

A NEW RESILIENT SMART MALWARE DETECTION USING DEEP LEARNING

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ABSTRACT

Now-a-days to observe cyber-attack are the usage of static and dynamic evaluation of request data. Static evaluation is primarily based on signature which we will suit current assault signature with new request packet information to become aware of packet is ordinary or consists of assault signature. Dynamic evaluation will use dynamic execution of application to notice malware/attack, however dynamic evaluation is time consuming. To overcome from this hassle and to enlarge detection accuracy with ancient and new malware attacks, we are the use of computing device mastering algorithms and evaluating prediction overall performance of a variety of computer gaining knowledge of 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, quite a number fashions Deep studying CNN resulted in most suitable overall performance in contrast to different models. To put into effect this work and to consider computer getting to know algorithms overall performance this work the usage of binary malware dataset known as 'MALIMG'. This dataset consists of 25 households of malware and utility will convert this binary dataset into grey pictures to generate educate and take a look at fashions for laptop gaining knowledge of algorithms. This algorithm changing binary statistics to photographs and then producing model, so they are referred to as as MalConv CNN and MalConv LSTM and any other algorithm refers as EMBER. Application convert dataset into binary pix and then used 80% dataset for education mannequin and 20% dataset for testing. Whenever we add new take a look at malware binary facts then utility will observe new take a look at statistics on teach mannequin to predict malware class.

Keywords: Malware detection, extreme learning machine, cyber-attacks.

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]–

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.

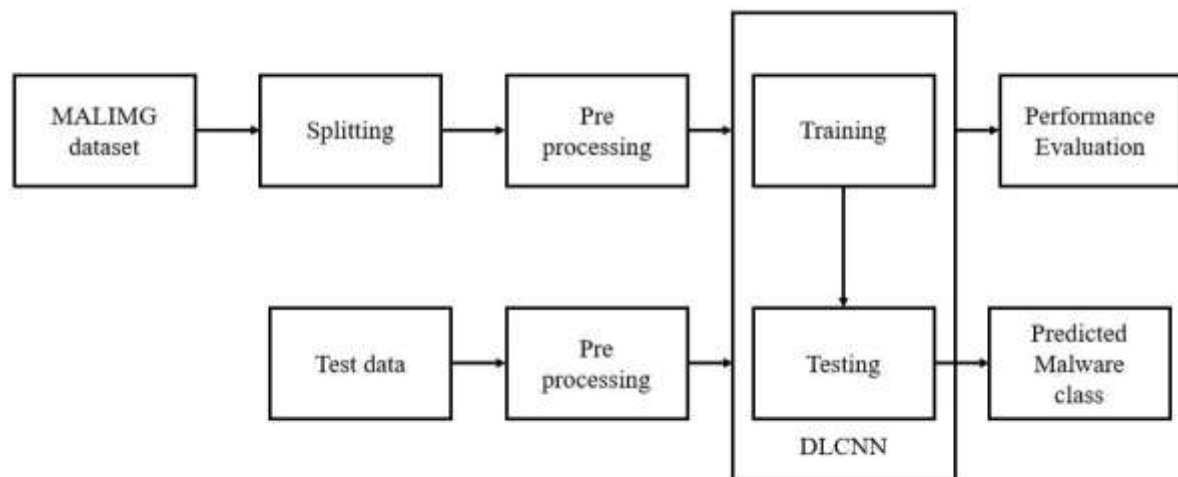


Fig. 1: Proposed block diagram.

Fig. 1 shows the block diagram of proposed method. Initially, MALIMG dataset is splitted 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 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, I_n 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.

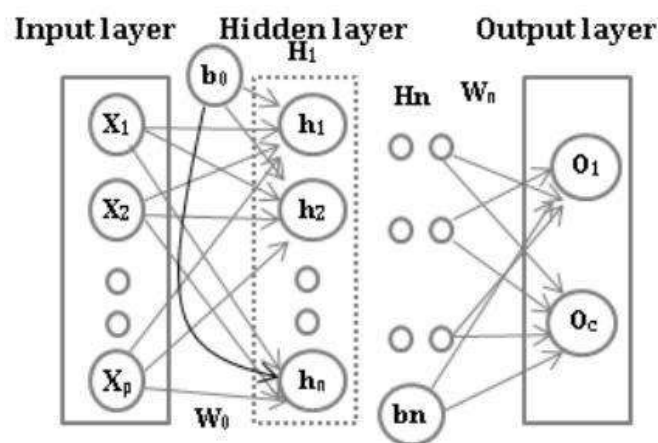


Fig. 2: DNN architecture.

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.

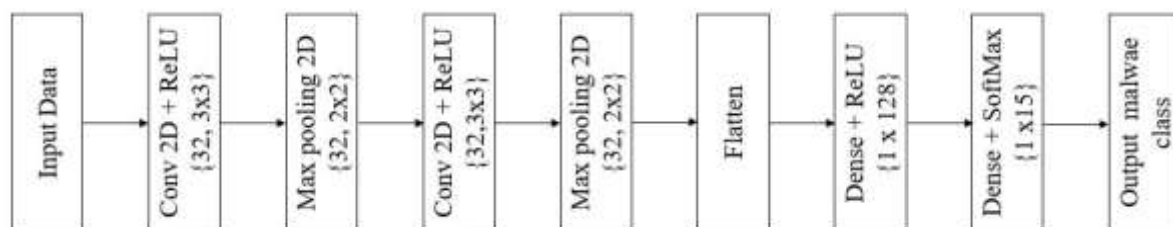


Fig. 3: Architecture of DLCNN for malware detection.

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.

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.

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 Allapple.A','Worm Allapple.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

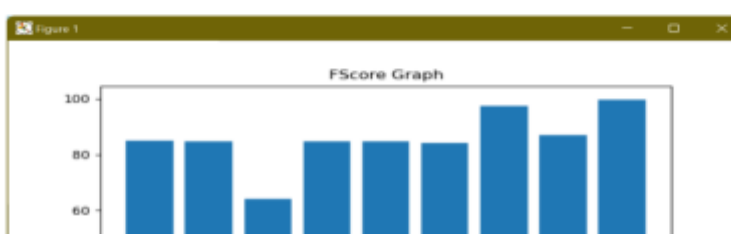
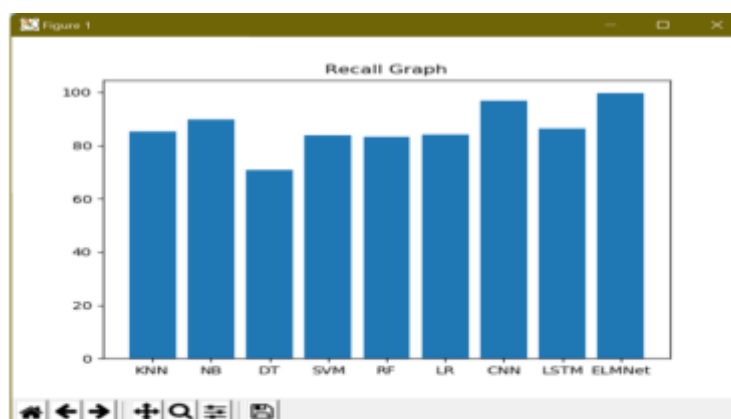
All new malware test files I saved inside images folder, and you can upload this files to predict it class. All algorithms detail you can read from paper.

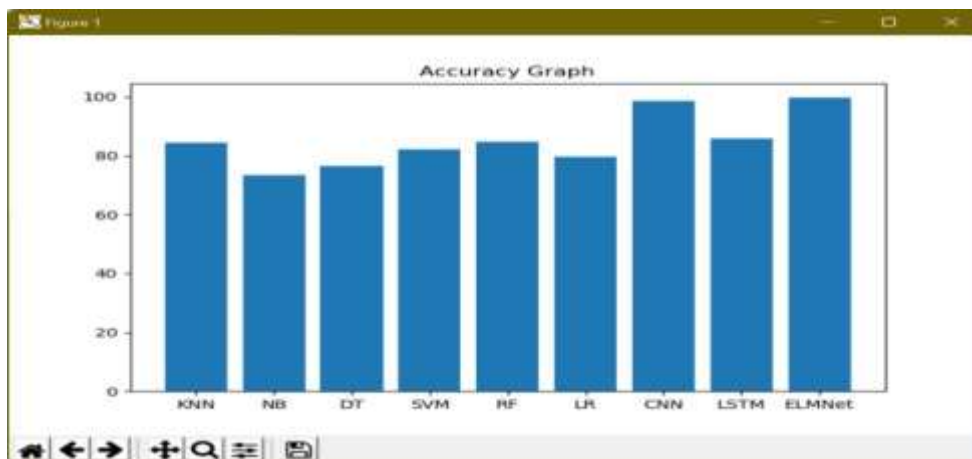
In above screen I am uploading 'maling.npz' binary malware dataset and after uploading dataset will get below screen. Now click on 'Ember SVM algorithm' button to read malware dataset and generate train and test model and then apply SVM algorithm to calculate its prediction accuracy, FSCORE, Precision and Recall. If algorithm performance is good then its accuracy, precision or recall values will be closer to 100. In above screen we got SVM precision, recall and F-Measure. Now click on 'Ember KNN Algorithm' button to get its performance. In above screen we got KNN details and now click on 'Naïve Bayes', Decision Tree and Logistic Regression buttons to get its performance details

In above screen we got Naïve Bayes, Decision Tree and logistic regression details and now click on 'Random Forest' button to get its performance. In above screen we got random forest details and now click on 'MalConv CNN' button to get its performance details. In above screen we got CNN performance values and now click on 'MalConv LSTM' button to run LSTM algorithm.

In above screen we can see LSTM details. In above screen we can see accuracy and other metrics from various algorithms where CNN got 98.41% accuracy which is higher as compared all the above algorithms. Now click on proposed ELMNet to get below output.

In above screen CNN got 98.41% accuracy and proposed ELMNet got 99.62% accuracy which is higher than any other algorithm. So, by employing ELM we can further increase malware prediction capability of the application. Now click on 'Precision, Recall & F-Measure' button to get comparison graph for all metrics and all algorithms





Now click on 'Predict Malware Family' button and upload binary file to get or predict class of malware.



In above graph I am uploading one binary file called 1.npy and below is the malware prediction of that file.

In above screen we can see uploaded test file contains 'Dialer Adialer.C' malware attack. Similarly, we can upload other files and predict class.

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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