Malware and Ransomware Detection Models

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Abstract

Cybercrime is one of the major digital threats of this century. In particular, ransomware attacks have significantly increased, resulting in global damage costs of tens of billion dollars. In this paper, we train and test different Machine Learning and Deep Learning models for malware detection, malware classification and ransomware detection. We introduce a novel and flexible ransomware detection model that combines two optimized models. Our detection results on a limited dataset demonstrate good accuracy and F1 scores.

Keywords— Malware, Ransomware, PE files, Antivirus, Cybersecurity, Artificial Intelligence

1 Introduction

The cybercrime economy has never been so lucrative. In 2021, the global cost of cybercrime campaigns damages reached about $6 trillion for individuals and companies \cite{1}. The trend is not expected to change since the estimated cost by 2025 is about $10.5 trillion. Since the beginning of the COVID-19 pandemic, cyber-attack campaigns have multiplied \cite{2} and according to AV-Test \cite{3}, 150 million new malicious files have been discovered in 2021, an increase of 36\% compared to 2020. Malware detection is therefore a major issue for individuals, companies and even governments. Recently, Republic of Costa Rica had to declare a state of national emergency due to a ransomware attack carried out by Conti hacker group \cite{4}. Despite the progress made in malware and ransomware detection, the problem remains and intensifies over time, mainly because hackers techniques are constantly and rapidly evolving. To perform faster remediation activities, it is very important for security teams to quickly identify the family or the category of a detected malware. This classification problem can be successfully addressed using Machine Learning (ML) and Deep Learning (DL) techniques as soon as enough labelled data are available. In this work, we are training different algorithms to detect malware and ransomware. In particular, we build a bi-layered ransomware detection model based on two ML and DL optimized models. Static techniques are used to extract Windows Portable Executable (PE) files prevalent features that are used to train our models.

1.1 Background and Related Work

Malicious software analysis is a major research trend due to the damages malware cause \cite{5}. With the recent advances in Artificial Intelligence, cybersecurity researchers shift their focus to Machine Learning and Deep Learning methods to improve malicious files detection and classification \cite{6,7,8}. Even if results are decent, these methods still need improvements \cite{9}.

Another problem in malware analysis is the detection of a particular type of malicious file, for instance ransomware. Ransomware aims at disabling the functionality of a computer, either by encrypting the machine (cryptographic-ransomware) \cite{10} as done by the well-known Wannacry virus \cite{11}, or by blocking access to the machine (locker-ransomware) as performed by Reveton malware \cite{12}. To regain the control of a computer, it is necessary to pay a ransom. Although this threat has been around for decades, it has intensified with the rise of cryptocurrencies which

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make it possible to receive a payment with a certain level of anonymity. We have seen the emergence of a Ransomware-as-a-Service business (RaaS) \[13\]. Even if defensive methods exist to prevent a ransomware attack \[14\]–\[18\], 54% of ransomware attacks against companies were successful in 2021 for an average estimated cost of 1.85 million USD per attack \[19\]. Despite the number of attacks has decreased compared to 2020 (73%), the average cost for companies has increased by 1.09 million USD because more of these companies have paid ransoms to get their data back. Ransomware attacks are still a major problem.

1.2 Contributions

This study aims to provide different approaches to malware detection and in particular to ransomware detection. Our main contribution is a model that takes a Portable Executable file as an input and detects if it is malicious or not, and if it belongs to the ransomware category. To the best of our knowledge, we didn’t find any similar approach for ransomware detection in the existing literature. Our model combines two optimized models for malicious file detection and ransomware classification.

1.3 Outline

In Section 2 we present datasets and feature extraction methods used for our experiments. In Section 3 we train the model for the first step: malicious file detection. In the Section 4 we create a model for the classification of malware families and in particular for the ransomware category. In the Section 5 we train a bi-layered model that performs malware and ransomware detection and compare it to a reference model. Finally, Section 6 summarizes this paper and discusses future work.

2 Dataset, Features and Models

2.1 Dataset

In this work, three different datasets are used. They all contain malicious and benign PE (Portable Executable) files in two different formats. These datasets are Ember, Bodmas and PEMachineLearning. PE files distribution and format are summarized in Table 1.

|                  | Malicious files | Benign files | Files format |
|------------------|-----------------|--------------|--------------|
| Ember            | 400,000         | 400,000      | Features     |
| Bodmas           | 57,293          | 77,142       | Features     |
| PEMachine Learning | 114,737        | 86,812       | PE files     |

**Ember**

Ember is a dataset by Anderson et al. \[20\]. It contains a total of 1.1M features extracted from 400K malicious files, 400K benign files and 300K unlabeled files. Anderson et al. also provide the necessary tooling used to generate the feature-based Ember dataset.

**Bodmas**

Bodmas \[21\] shared with us a dataset that contains 134,435 binary files in the same format as Ember with pre-extracted features together with the 57,293 malicious files in raw PE format. These files have been collected during one year between August 2019 and September 2020 and classified: authors indicate the category to which each file belongs to. Table 2 presents the distribution of malware families in the Bodmas dataset. The term "other" includes about ten other categories less represented in the Bodmas dataset such as "dropper", "downloader" or "informationstealer" for example.
PEMachineLearning Dataset

The third dataset used is PEMachineLearning, made available by M. Lester [22]. It contains 201,549 binary files including 114,737 malicious files. Malicious files were grabbed from different sources such as VirusShare[1], MalShare[2] and TheZoo[3].

2.2 Features

Training models for malware detection is a multi-step process. The first step consists in extracting information from the PE files. For this, we rely on two pre-processing algorithms. The first one, a.k.a the Ember method, is detailed by Anderson et al. [20] and converts a PE file into a vector of 2,351 features. The second one, a.k.a Grayscale method, was initially submitted by Nataraj et al. [23] and converts a binary file into an image which size being at least 64 × 64 pixels.

2.3 Models

In the following sections, we select four machine learning or deep learning models :

- Three models are trained using features extracted from PE files with the Ember extractor :
  - LightGBM,
  - XGBoost,
  - Dense Neural Network (DNN),
- a Convolution Neural Network (CNN) trained with PE files images created by the Grayscale extractor.

Our approach consists in chaining a malware detection model (benign vs malware) and a classification model (ransomware vs other malware). Both models are trained using our datasets and are then combined to produce our so called “bi-layered ransomware detection model”.

3 Detection of malicious files

In this section, we are discussing the detection of malicious software using different models of machine learning. For this, we use PEMachineLearning and then Bodmas dataset. PEMachineLearning has been divided into a training subset (70%), a validation subset (15%) and a test subset (15%).

The four models are first trained and tested on PEMachineLearning. We compare the models results using the F1 score and the accuracy score. Table 3 presents the results on the test subset. The algorithm XGboost performs better although LGBM and DNN F1 and accuracy scores are relatively close. We observe that the CNN is less efficient than the three other models even if scores are close to 0.95.

Subsequently, we test our model on malicious files from Bodmas dataset: the purpose is to validate the robustness of our trained models and to determine if they do not produce too many false negatives predictions i.e. true malware

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[1] https://virusshare.com/
[2] https://malshare.com/
[3] https://github.com/ytisf/theZoo
detected as benign. We focus on the false negative rate (FNR) as we consider it as an important metric. Each model FNR is showed in Table 4. We also add the number of undetected malware out of 57,293 files from Bodmas. The CNN model has a high FNR compared to the other models: it does not detect enough malware from Bodmas, meaning that this model does not have a good generalization capacity. On the contrary, the XGBoost and LGBM models have very close and low FNRs. They achieve good performances during the testing phase and have good generalization capacities. Finally, the DNN has a perfect score of zero undetected malware. As a comparison, we test the LGBM model provided by Ember [20] on the Bodmas dataset, it achieves a FNR of $1.42 \cdot 10^{-2}$.

In light of the results, the XGBoost model seems to be the most effective in detecting malicious files during training and testing phases. It provides the best results in term of efficiency with the best F1 and accuracy scores. It has a great generalization capacity with a low FNR on another dataset. LGBM model provides slightly lower but very close results. Its main advantage over XGBoost is its faster computing capacity [24]. The CNN is also quite efficient because it demonstrates good results on the test subset. However it does not have the same capacity of generalization as the two previous models. This conclusion may be biased, since the pre-processing may have an impact. Finally, the DNN seems to be the best model for our experiments with results close to XGBoost on the testing and training datasets and a perfect score on malware detection on the Bodmas dataset. But it requires more computing power for a rather small difference in the overall results. If we make a trade-off between computational resources and performance, our choice is the XGBoost, but it may depends on our use-case.

4 Malware Categories Classification and Ransomware Detection

The purpose of this section is to present some experiments and results in the context of malware classification. We pursue two objectives: the first one consists in identifying four of the most popular malware categories (cf Section 4.1). The second objective aims at detecting ransomware only and results are presented in Section 4.2. In both cases, i.e. malware classification and ransomware detection, we use the same two extractors and the same kind of models presented in Section 2. Regardless of the experiment, we mainly use Bodmas, and because of a lack of ransomware, we have manually labeled several malicious files from PEMachineLearning to reach a total of 2,000 ransomware.

4.1 Malware classification

Here, we are classifying malware into the four most popular and frequently encountered malware’s categories i.e. Trojan, Worm, Backdoor and Ransomware. All other categories fall into the "Other" category. For each of these category, we select 2000 malicious files from Bodmas and PEMachineLearning dataset. This balanced dataset has been split into a training subset (70%), a validation subset (15%) and a test subset (15%). We decided to use a balanced dataset instead of using all available data to limit overfitting.

To determine which model is the most accurate, we rely on the accuracy score and the F1 score. Results are summarized in Table 5. The best results are obtained using LightGBM, even if XGBoost and DNN performances are really close. With an average accuracy score of 0.9413 and an average F1 score of 0.9412, these three models appear to be good candidates for malware classification even if these classification results should be improved.
Table 5: Results of the malware category classification models

|       | LGBM   | XGBoost | DNN   | CNN   |
|-------|--------|---------|-------|-------|
| Accuracy | 0.9442 | 0.9427  | 0.9369 | 0.7270 |
| F1 Score | 0.9440 | 0.9425  | 0.9370 | 0.7197 |

On the contrary, CNN doesn’t perform as good as other models and its results may not be considered as reliable. According to us, this is not only due to a low number of samples during training phase, but also to under optimized pre-processing parameters. For example, it would be interesting to increase the size of the images coding the PE file (the images size is 64x64 pixels for our CNN).

4.2 Ransomware Detection

For this experiment, we use the same dataset as in Section 4.1. This dataset is composed of 2,000 ransomware and 8,000 other malicious files. Table 6 summarizes the accuracy and F1 scores after training. LGBM, XGBoost and DNN achieve almost the same performance with scores close to 1 on the testing dataset. CNN has also surprisingly good results.

Table 6: Results of the ransomware detection models

|       | LGBM   | XGBoost | DNN   | CNN   |
|-------|--------|---------|-------|-------|
| Accuracy | 0.9954 | 0.9948  | 0.9938 | 0.9830 |
| F1 Score | 0.9971 | 0.9969  | 0.9967 | 0.9823 |

If we should select the better model, we would go for the LGBM model even if DNN and XGBoost are also good candidates. Our results demonstrate that it seems easier to separate the ransomware category from others than to classify malware into five categories as done in Section 4.1.

5 Bi-Layered Model for Malware and Ransomware Detection

In this section, we are considering a bi-layered model that detects malware among benign files and then identifies if these detected malware belong to the ransomware category. To validate this approach, we also train a benchmark model to identify a ransomware given a dataset of benign and malicious files.

This bi-layered model combines a model from Section 3 and a second model from 4.2. Given our previous results, we choose to focus on LGBM, XGBoost and DNN models, the CNN being too inaccurate to be selected. We compare each bi-layered model with a benchmark model, it is a classification model trained to determine if a file is benign, malicious or a ransomware. LGBM, XGBoost and DNN models are trained and also take as input a features vector created with the Ember. We train all our models with a dataset composed of 2,000 ransomware, 8,000 other malware and 8,000 benign files from PEMachineLearning. Figure 1 presents the architecture of the aggregated bi-layered model and benchmark model.

For each model, Table 7 summarizes the accuracy and F1 scores. The first observation that can be made is that bi-Layered model has slightly better results. However we would need to train our models on more data to confirm our conclusions.

6 Conclusion & Future Work

6.1 Conclusion

In this paper, we have implemented and tested different models of machine learning and deep learning for malware detection, malware classification and ransomware detection. Good results are obtained with models trained using Ember preprocessing techniques. An original contribution of this work is our so-called “bi-Layered model” which
combines two optimized ML models. This model has a slightly better efficiency than a single classification model trained to differentiate between benign files, malicious files and ransomware. Moreover, being composed of two separated parts, each sub-model can be trained independently and possibly replaced if a better model should be available for a given task (malware detection or malware classification). Even if we mainly focus on a ransomware versus other malware detection, our approach can easily be derived to detect a specific malware category like trojan, worm or backdoor for instance. We hope this paper can help improve cybersecurity tools for malware detection by providing new perspectives.

### 6.2 Future Works

To accelerated malware analysts activities, we want to enrich results provided by Machine Learning and Deep Learning algorithms. In [25], we implement a model that can determine if a file is obfuscated or not. We also plan to leverage XAI (Explainable Artificial Intelligence) and IML (Interpretable Machine Learning) methods to provide decision insights. Finally, we must test the robustness of our different algorithms against adversarial attacks using for instance techniques as in [26].

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**Figure 1: Ransomware models diagrams**

![Diagram of Bi-Layered Model](image1)

![Diagram of Benchmark Model](image2)

Table 7: Results for Benchmark and Bi-Layered models

| Model  | Accuracy | F1 Score |
|--------|----------|----------|
|        | Benchmark | Bi-Layered | Benchmark | Bi-Layered |
| LGBM   | 0.9895   | **0.9936** | 0.9898    | **0.9935** |
| XGBoost| 0.9896   | 0.9924    | 0.9895    | 0.9925     |
| DNN    | 0.9867   | 0.9913    | 0.9868    | 0.9915     |
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