[Egyptian Informatics Journal 24 (2023) 81–94](https://doi.org/10.1016/j.eij.2022.12.002)

Contents lists available at [ScienceDirect](http://www.sciencedirect.com/science/journal/11108665)

Egyptian Informatics Journal

journal homepage: [www.sciencedirect.com](http://www.sciencedirect.com/)

[](http://crossmark.crossref.org/dialog/?doi=10.1016/j.eij.2022.12.002&domain=pdf)Detection of malware in downloaded files using various machine learning models

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a r t i c l e i n f o

*Article history:*

Received 13 August 2022

Revised 12 November 2022

Accepted 1 December 2022

Available online 19 December 2022

*Keywords:* Cryptography SHA 256

AES LSB

Security

a b s t r a c t

Malware has become an enormous risk in today’s world. There are different kinds of malware or mali- cious programs found on the internet. Research shows that malware has grown exponentially over the last decade, causing substantial financial losses to various organizations. Malware is a malicious program or software that proves exceedingly harmful to the user’s computer. The user’s system can be affected in several ways. The proposed solution uses various machine learning techniques to detect whether a file downloaded from the internet contains malware or not. This research aims to use different machine learning algorithms to differentiate between malicious and benign files successfully. The main idea is to study different features of the downloaded file like MD5 hash, size of the Optional Header, and Load Configuration Size. Based on the analysis performed on these features, the files will be classified as mali- cious or non-malicious. The models are trained on these different features which enables them to learn how to classify files. The models after proper training will be compared among each other based on var- ious criteria. This comparison is made with the help of the Validation and Test datasets. Finally, the model with the best accuracy will be selected. This process helps in identifying all those types of malware that can have a detrimental impact on the user’s system after getting infected. The approach used here will be able to detect malware like Adware, Trojan, Backdoors, Unknown, Multidrop, Rbot, Spam, and Ransomware. After training and testing various machine learning models, the Random Forest Classifier was found to be the most accurate. It’s accuracy went as high as 99.99% in the case of the test dataset. This was closely followed by the XGBoost model with an accuracy of 99.68%. The results of five different models have been compared with those obtained in the previous research. These include the Decision Tree Classifier (99.57% accuracy), Random Forest Classifier (99.99% accuracy), Gradient Boosting Model (99.09% accuracy), XGBoost Model (99.68% accuracy), and AdaBoost Model (98.87% accuracy). Four out of five of these models have been found to have accuracies greater than those obtained in previous research works.

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1. Introduction

Over the last decade, there has been an 87% increase in malware infections and potentially unwanted programs. A significant con- tribution comes from downloaded files from the internet [[1]](#_bookmark20). Many

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q Peer review under responsibility of Faculty of Computers and Information, Cairo University.

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websites specialize in distributing vicious loads by offering them up as commodities or bundling the desired installer with new programs.

‘‘Malware is a program that is malicious in intent. It is designed to harm the computer belonging to the victim”. These so-called programs in the form of malware can cause harm to a victim’s computer in many ways, including manipulating the computer’s data, encrypting delicate data, or even monitoring the victim’s activity without his/her consent.

The risk of computers that store most of our essential data get- ting infected by malware has increased exponentially [[2]](#_bookmark22). The cause of these infections occurs due to files downloaded from the vast world of the internet. It takes just seconds for our systems to get compromised. Moreover, these hackers can intrude into

<https://doi.org/10.1016/j.eij.2022.12.002>

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our system to steal precious information and passwords. This impacts people of all communities, from middle-class men to pri- vate firms to government agencies [[3]](#_bookmark24). All of this makes the detec- tion of malware an essential requirement or need in the current scenario [[4]](#_bookmark26).

Over the past few years, the risk of financial fraud using tech- nology has been rising and due to their large numbers some orga- nizations and security-providing companies are forced to use automated or semi-automated analysis [[5]](#_bookmark28). These are mainly ana- lyzing the trends of fraud to develop an efficient detection system. But the time for any kind of defense system is very uncertain in the current situation which eventually harms the user.

Malware detection is scanning the system and its files to detect malware. It is effective at detecting malware because it involves advanced tools and approaches. It is pretty complex [[6]](#_bookmark29).

and b, which would provide a best-fit line for data points and minimize the error between the predicted value and actual value. This technique is accurately depicted in [Fig. 1](#_bookmark4).

1. Logistic Regression: Logistic Regression is one of the most common machine learning algorithms under supervised machine learning. It uses a set of independent variables for ana- lyzing categorical dependent variables. It gives probabilistic values between 0 and 1 instead of discrete values, as shown in [Fig. 2](#_bookmark5). Logistic regression is used for solving classification problems where we fit an ”S” shaped logistic function and pre- dict two maximum values between 0 and 1. Logistic regression can classify the observations using different data types and quickly determine the most influential variables for classifica- tion. The equation for Logistic Regression can be represented as shown in [2](#_bookmark1):

]=

Habitually, swindlers on the internet get to know the Internet

log[ *y b*

+ *b* × *x*

+ *b* × *x*

+ ... + *b* × *x*

(2)

terms which are becoming fashionable as victims try to download some software, and these spreaders successfully make them land

1 — *y*

0 1 1 2 2 *n n*

on their websites. These spreaders use many techniques for this, one of which is using SEO ways[[7]](#_bookmark30) to move up in the rank list of hunting results. They also spend hefty amounts on advertising their websites. These spreaders conceal malware in files that the victim will download or program malware so that if a user lands on the page, his computer will get infected [[8]](#_bookmark31). These swindlers take advantage of these users’ desperation to download illegal files or to get some software. Hence, by these techniques, the user gets convinced that the website is harmless, downloads files from these websites, and becomes a victim of malware attacks [[9]](#_bookmark35).

A classic case of a specific type of malware attack is called ran- somware. As the name suggests this is a type of malware attack where these swindlers hold data hostage until a ransom amount is paid [[10]](#_bookmark37). After the payment of the amount also it is unsure whether the data is going to be returned or not or whether the data has been sold to some other party.

Standard and signature-based ways to detect malware are get- ting more compound as all the modern malware are disposed to various covers to maintain their anonymity. This malware also improves itself periodically to escape from anti-malware systems. Over the last ten years, machine learning has seen a massive engagement in many areas, including cyber security [[11]](#_bookmark38) [[12]](#_bookmark40). Cyber security experts firmly believe that using ML-driven anti- malware software will boost the detection of new-age malware. This will also help in the betterment of existing scanning engines. All this is evident from the past research papers on malware detec-

1. Decision Tree: Decision Tree is a supervised machine learning

technique that finds its use in classification and regression problems but is mainly preferred for solving classification prob- lems. As clear from the name, this classifier has a tree structure, where internal nodes represent features of a dataset, the deci- sion rules are represented by branches, and each outcome is represented by a leaf node (depicted in [Fig. 3](#_bookmark8)). Talking about nodes, there are two nodes Decision Node and Leaf Node. A decision node does decision-making and has multiple branches, whereas the leaf node depicts the decision output and has no further branches. The decision-making is done based on the fea- tures of a given dataset. So this algorithm is a graphical repre- sentation for getting all the possible solutions to a problem supporting given conditions. The algorithm used to make a decision tree is a CART(Classification and Regression Tree). Before diving into the CART algorithm, understanding impurity concepts, and their mathematics is essential. To measure impu- rity, we use Entropy and Ginni index. Entropy estimates the uncertainty in a given set. CART algorithm uses the Ginni index. Mathematically Entropy and Ginni index can be represented with the help of equations in [3 and 4](#_bookmark2) respectively.

∞

X

— *pi* \* *log*(*pi*) (3)

*i*=1

tion using machine learning techniques.[[13]](#_bookmark43) a simple solution in these kinds of situations in malware detection is to use machine learning wisely [[14]](#_bookmark44) [[15]](#_bookmark46). This is a great way to determine whether a file contains malware or not.

In this work, the available dataset will be used to train different machine learning models. However, first, let us go through some of the most common machine learning algorithms [[16]](#_bookmark17). These machine-learning algorithms can be applied to any given dataset.

1. Linear Regression: Linear Regression is based on supervised learning and performs regression tasks. Linear Regression mod- els a target prediction value based on independent variables. It performs the task of predicting a variable value (y) supported by a given independent variable (x). This technique finds the relationship between input (x) and output (y) variables as per Eq. [1](#_bookmark3). The linear regression model can be represented through the linear equation: [1](#_bookmark3)

*y* = *a* + *b*.*x* (1)

where x: input training data y: label to data a: intercept b: coef- ficient of x

Linear regression aims to determine the best possible values of a

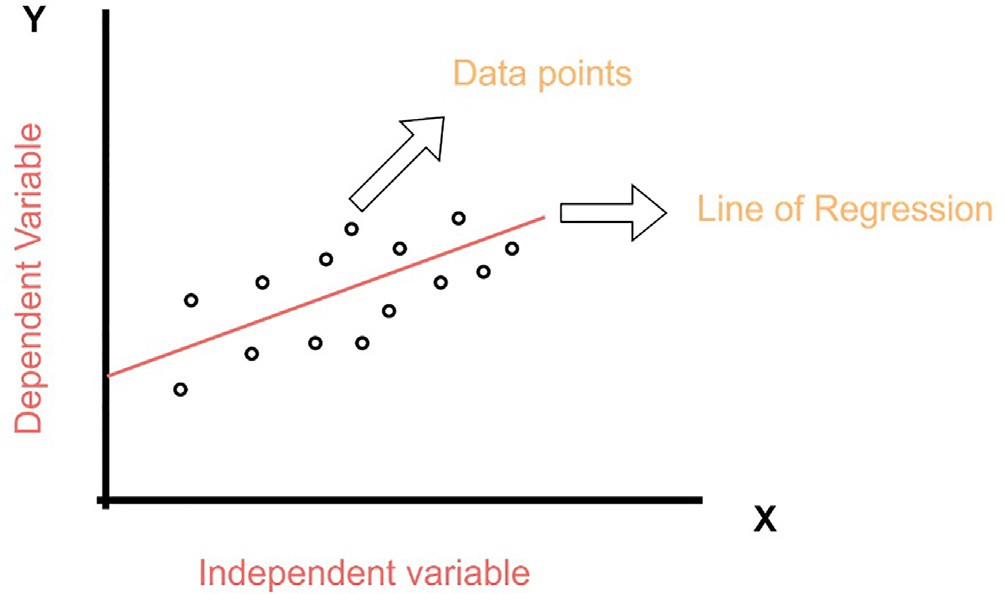
∞

1 —

X

*i*=1

*p*2 \* *log*(*pi* ) (4)

Fig. 1. Linear Regression.

*i*

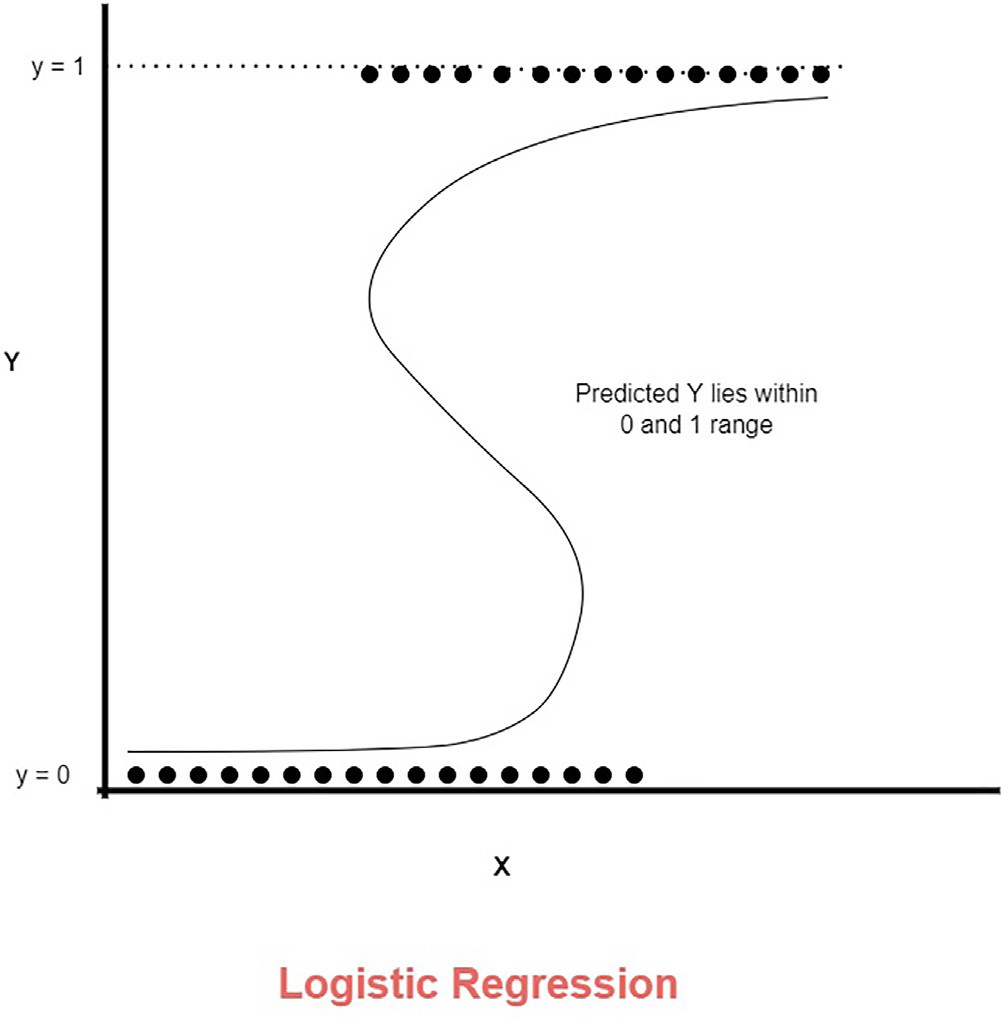


Fig. 2. Logistic Regression.

1. Support Vector Machine (SVM): The algorithm is among the most popular supervised learning algorithms, which can be used for regression and classification problems. The primary use of SVM is to tackle problems related to classifi- cation. The main aim of the SVM algorithm is to create the best line or decision boundary. This line will divide an n- dimensional space into n different classes. This will ensure that new data points can be allotted the best or the closest possible category. The best decision boundary which is formed is called a hyperplane. SVM selects extreme points or vectors while creating a hyperplane. The dimension of the hyperplane also depends on the features present in the dataset. Hyperplane divides data points into two parts through a line written as shown by the two Eqs. [5 and 6](#_bookmark6).

*y* = *a* \* *x* + *b* (5)

*a* \* *x* + *b* — *y* = 0 (6)

Assuming vector X= (x,y) and W= (a,-1), so equation in hyper- plane in vector form is written as in the Eq. [7](#_bookmark7).

*W* .*X* + *b* = 0 (7)

Algorithm 1: Decision Tree Pseudocode

Input: I, where ‘‘I” is a set of classified instances.

Output: Decision Tree

Require: I is not empty, no\_of\_attributes is greater than 0. 1: Procedure Build the Tree

2: Repeat

3: maximum\_gain = 0 4: split\_A = null

5: e = Entropy (Attributes)

6: for all Attributes a in S do

7: gain = Information\_Gain(a, e)

8: if gain is greater than maximum\_gain 9: then

10: maximum\_gain = gain

11: split\_A = a

12: end if

13: end for

14: Partition(I, split\_A)

15: until All partitions processed 16: End Procedure

1. Random Forest: A popular supervised learning technique in machine learning. Random Forests can be used for regres- sion and classification problems in machine learning. This technique is based on the concept of ensemble learning. In Ensemble Learning [[17]](#_bookmark17) the results of multiple classifiers are used together to solve a complex problem and improve the overall accuracy of the model as defined in [Fig. 4](#_bookmark9) [[18]](#_bookmark17). Random Forest contains many decision trees depending on various subsets of the given dataset and then takes the aver- age to improve predictive accuracy. More trees in the forest lead to higher accuracy and prevent overfitting. Random For- est has several advantages as it takes less training time than other algorithms. It also maintains accuracy when a large portion of data in the dataset is missing.

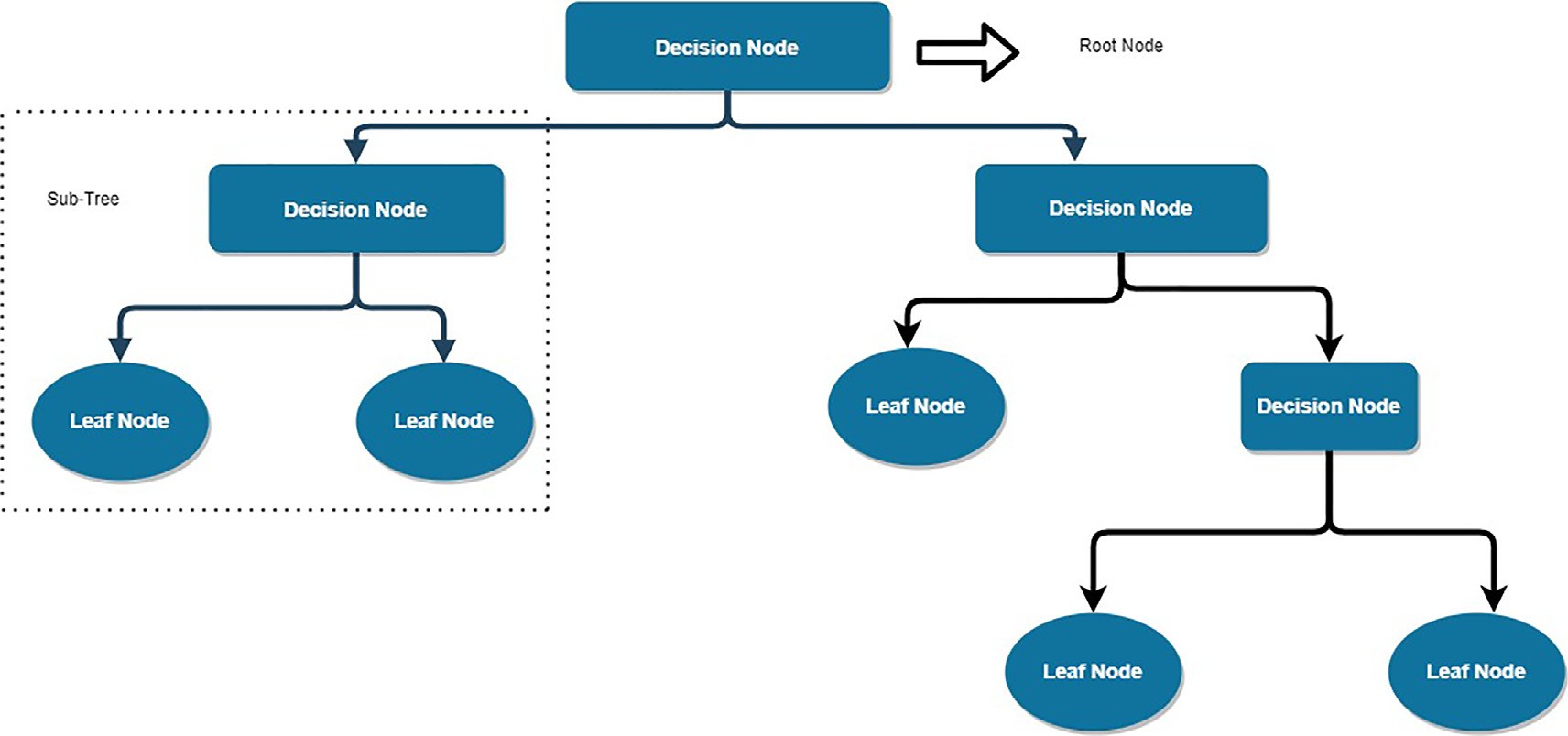
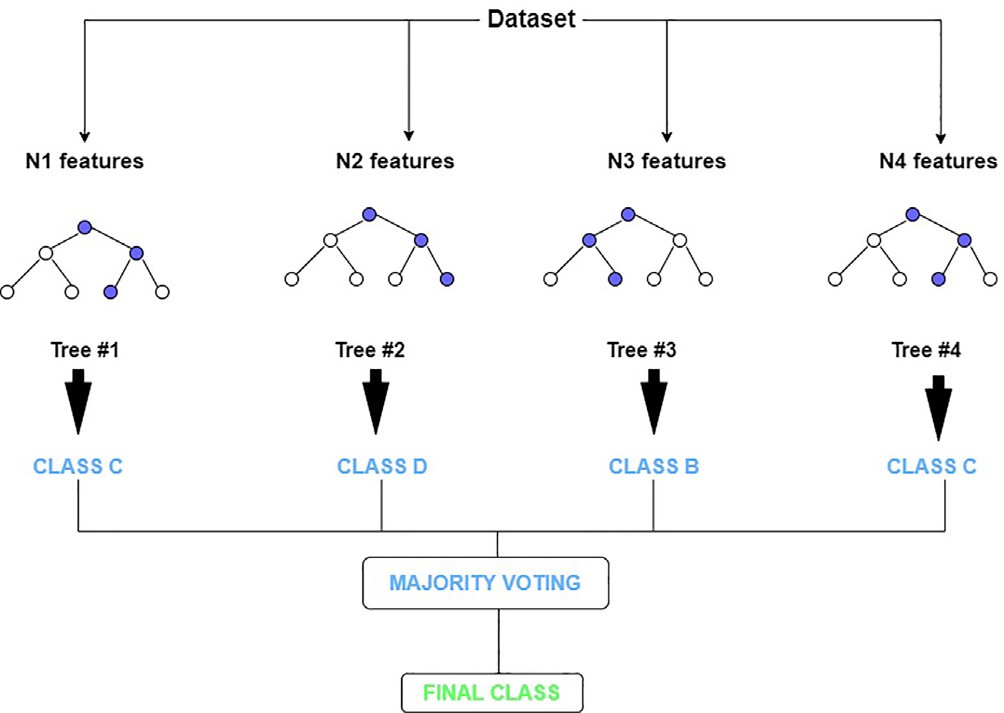


Fig. 3. Decision Tree.

*k n*

XX(||*xi* — *vj* ||)2 (8)

*i*=1 *j*=1

where,

||*xi* — *vj*||

represents Euclidean distance from

*xi*

to

*vj*

which happens to be repeated over all k points among the ”I” clusters, for n clusters.

Fig. 4. Random Forest.

Algorithm 2: Random Forest Pseudocode To generate c classifiers:

1. for i = 1 to c do
2. Randomly sample the training data TR with
3. replacement to produce *TRi*. e
4. *Createarootnode*; *Ri*containing *TRi*.
5. *CallBuildTree*(*Ri*)
6. end for

BuildTree Method

1. BuildTree(R)
2. if R contains instances of only one class then
3. return
4. else
5. Randomly select x% of the possible splitting
6. features in R.
7. Select the feature F with the highest information
8. gain to split on.
9. Create f child nodes of R, where F has f possible
10. values.
11. for i = 1 to f do
12. Set the contents of *Ri*to *TRi*, where *TRi*is all
13. instances in R that match *Fi*.
14. *CallBuildTree*(*Ri*).
15. end for
16. end if

Algorithm 3: K-Means Pseudocode

1. Specify the number K of clusters to assign.
2. Randomly initialize K centroids.
3. repeat
4. expectation: Assign each point to its closest
5. centroid.
6. maximization: Compute the new centroid (mean)
7. of each cluster.
8. until The centroid positions do not change.
   1. *Problem statement*

*‘‘Malware Detection in downloaded files using several different Machine Learning algorithms. Comparing these models based on parameters such as accuracy, efficiency, and F-1 Score. Finally, after proper comparison, determining the best model.*”

* 1. *Contribution of the study*

The main objective of this research work is to gain valuable insights from several different research papers available at various conferences and journals. These papers will be closely related to the kind of work defined in our problem statement. This will enable us to learn about various kinds of techniques that can be used to tackle the given problem. In today’s world, the threat posed by malware has increased by a tremendous amount. Malware can be used for several ill intentions, such as stealing passwords or files, rendering computers inoperable, etc. This makes it very

important to minimize the occurrence of malware. Through this

study, efficient Machine Learning models can be built for detecting

1. K-Means: K-Means Clustering is a type of unsupervised machine learning algorithm used for solving clustering prob- lems. The unlabelled dataset is grouped into several differ- ent clusters. K denotes the number of clusters required to be formed during the process. Each data point will belong to a single group [[19]](#_bookmark17). All the data points within a group will have similar properties. This algorithm is centroid based, and each cluster is associated with a centroid. Minimizing the sum of distances between the data point and their corre- sponding clusters is the main aim of this algorithm. The best value for K-centre points or centroid is calculated with the help of an iterative process. After this, each data point is assigned to the closest K-center. An accurate representation of this technique is shown in [Fig. 5](#_bookmark11).

K-means clustering targets minimizing an objective function such as squared error function [8](#_bookmark10) (See [Figs. 6–16](#_bookmark12)).

and classifying malware.

1. Motivation

Today, most of the critical data is stored on different types of electronic devices. The risk of these devices getting infected by malware has increased significantly. To be specific there has been a 74% increase in the spread of malware in the year 2022. The most common cause of these intrusions is through the files downloaded from the internet. Detecting malware on a system can be difficult, especially when downloaded along with a file from the internet. Researchers have highlighted that these malware attacks can be associated with social, economic, cultural, or political conflicts. Malware can wreak havoc on a system. Hackers can use it to steal passwords and files and render computers inoperable. A large number of breaches are reported every year. These breaches have affected almost all industries, from government operations to small and large businesses. For instance, in the year 2021, around

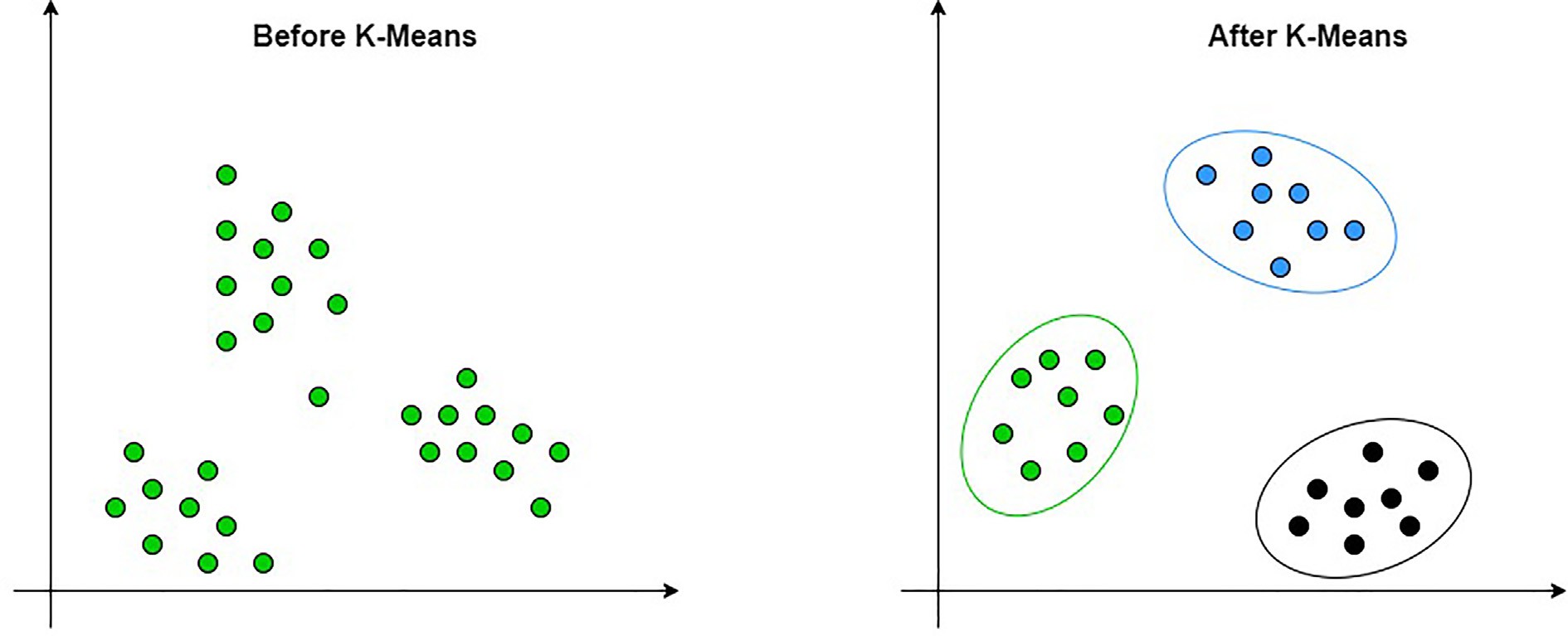


Fig. 5. K-Means.

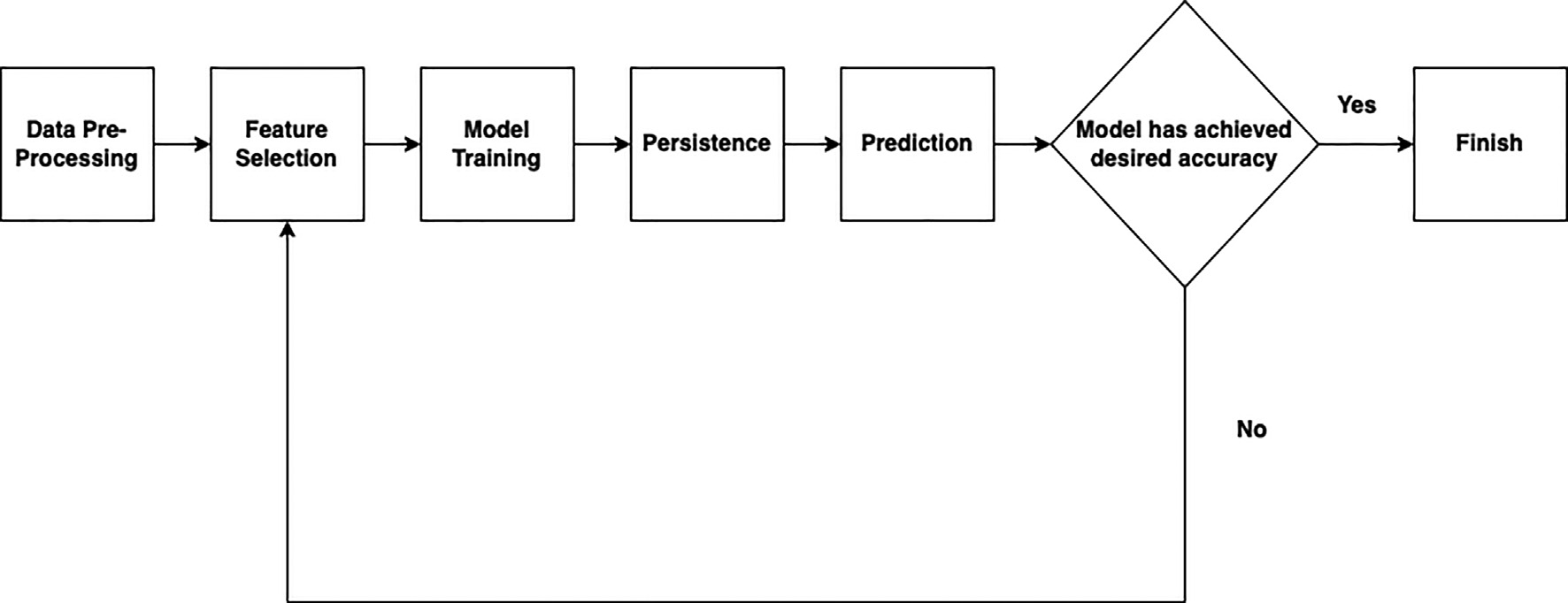


Fig. 6. Methodology Overview.

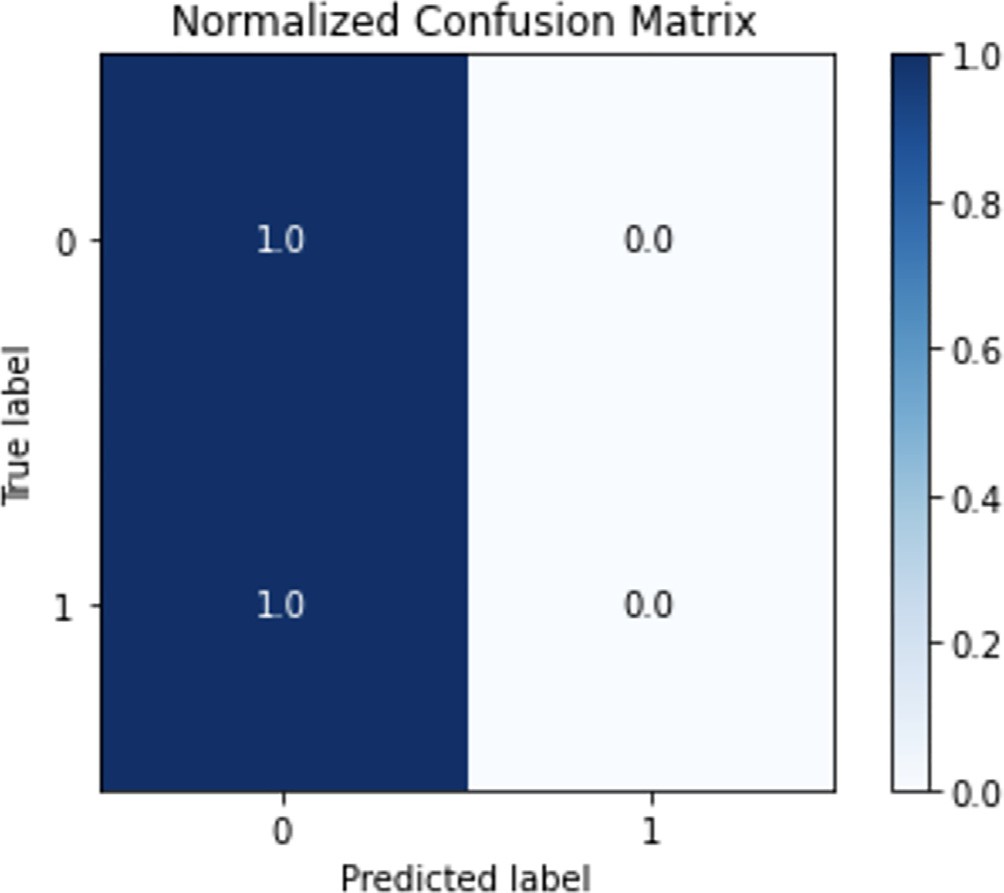
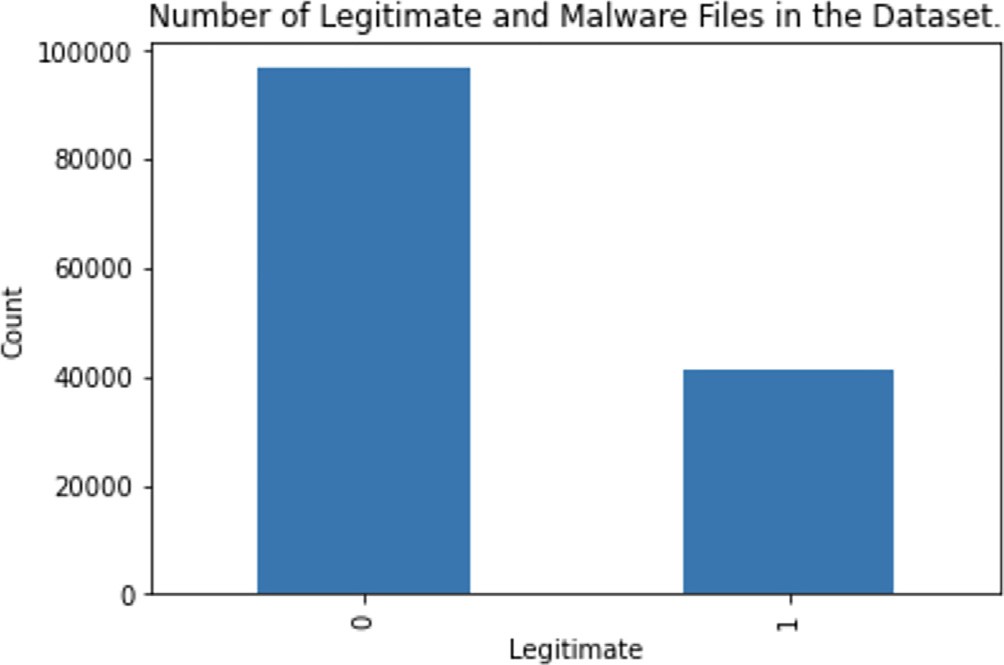


Fig. 7. Distribution of Legitimate and Malware Files. Fig. 8. Confusion Matrix: Logistic Regression.

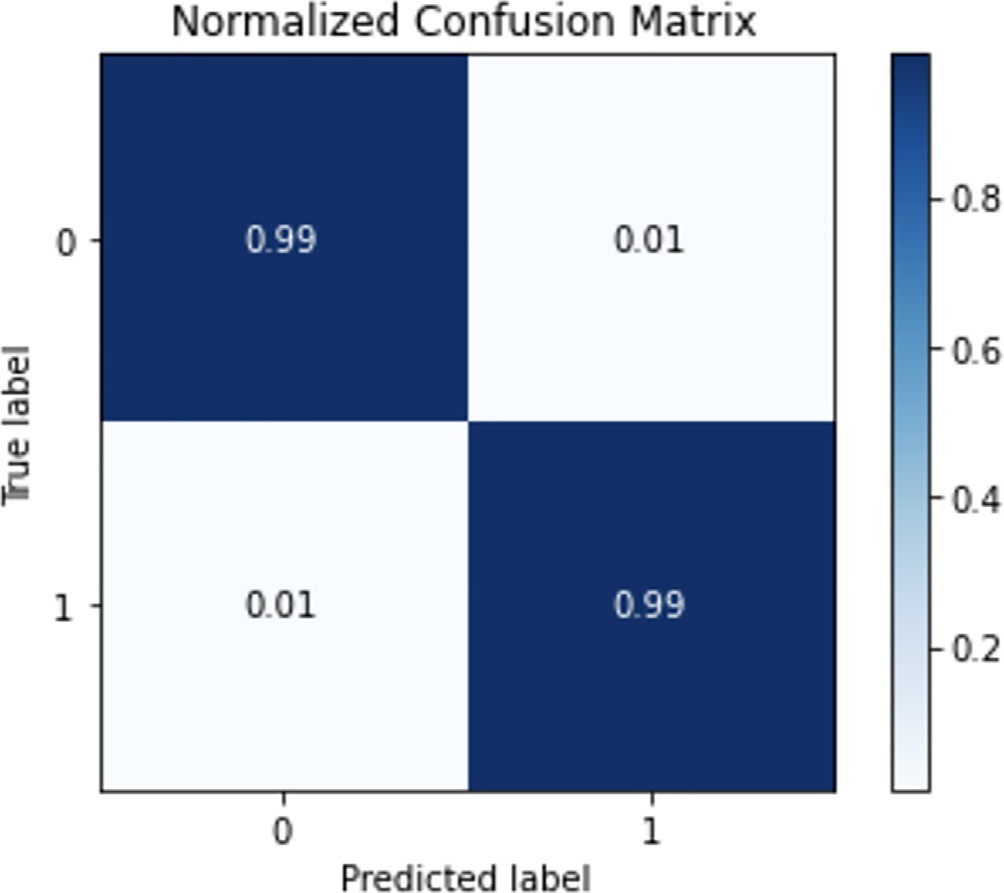
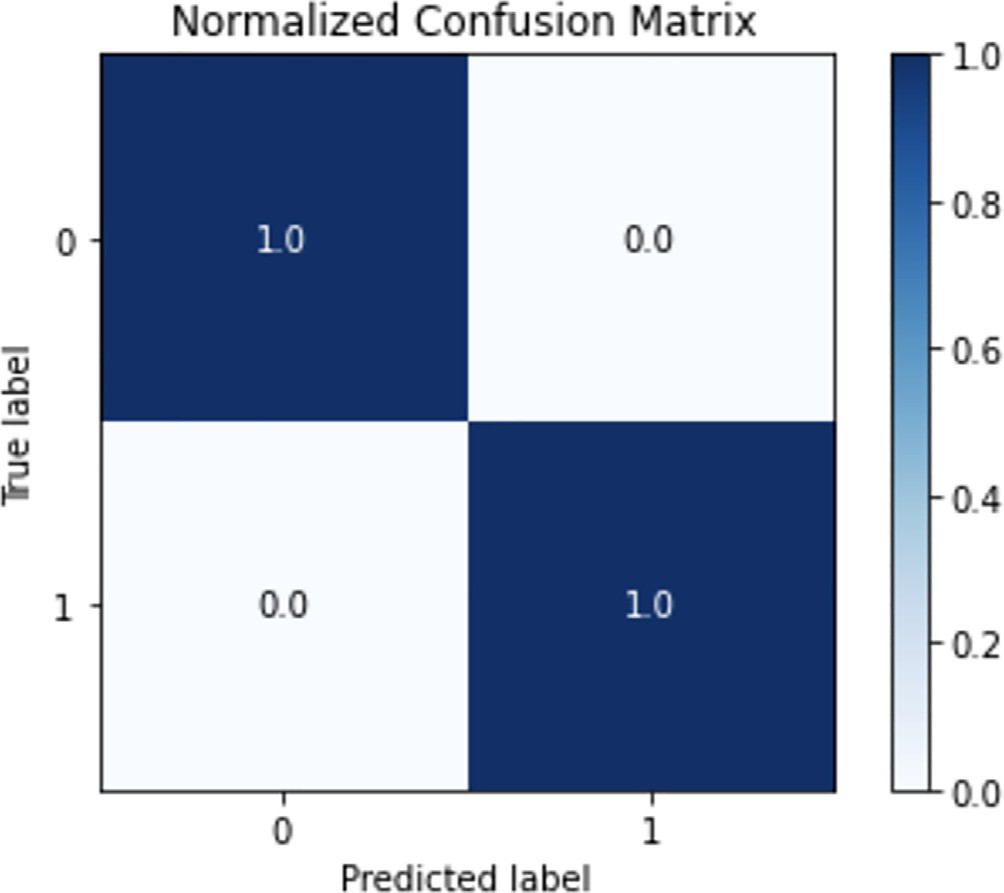
 

Fig. 9. Confusion Matrix: Decision Tree. Fig. 12. Confusion Matrix: XGBoost Model.

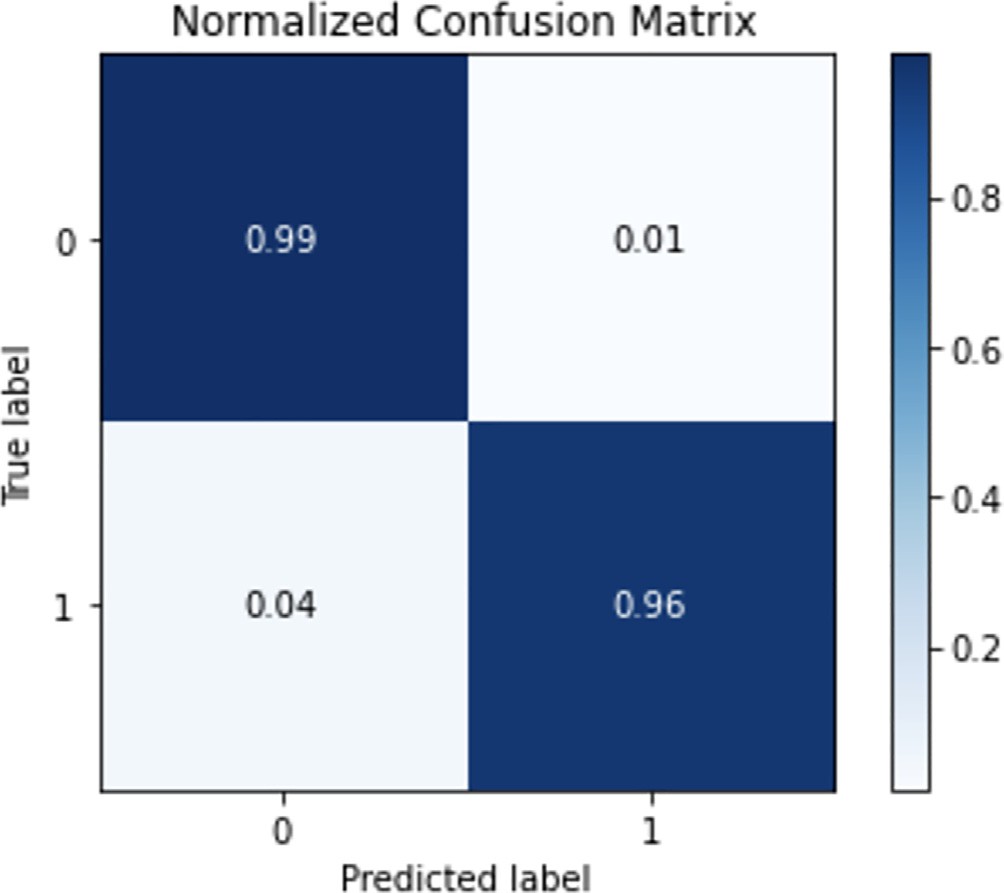
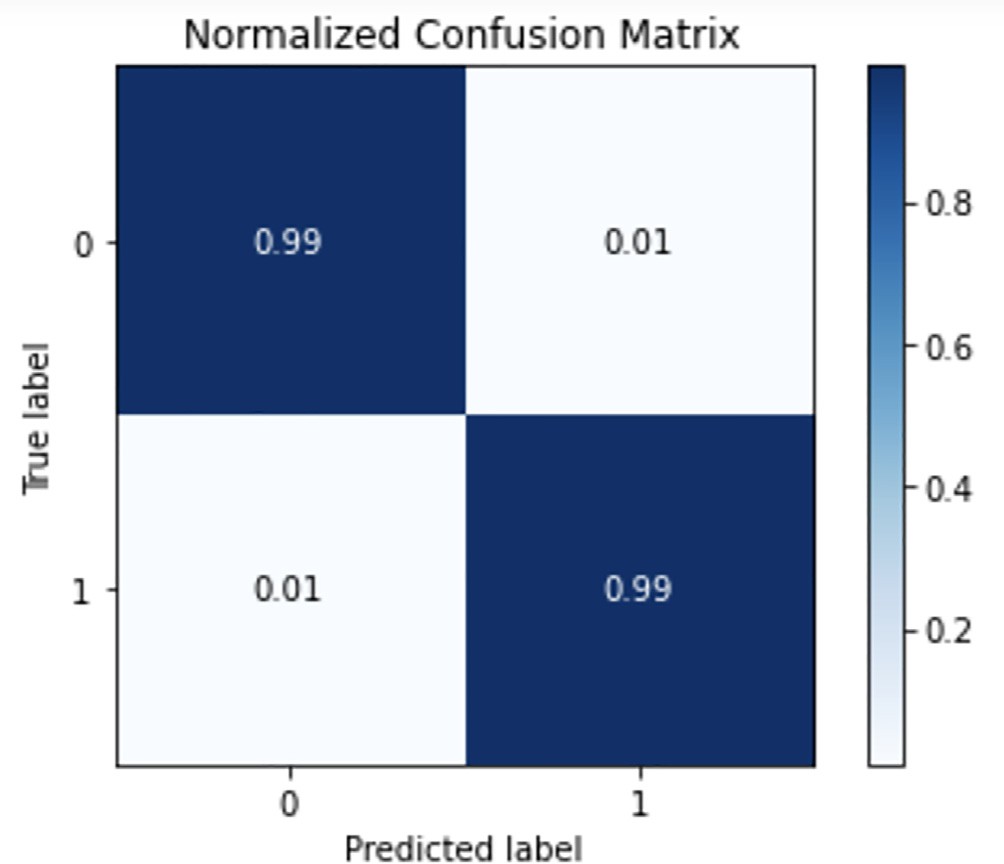
 

Fig. 10. Confusion Matrix: Random Forest.

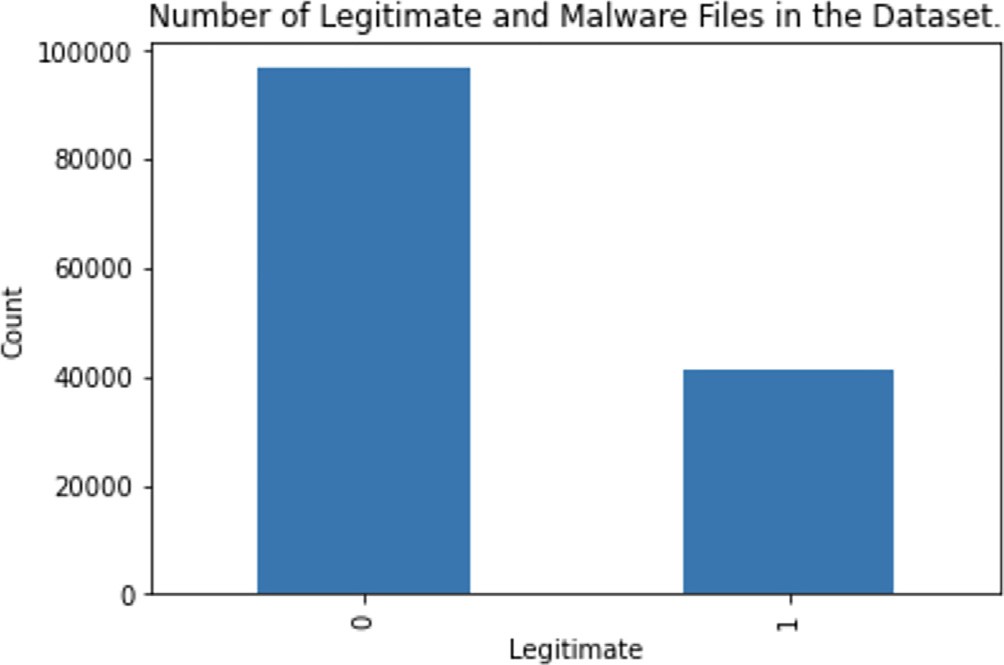


Fig. 11. Imbalanced Data.

Fig. 13. Confusion Matrix: Gradient Boosting Model.

61% of organizations experienced a ransomware attack. Once mal- ware is in action, it consumes large chunks of a system’s memory. This memory loss can slow down the system, which will cause much trouble for the user. After infecting a system, malware can also spread throughout the network in which the infected system is present. It has also been observed that malware has become 57 times more destructive in 2021 as compared that in 2015. This means that malware can damage not just one employee’s com- puter but the entire organization. It is estimated that by the year 2025, malware attacks can cost around $10.5 trillion annually.

All this highlights an urgent need for some proper methods to be developed to prevent these kinds of events or minimize their occurrence. Efficient machine learning algorithms for detecting malware can be a simple solution in these situations. For this dif- ferent machine learning models can be trained on different types

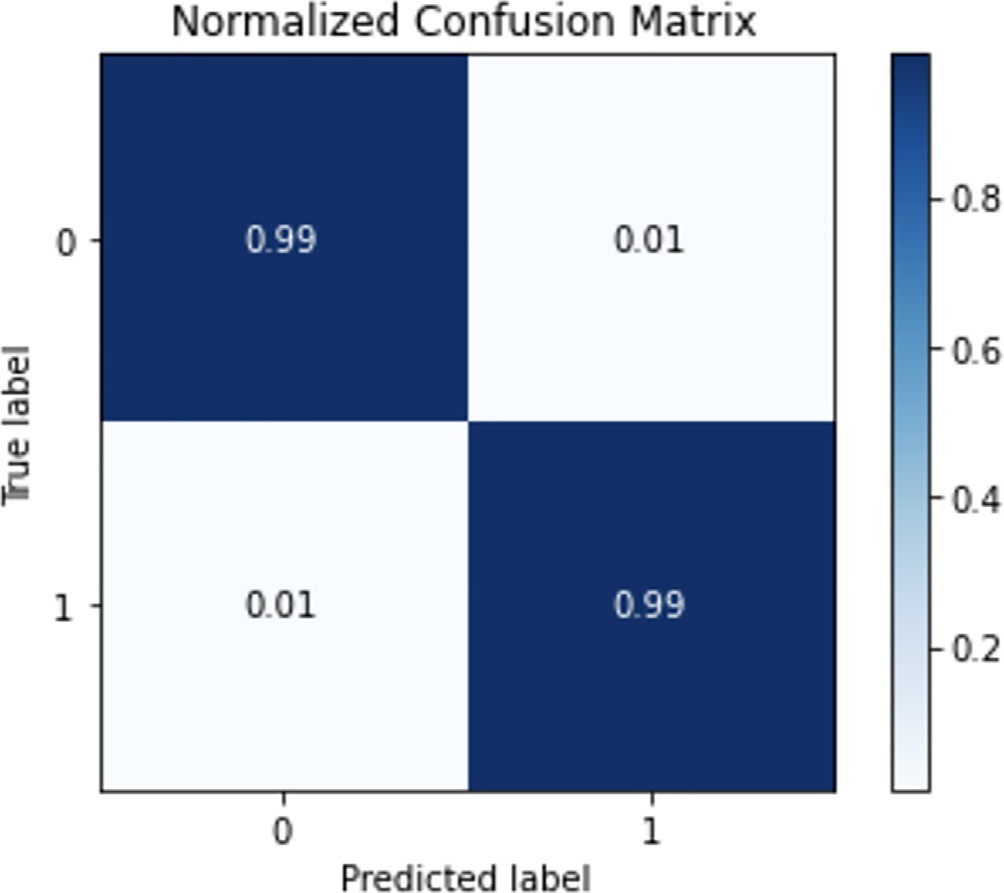


Fig. 14. Confusion Matrix: AdaBoost Classifier.

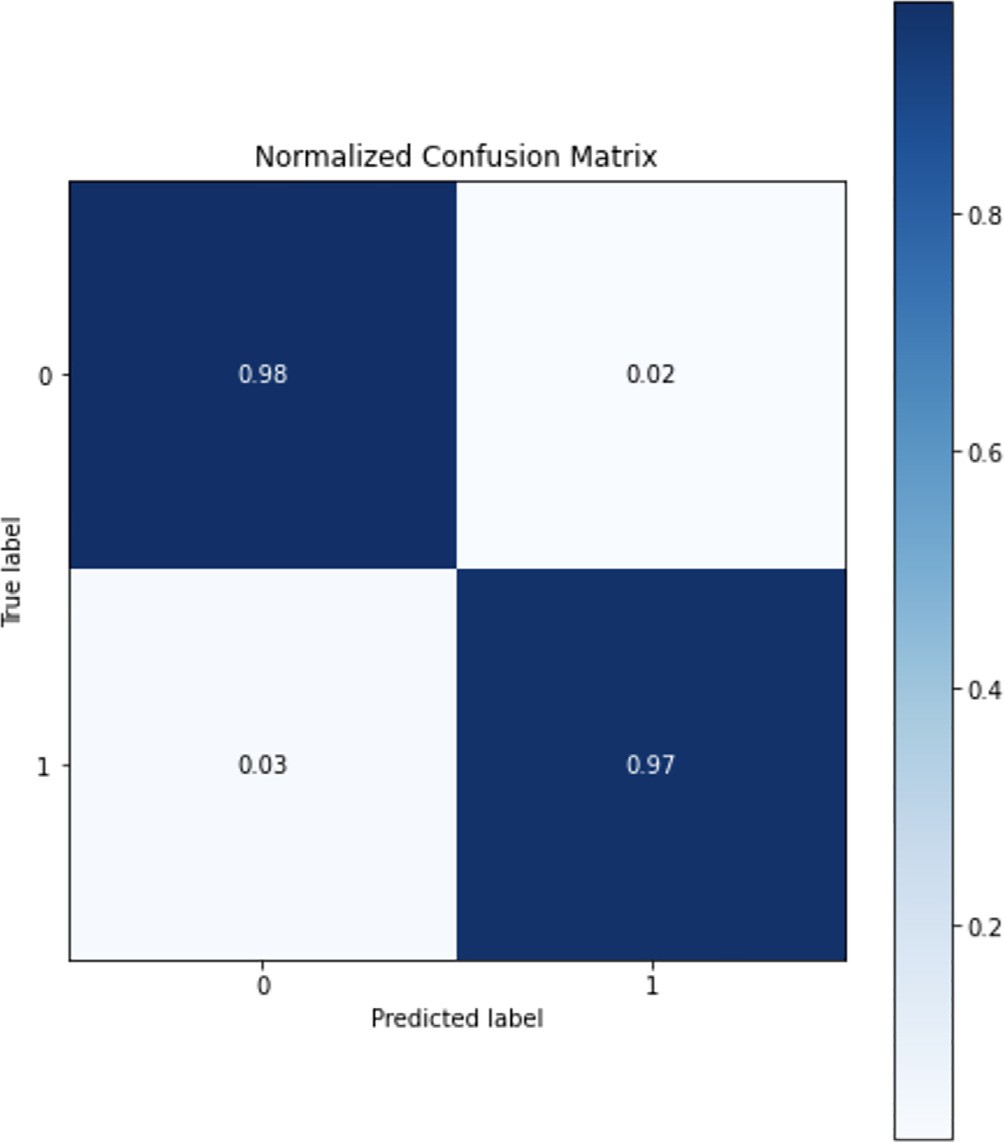


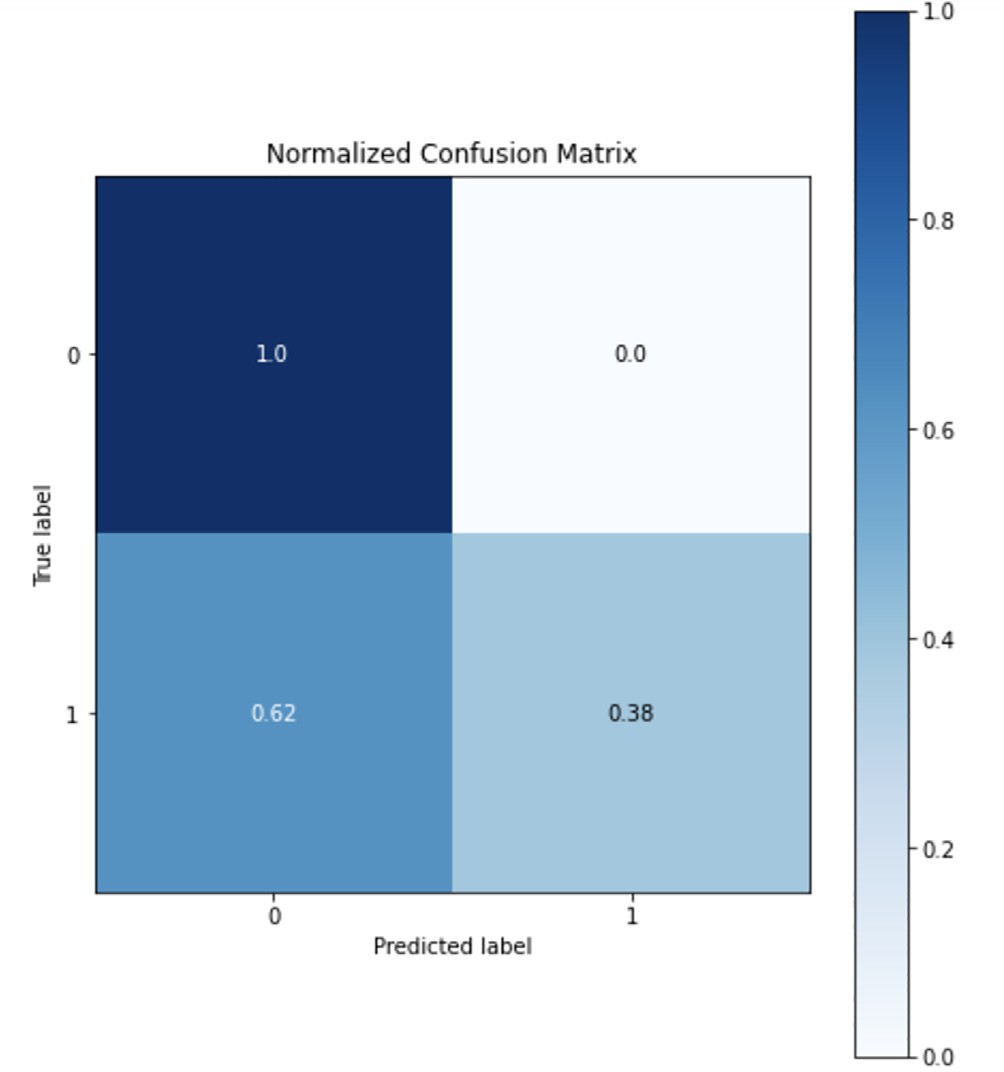
Fig. 15. Confusion Matrix: Principle Component Analysis.

of characteristics that a file possesses. This will enable the models to determine whether a file is containing malware or not.

1. Brief literature review

The main aim of the research by Jatin Acharya et al. [[20]](#_bookmark17) is to detect malicious URLs and programs and act upon them. Various signature matching and machine learning algorithms have been used for identification. A Random Forest Model has been trained based on the features obtained from the Executable headers of var-

Fig. 16. Confusion Matrix: K-Means Clustering.

ious files. The model obtained is then used for checking a given file and determining whether the file is malicious or not. In the case of URLs, a Logistic Regression Model has been trained on appropriate datasets. To perform feature extraction on the URLs, a tokenizer has been used by the regression model. The regression model is then trained on these values. After training, the model predicts whether the URL is shielded to visit or not. All these modules are combined to obtain the final application. This application will be used to protect the entire system against malicious software.

The research by N Udayakumar et al. [[21]](#_bookmark17) aims to understand different types of malware and how Machine Learning can detect and classify them. Several parameters have been used for the col- lection of data about various malware. These parameters are Debug Size, Export Size, Image Version, Resource Size, and Number of Sec- tions. For the classification of malware, three Machine Learning Algorithms have been used. These are Decision Trees, Multilayer Perceptron, and Multi SVM (Support Vector Machine). In the case of the Multi SVM Algorithm, several binary SVMs have been used to ensure proper multi-class classification. Finally, the experiment has concluded that the neural networks model has shown the best performance. This model has an accuracy of about 98% on the training dataset and 99% on the test dataset. Another interpreta- tion that has been made is that Debug Size is the essential feature and is also found to have the highest correlation.

The primary purpose of the research by Ajay Kumar et al. [[22]](#_bookmark17) is to apply efficient decision-making in the field of security. This decision-making will be implemented using various Machine Learning algorithms. A machine-learning-based technique is used to classify Windows PE files as malicious or non-malicious. A total of seven models were trained during the research. The models have been trained on the Brazilian Malware dataset. This dataset con- tains about 1,00,000 rows, with each row representing a file. There are about 57 features for each file in the dataset. Only 15 features have been selected by applying the Extra Trees Classifier to the pre-processed dataset. The models have been persistent, so they are not required to be trained repeatedly before making predic- tions. The Random Forest Model shows the most remarkable accu-

racy in the given dataset. Other models that have been used in the analysis are Logistic Regression, SVM (Support Vector Machine), Adaboost, Gradient Boost, XGBoost, and Decision Tree.

The main aim of the research by Sunita Choudhary et al.[[23]](#_bookmark18) is to detect and then classify polymeric malware. This is a type of malware that keeps on updating its key recognizable features. This makes it difficult to detect the malware using typical signature- based methods. Firstly, the behavior-based pattern of different types of malware is obtained with the help of static or dynamic analysis. After this, various types of Machine Learning techniques have been used to develop a social-based malware detection and classification model [[24]](#_bookmark19). These techniques include SVM (Support Vector Machine), KNN (K-Nearest Neighbors), Naïve Bayes, J48 Decision Tree, and MLP (Multi-Layer Perceptron). The Naïve Bayes technique distinguishes or categorizes malware based on condi- tional probability. The Multi-Naïve Bayes technique that has uti- lized the ’Bytes’ attribute is found to have the highest Detection Rate, whereas the Least False Positive Rate has been found in the case of the Signature Method with strings. Integrating all these techniques has led to the creation of a system that is exceptionally capable of detecting and classifying malware.

The research by Drago s Gavrilu t et al. [[25]](#_bookmark21) aims to employ dif- ferent machine learning algorithms and combine them to develop a versatile framework that can distinguish between malware files and clean files. In addition to classifying files, the experiment also aims to minimize the number of false positives. At first, the models were trained and tested successfully on medium-size datasets of malware and clean files. All the information obtained from this has been used to work with much larger datasets. Hence, a total of three datasets have been used, namely: training dataset, test dataset, and ’scale-up’ dataset. The perceptron algorithm has been modified five times. This is done to correctly recognize malware files, setting a target of 100% detection rate for each category. Although this goal could not be achieved, an efficient machine- learning framework has been obtained to recognize most of the malware samples.

The primary purpose of the research by Sanket Agarkar et al.

[[26]](#_bookmark23) is to develop efficient Machine Learning Models that can be used to identify malware and its family. These models have been used to develop behavior-based recognition and classification methods. Behavior-based identification of ransomware takes into consideration not only the identity of the file but also the different types of functions it will try to perform after a particular interval of time. For feature extraction from malware binary, two approaches have been used. These are Static and Dynamic Analyses. In the case of static analysis, the inspection is done without executing the malware file. The feature extraction is mainly from the PE header or dissecting executable file. In the case of dynamic analysis, the behavior of the executable file is monitored by running the file in a controlled environment. The experiment uses Machine Learning Methods: Light GBM, Decision Tree, and Random Forest. An accu- racy of 99.5% has been achieved in the case of the Light GBM Classifier.

The paper by Harith Ghanim Ayoub et al. [[27]](#_bookmark25) aims to exhibit several works in detecting encrypted viruses. Machine learning algorithms have implemented an accurate and efficient malware detector. The researchers advanced and tested a classifier based on the Hidden Markov Model (HMM) to detect viruses and their families. This method showed high performance and accuracy, close to 90.86%. The second method included structural entropy to detect viruses which gave 74.7% and could detect unknown ran- somware. Other methods were malware detection based on Opcode Frequency [[28]](#_bookmark27) which was implemented using different machine learning algorithms, namely Decision Tree, Boost, Ran- dom Forest, Support Vector Machine, which gave an accuracy of 80%, 86.67%, 96.67%, and 93.33% respectively.

The study aim by Sanjay Sharma et al. [[29]](#_bookmark32) is to study the opcode occurrence frequency for detecting unknown malware using different machine learning techniques. To fulfill this purpose, the researchers have used a dataset from the Kaggle Microsoft mal- ware classification challenge. The dataset used for this purpose contains 21653 assembly codes representing malware. This is a combination of 9 different families. These files weighed 4000, so to maintain the proportion of malware and benign, all files whose opcode weight was under were selected. Top features are selected and compared with the help of the fisher score, symmetric uncer- tainty, information gain, chi-square, and gain ratio. Each feature is run through a different classifier for selecting classifiers to deter- mine which classifier gives the best accuracy. Five classifiers, namely: Random Forest, NBT, LMT, J48 Graft, and REPTree, have also been used. After training and testing the dataset Random For- est, NBT, LMT, J48 Graft, and REPTree could detect malware with 100% accuracy.

The aim of the study by Hao Yang et al. [[30]](#_bookmark33) is to detect malware based on the TF-IDF model. The benefit of using NLP over other machine learning algorithms is that after processing the data, NLP gives better accuracy. In the construction of later models, the Random Forest classifier, Gradient boosting classifier, AdaBoost classifier, and ensemble models are used. Simultaneously, Convo- lutional Neural Network is also used for training because of its effi- ciency in extracting data information. The TF-IDF model is used to determine the TF-IDF value of each keyword in the traffic packet and does not carry out the splitting process on the traffic packet. The dataset has a total of 3000 data packets, including 1500 black-and-white data. Different classifiers are trained after key- word extraction and data set reconstruction from the TF-IDF model. The encrypted traffic data uses One-Hot Encoding, input to the above classifier, and CNN network training and detection. Machine learning with deep learning is a feasible solution to detect encrypted malware traffic data. With TF-IDF-based model accuracy of detection of encrypted traffic, malware has been 93%, which is bound to improve with further research and development in this area.

The research by Qing Wu et al. [[31]](#_bookmark34) is related to the Android Domain. Android device users and application growth has seen rapid growth in the past years; hence, the android environment faces more malware security threats [[32]](#_bookmark36). To detect Malware in Android devices and applications, researchers have proposed vari- ous detection techniques, including machine learning-based meth- ods with static features of apps as input vectors. Using complex machine learning models has been proven to be highly accurate in detecting Malware in Android applications, but their efficiency is not desirable. Some machine learning models like Logistic Regression, Naive Bayes, Support Vector Machine, Decision Tree, and Random Forest have proved their efficiency but have low accu- racy. Machine learning with a Deep neural network has been pro- ven to be more suitable for detecting Android Malware which mainly includes Deep Belief Networks, CNN neural networks, RNN neural networks, and Generative Adverbial Networks, and has achieved accuracy up to 99%.

The paper by Hemant Rathore et al. [[33]](#_bookmark39) aims to present the work on malware detection with various machine learning algo- rithms and deep learning models. For this purpose, opcode fre- quency has been used as a feature vector, and supervised and unsupervised learning has been used for malware classification. The researchers have worked on the problem of analysis and detection of malware as a binary classification problem where the two classes are malware and benign. The dataset for this experiment has been collected from various sources. One of them is an open-source repository known as Malaca Project for mal- ware samples. The collection of benign executable samples has been from different files in various Windows operating systems.

Anti-virus aggregators have been used to check for malware or benign in the executable file in the operating system. The dataset contained 2,819 benign and 11,308 malware executable files to generate feature vectors. Results show that in malware detection, random forest outperforms all three deep neural network models with the highest accuracy of 99.78% with random forest and vari- ance threshold.

The paper by Jinpei Yan et al. [[34]](#_bookmark41) aims to propose a unique type of malware detection method that can automatically learn the features of raw data. The name of this technique is MalNet. Malet learns about grayscale image and opcode sequences with the help of Convolutional Neural Networks (CNN) and Long- Short Term Memory (LSTM). This forms a basis for the classifica- tion of malware. Extraction of opcode sequences is done by a decompilation tool, whereas LSTM is capable of learning features about malicious code patterns and sequences. The dataset used contains samples of over 40,000, which contains 21,736 malware files and 20,650 benign files. This malware detection model goes through two stages. Finally, it achieves 99.88% accuracy, and rates for True Positive and False Positive are 99.14% and 0.1%, respectively.

* 1. *Research gap*

This paper also aims at overcoming some of the limitations that are being faced by the previous research works. These are as follows:

1. Only a limited number of machine learning models have been used in the previous works. In this research, a large number of machine-learning models have been trained and tested. This enables increasing the number of options that are available for classifying the downloaded files.
2. The accuracy of the classification of files has also been improved by a very large amount as compared to the accuracies obtained in the related works.
3. A much larger dataset has been used in comparison to the pre- vious related works. This helps in representing a much broader spectrum of malicious software. This also helps in making the machine learning models more robust and efficient.
4. In the previous works, the types of malware that are being detected are limited only to a very small amount. The machine learning models in this paper can detect a much larger number of malware. These include Adware, Trojan, Backdoors, Unknown, Multidrop, Rbot, Spam, and Ransomware.
5. Methodology
   1. *System architecture*
6. RAM: Minimum 8–16 Gb
7. CPU: Intel Corei5 7*th* Generation or more is preferred.
8. Storage: Minimum 128 GB or more.
9. OS: Linux/Windows/macOS
10. Internet: High-speed internet connectivity required.
    1. *Technology used*
11. Python
12. Sckit-Learn
13. Pandas
14. Matplotlib
15. Jupyter Notebook Or Google Colab
16. Basic Knowledge Of Machine Learning And Data Science
    1. *Algorithms/techniques*

There are several machine learning models that can be used for classification. These models can be broadly divided into two types: Supervised and Unsupervised. Some of the supervised machine- learning models include Logistic Regression, Decision Trees, Ran- dom Forest, and Support Vector Machine (SVM). On the other hand, some of the unsupervised machine-learning models include K- Means Clustering and Principal Component Analysis.

* + 1. *Logistic regression*

Logistic regression is a type of Supervised Machine Learning Algorithm. This is a statistical model that uses a logistic function to model a binary dependent variable. This is one of the most com- monly used methods in cases when the target or the dependent variable is categorical.

* + 1. *Decision tree*

Decision Tree is a Supervised Machine Learning Technique. This algorithm can be used for Regression as well as Classification Prob- lems. The overall structure of this classifier is in the form of a tree. It has the following parts:

1. Internal Nodes: Features of a Dataset.
2. Branches: Decision Rules.
3. Leaf Nodes: Outcomes
   * 1. *Random forest*

Random Forest is a Supervised Machine Learning Algorithm. This classifier contains a specific number of Decision Trees on different subsets of the provided dataset. The overall average of the results of the individual decision trees is used to improve the accuracy of the prediction. This concept is known as Ensemble Learning.

* + 1. *Support Vector Machine (SVM)*

Support Vector Machine is a very popular Supervised Machine Learning Technique. This algorithm can be used for classification as well as regression. The main aim of this method is to form the best decision boundary or line. This line is used to divide n- dimensional space into different classes. This allows for assigning the new data point to the correct category.

* + 1. *K-Means Clustering*

K-Means is a type of Unsupervised Machine Learning Tech- nique. This algorithm is used in the case of Clustering Problems. The unlabeled dataset is grouped into several different clusters. The K represents the number of clusters required to be created dur- ing the process. Each cluster is related to a centroid. This algorithm aims at minimizing the sum of distances between data points and their corresponding clusters.

* + 1. *One Hot Encoding*

One Hot Encoding is an encoding technique used to convert cat- egorical parameters into numeric values (in the form of 0s and 1s usually). This allows categorical information about the dataset in a form compatible with the various Machine Learning Algorithms. One of the possible examples of One Hot Encoding is shown below:

The following table displays a list of colors and their respective prices:

After implementing One Hot Encoding, the following table has been obtained:

1. Implementation and result
   1. *Data preprocessing*
      1. *Preparing the dataset*

For this work, a large number of different types of datasets that are related to malicious and benign files have been explored from different parts of the internet. These datasets from various sources have been combined to obtain the final dataset. This final dataset consists only of the most relevant or essential features related to the nature of a file. The dataset has about 130000 rows (data points) and 57 columns (features).

* + 1. *Exploratory data analysis*

This step involved getting utterly familiar with the dataset. Var- ious aspects of the dataset have been studied. During this process, all the essential features or attributes present in the dataset were identified [[36]](#_bookmark45). At the same time, all the irrelevant features were dropped from the dataset. Further exploration of the selected fea- tures was conducted to identify trends or patterns.

It is essential to understand the given dataset and gather as many insights as possible. This is crucial before sending the data to work with the model [[37]](#_bookmark47).

Two main events that took place during this process:

1. Dropping of the Name and MD5 columns (features) of the Dataset.
2. Performing Train-Test Split on the Orignal Dataset.
   1. *Result*

The results that have been observed in the case of supervised machine learning models are much better as compared to those obtained in the case of unsupervised machine learning models. Among supervised machine learning models, the Random Forest Model is the most accurate. On the other hand, in the case of unsu- pervised machine learning models, Principal Component Analysis has been observed to achieve the highest accuracy.

* + 1. *Logistic regression*

An accuracy of 70.11% has been achieved so far on the Training Dataset. On the other hand, an accuracy of 69.85% has been achieved on the Test Dataset. The F-1 Score of the Test Dataset is 0.0.

* + 1. *Decision tree*

An accuracy of 99.99% has been achieved on the Training Data- set. On the other hand, an accuracy of 99.14% has been achieved on the Test Dataset. The F-1 Score of the Test Dataset is 0.9859.

* + 1. *Random forest*

An accuracy of 98.24% has been achieved so far on the Training Dataset. On the other hand, 98.28% has been achieved on the Test Dataset. The F-1 Score of the Test Dataset is 0.9713.

* + 1. *Imbalanced data*

The figures that have been obtained for the Decision Tree Clas- sifier and Random Forest Classifier are very high. There are very high chances for this to indicate some kind of anomaly like Model Overfitting. After careful examination of both the dataset and the models, it was found that the reason for these high values was the data imbalance between the two output classes. In the given dataset, the number of Benign files is almost double that of Mal- ware files.

There are several ways to handle problems related to Imbal- anced Data.

1. Oversampling: In this technique, we increase the number of instances related to the Minority Class using replacement. This way, the number of instances of majority and minority classes becomes almost equal. After implementing this method, an accuracy of 99.99% was achieved with the Decision Tree Classi- fier, in the case of the Training Dataset. In the case of the Test Dataset, an accuracy of 99.59% was achieved with the Decision Tree Classifier. Whereas with Random Forest Classifier, accura- cies of 98.00% and 97.97% were observed for the Training and Test Dataset respectively. These accuracies improved after scal- ing the Dataset. With the Decision Tree Classifier, the accuracies were 99.99% (Training) and 99.57% (Testing). In the case of the Random Forest Classifier, the accuracies were 99.99% and 99.73% for the Training and Test Dataset respectively.
2. Undersampling: In this technique, we randomly delete several rows related to Majority Class. The result will be a dataset where the number of instances related to the two output classes is almost equal. After implementing this method, an accuracy of 100.00% was achieved with the Decision Tree Classifier, in the case of the Training Dataset. In the case of the Test Dataset, an accuracy of 99.23% was achieved with the Decision Tree Classifier. Whereas with Random Forest Classifier, accuracies of 98.00% and 97.90% were observed for the Training and Test Dataset respectively. These accuracies improved after scaling the Dataset. With the Decision Tree Classifier, the accuracies were 100.00% (Training) and 99.12% (Testing). In the case of the Random Forest Classifier, the accuracies were 100.00% and 99.44% for the Training and Test Dataset respectively.
3. Synthetic Minority Oversampling Technique (SMOTE): This technique also involves oversampling of the Minority Class. This method synthesizes new records or instances with the help of existing data. This synthesis involves the use of the K Nearest Neighbour Method. After implementing this method, an accu- racy of 99.99% was achieved with the Decision Tree Classifier, in the case of the Training Dataset. In the case of the Test Data- set, an accuracy of 99.35% was achieved with the Decision Tree Classifier. Whereas with Random Forest Classifier, accuracies of 98.03% and 97.87% were observed for the Training and Test Dataset respectively. These accuracies improved after scaling the Dataset. With the Decision Tree Classifier, the accuracies were 99.99% (Training) and 99.29% (Testing). In the case of the Random Forest Classifier, the accuracies were 99.99% and 99.61% for the Training and Test Dataset respectively.
4. Balanced Bagging Classifier: This classifier is the same as any standard classifier, but it supports additional balancing. This technique is another step for balancing the training set during the fitting data phase. After implementing this method, an accu- racy of 99.96% was achieved with the Decision Tree Classifier, in the case of the Training Dataset. In the case of the Test Dataset, an accuracy of 99.44% was achieved with the Decision Tree Classifier. Whereas with Random Forest Classifier, accuracies of 99.91% and 99.50% were observed for the Training and Test Dataset respectively.
   * 1. *Other models*
5. XGBoost Model: An accuracy of 99.96% has been achieved so far on the Training Dataset. On the other hand, an accuracy of 99.68% has been achieved on the Test Dataset.
6. Gradient Boosting Model: An accuracy of 99.10% has been achieved so far on the Training Dataset. On the other hand, an accuracy of 99.09% has been achieved on the Test Dataset.
7. AdaBoost Classifier: An accuracy of 98.89% has been achieved so far on the Training Dataset. On the other hand, an accuracy of 98.87% has been achieved on the Test Dataset.
   * 1. *Unsupervised machine learning models*
8. Principal Component Analysis: An accuracy of 97.21% has been achieved so far on the Training Dataset. On the other hand, an accuracy of 97.12% has been achieved on the Test Dataset.
9. K-Means Clustering: An accuracy of 69.03% has been achieved so far on the Training Dataset. On the other hand, an accuracy of 68.96% has been achieved on the Test Dataset.
   * 1. *Comparison with previous work* [*[22]*](#_bookmark17)

The results obtained for various models have been compared with those obtained in the research by Ajay Kumar et al. [[22]](#_bookmark17). Five models are common between the two works: Decision Tree Classi- fier, Random Forest Classifier, Gradient Boost, XGBoost, and Ada- Boost. An overall improvement in the accuracies (as compared to the previous work) can be observed in the case of Gradient Boost, XGBoost, and AdaBoost Models. These comparisons can be observed from [Fig. 17](#_bookmark15).

* 1. *Discussion*

Three different machine learning models (Logistic Regression, Decision Tree Classifier, and Random Forest Classifier) have been trained on the initially obtained dataset. The Decision Tree Classi- fier and Random Forest Classifier were found to have accuracies of 99.14% and 98.28% respectively. However, the initial dataset was

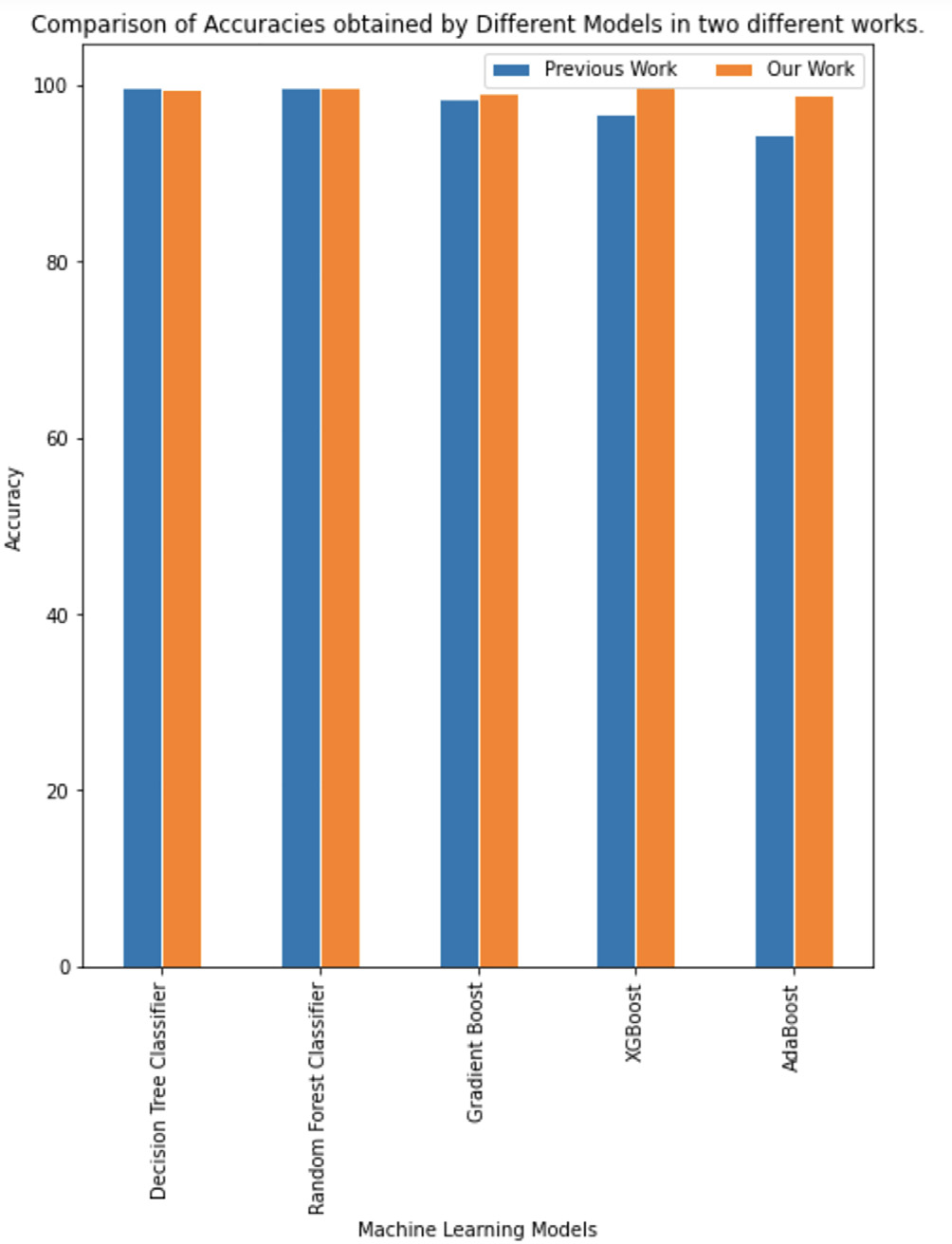


Fig. 17. Comparison Graph.

found to be highly imbalanced. In the given dataset, the number of Benign files is almost double that of Malware files. Several differ- ent techniques have been used to obtain a balanced dataset. Some of these include Oversampling, Undersampling, Synthetic Minority Oversampling Technique (SMOTE), and Balanced Bagging Classi- fier. Around 5 supervised and 2 unsupervised machine learning models have been trained on this balanced dataset.

The results of five of these models have been compared with those obtained in the previous research. These include the Decision Tree Classifier (99.57% accuracy), Random Forest Classifier (99.99% accuracy), Gradient Boosting Model (99.09% accuracy), XGBoost Model (99.68% accuracy), and AdaBoost Model (98.87% accuracy). Four out of five of these models have been found to have accuracies greater than those obtained in previous research works.

* 1. *Challenges faced*

The following are some of the major challenges faced during the implementation:

1. The obtained dataset had a lot of issues associated with it like a lack of uniform data formatting across a specific column, and rows with null values for various attributes. These were resolved by using several Data Preprocessing Techniques men- tioned in the Section [5.1](#_bookmark13).
2. In the beginning, the predictions made by the trained models were not very accurate. This problem was tackled by making several changes in the dataset and hyperparameter tuning of the models. All of this enabled us in improving the accuracies of the models by a very large amount.
3. There were a lot of attributes (columns) in the obtained dataset which were present in the categorical form. Efficient data encoding techniques were employed to convert the entries under these attributes into numerical values so that they can be used for training the models.
4. The dataset was found to be imbalanced right in the middle of the project. As a result of this, the trained models were making predictions in favor of one class as compared to the other. This was resolved by using various dataset-balancing techniques like oversampling, undersampling, Synthetic Minority Oversam- pling Technique (SMOTE), and Balanced Bagging Classifier. The outcomes of these techniques have been mentioned in Section [5.2.4](#_bookmark14).
5. Tradeoffs

There are several tradeoffs for using machine learning models for malware detection as compared to standard techniques:

1. The entire process of detecting any kind of malware using machine learning is very time-consuming when compared to standard methods. This is due to the amount of time required for the machine-learning models to learn from the highly com- plicated malware dataset.
2. To work efficiently, machine learning models require a very large amount of data containing information about all the pos- sible malware that might be there in the world. If these models are introduced to some new kind of malware that was not pre- sent in the training dataset, they might fail to detect that.
3. The dataset related to malware tends to be very complicated as it contains information regarding the various parameters of malware. This requires the use of a large number of resources.
4. In the case of some kind of malware, it might be possible that the standard methods can perform better in terms of accuracy as compared to machine learning techniques.
5. Conclusion

For this project, the obtained dataset was used for training sev- eral different supervised and unsupervised machine learning mod- els. Some of the main supervised machine learning models that were used include Logistic Regression, Decision Tree, and Random Forest Model. On the other hand, Principle Component Analysis and K-Means clustering are some of the unsupervised machine learning models that were used for this project. Several dataset balancing operations were also performed on the obtained dataset. Some of these techniques include Oversampling, Undersampling, SMOTE, and Balanced Bagging Classifier.

Out of all these models, the Random Forest Model was found to be the most accurate. Its accuracy went as high as 99.99% for the test dataset. This was followed by XGBoost (99.68%), Decision Tree

Table 1

Literature Review: Summary Table.

(99.57%), Gradient Boosting (99.09%), and AdaBoost Classifiers (98.87%). Finally, a comparison was made between the results obtained in this research and those of previous research. Four of five standard models had accuracies greater than those obtained in the previous research.

1. Future work

In the case of our project, a large number of ideas can be implemented both soon and over the long term. In the immedi- ate future, the primary goal will be to keep trying different Machine Learning Models and determine the best model per the needs. At the same time, there is also a need to improve the prediction accuracy of each model tried. There is also a need to take care of several things like avoiding multicollinearity and

Author and Year Contribution Scope Limitations

Jatin Acharya et al. [[20]](#_bookmark17) – 2021

Harith Ghanim Ayoub et al.

[[27]](#_bookmark25) – 2021

Using Machine Learning and Signature Matching to detect Malware, Malicious URLs, and Viruses.

Analysing various methods for detecting the encrypted virus.

The application obtained from this research can be used to keep users safe from various cyber- attacks. The application also allows the detection of mutated malware or viruses that the attackers have refined.

This paper demonstrates various machine learning algorithms and methods to detect encrypted malware.

The number of Machine Learning Models is limited to one for each main task. Also, this will not be able to handle new types of malware.

Malware detection accuracy can be further improved by improving feature selection and efficiency.

Hao Yang et al. [[30]](#_bookmark33) – 2021 Detecting encrypted malicious

traffic based on Natural Language Processing methods.

Qing Wu et al. [[31]](#_bookmark34) – 2021 Investigating different Android

Malware Static Detection Technology based on Machine Learning.

this research paper aims to detect malware based on TF-IDF (Term Frequency-Inverse Document Frequency) model.

Various machine-learning models have been proposed to detect Malware in Android devices and applications.

More models could be used for detection and to improve accuracy.

Lack of standard benchmark datasets. More models should be implemented to improve the accuracy.

Sanket Agarkar et al. [[26]](#_bookmark23) – 2021

Ajay Kumar et al. [[22]](#_bookmark17) – 2020

Sunita Choudhary et al. [[23]](#_bookmark18) – 2020

Sanjay Sharma et al. [[29]](#_bookmark32) – 2019

N Udayakumar et al. [[21]](#_bookmark17) – 2018

Hemant Rathore et al. [[33]](#_bookmark39) – 2018

Using efficient Machine Learning Models to identify the malware and the family it belongs to.

Using Machine Learning Algorithms to apply efficient Decision Making in the security field.

To detect and classify Polymeric Malware based on the behavior- based pattern.

Detecting Advanced Malware Using different Machine Learning Algorithms.

Detection and Classification of Malware using different Machine Learning Techniques.

Presenting the work on malware detection with various machine learning algorithms and deep learning models.

The static features extracted from legitimate and malicious executable files can be used to train different machine learning algorithms. As a result of this, the prediction of whether a given file is malicious or not can be performed very fast and efficiently.

The latest malware issues cannot be tackled with the help of traditional protection methods used by anti-virus. Machine Learning methods can be used efficiently in cybersecurity to protect against advanced malicious software. Polymeric malware is a type of malware that is difficult to detect with the help of typical signature-based methods. Behavior-based patterns of these kinds of malware can be obtained using static or dynamic analysis.

This paper aims to study the opcode occurrence frequency for detecting unknown malware by using different types of Machine Learning algorithms.

Various Machine Learning Algorithms can be used to detect and classify malware. This can act as a step toward resolving the Malware Crisis caused by different kinds of malware or malware programs.

Same models can also be used to detect more complex malware (polymorphic and metamorphic) in the future. Other deep learning techniques can also prove to be effective in the case of Malware Detection.

Several improvements must be made for this work to be applied in practical reality. A few more Machine Learning models could have been explored for detection and classification. Also, some advanced forms of polymeric malware may not be detected.

Limited to just the detection of Malware in Windows PE files. This cannot be used to predict whether it is safe to visit a particular website or not.

Several other Machine Learning models could also have been tried for classification. Some advanced forms of polymeric malware may not be detected.

Maximum size of the assembly code has been set to 147.0 MB. So it will not be able to detect malware in large files.

More Machine Learning Models could have been tried for classification. Also, this will find difficult to classify unknown malware types.

Deep learning models used were compelling enough, and there is scope for improving their accuracy.

Jinpei Yan et al. [[34]](#_bookmark41) – 2018 Proposal of MalNet, a malware

detection system that learns features automatically from raw data using CNN and LSTM.

MalNet also solves practical problems related

to the generation of Grayscale Image Generation, lengthy sequence learning, parallel computation of LSTM, and noise data processing.

Works only in case of Windows executable

file.

Drago s Gavrilu t et al. [[25]](#_bookmark21) – 2009

Developing a versatile framework by combining different Machine Learning Techniques to differentiate malicious and benign files.

A Machine Learning model should be such that it can detect as many malware samples as possible with a difficult-to-achieve constraint of zero false-positive rates. This can add to the standard methods of detection that anti-virus vendors use.

The methods used for malware detection are limited to perceptron. Many other Machine Learning techniques could also be used for classification.

Table 2

Pros & Cons: Logistic Regression.

PROS CONS

One of the most straightforward methods to implement. Poor performance in the case of Unstructured Data (such as images, audio, videos) No need for hyperparameter tuning. Does not work well with features that are highly correlated with each other.

Usually effective in the case of Structured Data (such as tables and lists). Not the best algorithm in terms of power. Several better algorithms are available. Can work with Scaled as well as Unscaled Data. Feature Scaling is not necessary. This algorithm assumes linearity between dependent and independent variables.

Table 3

Pros & Cons: Decision Tree.

Pros Cons

Fewer efforts are required for Data Preparation during the Data Preprocessing Stage. Very sensitive to even the slightest changes.

Normalization of data is not required. Can involve very complex calculations when compared to other algorithms.

Data Scaling is not necessary. Takes more amount of time to train the model.

Table 4

Pros & Cons: Random Forest.

Pros Cons

Can work with both Categorical and Continuous Data. Cannot work without implementing pruning.

Low sensitivity to outliers. Offers less accuracy for predictions as compared to other Machine Learning Techniques.

Easy to Interpret. Susceptible to Overfitting. Several better algorithms are available.

Nature is Non-Parametric. Involves very complex calculations, especially in the presence of many class variables.

Table 5

Pros & Cons: SVM.

PROS CONS

Memory Efficient. No probabilistic explanation for classification.

Very efficient in high-dimensional spaces. Does not work well with noisy data. It works well when a clear margin separates different classes. Scaling with number of dimensions Can warm-start the positions of centroids. Unsuitable for large datasets.

It works well when the number of dimensions exceeds the number of samples.

Will does not perform well when the number of training data samples is less than the number of features for each data point.

Table 6

Pros & Cons: K-Means Clustering.

PROS CONS

Suitable for Large Datasets. Clusters with uniform sizes are produced even for different sizes of the input data.

Relatively simple in the case of implementation. Not possible to find the optimal set of clusters for any given Problem [[35]](#_bookmark42).

Very flexible to different kinds of changes. Much inconsistency in the results when used multiple times.

Improved Clustering Accuracy. Need to manually specify the value of K (number of clusters).

Table 7

One Hot Encoding: Input Table.

Table 8

One Hot Encoding: Output Table.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Color | Price (in USD) |  | Gold | Red | Blue | Silver | Price ($) |
| Gold | 50 |  | 1 | 0 | 0 | 0 | 50 |
| Red | 20 |  | 0 | 1 | 0 | 0 | 20 |
| Blue | 25 |  | 0 | 0 | 1 | 0 | 25 |
| Silver | 40 |  | 0 | 0 | 0 | 1 | 40 |
| Gold | 50 |  | 1 | 0 | 0 | 0 | 50 |

avoiding model overfitting. This is especially true in the case of Decision Tree and Random Forest Models. During these different

processes, the main priority will always be to achieve the high- est accuracy while ensuring that problems like multicollinearity

Table 9

Studying the Dataset.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Param. | Machine | Size Of Optional Header | Characteristics | Major Linker Version |
| count | 138047 | 138047 | 138047 | 138047 |
| mean | 4259.069274 | 225.845632 | 4444.145994 | 8.619774 |
| std | 10880.34725 | 5.121399 | 8186.782524 | 4.088757 |
| min | 332 | 224 | 2 | 0 |
| 25% | 332 | 224 | 258 | 8 |
| 50% | 332 | 224 | 258 | 9 |
| 75% | 332 | 224 | 8226 | 10 |
| max | 34404 | 352 | 49551 | 255 |

and overfitting do not occur. Several things can be implemented on a long-term basis. For instance, the ability to detect whether a given file contains malware or not can be combined with the ability to detect what kind of malware the given file contains. Similarly, the project can also implement the idea of determining the primary source of virus or malware from where the file got infected (See [Tables 1–9](#_bookmark16)).

Declaration of Competing Interest

The authors declare that they have no known competing finan- cial interests or personal relationships that could have appeared to influence the work reported in this paper.

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