

Detection of Malicious Binaries by Deep Learning Methods

Anantha Rao Chukka¹ and V. Susheela Devi²

¹Defence Research and Development Organisation, India

²Indian Institute of Science, Bengaluru, Karnataka, 560012, India

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Abstract: Modern day cyberattacks are complex in nature. These attacks have adverse effects like loss of privacy, intellectual property and revenue on the victim institutions. These attacks have sophisticated payloads like ransom-ware for money extortion, distributed denial of service(DDOS) malware for service disruptions and advanced persistent threat(APT) malware to possess complete control over the victims computing resources. These malware are metamorphic and polymorphic in nature and contains root-kit components to maintain stealth and hide their malicious activity. So conventional defence mechanisms like rule-based and signature based mechanisms fail to detect these malware. Modern approaches use behavioural analysis(static analysis, dynamic analysis) to identify this kind of malware. However behavioural analysis process is hindered by factors like execution environment detection, code obfuscation, anti virtualization, anti-debugging, analysis environment detection etc. Behavioural analysis also requires domain expert to review the large amount of logs produced by it to decide on the nature of the binary which is complex, time consuming and expensive. To deal with these problems we proposed deep learning methods, where convolutional neural network model is trained on the image representation of the binary to decide the binary nature as malicious or benign. In this work we have encoded the binaries into images in a unique way. Deep convolution neural network is trained on these images to learn the features to identify the binary as malicious or normal. The malware and benign samples for the dataset creation are collected from online sources and windows operating system along with compatible third party application software respectively.

1 INTRODUCTION

1.1 Malware Analysis

Malware(Mullins, 2017), short for malicious software, consists of programming designed to disrupt or deny operation, gather information that leads to loss of privacy or exploitation, gain unauthorized access to system resources, and other such abusive behaviour. Some of the well known malware examples are trojan, ransom-ware, boot-kit, root-kit etc. Analysing malware provides deep insight into the activities performed by the malware such as file-system modifications, network connections established, persistent and stealth activity and information gathering on the victim's computing resources. This information facilitates the security researchers to develop defence mechanisms. Malware analysis is mainly categorized into two types.

1. **STATIC ANALYSIS** (Ligh et al., 2010). In this process the sample will be examined without running it, by specialized tools like dis-assemblers. Static code analysis is the major component of the static analysis which examines the instruction sequences to establish the execution behavioural characteristics. Meta information collection is another component which collects file meta-information like compiler environment, digital signatures, sample type and portable executable file characteristics.
2. **DYNAMIC ANALYSIS** (Ligh et al., 2010). In this process the sample activity will be monitored by running it in contained environment. Various system monitoring tools and techniques are used to log the file-system, network, persistent and other system activity.

1.2 Deep Learning

(Epelbaum, 2017) Deep learning methods are used to learn data representations(features) at multiple abstraction levels by composing many layers of artificial neural network units. The feature learning is hierarchical where the starting layer represents low-level features and the abstraction level increases with each further layer. The major advantage of the deep learning methods is automatic learning of features by training on large amount of data without any human feature engineering. Our work uses convolutional neural network, a kind of deep neural network specifically used for computer vision applications.

1.2.1 Convolutional Neural Network (CNN)

(O'Shea and Nash, 2015), (Tutorial, 2017) The CNN architecture consists of three major building blocks.

1. **CONVOLUTIONAL LAYERS.** These layers consist of a number of filters. The convolution operation is expressed in terms of neural network operations where the filters represent the neurons. The output of filter applied on previous layer is called as a feature map.
2. **POOLING LAYERS.** These layers are used to down sampling of the feature map. These layers are inserted after one or more convolutional layers. The pooling layer reduces the over-fitting by generalizing the feature representations. It reduces the number of parameters in the following layers leading to reduction in computation time.
3. **FULLY CONNECTED LAYERS.** These are general feed forward neural network layers applied at the end of convolution and pooling layers to combine the features and make predictions of the network.

The CNN also has operations like padding for proper adjustment of filters at the image boundaries, normalization for stable learning and regularization to reduce the over-fitting.

The Malware analysis procedures(Static analysis, Dynamic analysis) have some disadvantages. Static code analysis takes a long time and requires a domain expert to do the analysis. Code obfuscation techniques hinder this process sometimes. Dynamic analysis requires detection of the target execution environment which is complex. It also generates huge logs and requires a domain expert to carry out the review. Modern malware authors use techniques like anti-debugging, anti-monitoring, virtual environment detection, analysis environment detection which hinders both the analysis techniques. Our approach is not

dependent on static and dynamic analysis. It directly operates on raw binary thereby avoiding these difficulties. The time required for deciding whether the binary is malicious or not is minimal, once the deep neural network training is completed.

The Malware detection process presented in this paper has two major steps 1. *Transforming the binaries into images* and 2. *Training a deep convolutional neural network on these images*. The present system design is focused on detecting 32-bit portable executable binaries of Microsoft Windows Operating System. The Portable Executable (PE)(Goppit, 2006) format is a file format for executable, object code, DLLs etc. used in 32-bit and 64-bit versions of Windows operating systems. The proposed system architecture is file format and operating system independent. So the system can be easily extended to other file formats and operating systems by training the neural network on appropriate datasets.

The rest of this paper is organized as follows. Section 2 describes the related work, Section 3 describes the proposed malware detection system architecture , Section 4 describes results, Section 5 describes conclusion and Section 6 describes future work.

2 RELATED WORK

Recently machine learning methods especially deep learning techniques are helping to solve some of the complex problems in different problem domains. Some authors used these techniques to detect malware and cluster malware into families. Joshua Saxe and Konstantin Berlin (Saxe and Berlin, 2015) have proposed a four layer deep feed-forward neural network with feature vectors constructed by aggregation of byte entropy, PE Imports and PE meta-data features. Edward Raff et al.(Raff et al., 2017) have used convolution neural networks with raw byte embeddings to detect the malware.

In earlier work we have used machine learning models on feature sets like file meta information, import functions, opcode sequences, API sequences, API Normal and custom flags to classify the binary as malware or benign. We created different meta datasets by combining the predictions of multiple machine learning models on individual feature sets to improve the classification accuracy. This system is dependent on static and dynamic malware analysis. So it encounters the same problems like execution environment detection, anti-debugging etc. as discussed in Section 1.

Lakshmanan Nataraj et al.(Nataraj et al., 2011) have used visualization and automatic classification

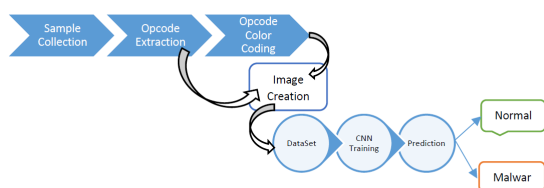


Figure 1: System Architecture.

of malware into families by treating malware binaries as grey scale images where raw bits represent pixels. They extracted GIST features(Torralba et al., 2003) from these images and used k-NN classifier to classify them. Our approach also uses similar thought process by treating binaries as images. However our system differs in following ways

1. **IMAGE CREATION.** Our image constructing process completely differs from Lakshmanan Nataraj et al.(Nataraj et al., 2011). We transformed binaries into colour images by treating opcodes as colour coded pixels instead of treating raw bits as grey scale pixels. This approach has advantages in capturing the patterns in malware instruction sequences. The raw byte grey scale image is noisy because PE binary has lot of sections which varies frequently and have little impact on behavioural patterns of the binary.
2. **LEARNING PROCESS.** We used deep learning techniques to learn the features automatically and predict the unknown binary category instead of the traditional k-NN classifier over GIST features.

3 PROPOSED SYSTEM

The proposed system architecture is depicted in Figure 1. In the first stage datasets are created by transforming the binaries(both benign and malware) into colour images by mapping the opcodes in the binary to colour pixels. Next a deep convolutional neural network is trained on the image datasets to learn the feature filters and weights of the network. Later these parameters(feature filters + weights) are used to predict the unknown binary as malware or benign.

3.1 Sample Collection

Deep learning models are dependent on large amount of quality data to learn better feature representations. The information security researchers worldwide are maintaining the repositories of malware for the collaborative research and developing defence mechanisms. Lenny Zeltser(Zeltser, 2020) compiled some of the well known resources which in-

cludes Contagio malware dump(MilaParkour, 2020), VirusShare(Mellissa, 2020) and Malwr(Community, 2017) repository. We have collected 12500 malware samples from the VirusShare(Mellissa, 2020) for the present experiment.

Benign Portable Executable(PE) files are collected by filtering *application/x-msdownload*(MSDN, 2016) Multi-purpose Internet Mail Extension(MIME) from Operating System and third party application software files. The files have 5MB size restriction. Total 12500 benign PE files are used for the current experiment. The major reason behind the size restriction is to avoid large software files which are generally used as carriers for the smaller size malware payloads. The large files also generate millions of opcodes which makes the image creation process time consuming and computationally expensive. All the samples(both malware and normal) are windows 32-bit architecture compatible. Windows 32-bit and 64-bit executables differ in the instruction types, alignments and other architectural characteristics. So mixing both types of executables will lead to noisy and inaccurate data.

3.2 Image Creation

The image creation has following three major steps and Algorithm 1 describes the image creation process in detail.

1. *Collect unique opcodes over the complete sample collection.*
2. *Map each opcode to unique colour code.*
3. *Transform each sample into image by arranging the opcodes in given image shape and replacing opcodes with respective colour codes.*

3.3 Datasets

We have created two types of datasets from the sample collection.

1. **TYPE1.** It is a dataset with 384×384 size three channel colour images created by arranging opcodes into 384×384 grid and mapping them with respective colour codes.
2. **TYPE2.** It is a dataset with 384×384 size three channel colour images created using 8×8 sub-grids of opcodes. The sub-grids are used to exploit the spatial correlation among the instruction sequences. The opcodes in sub-grids are mapped to respective colour codes to form the image.

We have used a total of 25000(12500 Normal + 12500 Malicious) samples for the dataset creation. The par-

Algorithm 1: Sample Binary to Image Conversion.

```

1: procedure CONVERTTOIMAGES(source, destination,
    size)
2:   for all sample  $\in$  source do
3:     opcodes  $\leftarrow$  ExtractOpCodes(sample)  $\triangleright$  *1
4:     SaveToFile(opcodes, destination)
5:   end for
6:   opcode_set  $\leftarrow$   $\Phi$ 
7:   for all sample_ops  $\in$  destination do
8:     opcode_set  $\leftarrow$  opcode_set  $\cup$  sample_ops  $\triangleright$  *2
9:   end for
10:  color_mapper  $\leftarrow$  {}
11:  for all opcode  $\in$  opcode_set do
12:    color_code  $\leftarrow$  GetRGBCode()  $\triangleright$  *3
13:    color_mapper[opcode]  $\leftarrow$  color_code
14:  end for
15:  color_mapper[pad_code]  $\leftarrow$  pad_color
16:  for all sample_ops  $\in$  destination do
17:    t_grid  $\leftarrow$  CGrid(size, sample_ops)  $\triangleright$  *4
18:    s_img  $\leftarrow$  mapper(t_grid, color_mapper)
19:    SaveToFile(s_img, destination)
20:  end for
21: end procedure

```

- *1: *ExtractOpCodes* uses python *diStorm* (Dabah, 2020) library to collect opcodes
- *2: Union Collects Unique Opcodes
- *3: *GetRGBCode* returns unique color code which is not present in *color_mapper*
- *4: *CGrid* returns opcodes arranged in grid with given size(*width*, *height*). If opcodes exceeds the size it discards remaining opcodes. Otherwise it pads the grid with default padding code

tioning of the dataset into train, validations and test set is as follows.

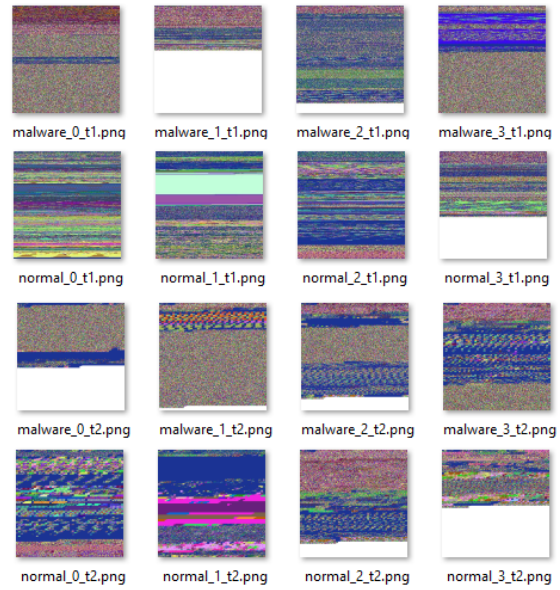
- **TRAINING.** 18000 Samples (9000 from each class i.e Normal and Malicious)
- **VALIDATION.** 2000 Samples (1000 from each class i.e Normal and Malicious)
- **TEST.** 5000 Samples (2500 from each class i.e Normal and Malicious)

Figure 2 provides some of the example sample images of the datasets.

3.4 Convolution Neural Network

(Howard and Thomas, 2020), (Chollet, 2020) and (Team, 2020) The Convolutional neural network architecture is depicted in Figure 3. The model has 6 convolution layers, 3 Max-pooling layers along with fully connected network of 2 dense layers and one binary output layer.

Each convolution layer is equipped with 10 percent dropout to reduce over-fitting and batch normalization for stable learning. The convolution layers



- *malware_*_t[1|2].png*: Type[1|2] Malware Images
- *normal_*_t[1|2].png*: Type[1|2] Normal Images

Figure 2: Example Samples.

uses zero-padding to make the filters fit properly at the image borders. 2×2 size Max-pooling is applied after every two convolutions with stride 2 on both dimensions. All convolution layers are used RELU activation units. 3×3 size convolution filters are doubled for every two convolution layers.

The dense layers are equipped with 50 percent drop out on each layer to reduce over-fitting. The batch normalization is applied on each layer for stable learning. The dense layers have 256 units on each layer with RELU activation units. The binary output layer uses SIGMOID activation unit which is most suitable for binary classification.

Since our problem is in binary classification domain, we have compiled the model with the following parameters.

- **RMSPROP.** Optimizer
- **BINARY CROSS-ENTROPY.** Loss function
- **ACCURACY.** is performance metric.

3.5 Training

(Howard and Thomas, 2020), (Chollet, 2020) and (Team, 2020) We have used model ensemble for better performance. Four models are trained on the data. Each model training is described as follows along with hyper parameters.

- **BATCH SIZE.** The batch size is fixed at 16.

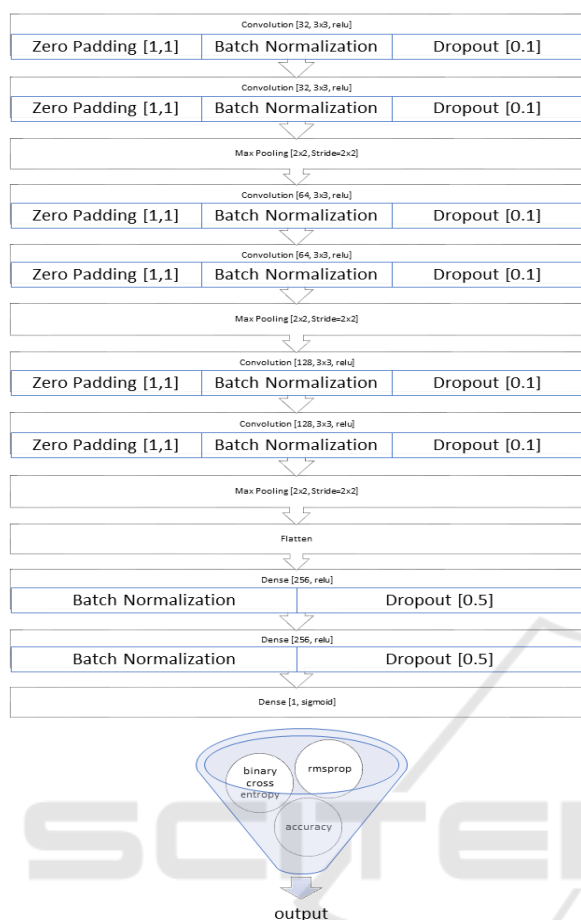


Figure 3: Model Architecture.

- **EPOCHS.** 50 epochs are used in total.
- **LEARNING RATE.** Dynamic learning rate is used. The first epoch is trained with learning rate 0.001. The next 4 epochs used 0.1, after that 15 epochs used 0.01 and later 30 epochs used 0.001.

Data augmentation is used on training data to improve the performance. Two types of models are saved.

1. **Best Accuracy Model.** A model with best accuracy (maximum accuracy) over 50 epochs.
2. **Least Loss Model.** A model with minimum loss (minimum loss) over 50 epochs

The final models are constructed as follows

- **MEAN CLASSIFIER (ACCURACY).** Average accuracy over four best accuracy models.
- **MEAN CLASSIFIER (LOSS).** Average accuracy over four least loss models

The training is performed on NVIDIA Tesla K40c with 12GB GPU memory. The development environment is in Python with Keras API with Tensor-

Flow backend. The training time per epoch is approximately 18 minutes. The total training time per dataset is 60 hours (15H per model * 4 Models).

3.6 Challenges Faced

we have faced the following challenges during the development.

- **Batch Size.** We are unable to perform the training with large batch sizes because of the GPU memory restriction. The batch size is restricted to 16.
- **Image Size.** The average opcodes per binary is 206485. However we restricted the image size to $384 \times 384 = 147456$ pixels. The reason behind this is that convolution takes longer time with increasing image size.
- **Hyper Parameter Tuning.** We are able to experiment with small number of values for hyper parameters like DROPOUT, NUMBER OF CONVOLUTION LAYERS, POOLING SIZE AND FILTERS PER LAYER because of the longer training time and hardware constraints.
- **Diversity of Binaries.** Normal binaries are collected from the operating system and limited third party software. So the samples may not be diverse as real time normal files. At the same time we have not established the diversity in the VirusShare samples which we have used for our malware category.

All these challenges will be addressed in future work.

4 RESULTS

4.1 Type1 Dataset

Figure 4 shows that the training of models with Type1 dataset is smooth over the 50 epochs. Some fluctuation is there with validation loss. However mostly it progressed towards minimum direction except for the MODEL0 which is random over the 50 epochs period. It shows that the MODEL0 is struggling to find its optimum weights. This behaviour of MODEL0 is corroborated with the accuracy curves in Figure 6 where MODEL0 validation accuracy is not in agreement with the training accuracy for most of the time. All remaining model accuracies are in agreement with the training accuracy in large part of the training phase. This clearly indicates the models are not over-fitting the data.

The ensemble of the models is used when the model performance is poor. In this case MODEL0

Table 1: Classification accuracy with best accuracy model.

DATA		CLASSIFIER									
		MODEL0		MODEL1		MODEL2		MODEL3		MEAN	
SET		VALID	TEST	VALID	TEST	VALID	TEST	VALID	TEST	VALID	TEST
	ACC	0.9710	0.9724	0.9765	0.9792	0.9740	0.9748	0.9805	0.9796	0.9755	0.9765
TYPE1	LOSS	0.1333	0.1291	0.0990	0.0808	0.1286	0.1259	0.0834	0.0855	0.1110	0.1053
	ACC	0.9835	0.9776	0.9805	0.9758	0.9815	0.9710	0.9785	0.9750	0.9810	0.9748
TYPE2	LOSS	0.0759	0.0954	0.1731	0.1753	0.1142	0.1244	0.1174	0.1369	0.1202	0.1330

Table 2: Classification accuracy with least loss model.

DATA		CLASSIFIER									
		MODEL0		MODEL1		MODEL2		MODEL3		MEAN	
SET		VALID	TEST	VALID	TEST	VALID	TEST	VALID	TEST	VALID	TEST
	ACC	0.9670	0.9681	0.9760	0.9748	0.9645	0.9692	0.9785	0.9780	0.9715	0.9725
TYPE1	LOSS	0.1013	0.0960	0.0949	0.0950	0.1167	0.1102	0.0832	0.0810	0.0990	0.0955
	ACC	0.9835	0.9776	0.9760	0.9738	0.9795	0.9754	0.9765	0.9742	0.9789	0.9752
TYPE2	LOSS	0.0759	0.0954	0.0938	0.0970	0.0848	0.0917	0.1006	0.1087	0.0888	0.0982

performance is poor. We take average of the performance of four models results to give our final prediction. Due to this the prediction will be robust and the ensemble also helps in improving the classifier performance.

By averaging the results of multiple models, the performance of our model prediction is robust and also improves the performance of our final prediction. Tables 1 and 2 provide the accuracy and loss with respect to different models compared with model ensemble(Mean) model. Type1 dataset achieved 97.65 percent accuracy with Mean model(Accuracy) and 97.25 percent with Mean model(Loss). There is a small difference between the validation and test datasets losses and validation and test datasets accuracies per model, and is consistent across all models. It clearly indicates that the model prediction is consistent with increasing unknown data(Validation and Test datasets sizes are 2000 and 5000 respectively). We can conclude from this result along with the accuracy comparison with training data from Figure 6 that the model is generalized properly without over-fitting on the training data.

4.2 Type2 Dataset

The training with Type2 dataset is not smooth as it was in Type1 dataset. This can be observed from Figures 7 and 8. The validation loss curves are randomly fluctuating. From Figure 9 we can observe that

the validation accuracy is slightly deviating from the training accuracy over a lot of epochs. This clearly indicates that the model is over-fitting the data. This can be observed from the results provided in Tables 1 and 2. The Mean model(accuracy) has 98.10 percent accuracy with validation data and 97.48 percent accuracy with test dataset. In the same manner Mean model(Loss) has 97.89 percent accuracy with validation data and 97.52 percent of accuracy with test data. This clearly shows that the model performance is deteriorating fast as unknown data increases as compared to Type1 dataset.

Even though Type2 dataset is unable to generalize well compared to Type1 dataset, it has the following advantages

- The validation accuracy of Type2 dataset from both(accuracy, loss) Mean models is more compared to Type1 dataset. So with proper tuning of regularization parameters we can achieve good performance by reducing the over-fitting.
- The Type2 dataset over-fitting margin is large compared to Type1 dataset. However it is still a reasonable model because the margin is small (around 0.5 percent accuracy difference).

Our deep learning model has achieved 97.65% accuracy with training on 18000 samples which is better than the Edward Raff et al.(Raff et al., 2017) approach in their work titled 'Malware Detection by Eating a Whole EXE' where they achieved 94% accuracy with training on 2 million corpus.

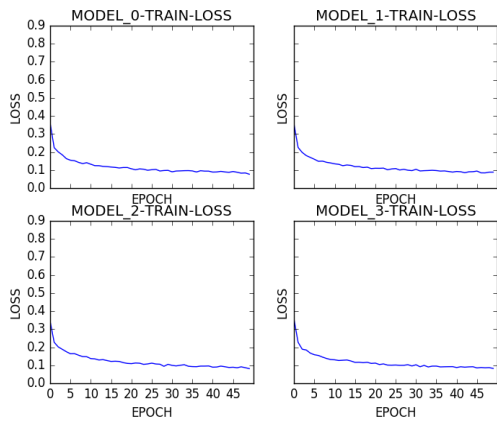


Figure 4: Type1 Dataset Training Loss.

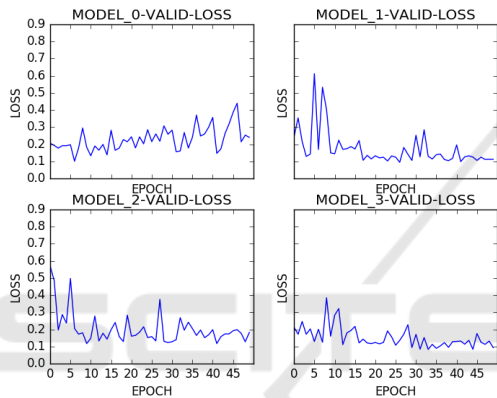


Figure 5: Type1 Dataset Validation Loss.

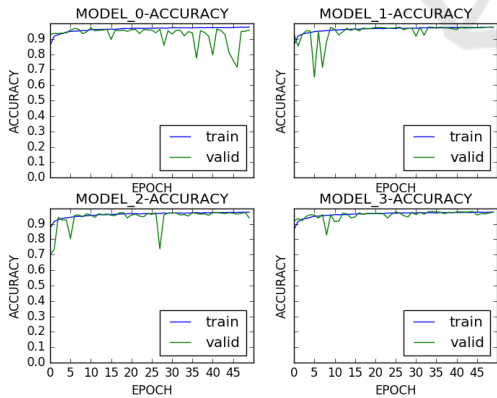


Figure 6: Type1 Dataset Accuracy.

5 CONCLUSION

In this paper we have presented detection of malicious windows binaries with deep learning approaches. The windows binaries are converted into colour images by extracting opcodes from the binaries and map-

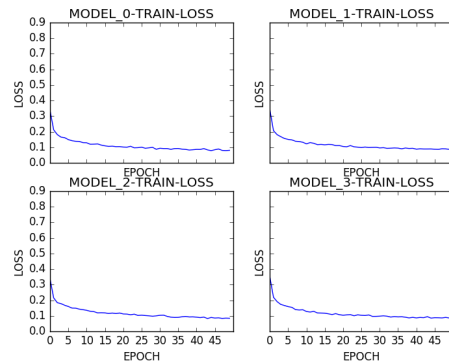


Figure 7: Type2 Dataset Training Loss.

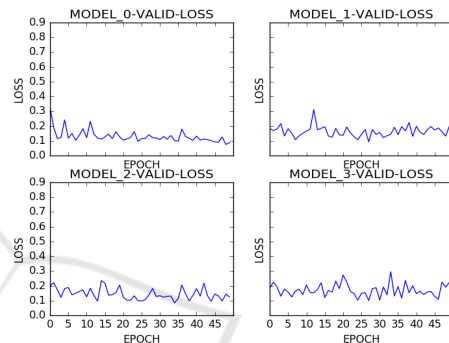


Figure 8: Type2 Dataset Validation Loss.

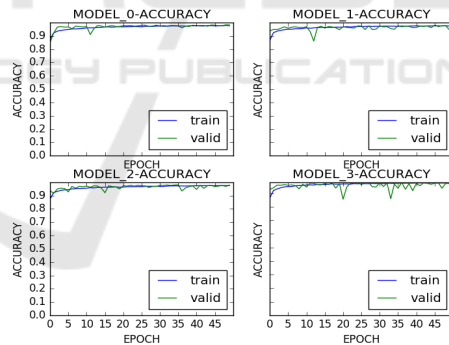


Figure 9: Type2 Dataset Accuracy.

ping them into colour pixels. Convolutional neural network is trained on these images to learn the features filters and weights of the network. Two types of datasets are used for training, Type1 dataset is 383×384 pixel images where each image is created by arranging the opcodes in 383×384 grid and mapping them into respective colour codes, Type2 dataset also has 383×384 pixel images where each image is created by arranging opcodes blocks of size 8×8 and mapping opcodes in block into respective colour codes. Two types of models (Best accuracy, Least Loss) are saved for the prediction. Model ensem-

ble is used where multiple models are trained on the dataset and the final models (Mean accuracy, Mean Loss) are constructed by taking the average of the results. The results show that Type1 dataset learning is smooth and produced 97.65% accuracy with Mean accuracy model and 97.25% with Mean loss model. Type2 dataset is somewhat over-fitting the data and produced 97.48% accuracy with Mean accuracy model and 95.52% accuracy with mean loss model. However Type2 dataset performance can be improved by adjusting the regularization parameters because it has high validation accuracy. In this work we have used deep learning methods on the image representations of the binaries to detect the nature of the binary as malicious or benign. This mechanism is unique in nature by working directly on raw binaries thus avoiding all the difficulties in malware analysis process. The accuracy of our model is more than 97 percent which is reasonably good in the malware detection domain.

6 FUTURE WORK

We plan to experiment with the models by tuning the parameters of the network to improve the accuracy. We are also planning to extend this mechanism to other file formats like Microsoft Office documents (Word, Power Point, Excel), Portable Document Format (PDF) and Web Application (HTML, HTA, JS) and Operating Systems like Linux, MacOS by training the model on appropriate file formats. The current mechanism assigns unique colour codes to unique opcodes. However we are trying to assign colour code mapping per group basis where opcodes are placed in groups based on their functional similarities like data transfer, control instructions etc. The future work will also address the challenges described in Section 3.

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