Guide **Ms. MANJU C NAIR M.E(PhD.)** for her valuable guidance, suggestions and constant encouragement paved way for the successful completion of my project work.

I wish to express my thanks to all Teaching and Non-teaching staff members of the **Department of Computer Science and Engineering** who were helpful in many ways for the completion of the project.

ABSTRACT

The Android smartphone, with its wide range of uses and excellent performance,has attracted numerous users. Still, this domination of the Android platform also has motivated the attackers to develop malware. The traditional methodology which detects the malware based on the signature is unfit to discover unknown applications. In this paper, we tried to detect whether an application is malware or not using Static Analysis. We considered all the permissions that an application asks for and took them as input to feed our machine learning models. We built different classifiers using different machine learning algorithms such as Support Vector Machine(Linear and RBF), Logistic Regression,Random Forest Algorithm, Gaussian Naive-Bayes, Decision Tree Method etc., and we compared their performances.

Mobile gadgets have become ubiquitous in this age of lightning-fast technical development. On the other hand, malware has become a much bigger concern as Android has become more prevalent. The ever-changing nature of Android malware makes it imperative to investigate alternative techniques of detection, since traditional ones frequently fail to keep pace. A method for detecting Android malware using machine learning (ML) is suggested in this research. The suggested method improves mobile user security by efficiently identifying and classifying Android malware using ML techniques. A number of features are used by the system to get useful information from Android apps, including permission requests, API calls and system calls. Decision trees, support vector machines (SVMs), neural networks, and other ML techniques are given these characteristics in order to train and construct strong models that can distinguish between safe and dangerous applications.The suggested approach has shown encouraging results in experimental assessment, with high detection rates of Android malware. In addition, ML models can adjust and acquire knowledge from fresh malware samples, guaranteeing ongoing defense against new dangers. As a whole, this study demonstrates how ML may improve Android malware detection, which is a great step toward meeting the difficulties of mobile security head-on.

Keywords:Static Analysis, Dynamic Analysis, Feature Selection

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF ABBREVIATIONS

ABBREVIATION	EXPANSION
API	APPLICATION PROGRAM INTERFACE
APK	ANDROID APPLICATION PACKAGE
KNN	K-NEARST NEIGHBOURS
MDM	MOBILE DEVICE MANAGEMENT
SVM	SUPPORT VECTOR MECHINE
URL	UNIFO RESOURCE LOCATOR
WEKA	WAIKATO ENVIRONMENT FOR KNOWLEDGE ANALYSIS

CHAPTER 1

INTRODUCTION

Recent years, with the rapid development of smartphones, Android is becoming more and more popular. According to the IDC report shown in the 2021 year, Android market share will reach 85.3% until the end of 2021. Android has been more and more indispensable with its open source character and advantages of free in our daily life. However, the number of malicious software is also growing rapidly. Therefore, how to detect the Android malware with a high accurate rate is a hot issue. Traditional detection approach based on signature is widely used both in Android devices and PC by extracting the signature from APK and comparing it with the malicious signature in the virus database.However, this approach is limited to detect unknown malwares which do exist in the virus database.

Due to its open platform and lack of restrictions on installed applications, Android is more prone to cyber attacks. Malware is software developed by attackers to steal, destroy, or damage information and assets. Malware threatens user’s privacy and security by enabling attackers to gain access, monitor and spy on victims' devices. Hence, the detection of Android malware is vital to create a safe environment for 2.5 billion Android users.

Malware detection approaches are divided into two; the first approach is using traditional non-machine learning techniques which include the detection using signature based, dynamic taint analysis and permissions based. While the second approach is with the use of machine learning algorithms to build a model that would detect and prevent malware from infecting end devices. However, traditional malware detection methods are unable to detect unseen malwares and are more time consuming when compared with machine learning algorithms. [4] In this paper a machine learning model is built to detect malware attacks on android devices. The model was tested on the dataset CICMal Droid2020 using four different classifiers.

1.1 OBJECTIVE

To implement a machine learning model that can detect the presence of any malware in an android application accurately.

1.2 MOTIVATION

In June 2021, Android retained its status as the world's most popular mobile operating system, with a market share of about 73 percent. As Android has grown in popularity,so has the amount of malware targeting the platform. Android has been the most popular target for malware makers since 2010, accounting for more than 90% of all mobile malware.

Android applications can be downloaded from a lot of sources including third-party app stores. These application stores serve as a point of entry for malware to spread quickly. The most common strategy used by malware creators is Repackaging, which involves embedding the harmful code segment within a legal application making the application malicious, and distributing it through third-party stores. Their malware programs are designed to get root access, stealing personal information, setting up mobile botnets and many more. So far, there are a large number of malware discovered, some of which are more dangerous than others. They are harmful because they have the potential to steal user's personal information, as well as sending this data to remote servers.So, there is a need to develop models that can detect the presence of Android malware with accuracy and that is our motivation.

1.3 PROBLEM STATEMENT

Smartphones have become the most used device in one's day to day life. They facilitate users with a variety of applications that are enriched with powerful features. It is almost impossible for anyone these days to spend a day without their smartphones.Out of all smartphones, Android smartphones are the ones that are widely used. This increasing popularity of Android smartphones has also attracted malicious attackers. This malicious activity can be done by either a single application or a group of applications working together. The objective of this project is to create a model that can detect such malicious applications.

CHAPTER 2

LITERATURE SURVEY

2.1 INFERENCES FROM LITREATURE SURVEY

We studied the techniques that are proposed to identify Android malwares. In his work, Anshul et al. [1] presented an idea to detect Android Malwares by Network traffic analysis. Their approach is used to identify malware on Android that is operated by a remote server. These malwares either accept orders from the server or leak sensitive data to it. First, they analyzed the network traffic of android malwares and then the traffic of normal applications. They discovered the characteristics that distinguish malware traffic from non-malware traffic.. And in the second phase, they built a classifier using these network traffic features which can detect the malwares.

In another work, Anshul et al. [2] proposed a technique called the PermPair method. They approached the goal by considering every pair of permissions as the possible input feature and finally decided on each pair, if that combination is vulnerable. Their method includes data sets from 3 different sources called Genome ,Debris and Koodoos. Their approach had 3 phases. In the first phase, they constructed 4 different graphs by extracting permission pairs from each application.

Out of the 4 graphs, 3 graphs are for malwares and 1 graph is for benign applications. In the second phase, they dealt with merging 3 malicious graphs into a single malicious graph. At the end of this phase, they ended up with two graphs, one for malicious and one for benign. In the third and final phase of their method, they developed a model that calculates two scores called normal score and malicious score for every application and decides whether a particular application is malware or not.

The most commonly used properties in static and dynamic Android malware detection are permissions and network traffic features respectively. Static permissions cannot identify sophisticated malware, which is capable of update attacks. And coming to dynamic network traffic, it cannot detect malware samples without a network connection. There fore, a hybrid model integrating both of these

properties is proposed. They extracted both permissions and network traffic features and made them into a single vector.
Using the K-medoids method, they partitioned the vectors into K clusters. And they used the K-Nearest Neighbours method, to classify whether a particular application is malicious or not. They made sure that K is odd, just to make sure out of K nearest neighbours, the count of malicious and benign neighbours is not the same.

In another work, Zhenlong Yuan et al. [3] proposed a technique to associate static features with dynamic features and then classify the given android applications as malicious or safe. They got the features they used as input to their model in three stages:

- Static Phase
- Sensitive APIs
- Dynamic Phase

Static phase includes the permissions that are obtained by unzipping the apk file and parsing xml files obtained later. Another file classes.dex accounts for the sensitive api calls . To obtain the dynamic features, they used to install the apk files on droidbox, which is an extended sandbox of Taintdroid, which is itself capable of recording the network traffic,information leak and other run time analytics that could play a major role in determining an app as malware or not. They implemented an online android detection engine based on deep learning models.They are able to develop a deep learning model that outperforms many state of art machine learning techniques.

In another work, Suleiman et al. [4] examined the use of varied machine learning techniques in a parallel classification approach to Android malware detection .The proposed method made use of a variety of properties,API calls, instructions, and other API-related topics were provided.The recent rise of Android usage Malware and its ever-increasing ability to be detected ,current signature-based techniques are avoided.The classification approach adapted by them is a realistic option.The method that not only gives a supple mental tool but also it has the potential to improve Android malware detection, but it also has some drawbacks.
It only permits different classifiers' strengths to be combined. Assisting with further phases of analysis Moreover the planned from a performance standpoint, the

technique is great since it is economical when it comes to classifying an unknown instance because the app's static features are consumed and also chosen features are con sumed. Models for constituent categorization have a minimal computational cost before making a categorization judgement.

Xingquan Zhu et al. [5] proposed a feature based learning method that takes input as the permissions and api calls an app is intended to make during its life time. The proposed frame work consists of 4 different phases. They are:

- App Analyser (decompresses) the apk file
- Fetches permissions and api calls
- Feature generator (Generate binary datasets)
- Data mining models(SVM, Bagging, Decision Tree)

Though this approach doesn't involve any dynamic analysis , this approach of com plimenting the permissions with the api calls improves the performance of the model and helps in the better performance of the model. To obtain input parameters from bundled Android apps.

Justin et al. [6] used an apk called Androguard. This androguard is used to obtain permission features from the jar files included in the android apk file. They then utilised the Scikit learn framework, a python library. It gives a straightforward interface to LIBSVM , to train a SVM having 1 class, utilising these obtained features. They aimed to reduce the high false positive rates generally seen in these android malware detection techniques.

They are only reported after testing data as malware if it differs sufficiently from the training data, which is ideal for their purposes because the range of benign applications are more widely available than malicious applications.For the Android operating system, they introduced a revolutionary malware detection solution which works on the principle of ML.

In Zi Wang et al. [7], they offered Droid Deep Learner, an Android malware characterization and identification strategy that uses a deep learning algorithm to distinguish malicious Android apps from benign ones.They carried out a series of tests to ensure that the suggested technique was both legitimate and effective,and compared the performance of the proposed Droid Deep Learner with that of SVM,

which is one of the most effective and commonly used algorithms for malware detection.They ran a variety of experiments using real Android app datasets to validate the malware detection technique, and the findings suggest that the scheme can accurately identify malware in the Android. When compared to traditional solutions which works on SVM as backbone, experiment results suggest that the proposed system is capable of accurately identifying malware.

In Hyo-Sik Ham et al. [8], a study is undertaken on the detection of malware using an Android device, which is the most commonly used as an attack point by attackers. This paper presents a feature selection and experimentation technique for lowering the number of malware detections that are false positives and improving device performance degradation that has been identified as a problem in the current system Machine learning based mobile malware detection.
This model also analyses malware detection methods and performance of machine learning classifiers.First, they must compare the agent's resource consumption to that of an existing agent that is monitoring all features. In the future, more improved variations of Android malware could be collected to investigate their attributes.
Also, a research could be conducted on identifying new malwares that doesn't exist in the known directory.As there are a many number of permissions an application requests for during the installation , It is important to pick out the most prominent permissions among those that affect the malicious activity of the application. Feature selection is the phase that facilitates the developers with this task. The dataset generated after this feature selection accounts for the more accurate results.

In this paper, Pehlivan et al. [9] used a tool called Waikato Environment for Knowledge Analysis (WEKA) to achieve feature selection. The metrics that are employed in evaluation of effective feature selection are True Positive Rate, False Positive Rate and Precision. They also took accuracy as one of their metrics. A feature is employed in the classification dataset on the basis of Gain Attribute Evaluation attribute. The higher is this attribute, the more impact the feature keeps on the output. They considered this gain attribute to decide whether a feature is to be included in the training data set or not.

In another work, Fereidooni et al. [10] used a tool named unitPdroid written in python3 to extract the prominent features i.e.,a technique used in feature engineering . The permissions have been extracted from the class.xml file unzipped from the apk file of the android application. The permissions are then processed and modified into binary features so that it could be easier to train our classification models. This approach also incorporates the suspicious API calls as a feature that can affect the malicious activity of the application. This paper employed an approach called dalvik byte code analysis to determine if an application is malware. This analysis is based on the kind of information that the application is forwarding to the remote servers. If the application forwards the sensitive information or anything serious, it's rated more probably as the malware.They are able to achieve results more efficiently than many conventional state of art techniques.

2.2 OPEN PROBLEMS IN EXISTING SYSTEM

- **Zero-Day Exploits:** Detecting zero-day vulnerabilities and exploits remains a significant challenge. Zero-day malware attacks leverage previously unknown vulnerabilities, making them difficult to detect using traditional signature-based methods.

- **Evasion Techniques:** Malware developers are continually developing evasion techniques to bypass detection systems, such as code obfuscation, encryption, and polymorphic malware. Detecting and mitigating these techniques is an ongoing challenge.

- **Privacy-Preserving Detection:** Balancing the need for malware detection with user privacy is a complex problem. Designing detection systems that can analyze app behavior without compromising user privacy is a critical concern.

- **Resource-Efficient Solutions:** Android devices vary in terms of computational power and available resources. Creating malware detection solutions that are resource-efficient and can run on a wide range of devices, including low-end

smartphones, is an ongoing challenge.

- **User-Centric Approaches:** Developing solutions that involve users actively in the detection process while minimizing their efforts and disruptions. For instance, providing users with actionable information and control over the permissions granted to apps.

- **Adversarial Machine Learning:** Malicious actors can use adversarial machine learning techniques to manipulate or evade detection models. This necessitates the development of more robust and resilient machine learning models.

- **Dynamic Analysis:** Real-time analysis of apps' behavior is crucial for malware detection. However, this can be resource-intensive and may require sophisticated analysis tools to keep up with the evolving malware landscape.

- **Scalability:** As the number of Android apps grows exponentially, the scalability of malware detection systems becomes a concern. Efficiently processing and analyzing a vast number of apps and updates in real-time is an ongoing challenge.

- **User Education:** Educating users about the risks of downloading apps from unofficial sources, the importance of keeping their devices and apps up to date, and recognizing potential threats is an open problem. User awareness is a critical component of the overall security landscape.

- **Attribution and Tracking:** Identifying the source of malware, tracking malicious actors, and taking legal actions against them can be challenging, particularly in the case of sophisticated malware campaigns.

- **False Positives and Negatives:** Reducing false positives and false negatives in malware detection remains an ongoing challenge.

CHAPTER 3

AIM AND SCOPE OF THE PRESENT INVESTIGATION

3.1 AIM:

Detecting malicious software specifically designed to target Android devices. Protecting user data, privacy, and device integrity. Preventing financial losses and identity theft resulting from malware attacks. Maintaining the stability and performance of Android devices.

3.2 SCOPE:

- **Detection Techniques:** Employing various methods such as signature-based detection, anomaly-based detection, behavior-based detection, and machine learning algorithms to identify and classify malware.

- **Malware Types:** Addressing a wide range of malware types including but not limited to viruses, trojans, ransomware, spyware, adware, and phishing apps.

- **App Stores:** Assessing applications from official and third-party app stores to identify potentially harmful software.

- **Static Analysis:** Examining the code and structure of Android applications without executing them to identify suspicious patterns or behaviors.

- **Dynamic Analysis:** Running applications in controlled environments or sandboxes to observe their behavior and detect malicious activities at runtime.

- **Permission Analysis:** Scrutinizing the permissions requested by applications to detect overly permissive or suspicious behavior.

- **Network Traffic Analysis:** Monitoring network communications initiated by applications to identify suspicious connections or data exfiltration attempts.

- **Heuristic Analysis:** Using predefined rules and patterns to flag potentially malicious behaviors or code structures.

- **Zero-Day Threats:** Developing techniques to detect previously unseen or unknown malware variants through advanced anomaly detection or machine learning models trained on large datasets.

- **User Education:** Educating Android users about safe browsing habits, app installation best practices, and recognizing signs of potential malware infections.

- **Collaboration:** Collaborating with cybersecurity communities, industry partners, and researchers to share threat intelligence, improve detection capabilities, and respond effectively to emerging threats.

- **Updates and Patch Management:** Ensuring timely delivery of security updates and patches to address vulnerabilities exploited by malware.

3.3 RISK ANALYSIS OF THE PROJECT

3.3.1 Feasibility Study

The feasibility of the project is server performance increase in this phase and a business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis, the feasibility study of the proposed system is to be carried out. For feasibility analysis, some understanding of the major requirements for the system is essential.

Three key considerations involved in the feasibility analysis are

● Economical feasibility
● Technical feasibility
● Operational feasibility

3.3.2 Economical Feasibility

This study is carried out to check the economic impact that the system will have on the organization. The amount of funds that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased.

3.3.3 Technical Feasibility

This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on the available technical resources. This will lead to high demands being placed on the client. The developed system must have modest requirements, as only minimal or null changes are required for implementing this system.

3.3.4 Operational Feasibility

The aspect of the study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity.

The level of acceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar with it. His level of confidence must be raised so that he is also able to make some constructive criticism, which is welcomed, as he is the final user of the system

3.4 REQUIREMENTS SPECIFICATION

3.4.1 Hardware specifications:

- Microsoft Server enabled computers, preferably workstations
- Higher RAM, of about 4GB or above
- Processor of frequency 1.5GHz or above

3.4.2 Software specifications:

- Python 3.6 and higher
- Google colab

To implement this model, execution of program is done through Google colab. Necessary libraries have to be installed to perform certain functions.

CHAPTER 4

DESCRIPTION OF PROPOSED SYSTEM

Behavioral Analysis and Machine Learning: Implement a hybrid approach that combines behavioral analysis and machine learning techniques. This system will continuously monitor and analyze app behavior to detect anomalies and malicious activities.Real-time Threat Intelligence: Integrate real-time threat intelligence feeds to stay updated on the latest malware threats and attack vectors. This information can help the system adapt to new threats more effectively.User-Centric Design: Develop a user-centric system that empowers users to actively participate in the detection process. This can include user-friendly dashboards and tools for understanding and managing app permissions.

Key Components:

- **Dynamic Behavior Analysis:** Implement a real-time monitoring system that tracks app behavior, including network activity, file access, and system interactions. Use machine learning to create behavioral profiles for both known and unknown apps.

- **Machine Learning Models:** Employ machine learning models, such as deep learning neural networks, to detect patterns of malicious behavior. Train these models on large datasets of benign and malicious app behavior.

- **Anomaly Detection:** Use anomaly detection algorithms to identify deviations from normal app behavior. This can help in detecting zero-day exploits and previously unseen malware.

- **Static Analysis:** Continue to use static analysis methods, such as code scanning and permission analysis, to identify known vulnerabilities and risky app behaviors during the installation phase.

- **Privacy-Preserving Analysis:** Develop mechanisms to ensure user privacy is

protected during the analysis process. Implement differential privacy techniques to aggregate and anonymize user data.

- **Resource Optimization:** Create resource-efficient algorithms to ensure that the detection system has minimal impact on device performance and battery life. This is crucial for user satisfaction.

4.1 SELECTED METHODOLOGY OR PROCESS MODEL

4.1.1 Dataset

Any machine learning model needs a dataset over which it can be trained. So data collection is one of the most important steps. We've worked on 3 different datasets and compared their result against each other

• 1st dataset is collected from google comprised of 70 different application each having a set of 17 permission

• 2nd is downloaded from Kaggle which has 184 different permissions or we can say

features list for 29999 apps individually.

• 3rd one is downloaded from Kaggle. It has 138047 records with each record consisting 57 columns(permissions)

For training and testing purposes, we split the dataset into two parts. We used 80% of the dataset for training the machine learning model and the remaining 20% dataset was used for testing every machine learning model and calculating the performance of each model with metrics such as accuracy, f1-score, precision and recall.

4.1.2 Feature Engineering

The feature set used for training has a big impact on machine learning. Several research have found that certain features are helpful in training machine learning-based malware classifiers. That is the reason we have used feature engineering in our implementation. In supervised learning, we will use Feature engineering, which is the process of selecting, manipulating, and changing raw data into features.
We use Feature Engineering for the following reasons:

- To remove imputation
- Handling outliers
- To achieve Normalization
- Null Value Handling
- To remove invalid data
- To achieve scaling

4.2 DATA PREPROCESSING

The process of converting raw data into a comprehensible format is known as data preparation. We can't work with raw data, thus this is a key stage in machine learning. Before using machine learning or data mining methods, make sure the data is of good quality.The purpose of data preprocessing is to ensure that the data is of good quality. The following criteria can be used to assess quality accuracy, completeness, consistency, trustworthy, understandablity.

Data Preporocessing involves the following steps:

- **Data Cleaning:** Correcting or deleting incorrect, corrupted, improperly formatted duplicate, or incomplete data.We have removed those columns having missing values. We've removed any undesirable observations from our datasets, such as duplicates or irrelevant observations

- **Data Transformation:** Changing data from one format to another. For string columns and decimal columns such as price, they're converted to binary.

- **Data integration:** combining data from a variety of sources, including databases (both relational and non-relational), data cubes, files, and so on.

- **Data reduction:** It is possible to reduce the amount of records, characteristics, or dimensions. It is carried out during feature selection using correlation matrix.

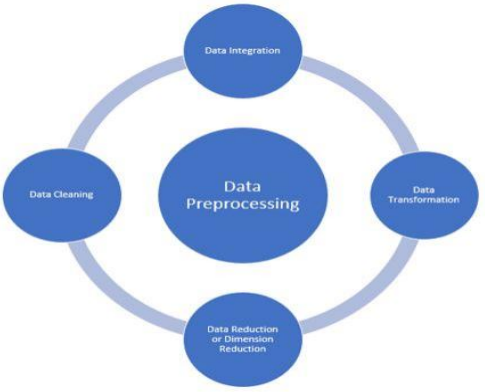


Fig No. 4.2.1 Data Preprocessing

4.3 FEATURE SELECTION

Feature Selection is a dimensionality reduction procedure that reduces a large set of raw data into smaller groups for processing. Feature selection aims to maximise relevance while reducing repetition. To accomplish efficient data reduction, feature selection approaches can be utilised in data pre-processing. This is accomplished by Correlation Coefficient Matrix.

We need to establish an absolute value as the variable selection threshold. If the predictor variables are found to be associated, we can exclude the variable having the lowest correlation coefficient value with the target variable.

After the process of feature selection, we are left with 54 columns which we are going to consider as features that we use for training the machine learning models.We computed the correlation coefficients for each feature pair. Correlation coefficient between two variables tells us how those two variables are dependent on each other.

4.4 DESCRIPTION OF PROGRAMMING LANGUAGE AND SOFTWARE

We have worked on last dataset in detail and for remaining we have tested accuracy and compared its result. We made sure that the dataset contained enough examples for both the malware and benign applications. There are 41323 examples for benign applications and 96724 applications for malicious applications. So, we can say that the dataset is not skewed. Each permission column is a binary

column,indicating a permission is asked or not.

4.4.1 Python:

Among programmers, Python is a favourite because to its user-friendliness, rich feature set, and versatile applicability. Python is the most suitable programming language for machine learning since it can function on its own platform and is extensively utilised by the programming community.Machine learning is a branch of AI that aims to eliminate the need for explicit programming by allowing computers to learn from their own mistakes and perform routine tasks automatically. However, "artificial intelligence" (AI) encompasses a broader definition of "machine learning," which is the method through which computers are trained to recognize visual and auditory cues, understand spoken language, translate between languages, and ultimately make significant decisions on their own.

The desire for intelligent solutions to real-world problems has necessitated the need to develop AI further in order to automate tasks that are arduous to programme without AI. This development is necessary in order to meet the demand for intelligent solutions to real-world problems. Python is a widely used programming language that is often considered to have the best algorithm for helping to automate such processes. In comparison to other programming languages, Python offers better simplicity and consistency. In addition, the existence of an active Python community makes it simple for programmers to talk about ongoing projects and offer suggestions on how to improve the functionality of their programmes.

4.4.2 Google colab:

Google Colab (short for Google Colaboratory) is a cloud-based platform provided by Google that allows users to create and run Jupyter notebooks in a web-based environment. It provides free access to computational resources, including CPU and GPU, and is particularly popular in the fields of data science, machine learning, and deep learning.

Key Features of Google Colab:

- **Free and Cloud-Based:** Google Colab is free to use and hosted in the cloud. Users don't need to install any software on their local machines.

- **Jupyter Notebooks:** Users can create, edit, and run Jupyter notebooks directly in the browser. This makes it a convenient platform for data analysis, research, and collaborative work.

- **High-Performance GPUs:** Google Colab provides free GPU resources, allowing users to accelerate machine learning and deep learning tasks. This is particularly valuable for training large neural networks.

- **Integration with Google Drive:** Colab is tightly integrated with Google Drive, making it easy to store, share, and collaborate on notebooks and data files.

- **Pre-installed Libraries:** Colab comes with many pre-installed data science and machine learning libraries, similar to Anaconda, making it accessible for data analysis and model development.

- **Community and Collaboration:** Users can collaborate on notebooks in real-time, making it an excellent platform for teamwork and sharing knowledge within the data science and machine learning communities.

- **Support for Markdown:** In addition to running code, Google Colab supports Markdown, allowing users to create documentation and reports within their notebooks.

4.4.3 Using Google Colab:

To get started with Google Colab, you need a Google account. Here's a basic outline of how to use it:

- **Access Google Colab:** Open your web browser, go to Google Colab, and sign in with your Google account if you're not already logged in.

- **Create a New Notebook:** Click on "New Notebook" to create a new Jupyter notebook. You can then add code, text, and visualizations to your notebook cells.

- **Run Code:** Use the provided cells to write and run Python code. You can execute each cell independently or run the entire notebook.

- **Access GPU:** If you need GPU resources, you can enable them in the "Runtime" menu. Google Colab provides free GPU access for a limited time in each session.

- **Save and Share:** You can save your notebooks to Google Drive and share them with others for collaborative work.

4.4.4 Logistic Regression :

Logistic Regression is a predictive analytic technique built on the notion of probabilities. It is a Machine Learning algorithm that would be used for problems which involves classifying. Here, we will have a hypothesis function which will tell us the probability that a sample belongs to a particular class. In logistic regression, we use sigmoid function as hypothesis function.

$$h_\theta(x) = \sigma(x^T\theta)$$

$$\sigma(x^T\theta) = \frac{1}{1 + e^{-x^T\theta}}$$

Ideally we will want the logistic regression classifier to give an accurate prediction. For that, we have to find θ that minimizes the cost function J(θ). We do that using gradient descent algorithm

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[(1-y^i)\log(1-p^i) + y^i\log(p^i)]$$

where p^i is the probability that i is a malicious application and y^i is the labelled class for that application.

4.4.5 K-Nearest Neighbours:

K-Nearest Neighbors is a straightforward machine learning approach that may be applied to regression problems as well as tasks involving classifying. In KNN, we look for K applications that are nearest to the given instance application. We note down the classes of all those K applications and count how many times each class appeared. The class that appeared the most will be the class of our instance application. Here the K nearest neighbours are chosen using the euclidean distance.

Here we have to choose the K value that gives the least training error rate. There isn't any particular method to do that but when we plot error rate and k on a 2D-plane, we can take the K value that gives us least error.

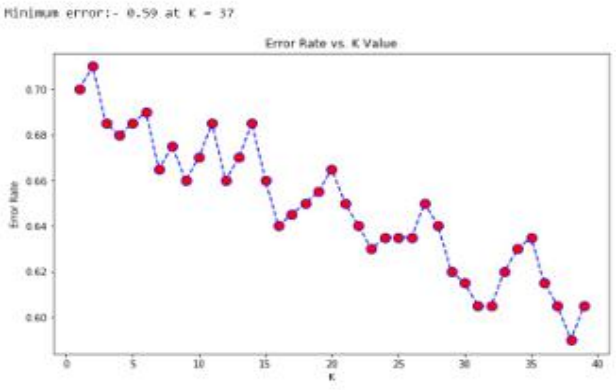


Fig No. 4.4.5.1 K-Nearest Neighbours

4.4.6 SVM Linear :

A SVMLinear classifier is built to fit the data you supply and provide a hyperplane that f its well and classify your data into different classes. Following that, you may input some attributes to your classifier to check what the projected class is once you've obtained the hyperplane.

Support Vectors are the points which can be considered as edge cases. They are very nearer to the hyperplane. The two support vectors corresponding to either classes be nign and malicious respectively are equidistant to the hyperplane with maximum margin possible.

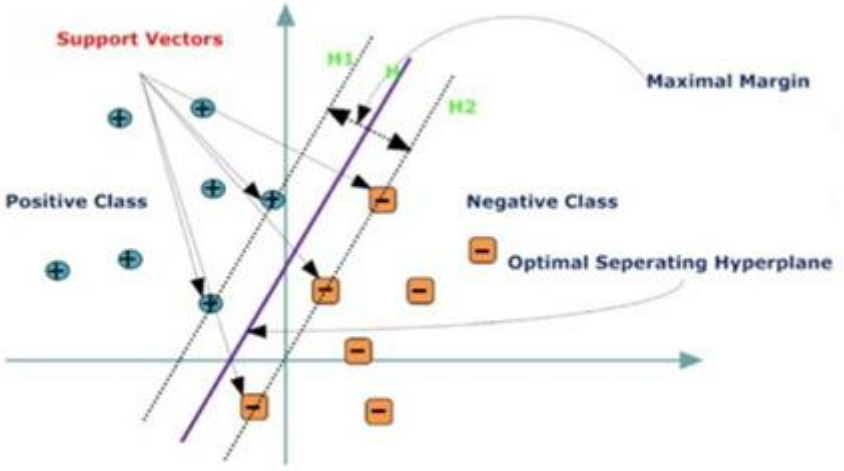


Fig No. 4.4.6.1 Support Vector Machine

4.4.7 Decision Tree:

Decision Trees are a non-parametric supervised learning approach which can be used for classifying problems as well as regression problems. The sole objective is to construct a machine learning model that guesses the class of a given instance by learning basic decision rules from feature values.

First, we will calculate the entropy. It is also known as measure of uncertainity. Then for each attribute A, we calculate information gain. The attribute with maximum value for information gain will be selected as the root node and this process continues. The formulas for entropy and Information gain are:

$$E(S) = -[p\log(p) + (1-p)\log(1-p)]$$

$$Gain(S,A) = E(S) - \sum_{v} p_v E(S_v)$$

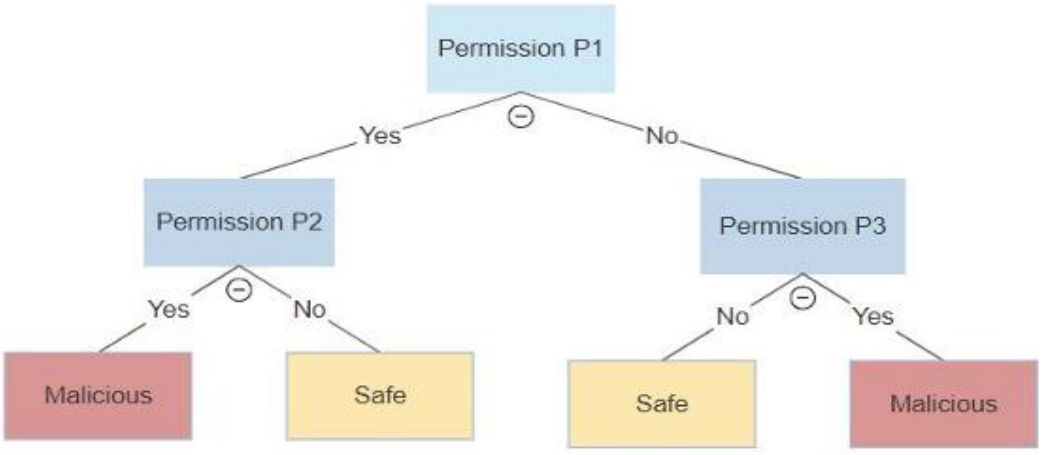


Fig No. 4.4.7.1 Illustration of Decision Tree

4.4.8 Random Forest Method :

Random Forest algorithm is a supervised learning method of machine learning. It produces a ”forest” out of a collection of multiple decision trees. These trees are often trained using an approach called bagging approach. The main idea of this approach is that combining many learning models enhances total output. In simple words, random forest is a method of combining many decision trees to get a more accurate and reliable prediction.

Random Forest is a Machine learning classifier that has various decision trees on different subsets of input datasets and takes the majority of them to improve the performance of the model. The more number of decision trees we take, the higher the performance of our model will be.

Decision Trees: Random Forest builds multiple decision trees during training. Each decision tree is trained on a random subset of the training data and uses a random subset of features at each split point. This randomness helps to decor relate the individual trees and reduce over fitting.

Bootstrap Aggregating (Bagging): Random Forest employs a technique called bagging, which involves sampling the training data with replacement to create multiple subsets, each of which is used to train a decision tree. This process helps

to introduce diversity among the trees.

Voting Mechanism: During the prediction phase, each decision tree in the Random Forest independently predicts the target variable (in classification tasks, it votes for the class; in regression tasks, it provides a numerical prediction). The final prediction is then determined by aggregating the predictions of all the trees. In classification tasks, this is typically done by majority voting, while in regression tasks, it is often done by averaging the predictions.

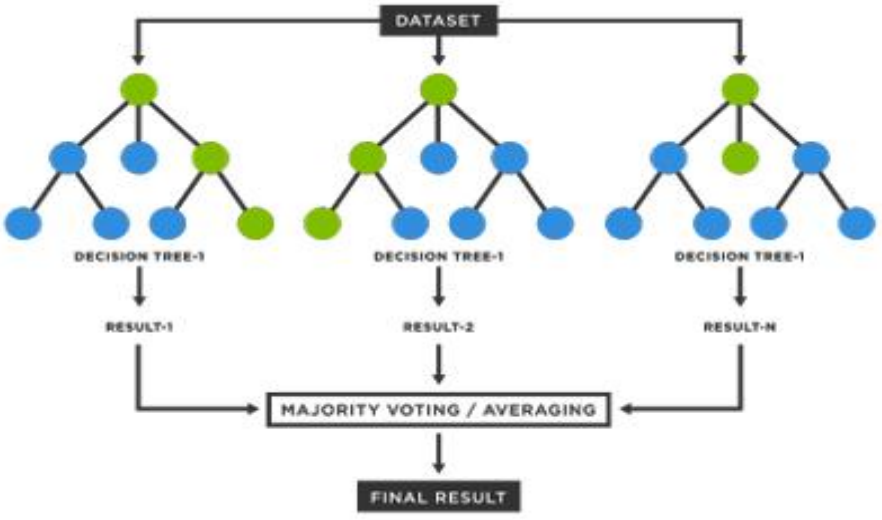


Fig No. 4.4.8.1 Illustration of Random Forest

4.4.9 Gaussian Naive Bayes :

A collection of classification algorithms which are based on a theorem named after Bayes together forms a Naive Bayes classifier. It isn't a single algorithm. It is a group of algorithms sharing one common principle i.e., every pair of features which are used in classification are independent of each other.

For two events E_a, E_b Bayes theorem tells that:

$$P(E_a|E_b) = P(E_b|E_a) * \frac{P(E_a)}{P(E_b)}$$

Using this principle for classification task, we can say that:

$$Pr(class|attributes) = Pr(attributes|class) * \frac{Pr(class)}{Pr(attributes)}$$

As we have two classes malicious and safe, we will calculate the probabilities for the application to be in malicious class and to be in safe class. The class for which the probability value is higher, is the class to which the application belongs to.

$$\hat{class} = argmax_{class} P(class/attribute)$$

4.4.10 Anaconda Spyder Software:

Spyder is an open-source integrated development environment (IDE) specifically designed for Python programming, with a focus on scientific computing, data analysis, and machine learning tasks. It features a comprehensive set of tools tailored to meet the needs of Python developers working in these domains. At its core is a feature-rich code editor that supports syntax highlighting, code completion, and code folding to enhance the coding experience. One of its standout features is the integrated IPython console, allowing for interactive code execution and real-time result visualization, along with the ability to plot graphs directly within the console. Spyder also provides a Variable Explorer for inspecting variables in memory, a built-in debugger for efficient debugging, and a profiler for optimizing code performance.

It seamlessly integrates with popular scientific libraries like NumPy, pandas, SciPy, and scikit-learn, facilitating a unified environment for scientific computing and data analysis tasks. Spyder's customizable layout, documentation integration, and cross-platform support further contribute to its appeal among researchers, data scientists, and developers seeking an efficient and powerful Python IDE.

Key features of Spyder include:

- **Editor:** Spyder features a multi-pane editor with syntax highlighting, code completion, and integrated code analysis tools to help developers write Python code efficiently.

- **Interactive Console:** Spyder includes an IPython console within the

IDE, allowing developers to execute Python code interactively, view results immediately, and debug their code efficiently.

- **Variable Explorer:** The Variable Explorer in Spyder allows users to inspect and manipulate variables in memory during program execution, making it easier to debug and understand code behavior.

- **Debugger:** Spyder includes a built-in debugger that allows developers to step through code, set breakpoints, and inspect variables to identify and fix errors in their Python programs.

- **Documentation Browser:** Spyder integrates a documentation browser that provides quick access to documentation for Python libraries and modules, making it easier for developers to find information and learn about different functions and classes.

- **Integration with other tools:** Spyder seamlessly integrates with other tools commonly used in the data science and scientific computing ecosystem, such as NumPy, pandas, matplotlib, and scikit-learn.

CHAPTER 5
IMPLEMENTATION DETAILS

User Feedback and Reputation Systems:Incorporate user feedback and reputation systems to identify potentially harmful applications based on community reports or ratings. Users can report suspicious behavior, rate applications, or provide feedback on their experiences. This data can be aggregated and analyzed to flag potentially malicious applications.

App Signature Verification:Verify the digital signatures of applications to ensure they haven't been tampered with or repackaged. Legitimate developers sign their apps with cryptographic keys, and verifying these signatures can help detect unauthorized modifications or fake versions distributed by malicious actors.

System Updates and Patch Management:Regularly update the malware detection system to incorporate new threat intelligence, improve detection algorithms, and address vulnerabilities. Additionally, ensure that the underlying Android operating system is up-to-date with the latest security patches to mitigate known vulnerabilities exploited by malware.

User Education and Awareness:Educate users about safe app installation practices, such as downloading applications only from official app stores like Google Play Store, avoiding apps from unknown sources, reviewing permissions before installation, and being cautious of suspicious links or advertisements.

Continuous Monitoring and Response:Implement mechanisms for continuous monitoring of application behavior, both at runtime and post-installation. This includes real-time monitoring of system events, network traffic, and file system activities to detect and respond to emerging threats promptly.

Privacy Protection Mechanisms:Ensure that the malware detection system respects user privacy by implementing robust data protection measures. Limit the collection and storage of sensitive user data to what is strictly necessary for malware detection.

Integration with Mobile Device Management (MDM) Solutions:Integrate with Mobile Device Management solutions to enforce security policies, remotely install updates, and blacklist or quarantine suspicious applications across managed devices. This provides centralized control and visibility over the security posture of deployed Android devices.

Collaboration and Information Sharing:Foster collaboration and information sharing among security researchers, industry partners, and cybersecurity organizations to exchange threat intelligence, share best practices, and collectively combat the evolving landscape of Android malware threats.

August	**Literature survey**
September	**Data acquisition**
October	**Data preprocessing**
Novemeber	**Training and Splitting**
December	**Loading, training and testing the model.**
January	**Predicting the output and generating the final report**

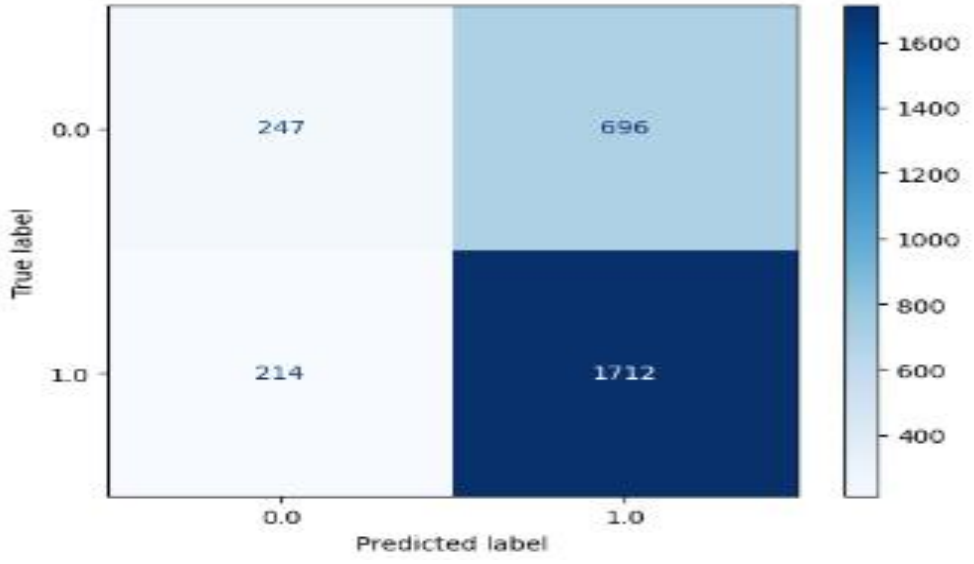
CHAPTER 6

RESULTS AND DISCUSSION PERFORMANCE ANALYSIS

6.1 RESULTS

As android malwares are increasing day to day, we wanted to present a model that can detect malwares accurately. We considered the permissions asked by an android application as the features to our machine learning model. This comes under Static Analysis. The idea of considering these permissions as features worked well. We got good accuracy from most of the machine learning models that were implemented. The Random forest got the highest accuracy . Out of all the remaining models, SVM and KNN performed well. And Gaussian Naive Bayes model got the least accuracy among all the models that we implemented.

```
****  Random Forest Classifier  ****

Training :

Accuracy score     :    68.28163123039387
Precision score    :    0.7109634551495017
ROC AUC score      :    0.6629451971073957
AUC score          :    0.5754094497466713

*************************************************

Testing :

Accuracy score     :    77.09471237652528
Precision score    :    0.7661880630630631
ROC AUC score      :    0.8250406702862998
AUC score          :    0.6818583767137532

Confusion Matrix :
```



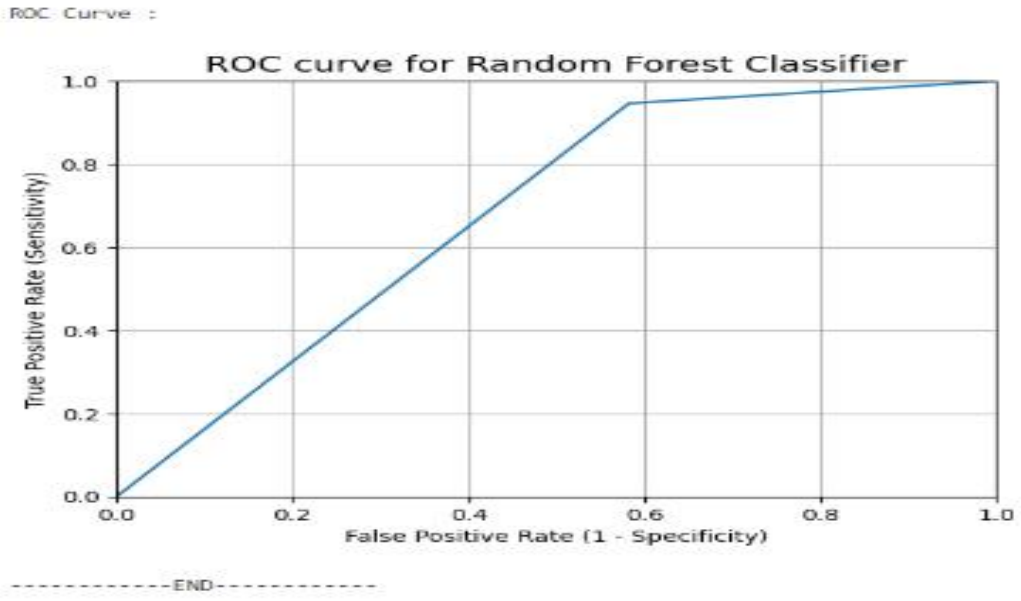


Fig No. 6.1.1 Best Accuracy Algorithm

Firstly, it employs supervised learning to classify applications based on labeled samples. These samples are manually labeled by security experts, indicating whether each application is benign or malicious. Through this process, the ML model can learn from the labeled data and make accurate predictions for new, unseen applications. Moreover, the system employs unsupervised learning to discover previously unknown and emerging malware. Unsupervised learning techniques enable the ML model to detect anomalies and identify potentially new forms of malware without relying solely on pre-existing knowledge. This capability is particularly important for staying ahead of cybercriminals who continually develop new and sophisticated attacks.

6.2 PERFORMANCE ANALYSIS

To enhance the effectiveness of the system, it regularly updates its ML models using up-to-date data from various sources, including reputable security vendors, app stores, and crowdsourcing initiatives. This continuous learning process enables the system to adapt and improve its accuracy in detecting rapidly evolving malware threats. Overall, this ML-based system for Android malware detection enables efficient and reliable identification of malicious applications, safeguarding Android users from potential security risks and ensuring the security of their

devices and data.
we can see the confusion matrices for various models. Confusion matrix compares the predicted classes with actual classes of applications. We can obtain the values of True Positive, False Positive, True Negative and False Negative from these confusion matrices.

Accuracy can be computed by dividing the number of correctly classified applications by total number of applications.

$$Accurcy = \frac{No.ofcorrectlyclassifiedapplications}{Totalno.ofapplications}$$

Precision can be computed by dividing the number of applications that are predicted correctly that they belong to a particular class by the number of applications that are predicted to be in that particular class.

$$Precision = \frac{TP}{TP + FP}$$

Recall can be computed by dividing the number of applications that are predicted correctly that they belong to a particular class by the number of applications that should actually be in that particular class.

$$Recall = \frac{TP}{TP + FP}$$

F1-score is a metric involving both Precision and Recall and can be computed as:

$$F1 - score = \frac{2 * Precision * Recall}{Recall + Precision}$$

For Sequential Neural Network, we took 3 hidden layers of length 16, 8 and 1.
We used relu activation function for the hidden layers and sigmoid function for the output layer.

LEARNING MODELS	TRAINING ACCURACY	TESTING ACCURACY
Logistic Regression Model	66.5%	67.6%
Support Vector Machine Model	61.6%	71.4%
Random Forest Classifier	66.4%	77.6%
Adaboost Classifier	66.5%	67.5%
Multinomial Naive Bayes	66.2%	67.5%
KNN Classifier	65.6%	71.5%

CHAPTER 7

SUMMARY AND CONCLUSIONS

7.1 CONCLUSION

Last but not least, the ML-based solution for Android malware detection is a great and efficient way. The technology is able to detect and categorize possible malware in Android apps with high accuracy by using ML algorithms. Users are able to safeguard their devices and data against harmful apps using this feature. This system is dependable and flexible enough to keep up with emerging threats since it can learn and adapt to new malware types regularly. In sum, our ML-based approach provides an extensive and powerful answer to the problem of Android malware detection.

But, a set of android applications operating together can carry out a malicious activity. We call them colluding apps. In this, the malicious activity is carried out by more than one application. Each application participating in collusion does a small part of the malicious action. These applications communicate with each other through covert channels. Sometimes when a malicious activity cannot be performed by a single application, it might be possible that a group of applications coordinating with each other can perform that malicious activity. This phenomenon is called Application Collusion. It is an emerging threat.

The reason behind why we are calling this as an emerging threat is because most of the android malware detectors scan the applications individually when determining whether it is a malware or not. But as the malicious activity here is being carried out by a group of applications, those traditional detectors cannot detect this. So, we need a model to detect these colluding applications. Till now, very little research has been done on this and there is scarcity for datasets

7.2 FUTURE WORK

Improving the current model and investigating new approaches to increase efficiency and accuracy should be the focus of future work on the system for Android malware detection using Machine Learning (ML). To begin, in order to better enhance the detection process, researchers might investigate more complex ML techniques including ensemble approaches and deep learning. To improve classification results, more complex characteristics may be extracted from Android malware samples using deep learning methods such as Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN).

The second way to improve the system's performance is to use dynamic analytic methods. The technology is able to identify possible malicious activities more efficiently by monitoring the runtime behavior of Android applications and capturing real-time information about their activity. To further improve processing speed and decrease computing overhead, researchers might look into feature selection approaches to find the most important characteristics and lower the dataset's dimensionality. Last but not least, it would be beneficial to compile a big collection of malware samples, both known and unknown, tailored to Android malware detection. Training and evaluating the system under varied real-world circumstances would be much easier with such a dataset, resulting in more robust and accurate outcomes.

We are trying to create or obtain a few applications that can perform collusion, so that we can do some research on them which may eventually help in creating a model that can detect colluding applications. Firstly, we have to obtain a template for collusion. Then, we have to try to split a malicious task into various steps and make each application perform one of the steps. By doing this, we can achieve collusion.

REFERENCES

[1] A. Arora, S. Garg, and S. K. Peddoju, “Malware detection using network traffic of analysis in android based mobile devices,” in 2014 Eighth International Conference on Next Generation Mobile Apps, Services and Technologies, pp. 66–71, 2014.

[2] A. Arora, S. K. Peddoju, and M. Conti, “Permpair: Android malware detection using permission pairs,” IEEE Transactions on Information Forensics and Security, vol. 15, pp. 1968–1982, 2020.

[3] Z. Yuan, Y. Lu, and Y. Xue, “Droiddetector: android malware characterization and detection using deep learning,” Tsinghua Science and Technology, vol. 21, no. 1, pp. 114–123, 2016.

[4] S. Y. Yerima, S. Sezer, and I. Muttik, “Android malware detection using parallel machine learning classifiers,” in 2014 Eighth International Conference on Next Generation Mobile Apps, Services and Technologies, pp. 37–42, 2014.

[5] N. Peiravian and X. Zhu, “Machine learning for android malware detection using permission and api calls,” in 2013 IEEE 25th International Conference on Tools with Artificial Intelligence, pp. 300–305, 2013.

[6] J. Sahs and L. Khan, “A machine learning approach to android malware detection,” in 2012 European Intelligence and Security Informatics Conference, pp. 141–147, 2012.

[7] Z. Wang, J. Cai, S. Cheng, and W. Li, “Droiddeeplearner: Identifying android malware using deep learning,” in 2016 IEEE 37th Sarnoff Symposium, pp. 160–165, 2016.

[8] H.-S. Ham and M.-J.Choi, “Analysis of android malware detection performance using machine learning classifiers,” in 2013 International Conference on ICT

Convergence (ICTC), pp. 490–495, 2013.

[9] U. Pehlivan, N. Baltaci, C. Acart¨urk, and N. Baykal, “The analysis of feature selection methods and classification algorithms in permission based android malware detection,” in 2014 IEEE Symposium on Computational Intelligence in CyberSecurity (CICS), pp. 1–8, 2014.

[10] H. Fereidooni, M. Conti, D. Yao, and A. Sperduti, “Anastasia: Android malware detection using static analysis of applications,” in 2016 8th IFIP International Conference on New Technologies, Mobility and Security (NTMS), pp. 1–5, 2016.

[11] Doberstein, C., Charbonneau, É., Morin, G., & Despatie, S. (2022). Measuring the acceptability of facial recognition-enabled work surveillance cameras in the public and private sector. Public Performance & Management Review, 45(1), 198-227.

[12] Selwyn, N., Campbell, L., & Andrejevic, M. (2023). Autoroll: Scripting the emergence of classroom facial recognition technology. Learning, Media and Technology, 48(1), 166-179.

[13] Hsu, C. S., Tu, S. F., & Chiu, P. C. (2022). Design of an e-diploma system based on consortium blockchain and facial recognition. Education and Information Technologies, 1-25.

[14] Parhi, M., Roul, A., Ghosh, B., & Pati, A. (2022). Ioats: An intelligent online attendance tracking system based on facial recognition and edge computing. International Journal of Intelligent Systems and Applications in Engineering, 10(2), 252-259.

[15] Urquhart, L., & Miranda, D. (2022). Policing faces: the present and future of intelligent facial surveillance. Information & communications technology law, 31(2), 194-219.

[16] Gupta, S., Modgil, S., Lee, C. K., & Sivarajah, U. (2023). The future is

yesterday: Use of AI-driven facial recognition to enhance value in the travel and tourism industry. Information Systems Frontiers, 25(3), 1179-1195.

[17] Karpagam, M., Jeyavathana, R. B., Chinnappan, S. K., Kanimozhi, K. V., & Sambath, M. (2023). A novel face recognition model for fighting against human trafficking in surveillance videos and rescuing victims. Soft Computing, 27(18), 13165-13180.

[18] McElroy, E., & Vergerio, M. (2022). Automating gentrification: Landlord technologies and housing justice organizing in New York City homes. Environment and Planning D: Society and Space, 40(4), 607-626.

[19] Zhang, X., Zhang, X., & Dolah, J. B. (2022). Intelligent Classroom Teaching Assessment System Based on Deep Learning Model Face Recognition Technology. Scientific Programming, 2022.

[20] Revathy, G., Raj, K. B., Kumar, A., Adibatti, S., Dahiya, P., & Latha, T. M. (2022). Investigation of E-voting system using face recognition using convolutional neural network (CNN). Theoretical Computer Science, 925, 61-67.

APPENDIX

A. SOURCE CODE

```
!pip install google-play-scraper  #for scraping info about apk files from google repository
!pip install androguard   #for analyaing apk
!pip install scikit-plot   #for plotting from sklearn
!pip install pyfiglet   #importing for designing the CLI
#imported necessary libraries
from IPython.display import Javascript
Defresize_colab_cell():
#to increase size of colab cell
display(Javascript('google.colab.output.setIframeHeight(0,true,{maxHeight: 10000})'))
get_ipython().events.register('pre_run_cell', resize_colab_cell)
import warnings #to supress  warnings so that if any uncritical warningss will not show while executing
warnings.filterwarnings("ignore", category=DeprecationWarning)
from google.colab import drive  #mounting google drive for taking dataset and other files from google drive
drive.mount('/content/drive')
from androguard.misc import AnalyzeAPK
import androguard
import pickle
from google_play_scraper import app
import pandas as pd
import numpy as np
import IPython
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
#import shap
import scikitplot as skplt
import pickle
import pyfiglet
import sys
from termcolor import colored, cprint
from sklearn import model_selection
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score, roc_auc_score, precision_score, roc_curve, auc
import matplotlib.pyplot as plt
from sklearn.datasets import make_classification
from sklearn.metrics import ConfusionMatrixDisplay,confusion_matrix
#from sklearn.metrics import plot_confusion_matrix
import numpy as np
train_acc = []
test_acc = []
train_prec = []
test_prec = []
```

```
#Reading data into a variable
import pandas as pd
df = pd.read_csv("/content/drive/MyDrive/final project-20230922T140331Z-
001/final project/new_permissions.csv") #reading the dataset for training
df.head()
df.tail()
df=df.dropna()
df.tail()
df.columns.isnull()
df.info()
for i in df.columns:          #list all columns and their default values
    print("{} : {}".format(i,list(pd.unique(df[i]))))
target = df.pop("LABEL")
x_train, x_test, y_train, y_test = train_test_split(df.iloc[:,:-1],target)
x_train.shape
y_train.shape
x_train.shape, x_test.shape, y_train.shape, y_test.shape
class ModelTraining:
  def proj_banner(self):  #function for showing banner
    ascii_banner = pyfiglet.figlet_format(" Malware")
    ascii_banner2 = pyfiglet.figlet_format(" Predictor")
    te = "\n © IIITMK, Thiruvananthapuram  © packed by \n\n\n"
    a111 = colored(ascii_banner, 'magenta', attrs=['blink'])
    a122 = colored(ascii_banner2, 'magenta', attrs=['blink'])
    co = colored(te, 'red', attrs=['blink'])
    print(a111)
    print(a122)
    print(co)
  def LogisticRegression_Model(self,x_train,x_test,y_train,y_test):  #function for
logistic regression
    from sklearn.linear_model import LogisticRegression
    model1 = LogisticRegression(solver='lbfgs', max_iter=1000)
    model1.fit(x_train, y_train)
    y_pred1 = model1.predict(x_test)
    p_text = "\n\n\n****  Logistic Regression  ****"
    prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
    print(prin_text)
    p_text = "\nTraining :\n"
    prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
    print(prin_text)
    p_text = "Accuracy score    :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = accuracy_score(y_test, y_pred1)*100
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    train_acc.append(p_ans)
    p_text = "Precision score   :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = precision_score(y_test, y_pred1)
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
```

```
print(prin_text,prin_ans)
train_prec.append(p_ans)
p_text = "ROC AUC score     :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = roc_auc_score(y_test, model1.predict_proba(x_test)[:,1])
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
fpr1, tpr1, thresholds1 = roc_curve(y_test, y_pred1)
p_text = "AUC score         :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = auc(fpr1, tpr1)
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
o_banner = "\n*****************************************\n"
o_banner_text = colored(o_banner, 'white', attrs=['bold','blink'])
print(o_banner_text)
y_pred1_train = model1.predict(x_train)
p_text = "\nTesting :\n"
prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
print(prin_text)
p_text = "Accuracy score    :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = accuracy_score(y_train, y_pred1_train)*100
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
test_acc.append(p_ans)
p_text = "Precision score   :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = precision_score(y_train, y_pred1_train)
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
test_prec.append(p_ans)
p_text = "ROC AUC score     :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = roc_auc_score(y_train, model1.predict_proba(x_train)[:,1])
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
fpr_t, tpr_t, thresholds_t = roc_curve(y_train, y_pred1_train)
p_text = "AUC score         :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = auc(fpr_t, tpr_t)
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)  # Calculate the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred1) # Print Confusion Matrix
p_text = "\nConfusion Matrix :\n"
prin_text = colored(p_text, 'cyan', attrs=['bold', 'blink'])
print(prin_text) # Display Confusion Matrix
disp = ConfusionMatrixDisplay(conf_matrix, display_labels=model1.classes_)
disp.plot(cmap='Blues', values_format='d')  # Show the plot
plt.show() # Save the model
```

```
 filename='/content/drive/MyDrive/ColabNotebooks/logistic_regression_model.pkl'
  with open(filename, 'wb') as file:
      pickle.dump(model1, file)
  p_text = "\nROC Curve :\n"  # plotting ROC curve graph
  prin_text = colored(p_text, 'cyan', attrs=['bold', 'blink'])
  print(prin_text) # Calculate ROC curve
  fpr_t, tpr_t, thresholds_t = roc_curve(y_train, y_pred1_train) # Plot ROC curve
  plt.plot(fpr_t, tpr_t)
  plt.xlim([0, 1])
  plt.ylim([0, 1])
  plt.rcParams['font.size'] = 12
  plt.title('ROC curve for Logistic Regression')
  plt.xlabel('False Positive Rate (1 - Specificity)')
  plt.ylabel('True Positive Rate (Sensitivity)')
  plt.grid(True)
  plt.show()
  o_banner = "\n------------END------------\n"
  o_banner_text = colored(o_banner, 'white', attrs=['bold', 'blink'])
  print(o_banner_text)
 def SVM_Model(self,x_train,x_test,y_train,y_test):  #function for SVM
  from sklearn.svm import SVC
  model2 = SVC(probability= True)
  model2.fit(x_train,y_train)
  y_pred2 = model2.predict(x_test)
  p_text = "\n\n\n****  Support Vector Machine  ****"
  prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
  print(prin_text)
  p_text = "\nTraining :\n"
  prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
  print(prin_text)
  p_text = "Accuracy score    :   "
  prin_text = colored(p_text, 'green', attrs=['bold','blink'])
  p_ans = accuracy_score(y_test, y_pred2)*100
  prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
  print(prin_text,prin_ans)
  train_acc.append(p_ans)
  p_text = "Precision score   :   "
  prin_text = colored(p_text, 'green', attrs=['bold','blink'])
  p_ans = precision_score(y_test, y_pred2)
  prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
  print(prin_text,prin_ans)
  train_prec.append(p_ans)
  p_text = "ROC AUC score     :   "
  prin_text = colored(p_text, 'green', attrs=['bold','blink'])
  p_ans = roc_auc_score(y_test, model2.predict_proba(x_test)[:,1])
  prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
  print(prin_text,prin_ans)
  fpr2, tpr2, thresholds2 = roc_curve(y_test, y_pred2)
  p_text = "AUC score         :   "
  prin_text = colored(p_text, 'green', attrs=['bold','blink'])
```

```
    p_ans = auc(fpr2, tpr2)
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    o_banner = "\n*******************************************\n"
    o_banner_text = colored(o_banner, 'white', attrs=['bold','blink'])
    print(o_banner_text)
    y_pred2_train = model2.predict(x_train)
    p_text = "\nTesting :\n"
    prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
    print(prin_text)
    p_text = "Accuracy score    :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = accuracy_score(y_train, y_pred2_train)*100
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    test_acc.append(p_ans)
    p_text = "Precision score   :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = precision_score(y_train, y_pred2_train)
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    test_prec.append(p_ans)
    p_text = "ROC AUC score     :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = roc_auc_score(y_train, model2.predict_proba(x_train)[:,1])
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    fpr_t2, tpr_t2, thresholds_t2 = roc_curve(y_train, y_pred2_train)
    p_text = "AUC score         :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = auc(fpr_t2, tpr_t2)
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans) # Calculate the confusion matrix
    conf_matrix = confusion_matrix(y_test, y_pred2) # Print Confusion Matrix
    p_text = "\nConfusion Matrix :\n"
    prin_text = colored(p_text, 'cyan', attrs=['bold', 'blink'])
    print(prin_text) # Display Confusion Matrix
    disp = ConfusionMatrixDisplay(conf_matrix, display_labels=model2.classes_)
    disp.plot(cmap='Blues', values_format='d') # Show the plot
    plt.show() # Save the model
    filename = '/content/drive/MyDrive/Colab Notebooks/svm_model.pkl'
    with open(filename, 'wb') as file:
        pickle.dump(model2, file)
    p_text = "\nROC Curve :\n"  # plotting ROC curve graph
    prin_text = colored(p_text, 'cyan', attrs=['bold', 'blink'])
    print(prin_text)
# Calculate ROC curve
    fpr_t2, tpr_t2, thresholds_t2 = roc_curve(y_train, y_pred2_train) # Plot ROC
curve
    plt.plot(fpr_t2, tpr_t2)
```

```
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.rcParams['font.size'] = 12
    plt.title('ROC curve for Support Vector Machine')
    plt.xlabel('False Positive Rate (1 - Specificity)')
    plt.ylabel('True Positive Rate (Sensitivity)')
    plt.grid(True)
    plt.show()
    o_banner = "\n------------END------------\n"
    o_banner_text = colored(o_banner, 'white', attrs=['bold', 'blink'])
    print(o_banner_text)
  def RandomForest_Classifier(self,x_train,x_test,y_train,y_test):  #function for
random forest classifier
    from sklearn.ensemble import RandomForestClassifier
    model3 = RandomForestClassifier()
    model3.fit(x_train,y_train)
    y_pred3 = model3.predict(x_test)
    p_text = "\n\n\n****  Random Forest Classifier  ****\n"
    prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
    print(prin_text)
    p_text = "\nTraining :\n"
    prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
    print(prin_text)
    p_text = "Accuracy score    :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = accuracy_score(y_test, y_pred3)*100
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    train_acc.append(p_ans)
    p_text = "Precision score   :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = precision_score(y_test, y_pred3)
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    train_prec.append(p_ans)
    p_text = "ROC AUC score     :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = roc_auc_score(y_test, model3.predict_proba(x_test)[:,1])
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    fpr3, tpr3, thresholds3 = roc_curve(y_test, y_pred3)
    p_text = "AUC score         :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = auc(fpr3, tpr3)
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    o_banner = "\n*******************************************\n"
    o_banner_text = colored(o_banner, 'white', attrs=['bold','blink'])
    print(o_banner_text)
    y_pred3_train = model3.predict(x_train)
```

```
p_text = "\nTesting :\n"
prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
print(prin_text)
p_text = "Accuracy score    :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = accuracy_score(y_train, y_pred3_train)*100
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
test_acc.append(p_ans)
p_text = "Precision score   :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = precision_score(y_train, y_pred3_train)
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
test_prec.append(p_ans)
p_text = "ROC AUC score     :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = roc_auc_score(y_train, model3.predict_proba(x_train)[:,1])
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
fpr_t3, tpr_t3, thresholds_t3 = roc_curve(y_train, y_pred3_train)
p_text = "AUC score         :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = auc(fpr_t3, tpr_t3)
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans) # Calculate the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred3) # Print Confusion Matrix
p_text = "\nConfusion Matrix :\n"
prin_text = colored(p_text, 'cyan', attrs=['bold', 'blink'])
print(prin_text) # Display Confusion Matrix
disp = ConfusionMatrixDisplay(conf_matrix, display_labels=model3.classes_)
disp.plot(cmap='Blues', values_format='d')  # Show the plot
plt.show()
p_text = "\nROC Curve :\n"
prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
print(prin_text)
plt.plot(fpr_t3, tpr_t3)
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.rcParams['font.size'] = 12
plt.title('ROC curve for Random Forest Classifier')
plt.xlabel('False Positive Rate (1 - Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.grid(True)
plt.show()  # Save the model
filename = '/content/drive/MyDrive/Colab Notebooks/random_forest_model.pkl'
with open(filename, 'wb') as file:
    pickle.dump(model3, file)
o_banner = "\n-----------END-----------\n"
o_banner_text = colored(o_banner, 'white', attrs=['bold', 'blink'])
```

```
    print(o_banner_text)
  def AdaBoost_Classifier(self,x_train,x_test,y_train,y_test):  #function for adaboost
clasifier
    from sklearn.ensemble import AdaBoostClassifier
    model4 = AdaBoostClassifier()
    model4.fit(x_train,y_train)
    y_pred4 = model4.predict(x_test)
    p_text = "\n\n\n****  AdaBoost Classifier  ****"
    prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
    print(prin_text)
    p_text = "\nTraining :\n"
    prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
    print(prin_text)
    p_text = "Accuracy score    :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = accuracy_score(y_test, y_pred4)*100
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    train_acc.append(p_ans)
    p_text = "Precision score   :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = precision_score(y_test, y_pred4)
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    train_prec.append(p_ans)
    p_text = "ROC AUC score     :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = roc_auc_score(y_test, model4.predict_proba(x_test)[:,1])
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    fpr4, tpr4, thresholds4 = roc_curve(y_test, y_pred4)
    p_text = "AUC score         :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = auc(fpr4, tpr4)
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    o_banner = "\n*********************************************\n"
    o_banner_text = colored(o_banner, 'white', attrs=['bold','blink'])
    print(o_banner_text)
    y_pred4_train = model4.predict(x_train)
    p_text = "\nTesting :\n"
    prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
    print(prin_text)
    p_text = "Accuracy score    :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = accuracy_score(y_train, y_pred4_train)*100
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    test_acc.append(p_ans)
    p_text = "Precision score   :   "
```

```
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = precision_score(y_train, y_pred4_train)
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    test_prec.append(p_ans)
    p_text = "ROC AUC score     :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = roc_auc_score(y_train, model4.predict_proba(x_train)[:,1])
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    fpr_t4, tpr_t4, thresholds_t4 = roc_curve(y_train, y_pred4_train)
    p_text = "AUC score         :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = auc(fpr_t4, tpr_t4)
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans) # Calculate the confusion matrix
    conf_matrix = confusion_matrix(y_test, y_pred4) # Print Confusion Matrix
    p_text = "\nConfusion Matrix :\n"
    prin_text = colored(p_text, 'cyan', attrs=['bold', 'blink'])
    print(prin_text) # Display Confusion Matrix
    disp = ConfusionMatrixDisplay(conf_matrix, display_labels=model4.classes_)
    disp.plot(cmap='Blues', values_format='d') # Show the plot
    plt.show() # Save the model
    filename = '/content/drive/MyDrive/Colab Notebooks/adaboost_model.pkl'
    with open(filename, 'wb') as file:
        pickle.dump(model4, file)
    p_text = "\nROC Curve :\n"  # plotting ROC curve graph
    prin_text = colored(p_text, 'cyan', attrs=['bold', 'blink'])
    print(prin_text)  # Calculate ROC curve
    fpr_t4, tpr_t4, thresholds_t4 = roc_curve(y_train, y_pred4_train) # Plot ROC
curve
    plt.plot(fpr_t4, tpr_t4)
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.rcParams['font.size'] = 12
    plt.title('ROC curve for AdaBoost Classifier')
    plt.xlabel('False Positive Rate (1 - Specificity)')
    plt.ylabel('True Positive Rate (Sensitivity)')
    plt.grid(True)
    plt.show()
    o_banner = "\n------------END------------\n"
    o_banner_text = colored(o_banner, 'white', attrs=['bold', 'blink'])
    print(o_banner_text)
  def Multinomial_NaiveBayes(self,x_train,x_test,y_train,y_test):  #function for
naive bayes
    from sklearn.naive_bayes import MultinomialNB
    model5 = MultinomialNB()
    model5.fit(x_train,y_train)
    y_pred5 = model5.predict(x_test)
    p_text = "\n\n\n****  Multinomial Naive Bayes  ****"
```

```
prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
print(prin_text)
p_text = "\nTraining :\n"
prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
print(prin_text)
p_text = "Accuracy score    :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = accuracy_score(y_test, y_pred5)*100
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
train_acc.append(p_ans)
p_text = "Precision score   :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = precision_score(y_test, y_pred5)
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
train_prec.append(p_ans)
p_text = "ROC AUC score     :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = roc_auc_score(y_test, model5.predict_proba(x_test)[:,1])
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
fpr5, tpr5, thresholds5 = roc_curve(y_test, y_pred5)
p_text = "AUC score         :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = auc(fpr5, tpr5)
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
o_banner = "\n*********************************************\n"
o_banner_text = colored(o_banner, 'white', attrs=['bold','blink'])
print(o_banner_text)
y_pred5_train = model5.predict(x_train)
p_text = "\nTesting :\n"
prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
print(prin_text)
p_text = "Accuracy score    :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = accuracy_score(y_train, y_pred5_train)*100
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
test_acc.append(p_ans)
p_text = "Precision score   :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = precision_score(y_train, y_pred5_train)
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
test_prec.append(p_ans)
p_text = "ROC AUC score     :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = roc_auc_score(y_train, model5.predict_proba(x_train)[:,1])
```

```
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    fpr_t5, tpr_t5, thresholds_t5 = roc_curve(y_train, y_pred5_train)
    p_text = "AUC score         :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = auc(fpr_t5, tpr_t5)
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
    print(prin_text,prin_ans) # Calculate the confusion matrix
    conf_matrix = confusion_matrix(y_test, y_pred5) # Print Confusion Matrix
    p_text = "\nConfusion Matrix :\n"
    prin_text = colored(p_text, 'cyan', attrs=['bold', 'blink'])
    print(prin_text) # Display Confusion Matrix
    disp = ConfusionMatrixDisplay(conf_matrix, display_labels=model5.classes_)
    disp.plot(cmap='Blues', values_format='d') # Show the plot
    plt.show() # Save the model
    filename = '/content/drive/MyDrive/Colab Notebooks/multinomial_nb_model.pkl'
    with open(filename, 'wb') as file:
        pickle.dump(model5, file)
    p_text = "\nROC Curve :\n"  # plotting ROC curve graph
    prin_text = colored(p_text, 'cyan', attrs=['bold', 'blink'])
    print(prin_text)  # Calculate ROC curve
    fpr_t5, tpr_t5, thresholds_t5 = roc_curve(y_train, y_pred5_train) # Plot ROC
curve
    plt.plot(fpr_t5, tpr_t5)
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.rcParams['font.size'] = 12
    plt.title('ROC curve for Multinomial Naive Bayes')
    plt.xlabel('False Positive Rate (1 - Specificity)')
    plt.ylabel('True Positive Rate (Sensitivity)')
    plt.grid(True)
    plt.show()
    o_banner = "\n------------END------------\n"
    o_banner_text = colored(o_banner, 'white', attrs=['bold', 'blink'])
    print(o_banner_text)
  def KNN_Classifier(self,x_train,x_test,y_train,y_test):  #function for KNN model
    from sklearn.neighbors import KNeighborsClassifier
    model6 = KNeighborsClassifier()
    model6.fit(x_train,y_train)
    y_pred6 = model6.predict(x_test)
    p_text = "\n\n\n****  KNN Classifier  ****"
    prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
    print(prin_text)
    p_text = "\nTraining :\n"
    prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
    print(prin_text)
    p_text = "Accuracy score    :   "
    prin_text = colored(p_text, 'green', attrs=['bold','blink'])
    p_ans = accuracy_score(y_test, y_pred6)*100
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
```

```
print(prin_text,prin_ans)
train_acc.append(p_ans)
p_text = "Precision score   :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = precision_score(y_test, y_pred6)
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
train_prec.append(p_ans)
p_text = "ROC AUC score     :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = roc_auc_score(y_test, model6.predict_proba(x_test)[:,1])
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
fpr6, tpr6, thresholds6 = roc_curve(y_test, y_pred6)
p_text = "AUC score         :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = auc(fpr6, tpr6)
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
o_banner = "\n*********************************************\n"
o_banner_text = colored(o_banner, 'white', attrs=['bold','blink'])
print(o_banner_text)
p_text = "\nTesting :\n"
prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
print(prin_text)
y_pred6_train = model6.predict(x_train)
p_text = "Accuracy score    :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = accuracy_score(y_train, y_pred6_train)*100
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
test_acc.append(p_ans)
p_text = "Precision score   :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = precision_score(y_train, y_pred6_train)
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
test_prec.append(p_ans)
p_text = "ROC AUC score     :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = roc_auc_score(y_train, model6.predict_proba(x_train)[:,1])
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans)
fpr_t6, tpr_t6, thresholds_t6 = roc_curve(y_train, y_pred6_train)
p_text = "AUC score         :   "
prin_text = colored(p_text, 'green', attrs=['bold','blink'])
p_ans = auc(fpr_t6, tpr_t6)
prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
print(prin_text,prin_ans) # Calculate the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred6)  # Print Confusion Matrix
```

```
    p_text = "\nConfusion Matrix :\n"
    prin_text = colored(p_text, 'cyan', attrs=['bold', 'blink'])
    print(prin_text) # Display Confusion Matrix
    disp = ConfusionMatrixDisplay(conf_matrix, display_labels=model6.classes_)
    disp.plot(cmap='Blues', values_format='d') # Show the plot
    plt.show()  # Save the model
    filename = '/content/drive/MyDrive/Colab Notebooks/knn_model.pkl'
    with open(filename, 'wb') as file:
        pickle.dump(model6, file)
    p_text = "\nROC Curve :\n"  # plotting ROC curve graph
    prin_text = colored(p_text, 'cyan', attrs=['bold', 'blink'])
    print(prin_text) # Calculate ROC curve
    fpr_t6, tpr_t6, thresholds_t6 = roc_curve(y_train, y_pred6_train) # Plot ROC
curve
    plt.plot(fpr_t6, tpr_t6)
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.rcParams['font.size'] = 12
    plt.title('ROC curve for KNN classifier')
    plt.xlabel('False Positive Rate (1 - Specificity)')
    plt.ylabel('True Positive Rate (Sensitivity)')
    plt.grid(True)
    plt.show()
    o_banner = "\n------------END------------\n"
    o_banner_text = colored(o_banner, 'white', attrs=['bold', 'blink'])
    print(o_banner_text)
  def evaluateAPK(self):  #model evaluation function
    content=input("Enter path to the apk file:")   #inputttting location of apk file from
user #spinner = Halo(text='', spinner='moon',interval=100) #spinner.start()
    a,d,dx=AnalyzeAPK(content)
    filename=a.get_package()  #get package name of apk
inp=pd.read_csv("/content/drive/MyDrive/finalproject/finalproject/Feature_selection.
csv")  #loads a empty dataset
    df5=pd.DataFrame(inp)  #loading csv to dtataframe
   # df5=df5.drop(df5.iloc[:,0:15],axis=1) #selelcting the needed colmns from
dataset
    df5=df5.drop(df5.iloc[:,-3:],axis=1)
    #df5=df5.rename(columns={'rating_count': 'rating_number'}) #changing the
name of dataset to make it same as original dataset
    df5=df5.append(pd.Series(int(0), index=df5.columns), ignore_index=True)
#adding a new row with all cells are 0
    perm=a.get_permissions() #androguard function for getting permission
    for item in df5.columns:  #comparing the list of permissions with column name
and if same change the value in cell as 1 and break. if not same set it back as 0
      for i in perm:
        if i==item:
          df5.at[0,item]=1
          break
        else:
          df5.at[0,item]=0
```

```
    df5.insert(len(df5.columns), 'LABEL','0')
    #df5.at[0,'rating_number']=float('4')
    flag=0
    for item in df5.columns:   #to know howmany vaild features ar added
      if df5.at[0,item]==1:
        flag+=1
    p_text = '\n'+str(flag)+' features are added\n'
    prin_text = colored(p_text, 'blue', attrs=['bold','blink'])
    print(prin_text)
    df5.to_csv('/content/drive/MyDrive/Colab Notebooks/extractor.csv',index=False)
#saving the updataed data to csv
    import joblib
    list3=['rf']
    for item in list3:        #running all the model from saved model files using pickle
module and predicting whether it malware or not
      list2='/content/drive/MyDrive/Colab Notebooks'+str(item)+'.sav'
      #Loading the saved model with joblib
      pipe = joblib.load(list2)  # New data to predict
      pr = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/extractor.csv')
      #pred_cols = list(pr.columns.values)[:-1]
      df2=pd.DataFrame(pr)
      pre=df2.iloc[:, :-1]
      Pre  # apply the whole pipeline to data
      pred21 =pipe.predict(pre)
      """if pred21==1:
        p_text = 'According to '+item+' this application tend to be : Malware'
        prin_text = colored(p_text, 'red', attrs=['bold','blink'])
        print(prin_text)
      elif pred21==0:
        p_text = 'According to '+item+' this application tend to be : Benign'
        prin_text = colored(p_text, 'green', attrs=['bold','blink'])
        print(prin_text)"""
    try:#check for  application details available from playstore
        result = app(filename,lang='en',country='us')
        p_text = 'Title             :'
        prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
        p_ans = result['title']
        prin_ans = colored(p_ans, 'green', attrs=['bold','blink'])
        print(prin_text,prin_ans)
        p_text = 'App ID                :'
        prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
        p_ans = result['appId']
        prin_ans = colored(p_ans, 'green', attrs=['bold','blink'])
        print(prin_text,prin_ans)
        p_text = 'Avg Rating            :'
        prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
        p_ans = str(result['score'])
        prin_ans = colored(p_ans, 'green', attrs=['bold','blink'])
        print(prin_text,prin_ans)
        p_text = 'Developer         :'
```

```
    prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
    p_ans = result['developer']
    prin_ans = colored(p_ans, 'green', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    p_text = 'Developer Address         :'
    prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
    p_ans = result['developerAddress']
    prin_ans = colored(p_ans, 'green', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    p_text = 'Genre             :'
    prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
    p_ans = result['genre']
    prin_ans = colored(p_ans, 'green', attrs=['bold','blink'])
    print(prin_text,prin_ans)  #print(result)
except Exception:  #if exception occurs this art is run
    p_text = 'Title             :'
    prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
    p_ans = a.get_app_name()
    prin_ans = colored(p_ans, 'green', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    p_text = 'App ID                :'
    prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
    p_ans = a.get_package()
    prin_ans = colored(p_ans, 'green', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    p_text = 'Avg Rating            :'
    prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
    p_ans = 'Not Found'
    prin_ans = colored(p_ans, 'green', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    p_text = 'Developer         :'
    prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
    p_ans = 'Not Found'
    prin_ans = colored(p_ans, 'green', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    p_text = 'Developer Address         :'
    prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
    p_ans = 'Not Found'
    prin_ans = colored(p_ans, 'green', attrs=['bold','blink'])
    print(prin_text,prin_ans)
    p_text = 'Genre             :'
    prin_text = colored(p_text, 'magenta', attrs=['bold','blink'])
    p_ans = 'Not Found'
    prin_ans = colored(p_ans, 'green', attrs=['bold','blink'])
    print(prin_text,prin_ans)
p_text = '\n\nThis application found to be a       : '
prin_text = colored(p_text, 'blue', attrs=['bold','blink'])
if pred21==1:
    p_ans = ' Malware '
    prin_ans = colored(p_ans, 'red', attrs=['bold','blink'])
```

```
        print(prin_text,prin_ans)
        print("\n\n")
#display(IPython.display.Audio("Malware_Project/Audio/en_malware.mp3",autopla
y=True)) #playing audio that this app is maware
    elif pred21==0:
        p_ans = ' Benign '
        prin_ans = colored(p_ans, 'green', attrs=['bold','blink'])
        print(prin_text,prin_ans)
        print("\n\n")
#display(IPython.display.Audio("Malware_Project/Audio/en_benign.mp3",autoplay
=True)) #playing audio that this app is maware #spinner.stop()
  def Observations(self): #for plotting the outputs
    p_text = "\nAccuracy :\n"
    prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
    print(prin_text)
    barWidth = 0.25
    fig = plt.subplots(figsize =(12, 8))
    br1 = np.arange(len(train_acc))
    br2 = [x + barWidth for x in br1]
    plt.bar(br1, train_acc, color ='r', width = barWidth,
            edgecolor ='grey', label ='Train')
    plt.bar(br2, test_acc, color ='g', width = barWidth,
            edgecolor ='grey', label ='Test')
    plt.xlabel('Machine Learning Models', fontweight ='bold', fontsize = 15)
    plt.ylabel('Accuracy', fontweight ='bold', fontsize = 15)
    plt.xticks([r + barWidth for r in range(len(train_acc))],
            ['Logistic Regression', 'SVM', 'Random Forest', 'Adaboost', 'Multinomial NB',
'KNN'])
    plt.legend()
    plt.show() #printing  the accuracy comparison bar graph
    p_text = "\n\n\nPrecision :\n"
    prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
    print(prin_text)
    barWidth = 0.25
    fig = plt.subplots(figsize =(12, 8))
    br3 = np.arange(len(train_prec))
    br4 = [x + barWidth for x in br3]
    plt.bar(br3, train_prec, color ='r', width = barWidth,
            edgecolor ='grey', label ='Train')
    plt.bar(br4, test_prec, color ='g', width = barWidth,
            edgecolor ='grey', label ='Test')
    plt.xlabel('Machine Learning Models', fontweight ='bold', fontsize = 15)
    plt.ylabel('Precision', fontweight ='bold', fontsize = 15)
    plt.xticks([r + barWidth for r in range(len(train_prec))],
            ['Logistic Regression', 'SVM', 'Random Forest', 'Adaboost', 'Multinomial NB',
'KNN'])
    plt.legend()
    plt.show()  #printing prcision comparison bargraph
def main():  #main functionwhich uses the clas w built
  cl = ModelTraining()
```

```
  cl.proj_banner()
  while True:
    try:
      p_text = "\n\n\n1. Train Using Maching Learning Models\n2. Evaluate the
model with new dataset\n3. Observations\n4. Exit\n\n"
      prin_text = colored(p_text, 'blue', attrs=['bold','blink'])
      print(prin_text)
      choice = int(input("Enter your choice :"))
      if choice == 1:
        while True:
          p_text = "\n\n\nSelect the Machine Learning Model you wanted to Train :\n"
          prin_text = colored(p_text, 'cyan', attrs=['bold','blink'])
          print(prin_text)
          p_text = " 1. Logistic Regression Model"
          prin_text = colored(p_text, 'green', attrs=['bold','blink'])
          print(prin_text)
          p_text = " 2. Support Vector Machine Model"
          prin_text = colored(p_text, 'green', attrs=['bold','blink'])
          print(prin_text)
          p_text = " 3. Random Forest Classifier"
          prin_text = colored(p_text, 'green', attrs=['bold','blink'])
          print(prin_text)
          p_text = " 4. Adaboost Classifier"
          prin_text = colored(p_text, 'green', attrs=['bold','blink'])
          print(prin_text)
          p_text = " 5. Multinomial Naive Bayes"
          prin_text = colored(p_text, 'green', attrs=['bold','blink'])
          print(prin_text)
          p_text = " 6. KNN Classifier"
          prin_text = colored(p_text, 'green', attrs=['bold','blink'])
          print(prin_text)
          p_text = " 7. All Models Together"
          prin_text = colored(p_text, 'green', attrs=['bold','blink'])
          print(prin_text)
          p_text = " 8. Go Back\n"
          prin_text = colored(p_text, 'green', attrs=['bold','blink'])
          print(prin_text)
          ch = int(input("Enter your choice :"))
          if ch == 1:
            cl.LogisticRegression_Model(x_train, x_test, y_train, y_test)
          elif ch == 2:
            cl.SVM_Model(x_train, x_test, y_train, y_test)
          elif ch == 3:
            cl.RandomForest_Classifier(x_train, x_test, y_train, y_test)
          elif ch == 4:
            cl.AdaBoost_Classifier(x_train, x_test, y_train, y_test)
          elif ch == 5:
            cl.Multinomial_NaiveBayes(x_train, x_test, y_train, y_test)
          elif ch == 6:
            cl.KNN_Classifier(x_train, x_test, y_train, y_test)
```

```
            elif ch == 7:
              cl.LogisticRegression_Model(x_train, x_test, y_train, y_test)
              cl.SVM_Model(x_train, x_test, y_train, y_test)
              cl.RandomForest_Classifier(x_train, x_test, y_train, y_test)
              cl.AdaBoost_Classifier(x_train, x_test, y_train, y_test)
              cl.Multinomial_NaiveBayes(x_train, x_test, y_train, y_test)
              cl.KNN_Classifier(x_train, x_test, y_train, y_test)
            else:
              p_text = "\nGoing Back To Main Menu!\n"
              prin_text = colored(p_text, 'red', attrs=['bold','blink'])
              print(prin_text)
              break
        elif choice == 2:
          cl.evaluateAPK()
        elif choice == 3:
          cl.Observations()
        else:
          p_text = "\nExiting....Thank you for using!\n"
          prin_text = colored(p_text, 'red', attrs=['bold','blink'])
          print(prin_text)
          break
      except Exception as e:
        print(e)
if __name__ == "__main__":
  main() #running the CLI
```

B. SCREEN SHOTS

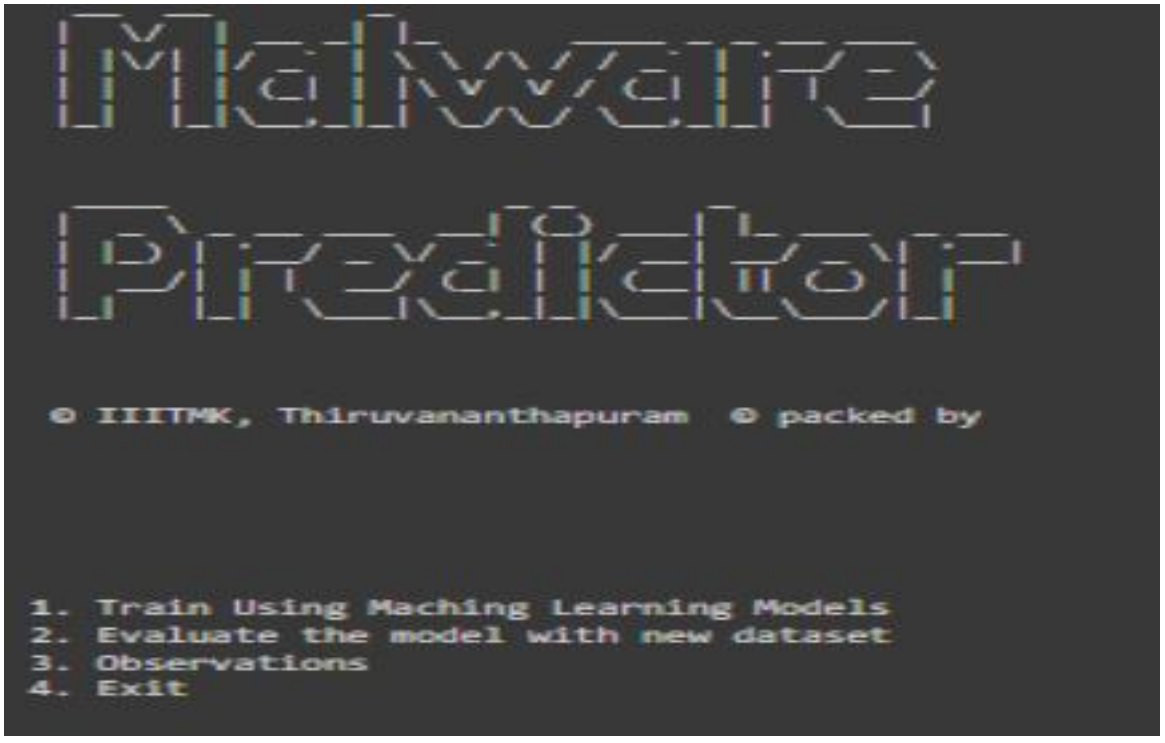


Fig No. B.1 Malware Predictor

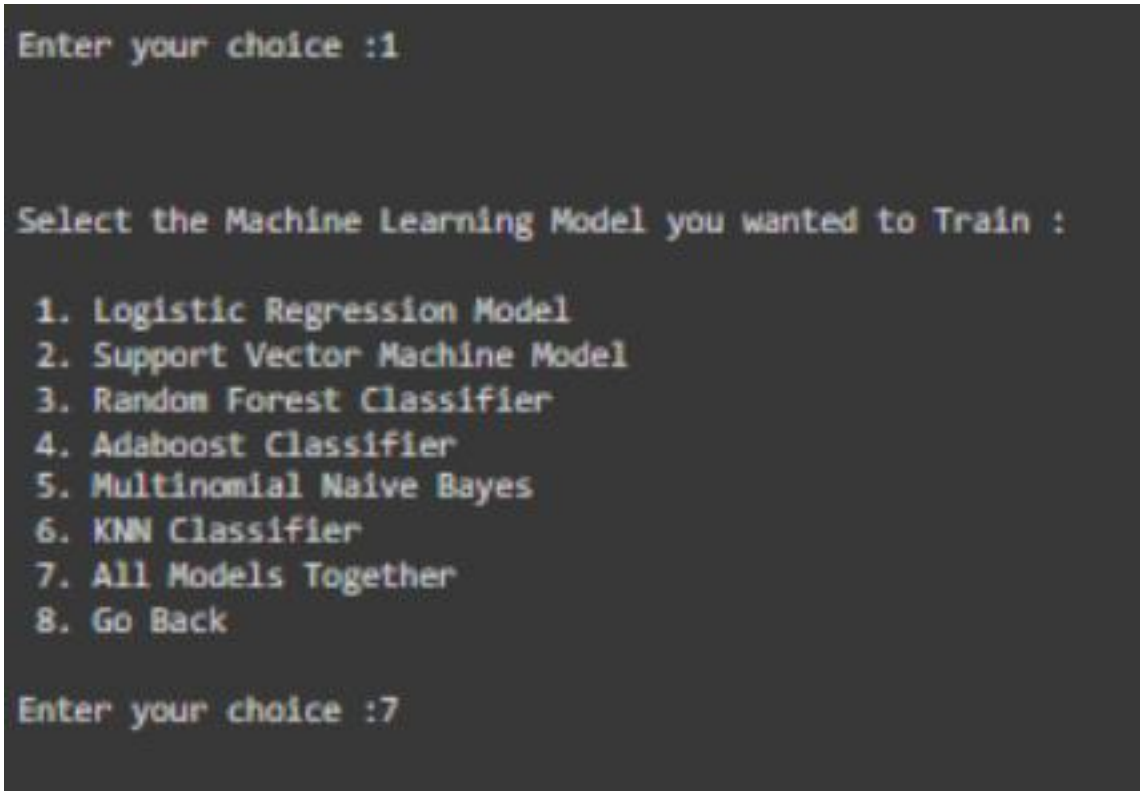


Fig No. B.2 List Of Learning Models

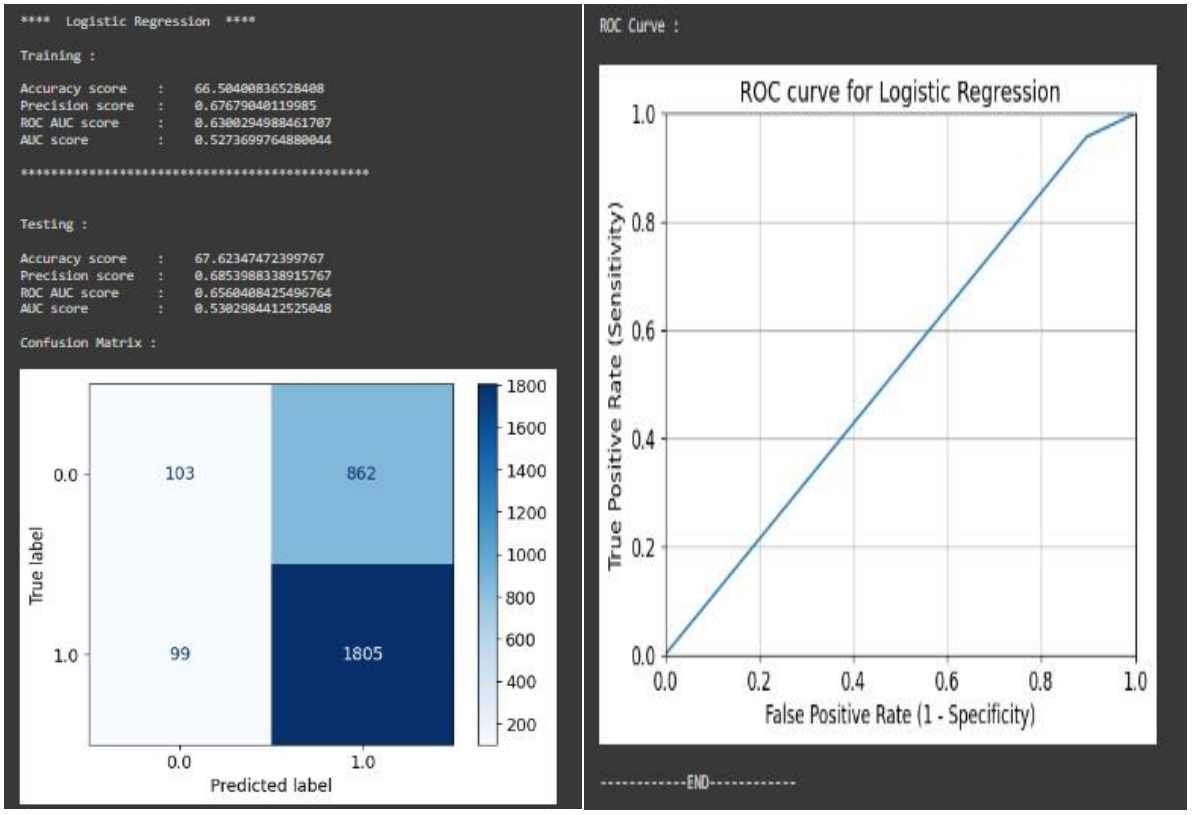


Fig No. B.3 Logistic Regression Model

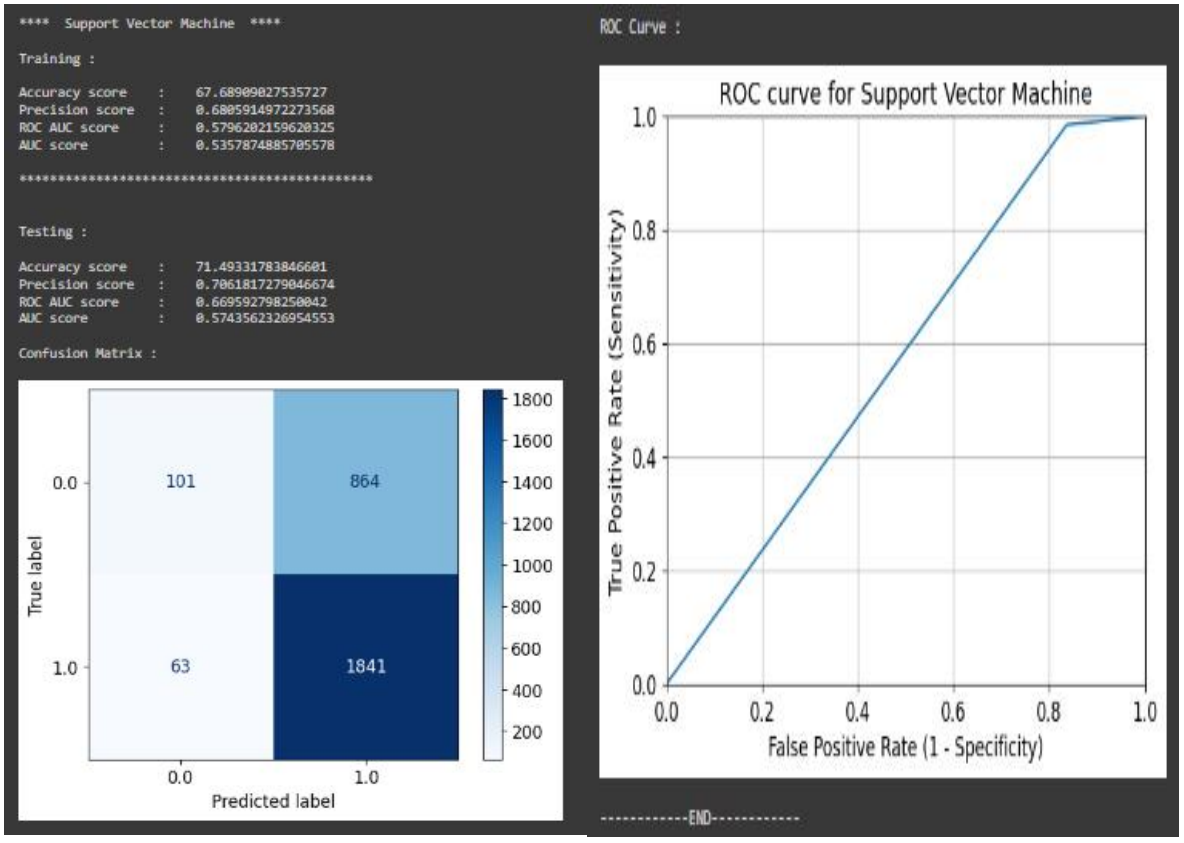


Fig No. B.4 Support Vector Machine Model

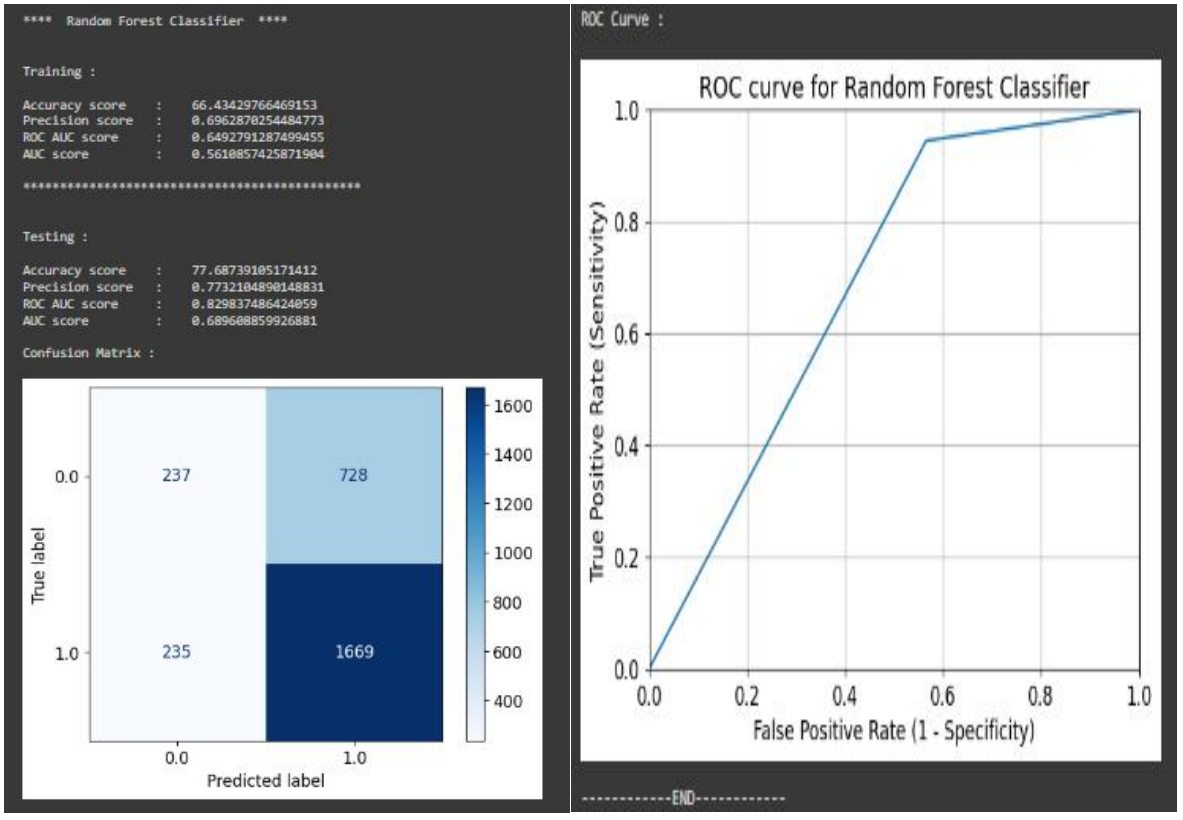


Fig No. B.5 Random Forest Classifier

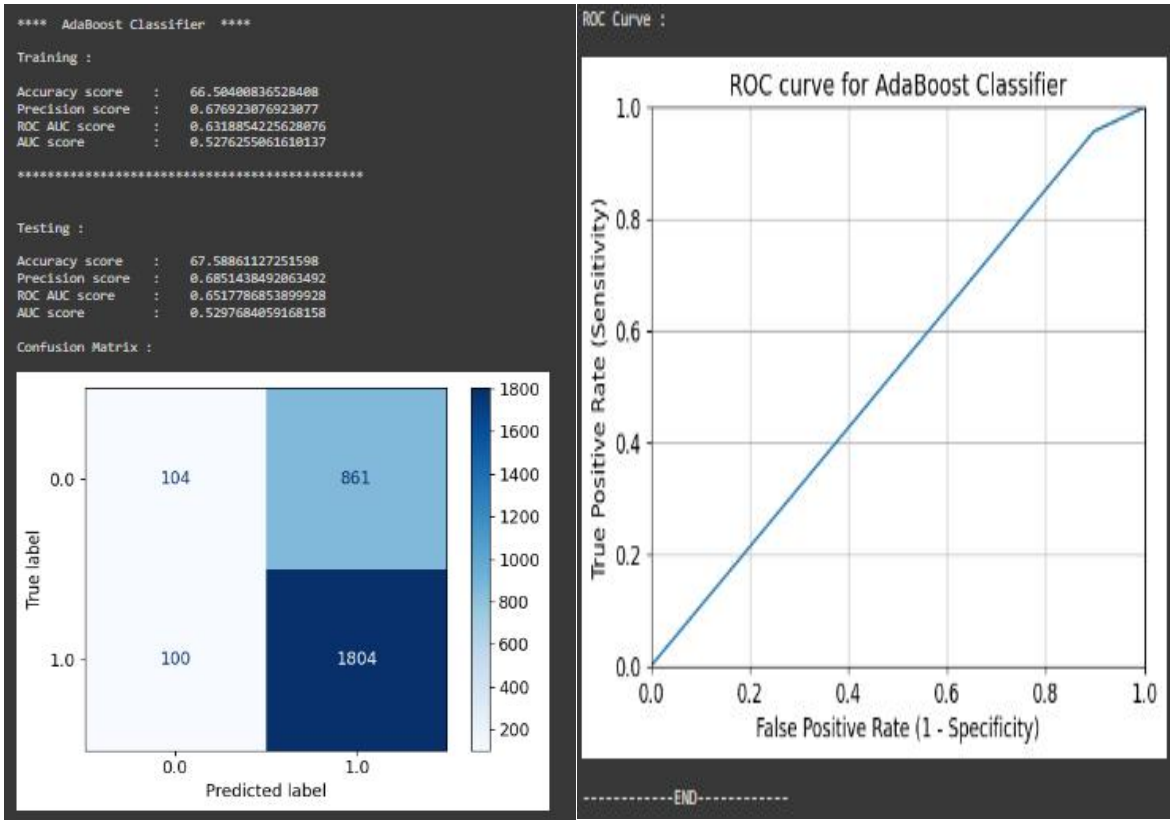


Fig No. B.6 Adaboost Classifier

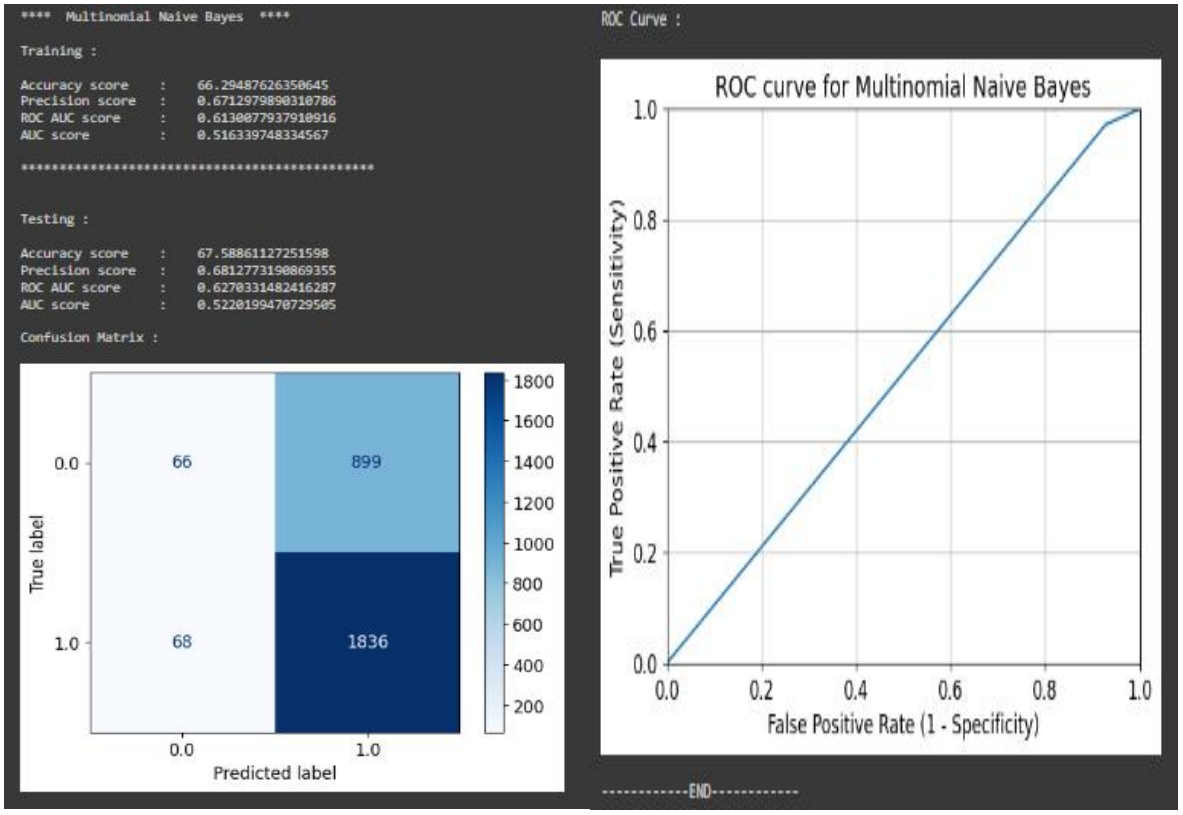


Fig No. B.7 Multinomial Naive Bayes

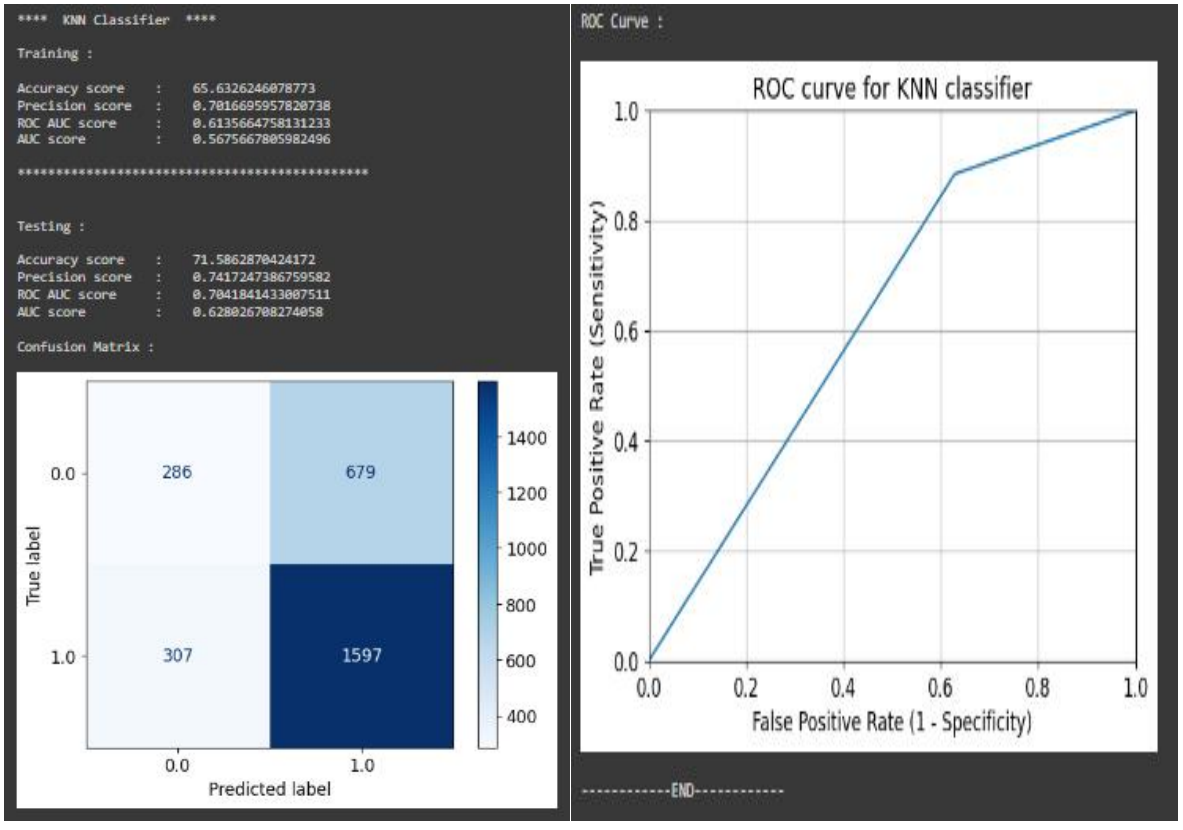


Fig No. B.8 KNN Classifier

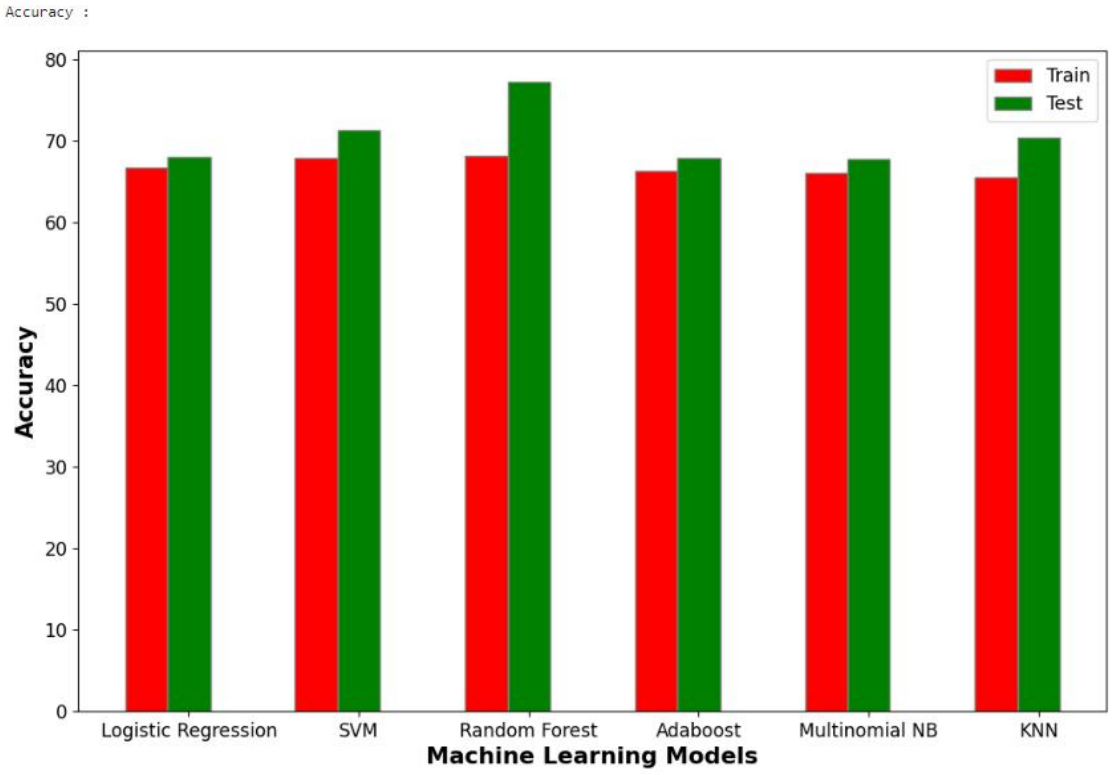


Fig No. B.9 Accuracy Bar Graph

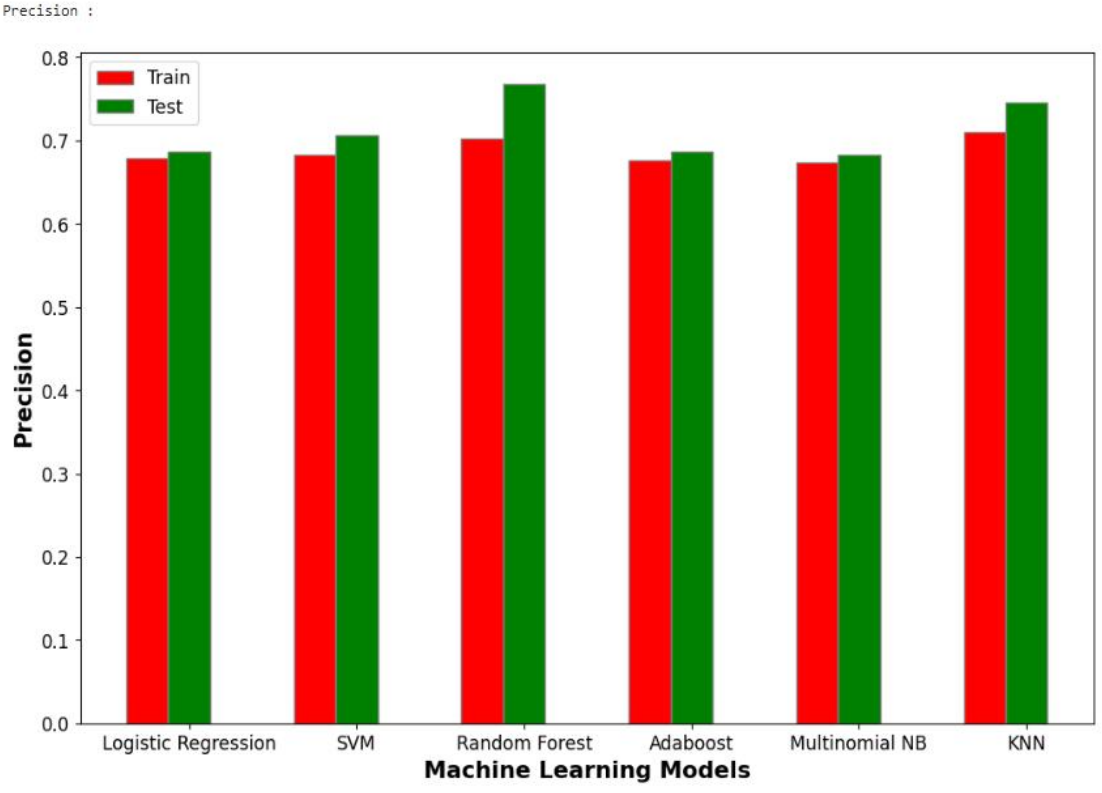


Fig No. B.10 Precision Bar Graph

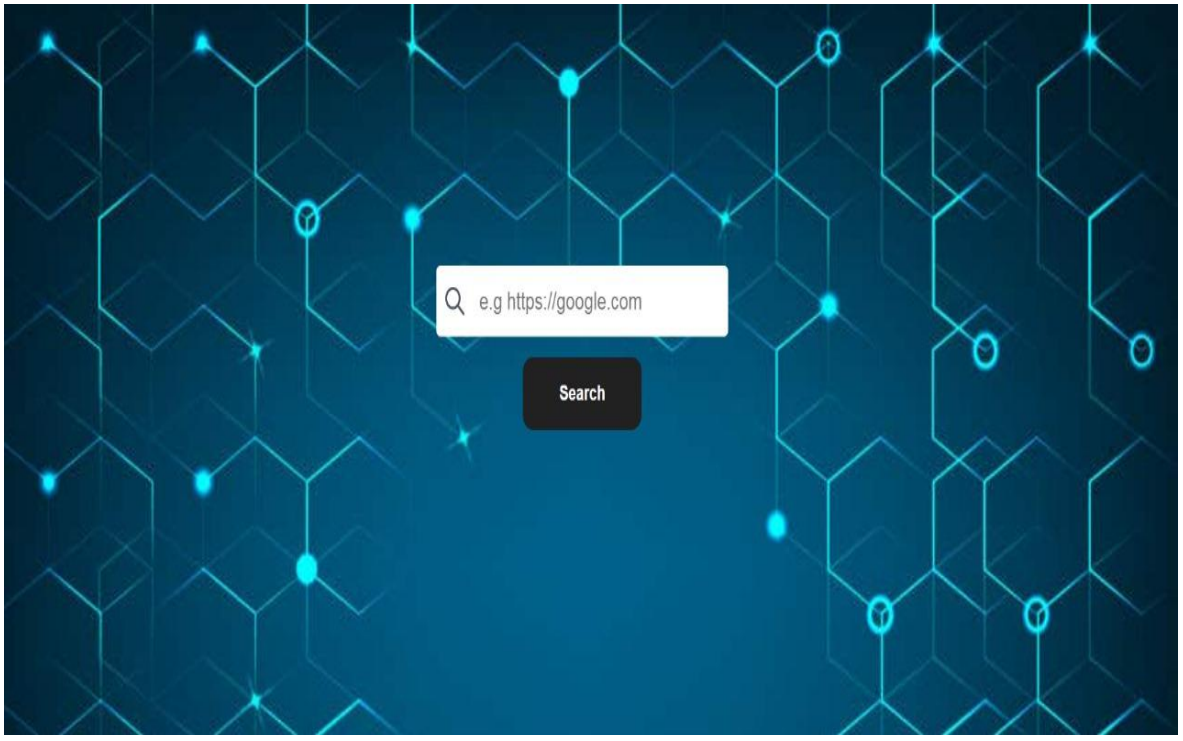


Fig No. B.11 Home Page

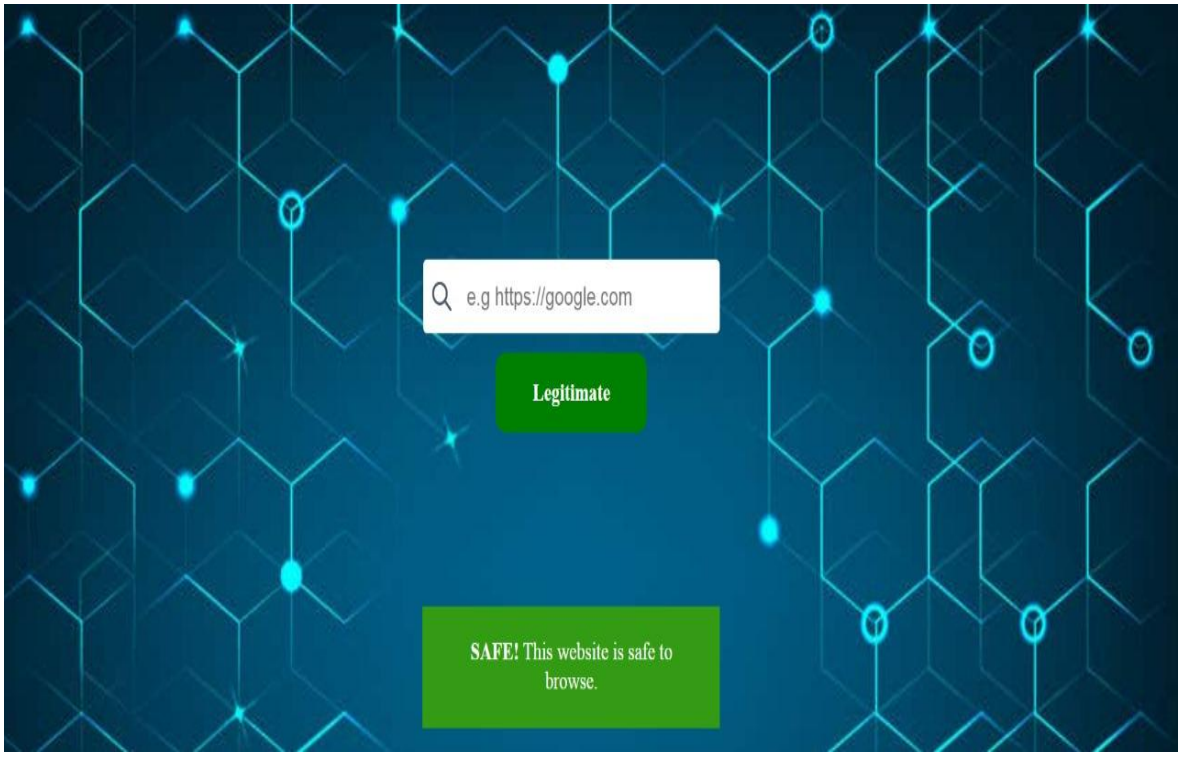


Fig No. B.12 Safe Url

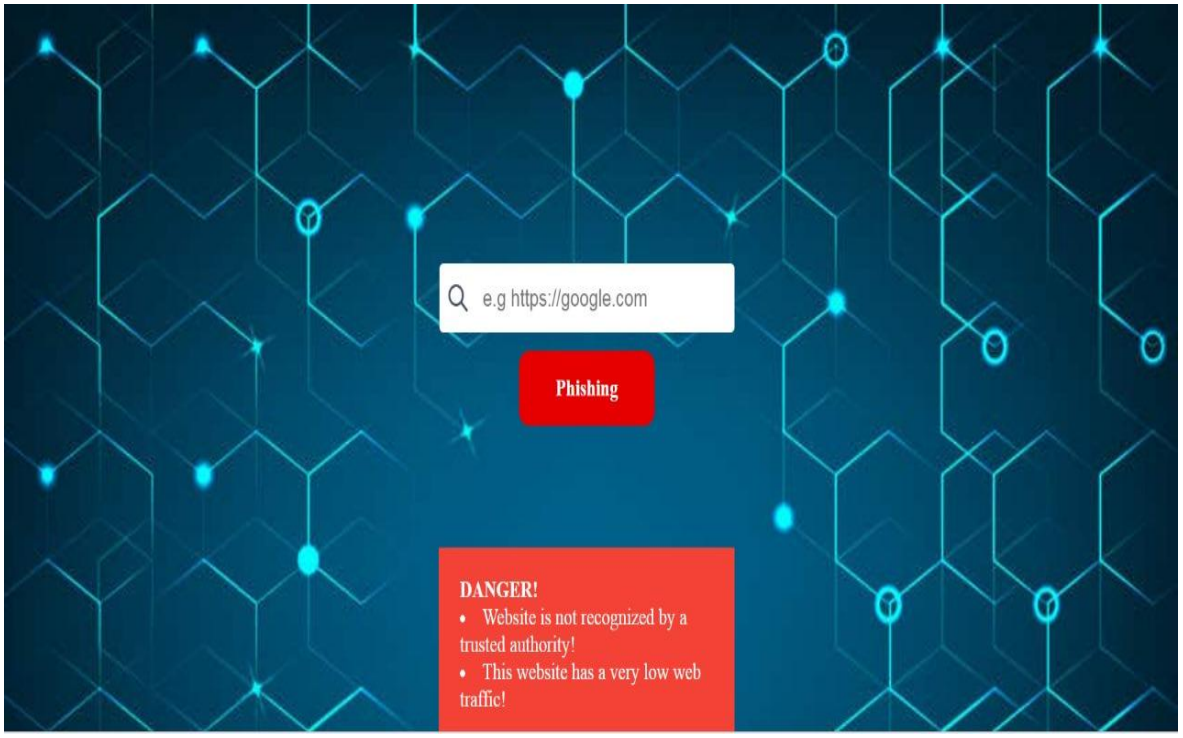


Fig No. B.13 Malware Url

C.RESEARCH PAPER

Android malware detection using ML

K. GEETHA MADHAV, STUDENT/CSE
SATHYABAMA UNIVERSITY
Chennai, India
geethamadhav92@gmail.com

G. SAMITHA, STUDENT/CSE
SATHYABAMA UNIVERSITY
Chennai, India
samithareddy27@gmail.com

MANJU C NAIR M.E (Ph.D)
SATHYABAMA UNIVERSITY
Chennai, India
manjunair.cse@sathyabama.ac.in

ABSTRACT

Mobile gadgets have become ubiquitous in this age of lightning-fast technical development. On the other hand, malware has become a much bigger concern as Android has become more prevalent. The ever-changing nature of Android malware makes it imperative to investigate alternative techniques of detection, since traditional ones frequently fail to keep pace. A method for detecting Android malware using machine learning (ML) is suggested in this research. The suggested method improves mobile user security by efficiently identifying and classifying Android malware using ML techniques. A number of features are used by the system to get useful information from Android apps, including permission requests, API calls, and system calls. Decision trees, support vector machines (SVMs), neural networks, and other ML techniques are given these characteristics in order to train and construct strong models that can distinguish between safe and dangerous applications. The suggested approach has shown encouraging results in experimental assessment, with high detection rates of Android malware. In addition, ML models can adjust and acquire knowledge from fresh malware samples, guaranteeing ongoing defense against new dangers. As a whole, this study demonstrates how ML may improve Android malware detection, which is a great step toward meeting the difficulties of mobile security head-on.

Adaptation, accuracy, decision trees, support vector machines, neural networks, mobile security, permission requests, features, machine learning, detection, and Android malware are some of the keywords.

I. INTRODUCTION

To safeguard Android users from the increasing danger of malicious software, research into Android malware detection by machine learning is an important area of study. Malware attacks have grown in importance due to the proliferation of Android smartphones and mobile applications. The detection of new and emerging malware variants is a challenge for traditional antivirus systems that rely on signatures. Consequently, machine learning methods have shown great promise in the fight against Android malware.

Machine learning algorithms can sift through mountains of data in search of anomalies and patterns that can tell good applications from bad ones. Permissions, system calls, API calls, and other contextual factors are some of the elements that these models consume from the applications. A huge dataset of known malicious and benign applications is used to train the algorithms so that they can properly categorize new and undiscovered apps.

In order to make sure that the machine learning models work well for Android malware detection, feature selection is crucial. Researchers often use a variety of feature extraction methods to get useful data from the applications. Methods like static and dynamic analysis, as well as hybrid methods, may be part of these strategies. To

get the most out of both static and dynamic analysis, hybrid methods combine their best features.

Android malware detection has made use of a number of machine learning methods, including decision trees, support vector machines, random forests, and deep learning models such as convolutional neural networks (CNNs). When compared side by side, the accuracy, efficiency, and scalability of each method is different. To improve performance in terms of recall, general accuracy, and precision, researchers are always looking for new methods and improving old ones.

There are a number of advantages to using machine learning for Android virus detection. Machine learning models may generalize from known malware samples to identify new and undiscovered types of malware, providing a proactive protection mechanism against zero-day assaults. Second, it provides a system that can scale to accommodate the vast amount of Android applications. Machine learning models may also adjust to new malware methods and learn from samples all the time to become better at detecting them.

Machine learning for Android malware detection has its benefits, but it also has its share of problems. Malware that can dynamically alter its code structure to dodge analysis is one example of an evasion strategy that attackers might use to avoid discovery. Model performance may also be affected by unbalanced datasets and high-dimensional feature fields. In order to overcome these obstacles and increase detection accuracy, researchers are hard at work creating robust approaches.

Finally, safeguarding Android users from the growing danger of malicious software has never been easier than with Android malware detection utilizing machine learning. We can make the mobile ecosystem safer for consumers by improving the accuracy and efficiency of identifying Android malware via the ongoing development and improvement of machine learning models and smart feature selection approaches.

II. LITERATURE SURVEY

[1] The study by Doberstein, Charbonneau, Morin, and Despatie (2022) explores the acceptability of facial recognition-enabled work surveillance cameras in the public and private sector. The authors examine the potential benefits and drawbacks of using facial recognition technology for monitoring employees' activities in the workplace. They discuss issues related to privacy, trust, and concerns about the misuse of facial recognition data.

[2] Selwyn, Campbell, and Andrejevic (2023) investigate the emergence of classroom facial recognition technology. They discuss the implications of using automated facial recognition systems in educational settings and analyze the potential benefits and risks for students and teachers. The authors highlight issues such as surveillance, the automation of decision-making processes, and the implications for privacy and autonomy.

[3] Hsu, Tu, and Chiu (2022) present a proposal for an e-diploma system based on consortium blockchain and facial recognition technology. They discuss the potential advantages of using these technologies for verifying the authenticity of diplomas and certificates, ensuring the security and integrity of educational credentials.

[4] Parhi, Roul, Ghosh, and Pati (2022) propose an intelligent online attendance tracking system based on facial recognition and edge computing. They describe a system that can automatically detect and track students' attendance using facial recognition technology. The authors discuss the potential benefits of such a system, including improved accuracy, efficiency, and convenience.

[5] Urquhart and Miranda (2022) analyze the present and future of intelligent facial surveillance in the context of policing. They discuss the challenges and implications of using facial recognition technology for law enforcement purposes, including issues related to bias, privacy, and civil liberties.

[6] Gupta, Modgil, Lee, and Sivarajah (2023) examine the use of AI-driven facial recognition technology to enhance value in the travel and tourism industry. The authors discuss how facial recognition can be used to improve customer experiences, streamline processes, and enhance security in various travel-related applications.

[7] Karpagam, Jeyavathana, Chinnappan, Kanimozhi, and Sambath (2023) propose a novel face recognition model for fighting against human trafficking in surveillance videos and rescuing victims. They present a system that can automatically identify and track individuals involved in human trafficking activities using facial recognition technology.

[8] McElroy and Vergerio (2022) explore the impact of landlord technologies and housing justice organizing in the context of gentrification in New York City homes. The authors discuss how automated technologies, including facial recognition, are being used by landlords to monitor tenants and increase rents, leading to concerns about housing rights and social justice.

[9] Zhang, Zhang, and Dolah (2022) present an intelligent classroom teaching assessment system based on deep learning model face recognition technology. They propose a system that can automatically assess student engagement and understanding in real-time using facial recognition technology, aiming to enhance the effectiveness of classroom teaching.

[10] Revathy, Raj, Kumar, Adibatti, Dahiya, and Latha (2022) investigate the use of face recognition using convolutional neural network (CNN) for an e-voting system. They propose a system that can verify the identity of voters using facial recognition technology, aiming to improve the security and integrity of electronic voting processes.

These literature surveys provide insights into various aspects of facial recognition technology, including its applications in surveillance, education, certification, tourism, law enforcement, housing, and voting systems. The studies highlight both the potential benefits and challenges associated with the widespread adoption of facial recognition technology in different domains.

III. EXISTING SYSTEM

There are certain issues with the current machine learning (ML) method that detects malware on Android devices. To begin, using just labeled training datasets is a big limitation. In order to train and learn, ML algorithms need massive amounts of data. For Android malware detection, this entails amassing a large collection of tagged samples, which should include both malicious and safe apps. The dearth of publicly accessible and well annotated datasets, however, makes it difficult to

acquire such datasets. Since the model can't generalize and identify malware samples that haven't been seen before, this constraint reduces ML's efficacy in identifying new and emerging malware threats.

The second issue is that ML-based detection systems have a tough time overcoming the obfuscation tactics used by malware writers. Malware developers are always thinking of new ways to avoid detection, and obfuscating code is a typical method. Malware may change its look and make it harder for ML algorithms to identify it as harmful by using code obfuscation methods like encryption or code mutation. Consequently, ML-based detection systems could produce false positives and negatives due to their inability to keep up with the constantly changing nature of malware.

An further issue with the current setup is the possibility of hostile assaults. To cause ML models to incorrectly categorize incoming data, adversarial assaults deliberately disturb or alter the data. By manipulating malware samples to make them seem harmless, attackers might evade the ML-based detection system in the context of Android malware detection. End users might be at risk of undetected malware infections due to this vulnerability, which is a major hazard.

Finally, machine learning (ML) malware detection systems might demand a lot of computing power. Deploying such systems on resource-constrained devices, such as smartphones, may be challenging because to the high computational and memory requirements of training and executing ML models. Another way that ML-based detection systems might affect the user experience is by slowing down application scanning and classification, which can be annoying for users.

Finally, the current system has its limits, but ML shows promise for Android malware detection. There are many obstacles to overcome, such as the need for labelled training datasets, difficulty in handling obfuscation methods, susceptibility to adversarial assaults, and the necessary computing resources. Improving the efficacy and usability of ML-based malware detection systems requires resolving these drawbacks.

IV. PROPOSED SYSTEM

Creating a method for identifying Android malware using machine learning is the objective of the proposed effort. One of the main goals is to use machine learning techniques to detect harmful applications and strengthen Android security against more complex malware. For this study, we need to gather a massive dataset of Android apps, both good and bad, from all sorts of categories and versions. To gather useful information about the applications, such as their permissions, API calls, system calls, and resource files, we will use feature extraction methods. Using methods like as grid search and cross-validation, the chosen algorithm will be trained on the dataset. We will investigate ensemble learning techniques, which combine several classifiers to get more accurate predictions, in an effort to improve the accuracy even more. In addition, the planned effort makes use of both static and dynamic analytic methods to glean more information and capabilities from the applications. While static analysis focuses on the app's assets, manifest files, and source code, dynamic analysis runs the app in a simulated environment to observe its behavior and collect runtime statistics. Malware detection accuracy will be enhanced by combining static and dynamic analysis, which will provide a more complete picture of the app's activities.we will compare it to current

malware detection techniques, such as heuristic-based and signature-based systems. To evaluate how well the strategy works, we will test performance indicators including recall, accuracy, and F1 score. Researchers hope that at the end of the project, Android users will have access to better security features and a model for detecting malware that is based on machine learning. Security companies, app shops, and mobile device makers may use this research's findings to proactively safeguard Android users from new malware risks.

V. SYSTEM ARCHITECTURE

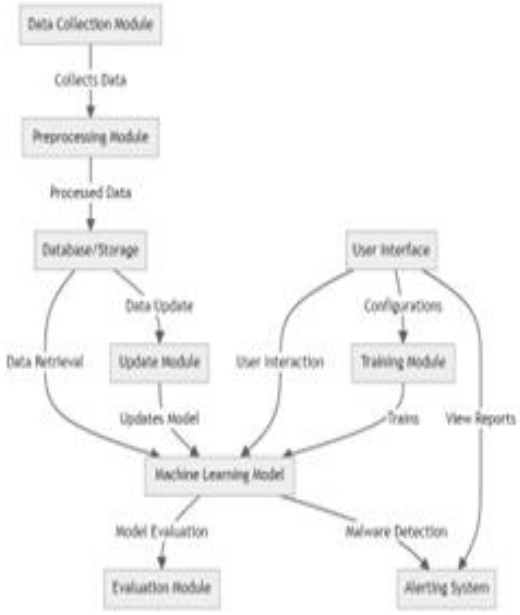


Fig. 1. System Architecture

VI. METHODOLOGY

1. Module 1: Data Collection and Preparation

In this module, the proposed system for Android malware detection using machine learning begins by collecting a diverse dataset of Android applications. This dataset will consist of both benign and malicious applications, with an emphasis on representing different malware families and variants. The data collection process involves gathering applications from various sources such as app stores, third-party markets, and security research repositories. The collected applications then undergo a preprocessing step to extract relevant features that will be used for classification. These features may include permissions, API calls, system calls, network traffic, and behavior analysis. The collected data is subsequently transformed into a suitable format to be fed into the machine learning model.

2. Module 2: Machine Learning Model Training

Once the dataset has been collected and prepared, the next module focuses on building a machine learning model for Android malware detection. Various machine learning algorithms can be employed, such as decision trees, random forests, support vector machines, or deep learning techniques like neural networks. The dataset is divided into training and testing sets, with the former used to train the model and the latter used to evaluate its performance. During the training phase, the model learns patterns and characteristics that distinguish between benign and malicious applications. This involves feature selection, feature engineering, and model optimization to improve the accuracy and efficiency of the detection system. The training process may also involve techniques like oversampling or undersampling to address class imbalance issues in the dataset.

3. Module 3: Real-Time Malware Detection and Classification

The final module focuses on implementing the trained machine learning model into a real-time Android malware detection system. This module involves integrating the developed model into an application or a service that can scan and classify incoming Android applications in real-time. When a new application is submitted for analysis, its features are extracted and fed into the

machine learning model, which then predicts whether the application is benign or malicious. To ensure timely detection and classification, the system should be designed to operate efficiently on mobile devices with limited resources. Continuous updates and retraining of the model are necessary to keep up with emerging malware threats and evolving trends in Android security. Additionally, integrating the system with cloud-based technologies allows for scalability and centralized management of the detection process.

VII. RESULT AND DISCUSSION

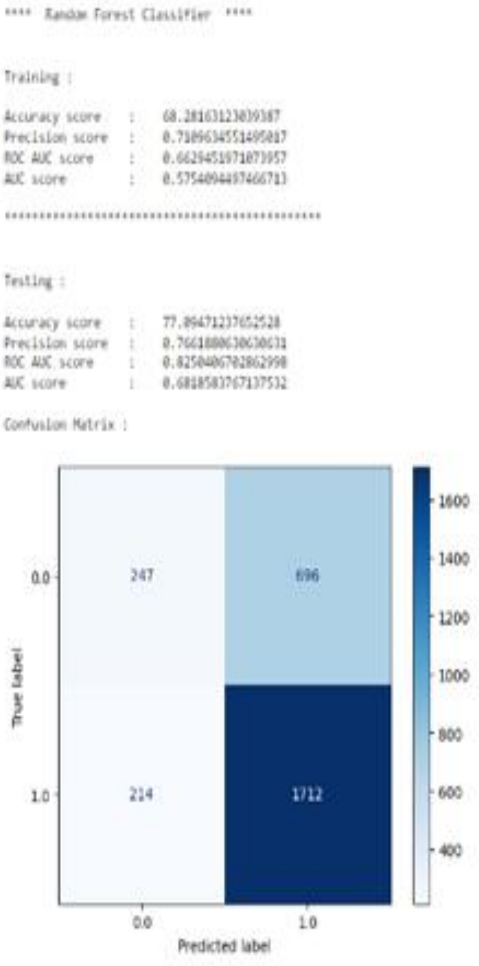
The system for Android malware detection using machine learning (ML) is designed to effectively identify and classify malicious applications targeting Android devices. Leveraging the power of ML algorithms, this system analyzes various features of a mobile application, such as its code structure, permissions, and behavior, to determine whether it exhibits malicious intent. By training ML models on large datasets of known malware samples, the system can learn to recognize patterns and distinguish between benign and malicious applications.

Firstly, it employs supervised learning to classify applications based on labeled samples. These samples are manually labeled by security experts, indicating whether each application is benign or malicious. Through this process, the ML model can learn from the labeled data and make accurate predictions for new, unseen applications.

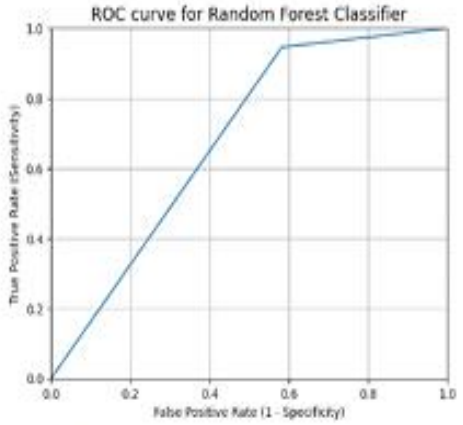
Moreover, the system employs unsupervised learning to discover previously unknown and emerging malware. Unsupervised learning techniques enable the ML model to detect anomalies and identify potentially new forms of malware without relying solely on pre-existing knowledge. This capability is particularly important for staying ahead of cybercriminals who continually develop new and sophisticated attacks.

To enhance the effectiveness of the system, it regularly updates its ML models using up-to-date data from various sources, including reputable security vendors, app stores, and crowdsourcing initiatives. This continuous learning process enables the system to adapt and improve its accuracy in detecting rapidly evolving malware threats.

Overall, this ML-based system for Android malware detection enables efficient and reliable identification of malicious applications, safeguarding Android users from potential security risks and ensuring the security of their devices and data.



ROC Curve :



----------END----------

VIII. CONCLUSION

Last but not least, the ML-based solution for Android malware detection is a great and efficient way. The technology is able to detect and categorize possible malware in Android apps with high accuracy by using ML algorithms. Users are able to safeguard their devices and data against harmful apps using this feature. This system is dependable and flexible enough to keep up with emerging threats since it can learn and adapt to new malware types regularly. In sum, our ML-based approach provides an extensive and powerful answer to the problem of Android malware detection.

REFERENCES

[1] Doberstein, C., Charbonneau, É., Morin, G., & Despatie, S. (2022). Measuring the acceptability of facial recognition-enabled work surveillance cameras in the public and private sector. Public Performance & Management Review, 45(1), 198-227.

[2] Selwyn, N., Campbell, L., & Andrejevic, M. (2023). Autoroll: Scripting the emergence of classroom facial recognition technology. Learning, Media and Technology, 48(1), 166-179.

[3] Hsu, C. S., Tu, S. F., & Chiu, P. C. (2022). Design of an e-diploma system based on consortium blockchain and facial recognition. Education and Information Technologies, 1-25.

[4] Parhi, M., Roul, A., Ghosh, B., & Pati, A. (2022). Ioats: An intelligent online attendance tracking system based on facial recognition and edge computing. International Journal of Intelligent Systems and Applications in Engineering, 10(2), 252-259.

[5] Urquhart, L., & Miranda, D. (2022). Policing faces: the present and future of intelligent facial surveillance. Information & communications technology law, 31(2), 194-219.

[6] Gupta, S., Modgil, S., Lee, C. K., & Sivarajah, U. (2023). The future is yesterday: Use of AI-driven facial recognition to enhance value in the travel and tourism industry. Information Systems Frontiers, 25(3), 1179-1195.

[7] Karpagam, M., Jeyavathana, R. B., Chinnappan, S. K., Kanimozhi, K. V., & Sambath, M. (2023). A novel face recognition model for fighting against human trafficking in surveillance videos and rescuing victims. Soft Computing, 27(18), 13165-13180.

[8] McElroy, E., & Vergerio, M. (2022). Automating gentrification: Landlord technologies and housing justice organizing in New York City homes. Environment and Planning D: Society and Space, 40(4), 607-626.

[9] Zhang, X., Zhang, X., & Dolah, J. B. (2022). Intelligent Classroom Teaching Assessment System Based on Deep Learning Model Face Recognition Technology. Scientific Programming, 2022.

[10] Revathy, G., Raj, K. B., Kumar, A., Adibatti, S., Dahiya, P., & Latha, T. M. (2022). Investigation of E-voting system using face recognition using convolutional neural network (CNN). Theoretical Computer Science, 925, 61-67.

D.CERTIFICATE

ANNAMALAI UNIVERSITY

(A State University - Accredited with 'A++' Grade by NAAC)

Annamalainagar – 608002

Faculty of Engineering and Technology

Department of Computer Science and Engineering

RCETT24

Certificate

AU 100

This is to certify that

Title of the Paper: Android Malware Detection using ML

Authors: *K. Geetha Madhav, G. Samitha, Manju C Nair*

contributed a paper in the **National Level Conference on Revolutionizing Computer Engineering: Trends and Technologies [RCETT24]** conducted by the Department of Computer Science and Engineering, Faculty of Engineering and Technology, Annamalai University, Anamalainagar-608002, Tamilnadu on 22nd February, 2024.

Coordinator, RCETT24	Head, Dept. of CSE	Dean, FEAT	Registrar (i/c)
Annamalai University	Annamalai University	Annamalai University	Annamalai University