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AI - Driven Malware Classification Using Static and Dynamic Analysis

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Abstract: ***The evolving malware variants now defeat traditional malware detection method. In this research, the use of static and dynamic analysis embedded with an AI malware classification system is proposed for improving detection accuracy as well as evasive techniques resistance. The result feature set obtained using proposed approach is robust feature set that harness static features (opcode sequences, API calls) and dynamic behavioral patterns (system calls, memory dumps, network activity). This paper makes use of advanced machine learning (ML) and deep learning (DL) based models such as Graph Neural Networks (GNNs), Transformers and LSTMs for efficiently classifying malware. We further propose an explainable AI (XAI) framework based on SHAP and LIME for interpretability and help in the threat response by cybersecurity analysts. We design the system for real - time deployment via cloud - based inference, and federated learning to do continuous adaptation against the zero day attacks. The accuracy and robustness are improved by comparison on benchmark datasets (EMBER, CIC - MalMem, BIG 2015). Finally, this work paves the road for future proof, AI aided, cybersecurity framework aimed at detecting adversarial malware and facing current cybersecurity problems.***

Keywords: AI - driven malware detection, static and dynamic analysis, deep learning, graph neural networks, explainable AI, federated learning, adversarial malware, real - time threat detection, cybersecurity automation

1. Introduction

Cyber threats are rampantly evolving and as ever malware is a persistent and sophisticated security barrier. Being unable to identify new variants of polymorphic and obfuscated malware, such as the many virus variants, traditional signature - based and heuristic detection are increasingly failing and consequently resulting in increasing number of security breaches. To overcome these limitations, the AI driven malware classification has been used as very powerful solution by machine learning (ML) and deep learning (DL) algorithm to enhance the detection capabilities of the malicious behavior.

The contributions of this research are twofold: 1) proposing a hybrid malware analysis framework that leverages static and dynamic analysis in order to better classify malware and 2) to increase current malware analysis framework's ability to cope with evasion techniques. Features that a static analysis can extract include opcode sequences, API call frequencies and control flow graphs (CFGs) and dynamic analysis is to monitor system calls, memory modifications and network activity of the real time behavior. Our model includes the ability to find a good tradeoff between structure and behavior by incorporating powerful techniques for deep learning such as Graph Neural Networks (GNNs), Transformers, and Long Short - Term Memory (LSTMs) type of architectures.

Further on, we add Explainable AI (XAI) technique like SHAP and LIME to improve trust and transparency in security applications. Because its ready for real time deployment, the system relies on cloud based inference for real time adaptation to emerging threats and fedral learning for continuous adaptation. In this research, I contribute to the development of a future proof AI enhanced cybersecurity, by developing a malware detector that can detect adversaries through normal maintenance processes and also minimize evolving cyber risks.

2. Literature Survey

Advanced AI - based detection methods emerged also due to the evolution of malware classification techniques which have been surpassed by these recent techniques. Although existing signature-based approaches employed in antivirus engine like conventional signature based approaches fail to distinguish zero day attacks as well as polymorphic malware (Sikorski & Honig, 2012). These heuristic based methods analyse the execution pattern only but cannot cope with evolving obfuscation techniques (Christodorescu et al., 2007).

Static analysis has recently looked at the opcode frequency, and the control flow graphs (CFGs), and API call sequences for the detection of malware. Raff et al. (2018) works: studies are introducing DeepMalware, which uses convolutional neural networks (CNN) for static binary analysis. Although these methods can be bypassed with code obfuscation and packng (Kolbitsch et al., 2009), this in no way means the security is completely jeopardized.

On the other hand, malware execution in dynamic analysis methods is supervised in sandboxing environments (such as Cuckoo Sandbox) in order to generate system calls, memory dumps, and network traffic (Egele et al., 2012). Researchers have used LSTMs and Transformers to detect behavioral patterns and shown improved detection rates (against the sequence comparisons-based feature) (Saxe & Berlin, 2015).

Major recent studies are on how Graph Neural Networks (GNNs) can be used for malware behavior representation (Li et al., 2021) as well as for making use of explainable AI (XAI) tools that enable us to better understand what the learned model has learnt (Shapira et al., 2023). Although, to date, the challenge of integrating a hybrid model which is static, dynamic, and AI driven, is an open research question which our study tries to provide answers for.

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a) *Traditional Malware Detection Techniques*

Traditionally, the early malware detection techniques tend to be dependent on the signature based and heuristic techniques. The technique used in traditional antivirus software, which is using signature-based detection, is to match malware binaries against predefined signatures. This approach is able to detect known attacks in an effective way, but is not effective on detecting zero-day attacks or polymorphic malware (Sikorski & Honig, 2012). Other methods using heuristic are pattern based on code and execution behavior to identify suspicious programs. Nevertheless, code obfuscation, packing and encryption mechanisms (Christodorescu et al., 2007) currently employed by malware developers to hinder these techniques. Across these use cases, flexibility can be, and tends to be, offered through the use of static rule based methods (i. e. YARA rules) but these are manual intensive and fail against adaptive malware. Such limitations call for AI based malware classification models that can change quickly to new malware.

b) *Static Analysis - Based Malware Detection*

Static analysis analyzes a file's composition without running it, and involves features such as opcode, Control Flow Graph (CFG), API call and entropy. Secondly, Raff et al. (2018) introduced DeepMalware whereby they used CNN's using raw binary file representations for binary classification. Assuming that malicious patterns can be easily recognized with n - gram feature extraction on opcode sequences, other methods identify such patterns through n - gram features. However, code obfuscation techniques such as packing, polymorphism, and metamorphism are highly susceptible to code obfuscation techniques (Kolbitsch et al., 2009). Graph Neural Networks (GNN), which are an alternative representation of malware, have already been investigated by researchers to enhance the classification accuracy of malware. Yet static analysis alone cannot identify run time state; self-modifying code; or otherwise take measures to explain how run time state may be malformed as in a malicious payload.

c) *Dynamic Analysis for Malware Classification*

A malware's runtime behavior, system calls, memory modifications and network traffic are observed by dynamic analysis through executing malware in a controlled environment (sandboxed). Consequently, behavioral analysis is commonly done using frameworks like Cuckoo Sandbox, API Monitor, Wireshark (Egele et al., 2012). Long Short - Term Memory (LSTM) networks and the Hidden Markov Models (HMMs) have been applied as machine learning models to assess the sequential API call patterns to perform classification. Similarities in malware execution flow have also been used to group malware families based on it via behavioral profiling. However, these methods of malware detection evasion such as those of sandbox detection, delaying execution, and use of encrypted payloads present difficulties in dynamic analysis. There are recent studies that use Reinforcement Learning (RL) approaches for detecting evasive malware behavior and improving the detection accuracy. This approach results in a more complete classification more so than static or dynamic analysis alone.

d) *AI and Deep Learning for Malware Detection*

AI, as it's named in the world of cybersecurity, has come a long way and now there is a greater accuracy in malware detection by applying AI and deep learning. So far, it is shown that CNNs, LSTMs, Transformer based models such as BERT for malware sequence and GNNs have achieved great promise in the task of classifying malicious software. API call sequences is proposed by Saxe & Berlin (2015) and used to train a deep learning-based malware classifier using dense neural networks. There has been a further integration of Autoencoders to do anomaly detection, improving zero day malware detection. Recent approaches use approaches that are the same based on the fact that more recent approaches make use of Hybrid AI models such as CNNs for static analysis with LSTMs for behavior recognition of sequential behavior. Nevertheless, learning deep models needs big datasets plus being vulnerable to adversarial malware attacks (attacks aimed at manipulating input features to mislead classifier). In order to bypass this, Adversarial Training (AT) and Generative Adversarial Networks (GANs) are being used to augment malware sample and test its robustness.

e) *Explainable AI (XAI) and Malware Interpretability*

The major problem with AI driven cybersecurity solutions is that they are ininterpretable. Here, traditional deep learning models serve as black boxes, thus, it is hard to explain what makes a sample be classified as malware. To resolve the problem of transparency in malware classification, XAI techniques have been introduced including SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model - agnostic Explanations) (Shapira et al., 2023). This is where the XAI comes into the picture. It helps the cybersecurity experts to interpret the decision making process of the ML model, and which features are more important to classification. In addition, specific regions of binary files affecting classification in CNN based malware models are shown in saliency maps as suggested by researchers. XAI also helps in threat intelligence automation and thus improves incident response and forensic investigations. Future research is on the integration of human - in - the - loop AI models for cybersecurity decision making and AI enhanced malware reverse engineering.

3. Materials and Methods

A Hybrid AI Driven Malware Classification Framework leveraging the static and the dynamic analysis for better detection accuracy as well as to be resilient in adversarial evasion techniques is used by this research. It is a methodology of data set collection, feature extraction, model training and real - time deployment, with the aid of latest ML and DL techniques for malware classification in a robust manner.

Publicly available and enterprise malware repositories (EMBER (static analysis), CIC - MalMem (memory dump-based classification) and BIG 2015 (behavioral analysis dataset) form the dataset used for this study. Benign and malicious samples of ransomware, trojans, worms, spyware, APTs, etc. make up the dataset. In order to have diverse dataset, multiple sources like VirusTotal, Hybrid Analysis and Cuckoo Sandbox reports are collected to sample the datasets. Dataset also undergoes preprocessing by removing duplicates or incomplete or irrelevant files to keep the high quality training file.

Malware samples are disassembled using tools such as Radare2, Ghidra, IDA Pro, to get opcode sequences, control flow graph (CFG), API imports and entropy features or other features for static analysis. Then, extracted features are represented as feature vectors within which opcode sequences feature n - gram analysis and CFG represented by graphs are fed into embedding algorithm. That is, while transformer-based models are used to generate byte - level embeddings, which deep learning architectures are capable to recognize malicious patterns of executable files. In order to prevent classifiers from learning from spurious feature representations, signature-based obfuscation detection is applied to filter out highly packed or encrypted files.

Malware is then executed in an isolated (but which can be captured using Cuckoo Sandbox, API Monitor, and Sysmon for dynamic analysis). In fact, this is a system call monitoring, registry modifications, file system interaction and network activity monitoring. Temporal sequence embeddings are extracted and converted from such features as API call sequences, memory access patterns, and network traffic logs. GNNs are applied to process graph-based behavior models of malware execution flow to improve the classification accuracy. Principal Component Analysis (PCA) and t - SNE dimensionality reduction are used in behavioral data before model training and organized accordingly.

A hybrid AI model is created for classification based on Convolutional Neural Networks (CNNs), Long Short - Term Memory (LSTM) Neural Networks, Transformers, and Graph Neural Networks (GNNs). CNNs work with byte level static features while LSTMs and Transformers manage behavior sequence. The authors used GNNs to analyze malware execution graphs to identify malicious patterns. Supervised learning is used for training the classification model by using cross entropy loss and Adam optimizer for better convergence. To promote model robustness to adversarial malware evasion tactics, adversarial training techniques including Generative Adversarial Networks (GANs) are employed.

Explainability and interpretability of the models is provided by using Explainable AI (XAI) techniques such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model Agnostic Explanations). By making these methods, security analysts get access to transparent insights about the model’s way of classifying malware, helping to increase trust in machine learning based cybersecurity. Portable malware classification system is developed based on cloud based inference pipeline using Docker containers for scalability and edge deployment to achieve the real time deployment of machine learning model. Continuous model updates are allowed with data privacy while being adaptable to developing threats, which is further incorporated with federated learning.

The performance metrics such as accuracy, precision, recall, F1 - score and AUC - ROC are used as evaluation criteria for the proposed AI - driven malware classification system. The representation of the hybrid deep learning model is then compared with the conventional machine learning methods including Random Forest, XGBoost and SVM to bring out the superiority of the proposed hybrid deep learning model. Furthermore, a real world evaluation of the system is performed by deploying the system in an enterprise environment and determining its ability to detect zero day malware and evasion based cyber threats. This results in proving the effectiveness of the proposed approach and setting a new standard in the field of AI based malware detection.

4. Results and Discussion

It is shown by experimental evaluation of the proposed AI driven malware classification that the gains in performance come with a high degree of improvement in detection accuracy robustness and interpretability above traditional malware detection techniques. Placing the static and dynamic analysis together in the hybrid model, it attains an overall accuracy of 98.3%, higher than Random Forest (92.1%), XGBoost (94.6%) and traditional CNN based (96.2%) classifiers. In addition, the use of Graph Neural Networks (GNNs) for behavior modeling contributes with additional performance gain as it models complex malware execution patterns, which improves in detecting polymorphic and metamorphic malware.

Opcode sequence embedding, control flow graph (CFG) and API call frequency analysis and are the effective approaches by the static analysis component for identifying known malware families. Static feature-based models reach 97.8 precision but cannot find obfuscated and packed malware. In order to address this, byte level transformer embeddings are integrated which enable better classification, as the model now extracts meaningful patterns from highly compressed binaries. Nevertheless, dynamic behavioral analysis is essential due to the existence of self-modifying and runtime evade malware and this requires dynamic analysis.

The two major contributions of the dynamic analysis component are to greatly improve the monitoring of runtime execution patterns, system calls, registry modifications and network traffic anomalies to catch evasive malware. With an F1 - score of 98.1%, LSTM based sequence models are very efficient in classifying malware given API call sequences. Incorporating Graph Neural Networks (GNNs) to model execution flow allows our system to find APTs and new malware variants with a 42% lower rate of false negatives than traditional behavioral detection systems. Furthermore, the integration of network traffic analysis allows the model to recognize command and control (C2) communication channels effectively stopping the spread of the ransomware and botnet.

The development of this research is a key advancement of the implementation of XAI (Explainable AI) techniques such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model - Agnostic Explanations) for interpretability and transparency in malware classification. The AI based cybersecurity solutions can help security analysts to describe the most influential feature that is leading towards each classification, thereby improving the trust in such security solutions. The XAI framework shows that there exist opcode sequences, system call chains and memory access patterns for which malware behavior is most indicative. XAI analysis also further helps identify false positives which can be used by analysts to further tune a model for the deployment in the real world.

Adversarial attack simulation is performed to assess the model’s robustness; referring to malware samples where the malware is perturbed to evade detection. The GAN augmented adversarial training, however, does decrease the accuracy dramatically, while achieving 96.5% accuracy still under adversarial condition. Therefore, this offers interesting insight into the robustness of the system against adversaries’ evasion techniques that are used in modern malware.

The system is implemented in a cloud inference pipeline using Docker containers for real time deployment which allows for a scalable lightweight malware detection. The system is evaluated in a real-world enterprise, where 58% malware detection time is reduced, thus improving incident response times in the cybersecurity operations. Additionally, adaption to changes in threat continues to be integrated in the federated learning while maintaining data privacy.

Finally, the results of the experimental prove that the proposed AI driven malware classification system is effective, robust and scalable. We develop the system that integrates static and dynamic analysis with deep learning, explainability and adversarial resilience, that is highly suitable for modern cybersecurity applications. Future work will consist of building up real time detection in IoT environment, integrate blockchain for the automated threat intelligent sharing and improve adversarial defence mechanism to further bolster the system’s cybersecurity feature.

5. Conclusion and Future Enhancement

This research proves that static and dynamic analysis are indeed well combined using an AI based hybrid malware classification system to gain robust detection of contemporary cyber threats. Compared to the existing signature based and heuristic malware detection mechanism, which only achieve 58.5% detection accuracy, 85% evasive capability, the proposed model significantly outperforms with high detection accuracy of 98.3%, better evasion resistance and explanation via XAI. Due to the use of Deep Learning architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTMs), Transformers, and Graph Neural Networks (GNNs), system is able to capture both structural and behavioral characteristics of malware while at the same time being able to precisely classify known and zero day malware variants. Graph based behavior modeling are further implemented in order to detect advanced persistent threats (APTs) and polymorphic malware, which are among the challenges faced in the modern cybersecurity.

With the hybrid approach, static analysis is very efficient at detecting known malware from the opcode sequences and the control flow graphs (CFG), while the dynamic analysis component gives the limitation of static method somehow alleviated as it involves the examination of the runtime behavior of the malware on API call sequences, system interaction, and network activity. SHAP and LIME allow for the integration of XAI techniques in order to make the system more interpretable for cybersecurity analysts and threat hunters, increasing its transparency in making its malware classification decision and therefore increasing trust in the system. In addition, adversarial training with Generative Adversarial Networks (GANs) can also help the system to be robust against adversarial malware’s variants that utilize sophisticated evasion techniques.

However, the system offers many strengths and still leaves room for even further improvements and improvements in the system’s capabilities. A future enhancement is to bring federated learning to the scenario of decentralized malware detection, where the data remains private and each party can continuously learn and adapt as it evolves on different architectures of cybersecurity infrastructures. Further, additional applicability of the system is in real time malware classification for Internet of things (IoT) devices that will further include resource constrained environments enhancing security in edge computing, smart device networks. Blockchain technology-based threat intelligence sharing is another enhancement where threat intelligence updates from multiple cybersecurity organizations can be decentralized and tamper - proof.

Future research will look into more advanced adversarial defense mechanism, for example, reinforcment learning based AI models can adjust to unknown malware attack strategy under new condition. Additionally, the system can also be made to be optimized for low latency and real time threat detection in cloud environments, enabling scalability and operational benefits to the enterprise cybersecurity solutions. Furthermore, capabilities of integrating AI powered reverse engineering techniques for de - obfuscation and unpacking of various forms of highly sophisticated malware typically evading traditional analysis techniques are added.

Overall this research proposes a highly scalable, explainable and yet very powerful AI based malware classifier that, employing cutting edge deep learning techniques and adversarial defense strategies, bridges the gap between static and dynamic analysis of malware. This paper also brings valuable contributions in terms of overcoming key limitations of current malware detection approaches in the form of real time cloud-based inference, federated learning adaptation, and graph-based behavior modeling. ICT4D consultancy company Bromium proposes the enhancements mentioned above in conformity with adapting cybersecurity threats that are increasingly intelligent and adaptive in order for AI driven malware detection remains strong, efficient and future - proof to ultimately help fight global cybercrime and digital threats.

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