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DEPARTMENT OF COMPUTER SCIENCE

# Malware Detection with malware images using CNN techniques

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# 1 Introduction

According to [1] malware detection is a crucial factor in cybersecurity, not only organizations, but whoever uses a technologic appliance, should strive to detect and validate malware incidents rapidly to minimize the damage. Our goal is to develop a Malware Detection System (MDS) able to provide a significant contribution of defense against malicious attacks. Instead of traditional MDS that uses feature extractions ML algorithms, we thought that could be interesting and challenging to develop a Convolutional Neural Network (CNN) trained to classify an executable file as malware or benign. This approach, as shown in the next pages, solves the time-consuming problem of traditional ML MDS.

## 2 Development

### 2.1 Training

We developed a training phase in which the CNN learns to detect malware and benign executable by their image representation. The image approach is a focal point of our approach, in fact analyzing a potential virus executable is not that easy as could be thought. Converting the exe in image prevents the time and resource consuming analysis of it's behaviour running it in a SandBox, which is one of the possible phases of a traditional malware detection. Our CNN is so trained to learn the features/textures of the image.

.....to continue

### 2.2 Executable conversion to image

To convert executable in image we developed a function called "exe\_to\_png" which takes in input the path of file  $\alpha$  to transform. For first instantiates a numpy array of shape [256, 256], then loops through every byte of the file  $\alpha$  and converts that byte into a pixel using big-endian approach. At the end of the computation is returned, and saved, always an image 256x256; if the executable doesn't fit the dimensions 256x256 the image is padded with zeros, conversely if the bytes of  $\alpha$  exceeds then the exceeding part is discarded. We decided to discard the exceeding bytes because the loss of informations is not comparable to the needed time that needs an eventual CNN trained by very big images of different sizes.



Figure 1: Conversion malware to image

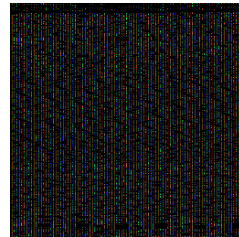


Figure 2: Conversion benign\_file to image

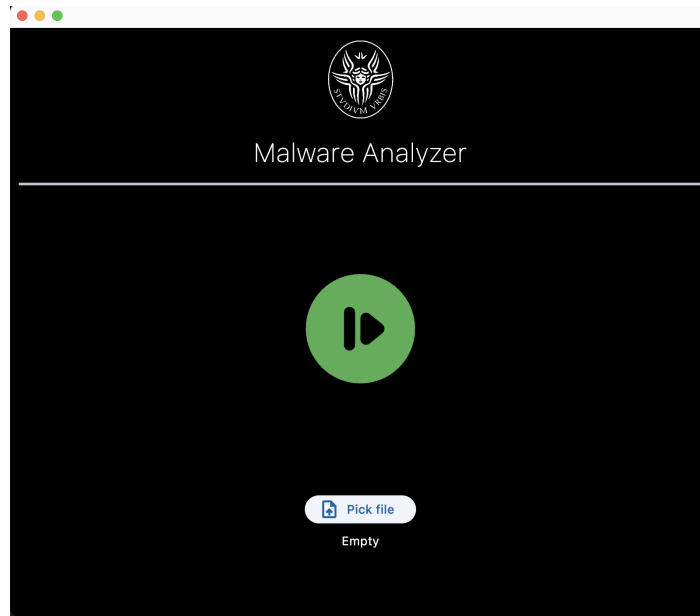
### 2.3 Building CNN

### 2.4 Testing

## 2.5 GUI window

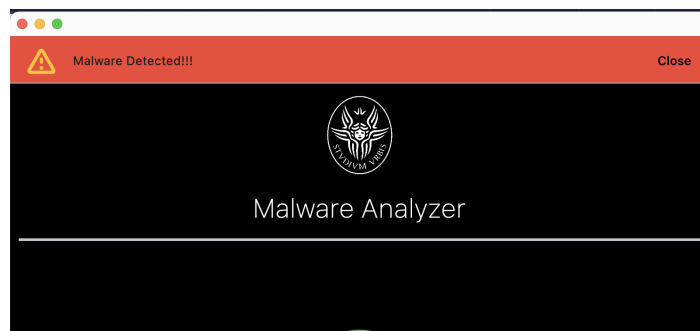
We designed and implemented a GUI for simplifying the interaction between user and CNN model. The GUI lets user upload file and analyze it clicking the run button 3.

Figure 3: GUI



When the detection is finished and the cnn computed if the file selected is a malware or not the result is shown by a popup 4.

Figure 4: GUI detection result



## 3 Conclusions

### 3.1 Dataset

We created the dataset used for this project collecting executables of malware and benign files and processing the relative images using 2.2. The dataset is accessible on [kaggle](#). The dataset is structured as follows:

```
data
├── train This directory holds
│   │   data for training.
│   ├── malware 4481 files.
│   └── benign 491 files.
└── test This directory holds
    │   data for testing.
    ├── malware 4489 files.
    └── benign 491 files.
```

### 3.2 Results

## References

- [1] Karen Scarfone (Scarfone Cybersecurity) Murugiah Souppaya (NIST). Guide to malware incident prevention and handling for desktops and laptops. Technical Report NIST Special Publication (SP) 800-83, Rev. 1, National Institute of Standards and Technology, Gaithersburg, MD, 2013.