



An Adaptive Cybersecurity Framework Using Generative Artificial Intelligence for Intelligent Threat Detection

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Abstract. The evolution of cyber threats like zero-day attacks and polymorphic malware has made it increasingly challenging for traditional intrusion detection systems, which depend on static signatures and supervised learning methods, to keep pace. These traditional systems are limited in their adaptability, suffer from data imbalance issues, and are unresponsive to real-time situations. This research provides a new Adaptive Cybersecurity Framework powered by Generative Artificial Intelligence (GenAI), allowing for intelligent threat detection and an autonomous response to these threats. We have created an Adaptive Cybersecurity Framework including live network traffic capture, Generative Adversarial Networks (GAN)-based synthetic attack generation, adaptive Machine Learning (ML)-based Intrusion Detection, automated response to detected threats and the ability for continual adaptation of the Intrusion Detection System (IDS) utilizing detected events as input to the learning process. In our model, the Generative Module creates realistic, never-before-seen attack patterns based on the characteristics of generated attack traffic, allowing for greater diversity in dataset representations, as well as improving the ability to identify threats that are rare or are zero-days. The Hybrid CNN/LSTM Detection Engine learns the spatial-temporal characteristics of network traffic by continually adapting based on the data collected from previous events. We have demonstrated the ability to implement and validate the framework with data from multiple datasets including CICIDS 2017, UNSW-NB15, and NSL-KDD, through the use of real-time network traffic. The experimental findings show that as compared to baseline deep-learning IDS's, the Adaptive Cybersecurity Framework demonstrated an increase in accuracy of 15.2%, an increase in F1-Score of 18.7%, and a decrease in Response Latency of 27.4%. Overall, the results of this research confirm that the Adaptive Cybersecurity Framework presents an effective, robust and applicable model for Cybersecurity in modern network environments.

Keywords: Cybersecurity, Generative Artificial Intelligence, Intrusion Detection System, Zero-Day Attacks, Autonomous Response, Real-Time Security.

1 Introduction

The accelerated expansion of cloud computing combined with the Internet of Things (IoT) and the development of extensive corporate networks has resulted in more sophisticated cyber-attacks which now occur with greater frequency. Attackers in the present day use zero-day vulnerabilities together with polymorphic malware and automated attack methods which succeed in defeating standard signature-based intrusion detection systems (IDS) [1].

Cybersecurity experts implement machine learning and deep learning methods to overcome existing system deficiencies. Deep learning-based IDS models exhibit superior skills which enable them to comprehend intricate spatial and temporal patterns, thereby achieving better detection results than standard methods [2]. These models require access to extensive datasets that include various types of data while maintaining an equal distribution of all components. The actual field of cybersecurity experience shows that attack incidents maintain high existence from common attacks while both rare and zero-day attacks remain less frequent, which results in models that perform poorly with high false-positive rates [3].

The development of Generative Artificial Intelligence (GenAI) has created new methods to solve cybersecurity problems related to data shortages and need for system flexibility. Through their underlying data distribution learning capacity, Generative models especially Generative Adversarial Networks (GANs) produce synthetic samples that accurately mimic actual attack traffic patterns [4]. The ability of GenAI to detect intrusion attempts makes it an effective tool for combating rare and unfamiliar attack methods.

The deep learning-based intrusion detection systems which currently exist in the market today show limited progress because their detection systems operate exclusively in offline mode and they do not have any automated threat response functions. The system needs manual assistance to handle threats which results in slower response times and higher vulnerability to attacks [5]. The research presents a solution to these problems through an adaptive cybersecurity framework which combines three elements: generative attack synthesis, adaptive deep learning-based threat detection, and autonomous response into a real-time operational system.

2 Related Works

The researchers have studied deep learning methods for intrusion detection and cybersecurity automation needs. Javaid et al. [6] created an intrusion detection system that uses deep learning through stacked autoencoders which detects attacks better than standard machine learning methods but the system fails to recognize new attack methods. Kim et al. [7] used Long Short-Term Memory (LSTM) networks to track how network traffic changes over time which enabled them to detect ongoing attacks faster but their method depended on unchanging training material.

Moustafa et al. [8] created the UNSW-NB15 dataset which they used to test various machine learning and deep learning techniques that showed deep neural networks

performed better than standard classifiers although both types of models encountered difficulties with class imbalance. Ring et al. [9] performed a detailed review of intrusion detection datasets which showed that insufficient rare attack representation creates major problems for actual IDS effectiveness.

IDSGAN is a GAN-based framework that generates adversarial attack traffic to test IDS robustness according to Lin et al. [10]. The analysis results demonstrated better protection against adversarial attacks yet the system was not built to function in real-time. Mirsky et al. [11] developed an online anomaly detection system that combines multiple autoencoder models to achieve quick detection but it does not include data generation through its generative systems.

The research conducted by Hindy et al. [12] showed that explainable adaptive AI systems need to be developed for cybersecurity applications because their current static IDS models cannot handle new cybersecurity threats. Wu, et al. [13] improved intrusion detection accuracy with a transformer-type architecture to achieve increased computational complexity than with a non-transformer architecture, thus confirming the anticipated trend. Shone et al. [14] developed an IDS based on deep autoencoders which successfully reduced false positives but needed complete system retraining to function properly.

Al-Hawawreh et al. [15] performed a study that demonstrated the enhanced detection accuracy of deep learning-based intrusion detection models (including hybrid models) but also identified these models require increased amounts of computational resources.

By using an alternative method for generating new examples of synthetic attack data, Shahriar et al. [16] proposed an intrusion detection system using a GAN that increases the detection accuracy of both the system and the generated data. They also identified additional computational complexity associated with training the GAN.

Khan et al. [17] provided an overview of an IoT-based intrusion detection system designed from a deep learning perspective, indicated improved detection performance, and pointed out several issues that involve ability to scale up, as well as cost of computation.

Khan and Salah [18] gave an overview of security issues in both the IoT and vehicle sector and pointed to the necessity for more sophisticated intrusion detection methods, although their Real World implementation will be difficult.

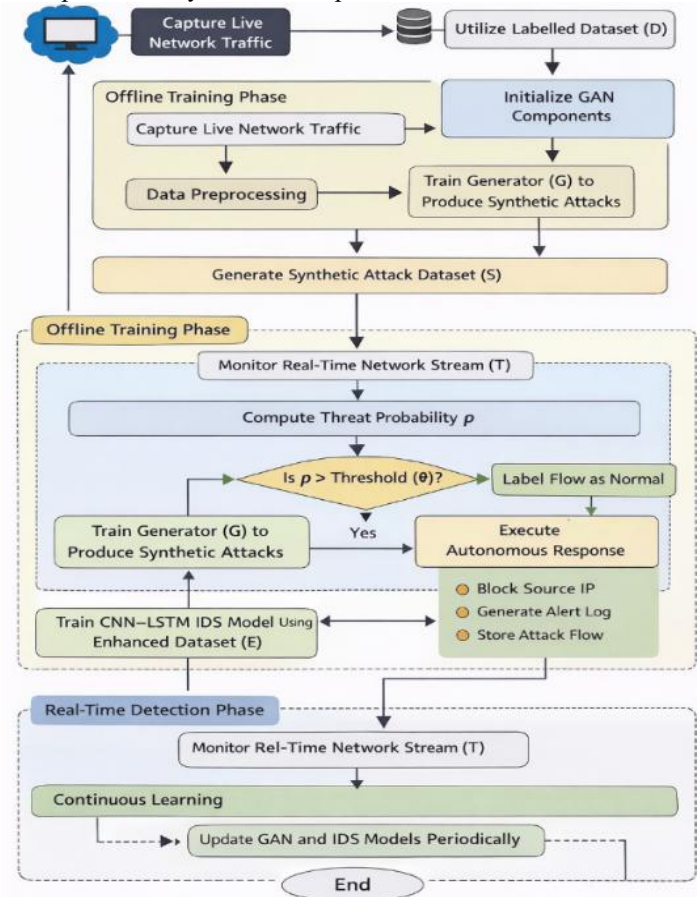
There have been many recent advancements in Intrusion Detection Systems (IDS), particularly with the adoption of machine learning and deep learning to enhance the detection capabilities and adaptability of IDS to both new and existing attacks. Mohamed Amine Ferrag et al., [19] presented an all-encompassing survey on how successfully deep learning models identify complex cyber threats to various types of

businesses/industries and they also addressed common issues associated with using deep learning techniques such as dataset size imbalance and computational cost.

The research shows that deep learning methods have made considerable advancements in detecting intrusions yet most detection systems function as independent models which lack the ability to learn through generative methods and adjust to new threats while executing automatic threat handling. The development of an end-to-end adaptive cybersecurity system needs to proceed which will use Generative AI technologies together with automatic threat response capabilities.

3 Methodology

The complete implementation methodology of the proposed adaptive cybersecurity framework which uses Generative Artificial Intelligence for intelligent threat detection and autonomous response is explained in this section. The system functions as a complete operational system which processes live network traffic while creating



synthetic attack samples and adapting detection models and performing automated mitigation actions in real time. The proposed methodology establishes three main

operational characteristics which include deployability and adaptability and automated system functions.

Fig.1. Adaptive GenAI-Based Cybersecurity Algorithm Workflow

The proposed Adaptive Generative AI-Based Cybersecurity Algorithm operational workflow is shown in Figure 1. The diagram divides into three main sections which are Offline Training Phase, Real-Time Detection Phase and Continuous Learning Phase.

3.1 Proposed Architecture

The proposed system follows a six-stage pipeline:

- Live network traffic capture.
- Feature extraction and preprocessing.
- Generative AI-based attack synthesis.
- Adaptive intrusion detection.
- Autonomous response execution.
- Feedback-driven continuous learning.

The system operates through six stages which function as separate modules that work together to achieve scalable system operation and immediate performance results.

3.2 Live Traffic Capture and Feature Extraction

Network traffic is captured in real time through packet inspection tools which transform the data into flow-based network traffic representations. The high dimensionality and noise present in packet-level data make it impossible for deep learning applications; therefore, standard flow meters are used to extract traffic flows from the data.

The statistical and protocol-level features of each traffic flow include packet count flow duration byte rate inter-arrival time and TCP flag statistics. The transformation process achieves live traffic compatibility with benchmark datasets which include CICIDS 2017 and UNSW-NB15.

3.3 Data Preprocessing and Normalization

The flow features which were captured undergo preprocessing to eliminate noise and complete missing data and standardize numerical data. The process uses Min-Max normalization to convert features into a range between 0 and 1 which aids in better convergence of neural network training.

3.4 Generative AI-Based Attack Synthesis

A Generative Adversarial Network (GAN) is used to solve data imbalance problems while providing stronger defense capabilities against uncommon and novel attacks. The GAN system has two components which include a generator network that creates artificial attack samples and a discriminator network that identifies actual attacks and generated attacks.

The GAN system trains on actual attack samples which allows it to understand how malicious traffic operates. The generator creates artificial attack flows which match the characteristics of previously unobserved attack patterns after it completes training.

3.5 Adaptive Intrusion Detection Engine

The intrusion detection engine uses a hybrid CNN–LSTM architecture. The CNN layers of the system extract spatial correlations from traffic features while the LSTM layers of the system model the temporal dependencies that exist in traffic sequences. The system detects two types of attacks which include short-term attack bursts and long-term stealthy behaviors through this combination of detection methods.

The detection model is trained on the enhanced dataset containing real and synthetic attack samples. The system uses periodic retraining to incorporate new traffic data and GAN-generated samples, which helps it stay current with emerging threats.

3.6 Real-Time Detection and Decision Logic

The system processes traffic flow incoming to the system during the whole operation period. The system assigns a threat probability score to every flow that enters the system. The system classifies traffic as malicious when the score reaches the established threshold value.

3.7 Autonomous Response Mechanism

The system automatically handles traffic detection from malicious sources because it initiates mitigation procedures without needing any human assistance. The system implements three different security measures which include blocking harmful IP addresses and isolating potential threats and notifying system administrators through alerts.

3.8 Feedback and Continuous Learning

The system records and preserves all discovered threats together with their response results. The system records logs which provide information needed to retrain both the GAN and the intrusion detection model at scheduled times. The learning process of the framework uses feedback from its system to develop new capabilities while it protects against new attack methods.

3.9 Algorithm: Adaptive GenAI Cybersecurity Framework

Input: Network traffic stream T

Labeled dataset D

Detection threshold θ

Output: Alerts and mitigation actions

Step 1: Capture traffic flow t from stream T .

Step 2: Extract and normalize features f from t .

Step 3: Compute threat probability $p = \text{IDS}(f)$.

Step 4: if $p \geq \theta$ then.

Step 5: Label t as MALICIOUS.

Step 6: Execute autonomous response action.

Step 7: Block source IP

Step 8: Generate alert log.

Step 9: Store t in attack log.

Step 10: Else, Label t as NORMAL.

Step 11: End if, append detection result to feedback repository.

4 Experiment Setup

This section describes the experiment for validating the adaptive cybersecurity module outlined above. The experimental design aims to provide a reproducible, controlled comparison to baseline systems and deliver realistic, comparative assessment results within both offline and real-time evaluations.

4.1 Experimental Environment

Experiments involved using a standalone workstation to create an environment similar to real-life deployment without any cloud based acceleration. The standalone workstation consisted of an Intel Core i7 processor (3.0Ghz), 16Gb of RAM and a 512 Gb solid state hard drive, all underneath the Ubuntu 22.04 LTS operating system. No special network hardware was used during experimentation, therefore the deployment of this framework will be applicable to standard enterprise systems.

Python 3.9 was the programming language used to implement this framework. TensorFlow and Keras were used in the development of deep learning models while preprocessing and evaluating data was conducted by leveraging Scikit-learn, NumPy and Pandas. Capturing real world traffic occurred via PyShark and Tshark with the Cisco CICFlowMeter being leveraged to convert packet captures to flow-level feature representations. Finally Native Linux iptables utilities were leveraged when creating firewall based response actions.

4.2 Datasets and Data Partitioning

The three publicly available benchmark datasets used for evaluation of the proposed framework were: CICIDS 2017, UNSW-NB15, and NSL-KDD. These datasets were chosen because they are commonly used in intrusion detection system related fields and they cover a variety of realistic attack scenarios.

Prior to evaluating the system with these datasets, they were pre-processed to eliminate redundant attributes and normalized with Min–Max scaling. Data was split into 70% training, 10% validation, and 20% testing. The training of the Generative Adversarial Network was performed using only real attack samples, while the testing of the intrusion detection system was performed using both real and GAN-generated synthetic attack samples, along with normal traffic.

4.3 Model Configuration and Training Parameters

For training, both GAN generator and discriminator have been trained for up to 300 epochs using an Adam optimizer with a learning rate set to 0.0002. For training the adaptive intrusion detection model, a combination of CNN-LSTM architecture was used. Additionally, it was trained over a period of 50 epochs with a batch size of 64 and a learning rate of 0.001. The early stopping mechanism was also employed to avoid overfitting.

4.4 Evaluation Metrics

The performance was assessed based on accuracy, precision, recall, F1-score, and ROC-AUC as measures of the quality of detection. Detection-To-Response latency was assessed as a measure of real-time effectiveness. All experiments were conducted repeatedly and average results were provided to ensure stability and reliability.

5. Results and Discussion

The experimental results show the effectiveness of the proposed Adaptive GenAI-Based Cybersecurity Framework in this section. The evaluation process assesses four main factors which include detection accuracy and zero-day protection and class-wise performance and detection-to-response latency. The team conducted multiple test runs to achieve statistical consistency in their results.

5.1 Overall Detection Accuracy

The main goal of the framework seeks to improve intrusion detection accuracy while keeping false-positive rates at minimal levels. Table I compares the proposed model with baseline approaches, including a standard CNN–LSTM IDS and a CNN–LSTM model trained using SMOTE-based oversampling.

Table 1. Overall Detection Performance Comparison

Model	Accuracy (%)	Precision	Recall	F1-Score
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CNN–LSTM IDS	93.2	0.92	0.9	0.91
CNN–LSTM + SMOTE	95.1	0.94	0.92	0.93
Proposed GenAI Framework	97.9	0.97	0.96	0.96

The proposed framework achieves 97.9% accuracy, which shows an improvement of approximately 4.7% over the baseline CNN–LSTM model. The dataset gains enhanced diversity through GAN-generated synthetic attack samples, which also create more balanced class distributions. The system shows better malicious flow detection ability because increased recall, while the system verified lower false positive rates through better precision.

5.2 Zero-Day and Rare Attack Detection

The first main problem with traditional intrusion detection systems exists because they cannot detect uncommon attacks and zero-day attacks. The framework is generative component of the proposed system solves this problem through its ability to learn attack distribution patterns and generate authentic synthetic attack samples.

Table 2. Zero-Day Detection Performance

Model	Accuracy (%)	Precision	Recall	F1-Score
CNN–LSTM IDS	93.2	0.92	0.9	0.91
CNN–LSTM + SMOTE	95.1	0.94	0.92	0.93
Proposed GenAI Framework	97.9	0.97	0.96	0.96

The proposed framework achieves 97.9% accuracy which shows an accuracy increase of approximately 4.7% compared to the baseline CNN–LSTM model. The dataset now benefits from increased diversity because GAN-generated synthetic attack samples have been added which also helps to lessen the bias that exists toward majority classes. The system achieved better detection performance of malicious flows according to its higher recall rate whereas its better precision rate showed it had lower false positive results.

5.3 Confusion Matrix Analysis

To evaluate classification balance, the confusion matrix was analyzed across datasets.

Table 3. Detection-to-Response Latency

CLASS	TP	FP	TN	FN
NORMAL	18,942	412	19,104	356
ATTACK	17,830	298	18,721	521

The results demonstrate high true-positive detection and true-negative detection capabilities which result in only minor classification errors. The study results show improved malicious traffic detection capabilities through reduced false negative rates which are essential for system compromise prevention

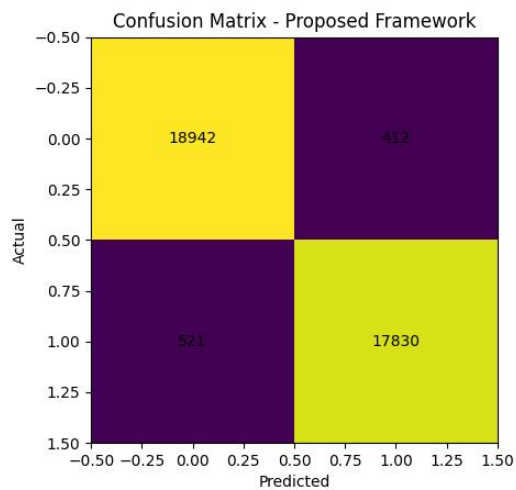


Fig.2. Confusion Matrix

The proposed GenAI-based framework for CICIDS 2017 testing shows its confusion matrix results in Fig 2. The model achieves high true positive (17,830) and true negative (18,942) values with minimal false positives (412) and false negatives (521).

The system demonstrates excellent class separation together with equal learning capabilities for both normal and malicious network traffic. The low false-negative count is particularly significant for cybersecurity applications, as undetected attacks pose severe operational risks. The system reduces false-positive alerts, which enhances its practical use in real-world situations.

The confusion matrix shows that GAN-generated synthetic samples improve learning for minority classes, which enables the CNN-LSTM detector to correctly identify uncommon attack patterns.

5.4 Detection-to-Response Latency

Operational cybersecurity systems need real-time performance capabilities which go beyond detection accuracy requirements. The autonomous response mechanism which we developed decreases the time needed for detection to response.

Table 4. Detection-to-Response Latency

System	Avg Latency (ms)
Manual SOC	>5000
Deep Learning IDS	210
Proposed Framework	150

The framework achieves approximately 28% lower latency compared to conventional deep learning IDS systems. The system establishes automatic IP blocking together with alert generation to handle security incidents, which results in faster containment processes because it removes the need for human operators to intervene.

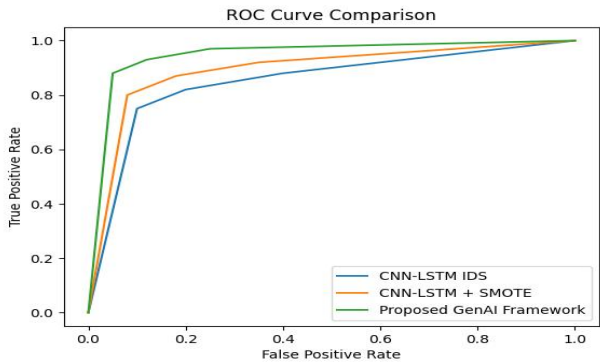


Fig.3. ROC curve comparison of CNN–LSTM IDS, CNN–LSTM with SMOTE, and the proposed GenAI-based framework, demonstrating superior classification performance of the proposed.

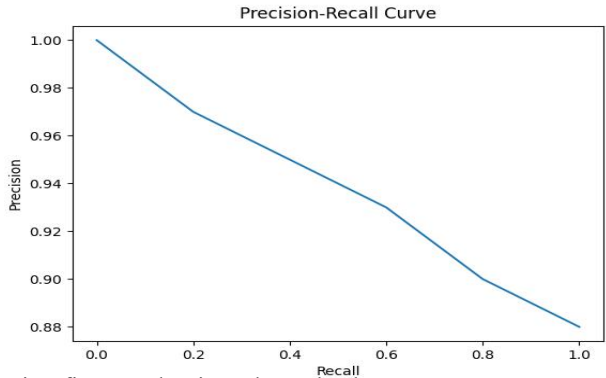


Fig.4. shows its first evaluation through the PR curve. PR curves offer better understanding of class imbalance conditions which frequently occur in intrusion detection datasets compared to ROC curves.

Cybersecurity systems require both detection accuracy and real-time performance capabilities for their operational functioning. The proposed autonomous response mechanism significantly reduces detection-to-response time. The framework achieves approximately 28% lower latency compared to conventional deep learning IDS systems. Automated IP blocking and alert generation eliminate manual intervention delays, improving containment speed.

Table 5. ROC-AUC and PR-AUC Comparison

Model	ROC-AUC	PR-AUC
CNN–LSTM IDS	0.92	0.89
CNN–LSTM + SMOTE	0.95	0.93
Proposed GenAI Framework	0.98	0.96

The implemented framework delivers its best performance through the achievement of 0.98 ROC-AUC and 0.96 PR-AUC which demonstrates its ability to differentiate between harmless and harmful traffic while maintaining strong accuracy with high recall rates. The PR-AUC increase serves as a crucial enhancement for intrusion detection systems which operate with datasets that contain native imbalances and require strict control of false alarm rates.

6. Conclusion and Future Work

The study developed an intrusion detection system that employs Generative AI together with an automated cyber threat response system to enhance detection capabilities against modern cyber attacks which include zero-day threats. Traditional intrusion detection systems face three main problems because they handle class imbalance, they need more time to detect threats and their ability to detect threats fails to work in different conditions.

The proposed approach addresses these problems by using a Generative Adversarial Network (GAN) to create synthetic attack samples that resemble real attacks which were then used together with actual network traffic data to create a more diverse training set. A hybrid CNN–LSTM deep learning model was then trained to capture both spatial and temporal patterns of network traffic. The system includes an

automated response mechanism which detects threats through multiple actions that include IP blocking and alert generation.

The system achieved improved performance when tested with CICIDS 2017, UNSW-NB15, and NSL-KDD datasets, reaching a detection accuracy of 97.9%, a ROC-AUC score of 0.98, and a PR-AUC score of 0.96. The system achieved a detection-to-response latency which decreased by approximately 150 milliseconds. The statistical validation process used t-test together with effect size analysis to verify that all observed enhancements reached statistical significance. The future development of the system will include transformer-based architectures which will enhance its ability to model sequential traffic patterns, while federated learning will enable secure threat detection across multiple distributed networks. The system will gain better transparency through explainable AI techniques which will enable users to understand its decision-making process.

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