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CYBERNET: DETECTION OF CYBER ATTACKS IN NETWORK USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

Now-a-days to detect cyber-attack are using static and dynamic analysis of request data. Static analysis is based on signature which we will match existing attack signature with new request packet data to identify packet is normal or contains attack signature. Dynamic analysis will use dynamic execution of program to detect malware/attack, but dynamic analysis is time consuming. To overcome from this problem and to increase detection accuracy with old and new malware attacks, we are using machine learning algorithms and evaluating prediction performance of various machine learning algorithms such as Support Vector Machine (SVM), Random Forest, Decision Tree, Naïve Bayes, Logistic Regression, KNearest Neighbours and Deep Learning Algorithms such as Convolution Neural Networks (CNN) and LSTM (Long Short-Term Memory). Among those, various models Deep learning CNN resulted in superior performance compared to other models.

To implement this work and to evaluate machine learning algorithms performance this work using binary malware dataset called ‘MALIMG’. This dataset contains 25 families of malware and application will convert this binary dataset into gray images to generate train and test models for machine learning algorithms. This algorithm converting binary data to images and then generating model, so they are called as MalConv CNN and MalConv LSTM and another algorithm refers as EMBER. Application convert dataset into binary images and then used 80% dataset for training model and 20% dataset for testing. Whenever we upload new test malware binary data then application will apply new test data on train model to predict malware class.

Keywords: Cybernet, Cyber-attacks, Machine learning.

1. INTRODUCTION

In this digital world of Industry 4.0, the rapid advancement of technologies has affected the daily activities in businesses as well as in personal lives. Internet of Things (IoT) and applications have led to the development of the modern concept of the information society. However, security concerns pose a major challenge in realising the benefits of this industrial revolution as cyber criminal’s attack individual PC’s and networks for stealing confidential data for financial gains and causing denial of service to systems. Such attackers make use of malicious software or malware to cause serious threats and vulnerability of systems [1]. A malware is a computer program with the purpose of causing harm to the operating system (OS). A malware gets different names such as adware, spyware, virus, worm, trojan, rootkit, backdoor, ransomware and command and control (C&C) bot, based on its purpose and behaviour. Detection and mitigation of malware is an evolving problem in the cyber security field. As researchers develop new techniques, malware authors improve their ability to evade detection.

When Morris worm made its appearance as the first ever computer virus in 1988-89, antivirus software programs were designed to detect the existence of such a malware by finding a match with the virus definition database updated from time to time. This is called signature-based malware detection, which can also perform a heuristic search to identify the behavior of malware. However, the major challenge in such classical approaches is that new variants of malware use antivirus evasion techniques such as code obfuscation and hence such signature-based approaches are unable to detect zero-day malwares [2]. Signature-based malware detection system requires extensive domain level knowledge to reverse engineer the malware using Static and dynamic analysis and to assign a signature for that. Moreover, signature-based system requires larger time to reverse engineer the malware and during that time an attacker would encroach into the system. In addition, signature-based system fails to detect new types of malware. Security researchers have identified that hackers predominantly use polymorphism and metamorphism as obfuscation techniques against signature-based detection. In order to address this problem, software tools are used to manually unpack the codes and analyse the application programming interface (API) calls.

Since this process is a resource intensive task, [3] presented an automated system to extract API calls and analyse the malicious characteristics using a four step methodology. In step 1, the malware is unpacked. In step 2, the binary executable is disassembled. Step 3 involves API call extraction. Step 4 involves API call mapping and statistical feature analysis. This was enhanced in [4] using a 5- step methodology incorporating machine learning algorithm (MLA) such as SVM with n-gram features extracted from large samples of both the benign and malicious executables with 10-fold cross validations. Later, in [5] a comparative study of various classical machine learning classifiers for malware detection was performed, and a framework for zero day malware detection was proposed. To handle malicious code variants, the sequence of API calls and their frequency of appearance of API calls passed into similarity based mining and machine learning methods [7]. The detailed experimental analysis was done on very large data set and to extract the features from malware binaries a unified framework proposed. In [8], API calls features and a hybrid of support vector machine (SVM) and Maximum-Relevance Minimum Redundancy Filter (MRMRF) heuristics were employed to present novel feature selection approaches for enhanced malware detection. Recently, with the increase in unknown malware attacks, the detailed information on obfuscated malware is discussed by [6] and many researchers are improving the MLAs for malware detection [9]. This forms the motivation of this research work.

2. LITERATURE SURVEY

Machine learning algorithms (MLAs) rely on the feature engineering, feature selection and feature representation methods. The set of features with a corresponding class is used to train a model in order to create a separating plane between the benign and malwares. This separating plane helps to detect a malware and categorize it into its corresponding malware family. Both feature engineering and feature selection methods require domain level knowledge. The various features can be obtained through Static and Dynamic analysis. Static analysis is a method that captures the information from the binary program without executing. Dynamic analysis is the process of monitoring malware behavior at run time in an isolated environment. The complexities and various issues of Dynamic analysis are discussed in detail by [10]. Dynamic analysis can be an efficient long-term solution for malware detection system. The Dynamic analysis cannot be deployed in end-point real time malware detection due to the reason that it takes much time to analyze its behaviour, during which malicious payload can get delivered. Malware detection methods based on Dynamic analysis are more robust to obfuscation methods when compared to statically collected data. Most commonly, the commercial anti-malware solutions use a hybrid of Static and Dynamic analysis approaches. The major issue with the classical machine learning based malware detection system is that they rely on the feature engineering, feature learning and feature representation techniques that require an extensive domain level knowledge [11], [12], [13]. Moreover, once an attacker comes to know the features, the malware detector can be evaded easily [14]. To be successful, MLAs require data with a variety of patterns of malware. The publicly available benchmark data for malware analysis research is very less due to the security and privacy concerns. Though few datasets exist, each of them has their own harsh criticisms as most of them are outdated. Many of the published results of machine learning based malware analysis have used their own datasets. Even though publicly available sources exist to crawl the malware datasets, preparing a proper dataset for research is a daunting task. These issues are the main drawbacks behind developing generic machine learning based malware analysis system that can be deployed in real time. More importantly, the compelling issues in applying data science techniques were discussed in detail by [15].

In recent days, deep learning, which is an improved model of neural networks has outperformed the classical MLAs in many of the tasks which exist in the field of natural language processing (NLP), computer vision, speech processing and many others [16]. During the training process, it tries to capture higher level representation of features in deep hidden layers with the ability to learn from mistakes. MLAs experience diminishing outputs as they see more and more data whereas deep learning captures new patterns and establishes associations with the already captured pattern to enhance the performance of tasks. There exists few research studies towards the application of deep learning architectures for malware analysis to improve cyber security [13], [11], [12], [17], [18], [18]–[24]. However, with Industry 4.0, the number of malwares is rapidly increasing in recent times. Since the continuous collection of malwares in real time results in Big Data, the existing approaches are not scalable with very high requirements for storage and time in making efficient decisions.

3. PROPOSED METHODOLOGY

Deep learning or deep neural networks (DNNs) takes inspiration from how the brain works and forms a sub module of artificial intelligence. The main strength of deep learning architectures is the capability to understand the meaning of data when it is in large amounts and to automatically tune the derived meaning with new data without the need for a domain expert knowledge. Convolutional neural networks (CNNs) and Recurrent neural networks (RNNs) are two types of deep learning architectures predominantly applied in real-life scenarios. Generally, CNN architectures are used for spatial data and RNN architectures are used for temporal data. The combination of CNN and LSTM is used for spatial and temporal data analysis.

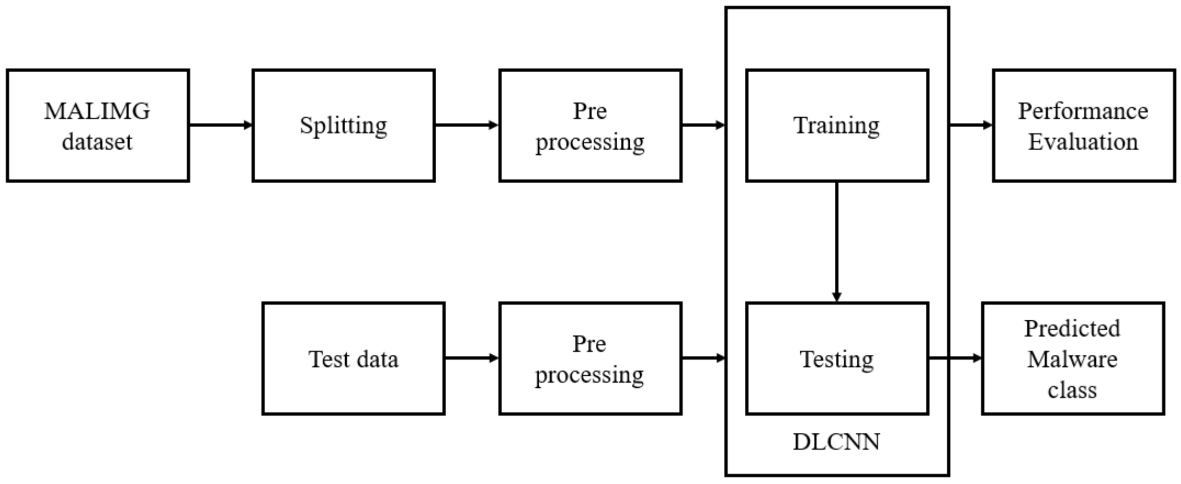


Fig. 1: Proposed block diagram.

Fig. 1 shows the block diagram of proposed method. Initially, MALIMG dataset is spitted into 80% for training and 20% for testing. Then, dataset preprocessing operation is performed to normalize the entire dataset. Further, DLCNN classifier is used for prediction of malware attack from test sample. The performance evaluation is carried out to show supremacy of proposed method.

3.1 MALIMG dataset

CICDDoS2019 contains benign and the most up-to-date common DDoS attacks, which resembles the true real-world data (PCAPs). It also includes the results of the network traffic analysis using CICFlowMeter-V3 with labeled flows based on the time stamp, source, and destination IPs, source and destination ports, protocols and attack (CSV files). Generating realistic background traffic was our top priority in building this dataset. We have used our proposed B-Profile system to profile the abstract behaviour of human interactions and generates naturalistic benign background traffic in the proposed testbed. For this dataset, we built the abstract behaviour of 25 users based on the HTTP, HTTPS, FTP, SSH and email protocols.

3.2 Preprocessing

Data preprocessing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model. When creating a machine learning project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way. So, for this, we use data preprocessing task.

Need of Data Preprocessing: A real-world data generally contains noises, missing values, and maybe in an unusable format which cannot be directly used for machine learning models. Data preprocessing is required tasks for cleaning the data and making it suitable for a machine learning model which also increases the accuracy and efficiency of a machine learning model.

- Getting the dataset
- Importing libraries
- Importing datasets
- Finding Missing Data
- Encoding Categorical Data
- Splitting dataset into training and test set
- Feature scaling

Importing Libraries: To perform data preprocessing using Python, we need to import some predefined Python libraries. These libraries are used to perform some specific jobs. There are three specific libraries that we will use for data preprocessing, which are:

Numpy: Numpy Python library is used for including any type of mathematical operation in the code. It is the fundamental package for scientific calculation in Python. It also supports to add large, multidimensional arrays and matrices. So, in Python, we can import it as:

```
import numpy as nm
```

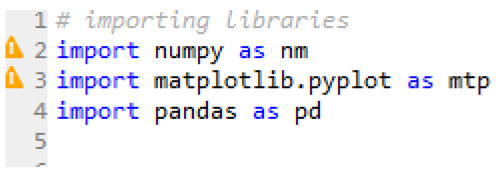
Here we have used nm, which is a short name for Numpy, and it will be used in the whole program.

Matplotlib: The second library is matplotlib, which is a Python 2D plotting library, and with this library, we need to import a sub-library pyplot. This library is used to plot any type of charts in Python for the code. It will be imported as below:

```
import matplotlib.pyplot as mpt
```

Here we have used mpt as a short name for this library.

Pandas: The last library is the Pandas library, which is one of the most famous Python libraries and used for importing and managing the datasets. It is an open-source data manipulation and analysis library. Here, we have used pd as a short name for this library. Consider the below data:



```python
# importing libraries
import numpy as nm
import matplotlib.pyplot as mtp
import pandas as pd
```

Handling Missing data: The next step of data preprocessing is to handle missing data in the datasets. If our dataset contains some missing data, then it may create a huge problem for our machine learning model. Hence it is necessary to handle missing values present in the dataset. There are mainly two ways to handle missing data, which are:

- By deleting the particular row: The first way is used to commonly deal with null values. In this way, we just delete the specific row or column which consists of null values. But this way is not so efficient and removing data may lead to loss of information which will not give the accurate output.
- By calculating the mean: In this way, we will calculate the mean of that column or row which contains any missing value and will put it on the place of missing value. This strategy is useful for the features which have numeric data such as age, salary, year, etc.

Encoding Categorical data: Categorical data is data which has some categories such as, in our dataset; there are two categorical variables, Country, and Purchased. Since machine learning model completely works on mathematics and numbers, but if our dataset would have a categorical variable, then it may create trouble while building the model. So, it is necessary to encode these categorical variables into numbers.

Feature Scaling: Feature scaling is the final step of data preprocessing in machine learning. It is a technique to standardize the independent variables of the dataset in a specific range. In feature scaling, we put our variables in the same range and in the same scale so that no variable dominates the other variable. A machine learning model is based on Euclidean distance, and if we do not scale the variable, then it will cause some issue in our machine learning model. Euclidean distance is given as:

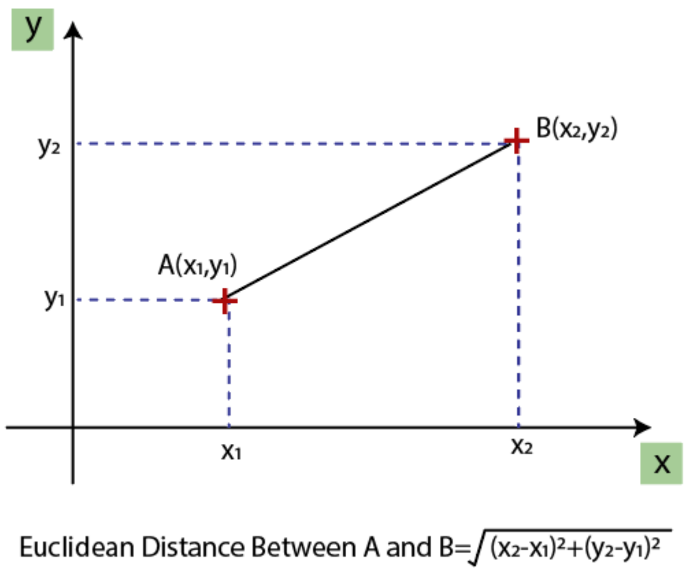
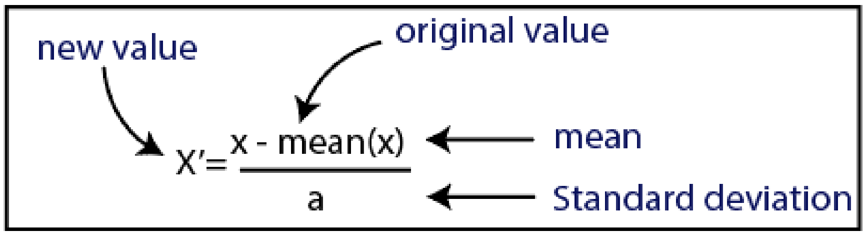


Fig. 2: Feature scaling.

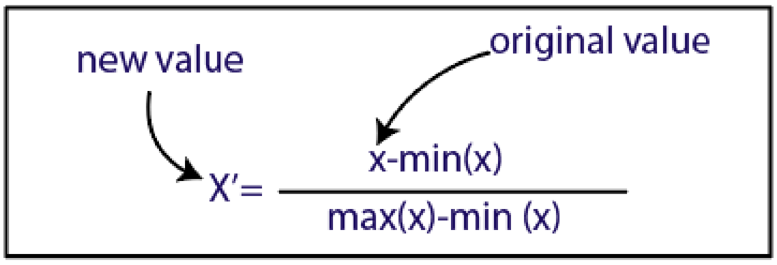
If we compute any two values from age and salary, then salary values will dominate the age values, and it will produce an incorrect result. So, to remove this issue, we need to perform feature scaling for machine learning.

There are two ways to perform feature scaling in machine learning:

Standardization



Normalization



3.3 Splitting the Dataset

In machine learning data preprocessing, we divide our dataset into a training set and test set. This is one of the crucial steps of data preprocessing as by doing this, we can enhance the performance of our machine learning model. Suppose if we have given training to our machine learning model by a dataset and we test it by a completely different dataset. Then, it will create difficulties for our model to understand the correlations between the models. If we train our model very well and its training accuracy is also very high, but we provide a new dataset to it, then it will decrease the performance. So, we always try to make a machine learning model which performs well with the training set and also with the test dataset. Here, we can define these datasets as:

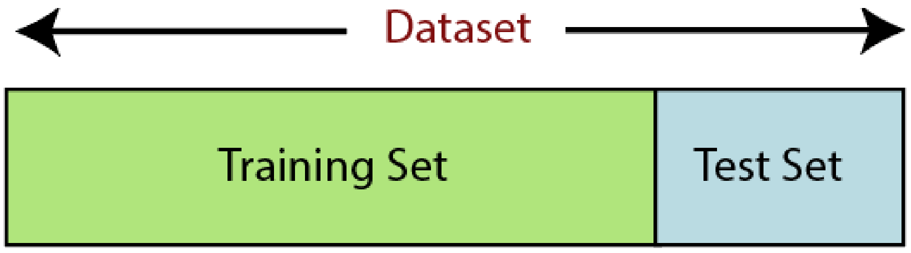


Fig. 3: Splitting the dataset.

Training Set: A subset of dataset to train the machine learning model, and we already know the output.

Test set: A subset of dataset to test the machine learning model, and by using the test set, model predicts the output.

For splitting the dataset, we will use the below lines of code:

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test= train_test_split(x, y, test_size= 0.2, random_state=0)
```

Explanation

- In the above code, the first line is used for splitting arrays of the dataset into random train and test subsets.
- In the second line, we have used four variables for our output that are
- x_train: features for the training data
- x_test: features for testing data
- y_train: Dependent variables for training data
- y_test: Independent variable for testing data
- In train_test_split() function, we have passed four parameters in which first two are for arrays of data, and test_size is for specifying the size of the test set. The test_size maybe .5, .3, or .2, which tells the dividing ratio of training and testing sets.
- The last parameter random_state is used to set a seed for a random generator so that you always get the same result, and the most used value for this is 42.

3.4 DLCNN

A feed forward neural network (FFN) creates a directed graph in which a graph is composed of nodes and edges. FFN passes information along edges from one node to another without formation of a cycle. Multi-layer perceptron (MLP) is a type of FFN that contains 3 or more layers, specifically one input layer, one or more hidden layer and an output layer in which each layer has many neurons, called as units in mathematical notation. The number of hidden layers is selected by following a hyper parameter tuning approach. The information is transformed from one layer to another layer in forward direction without considering the past values. Moreover, neurons in each layer are fully connected.

Convolutional network or convolutional neural network or CNN is supplement to the classical feed forward network (FFN), primarily used in the field of data processing. Here, m denotes number of filters, ln denotes number of input features and p denotes reduced feature dimension, it depends on pooling length. In this work, CNN network composed of convolution 1D layer, pooling 1D layer and fully connected layer. A CNN network can have more than one convolution 1D layer, pooling 1D layer and fully connected layer. In convolutional 1D layer, the filters slide over the 1D sequence data and extracts optimal features. The features that are extracted from each filter are grouped into a new feature set called as feature map. The number of filters and the length are chosen by following a hyper parameter tuning method. This in turn uses non-linear activation function, ReLU on each element.

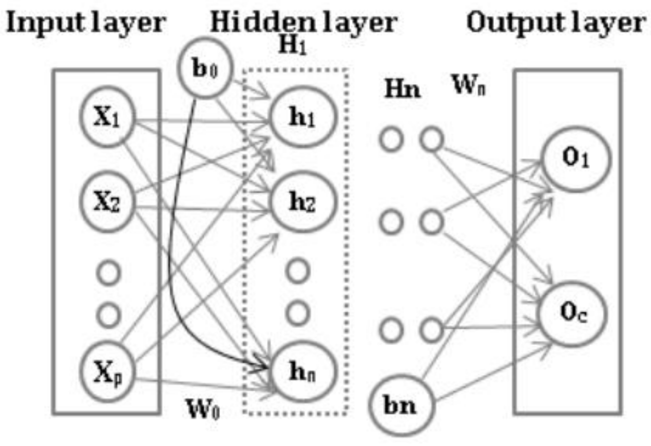


Fig. 4: DNN architecture.

The dimensions of the optimal features are reduced using pooling 1D layer using either max pooling, min pooling or average pooling. Since the maximum output within a selected region is selected in max pooling, we adopt max pooling in this work. Finally, the CNN network contains fully connected layer for classification. In fully connected layer, each neuron contains a connection to every other neuron. Instead of passing the pooling 1D layer features into fully connected layer, it can also be given to recurrent layer, LSTM to capture the sequence related information. Finally, the LSTM features are passed into fully connected layer for classification.

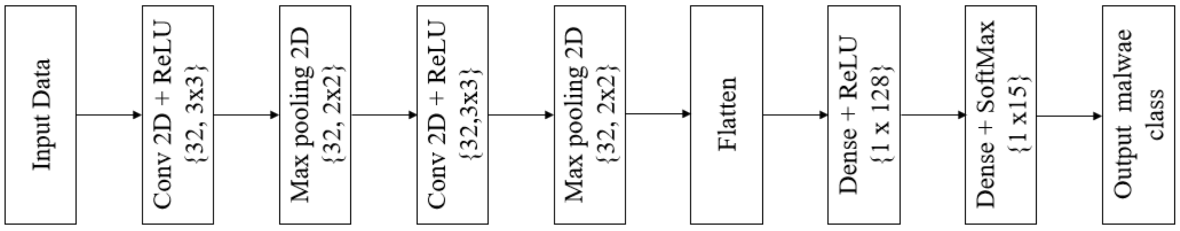


Fig. 5: Architecture of DLCNN for malware detection.

Table. 1: Layers description.

Layer Names	No. of filters	Kernel size	Feature size
Conv 2D +ReLU	32	3 x 3	62x62x32
Max pooling 2D	-	3 x 3	31x31x32
Conv 2D+ReLU	32	3 x 3	29x29x32
Max pooling 2D	-	3 x 3	14x14x32
Flatten	-	1x6272	1x6272
Dense +ReLU		1 x 128	1 x 256
Dense + SoftMax		1 x 15	1 x 15

Convolutional neural networks are generally composed of three parts. Convolution layer for feature extraction. The convergence layer, also known as the pooling layer, is mainly used for feature selection. The number of parameters is reduced by reducing the number of features. The full connection layer carries out the summary and output of the characteristics. A convolution layer is consisting of a convolution process and a nonlinear activation function ReLU. A typical architecture of CNN model for malware class recognition is shown in Fig 5.

The leftmost data is the input layer, which the computer understands as the input of several matrices. Next is the convolution layer, the activation function of which uses ReLU. The pooling layer has no activation function. The combination of convolution and pooling layers can be constructed many times. The combination of convolution layer and convolution layer or convolution layer and pool layer can be very flexibly, which is not limited when constructing the model. But the most common CNN is a combination of several convolution layers and pooling layers. Finally, there is a full connection layer, which acts as a classifier and maps the learned feature representation to the sample label space.

Convolutional neural network mainly solves the following two problems.

1) Problem of too many parameters: It is assumed that the size of the input picture is $50 * 50 * 3$. If placed in a fully connected feedforward network, there are 7500 mutually independent links to the hidden layer. And each link also corresponds to its unique weight parameter. With the increase of the number of layers, the size of the parameters also increases significantly. On the one hand, it will easily lead to the occurrence of over-fitting phenomenon. On the other hand, the neural network is too complex, which will seriously affect the training efficiency. In convolutional neural networks, the parameter sharing mechanism makes the same parameters used in multiple functions of a model, and each element of the convolutional kernel will act on a specific position of each local input. The neural network only needs to learn a set of parameters and does not need to optimize learning for each parameter of each position.

2) Data stability: Data stability is the local invariant feature, which means that the natural data will not be affected by the scaling, translation, and rotation of the data size. Because in deep learning, data enhancement is generally needed to improve performance, and fully connected feedforward neural is difficult to ensure the local invariance of the data. This problem can be solved by convolution operation in convolutional neural network.

3.5 DLCNN Layers

According to the facts, training and testing of DLCNN involves in allowing every source data via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from [0,1].

Convolution layer as depicted in Fig. 6 is the primary layer to extract the features from a source data and maintains the relationship between pixels by learning the features of data by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source data $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an data (here $d = 3$, since the source data is RGB) and a filter or kernel with similar size of input data and can be denoted as $F\left(k_x, k_y, d\right)$.

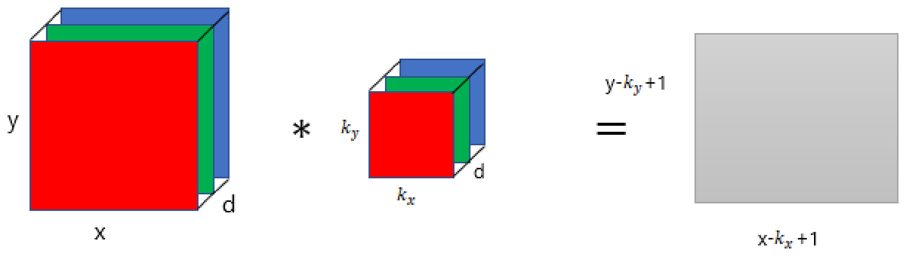


Fig. 6: Representation of convolution layer process.

The output obtained from convolution process of input data and filter has a size of $C\left((x - k_x + 1), (y - k_y + 1), 1\right)$. Let us assume an input data with a size of 5×5 and the filter having the size of

3×3. The feature map of input data is obtained by multiplying the input data values with the filter values as given in Fig. 7.

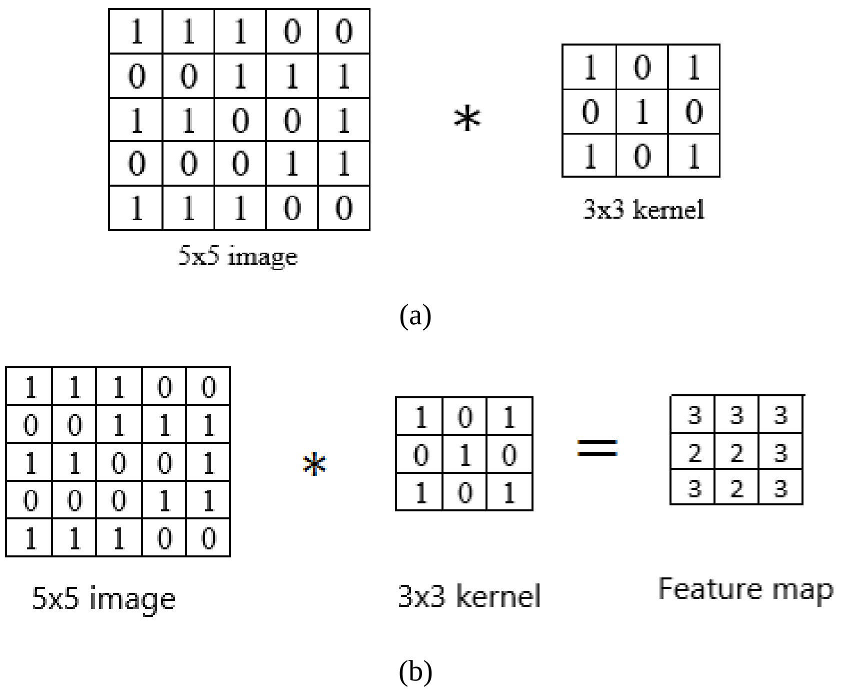


Fig. 7: Example of convolution layer process (a) an data with size **5** $\times$ **5** is convolving with **3** $\times$ **3** kernel (b) Convolved feature map.

3.5.1 ReLU layer

Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$

3.5.2 Max pooing layer

This layer mitigates the number of parameters when there are larger size datas. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

3.6 Softmax classifier

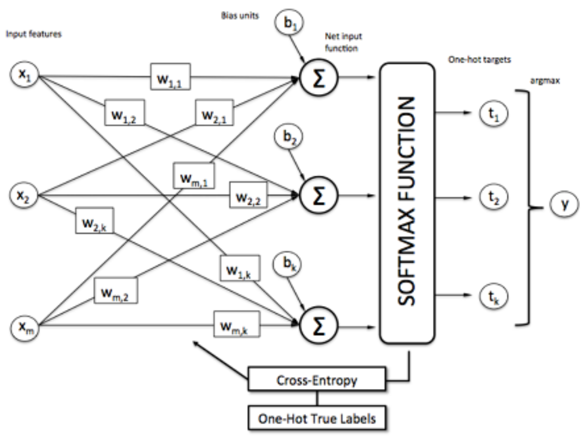


Fig. 8: Malware class prediction using SoftMax classifier.

Generally, as seen in the above picture softmax function is added at the end of the output since it is the place where the nodes are meet finally and thus, they can be classified. Here, X is the input of all the models and the layers between X and Y are the hidden layers and the data is passed from X to all the layers and Received by Y. Suppose, we have 10 classes, and we predict for which class the given input belongs to. So, for this what we do is allot each class with a particular predicted output. Which means that we have 10 outputs corresponding to 10 different class and predict the class by the highest probability it has.

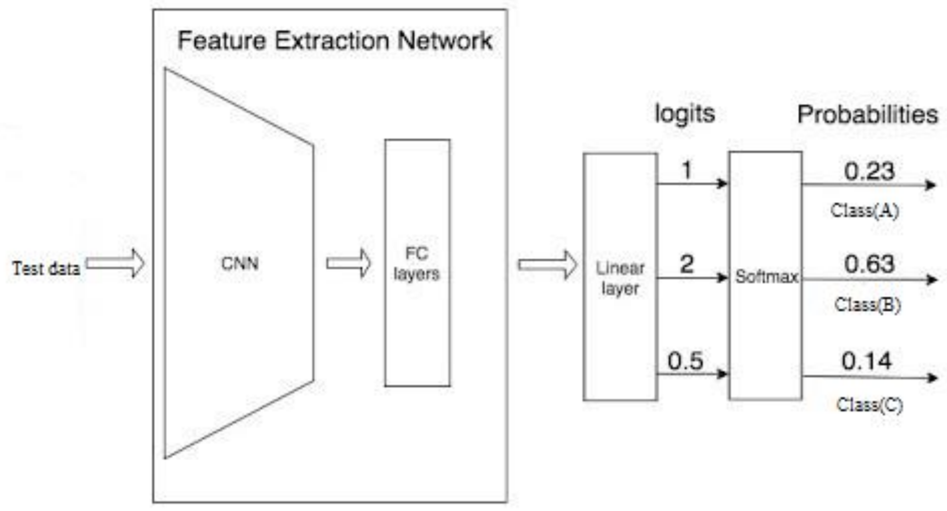


Fig. 9: Example of SoftMax classifier.

In the normal case, we predict whether the malware is A. But in this case, we must predict what is the object that is present in the picture. This is the place where softmax comes in handy. As the model is already trained on some data. So, as soon as the picture is given, the model processes the pictures, send it to the hidden layers and then finally send to softmax for classifying the picture. The softmax uses a One-Hot encoding Technique to calculate the cross-entropy loss and get the max. One-Hot Encoding is the technique that is used to categorize the data. In the previous example, if softmax predicts that the object is class A then the One-Hot Encoding for:

Class A will be [1 0 0]

Class B will be [0 1 0]

Class C will be [0 0 1]

From the diagram, we see that the predictions are occurred. But generally, we don't know the predictions. But the machine must choose the correct predicted object. So, for machine to identify an object correctly, it uses a function called cross-entropy function.

So, we choose more similar value by using the below cross-entropy formula.

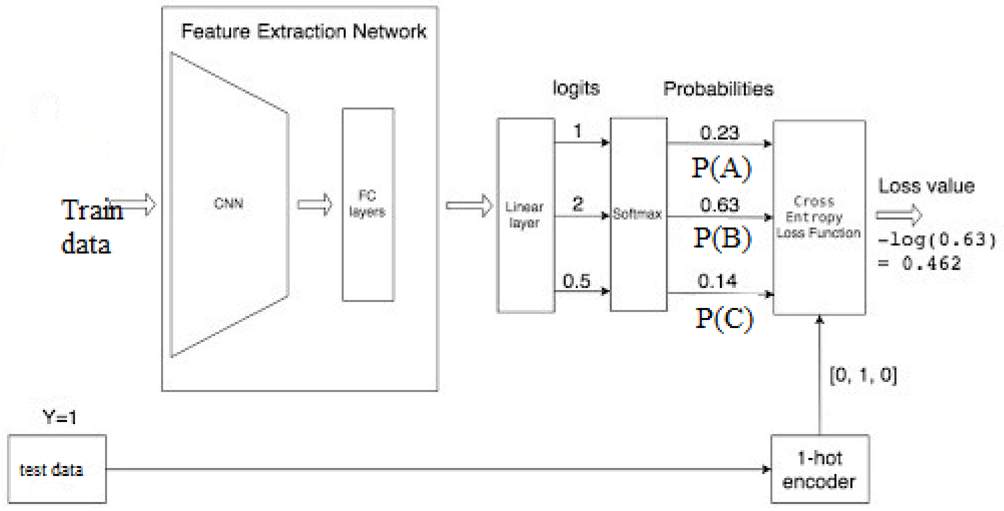


Fig. 10: Example of SoftMax classifier with test data.

In the above example we see that 0.462 is the loss of the function for class specific classifier. In the same way, we find loss for remaining classifiers. The lowest the loss function, the better the prediction is. The mathematical representation for loss function can be represented as: -

$$LOSS = np.sum(-Y * np.log(Y\_pred))$$

3.7 Advantages of proposed system

- Accuracy is high.
- More reliable.

4. RESULTS AND DISCUSSION

To implement this project and to evaluate machine learning algorithms performance author is using binary malware dataset called 'MALIMG'. This dataset contains 25 families of malware and application will convert this binary dataset into gray images to generate train and test models for machine learning algorithms. These algorithms converting binary data to images and then generating model, so they are called as MalConv CNN and MalConv LSTM and other algorithm refers as EMBER. Application convert dataset into binary images and then used 80% dataset for training model and 20% dataset for testing. Whenever we upload new test malware binary data then application will apply new test data on train model to predict malware class. In dataset total 25 families of malware, we can see and below are their names.

'Dialer Adialer.C','Backdoor Agent.FYI','Worm Allaple.A','Worm Allaple.L','Trojan Alueron.gen','Worm:AutoIT Autorun.K',

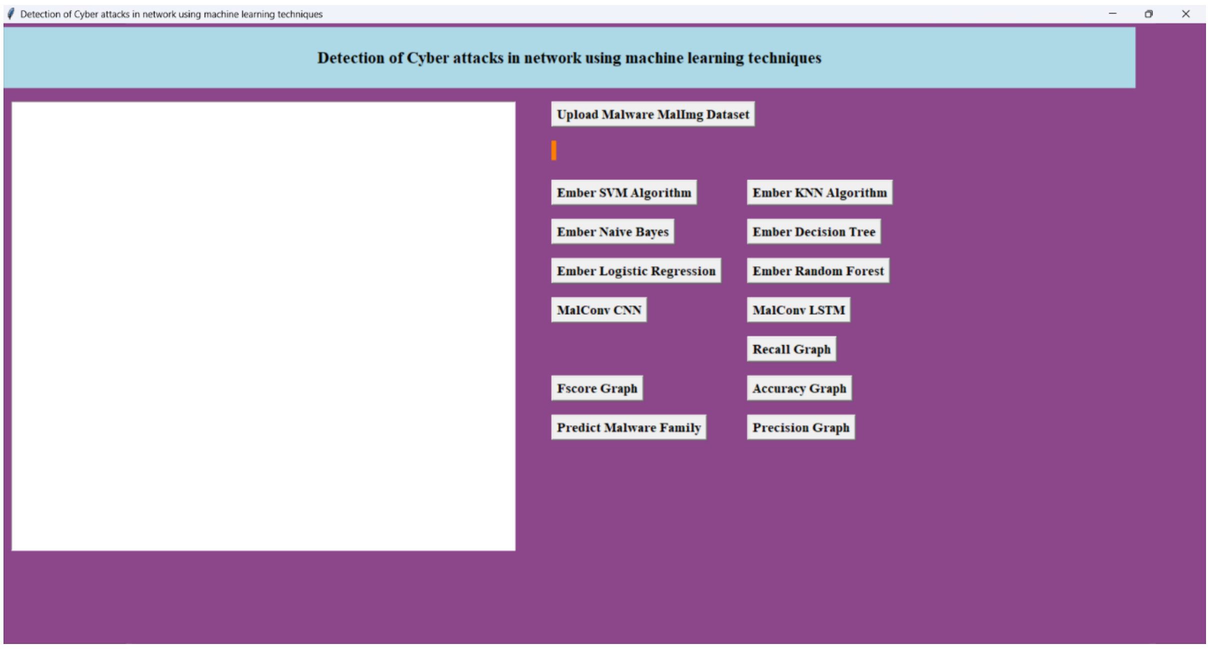
'Trojan C2Lop.P','Trojan C2Lop.gen','Dialer Dialplatform.B','Trojan Downloader Dontovo.A','Rogue Fakerean','Dialer Instantaccess',

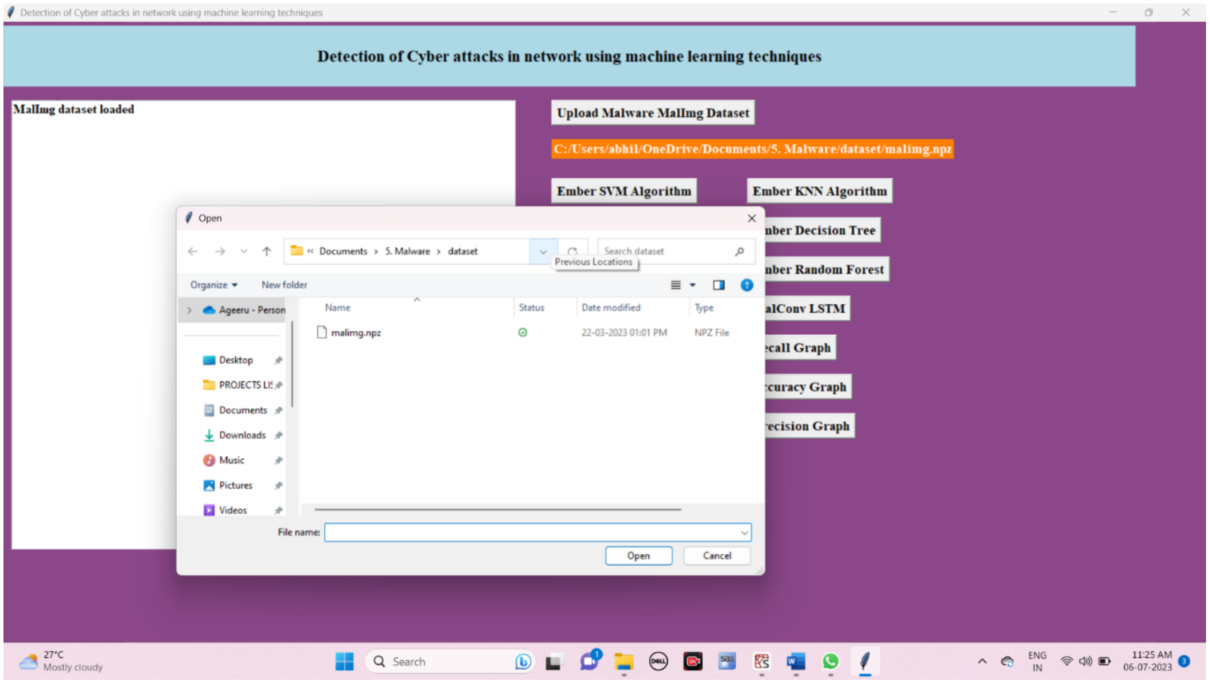
'PWS Lolyda.AA 1','PWS Lolyda.AA 2','PWS Lolyda.AA 3','PWS Lolyda.AT','Trojan Malex.gen','Trojan Downloader Obfuscator.AD', 'Backdoor Rbot!gen','Trojan Skintrim.N','Trojan Downloader Swizzor.gen!E','Trojan Downloader Swizzor.gen!I','Worm VB.AT',

'Trojan Downloader Wintrim.BX','Worm Yuner.A'

All above names are the malware families

All new malware test files I saved inside images folder, and you can upload this files to predict it class. All algorithms detail you can read from paper.


Detection of Cyber attacks in network using machine learning techniques
Detection of Cyber attacks in network using machine learning techniques
Upload Malware MalImg Dataset
Ember SVM Algorithm
Ember KNN Algorithm
Ember Naive Bayes
Ember Decision Tree
Ember Logistic Regression
Ember Random Forest
MalConv CNN
MalConv LSTM
Recall Graph
Fscore Graph
Accuracy Graph
Predict Malware Family
Precision Graph


MalImg dataset loaded

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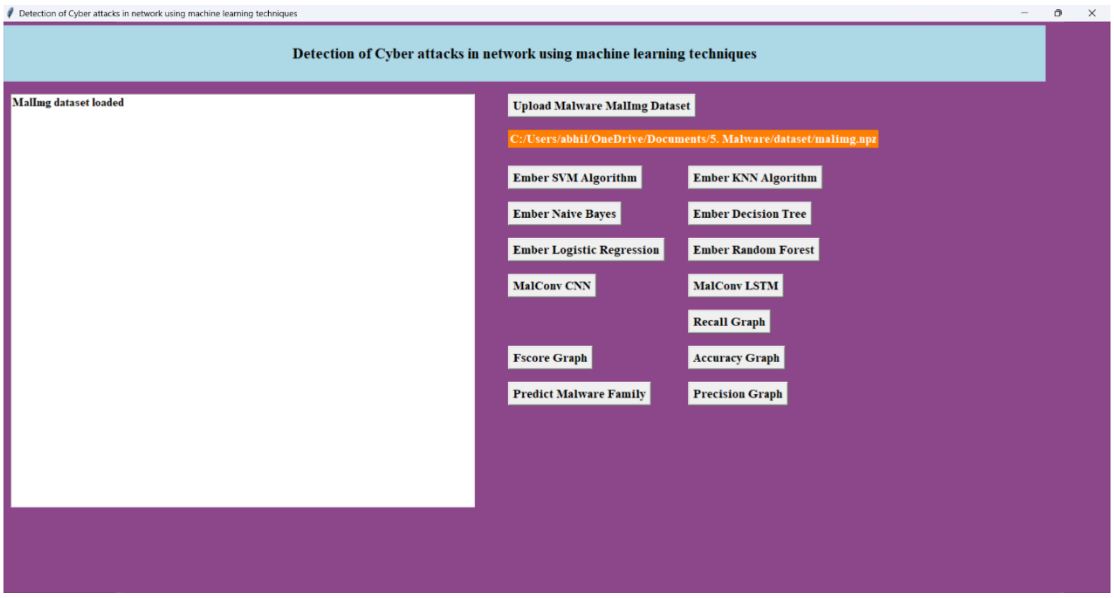
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Ember KNN Algorithm
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Ember Random Forest
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MalConv LSTM
Recall Graph
Fscore Graph
Accuracy Graph
Predict Malware Family
Precision Graph

```
MalImg dataset loaded
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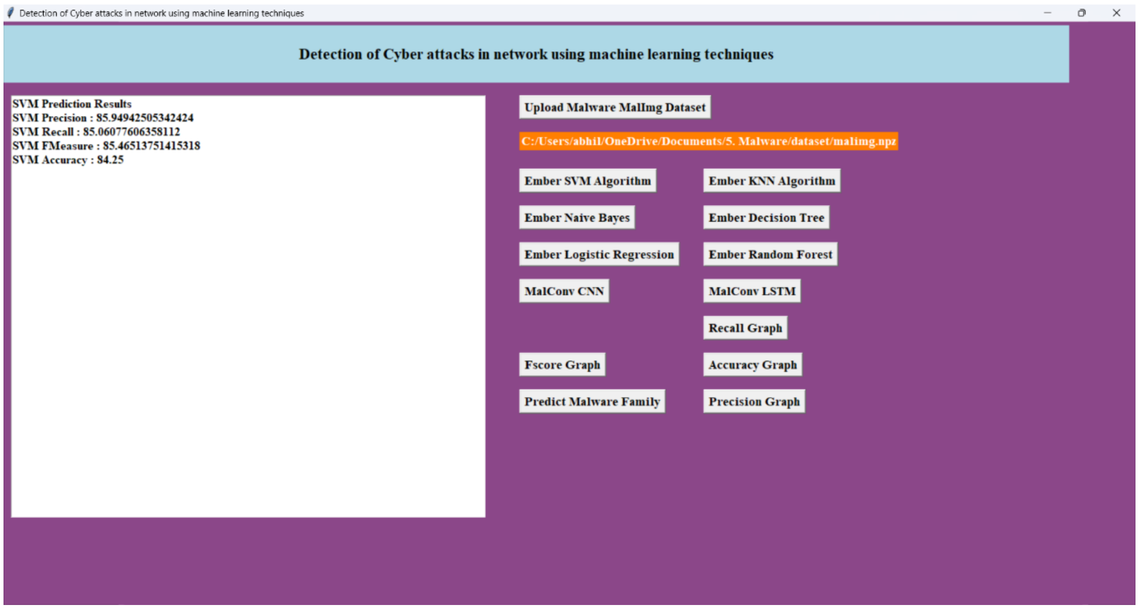
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SVM Prediction Results
SVM Precision : 85.94942505342424
SVM Recall : 85.06077606358112
SVM FMeasure : 85.46513751415318
SVM Accuracy : 84.25
```

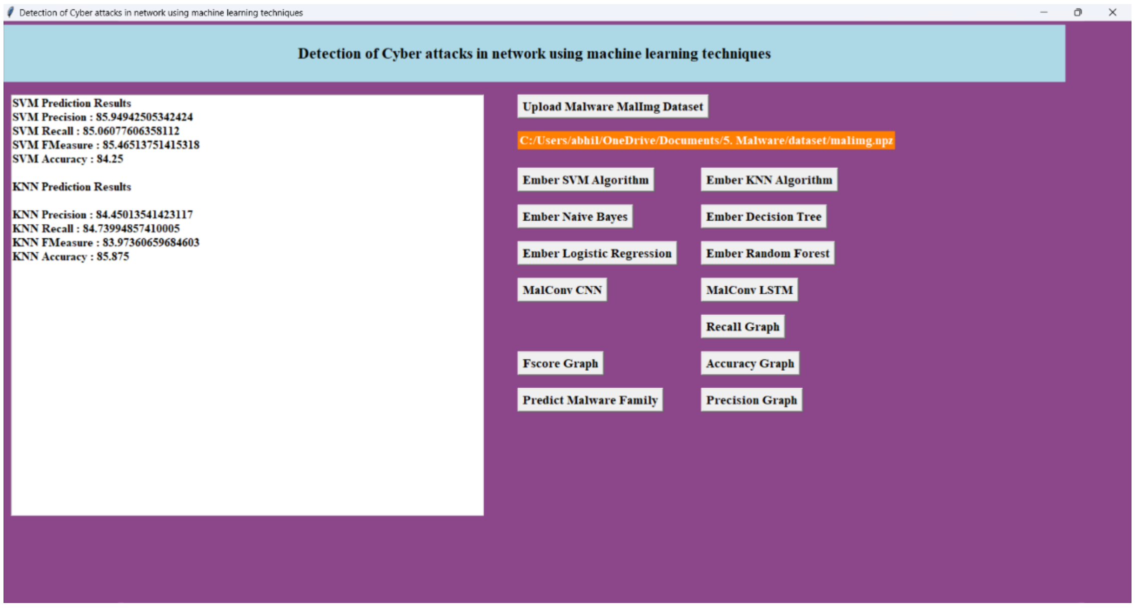
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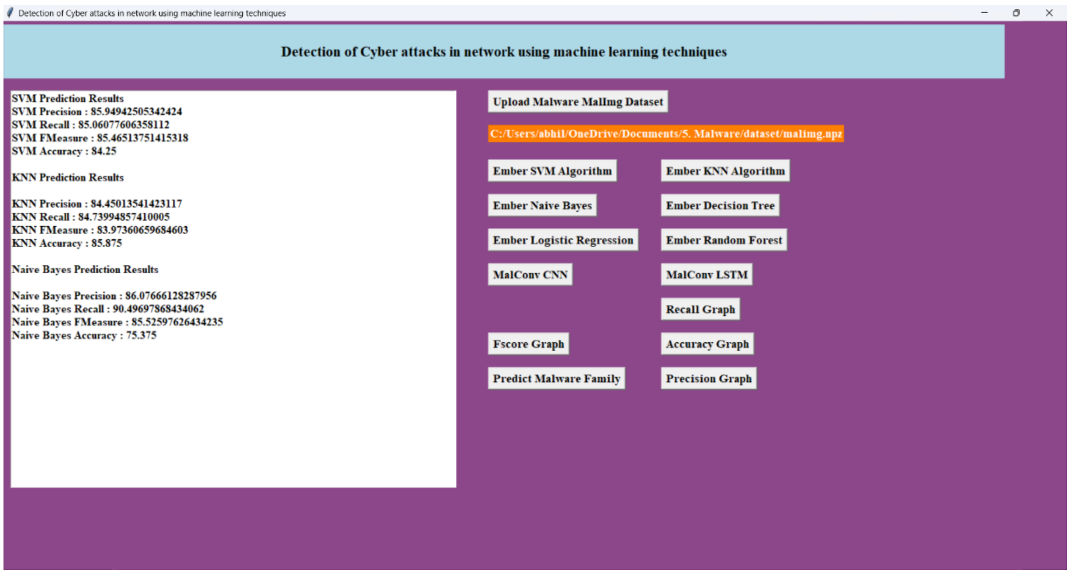
KNN Prediction Results

KNN Precision : 84.45013541423117
KNN Recall : 84.73994857410005
KNN FMeasure : 83.97360659684603
KNN Accuracy : 85.875
```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Naive Bayes Prediction Results

Naive Bayes Precision : 86.07666128287956
Naive Bayes Recall : 90.49697868434062
Naive Bayes FMeasure : 85.52597626434235
Naive Bayes Accuracy : 75.375
```

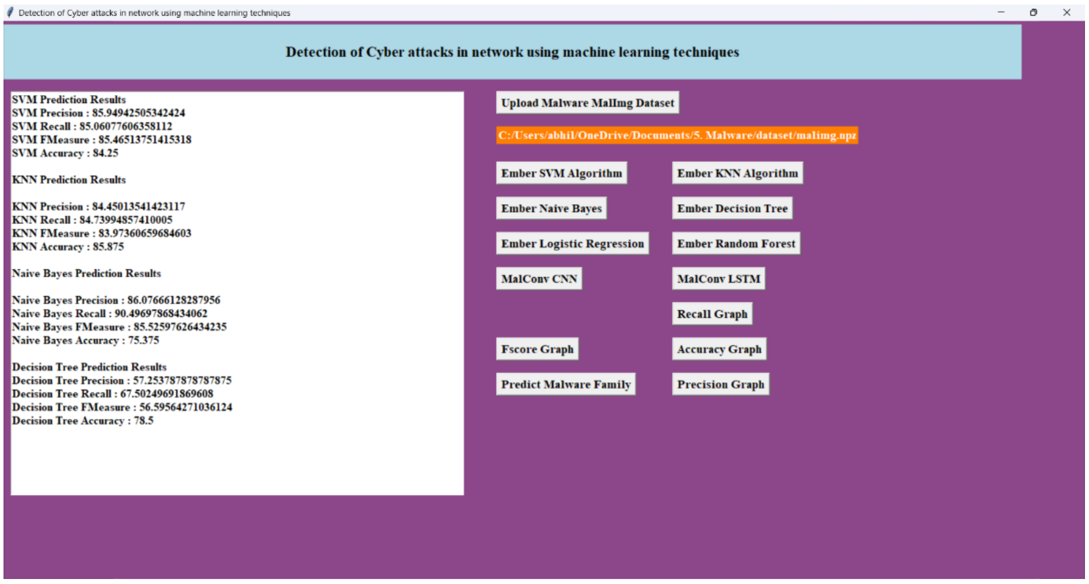
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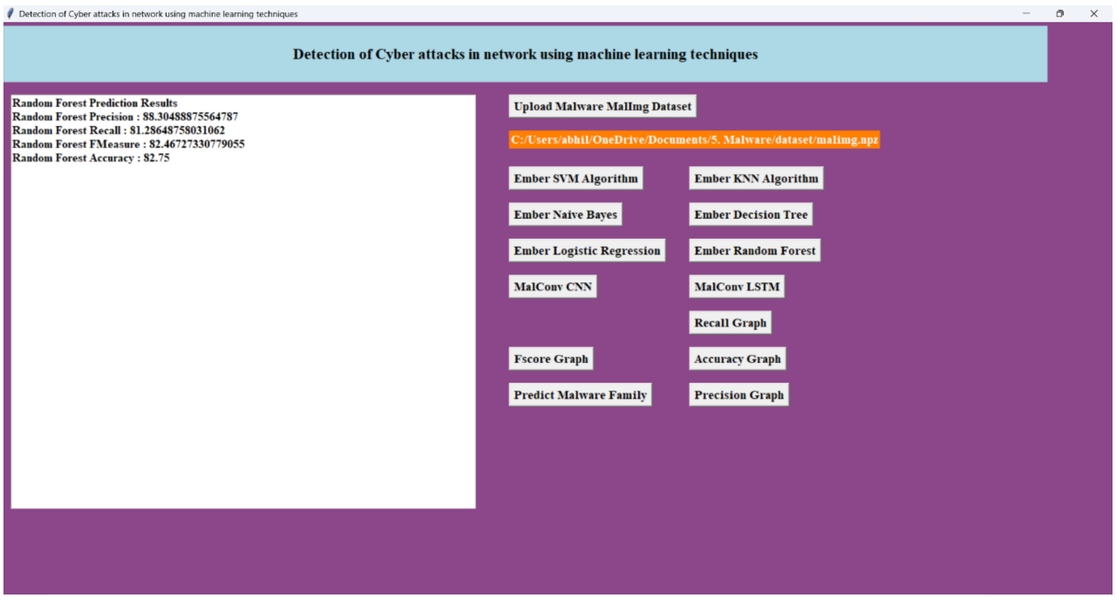
Naive Bayes FMeasure : 85.52597626434235
Naive Bayes Accuracy : 75.375

Decision Tree Prediction Results
Decision Tree Precision : 57.253787878787875
Decision Tree Recall : 67.50249691869608
Decision Tree FMeasure : 56.59564271036124
Decision Tree Accuracy : 78.5
```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Random Forest Prediction Results
Random Forest Precision : 88.30488875564787
Random Forest Recall : 81.28648758031062
Random Forest FMeasure : 82.46727330779055
Random Forest Accuracy : 82.75
```

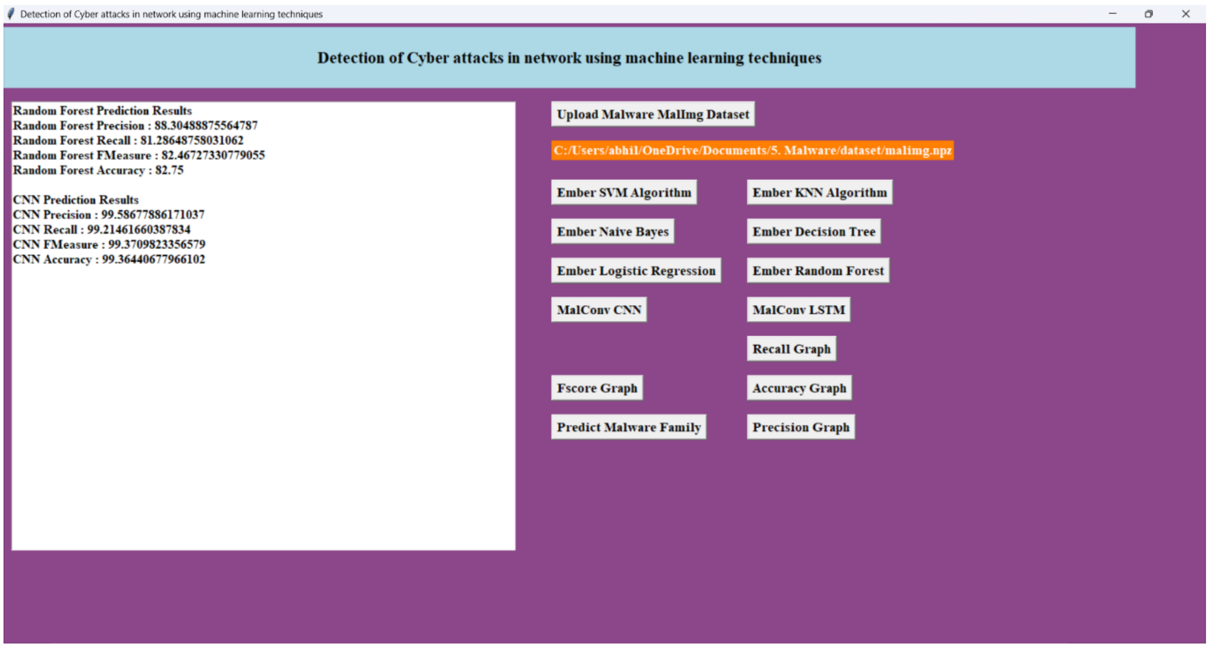
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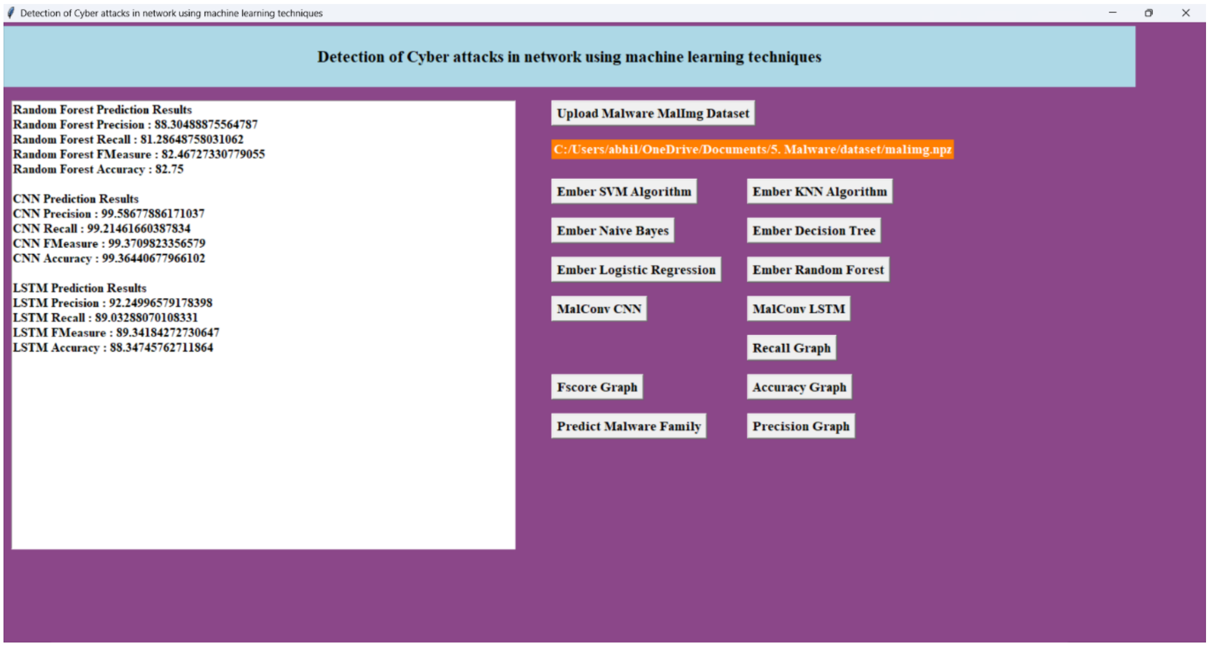
Random Forest Accuracy : 82.75

CNN Prediction Results
CNN Precision : 99.58677886171037
CNN Recall : 99.21461660387834
CNN FMeasure : 99.3709823356579
CNN Accuracy : 99.36440677966102
```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CNN Precision : 99.58677886171037
CNN Recall : 99.21461660387834
CNN FMeasure : 99.3709823356579
CNN Accuracy : 99.36440677966102

LSTM Prediction Results
LSTM Precision : 92.24996579178398
LSTM Recall : 89.03288070108331
LSTM FMeasure : 89.34184272730647
LSTM Accuracy : 88.34745762711864
```

5. CONCLUSION AND FUTURE SCOPE

This project proposed an efficient malware detection and designed a highly scalable framework to detect, classify and categorize zero-day malwares. This framework applies neural network on the collected malwares from end user hosts and follows a two-stage process for malware analysis. In the first stage, a hybrid of static and dynamic analysis was applied for malware classification. In the second stage, malwares were grouped into corresponding malware categories using image processing approaches. Various experimental analysis conducted by applying variations in the models on publicly available benchmark dataset and indicated the proposed model outperformed classical MLAs. The developed framework is capable of analyzing large number of malwares in real-time and scaled out to analyse even larger number of malwares by stacking a few more layers to the existing architectures. Future research entails exploration of these variations with new features that could be added to the existing data.

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