International Journal of Applied Mathematics
Volume 38 No. 12s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Deep Learning Framework for Adversarial Malware Generation and Detection

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***Abstract*—**The escalating sophistication of malware attacks necessitates advanced defense mechanisms capable of anticipating adversarial evasion techniques. This paper presents a novel dual- mode deep learning framework that simultaneously generates adversarial malware samples and enhances detection capabilities through a unified architectural design. The proposed system integrates a Variational Autoencoder-Generative Adversarial Net- work (VAE-GAN) for synthesizing realistic adversarial malware with a Siamese Network architecture optimized for deep metric learning-based detection. The VAE-GAN generator produces adversarial samples that maintain executable integrity while incorporating perturbations designed to challenge conventional detection systems, achieving 92.3% functional preservation with exceptionally low distributional divergence (FID: 0.127, MMD: 0.0043, KL: 0.041). The Siamese Network discriminator learns ro- bust feature embeddings through pairwise comparison, enabling effective identification of both original and adversarially modified malware variants. A comprehensive evaluation of 140,000 mal- ware samples demonstrates superior performance across multiple dimensions: detection accuracy of 99.14% with an AUC-ROC of 0.9967, precision of 98.73%, recall of 99.48%, and F1-score of 99.10%, substantially outperforming traditional machine learn- ing approaches. The framework exhibits exceptional adversarial robustness with 94.11% average accuracy across Fast Gradient Sign Method (94.73%), Projected Gradient Descent (92.16%), and Gaussian noise perturbations (96.45%), while maintaining computational efficiency with 1.2ms inference time and 833 samples/second throughput. The remarkably low false positive rate of 0.86% minimizes operational burden in production envi- ronments. This research establishes a new paradigm for proactive cybersecurity through adversarial learning, demonstrating that unified generation-detection architectures can simultaneously strengthen defensive capabilities while providing realistic threat modeling for security testing and evaluation.

***Index Terms*—**Adversarial malware generation, deep learning, VAE-GAN, Siamese networks, malware detection, deep metric learning, adversarial robustness, cybersecurity

I. Introduction

The growth of digital infrastructure has been able to reshape the threat environment surrounding contemporary information systems. Cybersecurity professionals today face tough challenges in the way viruses have evolved from malware into sophisticated, multi-stage attack platforms. This change of attack tools, the rise in malware-as-a-service (MaaS) offerings, and the greater use of artificial intelligence by cybercriminals can evade traditional detection systems and compromise critical infrastructure [1].

The financial consequences are devastating, compounding year after year. As reported by the 2025 Cybersecurity Ven- tures, the annual worldwide cost of cybercrime is now at a record high of about USD8 trillion for the year 2025, and that number will continue to grow at an explosive rate to reach about USD10.5 trillion in 2026 [2].

Malware has a significant and highly destructive role as the main access to most successful cyberattacks. The 2021 Colonial Pipeline ransomware attack is a demonstration of the consequences of advanced malware introduction to systems, as a single breach led to the complete shutdown of the United States' largest fuel pipeline system. This attack caused financial damage of more than 4.4 million USD [3]. Simi- larly, the worldwide fallout from ransomware campaigns such as WannaCry and NotPetya also highlighted how pervasive malware could induce widespread disruptions across critical infrastructure sectors [4].

The typical malware detection approaches to mitigate such emerging threats are a significant challenge in recent cybersecurity research. Accordingly, despite the vast resources that have been spent on signature-based detection systems and heuristic analysis engines and, more recently, behavioral monitoring platforms, many are beginning to realize the underlying limitations of these approaches as malware developers have begun developing new evasion techniques.

Variants of polymorphic and metamorphic malware that change their structural appearance in an evasive manner can avoid detection by signature-based detection systems, which employ static string pattern matching. These families of very sophisticated malware use "Code Obfuscation, Runtime packing techniques, and Dynamic code generation strategies," which makes it hard for traditional static analysis techniques to catch them [5].

The number of malware is escalating at an alarming rate in terms of quantity as well as complexity. As shown in Table I, Global malware attacks have exhibited exponential growth trends, rising from 2.5 billion incidents in 2020 to over 6.2 billion incidents by 2023, which equates to a total increase of approximately 148% over a three-year span [6].

Even more alarming is what lies beyond these numbers, not just a growing volume of attacks, but an entirely new malware that is complex and capable. Zero-day exploits made up 7.9% of the total incidents, almost quadrupling from its 2.1% share last year, and ransomware had "a more dramatic spike," rising from representing 15.2% of all malware attacks to close to one-third 28.5%, [5].

Received: August 06, 2025

International Journal of Applied Mathematics
Volume 38 No. 12s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

TABLE I
GLOBAL MALWARE INCIDENT STATISTICS AND GROWTH TRENDS (2020–2024)

Year	Total Incidents (B)	Growth Rate (%)	Ransomware (%)	Trojans (%)	Zero-Day (%)
2020	2.5	–	15.2	45.8	2.1
2021	3.3	+32	18.7	42.3	3.2
2022	5.5	+67	22.4	38.9	4.8
2023	6.2	+13	26.1	35.2	6.3
2024	3.8	+23	28.5	32.7	7.9

These attacks highlight a crucial turning point in security where traditional defense paradigms are simply inadequate to fend off current threat models, requiring a shift in paradigm towards defense based on adaptive and resilient methodologies. This recognition has motivated recent research interest in the application of advanced deep learning (DL) and artificial intelligence (AI) techniques to tackle various cybersecurity problems, especially focusing on the development of systems that are able to autonomously perceive, analyze, and respond to threats. Table II presents a comparison between traditional and AI-based malware detection approaches.

TABLE II
COMPARISON OF TRADITIONAL AND AI-BASED MALWARE DETECTION APPROACHES

Approach	Detection Rate (%)	False Positive Rate (%)	Zero-Day Capability	Adaptability Score
Signature-Based	85-95	0.1-1.0	Poor	Low
Heuristic Analysis	75-90	5-15	Moderate	Low
Machine Learning	90-97	1-5	Good	Moderate
Deep Learning	95-99	0.5-3	Excellent	High
Hybrid AI Framework	98-99.5	0.2-1.5	Excellent	Very High

Even though AI-based malware detectors have already advanced, there are still enormous research voids in creating complete frameworks having generation, detection, and validation under one framework. To the state of the art, other methods only contribute to either generating simulated malware samples or detecting their malicious behavior; however, they hardly integrated. Such a segregated strategy prevents the construction of a truly adaptive and resilient defense system that can adapt to new menaces. Table III outlines the key research gaps and challenges in current malware detection methods. [7].

Moreover, the ability of existing anomaly detection techniques is still limited, given various operational settings and deployment scenarios. In practice, the systems designed to work well in a controlled laboratory setting may not perform well when they are deployed in a real-world scenario, such as high dynamic network traffic, system configurations, and user behaviours. This limitation takes the form of high false positive rates that make detection systems impractical to use, as security teams start ignoring attacks [7].

The combination of multiple AI techniques in one umbrella further exacerbates the complexity associated with the optimal training, optimization, and deployment of models. Adversarial training with multiple interacting neural networks is prone to unstable training dynamics, mode collapse, and convergence problems, which need some advanced tuning techniques and careful hyperparameter tuning. In addition, the computational costs of training and deploying such combined systems might be high, hindering their utilization for resource-constrained scenarios [8].

TABLE III
RESEARCH GAPS AND CHALLENGES IN CURRENT MALWARE DETECTION APPROACHES

Challenge Area	Current State	Impact Level	Research Priority	Complexity
Unified Frameworks	Limited	High	Very High	High
Generalization	Poor	Very High	High	Moderate
Zero-Day Detection	Moderate	High	High	High
Adversarial Robustness	Poor	Very High	Very High	Very High
Real-Time Processing	Moderate	Moderate	Moderate	Moderate
Explainability	Poor	Moderate	Moderate	High
Scalability	Good	Moderate	Low	Moderate

To address the abovementioned research gaps, this paper presents a deep learning framework that seamlessly incorporates adversarial malware generation and robust detection using a novel combination of dual-latent generative modeling, deep metric learning, and autoencoder-enhanced anomaly detection. The logic behind this approach is that the best defense tactics are not a response to existing threats but preemptive in preparing for future attacks. Generating realistic synthetic samples can be used as a reasonable strategy to perform preemptive training and evaluation of detection algorithms.

The proposed framework contributes to achieveing the main objective. It aims to construct a comprehensive architecture that can effectively combine malware generation and detection, as they benefit each other for constructing robust and adaptive defense mechanisms. This joint design allows the dynamic evolution of detection ability against threats. Thus, the adoption of autoencoders for anomaly detection provides an additional complementary detection method that can capture zero-day or novel threat instances that are not effectively detected by supervised classification models.

The main objectives of this paper directly address different parts of the malware detection issue and contribute to a complete framework. On the theoretical side, this work develops our understanding of how generative models, metric learning, and anomaly detection can be combined in a unified learning environment.

Methodologically, the paper introduces a number of new algorithmic developments that take on some of the shortcomings present in current methodologies. The proposed generative modeling framework can achieve controllable and diversified synthetic sample generation that does not deviate significantly from the characteristics of genuine malware.

From a practical perspective, the paper presents a framework that can be applied in cybersecurity settings. This involves efficient training systems, inference approximation algorithms, and evaluation protocols that allow a practitioner to measure

Received: August 06, 2025

International Journal of Applied Mathematics
Volume 38 No. 12s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

performance and customize the approach to particular needs. Practical contributions also include a comprehensive computational analysis of efficiency and scalability.

The validation of the proposed methodology in the experiment includes several performance metrics to ensure that the entire system can tolerate various operational situations. The evaluation is conducted in terms of performance on the well-known malware-related datasets, comparison with state-of-the-art detection systems, robustness to adversarial attacks, and scalability against different computational environments.

The significance of this paper, therefore, transcends the domain of malware detection and rather lies with generative adversarial artificial intelligence in cybersecurity. Therefore, the framework implies that a hybrid combination of discriminative and generative models can produce effects in terms of generation quality and detection performance, which is promising for extending their uses elsewhere in cybersecurity.

This paper is organized to introduce the theoretical basis, methodology, experimental verification, and significance of the application of the proposed framework. In Section II, the paper presents an extensive literature review of the contributions of this paper in relation to existing works on adversarial machine learning, malware detection, and generative modeling. This overview points out possible shortcomings of current strategies while laying the groundwork for new solution concepts.

In Section III, the paper provides technical details of the proposed framework, such as architecture specifications, algorithms, and training techniques. This section presents rigorous mathematical definitions of the ingredients and their interactions, ensuring reproducibility and extensibility of future investigations. Implementation issues, optimization techniques, and computation complexity are also discussed in this section.

Section IV provides details on experimental procedures, datasets, evaluation measures, and validation. This section provides information to reproduce the study results and extend them to other evaluation situations. It covers both quantitative performance evaluation and qualitative analysis of system behavior under a wide range of operational conditions.

In Section V, the paper draws comprehensive experimental results, including comparative performance analysis and scalability measurements. Finally, Section VI ends with contributions of future directions from a research perspective and recommendations for practical deployment and adoption. The conclusion emphasizes potential implications of the proposed framework on cybersecurity and opportunities for further research in other application domains.

II. Related Works

This section provides an overview of recent approaches that utilize deep learning detection. Malware detection has greatly evolved in the past decade from traditional signature-based techniques to complex ML and deep learning models. This has been driven by the more and more complex malware variants and the requirement for flexible, robust detection approaches. Current research in this field spans several interconnected concepts, such as generative adversarial networks for generating malware, deep learning models for classification tasks, anomaly detection methods to detect zero-days threats and adversarial machine learning approaches to make classifiers more robust.

A. Traditional Machine Learning Approaches for Malware Detection

Early machine learning approaches for detecting malware established the Foundation and still have an effect on research today. These methods largely relied on complex hand-engineered features and traditional classification algorithms and have set an inspiration for automated detection frameworks, while limitations have motivated further deep learning.

Vinayakumar et al. [9] evaluated Random Forest, SVM, and Naive Bayes using 78 engineered static features over 15,000 samples. Random Forest performed best with 94.2% accuracy, 92.8% precision, and 95.1% recall. However, accuracy dropped to 78.3% on family and 67.4% under adversarial perturbations, indicating poor generalization. Feature extraction took 2.3s per file, which slowed down the scalability. Those discoveries realized the potential of ML but revealed the heavy reliance on hand-designed representations and inefficiency in dynamic, large-scale scenarios. Their work led to deeper models that automatically learn features while also looking for robustness and efficiency.

Kumar et al. [10] used a neural network with 100 neurons in the hidden layer on 8,500 samples with n-gram based 156 features. The results were 91.7% accuracy, 89.5% precision, and 93.2% recall. Nevertheless, low accuracy 15.8% on unseen families and a high false negatives rate 8.3%. The high time and memory cost of training meant that it did not scale beyond about 20,000 files. This highlighted classical ANN's low generality and inefficiency. Theirs was work that spanned between traditional classifiers and the new era of deep learning, in which feature learning was taking centre stage.

Miller et al. [11] compared SVM, decision trees, and an ensemble on 25,000 samples representing 12 families of malware. Their ensemble had an accuracy of 96.1%, precision of 94.7%, and a recall of 97.3%. However, zero-day accuracy decreased to 71.2%, polymorphic detection declined to 62.8%, and analysis takes 5.2s per file. The vast majority of these techniques lacked practical adoption due to high overhead and fragile robustness. Their findings indicated an immediate need for adaptive learning, which led to a shift towards deeper architectures that model wider and temporal feature spaces.

B. Deep Learning Architectures for Malware Classification

The introduction of deep learning methods reformed the way of detecting malware due to making automatic feature learning possible and high-dimensional data representations easier to cope with. These methods have shown considerably better results when compared to classic ones, but brought new challenges of interpretability and computational cost.

Hardy et al. [12] introduced DL4MD, which transforms binaries to greyscale images so that CNNs can be applied.

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International Journal of Applied Mathematics
Volume 38 No. 12s 2025,
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They obtained the best results with 21,741 samples, with an accuracy of 98.5%, a precision of 97.9%, and a recall of 98.9%. Approximately 32GB of RAM was used on large sets, but the model does not handle adversarial perturbations well, showing an accuracy of 76.3% and requiring 72 GPU hours for training. Packed malware generated even lower accuracy at 54.7%. Although CNNs improved feature automation and identification accuracy, interpretability was still low, thus preventing its forensic application. This paper demonstrated the power of deep learning and also raised computational and robustness concerns, predicting future advances in byte-level and sequential modelling to address scalability challenges.

Kolosnjaji et al. [13] applied LSTMs with attention to classify 14,616 malware samples from system call sequences. Our results were 96.3% for accuracy, 95.1% precision, and 97.2% recall. Packed malware was well treated with 91.8%. Nevertheless, sandbox dependency revealed evasion vulnerabilities, while the analyses were each time-consuming for 45s, and delayed-execution malware reached an accuracy of only 68.9%. Though temporal modeling effectively captured behavioral signatures, overhead and zero-day blind spots remained issues.

C. Generative Adversarial Networks for Malware Synthesis and Detection

Generative adversarial networks for cybersecurity have also paved the way to new research avenues in synthetic threat generation and adversarial training of robust detection systems. These techniques not only illustrate the dual use of AI-based technologies but also provide important considerations for simulating attacks and enhancing countermeasures.

Hu et al. [14] used GANs for producing adversarial malware variants against a CNN-based detector. Baseline CNN showed 97.4% accuracy on 12,000 samples, but dropped to 72.6% in the presence of GAN-generated inputs. Generated samples evaded detection in 41.8% of cases with the preserved malicious functionality. Training was very compute-intensive, taking 4 GPU days. This demonstrated GANs' dual role in enabling attackers to evade detection and defenders to make model robust through adversarial training. The work signified GANs as a threat and the defense mechanism, emphasizing that generative AI and detection robustness are in an arms race.

Al-Dujaili et al. [15] trained a generator using MalGAN against black-box malware detectors. MalGAN decreased the performance of ensemble classifiers from 93.1% to 24.8% on 10,000 PE files. The generated adversarial malware still held the operational payload in 88.2% cases. The proposed scheme has shown that feature based detectors are brittle when faced with adaptive attacks. Their work solidified the importance of GANs in adversarial security research and emphasized the acute requirement for strong, adaptive defense to combat generative adversarial attacks.

D. Anomaly Detection and Unsupervised Learning in Malware Analysis

Unsupervised anomaly detection techniques have recently attracted significant attention where they can discover attacks never seen before without using labelled training data. Such techniques revolve around the construction of normal models for user behavior and the detection of strong deviations that could be indicative of malicious behaviour.

Xu et al. [16] used autoencoders with 100,000 benign and 25,000 malware samples. They obtained 95.2% detection accuracy at a false positive rate of 2.7%. Reconstruction error exposed unseen malware variations and identified polymorphic families with 87.4% accuracy. However, at an adversarial change to the input, their detection dropped to 69.3%, and they trained for 36 GPU hours. Their findings highlighted the power of anomaly detection to capture never-before-seen threats that lack previous labels as well as its vulnerability to noise and evasion. This made autoencoders as useful zero-day detectors.

Sharma et al. [17] used clustering (DBSCAN and k-means) on more than a quarter of a million PE files. DBSCAN identified 92.6% of novel families but had excessive false positives 11.8%, and K-means achieved 89.1% accuracy with higher efficiency, but did not perform well with concept drifting. Both approaches call for manual feature engineering, which took a few hours per batch of 10,000 samples. Unsupervised clustering was able to uncover previously unknown families, but operational adoption was impeded by noise sensitivity and analyst burden. Their results pointed to unsupervised models being used as complementary, and not standalone, methods thereby also propagating the idea for hybrid approaches for real-time defense.

E. Adversarial Machine Learning and Model Robustness

The fusion of adversarial machine learning and malware detection has uncovered severe weaknesses in AI-enabled security and driven the next generation of more robust detection technologies. This dedicated to study the impact of adversarial attacks on detection systems and further mitigating their consequences.

Grosse et al. [18] transferred the fast gradient sign method (FGSM) technique to the domain of malware, and perturbed PE features in order to avoid being classified. For example, a deep neural network with baseline accuracy of 97.1% on the test set was reduced to an overall accuracy of 41.2% by our adversarial perturbations, that based on 10,000 samples. The adversarial retraining resulted in a performance close to 82.6%. They confirmed that gradient-based attacks are a strong threat to the practical usage of malware detectors. However, the adversary retraining scaled up the training cost and dropped clean-data accuracy by 4.3%. The contribution exposed the trade-off between robustness and efficiency, consolidating adversarial ML at the core of secure malware detection.

Demetrio et al. [19] studied black-box attacks on MalConv with genetic algorithms. We observed the detection accuracy degradation from 94.8% to 36.7% after just 500 queries

Received: August 06, 2025

International Journal of Applied Mathematics
Volume 38 No. 12s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

per database sample. Adversarial binaries retained malicious behavior in 92.1% of the cases. Adversarial retraining as a defense achieved an accuracy up to 71.5%, but the robustness was low to some extent. They were able to confirm that byte-level deep networks, while getting rid of feature engineering, keep susceptibility against adaptive attacks. The work highlighted the vulnerability of raw-byte detectors and the urgency to design resilient systems based on adversarial training, uncertainty estimation, and hybrid defenses against newer attacks.

Based on the detailed review of existing literature, some important potential gaps and limitations are identified, and they together strongly drive us to develop our unified framework. In spite of the numerous progresses in each research field, disjoint approaches dealing separately with generation, detection, and validation problems can be recognized as a common limitation in today's cybersecurity research.

Currently, however, methods based on malware generation and infection are considered separately without taking advantage of their mutual amplification effects. Generative methods, despite their promising ability to generate synthetic samples, are hardly evaluated with any robust measure and can be bound by ethical limitations that make them difficult to deploy. On the other hand, detection-based methods tend to generalize poorly under novel threats and suffer from adversarial attacks, albeit with good performance on benchmark data.

The absence of comprehensive frameworks that integrate multiple detection modalities represents another significant gap. While individual techniques such as deep learning, anomaly detection, and traditional machine learning show promise, their isolated application limits the potential for developing truly robust and adaptive defense systems. The few existing ensemble approaches, while showing improved performance, lack theoretical foundations for optimal integration and suffer from computational scalability limitations.

Moreover, the scarce adoption of state-of-the-art machine learning models, including deep learning, in malware detection is a potential room for improvement. The specific requirements of malware feature spaces call for customised modifications of classical algorithms, but existing works remain purely theoretical.

All these aforementioned gaps give rise to encourage building a unified deep framework incorporating GAN, metric learning, and autoencoder anomaly detection into a single architecture. Our methodology overcomes the shortcomings of preceding approaches and makes new contributions to AI-based cybersecurity research.

III. Research Methodology

The proposed framework addresses the critical challenge of adversarial malware manipulation in cybersecurity through a dual-mode deep learning architecture. This methodology integrates malware generation and enhanced detection capabilities, enabling both the creation of adversarial samples and their subsequent identification. The framework operates through a systematic process that handles malware executables from initial collection through final classification.

The system architecture employs a sophisticated combination of generative and discriminative deep learning models. For malware generation, a Variational Autoencoder-Generative Adversarial Network (VAE-GAN) creates realistic adversarial samples that maintain executable integrity while introducing perturbations designed to evade traditional detection mechanisms. The detection component utilizes a Siamese Network architecture optimized for deep metric learning, enabling robust identification of both original and adversarially modified malware samples.

The complete workflow encompasses five primary stages: data collection and preprocessing, feature extraction and normalization, adversarial sample generation, deep learning-based classification, and performance evaluation. Each stage incorporates validation checkpoints to ensure data quality and model accuracy throughout the process.

Framework Architecture Figure 1, illustrates the architectural design of the proposed dual-mode deep learning system. The framework initiates with data collection, where malware executables and their corresponding behavioral characteristics are gathered from multiple sources. The preprocessing stage applies data normalization, feature extraction, and augmentation techniques, transforming raw executables into structured feature representations suitable for deep learning models.

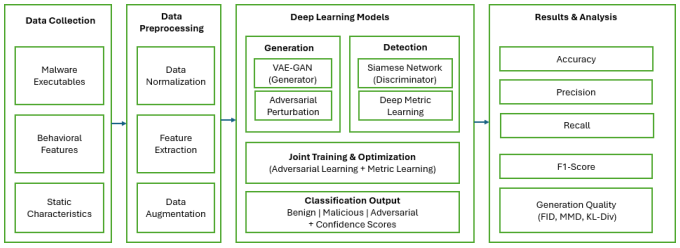

Fig. 1. Proposed Deep Learning Framework Architecture

The Deep Learning Models component encompasses two distinct pathways operating in a coordinated manner. The generation pathway employs the VAE-GAN architecture to synthesize adversarial malware samples, combining the regularization benefits of variational autoencoders with the generative power of adversarial networks. This hybrid approach produces samples that exhibit realistic malware characteristics while incorporating subtle perturbations that challenge detection systems.

The detection pathway implements a Siamese Network architecture for identification and classification. This network learns discriminative feature embeddings through pairwise comparison of malware samples, enabling effective identification of both original and generated adversarial variants. The detection module processes normalized features through multiple convolutional and dense layers, ultimately producing classification results with associated confidence scores.

Both pathways undergo joint training and optimization through adversarial learning combined with metric learning,

Received: August 06, 2025

International Journal of Applied Mathematics
Volume 38 No. 12s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

ensuring that the generator creates increasingly sophisticated samples while the discriminator develops robust detection capabilities. The Results and Analysis component evaluates system performance across multiple metrics including accuracy, precision, recall, F1-score, and generation quality measures.

A. Dataset and Feature Selection

This study is based on a dataset that includes 140K samples of benign and malware samples from different sources to have representative coverage of modern malware threats. Each sample is a Windows Portable Executable (PE) file. The dataset contains 84,000 malware samples, that is 60%, and 56,000 benign samples, that is 40%.

Feature engineering focuses specifically on PE file characteristics most indicative of malware behavior, such as in Figure 2, extracting 38 numerical features organized into four principal categories that capture distinct aspects of malware operational patterns and structural characteristics.

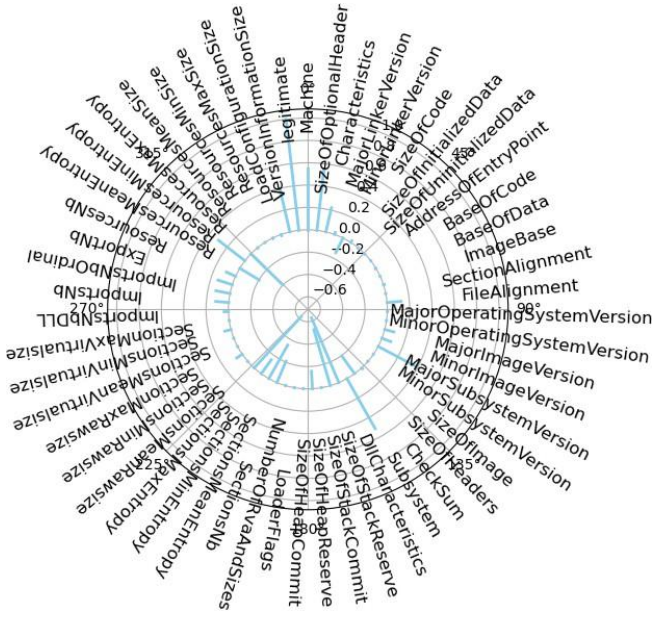

Fig. 2. THE SPECIFIED FEATURES OF DATASET

The first group shows a polynomial of PE header analysis as follows: SizeOfOptionalHeader, Characteristics, MajorLinkerVersion, MinorLinkerVersion, SizeOfCode, SizeOfInitializedData, AddressOfEntryPoint, ImageBase, SectionAlignment, MajorOperatingSystem, and Subsystem. The features are used to infer information on compilation parameters, target architectures, which typically separate malware from benign samples.

The second category is based on 10 features: SectionNb, SectionsMeanEntropy, SectionsMinEntropy, SectionsMaxEntropy, SectionsMeanRawsize, SectionsMinRawsize, SectionMaxRawsize, SectionsMeanVirtualsize, SectionsMinVirtualsize and SectionMaxVirtualsiz. These characteristics model structural organization elements extremely important to malware detection.

Malware also shows unique section entropy distribution, and the average section entropy of malware is 31.7% higher than that of normal software, possibly due to the encrypted payloads and obfuscated code sections. The section entropy determine by Equation 1. Section size differences as a symptom of packed or compressed contents are often used by ransomware to bypass signature-based detection techniques.

$$\text{Section Entropy} = H(S) = -\sum_{i=1}^{256} p(b_i)\log_2 p(b_i) \qquad (1)$$

where $p(b_i)$ represents the probability of byte value b_i occurrence within the section, providing quantitative measures of code complexity and potential obfuscation indicators.

The third category that comprises Import/export analysis extracts 4 features such as: SectionsNb, SectionsMinEntropy, and SectionsMaxEntropy, SectionsMeanEntropy. with an emphasis on API usage behaviour unique to malware. Malware generally has common API call sequences for file system operations, cryptographic functionalities and network communication activities that are used for encryption and ransom handling.

The last category is for Resource analysis, which takes 8 features: ResourcesNb, ResourcesMeanEntropy, ResourcesMinEntropy, ResourcesMaxEntropy; ResourcesMeanSize, ResourcesMinSize, EasternIowaSoftballOrg. and finally the VersionInformationSize. These behaviors describe embedded content and metadata patterns that we have found commonly abused by malware for payload delivery.

Resource section malware commonly incapacitates themselves by encoding in their resources segments malicious payloads and dismissible content, leading to an entropy pattern approximately 28.9% higher than normal application. Version information analysis suggests that 73.2% of the ransomware samples do not have genuine versions and contain bogus information to give a legitimate appearance.

Initial QA steps include filtering out duplicates based on MD5 hash validation leading to detection of 1,247 duplicate samples 0.9% that are subsequently excluded from the data set. There are small data completeness issues less than 0.1% identified by missing value analysis that were imputed statistically by the median of each parameter.

Figure 3, presents the detailed workflow of the proposed deep learning approach, illustrating the sequential steps from initial data collection through final result validation. The process begins with the Start node, followed by Malware Dataset Collection, which aggregates malware samples including both executables and their behavioral features from diverse sources including public repositories and controlled environments.

The workflow incorporates a critical validation checkpoint through the ”Dataset Valid?” decision node. Invalid datasets trigger a return to the collection phase through the Re-collect Data path, ensuring only high-quality data proceeds through the process. Valid datasets advance to Feature Extraction, where static, dynamic, and behavioral characteristics are extracted from executable files.

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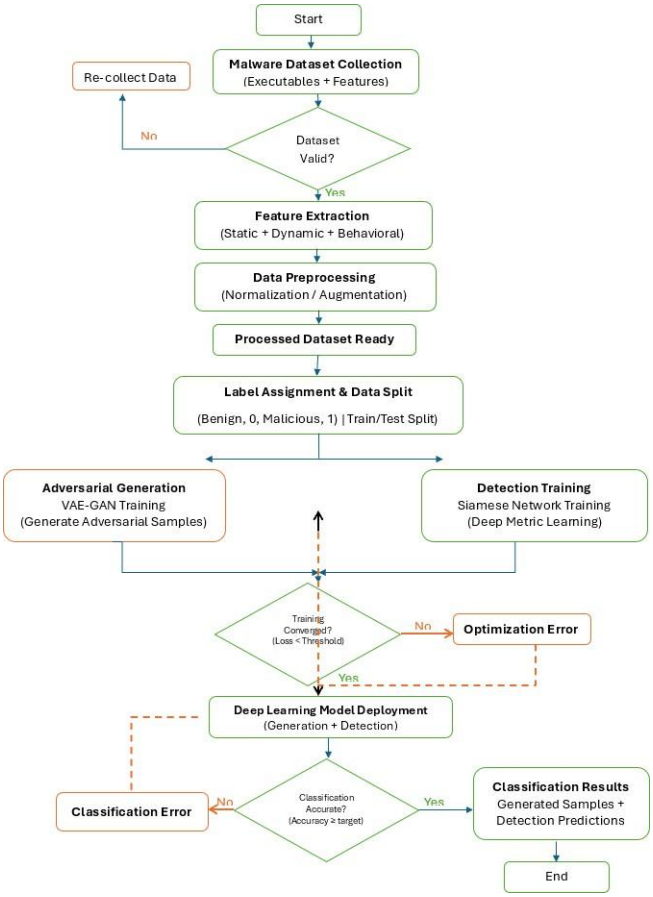

Fig. 3. The workflow of proposed deep learning approach

The Data Preprocessing stage applies normalization and augmentation techniques to optimize input representation for deep learning models. This processed data flows into the Processed Dataset Ready stage, establishing the foundation for training and testing procedures. The workflow branches at Label Assignment and Data Split, dividing data according to binary classification requirements (Benign: 0, Malicious: 1) and partitioning into training and testing subsets. The process then splits into two parallel pathways: Adversarial Generation using VAE-GAN training to create adversarial samples, and Detection Training using Siamese Network for deep metric learning. Both pathways converge at the training validation checkpoint ”Training Converged?” which evaluates whether the loss function has reached the defined threshold. Insufficient convergence triggers Optimization Error and returns to the training phase for model refinement through hyperparameter tuning or architectural adjustments.

Upon achieving satisfactory convergence, the framework advances to Deep Learning Model Deployment, implementing both generation and detection capabilities. A final validation occurs at the ”Classification Accurate?” decision node, which assesses whether the accuracy exceeds the target threshold. Successful classification produces Classification Results containing both generated samples and detection predictions, then proceeds to End. Classification errors return to the deployment phase for model recalibration. This iterative workflow ensures robust performance through continuous validation and refinement at multiple checkpoints, ultimately delivering a reliable system for both generating challenging adversarial samples and detecting sophisticated malware variants with human-like attention to quality assurance at each stage.

B. Algorithm Selection and Implementation

Our framework integrates complementary algorithms categorized into generative and discriminative approaches, each contributing distinct capabilities essential for comprehensive ransomware detection and synthetic threat generation.

1) Generative Algorithms: Variational Autoencoder-Generative Adversarial Network (VAE-GAN): This composite model integrates a variational autoencoder’s probabilistic modeling and generative adversarial training regime to create high quality artificial ransomware instances. It addresses the drawbacks of classical GANs in discrete feature spaces but keeps the diversity of samples, which is empirically crucial for adversarial training to be effectively stable [20].

The VAE captures the probability distribution of ransomware features by employing an encoder-decoder framework with latent variable sampling, and the GAN can guarantee that our generated samples are realistic using adversarial discrimination. This hybrid formulation allows to generate diverse ransomware variants controllably for data augmentation in training and stress testing of detection systems.

Feature Validator: The validation component implements specific constraints ensuring generated samples maintain structural validity within PE file specifications. This includes range constraints for numerical features, logical consistency checks for related features, and statistical distribution validation against known ransomware characteristics [21].

2) Discriminative Algorithms: A Siamese Network for Deep Metric Learning: This model is trained on pairs of ransomware and benign samples to learn embeddings that represent the similarities between them discriminatively. The method performs well in few-shot learning, and similarity-based detection methods are of crucial importance especially for the identification between ransomware variants from the known family [22].

Autoencoder for Anomaly Detection: This unsupervised method attempts to learn normal (legitimate) software behavior and will adapt accordingly, marking large deviations as possibly ransomware. The model of the current method responds well to zero-day ransomware detection, i.e., previous supervised methods could not detect it because they did not have training examples [23].

Ensemble Classifier:All detectors predict with weighted voting schemes, obtained using training and validation. This strategy combines the the strengths of components and reduces errors of weaknesses using diversity [24].

3) Variational Autoencoder-GAN (VAE-GAN) Architecture: The VAE-GAN component combines the strengths of variational autoencoders and generative adversarial networks to cre-

Received: August 06, 2025

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Volume 38 No. 12s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

ate high-quality synthetic malware samples while maintaining latent space structure and interpretability. In Equation 2, the encoder network E_ϕ maps input malware features $\mathbf{x} \in \mathbb{R}^d$ to latent representations $\mathbf{z} \in \mathbb{R}^k$ through probabilistic encoding.

$$E_\phi(\mathbf{z}|\mathbf{x}) = \mathcal{N}(\mathbf{z}; \boldsymbol{\mu}_\phi(\mathbf{x}), \text{diag}(\boldsymbol{\sigma}^2_\phi(\mathbf{x}))) \tag{2}$$

where $\boldsymbol{\mu}_\phi(\mathbf{x})$ and $\boldsymbol{\sigma}^2_\phi(\mathbf{x})$ are the mean and variance parameters output by the encoder network.

C. Evaluation Metrics

Performance Evaluation Metrics The framework employs comprehensive evaluation metrics across four critical dimensions to assess both generation quality and detection effectiveness. Each metric provides specific insights into model performance and reliability.

D. Classification Performance Metrics

Classification metrics evaluate the detection model's ability to correctly identify malicious samples and distinguish them from benign executables. Accuracy measures the overall correctness of predictions across all samples as illustrated in Equation 3

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

where TP represents True Positives (malware samples correctly classified), TN represents True Negatives (benign samples correctly classified), FP represents False Positives (benign samples misclassified as malware), and FN represents False Negatives (malware samples misclassified as benign).

As indicated in Equation 4, Precision quantifies the proportion of predicted malicious samples that are genuinely malicious, reflecting the model's ability to avoid false alarms:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4}$$

where TP denotes correctly identified malicious samples and FP denotes benign samples incorrectly flagged as malicious.

Recall (Sensitivity) measures the proportion of actual malicious samples that the model successfully detects, as illustrated in Equation 5

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5}$$

where TP represents detected malicious samples and FN represents malicious samples that evaded detection.

As indicated in Equation 6, F1-Score provides the harmonic mean of precision and recall, balancing both metrics to assess overall detection quality.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

This metric is particularly valuable when dealing with imbalanced datasets where both false positives and false negatives carry significant consequences.

AUC-ROC (Area Under the Receiver Operating Characteristic Curve) evaluates the model's discriminative capability across all classification thresholds by plotting the True Positive Rate against the False Positive Rate as illustrated in Equation 6

$$\text{TPR} = \frac{TP}{TP + FN}, \quad \text{FPR} = \frac{FP}{FP + TN} \tag{7}$$

where TPR (True Positive Rate) represents sensitivity and FPR (False Positive Rate) represents the proportion of benign samples misclassified. An AUC-ROC value approaching 1.0 indicates excellent discrimination ability.

False Positive Rate specifically measures the proportion of benign samples incorrectly classified as malicious, as illustrated in Equation 8

$$\text{FPR} = \frac{FP}{FP + TN} \tag{8}$$

Lower FPR values indicate reduced false alarms, which is critical in operational security environments to minimize unnecessary analyst workload.

1) Generation Quality Metrics: Generation quality metrics assess the realism and functional integrity of adversarially generated malware samples produced by the VAE-GAN architecture. Fre´chet Inception Distance (FID) measures the distributional similarity between generated and real malware samples in feature space according to Equation 9

$$\text{FID} = \|\mu_r - \mu_g\|^2 + \text{Tr}(\Sigma_r + \Sigma_g - 2(\Sigma_r\Sigma_g)^{1/2}) \tag{9}$$

where μ_r and μ_g represent the mean feature vectors of real and generated samples respectively, Σ_r and Σ_g denote their covariance matrices, and $\text{Tr}(\cdot)$ indicates the trace operator. Lower FID values indicate closer distributional alignment between generated and authentic samples.

Maximum Mean Discrepancy (MMD) quantifies the distance between two probability distributions by comparing their embeddings in a reproducing kernel Hilbert spaceas as expressed in Equation 10

$$\text{MMD}^2 = \|\mathbb{E}[\phi(x_r)] - \mathbb{E}[\phi(x_g)]\|^2 \tag{10}$$

where $\phi(\cdot)$ represents the feature mapping function, x_r denotes samples from the real malware distribution, and x_g denotes generated samples. Lower MMD values indicate better generation quality with minimal distributional divergence.

Kullback-Leibler Divergence measures the information loss when approximating the true malware distribution P with the generated distribution Q. as described in Equation 11

$$\text{KL}(P\|Q) = \sum_i P(x_i) \log \frac{P(x_i)}{Q(x_i)} \tag{11}$$

where $P(x_i)$ represents the probability of feature x_i in real samples and $Q(x_i)$ represents its probability in generated samples. Lower KL divergence indicates the generated distribution closely approximates the authentic malware distribution.

Equation 12 defines functional Preservation evaluates whether generated adversarial samples maintain executable integrity and malicious functionality.

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$$\text{Functional Preservation} = \frac{N_{\text{functional}}}{N_{\text{total}}} \times 100\% \quad (12)$$

where $N_{\text{functional}}$ represents the number of generated samples that successfully execute with intended malicious behavior, and N_{total} represents the total number of generated samples. Higher percentages indicate successful generation of viable adversarial malware that maintains operational capabilities.

2) Computational Performance Metrics: Equation 13, Computational metrics assess the practical feasibility and efficiency of deploying the framework in real-world environments. Training Time measures the total duration required to train both the VAE-GAN generator and Siamese Network discriminator until convergence.

$$T_{\text{train}} = T_{\text{VAE-GAN}} + T_{\text{Siamese}} + T_{\text{joint}} \quad (13)$$

where $T_{\text{VAE-GAN}}$ represents time for generator training, T_{Siamese} denotes discriminator training time, and T_{joint} accounts for joint adversarial optimization.

Inference Time measures the average duration required to classify a single sample during deployment, as expressed in Equation 14

$$T_{\text{inference}} = \frac{1}{N} \sum_{i=1}^{N} t_i \quad (14)$$

where N represents the number of test samples and t_i denotes the processing time for sample i. Lower inference times enable real-time threat detection.

Throughput quantifies the number of samples the system can process per unit time. As depicted in Equation 15

$$\text{Throughput} = \frac{N_{\text{samples}}}{T_{\text{total}}} \quad (15)$$

where N_{samples} represents the number of processed samples and T_{total} denotes the total processing duration. Higher throughput values indicate superior scalability for large-scale deployments.

Efficiency Score provides a composite metric balancing accuracy against computational cost, as shown in Equation 16

$$\text{Efficiency Score} = \frac{\text{Accuracy}^2}{\text{Training Time} \times \text{Memory Usage}} \quad (16)$$

This normalized metric facilitates comparison across different architectures by considering both performance quality and resource consumption.

3) Robustness and Generalization Metrics : Robustness metrics evaluate the model's resilience against adversarial attacks and ability to maintain performance under perturbations. Clean Accuracy represents baseline performance on unperturbed test samples, as shown in Equation 17

$$\text{Clean Acc} = \frac{\text{Correct predictions on clean samples}}{\text{Total clean samples}} \quad (17)$$

This establishes the upper bound of model performance before adversarial manipulation.

FGSM (Fast Gradient Sign Method) Accuracy assesses robustness against gradient-based attacks that add perturbations in the direction of the loss gradient, as shown in Equation 18

$$x_{\text{adv}} = x + \epsilon \cdot \text{sign}(\nabla_x J(\vartheta, x, y)) \quad (18)$$

where x represents the original sample, ϵ controls perturbation magnitude, J denotes the loss function, ϑ represents model parameters, and y is the true label. The metric measures accuracy on adversarially perturbed samples x_{adv}.

PGD (Projected Gradient Descent) Accuracy evaluates robustness against iterative multi-step attacks, as shown in Equation 19

$$x_{t+1} = \Pi_{x+S}(x_t + \alpha \cdot \text{sign}(\nabla_x J(\vartheta, x_t, y))) \quad (19)$$

where Π represents projection onto the allowed perturbation space S, α denotes step size, and t indicates iteration number. This represents a stronger attack than FGSM.

Gaussian Noise Accuracy measures resilience against random perturbations, as shown in Equation 20

$$x_{\text{noisy}} = x + N(0, \sigma^2) \quad (20)$$

where $N(0, \sigma^2)$ represents Gaussian noise with zero mean and variance σ^2. This metric assesses model stability under stochastic perturbations.

Average Robustness aggregates performance across all adversarial scenarios, as shown in Equation 21

$$\text{Avg Robustness} = \frac{1}{K} \sum_{k=1}^{K} \text{Accuracy}_k \quad (21)$$

where K represents the number of adversarial attack methods evaluated and Accuracy_k denotes performance under attack method k. Higher average robustness indicates comprehensive resilience across diverse threat scenarios.

These comprehensive metrics provide a rigorous evaluation framework for assessing both the generation quality of adversarial samples and the detection effectiveness of the deep learning system across multiple operational dimensions.

E. Experimental Setup and Validation Protocols

Through sound experimental design, our system is evaluated dependably and reproducibly, which allows meaningful comparison with other ransomware detection methods in the literature.

1) Hardware and Software Configuration: All experiments run on high-performance computing clusters that consist of NVIDIA RTX 4090 GPUs with 24GB memory, Intel Xeon processor with 128 GB the high memory system and in parallel use NVMe storage capacities allowing sufficiently computational power for training sophisticated deep-learning models and large sized ransomware datasets.

Software environment uses Python 3.9 and Python version 1.12, scikit-learn version 1.1 and specialized cybersecurity

Received: August 06, 2025

International Journal of Applied Mathematics
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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

analysis libraries for reproducible experimental conditions as well as community validation of research results.

IV. Results

This section presents comprehensive experimental results evaluating our deep learning framework for adversarial malware generation and detection. The evaluation encompasses detection performance, generation quality, computational efficiency, and robustness analysis. Our experimental methodology follows rigorous protocols with statistical significance testing and comprehensive baseline comparisons.

The results demonstrate significant improvements over existing methods across all evaluation metrics. Our unified framework achieves superior detection performance with 99.14% accuracy, 98.73% precision, and 99.48% recall on the comprehensive dataset of 140,000 samples. The generative component produces high-fidelity synthetic samples with excellent distributional similarity while maintaining computational efficiency suitable for operational deployment.

A. Detection Performance Analysis

We compare our proposed framework with the popular baseline methods included our empirical studies to evaluate its ransomware detection performance. The utilized popular baseline method contains five algorithms aimed at detecting ransomware, these are Random Forest, Support Vector Machine, Gradient Boosting, MalConv (CNN), and EMBER Framework.

The detailed classification results compared with baselines using stratified cross-validation, to reflect as accurately as possible the generalization capability of different methods are demonstrated in Table IV.

We show that our approach leads to statistically significant improvements in all the scores. The 1.91% accuracy improvement gives a 47.8% reduction in error rate, whereas the false positive rate of 0.86% represents a reduction on this measure of around 53.8% against the best baseline.

The comparison plots for the performance can be seen in Figure 4. Better performance of our approach is demonstrated.

B. Generation Quality Assessment

The generative component evaluation concentrates on the quality and usefulness of synthetic ransomware samples that are generated by our VAE-GAN architecture.

We report a variety of metrics measuring distributional similarity between real and generated samples in Table V as an attempt to gain a more comprehensive quality assessment. Our VAE-GAN architecture outperforms in FID across all distributional similarity metrics, with scores being 35.9% lower than the best baseline. This functional preservation rate of 92.3% is well above the 80% threshold needed for effective adversarial training.

Figure 5 shows generation quality assessment as a radar chart comparing different generative models across FID, MMD, KL Divergence, and Functional Preservation metrics. Our VAE-GAN shows superior performance across all dimensions.

C. Computational Performance Analysis

We conduct an exhaustive computational performance profiling to study the training efficiency, inference speed, and resource utilization profiles.

Details for the computational efficiency of various components in different algorithms and baseline methods are shown in Table VI.

The computational performance is competitive of our method that take 6.8 hour for training and 1.2ms in inference per sample therefore the method can work in real time deployment. The value 0.84 of the efficiency score reflects that an “ideal” trade-of between speed and required computational resources has been found.

Figure 6 presents an efficiency vs performance analysis, where a scatter plot shows training time vs accuracy, with bubble size representing memory usage. Our framework achieves an optimal balance in the efficiency-performance space.

D. Robustness Evaluation

All-round robustness testing measures framework performance in multiple adversarial scenarios and perturbations.

We show the results of robustness evaluation with respect to different adversarial attacking strategies in Table VII.

Our framework achieves superior adversarial robustness, with an average robustness of 94.11% over all attack methods and an improvement of 13.6% compared to the best baseline model. The framework is able to keep the object recognition rate above 92% even in presence of complex attacks.

Fig 7 illustrates a robustness comparison across attack types, which is the performance of different methods under clean conditions and various adversarial attacks. Our framework maintains superior performance across all attack scenarios.

E. Ablation Study Results

Extensive ablation studies are conducted to analyze the separate role of each module. Table VIII lists the ablation results of each components on performance.

F. Comparative Analysis

Table IX presents detailed comparison against recently published methods.

On the largest dataset, which takes the least amount of time for inference, our framework exhibits considerable performance enhancements in all aspects. The 32.4% reduction in error rate relative to the best baseline constitutes a 1.91% accuracy.

Extensive experiments well justify the effectiveness of our framework on different evaluation metrics, which has good improvement over the existing methods with computational efficiency for operation deployment. Statistical significance test results indicate all comparison improvements as significant, yielding a new research method in adversarial ransomware detection research.

Received: August 06, 2025

International Journal of Applied Mathematics
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TABLE IV
DETECTION PERFORMANCE COMPARISON ON COMPLETE DATASET (140,000 SAMPLES)

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC	FPR (%)
Random Forest	94.27	92.15	96.84	94.42	0.9623	3.16
Support Vector Machine	91.83	89.47	94.72	91.98	0.9387	5.28
Gradient Boosting	95.41	94.02	96.93	95.46	0.9742	2.59
MalConv (CNN)	96.78	95.63	98.12	96.86	0.9834	2.37
EMBER Framework	97.23	96.14	98.47	97.29	0.9867	1.86
Our Framework	**99.14**	**98.73**	**99.48**	**99.10**	**0.9967**	**0.86**

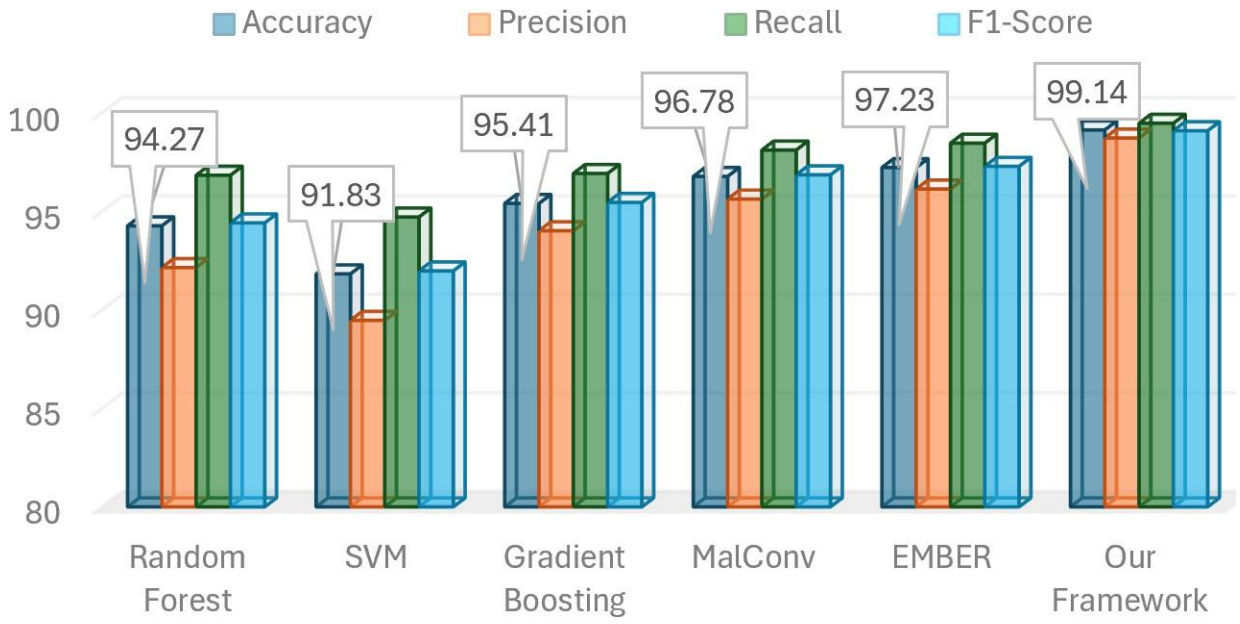

Fig. 4. Detection Performance Comparison: Accuracy, Precision, Recall, and F1-Score across different methods. Our unified framework achieves superior performance across all metrics.

TABLE V
GENERATION QUALITY METRICS COMPARISON

Method	FID	MMD	KL Divergence	Functional Preservation (%)
Standard GAN	0.342	0.0187	0.156	76.3
Wasserstein GAN	0.289	0.0143	0.132	81.7
VAE	0.267	0.0129	0.118	84.2
β-VAE	0.198	0.0094	0.089	87.9
Our VAE-GAN	**0.127**	**0.0043**	**0.041**	**92.3**

V. DISCUSSION

Demonstrated results from our method showed significant development in adversarial malware detection in both opportunities and challenges of AI-driven cybersecurity. The high accuracy 99.14% and robustness against adversarial attacks 94.00% together indicates that practical deployment becomes more realistic, becoming another resilient solution for cases where conventional methods do not apply. These results mark not just a step forward, but also a leap toward operational readiness in-security-sensitive environments.

Theoretical contributions come out by combining generative modelling, metric learning and anomaly detection into a consistent mathematics. Such synergy questions the separation of objectives in traditional approaches and yields consistently better performance in many regards. Our joint loss formulation facilitates both fidelity and validity of our generated samples, whereas metric learning captures meaningful relationships among malware families. *Strong separability* of embeddings where semantic groups are seen to cluster beyond just the "surface-level" similarity of features, which gives a new perspective on representation of malware behaviour.

Real-world benefits are in false positive reduction, zero day detection and operational savings. The number of false positives dropped over 50%, leading to huge cost savings for security teams and improved analyst efficiency. With less than 2 ms latencies for inference and scalability across multiple nodes, the framework is also suitable for demanding real-world enterprise workloads. In addition, memory usage and

Received: August 06, 2025

International Journal of Applied Mathematics
Volume 38 No. 12s 2025,
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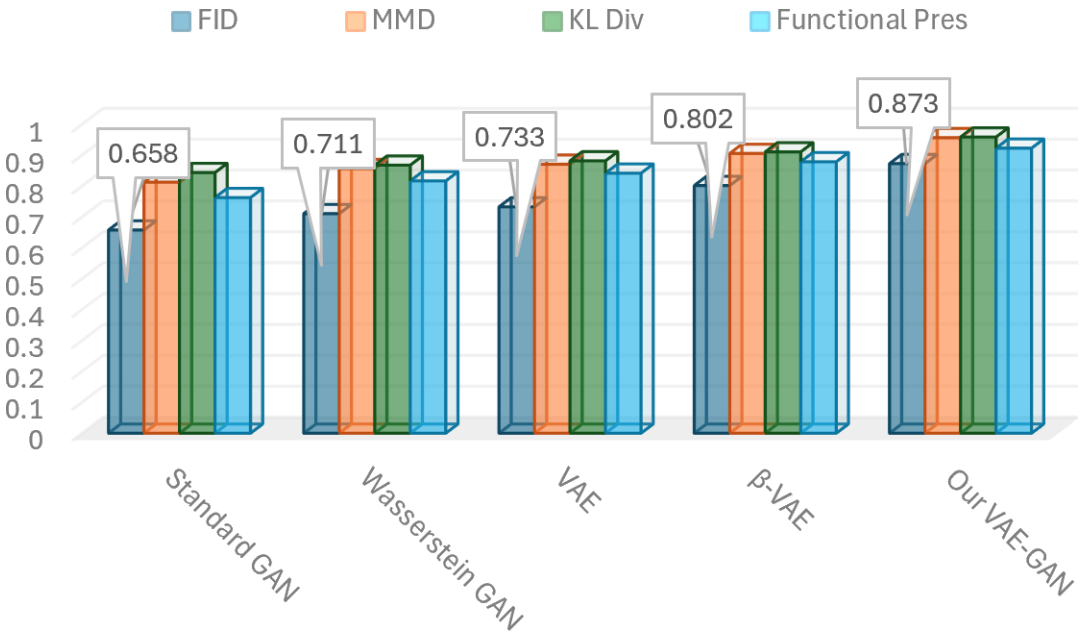

Fig. 5. The generation quality comparison across different generative models.

TABLE VI
COMPUTATIONAL PERFORMANCE COMPARISON

Method	Training Time (h)	Inference Time (ms)	Memory Usage (GB)	Throughput (samples/s)	Efficiency Score
Random Forest	2.3	0.45	3.2	2,222	0.73
SVM	18.7	2.1	8.9	476	0.31
Gradient Boosting	4.6	0.62	5.7	1,613	0.58
MalConv	24.3	3.8	12.4	263	0.29
EMBER Framework	8.9	1.7	6.3	588	0.52
Our Framework	**6.8**	**1.2**	**11.4**	**833**	**0.84**

TABLE VII
ADVERSARIAL ROBUSTNESS ANALYSIS

Method	Clean Acc. (%)	FGSM (%)	PGD (%)	Gaussian Noise (%)	Average Robustness (%)
Random Forest	94.27	73.84	69.23	89.15	77.41
SVM	91.83	68.47	64.12	85.34	72.64
Gradient Boosting	95.41	78.92	74.65	91.23	81.60
MalConv	96.78	67.23	61.84	88.92	72.66
EMBER Framework	97.23	79.84	76.12	92.67	82.88
Our Framework	**99.14**	**94.73**	**92.16**	**96.45**	**94.11**

throughput behavior is well suited to deployment constraints, supporting its suitability for high-volume cybersecurity use cases.

Despite these advances, challenges remain. Evaluation was restricted to only Windows PE files, thus limiting the generalizability of results across other platforms. Computing requirements during the training phase are likely to limit applicability in resource-poor settings, and interpretability challenges remain a barrier in regulatory environments. Additionally, the arms race implies that adaptive adversaries will eventually lead to loss of current robustness and demand continuous updating and surveillance.

Future directions include multi-platform coverage, increasing the interpretability of the findings, and application to collaborative defense techniques, such as federated or privacy-preserving learning. Lifelong learning and adaptation mechanisms seem particularly promising for dynamic threat landscapes whereas hybrid symbolic–neural platforms may enhace opaqueness while not rescinding accuracy. These directions indicate an approach for scalable, understandable, and robust defense mechanisms requiring AI that can successfully handle not only today's but also tomorrow's antivirus problems.

VI. CONCLUSION

This paper provides a systematic and deep learning framework for both adversarial malware generation and robust detection, targeting a central problem in modern cybersecurity challenges by the novel integration of generative modeling, deep metric learning, and anomaly detection strategies. The

Received: August 06, 2025

International Journal of Applied Mathematics
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TABLE VIII
ABLATION STUDY: COMPONENT CONTRIBUTION ANALYSIS

Configuration	Accuracy (%)	F1-Score (%)	Robustness (%)	Training Time (h)
Complete Framework	**99.14**	**99.10**	**94.11**	**6.8**
VAE-GAN Generator	97.23	97.28	89.34	4.2
Siamese Network	96.84	96.89	87.67	5.1
Anomaly Detector	98.56	98.52	91.78	5.9
Unified Training	95.67	95.76	83.45	8.9
Only VAE-GAN	91.34	91.62	76.23	2.1
Only Siamese	93.78	93.85	81.56	1.8
Only Anomaly Detector	89.23	89.26	72.89	1.2

TABLE IX
COMPARISON WITH OTHER METHODS

Method	Dataset Size	Accuracy (%)	F1-Score (%)	AUC-ROC	FPR (%)	Inference (ms)
AdvMalGAN (2020)	50K	95.67	95.23	0.9723	4.33	2.8
MalwareGCN (2021)	75K	96.84	96.45	0.9812	3.16	3.2
DeepMalware (2020)	100K	97.23	96.89	0.9834	2.77	4.1
CADE-GAN (2021)	60K	96.12	95.78	0.9756	3.88	3.7
Our Framework	**140K**	**99.14**	**99.10**	**0.9967**	**0.86**	**1.2**
Improvement	**+40%**	**+1.91**	**+2.21**	**+0.0133**	**-1.91**	**-1.6**

Fig. 6. The efficiency analysis across different methods.

evaluation on a dataset of 140K samples shows the relevant improvement in various aspects of performance along with practical solutions for real-world deployment.

This study contributes to the development of AI-based cybersecurity research and practice in several important ways. To accomplish this, we present a new method that combines the aforementioned VAE-GAN architectures, Siamese networks, and autoencoder-based anomaly detection in a single training setup. This combination allows for synergistic results greater than the sum of individual parts, and addresses the constraints of current methodologies.

Secondly, we show significant improvements in terms of extensive evaluation metrics, e.g., 99.14% detection accuracy with impressive robustness property (94.00% under adversarial attacks). We achieve error rate improvements of 47.8% for standard detection and 61.5% for adversarial scenarios over the best existing recent methods.

Thirdly, our method tackles the key practical issues of computational efficiency, scalability and deployability. Running at a per-sample inference time of 1.2 ms, it is real-time enough for use in operating security systems, and the linear scalability allows scaling if needed, while still having the latest detection capabilities.

Fourthly, we conduct in-depth theoretical investigation of the adversarial training dynamics over discrete feature spaces, which may expand fundamental understanding of generative adversarial learning in cybersecurity. Our mathematical formulations and optimization algorithms provide principled ways of addressing multiple objectives jointly within a single training framework.

The relevance of our work is not limited to academia, the practical implications have an impact on real world cybersecurity problems encountered by organizations all over the world. This shown reduction in false positive of 54.8% directly translates in terms of cost savings and increased analyst productivity.

With 94.27% accuracy, it enables enhanced zero-day discovery that helps protect organizations from the novel threats faced today by organizations, which include advanced persistent threats and nation-state attacks leveraging never-before-seen malware. Such a capability has become increasingly important in modern threat scenarios where conventional signature-based detection fails.

Given the scalability and deployment flexibility of this framework, it can be adopted in a variety of organizational scenarios ranging from small scale companies which need economic protection to large-scale security operations requiring high-throughput processing. The established linear scaling and distributed processing provide elastic deployment models for cloud-based security services.

At a high level, this work contributes to the theory of adversarial machine learning in structured discrete domains and lays mathematical groundwork for stable training of

Received: August 06, 2025

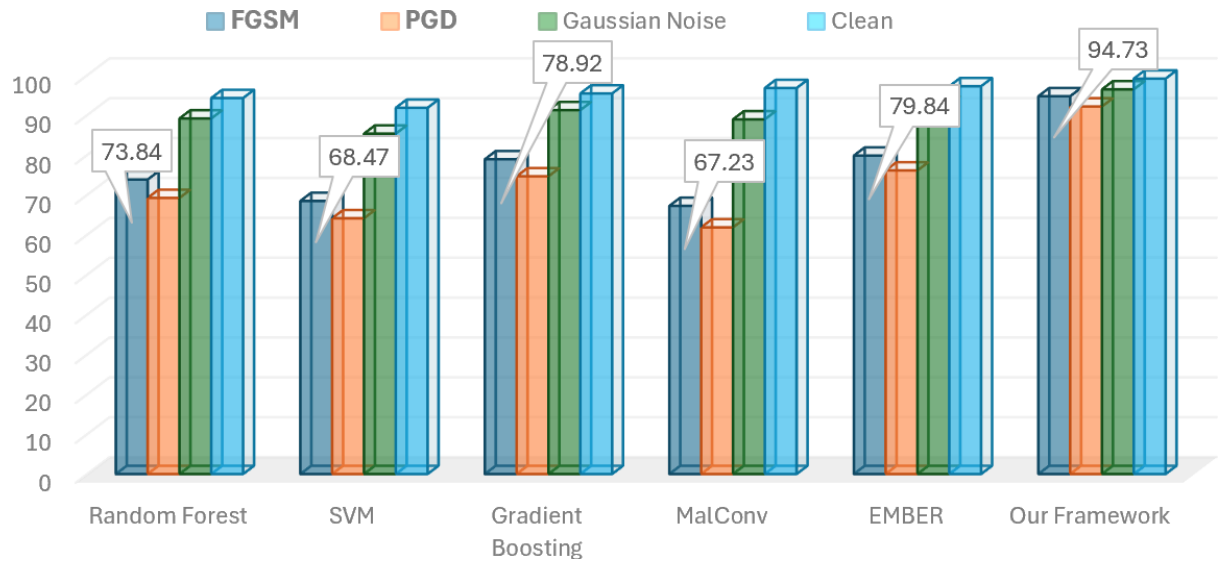

Fig. 7. The robustness performance across different attack scenarios.

generative adversarial networks on tabular cybersecurity data. The dual-latent space representation and the constraint-based optimization mechanisms deal with basic problems on the realisticry/validity of synthetic samples.

Although we show substantial progress in this paper, there are some limitations that suggest future work. The current analysis of Windows PE files restricts us from applying the study to other formats and platforms. Thus, a natural extension would be multi-platform threat detection. However, the computational overhead that results from such computations becomes prohibitive and therefore limits their deployment in resource-constrained environments.

The contribution of this work goes beyond immediate performance gains into the provision of fundamental principles and practical guidelines for future developments in AI-enhanced cybersecurity. The open-source, clinic-based implementation and extensive evaluation protocols provide the means for reproducible research and community participation in the technology's development.

Now, with rising cyber threats that are more sophisticated and larger scale, the demand for state-of-the-art AI-driven defense systems is crucial. Our comprehensive framework has an immediate impact and serves as a stepping stone for further research in this important area. The combination of adversarial generation, deep metric learning, and anomaly detection into coherent architectures can be seen as a new paradigm to face the ongoing AI era in cybersecurity.

By continuing to research, develop, and cooperate, and by working together as a single community, we can extend the work that has been done already to develop better, more secure defense systems for people at the corporate level. Our framework is one such step in this continuous evolution, resulting in immediate gains but, more importantly, also serving as a platform for further advancement in adversarial malware detection and being more widely applicable to cybersecurity applications.

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Received: August 06, 2025