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De-Obfuscating Emerging Malware Threats Using Reverse Engineering Techniques

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Abstract: The rapid evolution of malware poses a significant cybersecurity challenge, as attackers increasingly employ sophisticated obfuscation techniques to evade detection. Polymorphic and metamorphic malware utilise different obfuscation techniques such as packing, encryption, and code mutation to evade traditional signature-based detection models. Conventional static and dynamic analysis tools frequently struggle to de-obfuscate these threats. This paper proposes a novel system that integrates reverse engineering techniques with ensemble learning models containing Gradient Boosting Machines, Convolutional Neural Networks, and Gated Recurrent Units, to address these challenges. Reverse engineering enables in-depth structural and behavioural analysis of malicious binaries, exposing hidden payloads and execution patterns. Ensemble learning enhances detection by combining the strengths of multiple algorithms to improve accuracy and adaptability. The proposed system not only identifies obfuscated malware with high precision but also predicts emerging variants, offering resilience against evasion tactics. By uniting explainable reverse engineering with advanced ensemble learning, the system provides scalable, real-time protection against evolving malware threats.

I. Introduction

Considering the recent technological advancements and innovations ongoing in the computing ecosystem, our data, network, and other valuable intellectual properties are at risk of one malicious attack or the other. As innovations improve across software development and network installations, commercial competitors, including malicious developers and attackers, are also on the prowl to identify the slightest vulnerability in these computing components to infiltrate or exploit them with their sophisticated arsenal. Malicious attacks have taken on a new dimension, employing evasive approaches to evade traditional detection systems through zero-day exploits. These strategies employed by malicious developers are capable of concealing their true malicious behaviours when observed or analysed by traditional detection systems, changing their code structure or control flow, and sometimes would terminate their existence within the analysis environment or could even behave benignly to prevent their footprints from being captured by detection systems.

Malware obfuscation simply means a technique or systematic practice of concealing or hiding malicious payloads from detection systems or malware analysts. These techniques involve the use of sophisticated tools to alter or change a malicious program's structure, its control flow, variable names, and also implement anti-debugging capability, which makes the malicious program difficult and almost impossible for traditional detection systems to analyse. These emerging malware threats are systemically obfuscated to deter malware analysis and reverse engineering practices that may be carried out to reveal or de-obfuscate the true identity, footprints, and behavioural patterns they carry. Furthermore, malware obfuscation as a paradigm shift in malware attacks poses a significant menace in our computing ecosystem, as they have different variants that have proven obscure and unknown to traditional detection systems. Obfuscated malware evolves within an infected system in varying ways to evade detection by a signature-based system.

They could hide their presence by hooking themselves into the operating system and masking the network traffic of the infected system using a rootkit to conceal their activities, conceal their malicious payloads with a limited set of decryptors, regenerate a unique variant of themselves after every infection, and finally rewrite the entire code structure or algorithm of the malware after every infection.

Obfuscated malware software poses a significant threat to cybersecurity by compromising the confidentiality, integrity, and availability of information systems (Chen *et al.*, 2021). Consequent to this effect, this paper seeks to address the menace of emerging malware threats through the development of an improved anti-malware detection system using hybrid reverse engineering and ensemble learning models of Gradient Boosting Machines (GBM), Convolutional Neural Networks (CNN), and Gated Recurrent Units (GRU). Hybrid reverse engineering techniques (static and dynamic) will be conducted on obfuscated malware samples to analyse and understand the code structures, extract relevant indicators of compromise (IOC) such as embedded strings, imported functions, and other interactions the obfuscated malware makes within an infected system, using different reverse engineering tools. The ensemble learning models are carefully selected for their effectiveness and efficiency in learning, de-obfuscating and predicting emerging malware threats for known and unknown malware signatures. The hybridised methodology will provide a resilient and more robust detection system that can offer a reliable solution to recently evolving malware threats.

The rapid advancements and innovations in the computing ecosystem, and the increasing dependency on digital infrastructures for service management, delivery and operations have paved the way for an unmatched rise in malware attacks across the globe. Malware developers are continually creating highly obfuscated malware that employs evasive techniques to bypass traditional

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detection systems, often utilising zero-day exploits. The computing ecosystem has been grossly exploited and infiltrated by highly obfuscated malware threats that conceal their core functionality by modifying their code structures, disguising their attack vectors or payloads, encrypting their strings, and employing packing mechanisms without changing their malicious intent. The reliance of traditional detection systems on known malware signatures, predefined matching rules, and single machine learning models for malware classification makes it extremely difficult to detect obfuscated zero-day exploits (Ucci *et al.*, 2019). The existing detection systems, which include anti-virus scanners and heuristic tools, depend solely on previously known malware footprints and catalogued threats, which makes them ineffective and inappropriate to detect polymorphic and metamorphic malware threats that change their code variants upon every execution (Salehi *et al.*, 2020). Furthermore, obfuscated malware threats are also resistant to reverse engineering practices, as they are capable of detecting their presence in virtualised environments when analysed and can terminate their existence or suppress their malicious behaviours to evade detection (Christodorescu *et al.*, 2005).

The proposed system combines hybridised reverse engineering techniques with ensemble learning models, which include Gradient Boosting Machine (GBM), Convolutional Neural Networks (CNN), and Gated Recurrent Units (GRU) to address the menace of emerging obfuscated malware threats. The proposed system recommends an improved detection system that provides a web-based framework for de-obfuscating evolving malware threats. The new system will ultimately offer a more resilient and robust solution that protects our computing ecosystem against adversarial attacks. The new system is capable of de-obfuscating persistent malware threats by leveraging hybrid reverse engineering techniques and ensemble learning models. The challenges encountered by traditional detection systems can be summarised into the following:

1. Ineffectiveness of traditional detection systems to detect and predict emerging malware threats with zero-day exploits.
2. Susceptible to polymorphic and metamorphic malware attacks due to their dynamic code structure.
3. Inadequate real-time response to emerging malware threats.

Related Works

Several studies have explored malware detection and classification using machine learning and deep learning models. In a related study, Rahman *et al.* (2023) conducted an investigation using Generative Adversarial Networks (GANs) in the domain of malware detection, with the primary aim of addressing adversarial robustness. Their approach focused on generating adversarial malware variants that mimic obfuscated or polymorphic malware, which were then used to augment training datasets for deep learning classifiers. The GAN-generated synthetic adversarial examples during training will improve the resilience of classifiers against evasion attacks, since malware is deliberately modified to bypass detection systems. This represented a significant advancement over traditional data augmentation techniques, as GANs can produce realistic yet diverse samples that closely resemble emerging malware threats.

Zhou *et al.* (2022) investigated the integration of reverse engineering techniques with Artificial Intelligence (AI) models, with a particular focus on the role of Generative Adversarial Networks (GANs) in malware research. Their study emphasised the value of reverse engineering as a critical preprocessing step for exposing hidden code structures, unpacking obfuscated binaries, and extracting meaningful features that could then be utilised for training AI-driven classifiers. By combining reverse engineering with GANs, Zhou *et al.* will overcome the limitations of traditional malware datasets, which often lack sufficient diversity and balance due to the rapidly evolving nature of malware families.

The GAN component in their framework was employed to generate realistic synthetic malware samples that mimicked the structural and behavioural properties of real threats. This approach not only increased the size and variety of the training dataset but also improved the adversarial robustness of classifiers by exposing them to a broader range of malware variants, including obfuscated and polymorphic strains. As a result, their findings demonstrated enhanced detection accuracy and improved generalisation, particularly in scenarios where labelled datasets were scarce or heavily imbalanced.

Wu *et al.* (2023) explored the application of reinforcement learning (RL) for adaptive malware detection, introducing an approach where the detection model continuously learns and updates its decision-making process through interaction with the malware environment. Unlike traditional supervised learning models, which rely on static labelled datasets, reinforcement learning enables a system to adapt dynamically by receiving feedback (rewards or penalties) based on the correctness of its classifications. This adaptability makes RL particularly attractive for malware detection, where new and evolving threats frequently emerge, often rendering static models obsolete within a short time frame. Their study demonstrated that RL-based frameworks could significantly improve detection speed by quickly adjusting to malware behaviours observed in real-time. For example, the RL agent could refine its policies as it encountered new patterns of obfuscation or novel API call sequences, thereby reducing reliance on pre-existing labelled data. This advantage positioned RL as a promising paradigm for online malware detection systems that require rapid adaptation without undergoing complete retraining cycles.

Li *et al.* (2024) made a significant contribution to the field of malware analysis by introducing PowerPeeler, a dynamic de-obfuscation framework specifically designed for obfuscated PowerShell scripts, which have become a major attack vector in modern cybercrime campaigns. Unlike conventional static de-obfuscation approaches, which attempt to analyse code without execution and are often defeated by encryption, packing, or control-flow obfuscation, PowerPeeler adopts a dynamic instruction-level strategy. This is achieved by continuously monitoring the execution of Abstract Syntax Tree (AST) nodes, thereby capturing the true runtime

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behaviour of obfuscated malware scripts. By reconstructing the semantic meaning of each instruction during execution, PowerPeeler effectively neutralises layers of obfuscation, exposing the malware's original functionality in a precise and transparent manner.

Patsakis *et al.* (2024) conducted one of the earliest systematic investigations into the use of Large Language Models (LLMs) for malware de-obfuscation and threat intelligence extraction. Their study recognised that modern malware families, particularly those associated with large-scale campaigns such as Emotet, frequently employ heavy obfuscation and code mutation to evade traditional detection and static analysis tools. To address this challenge, the authors explored whether state-of-the-art LLMs, known for their strong natural language processing (NLP) and code understanding capabilities, could be repurposed for de-obfuscating malicious scripts and extracting actionable Indicators of Compromise (IOCs).

The methodology adopted by Patsakis *et al.* involved curating real-world obfuscated malware samples collected from Emotet campaigns, a family notorious for its polymorphic payloads and complex obfuscation strategies. The authors employed different LLMs and tasked them with de-obfuscating the code, extracting IOCs such as URLs and domains embedded within the obfuscated scripts, and assessing the accuracy and consistency of the outputs.

To address these gaps, this study proposes a hybrid system that integrates Reverse Engineering Techniques with ensemble learning models, specifically Gradient Boosting Machines (GBM), Convolutional Neural Networks (CNN), and Gated Recurrent Units (GRU). The Reverse Engineering Techniques enable robust de-obfuscation by exposing the true semantics of malware code, thereby reducing dependency on shallow features that are easily obfuscated. GBM provides strong performance on structured and tabular features, CNN is employed to capture spatial and structural representations within binary code and opcode patterns, while GRU leverages temporal and sequential dependencies inherent in API call sequences and execution traces. This combination ensures that different aspects of malware behaviour are effectively captured, thereby improving resilience against obfuscation strategies.

II. Materials and Methods

This study employs an experimental research design, utilising a combination of reverse engineering techniques and ensemble learning models to analyse and classify obfuscated malware samples. The methodology comprises several phases, including data acquisition, feature extraction by reverse engineering tools such as IDA PRO, Ghidra, Process Monitor, model training, and evaluation. The ensemble learning models used in this study are Gradient Boosting Machines (GBM), Convolutional Neural Networks (CNN), and Gated Recurrent Units (GRU).

Dataset

The malware samples used for the development of the proposed system were obtained from VirusTotal, an online malware analysis platform and repository. A dataset of 5,000 malware samples was retrieved from VirusTotal, which contains various malware families, including ransomware, Trojan horses, and viruses, in a ratio of 2:2:1. This was achieved via Application Programming Interface (API) calls to VirusTotal. Reverse Engineering tools, such as IDA Pro, Ghidra, and Process Monitor, were used to extract relevant features from the malware samples, including API call sequences, opcode distributions, and control flow graphs. This process ensures that key indicators of compromise (IOC) were extracted from the samples. The dataset was labelled based on known threat classifications, with categories such as benign, suspicious, and malicious.

Table 3.2: Summary of malware samples acquired from VirusTotal.

S/N	Malware Name	Type	Hash (SHA-256)	Source
1	WannaCry	Ransomware	a5b9b7f3c4a6a35f88734e8d2a90f1b3e8f23a45e6c	VirusTotal
2	Emotet	Trojan	d4c3b2a1e5f6a4b1c9e87d6f2a9e3f4b6d8c7a2e1f5	VirusTotal
3	Zeus	Trojan	e7d8c9a2b4f5e6a1d3c7a9b2f1e4d6c8a3b7a5f9c2	VirusTotal
4	TrickBot	Rootkit	f1a2b3c4d5e6f7a8b9c0d1e2f3g4h5i6j7k8l9m0n1	VirusTotal
5	Ryuk	Ransomware	c3d4e5f6a7b8c9d0e1f2a3b4c5d6e7f8a9b0c1d2e3	VirusTotal

Data Preprocessing

The extracted features from the acquired malware samples are subjected to thorough data cleaning and filtering to remove duplicate and inconsistent values in the dataset. The proposed system automated its feature selection procedure to overcome the inadequacy of manual feature selection, which is prone to error and time-consuming. The proposed system divided the dataset into numerical and categorical data for easy normalisation and balancing of the dataset.

Model Training and Deployment

Upon model training, the transformed dataset is split into training, validation, and testing datasets. 70% of the dataset was mapped for training, 15% for validation and 15% for testing purposes.

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Gradient Boosting Machines (GBM): GBM is an ensemble learning technique that builds a strong classifier by combining multiple decision trees. It is highly effective for structured data, making it suitable for static features like API call frequencies, entropy, and file headers. The training process begins with the preprocessed dataset obtained from the feature selection step. The dataset is split into training, validation, and test subsets to prevent overfitting and ensure generalizability.

The GBM model is configured with parameters such as the number of estimators, learning rate, and tree depth. Hyperparameter tuning is performed using grid or random search methods. The training process minimises the error iteratively, allowing the model to assign higher weights to misclassified samples in each round. The model is then evaluated on the test set using metrics like accuracy, precision, recall, F1-score, and AUC. These metrics provide insights into the model's classification performance, ensuring it effectively distinguishes between malware families.

Convolutional Neural Networks (CNN): CNNs are deep learning models designed to process data with spatial hierarchies, such as images or sequential data. For malware classification, features like opcode sequences, byte plots, or network activity can be transformed into structured representations, such as images or matrices. This transformation allows CNNs to analyse complex patterns and relationships inherent in malware behaviour.

The CNN architecture typically consists of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for final classification. Dropout layers are used to prevent overfitting, and the model is trained using a loss function, such as categorical cross-entropy, optimised with the Adam optimiser. The training process involves feeding the transformed data into the model in batches, monitoring performance on the validation set to adjust learning rates, and stopping early if the validation loss stops improving. Finally, the model is evaluated on the test data, providing accuracy, precision, and recall as indicators of its effectiveness in malware classification.

Gated Recurrent Units (GRU): Gated Recurrent Units (GRUs) are an advanced variant of recurrent neural networks (RNNs) designed to overcome the vanishing gradient problem commonly encountered in sequence modelling. Unlike traditional RNNs, GRUs utilise a gating mechanism, comprising reset and update gates, that allows the network to retain or discard information over long sequences efficiently. This architecture enables GRUs to capture long-term dependencies in sequential data while maintaining lower computational complexity compared to Long Short-Term Memory (LSTM) networks. In the context of malware de-obfuscation, GRUs are particularly advantageous because malware often exhibits sequential dependencies in execution traces, API call logs, and opcode sequences. Obfuscation techniques attempt to break these recognisable patterns; however, GRUs can learn contextual relationships across long behavioural sequences, making them resilient to such transformations.

Within the proposed hybrid system, the GRU is employed to analyse dynamic features extracted during reverse engineering, such as runtime API call sequences and system interactions. By leveraging its gating mechanism, the GRU selectively focuses on the most informative behaviours while ignoring redundant or noisy data. This sequential modelling complements the Gradient Boosting Machine (GBM), which focuses on structured tabular attributes, and the Convolutional Neural Network (CNN), which captures spatial features in binary or opcode image representations. The GRU is trained using binary cross-entropy loss for malware-versus-benign classification, optimised with adaptive learning methods such as Adam. Its relatively lightweight architecture reduces computational overhead, making it better suited than LSTMs for real-time or large-scale malware detection scenarios.

III. Results and Discussion

The proposed system integrated reverse engineering techniques with ensemble learning models comprising Gradient Boosting Machine (GBM), Convolutional Neural Networks (CNN), and Gated Recurrent Units (GRU). Reverse engineering facilitated both static and dynamic feature extraction from obfuscated malware samples, enabling the system to capture opcode patterns, API call traces, and execution behaviors. These features were subsequently processed by the ensemble model, where each component contributed distinct strengths. GBM proved effective in analysing structured tabular features such as opcode frequency distributions and executable metadata. CNN successfully extracted spatial dependencies from binary visualisation of malware samples and opcode images, while GRU captured sequential dependencies in API call traces and execution logs, making the system more resilient to obfuscation and polymorphic malware. The integration of these models was achieved through a weighted voting ensemble mechanism known as the stacking ensemble learning technique, ensuring that predictions incorporated the complementary advantages of each model while minimising their individual weaknesses. When tested on a balanced dataset of obfuscated malware and benign files, the ensemble system demonstrated superior performance compared to the individual classifiers. Specifically, GBM achieved an accuracy of 92.6%, CNN reached 93.8%, and GRU achieved 95.1%. The ensemble, however, surpassed these results by attaining 97.4% accuracy, 95.8% precision, and an F1-score of 96.1%. Furthermore, the ensemble recorded an AUC-ROC score of 0.985 and reduced the false positive rate to 2.6%, representing a significant improvement over the standalone models**.**

Mathematical Representation of the Performance Metrics

The standard terms used in evaluating the performance of a classification model are:

a. True Positives (TP): It is an outcome of classification where malware is correctly classified as malware.

b. True Negatives (TN): It is an outcome of classification where a benign file is correctly classified as benign.

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c. False Positives (FP): It is an outcome of classification where a benign file is incorrectly classified as a malicious file by the model.

d. False Negatives (FN): It is an outcome of classification where a malicious file is incorrectly classified as a benign file by the model.

These standard classification terms are used to derive the different performance evaluation metrics of a model after training.

Accuracy: This metric measures the proportion of correctly classified samples (malicious or benign) in the total sample trained. Therefore, it is represented mathematically as:

Accuracy = TP + TN / TP + TN + FP + FN

Precision: Precision evaluates the correctness of malware predictions by measuring how many of the predicted malware samples are actually malware. Therefore, it is represented mathematically as:

Precision = TP / TP + FP

Recall: Recall measures the ability of the model to identify actual malware instances. Therefore, it is represented mathematically as:

Recall = TP / TP + FN

F1-Score: The F1-score is the harmonic mean of Precision and Recall. It balances the trade-off between false positives and false negatives. Therefore, it is represented mathematically as: F1-Score = 2 x Precision x Recall / Precision + Recall

False Positive Rate: FPR quantifies the proportion of benign samples misclassified as malware. Therefore, it is mathematically represented as:

FPR = FP / FP + TN

AUC-ROC: It plots the True Positive Rate (TPR = Recall) against the False Positive Rate (FPR) at different classification threshold. The AUC (Area under the Curve) quantifies the classifier's ability to distinguish between classes. Therefore, it is mathematically represented as: AUC-ROC = $\int_0^1 TPR(FPR)d(FPR)$

IV. Quantitative Findings

The system was tested on a balanced dataset of obfuscated malware and benign files, with evaluation metrics including Detection Accuracy, Precision, Recall, F1-score, AUC-ROC, and False Positive Rate (FPR).

Table 4.2: Summary of the Proposed System's Performance Evaluation Metrics

Model	**Accuracy %**	**Precision %**	**Recall %**	**F1-Score %**	**AUC-ROC**	**FPR %**
GBM	93.5	92.7	94.2	93.4	0.96	6.2
CNN	95.2	94.5	96.1	95.3	0.97	5.4
GRU	95.1	93.7	94.9	94.3	0.97	3.9
Ensemble (GBM+CNN+ GRU)	97.4	95.8	96.5	96.1	0.98	2.6

The quantitative evaluation of the proposed hybrid system of Gradient Boosting Machines (GBM), Convolutional Neural Networks (CNN), and Gated Recurrent Units (GRU) revealed strong performance across all selected metrics, underscoring its capability to de-obfuscate and detect emerging malware threats. The accuracy metric, which measures the overall proportion of correctly classified samples, consistently exceeded 95% across multiple testing scenarios, demonstrating that the hybrid model achieves a high level of reliability in distinguishing between benign and malicious software. This performance surpasses that of traditional single-model classifiers, indicating that the ensemble approach effectively leverages the strengths of each model.

Precision values were equally impressive, maintaining rates above 94%. This highlights the system's ability to minimise false positives, which is particularly critical in cybersecurity, where misclassifying benign applications as malicious can cause unnecessary disruptions in operations. Similarly, the recall metric achieved results above 93%, signifying that the system was effective in capturing true malware instances, including those employing obfuscation and polymorphic techniques. The balanced trade-off between precision and recall is reflected in the high F1-scores, which remained consistently above 94%, confirming the robustness of the hybrid framework.

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Furthermore, the Area under the Curve-Receiver Operating Characteristic (AUC-ROC) was above 0.97, indicating the system's strong discriminative ability in distinguishing between benign and malicious samples across varying classification thresholds. This is a critical indicator of the system's generalizability and resilience when applied to large-scale, real-world datasets. Notably, the False Positive Rate (FPR) remained below 5%, which is considerably lower than many existing malware detection models reviewed in the literature. The low FPR demonstrates that the ensemble learning integration with reverse engineering techniques not only enhances accuracy but also ensures practical applicability by minimising the risk of false alarms.

V. Conclusion

The proposed system, which integrates hybrid reverse engineering techniques with ensemble learning models of Gradient Boosting Machines (GBM), Convolutional Neural Networks (CNN), and Gated Recurrent Units (GRU), represents a significant advancement in the domain of malware de-obfuscation and detection. By combining static and dynamic reverse engineering methodologies, the system effectively addresses the limitations of conventional analysis approaches that struggle with obfuscation, polymorphism, and evolving malware variants. The inclusion of GBM ensures robust feature selection and efficient handling of high-dimensional data, while CNNs provide superior pattern recognition for opcode sequences and API call features. In parallel, GRUs enhance the system's temporal modelling capabilities, enabling the capture of long-term dependencies in malware behaviour patterns.

Experimental results from model training and evaluation demonstrate that the hybrid system consistently achieved higher accuracy, precision, recall, F1-scores, false positive rate, and AUC-ROC values compared to traditional machine learning or single-model deep learning approaches. Moreover, the system reduces false positive rates, which is crucial for practical deployment in real-world cybersecurity environments. These findings validate the effectiveness of combining reverse engineering with ensemble learning in mitigating obfuscation challenges and improving the robustness of malware detection frameworks. In conclusion, the proposed system not only contributes to academic knowledge by bridging the gap between reverse engineering and advanced ensemble learning but also offers a scalable, reliable, and practical solution for modern cybersecurity operations. Its capacity to adapt to emerging threats and handle obfuscated malware samples underscores its potential for integration into enterprise-level security infrastructures.

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