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Computational Approach for Malware Detection System - Deep Learning

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The malware industry continues to be a well-organized, well-funded market dedicated to evading traditional security measures. Once a computer is infected by malware, criminals can hurt consumers and enterprises in many ways. Malware is one of the most serious security threats on the Internet today. In fact, most Internet problems such as spam e-mails and denial of service attacks have malware as their underlying cause. That is, computers that are compromised with malware are often networked together to form botnets, and many attacks are launched using these malicious, attacker-controlled networks.

Malware is a persistent and growing threat, and traditional security measures can struggle to keep pace with the ever-evolving techniques used by malware authors. Fortunately, machine learning and deep learning has shown promise as a means of detecting and preventing malware infections.

One of the key advantages of machine-based approaches is that they can adapt to new and previously unseen malware threats, whereas traditional signature-based approaches can only detect known malware variants. Models can be trained on large datasets of both benign and malicious software to learn the characteristics that distinguish malware from legitimate software, allowing them to identify new, unknown malware based on these learned patterns.

Deep learning models are particularly well-suited for identifying patterns and features in complex, high-dimensional data, such as the raw binary code of software applications, which can be a challenging task for traditional machine learning algorithms. These networks learn to extract relevant features from the binary code, such as opcode sequences and control flow graphs, that can be used to distinguish between malicious and legitimate software. Once trained, these models can be used to classify new, previously unseen software as either malware or benign.

Why Deep Learning?

Nowadays deep learning has dominated the various computer vision tasks. Not only these deep learning techniques enabled rapid progress in this competition, but even surpassed human performance in many of them. One of these tasks is Image Classification. Unlike more traditional methods of machine learning techniques, deep learning classifiers are trained through feature learning rather than task-specific algorithms. What this means is that the machine will learn patterns in the images that it is presented with rather than requiring the human operator to define the patterns that the machine should look for in the image. In short, it can automatically extract features and classify data into various classes.

Early layers learn how to detect low-level features like edges, and subsequent layers combine features from earlier layers into a more holistic and complete representation. We can transform a malware/benign file into a grayscale image using the method described later. Then we can apply these deep learning techniques on the generated images to classify them as malware or benign.

Types of Malware

Types	**Purpose**	**Example**
Spyware	Spyware collects its victims' user activity data without their knowledge.	DarkHotel
Adware	Adwares serves unwanted advertisements. It generates revenue for its developers by automatically generating adverts on your screen, usually within a web browser.	Fireball
Trojan	Trojan disguises itself as a desirable code. It misleads users of its true intent	Emotet
Ransomware	Ransomwares purpose is to disable its victims' access to data until the ransom is paid.	RYUK
Rootkits	Rootkits gives the remote control of Victims Device.	Zacinlo
Keyloggers	Keylogger is a type of surveillance technology used to monitor and record each keystroke on a specific computer.	Olympic Vision
Wiper Malware	Wiper Malware is built with the sole purpose to erase the victims data beyond recoverability.	WhisperGate
Bots	Bots launch a broad flood of attacks. Malware bots and internet bots can be	Echobot

	programmed/hacked to break into user accounts, scan the internet for contact information, to send spam, or perform other harmful acts.	
Mobile Malware	These infect mobile devices. It targets mobile phones or wireless-enabled Personal digital assistants, by causing the collapse of the system and loss or leakage of confidential information.	Triada
Fileless Malware	It makes changes to the files native of the OS. It does not rely on files and leaves no footprint, making it challenging to detect and remove.	Astaroth
Worms	Worms spread throughout the network by replicating itself.	Stuxnet

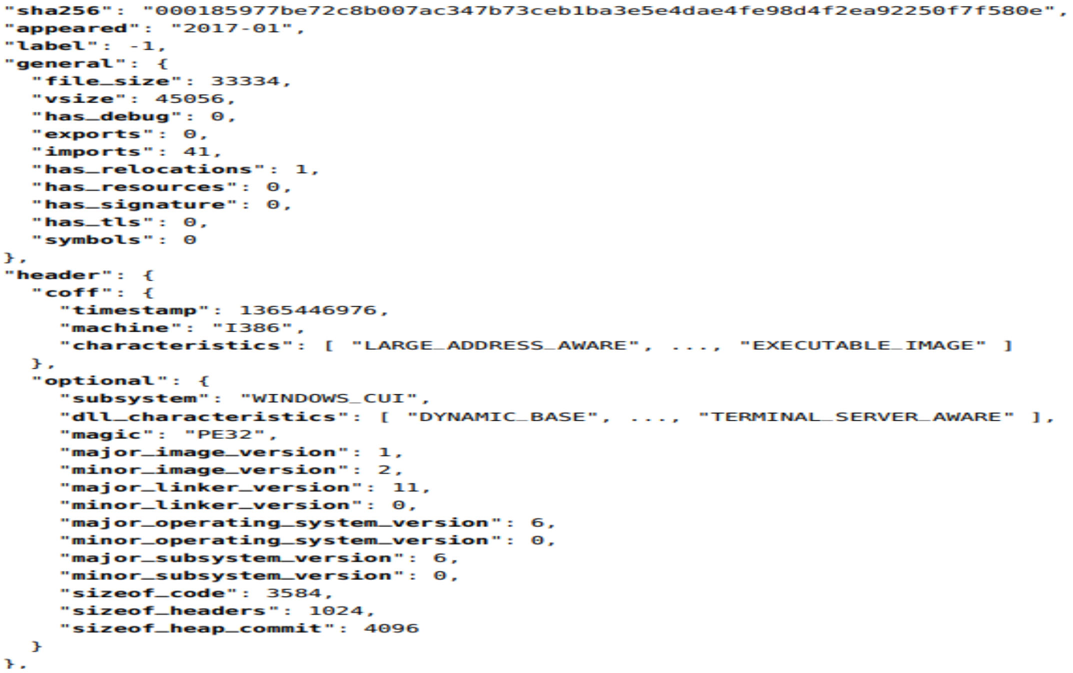
Data we are approaching

We are using EMBER (Elastic Malware Benchmark for Empowering Researchers) dataset for our project and research purpose.The EMBER dataset is a collection of features from PE (Portable Executable) files that serve as a benchmark dataset for researchers. The EMBER2017 dataset contained features from 1.1 million PE files scanned in or before 2017 and the EMBER2018 dataset contains features from 1 million PE files scanned in or before 2018. This repository makes it easy to reproducibly train the benchmark models, extend the provided feature set, or classify new PE files with the benchmark models.

A labeled benchmark dataset for training machine learning models to statically detect malicious Windows portable executable files. The dataset includes features extracted from 1.1M binary files: 900K training samples (300K malicious, 300K benign, 300K unlabeled) and 200K test samples (100K malicious, 100K benign). Our aim is to do comparative analysis on this dataset using different machine learning and deep learning algorithms to derive new insights, which leads to optimized performance in an experiment.

EMBER github Source :- https://github.com/elastic/ember
EMBER paper Source :- https://arxiv.org/abs/1804.04637

DATA Layout Format:-



```
"sha256": "000185977be72c8b007ac347b73ceb1ba3e5e4dae4fe98d4f2ea92250f7f580e",
"appeared": "2017-01",
"label": -1,
"general": {
  "file_size": 33334,
  "vsize": 45056,
  "has_debug": 0,
  "exports": 0,
  "imports": 41,
  "has_relocations": 1,
  "has_resources": 0,
  "has_signature": 0,
  "has_tls": 0,
  "symbols": 0
},
"header": {
  "coff": {
    "timestamp": 1365446976,
    "machine": "I386",
    "characteristics": [ "LARGE_ADDRESS_AWARE", ..., "EXECUTABLE_IMAGE" ]
  },
  "optional": {
    "subsystem": "WINDOWS_CUI",
    "dll_characteristics": [ "DYNAMIC_BASE", ..., "TERMINAL_SERVER_AWARE" ],
    "magic": "PE32",
    "major_image_version": 1,
    "minor_image_version": 2,
    "major_linker_version": 11,
    "minor_linker_version": 0,
    "major_operating_system_version": 6,
    "minor_operating_system_version": 0,
    "major_subsystem_version": 6,
    "minor_subsystem_version": 0,
    "sizeof_code": 3584,
    "sizeof_headers": 1024,
    "sizeof_heap_commit": 4096
  }
},
```

Fig 1 :Raw features extracted from a single PE file.

The EMBER dataset consists of a collection of JSON lines files, where each line contains a single JSON object. Each object includes the following types in data:

- The sha256 hash of the original file as a unique identifier;
- Coarse time information (month resolution) that establishes an estimate of when the file was first seen;
- A label, which may be 0 for benign, 1 for malicious or -1 for unlabeled; and
- Eight groups of raw features that include both parsed values as well as format-agnostic histograms.