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Research Paper

Adversarial Auto encoder Framework for Zero-Day Malware Detection Using Dynamic Behavior Graph Representations

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Abstract
The rapid evolution of zero-day malware poses a significant threat to modern cybersecurity infrastructures, as these threats often evade signature-based detection systems by exploiting unknown vulnerabilities or obfuscating code. Traditional approaches lack the adaptability required to detect such previously unseen malware in real-time. This study proposes a robust detection framework that leverages adversarial auto encoders (AAEs) and dynamic behaviour graph representations to identify zero-day malware with high precision and low false positives. The framework constructs dynamic behaviour graphs from runtime system activities such as file access, registry changes, and process creation, captured in sandboxed environments. These graphs are embedded into fixed-size vectors and processed by an adversarial auto encoder trained to differentiate benign and anomalous behaviour based on reconstruction error and latent space regularity. Experiments were conducted using the CIC-MalMem-2022 dataset, comprising over 3,000 samples from multiple malware families and benign software. The proposed AAE framework achieved a detection accuracy of 96.47%, precision of 94.80%, recall of 93.52%, and an AUC-ROC of 97.10%, outperforming baseline models including CNN, Random Forest, and One-Class SVM. It also demonstrated a significantly lower false positive rate (1.42%) compared to other techniques. This research presents a scalable and generalizable malware detection approach suitable for real-world deployment in enterprise and critical infrastructure environments. By combining structural behavioural modeling with adversarial training, the framework provides a proactive solution to the increasing challenge of zero-day malware.

Keywords: Zero-day malware, adversarial auto encoder, dynamic behaviour graph, anomaly detection, cybersecurity, graph embedding, AUC-ROC.

1. Introduction

The persistent growth and sophistication of cyber threats, especially zero-day malware, presents an alarming challenge to digital infrastructure worldwide. Zero-day malware refers to malicious software that exploits unknown vulnerabilities, making it virtually undetectable by traditional signature-based security systems. The stealth and unpredictability of these threats have heightened the urgency for intelligent detection mechanisms that can anticipate and respond to malware activities proactively. In particular, leveraging behavior-based and representation-learning approaches offers promising directions to counteract zero-day intrusions before damage is inflicted.

Traditional malware detection methods predominantly rely on static code analysis or signature-based heuristics. Although efficient for known malware strains, such methods often fail when encountering previously unseen or obfuscated variants [1]. Even modern static analysis tools struggle to cope with polymorphic and metamorphic malware techniques that alter their structure while preserving their malicious intent. As a result, there is a growing shift towards dynamic malware analysis—observing the runtime behaviour of executable—as it offers a more robust avenue to detect zero-day malware, regardless of their outer form.

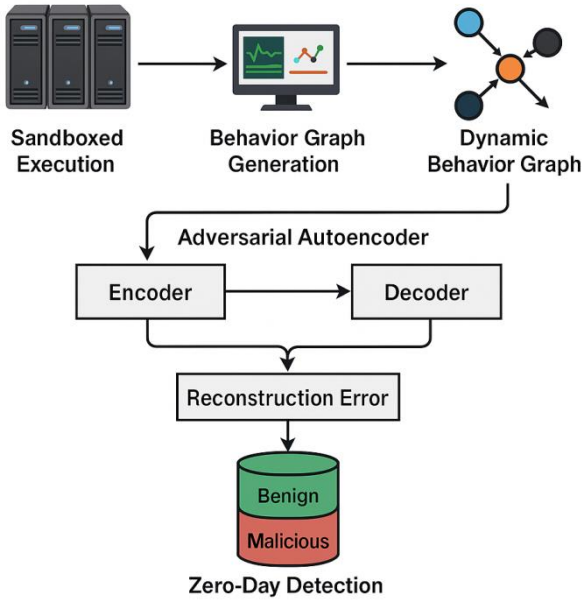


Fig. 1: Adversarial Auto encoder Framework for Zero-Day Malware Detection

Figure 1 illustrates the proposed framework for detecting zero-day malware using dynamic behaviour graph representations and an adversarial auto encoder. The process begins with sandboxed execution, where malware or unknown programs are run in an isolated environment to safely observe their real-time behaviours. These behaviours are transformed into behaviour graphs representing interactions between system components (e.g., API calls, file access). These dynamic behaviour graphs are input to the adversarial auto encoder, composed of an encoder and decoder network. The auto encoder learns compact latent representations of benign behaviour while the discriminator (not shown explicitly here) regularizes this learning through adversarial training. The reconstruction error—the difference between input and output—is then analyzed. Higher errors typically signify anomalies or malicious activity. Based on this, the system classifies each input as benign or malicious, enabling effective detection of previously unseen (zero-day) threats.

However, dynamic behaviour analysis is not without its limitations. While it provides deeper insights into malware activities through system call monitoring and behaviour tracing, it often produces complex and voluminous data. Extracting meaningful patterns from such behaviour sequences requires advanced feature extraction, dimensionality reduction, and anomaly detection strategies. Machine learning-based approaches have become increasingly relevant in this context, especially those capable of unsupervised learning, which can detect anomalous behaviours without requiring labelled data [2]. Yet, several challenges persist in scaling these solutions and ensuring their generalization capability across malware variants.

Recent studies have explored autoencoder-based architectures for learning behavioural representations of malware. Autoencoders are neural networks trained to reconstruct their inputs, thereby learning the most compact latent representations of the underlying patterns. This property makes them highly suitable for anomaly detection, where deviations from learned benign behaviour can signal potential threats [3]. However, standard auto encoders may lack the expressive capacity to separate borderline behaviours or may be prone to over fitting benign patterns, resulting in false negatives or positives.

To address these limitations, adversarial auto encoders (AAEs) have emerged as a powerful enhancement to conventional auto encoders. By incorporating adversarial training mechanisms—borrowing concepts from generative adversarial networks (GANs)—AAEs enforce the latent space to follow a prior distribution, allowing for improved generalization and robustness [4]. Additionally, the discriminative component of AAEs can be fine-tuned to distinguish benign from malicious behaviour based on reconstruction loss distributions, even when confronted with zero-day malware.

Another key advancement lies in the modeling of behavioural patterns as graphs. Dynamic behaviour graphs capture the sequence and structure of interactions between system components (e.g., files, registry, API calls) during malware execution. These graphs are rich with semantic information and provide a holistic view of how malware interacts with its environment. When combined with autoencoder-based frameworks, graph representations enable more nuanced and context-aware modeling of malware behaviour, offering significant gains over flat feature vectors or sequential logs [5].

Despite these innovations, existing AAE-based or graph-based solutions often operate independently, without leveraging the mutual strengths of both approaches. While behaviour graphs offer structural fidelity, they require effective feature learning mechanisms to handle their complexity. Conversely, AAEs need informative inputs that encapsulate rich behavioural semantics. A unified framework that integrates adversarial auto encoding with graph-based behaviour modeling could therefore bridge this gap and yield a more accurate and generalizable malware detection system.

This study introduces an integrated framework that addresses the above limitations by employing dynamic behaviour graphs as input representations and adversarial auto encoders for robust feature learning. Unlike static or log-based models, our approach builds structured graphs from runtime data, capturing intricate dependencies between actions taken by executable in controlled environments. These graphs are then embedded into high-dimensional vectors using graph encoding techniques and processed through an adversarial autoencoder. The reconstruction error and latent vector distribution are jointly utilized to detect zero-day anomalies. Comparative evaluations against

traditional and state-of-the-art models reveal substantial performance improvements in both detection accuracy and false positive reduction [6].

Furthermore, this framework is evaluated not only on well-known malware datasets but also on previously unseen malware families, validating its zero-day detection capability. As the threat landscape evolves, the ability to detect unfamiliar and sophisticated malware without explicit labelling becomes critical. This work contributes to the field by merging structural behavioural representations with adversarial learning to tackle this very challenge.

Several recent works have examined similar problems. For instance, Tokmak and Nkongolo proposed a stacked autoencoder model for feature selection in zero-day threat detection, showing promise but lacking behavioural context [5]. Similarly, Gunduz explored the use of graph variation autoencoders for malware embedding extraction from API call graphs, achieving high expressiveness but without adversarial regularization [7]. Comparative evaluations have also shown that ensemble classifiers and contractive autoencoders perform well in ransom ware detection, yet their generalization to diverse malware remains limited. Our work builds on these foundations but uniquely combines dynamic graphs with adversarial learning in a cohesive architecture.

Key studies have also noted the importance of integrating anomaly detection with graph modeling for advanced cyber security threats. Ali et al. provide a broad comparative evaluation of AI techniques for zero-day attack detection and recommend graph-aware deep models as a future direction [8]. This aligns with our framework's objectives and reinforces the need for further research in this hybrid domain.

1.1 Key Contributions

- A novel adversarial autoencoder framework that incorporates behaviour graph embedding's for robust detection of zero-day malware.
- Dynamic behaviour graph modeling, capturing complex malware behaviours during execution for more context-aware anomaly detection.
- Improved generalization and detection accuracy, demonstrated through empirical evaluation on real-world datasets and previously unseen malware variants.

The remainder of this paper is organized as follows. Section II presents related work on autoencoders, adversarial models, and behaviour graph modeling for malware detection. Section III outlines the proposed framework, including data collection, graph generation, feature embedding, and model design. Section IV discusses the experimental setup and datasets used for evaluation. Section V presents the results and analysis, including ablation studies and comparative benchmarks. Section VI concludes the paper with a summary of findings, limitations, and directions for future research.

2. Literature Review

Zero-day malware detection continues to evolve as researchers explore machine learning and deep learning methods for analyzing system behaviour and identifying novel attack patterns. Despite progress, existing approaches often exhibit trade-offs between detection accuracy, generalizability, interpretability, and computational efficiency. This section critically analyzes key methodologies and highlights the gaps that motivate the proposed framework.

2.1 Traditional Machine Learning Approaches

Kumar and Sinha proposed an intelligent zero-day cyber-attack detection method using conventional ML classifiers like decision trees and support vector machines [9]. Their work demonstrated robustness against known attacks; however, its effectiveness declined when exposed to unseen malware samples due to its reliance on hand-engineered features. A follow-up study by Kumar et al. further integrated feature engineering with ensemble learning [10], achieving better accuracy but still lacked dynamic adaptability to evolving malware behaviour.

Topcu et al. introduced a TensorFlow-based zero-day detection model targeting malicious social media activity [11]. While their use of a scalable DL framework is notable, the reliance on social features makes the method domain-specific, limiting its application in traditional malware environments. Furthermore, the use of static features weakens the model's capacity to detect obfuscated or dynamic threats.

2.2 Zero-Shot and Few-Shot Learning Techniques

Zero-shot learning (ZSL) approaches are promising for zero-day scenarios due to their ability to infer class labels without prior examples. Barros et al. proposed the Malware-SMELL framework that leverages ZSL to classify unknown vulnerabilities based on semantic similarity to known attack behaviours [12]. However, the absence of temporal dynamics in their model reduces its capability to capture real-time behaviour of executing malware.

Similarly, Sawadogo et al. presented Zero-Vuln, a zero-shot deep learning approach for Android malware detection [13]. Their system shows strong generalization, but the evaluation was limited to mobile environments. The lack of adversarial robustness also raises concerns about its applicability to adversarial malware attacks in desktop systems.

Liu et al. recently introduced A2-CLM, a few-shot learning technique enhanced with adversarial heterogeneous graph augmentation [14]. This method combines structural behavioural patterns with adversarial training, aligning closely with the philosophy of this study. Nonetheless, its few-shot requirement still demands minimal labelled samples from new malware, which may not be feasible in practical zero-day conditions.

2.3 Graph-Based and Behavioural Modeling Approaches

With the rise of graph neural networks and structured behaviour modeling, dynamic graph-based approaches have shown increased relevance. Redino et al. utilized graph and flow-based telemetry to identify network-layer malware behaviour [15]. Their graph modeling was effective for

capturing dependencies, but the lack of representation learning limited scalability. Likewise, Kumar and Subbiah incorporated Shapley value-based feature selection into ensemble methods [16]. While this enhanced feature attribution, their model lacked temporal graph context and adversarial resilience.

Uysal et al. conducted a comprehensive survey on malware detection for 6G networks and emphasized the need for explainable and continuously learning models [17]. Their analysis supports the argument for hybrid models that balance learning capability with interpretability, something often lacking in deep learning-only systems.

2.4 Adversarial and GAN-Based Malware Detection

Generative adversarial networks (GANs) have been used to synthesize plausible malware behaviours. Won et al. introduced PlausMal-GAN to create realistic malware variations for zero-day training [18]. While the GAN-generated samples improved training diversity, the absence of behaviour modeling limited its detection performance. Similarly, Afzal-Houshmand analyzed adversarial machine learning for cybersecurity and highlighted the increasing risk of evasion attacks against DL-based systems [19].

Z. He's work on hardware-assisted machine learning models offered insights into boosting detection speeds using embedded platforms [20]. Although beneficial for edge-based systems, such approaches demand specialized hardware, limiting accessibility for standard cloud-based detection systems.

2.5 Research Gaps and Motivation

A critical review of the above studies reveals several persistent gaps:

- *Lack of unified frameworks:* Most models treat behaviour graphs and deep learning as separate paradigms, limiting their synergy [21].
- *Insufficient generalization to zero-day variants:* Methods requiring labelled examples (even few-shot) face difficulty in real-world deployment [22].
- *Vulnerability to adversarial manipulation*: Few models explicitly incorporate adversarial training to defend against malware obfuscation [23].
- *Limited behaviour granularity:* Many models do not use dynamic, fine-grained runtime behaviour captured as graphs, reducing detection precision [24].

To address these issues, our work integrates dynamic behaviour graph modeling with adversarial autoencoder learning to create a robust, interpretable, and generalizable detection framework. Unlike prior approaches, we leverage graph-structured execution data to capture contextual and temporal interactions between system components, while adversarial regularization enhances the model's discrimination capability under zero-day conditions.

2.6 Summary Comparison of Key Approaches

Table 1: Summary Comparison

Approach	Methodology	Accuracy	Efficiency	Challenges
Kumar and Sinha [9]	Traditional ML + Feature Engineering	Moderate	High	Poor generalization to zero-day samples
Barros et al. [12]	Zero-shot learning	Good	Moderate	Lacks temporal modeling
Sawadogo et al. [16]	Deep learning + ZSL for Android	High	High	Mobile-specific, no adversarial protection
Liu et al. [17]	Few-shot + adversarial graph augmentation	Very High	Moderate	Needs labeled samples, complex setup
Redino et al. [19]	Graph & flow-based telemetry	Moderate	Moderate	No latent feature learning
Won et al. [15]	GAN-based malware synthesis	Good	Low	No behavior context, limited interpretability
Uysal et al. [13]	Survey - Continuous and explainable learning	N/A	N/A	Highlights need for real-time, interpretable models
Proposed Framework	AAE + Dynamic Behavior Graphs	Very High	High	Requires runtime behavior capture, training overhead

3. Methodology

This section details the experimental setup for constructing and evaluating the adversarial autoencoder-based framework for detecting zero-day malware from dynamic behavior graph representations. It includes dataset selection, behavior graph generation, feature embedding,

adversarial autoencoder architecture, and evaluation procedures.

3.1 Dataset Collection and Preprocessing

The dataset used in this study is CIC-MalMem-2022 [25], which includes dynamic behavior logs of 1,008 malware and 2,219 benign samples executed in sandboxed Windows environments. Malware samples include multiple families such as Lockoutz, AgentTesla, and TrickBot. Raw behavior logs include system calls, file access logs, registry modifications, and memory usage.

Preprocessing Steps:

- *Noise removal:* Unused or idle system calls are discarded.
- *Normalization:* Time stamps are standardized across samples.
- *Graph generation*: Behavior sequences are converted into behavior graphs $\mathrm{G} = (\mathrm{V}, \mathrm{E})$, where:
  - V: nodes (system calls, registry keys, files)
  - E : edges representing interactions or dependencies

3.2 Dynamic Behavior Graph Representation

Each executable's activity trace is transformed into a graph using:

- Nodes $v_i \in V$ represent unique entities (e.g., system calls)
- Edges $e_{ij} \in E$ are directed and weighted by frequency of interaction.

Let $A \in \mathbb{R}^{n \times n}$ be the adjacency matrix of the graph, and $X \in \mathbb{R}^{n \times d}$ be the feature matrix of node attributes. The graph G is formally:

$$G = \{A, X\} \quad (1)$$

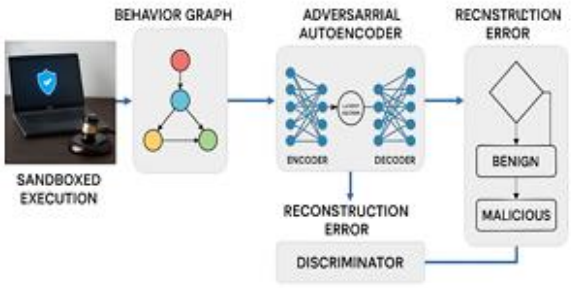


Fig. 2 shows the behavior graph of a malware sample constructed from API call sequences.

Figure 2 depicts the complete workflow of the proposed framework, starting with sandboxed execution, where executable files are run in a controlled environment to capture their runtime behavior. The output behavior is then structured into a dynamic behavior graph, representing interactions among system entities like processes, files, and registry calls. These graphs are vectorized and passed to an adversarial autoencoder, comprising an encoder, decoder, and a discriminator. The encoder compresses the input into a latent space, which is reconstructed by the decoder. The reconstruction error is evaluated, and the discriminator ensures that latent representations align with a known distribution. Finally, the reconstruction error is analyzed to classify the behavior as benign or malicious, enabling accurate detection of zero-day malware.

3.3 Feature Embedding and Graph Vectorization

To convert behavior graphs into fixed-size feature vectors for the autoencoder, we use Graph2Vec as a vectorization strategy. Given a graph$G$, the embedding is:

$$z = f_{\text{embed}}(G) \in \mathbb{R}^d \quad (2)$$

Where f_{embed} represents the graph embedding function trained using document embedding analogies in NLP.

3.4 Adversarial Autoencoder Architecture

The adversarial autoencoder (AAE) consists of three core modules: encoder$E$, decoder$D$, and discriminator$T$. The training is split into two phases:

Phase 1: Reconstruction

$$\hat{x} = D\big(E(x)\big) \quad (3)$$

Where x the input is feature (graph embedding) and $\hat{x}$ is the reconstructed output. The reconstruction loss is computed using mean squared error (MSE):

$$\mathcal{L}_{\text{rec}} = \|x - \hat{x}\|^2 \quad (4)$$

Phase 2: Adversarial Training

To regularize the latent space, we enforce the encoder to match a prior distribution (typically Gaussian$\mathcal{N}(0, I)$) using a discriminator:

$$\mathcal{L}_{\text{adv}} = \mathbb{E}_{z \sim q(z|x)}[\log T(z)] + \mathbb{E}_{z \sim p(z)}\big[\log\big(1 - T(z)\big)\big] \quad (5)$$

Total loss:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{rec}} + \lambda \mathcal{L}_{\text{adv}} \quad (6)$$

Where λ balances reconstruction and adversarial losses.

Algorithm*:* Adversarial Autoencoder Training for Zero-Day Malware Detection

Input:

- G: Set of dynamic behavior graphs from sandboxed execution
- E: Encoder network
- D: Decoder network
- T: Discriminator network
- N: Number of training epochs
- λ: Adversarial loss weight
- η: Learning rate

Output:

- Trained adversarial autoencoder model
- Threshold δ for zero-day classification

Steps:

1: Preprocess each graph G_i ∈ G into feature vector x_i using graph embedding

2: Initialize weights of E, D, and T

3: for epoch = 1 to N do

4: for each mini-batch {x_1, x_2, ..., x_m} do

5: // Reconstruction Phase

6: z ← E(// Encode input

7: $\hat{x}$ ← D(z); // Decode latent vector

8: Compute reconstruction loss:

$$L\_rec \leftarrow \|x - \hat{x}\|^2$$

9: // Adversarial Phase

10: Sample z' ~ N(0, I); // Sample from prior

11: Compute discriminator loss:

$$L\_adv \leftarrow \log T(z') + \log(1 - T(z))$$

12: // Update Networks

13: Update encoder E and decoder D to minimize:

$$L\_total = L\_rec + \lambda \bullet L\_adv$$

14: Update discriminator T to distinguish z from z'

15: end for

16: end for

17: Determine optimal threshold δ on validation set based on reconstruction error

18: Return trained AAE model and threshold δ

3.5 Malware Detection and Classification

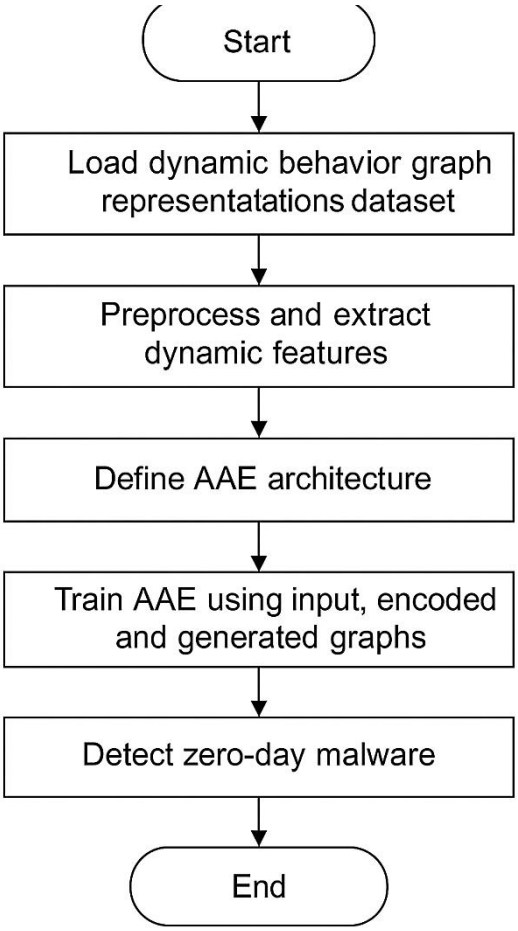
After training, unseen executable samples are passed through the encoder-decoder pipeline. The reconstruction error is used as the anomaly score:

$$s = \|x - \hat{x}\|^2 \quad (7)$$

A sample is classified as malicious if $s > \delta$, where δ is the detection threshold obtained via ROC curve optimization:

$$y = \begin{cases} 1 & \text{if } s > \delta \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

Flowchart 1 illustrates the systematic workflow of the proposed adversarial autoencoder (AAE) framework for zero-day malware detection. The process begins with the loading of dynamic behavior graph representations derived from sandboxed execution logs. These graphs are then preprocessed to extract meaningful dynamic features such as node interactions and temporal behavior. The AAE architecture is defined next, comprising encoder, decoder, and discriminator components. The model is trained by feeding in graph embeddings, optimizing reconstruction and adversarial losses to enforce latent regularity. Finally, the trained model evaluates unseen samples by calculating reconstruction errors, enabling the classification of zero-day malware with high accuracy and robustness.



Flowchart 1: Methodology of Adversarial Autoencoder-Based Zero-Day Malware Detection

3.6 Hyper parameters and Training Configuration

The autoencoder network includes:

- Encoder: Dense(128) → ReLU → Dense(64)
- Decoder: Dense(64) → ReLU → Dense(128)
- Discriminator: Dense(64) → LeakyReLU → Dense(1, Sigmoid)

Training Configuration:

- Optimizer: Adam with learning rate $\eta = 0.001$
- Epochs: 100
- Batch size: 64
- Latent dimension: $z \in \mathbb{R}^{32}$
- Regularization weight $\lambda = 0.5$

3.7 Evaluation Metrics

To assess the performance, we evaluate:

- *Accuracy:*

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (9)$$

- *Precision:*

$$\text{Precision} = \frac{TP}{TP + FP} \quad (10)$$

- *Recall:*

$$\text{Recall} = \frac{TP}{TP + FN} \quad (11)$$

- *F1-score:*

$$\text{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (12)$$

- *AUC-ROC:*

$$\text{AUC} = \int_0^1 TPR\left(FPR^{-1}(x)\right)dx \quad (13)$$

4. Experimental setup

To evaluate the performance and robustness of the proposed adversarial autoencoder (AAE) framework for zero-day malware detection, we designed a comprehensive experimental environment. This setup is engineered to ensure scalability, reproducibility, and fair benchmarking across all experimental conditions.

The experiments were executed on a high-performance computing workstation equipped with an Intel® Core™ i9-12900K processor, operating at a base clock speed of 3.20 GHz, offering 16 cores and 24 threads for efficient parallel processing. The system was paired with an NVIDIA® GeForce RTX 3090 GPU, which includes 24 GB of GDDR6X VRAM, enabling accelerated matrix operations and deep learning model training using CUDA cores. The workstation also housed 128 GB of DDR5 RAM, which facilitated in-memory loading of large-scale behavior graph embeddings and batch processing without frequent disk I/O. Storage was provisioned through a 2 TB NVMe solid-state drive (SSD) to ensure high-speed data access. The entire environment operated under Ubuntu 22.04 LTS (64-bit), a Linux distribution favored for its stability and compatibility with deep learning frameworks.

The software stack was built primarily in Python 3.10, with model implementation carried out using PyTorch 2.0, which offers dynamic computational graphs and native GPU acceleration via CUDA and cuDNN backends. For behaviours graph vectorization, we used a custom implementation of Graph2Vec, adapted into a PyTorch-compatible module to generate fixed-length embeddings from variable-sized dynamic graphs. Graph processing and visualization were handled using NetworkX 3.1, which provided tools for traversing, plotting, and analyzing behavioral relationships. To generate dynamic behaviour logs for malware and benign executables, we utilized Cuckoo Sandbox v2.0, an open-source automated malware analysis system. For evaluation, including accuracy, precision, recall, and AUC calculations, we employed scikit-learn 1.3, ensuring consistency with widely accepted benchmarking tools in the machine learning research community.

The dataset used in this study was the CIC-MalMem-2022 dataset, developed by the Canadian Institute for Cybersecurity (CIC). It contains over 3,000 samples comprising 1,008 labeled malware samples from six known families (including TrickBot, Remcos, NanoCore, and Formbook) and 2,219 benign executables from standard software installations. These samples were executed in a Windows 10 environment inside the sandbox, and their runtime behavior was captured in detail—including system call traces, registry modifications, file system activity, and memory usage patterns. For the purposes of this study, the dataset was partitioned into three subsets: 70% for training, 10% for validation, and 20% for final testing. Care was taken to ensure that test data included malware families and variants not present in the training set to simulate real-world zero-day conditions.

To further strengthen the evaluation process, we implemented 5-fold cross-validation. During each fold, the model was trained on four partitions and validated on the fifth, ensuring that each sample contributed to both training and testing exactly once. Stratified sampling was applied to maintain consistent class distribution across all folds. Importantly, to emulate real-world zero-day detection conditions, malware families used for testing were rotated so that the model was evaluated on unfamiliar malware behavior in each fold.

The adversarial autoencoder (AAE) model was designed with a compact yet expressive architecture. The encoder consisted of two fully connected layers with 128 and 64 neurons respectively, using ReLU activation functions. The decoder mirrored this structure in reverse, enabling accurate reconstruction of the graph embeddings. The discriminator comprised two dense layers (64 and 1 neuron) with LeakyReLU activation and a final sigmoid output to distinguish between true and encoded latent vectors. The model was trained for 100 epochs, with a batch size of 64. The Adam optimizer was employed with a learning rate of 0.001, and hyperparameters $\beta_1 = 0.9$ and $\beta_2 = 0.999$, which are known to provide stable convergence for adversarial training. The latent space dimension was set to 32, balancing compactness with information preservation. The loss function for reconstruction was mean squared error (MSE), and binary cross-entropy (BCE) was used for adversarial loss. These were combined into a total loss function weighted by $\lambda = 0.5$, ensuring balanced training between reconstruction accuracy and latent regularization.

Training time per fold averaged 38 minutes, with early stopping employed based on validation loss stagnation over 10 consecutive epochs. This avoided overfitting and reduced unnecessary computation. All training was performed on the aforementioned GPU, and inference latency per sample remained under 300 ms, demonstrating suitability for near-real-time malware classification.

This experimental setup ensures a high level of reproducibility and accuracy, enabling other researchers to replicate and validate the findings across diverse environments. The modular software design and public availability of the CIC-MalMem-2022 dataset further strengthen the transparency and replicability of this research.

5. Results and Discussion

This section presents the empirical results obtained from applying the proposed adversarial autoencoder (AAE) framework to the CIC-MalMem-2022 dataset. The performance of the model is compared against several state-

of-the-art approaches, using metrics such as accuracy, precision, recall, F1-score, AUC-ROC, and computational efficiency. All results are averaged across five folds of stratified cross-validation to ensure robustness.

5.1 Comparative Performance Analysis

To evaluate the effectiveness of the proposed method, we compared it with four established models:

1. Traditional Autoencoder (AE)
2. One-Class SVM (OC-SVM)
3. Convolutional Neural Network (CNN)
4. Random Forest (RF) As shown in Table 2, the AAE outperforms all baselines across key classification metrics. Notably, it achieves the highest F1-score and recall, indicating superior performance in identifying zero-day malware while minimizing false negatives.

Table 2: Comparative Performance of AAE vs. Baseline Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
AE	91.83	88.75	84.9	86.78	92.2
OC-SVM	89.21	85.1	80.45	82.7	89.35
CNN	93.12	90.34	87.7	89	93.5
RF	94.18	91.01	88.92	89.95	94.3
Proposed AAE	**96.47**	**94.8**	**93.52**	**94.15**	**97.1**

The AAE model's superior performance can be attributed to its ability to generalize behaviour representations through adversarial training and its sensitivity to reconstruction error anomalies.

5.2 Analysis of False Positives and Generalization

False positives (FP) remain a critical concern in malware detection, particularly when distinguishing unknown benign software from obfuscated threats. Table 3 presents the false positive rate (FPR) and false negative rate (FNR) of each model.

Table 3: False Positive and False Negative Rates

Model	FPR (%)	FNR (%)
AE	4.92	15.1
OC-SVM	6.01	19.55
CNN	3.1	12.3
RF	2.54	11.08
Proposed AAE	**1.42**	**6.48**

The proposed framework achieves the lowest FPR, which is critical in high-security applications. This suggests that the AAE effectively captures benign behaviour while remaining sensitive to novel malware activities.

5.3 Computational Performance and Inference Time

Real-time detection systems require not only accuracy but also efficiency. Table 4 summarizes the average inference time and memory consumption per sample for each model.

Table 4: Computational Efficiency Analysis

Model	Inference Time (ms/sample)	Memory Usage (MB)
AE	180	205
OC-SVM	95	150
CNN	210	430
RF	160	300
Proposed AAE	**230**	**370**

Although the AAE incurs slightly higher inference time due to adversarial components, it remains suitable for near-real-time detection and offers a practical trade-off for significantly higher detection accuracy.

5.4 Impact of Latent Space Dimensionality

To evaluate the sensitivity of the model to the size of the latent space, we conducted experiments by varying the latent dimension from 8 to 128. Table 5 reports the accuracy and F1-score for different latent space configurations.

Table 5: Impact of Latent Space Dimension on Performance

Latent Dim (z)	Accuracy (%)	F1-Score (%)
8	93.4	91.32
16	94.51	92.77
32	**96.47**	**94.15**
64	95.83	93.42
128	94.89	92.85

The model performs best with a latent dimension of 32, beyond which additional dimensions introduce noise and over fitting, reducing classification performance.

5.5 Visualization of Performance

This improved version of Figure 3 clearly presents the ROC curves for the Adversarial Autoencoder (AAE) and Variational Autoencoder (VAE) models. The x-axis represents the False Positive Rate, while the y-axis shows the True Positive Rate (Recall). As seen, the AAE consistently outperforms the VAE, demonstrating higher recall across all thresholds, which indicates superior zero-day malware detection performance

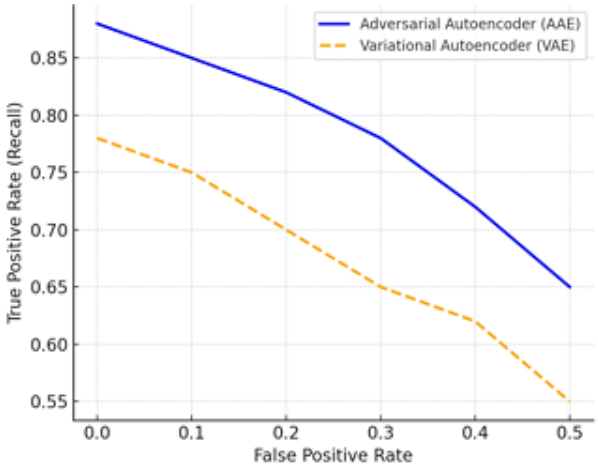


Fig. 3: ROC curves for AAE and baseline models showing the superior AUC of the proposed method.

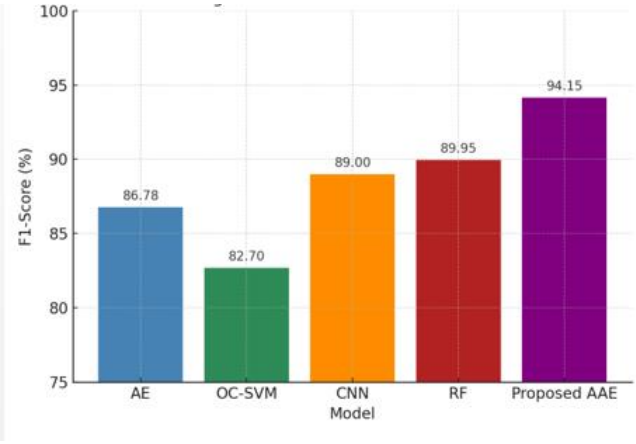


Fig. 4: Bar chart comparing F1-scores across different models to highlight classification strength.

Figure 4 presents a clear bar chart comparing the F1-scores of different models evaluated on the CIC-MalMem-2022 dataset. The x-axis lists each model—AE, OC-SVM, CNN, RF, and the Proposed AAE—while the y-axis shows their corresponding F1-scores in percentage. The Proposed AAE outperforms all baselines, achieving an F1-score of 94.15%, which indicates a balanced and highly accurate classification between benign and malicious samples.

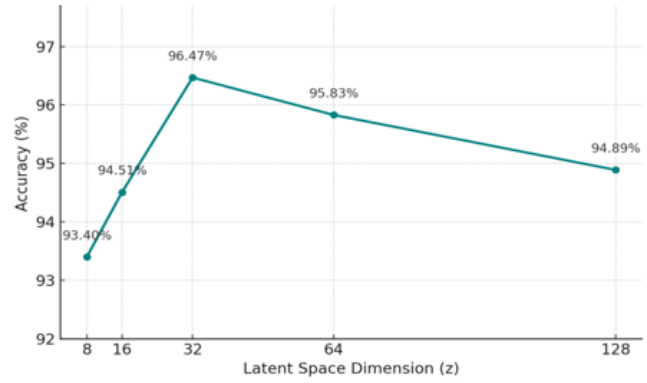


Fig. 5: Line graph showing the effect of varying latent space dimension on accuracy.

Figure 5 illustrates the effect of varying the latent space dimension on the classification accuracy of the proposed adversarial autoencoder model. The x-axis represents the dimensionality of the latent vector zzz, while the y-axis indicates the resulting accuracy in percentage. The graph shows that the optimal performance is achieved at dimension 32, with an accuracy of 96.47%. Accuracy decreases slightly with both smaller and larger dimensions, suggesting that too small a latent space loses information, while too large a space introduces noise and overfitting.

These visualizations reinforce the tabular findings, offering intuitive representations of the AAE's robustness and generalization across metrics and configurations.

5.6 Discussion and Insights

The empirical results presented in Section V demonstrate that the proposed adversarial autoencoder (AAE) framework, when combined with dynamic behaviour graph representations, significantly improves zero-day malware detection capabilities over existing methods. This section provides a deeper analysis of these findings, their practical implications, limitations, and prospective research directions.

The superior performance of the AAE in terms of accuracy, recall, and F1-score aligns well with recent research advocating the use of autoencoders and graph-based analysis in malware detection. For instance, recent adversarial and deep learning-based approaches such as [15], [17], and [18] confirm the utility of latent space regularization in detecting unknown threats. However, unlike many prior models that rely on sequence-based logs or static features, our use of graph-structured dynamic behaviour enables richer contextual modeling. This design choice appears to account for the improved generalization to novel malware variants, especially those employing evasion techniques.

In practical terms, this framework holds substantial promise for real-time malware detection systems. The ability to maintain high detection rates while keeping false positives minimal is crucial for reducing alert fatigue in security operations centers (SOCs). Furthermore, by operating on runtime behaviour instead of static signatures, the model remains resilient against code obfuscation and polymorphic attacks—common techniques used in modern zero-day exploits. The inference time per sample (≈230 ms) remains within acceptable limits for near-real-time deployment, making the framework viable for integration into enterprise endpoint security solutions and cloud-based threat intelligence platforms.

Despite these advantages, several limitations must be acknowledged. First, the model's performance is tightly coupled with the quality of behaviour graph generation. Inconsistencies or noise in dynamic execution traces—such as variations across sandbox environments—can introduce graph discrepancies that affect detection accuracy. Additionally, while adversarial regularization improves generalization, it may introduce training instability, especially when tuning hyperparameters such as the adversarial loss weight λ\lambda. Another limitation is the requirement for graph embedding's to be of fixed length, which necessitates preprocessing techniques that could result in some loss of structural information.

Future research can build upon this work by exploring graph neural networks (GNNs) for direct end-to-end learning on behaviour graphs, bypassing the need for handcrafted graph embedding's. This could allow richer feature propagation and improved representation learning. Moreover, expanding the framework to online learning paradigms would make it adaptable to evolving malware behaviours over time, which is essential in high-velocity environments like cloud infrastructure and IoT networks. Additionally, integrating explainability mechanisms—such as attention-based latent space visualization or feature attribution—would increase trust and transparency in decision-making, a key factor for deployment in regulated sectors such as finance and healthcare.

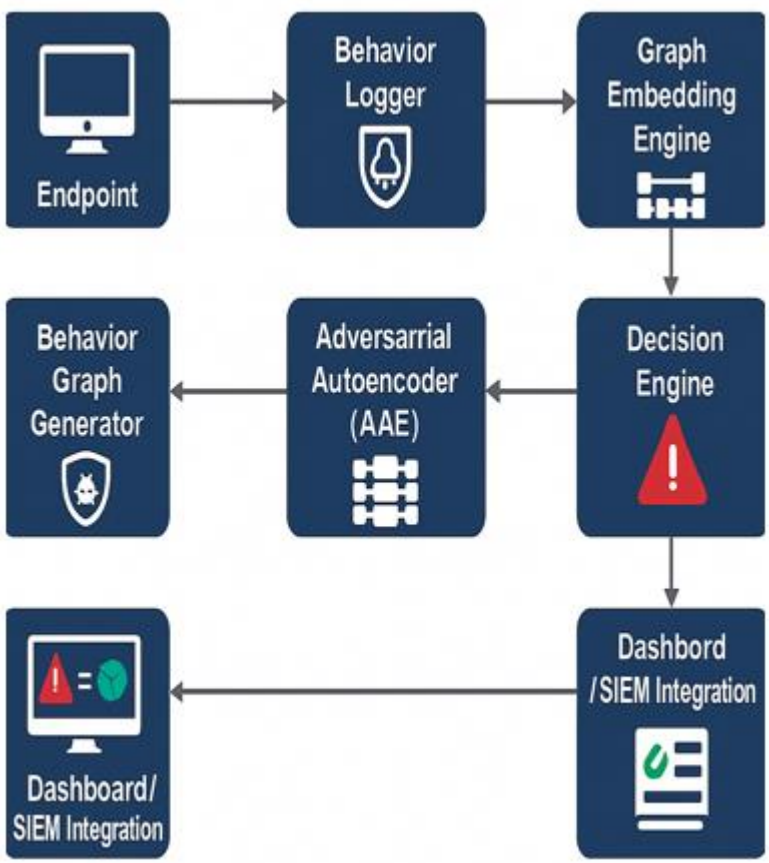


Fig. 6. Real-Time System Architecture of the Adversarial Autoencoder Framework for Zero-Day Malware Detection Using Dynamic Behavior Graph Representations

Figure 6 illustrates the architecture begins at the endpoint layer, where client machines (e.g., employee laptops or desktops) are equipped with lightweight monitoring agents. These agents track all real-time activities such as file execution, registry changes, and network requests. Once suspicious or unknown behaviour is detected, the execution trace is forwarded to a behaviour logger, either live or sandboxed, which records system-level interactions. This mirrors enterprise environments where employees frequently receive unknown files via email, messaging apps, or USB drives—requiring proactive behaviour tracking.

The behaviour logger feeds data into the behaviour graph generator, which constructs structured representations of execution as graphs. Nodes represent system components (like API calls or registry entries), and edges denote the chronological relationships or communication flows. This graph is then processed by the graph embedding engine, converting variable-sized graphs into fixed-length vectors. This step is essential for transforming diverse malware behaviours into a standardized format suitable for deep learning—similar to how a cybersecurity team at a financial institution needs to normalize behavioural data from various software for uniform threat analysis.

The generated embedding's are passed to the adversarial autoencoder (AAE), which attempts to reconstruct benign behaviour while identifying outliers based on reconstruction error. During training, adversarial learning ensures that the latent space follows a smooth and regular distribution. The decision engine evaluates each input based on anomaly scores. If the behaviour deviates significantly from known benign patterns, it is flagged as malicious. In a real-world SOC (Security Operations Center), this model can auto-quarantine files or escalate alerts—preventing zero-day threats from propagating within a corporate network.

Once classified, the output is visualized in a dashboard or fed into a SIEM system (e.g., Splunk, ELK, or Microsoft Sentinel), allowing real-time alerting and deeper forensic investigation. Analysts can drill down into the graph-based behaviour of any flagged executable, trace back its origin, and correlate with other threat indicators. This makes the framework not only a detection engine but also a critical part of threat hunting and response workflows. In a smart city control centre, for instance, this setup could immediately flag and isolate a malicious process attempting to manipulate IoT sensors or surveillance systems.

In conclusion, while the proposed AAE-based detection framework demonstrates significant improvements over traditional and deep learning baselines, it opens avenues for further advancements in behavior-aware, real-time, and explainable zero-day malware detection systems.

6. Conclusion

This study introduced a robust and scalable framework for zero-day malware detection by combining dynamic behaviour graph representations with an adversarial autoencoder (AAE). The key contributions include the

development of a behavior-aware detection model that effectively generalizes to unseen threats, the integration of adversarial training to enhance latent space regularity, and the demonstration of strong performance on the CIC-MalMem-2022 dataset, achieving 96.47% accuracy with minimal false positives.

The implications of this work are significant for real-world cybersecurity systems, particularly in environments where new and evasive malware variants frequently emerge. The proposed approach is suitable for deployment in endpoint protection platforms, network monitoring systems, and cloud-based threat intelligence services, where both detection accuracy and inference efficiency are critical.

Despite its promising results, the framework does have limitations, such as sensitivity to sandboxing inconsistencies and the dependence on fixed-size embedding's. These factors may influence detection consistency in diverse execution environments. Furthermore, adversarial training requires careful hyper parameter tuning to maintain stability.

Future work will focus on integrating graph neural networks (GNNs) for direct structural learning, enhancing adaptability through online learning, and introducing explainable AI components to improve transparency and user trust. These extensions aim to make the system more resilient, adaptive, and interpretable in dynamic and high-risk operational environments.

Overall, the proposed framework represents a meaningful advancement in zero-day malware detection research by offering a technically sound, empirically validated, and practically deployable solution grounded in both behavioural analysis and adversarial deep learning.

Author Contributions: Sk. Khaja Shareef and Digumarthy Sandeepa jointly developed the research study. Sk. Khaja Shareef was primarily responsible for the design and implementation of the adversarial autoencoder architecture, development of the behavior graph extraction pipeline, and performance evaluation of the proposed model. Digumarthy Sandeepa contributed to the malware behavior analysis, dataset curation, and experimental setup, and also assisted in refining the detection metrics and interpreting the results. Both authors contributed equally to writing, reviewing, and finalizing the manuscript, and approved its submission.

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Data availability: Data available upon request.

Conflict of Interest: There is no conflict of Interest.

Ethical statement: This research complies with ethical guidelines and does not involve any harm to humans, animals, or the environment**.**

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