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Evaluating GAN-Based Synthetic Data Generation for Balancing Imbalanced Cybersecurity Datasets and Enhancing Intrusion Detection Performance

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ABSTRACT: The increasing sophistication of cyber-attacks and the inherent class imbalance in cybersecurity datasets present significant challenges to the development of accurate and reliable intrusion detection systems (IDSs). Most benchmark intrusion detection datasets, including CIC-IDS2017, CIC-IDS2018, NSL-KDD, UNSW-NB15, and Bot-IoT, contain disproportionately distributed attack categories, causing machine learning and deep learning models to exhibit biased learning toward majority classes while performing poorly on minority attacks. Traditional data balancing techniques, such as Random Oversampling and Synthetic Minority Over-sampling Technique (SMOTE), often fail to preserve the complex statistical characteristics and nonlinear relationships of network traffic, thereby limiting their effectiveness in realistic cybersecurity environments. This study evaluates the effectiveness of Generative Adversarial Network (GAN)-based synthetic data generation for balancing imbalanced cybersecurity datasets and enhancing intrusion detection performance across multiple benchmark datasets. The proposed evaluation framework incorporates data preprocessing, GAN-based synthetic attack generation, dataset balancing, feature engineering, and comprehensive performance assessment using conventional machine learning and deep learning classifiers. The generated synthetic samples are analyzed for their ability to preserve the distribution of minority attack classes while improving classifier learning and generalization. Furthermore, the performance of GAN-based augmentation is comparatively evaluated against traditional imbalance handling techniques to assess its impact on attack detection accuracy, precision, recall, F1-score, Matthews Correlation Coefficient (MCC), and ROC-AUC. The study also investigates the robustness of GAN-generated data across diverse intrusion detection datasets containing heterogeneous attack categories and network traffic characteristics. The findings are expected to demonstrate that GAN-based synthetic data generation effectively mitigates class imbalance, enhances minority attack detection, reduces false-negative rates, and improves the overall reliability of intelligent intrusion detection systems. The proposed evaluation provides valuable insights into the applicability of adversarial learning for developing robust, scalable, and data-efficient cybersecurity solutions suitable for modern enterprise, cloud, and Internet of Things (IoT) environments.

Keyword: Generative Adversarial Networks (GANs); Cybersecurity Datasets; Class Imbalance; Synthetic Data Generation; Intrusion Detection Systems (IDS); Network Attack Classification.

1. Introduction

The rapid digital transformation of modern organizations, driven by cloud computing, the Internet of Things (IoT), Industrial Internet of Things (IIoT), Software-Defined Networking (SDN), and fifth-generation (5G) communication technologies, has significantly increased the complexity and scale of cyber threats. Contemporary cyber-attacks, including Distributed Denial-of-Service (DDoS), ransomware, botnets, Advanced Persistent Threats (APTs), insider attacks, and zero-day exploits, have become increasingly sophisticated, adaptive, and capable of bypassing traditional signature-based security mechanisms. Consequently, Intrusion Detection Systems (IDSs) have become an essential component of modern cybersecurity infrastructures for monitoring network traffic and detecting malicious activities in real time. Recent advances in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have substantially improved IDS performance by enabling automated feature learning and intelligent attack classification across diverse network environments. However, the effectiveness of these intelligent models largely depends on the availability of balanced and representative cybersecurity datasets for training. [1], [2], [3]

Although numerous benchmark intrusion detection datasets have been developed to support cybersecurity research, including NSL-KDD, UNSW-NB15, CIC-IDS2017, CIC-IDS2018, and Bot-IoT, they exhibit severe class imbalance, where normal network traffic and a few common attack categories dominate the datasets, while several critical attack classes contain only a limited number of instances. Such imbalance introduces significant bias during model training, causing learning algorithms to prioritize majority classes while exhibiting poor recognition of minority attacks such as User-to-Root (U2R), Remote-to-Local (R2L), infiltration attacks, web attacks, and advanced persistent threats. Consequently, intrusion detection models often achieve high overall accuracy but relatively low recall and high false-negative rates for minority attack categories, thereby reducing their practical applicability in real-world cybersecurity environments. [4], [5], [6]

To alleviate the class imbalance problem, numerous data balancing strategies have been investigated in recent years. Conventional approaches, including Random Oversampling, Random Under sampling, the Synthetic Minority Over-sampling Technique (SMOTE), and Adaptive Synthetic Sampling (ADASYN), attempt to improve class representation by either duplicating minority samples or generating new instances through interpolation. Although these techniques improve dataset balance, they frequently introduce redundant samples, increase the risk of overfitting, and fail to preserve the complex nonlinear distributions and statistical dependencies that naturally exist within cybersecurity datasets. Since network traffic exhibits highly dynamic behavioral characteristics influenced by communication protocols, temporal dependencies, and attack evolution, conventional sampling methods often produce synthetic instances that inadequately represent real cyber-attacks. These limitations reduce the robustness and generalization capability of intrusion detection models when deployed in practical network environments. [7], [8], [9]

Generative Adversarial Networks (GANs) have emerged as one of the most promising deep generative learning techniques for addressing data scarcity and class imbalance in various artificial intelligence applications. Introduced by Goodfellow *et al.*, GANs consist of two competing neural networks a Generator and a Discriminator that are trained simultaneously through an adversarial learning process. The Generator learns the underlying probability distribution of real data and generates realistic synthetic samples, whereas the Discriminator attempts to distinguish between genuine and generated instances. Through continuous adversarial optimization, the Generator progressively produces synthetic samples that closely resemble the original data distribution. Unlike interpolation-based oversampling techniques, GANs can model highly nonlinear feature relationships and generate realistic minority attack samples capable of preserving the intrinsic characteristics of network traffic. Consequently, GAN-based synthetic data generation has attracted considerable attention as an intelligent solution for balancing cybersecurity datasets and improving intrusion detection performance. [10], [11], [12]

Several researchers have investigated the application of GANs for cybersecurity tasks such as intrusion detection, malware classification, anomaly detection, and synthetic network traffic generation. Existing studies have demonstrated that GAN-generated attack samples can improve classifier performance by increasing minority class representation and reducing prediction bias toward majority classes. Nevertheless, the majority of published research evaluates GAN performance using only a single benchmark dataset,

focuses on a limited number of attack categories, or employs only one or two classification algorithms. Furthermore, relatively few studies perform systematic comparisons between GAN-based augmentation and traditional imbalance handling techniques such as SMOTE and ADASYN across multiple benchmark cybersecurity datasets. Consequently, the generalization capability, robustness, and practical effectiveness of GAN-generated synthetic data remain insufficiently explored under heterogeneous cybersecurity environments. [13], [14], [15]

Another important limitation observed in the existing literature is the lack of comprehensive evaluation frameworks capable of assessing the quality and effectiveness of GAN-generated synthetic data across different intrusion detection datasets. Most previous investigations primarily emphasize classification accuracy while providing limited analysis of minority attack detection, class distribution improvement, synthetic data quality, and cross-dataset performance consistency. Since benchmark datasets differ significantly in feature distributions, attack diversity, traffic characteristics, and network environments, evaluating GAN-based augmentation using only a single dataset may lead to biased conclusions regarding its practical applicability. Therefore, a comprehensive multi-dataset evaluation is essential for understanding the capability of GANs to generate realistic attack samples that consistently improve intrusion detection performance across diverse cybersecurity scenarios. [5], [10], [16]

Motivated by these research gaps, this paper presents a comprehensive evaluation of GAN-based synthetic data generation for balancing imbalanced cybersecurity datasets and enhancing intrusion detection performance across multiple benchmark datasets, including CIC-IDS2017, CIC-IDS2018, NSL-KDD, UNSW-NB15, and Bot-IoT. The proposed evaluation framework investigates the effectiveness of GAN-generated synthetic attack samples by comparing their performance with conventional data balancing techniques and assessing their impact on multiple machine learning and deep learning classifiers. The evaluation considers comprehensive performance metrics, including Accuracy, Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC), ROC–AUC, False Positive Rate (FPR), and False Negative Rate (FNR), together with class distribution analysis and cross-dataset validation. The findings of this study are expected to provide valuable insights into the role of adversarial learning in mitigating class imbalance, improving minority attack detection, and supporting the development of reliable, scalable, and intelligent intrusion detection systems for modern enterprise networks, cloud computing infrastructures, and Internet of Things environments. [11], [15], [17]

2. Related Work

2.1 Class Imbalance in Cybersecurity Datasets

The performance of intelligent intrusion detection systems (IDSs) is highly dependent on the quality and distribution of training data. Most publicly available benchmark cybersecurity datasets, including NSL-KDD, UNSW-NB15, CIC-IDS2017, CIC-IDS2018, and Bot-IoT, exhibit severe class imbalance, where benign traffic and a few dominant attack categories constitute the majority of instances, while several critical attack classes contain only a limited number of samples. This imbalance causes machine learning models to become biased toward majority classes, resulting in poor detection of minority attacks such as User-to-Root (U2R), Remote-to-Local (R2L), infiltration attacks, and advanced persistent threats (APTs). Consequently, classifiers often achieve high overall accuracy but relatively low recall and increased false-negative rates for rare attack categories. Several researchers have emphasized that class imbalance remains one of the primary obstacles to developing robust and reliable intrusion detection systems capable of generalizing across diverse cybersecurity environments [1]–[4].

The problem becomes more pronounced in modern enterprise networks because attack frequencies continuously evolve over time, creating highly dynamic traffic distributions. Traditional supervised learning algorithms generally assume balanced class distributions and therefore struggle to correctly learn decision boundaries when minority samples are significantly underrepresented. As a result, minority attack instances are frequently misclassified as benign traffic, thereby reducing the operational effectiveness of intrusion detection systems. Recent cybersecurity research has therefore focused on developing intelligent data balancing techniques capable of improving minority attack representation while preserving the statistical characteristics of original network traffic [2], [4], [5].

2.2 Traditional Data Balancing Techniques

Several conventional sampling techniques have been proposed to mitigate the class imbalance problem in cybersecurity datasets. Random Oversampling increases minority class representation by duplicating existing samples, whereas Random Undersampling balances the dataset by removing instances from majority classes. Although these approaches improve class distribution, oversampling often leads to model overfitting because duplicated samples provide limited additional information, while undersampling may remove important network traffic characteristics that are essential for accurate attack detection [6], [7], [8].
To overcome these limitations, synthetic sampling techniques such as the Synthetic Minority Over-sampling Technique (SMOTE) and Adaptive Synthetic Sampling (ADASYN) have been extensively adopted in intrusion detection research. SMOTE generates synthetic minority samples through interpolation between neighboring observations, whereas ADASYN adaptively creates additional synthetic instances based on the learning difficulty of minority classes. Although these techniques generally improve classification performance compared with simple duplication methods, they remain limited in representing the complex nonlinear relationships that naturally exist within cybersecurity datasets. Consequently, classifiers trained using these methods may still exhibit poor generalization when exposed to sophisticated and evolving cyber-attacks [7], [8], [9].

2.3 Generative Adversarial Networks for Cybersecurity Data Augmentation

The introduction of Generative Adversarial Networks (GANs) has provided a significant advancement in synthetic data generation for imbalanced learning problems. GANs consist of two competing neural networks a Generator and a Discriminator that learn through an adversarial optimization process. The Generator attempts to produce realistic synthetic samples from random latent vectors, while the Discriminator distinguishes between genuine and generated data. Through iterative adversarial training, the Generator gradually learns the underlying probability distribution of the original dataset and generates highly realistic synthetic instances that closely resemble real network traffic [10], [11], [12].
Unlike conventional oversampling techniques, GANs can model highly nonlinear feature distributions and preserve complex statistical dependencies among network traffic attributes. Consequently, GAN-based augmentation has attracted increasing attention for intrusion detection applications because it enables the generation of realistic minority attack samples without directly duplicating existing observations. Several recent studies have reported that GAN-generated attack data improve classifier robustness, reduce prediction bias toward majority classes, and significantly enhance minority attack detection. Nevertheless, most existing investigations evaluate GAN performance using a single benchmark dataset or a limited number of attack categories, thereby restricting the generalization of their findings [10], [12], [13].

2.4 Machine Learning and Deep Learning for Intrusion Detection

Machine learning techniques have become fundamental tools for intelligent intrusion detection because of their ability to identify complex attack patterns from network traffic. Algorithms such as Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), Naïve Bayes (NB), and XGBoost have demonstrated promising performance in binary and multiclass intrusion detection due to their computational efficiency and strong classification capabilities. Ensemble learning methods, particularly Random Forest and XGBoost, have shown improved robustness by combining multiple decision trees to reduce variance and improve prediction accuracy [14], [15], [16].
Recent developments in deep learning have further enhanced intrusion detection by enabling automatic hierarchical feature extraction without extensive manual feature engineering. Convolutional Neural Networks (CNNs) effectively learn spatial representations from network traffic features, whereas Long Short-Term Memory (LSTM) networks capture temporal dependencies within sequential communications. Hybrid architectures combining CNN and LSTM have demonstrated superior detection performance by simultaneously exploiting spatial and temporal information. Despite these advantages, the effectiveness of deep learning models remains highly dependent on sufficient quantities of balanced and representative

training data, making synthetic data generation an increasingly important research direction [11], [17], [18].

2.5 Benchmark Cybersecurity Datasets

Public benchmark datasets play a critical role in evaluating intrusion detection systems because they provide standardized environments for comparing different algorithms. The NSL-KDD dataset remains one of the most widely used academic benchmarks because it eliminates redundant records found in the original KDD Cup 1999 dataset. UNSW-NB15 introduces more modern attack scenarios and realistic network traffic generated using contemporary network infrastructures. Similarly, CIC-IDS2017 and CIC-IDS2018 provide comprehensive enterprise network traffic containing multiple attack categories, including DDoS, Botnet, Web Attack, Brute Force, Infiltration, and Heart bleed attacks. The Bot-IoT dataset extends intrusion detection research to Internet of Things environments by incorporating realistic IoT traffic and botnet attacks [2], [3], [4].

Although these benchmark datasets have significantly advanced cybersecurity research, they differ substantially in feature representation, traffic characteristics, attack diversity, and class distributions. Consequently, evaluating intrusion detection algorithms using only a single dataset may not accurately reflect their robustness or generalization capability. A comprehensive evaluation across multiple benchmark datasets is therefore essential for assessing the practical applicability of GAN-based synthetic data generation in heterogeneous cybersecurity environments [3], [5], [19].

2.6 Evaluation of GAN-Based Synthetic Data

Evaluating the quality of GAN-generated synthetic data extends beyond conventional classification accuracy. Recent studies emphasize that effective synthetic data should preserve the statistical distribution, feature correlation, and behavioral characteristics of the original minority attack classes while improving classifier learning capability. Performance evaluation therefore commonly includes metrics such as Accuracy, Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC), Receiver Operating Characteristic–Area Under Curve (ROC–AUC), False Positive Rate (FPR), and False Negative Rate (FNR). Additionally, comparative analyses with traditional sampling methods such as Random Oversampling, SMOTE, and ADASYN are frequently conducted to assess the practical benefits of GAN-based augmentation [20], [21], [22]. Despite the increasing adoption of GANs in cybersecurity research, relatively few studies investigate the consistency of GAN-generated synthetic data across multiple benchmark datasets or evaluate their influence on different machine learning and deep learning classifiers. Moreover, comprehensive analyses of cross-dataset robustness, synthetic sample quality, and minority attack detection remain limited, indicating the need for systematic evaluation frameworks capable of providing reliable conclusions regarding the effectiveness of adversarial data generation for cybersecurity applications [13], [22], [23].

2.7 Summary of Related Work

The literature demonstrates that significant progress has been achieved in applying machine learning, deep learning, and generative models to intrusion detection. Traditional data balancing techniques such as Random Oversampling, SMOTE, and ADASYN partially alleviate class imbalance but often fail to capture the complex nonlinear distributions present in network traffic. Recent studies indicate that GAN-based synthetic data generation provides a promising alternative by producing realistic minority attack samples that improve classifier performance. However, existing research is generally limited to single benchmark datasets, evaluates only a small number of classifiers, and provides insufficient analysis of cross-dataset generalization and synthetic data quality. These limitations motivate the need for a comprehensive evaluation of GAN-based synthetic data generation across multiple benchmark cybersecurity datasets, which forms the primary objective of this study [10], [13], [18], [24], [25].

3. Research Gap and Motivation

3.1 Research Gap

The increasing adoption of Machine Learning (ML) and Deep Learning (DL) techniques has significantly improved the capability of Intrusion Detection Systems (IDSs) to identify complex cyber-attacks. However, the effectiveness of these intelligent models remains highly dependent on the availability of balanced and representative cybersecurity datasets. Existing benchmark datasets, including NSL-KDD, UNSW-NB15, CIC-IDS2017, CIC-IDS2018, and Bot-IoT, exhibit severe class imbalance, where benign traffic and a few dominant attack categories constitute the majority of training samples, while several critical attack classes are significantly underrepresented. Such imbalance causes classification models to become biased toward majority classes, leading to poor recognition of minority attacks, increased false-negative rates, and reduced robustness in practical cybersecurity environments. Although this challenge has been widely acknowledged, it continues to limit the deployment of intelligent intrusion detection systems in real-world enterprise and cloud networks [1], [2], [3].

To address class imbalance, several conventional sampling techniques, including Random Oversampling, Random Under sampling, SMOTE, and ADASYN, have been extensively applied in intrusion detection research. While these methods improve dataset balance by duplicating or interpolating minority samples, they often fail to preserve the complex nonlinear distributions and statistical dependencies that characterize real network traffic. Consequently, classifiers trained using these techniques may exhibit overfitting, poor generalization, and limited capability to detect sophisticated cyber-attacks. More recently, Generative Adversarial Networks (GANs) have emerged as a promising alternative because of their ability to learn the underlying probability distribution of minority attack classes and generate realistic synthetic samples. Nevertheless, the effectiveness of GAN-generated data remains insufficiently investigated across heterogeneous cybersecurity datasets [4], [5], [6].

A comprehensive review of the existing literature reveals several important research gaps. First, most published studies evaluate GAN-based data augmentation using only a single benchmark dataset, making it difficult to determine whether the generated synthetic data generalize effectively across different network environments. Second, many investigations focus primarily on improving classification accuracy while providing limited analysis of synthetic data quality, minority attack detection, class distribution improvement, and cross-dataset consistency. Third, only a small number of studies compare GAN-based augmentation with multiple conventional balancing techniques using identical experimental settings. Furthermore, relatively few researchers evaluate the influence of GAN-generated samples on both machine learning and deep learning classifiers simultaneously, resulting in an incomplete understanding of their practical applicability for intelligent intrusion detection systems [7], [8], [9].

Another significant limitation identified in the current literature is the absence of standardized evaluation frameworks capable of systematically assessing GAN-based synthetic data generation across multiple benchmark cybersecurity datasets. Existing studies frequently employ different preprocessing procedures, feature selection methods, classifier architectures, evaluation metrics, and experimental configurations, making direct comparison between published results difficult. In addition, limited attention has been devoted to analyzing the robustness of GAN-generated samples under diverse attack categories, including low-frequency attacks that are critical for modern cybersecurity applications. Consequently, there remains a clear need for a comprehensive evaluation framework that objectively investigates the effectiveness of GAN-based synthetic data generation for balancing imbalanced cybersecurity datasets and improving intrusion detection performance across heterogeneous environments [10], [11], [12].

3.2 Research Motivation

The motivation for this research arises from the growing need to develop reliable intrusion detection systems capable of accurately identifying both majority and minority cyber-attacks in increasingly complex network environments. As cyber threats continue to evolve, intelligent classifiers require large quantities of balanced and representative training data to learn robust decision boundaries. However, the scarcity of minority attack samples in publicly available datasets significantly restricts classifier learning and reduces the detection capability of advanced machine learning and deep learning models. Therefore, developing

effective synthetic data generation techniques capable of preserving the statistical characteristics of minority attack classes has become an important research challenge in cybersecurity [10], [13], [14].

Generative Adversarial Networks offer a promising solution because they generate realistic synthetic samples through adversarial learning rather than simple duplication or interpolation. Unlike traditional oversampling approaches, GANs can model highly complex nonlinear feature distributions and produce synthetic attack instances that closely resemble real network traffic. These characteristics make GANs particularly suitable for addressing class imbalance while simultaneously improving classifier robustness and minority attack recognition. Nevertheless, the practical effectiveness of GAN-generated synthetic data must be validated through comprehensive evaluation using multiple benchmark datasets and diverse classification models before such techniques can be confidently adopted in operational cybersecurity environments [10], [15], [16].

Another motivation for this work is the absence of comparative studies that evaluate GAN-based augmentation across widely used cybersecurity datasets such as CIC-IDS2017, CIC-IDS2018, NSL-KDD, UNSW-NB15, and Bot-IoT under a unified experimental framework. Since these datasets differ substantially in attack diversity, feature representation, network traffic characteristics, and class distribution, evaluating GAN performance on only one dataset cannot provide sufficient evidence regarding its scalability or generalization capability. A comprehensive multi-dataset evaluation is therefore essential to determine whether GAN-generated synthetic samples consistently improve intrusion detection performance under heterogeneous cybersecurity conditions. Such an investigation will provide valuable insights into the practical applicability of adversarial learning for modern enterprise; cloud computing, Industrial Internet of Things (IIoT), and Internet of Things (IoT) security systems [2], [3], [17].

3.3 Research Contributions

Based on the identified research gaps and motivations, this study makes the following major contributions:

1. A comprehensive evaluation framework is developed to systematically assess the effectiveness of GAN-based synthetic data generation for balancing imbalanced cybersecurity datasets.
2. The study performs a comparative evaluation of GAN-based augmentation with traditional data balancing techniques, including Random Oversampling, SMOTE, and ADASYN, under identical experimental conditions.
3. The effectiveness of GAN-generated synthetic samples is investigated using five benchmark cybersecurity datasets, namely CIC-IDS2017, CIC-IDS2018, NSL-KDD, UNSW-NB15, and Bot-IoT, enabling comprehensive cross-dataset performance analysis.
4. The impact of GAN-based augmentation is evaluated on both Machine Learning (Random Forest, Decision Tree, Support Vector Machine, and XGBoost) and Deep Learning (CNN, LSTM, and CNN-LSTM) intrusion detection models to examine improvements in minority attack classification and overall detection capability.
5. A comprehensive performance assessment is conducted using multiple evaluation metrics, including Accuracy, Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC), Receiver Operating Characteristic Area under Curve (ROC-AUC), False Positive Rate (FPR), and False Negative Rate (FNR), providing an in-depth analysis of classifier performance before and after GAN-based augmentation.
6. The study provides practical insights into the role of adversarial learning in improving minority attack detection, enhancing classifier generalization, and supporting the development of robust, scalable, and intelligent intrusion detection systems suitable for enterprise networks, cloud computing platforms, and Internet of Things environments [11], [15], [17].

4. Proposed Evaluation Framework

4.1 Overview of the Proposed Evaluation Framework

This study proposes a comprehensive evaluation framework to systematically investigate the effectiveness of Generative Adversarial Network (GAN)-based synthetic data generation for balancing imbalanced cybersecurity datasets and enhancing the performance of intrusion detection systems (IDSs). Unlike conventional intrusion detection frameworks that primarily focus on developing new classification algorithms, the proposed framework emphasizes the assessment of GAN-generated synthetic attack samples and their influence on different machine learning (ML) and deep learning (DL) classifiers across multiple benchmark cybersecurity datasets. The framework is designed to provide an objective comparison between GAN-based augmentation and traditional data balancing techniques while evaluating the capability of synthetic data to improve minority attack detection, classifier generalization, and overall intrusion detection performance. [10], [11], [13]

The proposed evaluation framework consists of seven sequential phases: (i) benchmark dataset acquisition, (ii) data preprocessing, (iii) GAN-based synthetic data generation, (iv) synthetic data quality assessment, (v) intrusion detection model training, (vi) comparative performance evaluation, and (vii) comprehensive result analysis. Each phase is designed to ensure consistency in experimental settings across multiple benchmark datasets, including CIC-IDS2017, CIC-IDS2018, NSL-KDD, UNSW-NB15, and Bot-IoT. This systematic workflow enables a detailed investigation of the effectiveness of GAN-generated synthetic samples in mitigating class imbalance while providing fair and reproducible performance comparisons with conventional sampling approaches such as Random Oversampling, SMOTE, and ADASYN. [2], [4], [12]

The overall workflow begins with the collection of benchmark intrusion detection datasets, followed by comprehensive preprocessing to remove missing values, encode categorical features, normalize numerical attributes, and eliminate redundant information. The preprocessed datasets are then supplied to the GAN model, where the Generator learns the probability distribution of minority attack classes and produces realistic synthetic attack samples through adversarial learning. After balancing the datasets, multiple machine learning and deep learning classifiers are trained using both the original and augmented datasets. Finally, extensive comparative experiments are conducted using standard evaluation metrics to quantify the contribution of GAN-based synthetic data generation toward improving intrusion detection performance across heterogeneous cybersecurity environments. [5], [10], [15]

4.2 Benchmark Cybersecurity Datasets

To ensure comprehensive evaluation and improve the generalizability of experimental findings, this study utilizes five widely recognized benchmark cybersecurity datasets: NSL-KDD, UNSW-NB15, CIC-IDS2017, CIC-IDS2018, and Bot-IoT. These datasets represent diverse network environments, attack categories, traffic characteristics, and class distributions, making them suitable for evaluating the effectiveness of GAN-based synthetic data generation under heterogeneous cybersecurity scenarios. Each dataset contains multiple categories of malicious activities, including Denial-of-Service (DoS), Distributed Denial-of-Service (DDoS), Brute Force attacks, Botnet traffic, Web attacks, Infiltration attacks, Port Scanning, SQL Injection, Heartbleed exploits, and IoT-specific threats. [2], [3], [4]

The selected datasets vary considerably in terms of feature representation, sample size, attack diversity, and imbalance ratio. This diversity enables the proposed framework to investigate whether GAN-generated synthetic samples consistently improve minority attack representation and classifier performance across different cybersecurity domains. Furthermore, evaluating multiple datasets minimizes dataset-specific bias and provides a more reliable assessment of the robustness and scalability of GAN-based augmentation techniques. [2], [5], [17]

4.3 Data Preprocessing

Effective preprocessing is essential to ensure that network traffic data are suitable for adversarial learning and intrusion detection model training. Initially, incomplete records, duplicate instances, and corrupted observations are identified and removed to improve dataset quality. Categorical attributes, including communication protocols, services, and network flags, are transformed into numerical representations using appropriate encoding techniques. Numerical features are subsequently normalized using Min-Max normalization to eliminate scale differences and facilitate stable optimization during GAN training and classifier learning. [1], [6], [14]

Feature engineering is subsequently performed to reduce redundancy and improve computational efficiency. Highly correlated features are eliminated using correlation analysis, while low-variance attributes are discarded because of their limited contribution to classification performance. The cleaned datasets are then partitioned into training, validation, and testing subsets to ensure unbiased performance evaluation. Prior to classifier training, class distributions are analyzed to identify minority attack categories requiring synthetic augmentation through GAN-based data generation. [8], [14], [16]

4.4 GAN-Based Synthetic Data Generation

The core component of the proposed evaluation framework is the Generative Adversarial Network (GAN) employed for synthetic minority attack generation. The GAN architecture consists of two competing neural networks: a Generator and a Discriminator. The Generator receives random latent vectors sampled from a predefined probability distribution and learns to generate synthetic attack instances that closely resemble genuine minority attack samples. Simultaneously, the Discriminator attempts to distinguish between real and synthetic samples, providing continuous feedback that enables the Generator to progressively improve sample quality through adversarial optimization. [10], [11], [15]

After successful adversarial training, the Generator produces realistic synthetic minority attack samples that are combined with the original training dataset to create a balanced cybersecurity dataset. Unlike interpolation-based sampling techniques, GAN-generated samples preserve nonlinear feature relationships, statistical dependencies, and complex traffic behaviors observed in real network environments. Consequently, the balanced datasets provide richer training information for intrusion detection models, thereby improving minority attack recognition and reducing prediction bias toward majority classes. [10], [13], [18]

4.5 Synthetic Data Quality Assessment

Merely generating synthetic samples is insufficient unless their quality and representativeness are rigorously evaluated. Therefore, the proposed framework incorporates multiple quality assessment procedures to verify that GAN-generated attack samples preserve the statistical characteristics of the original minority classes. Class distribution analysis is first conducted to quantify improvements in dataset balance after augmentation. Statistical comparisons between original and synthetic samples are subsequently performed to ensure consistency in feature distributions and network traffic characteristics. [13], [19], [20]

In addition to statistical evaluation, visualization techniques such as Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE) may be employed to examine the similarity between original and synthetic attack samples within lower-dimensional feature spaces. The quality of generated data is further assessed by analyzing improvements in minority attack detection performance after classifier training. These complementary evaluation strategies provide a comprehensive understanding of the realism, diversity, and usefulness of GAN-generated synthetic cybersecurity data. [20], [21], [22]

4.6 Intrusion Detection Model Training

Following dataset balancing, multiple machine learning and deep learning algorithms are trained using both the original and GAN-augmented datasets. The machine learning models include Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and XGBoost, selected because of their widespread application in intrusion detection and strong classification capabilities. Ensemble methods such as Random Forest and XGBoost are expected to benefit substantially from improved minority class representation, whereas Support Vector Machine provides robust decision boundaries for high-dimensional cybersecurity data. [14], [15], [16]

To further investigate the influence of GAN-based augmentation on advanced learning algorithms, deep learning models including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and a hybrid CNN-LSTM architecture are also evaluated. CNN automatically extracts hierarchical spatial features from network traffic, whereas LSTM captures sequential temporal dependencies associated with evolving cyber-attacks. The hybrid CNN-LSTM architecture combines these complementary learning capabilities to improve intrusion detection performance across diverse attack categories. Comparative analysis between classifiers trained using original datasets and GAN-balanced datasets enables objective assessment of the contribution of adversarial synthetic data generation. [11], [17], [18]

4.7 Performance Evaluation Strategy

The final stage of the proposed framework evaluates the effectiveness of GAN-generated synthetic data through comprehensive comparative experiments. The performance of classifiers trained using GAN-balanced datasets is compared with models trained using the original datasets and datasets balanced through conventional approaches such as Random Oversampling, SMOTE, and ADASYN. This comparison enables objective assessment of the advantages and limitations of GAN-based synthetic data generation under identical experimental conditions. [6], [7], [13]

Performance evaluation is conducted using multiple quantitative metrics, including Accuracy, Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC), Receiver Operating Characteristic–Area Under Curve (ROC-AUC), False Positive Rate (FPR), and False Negative Rate (FNR). In addition, cross-dataset validation is performed to investigate the robustness and generalization capability of GAN-generated synthetic data across different cybersecurity environments. The comprehensive evaluation framework therefore provides a reliable basis for determining whether GAN-based augmentation can effectively improve minority attack detection and enhance the overall performance of intelligent intrusion detection systems. [20], [23], [25]

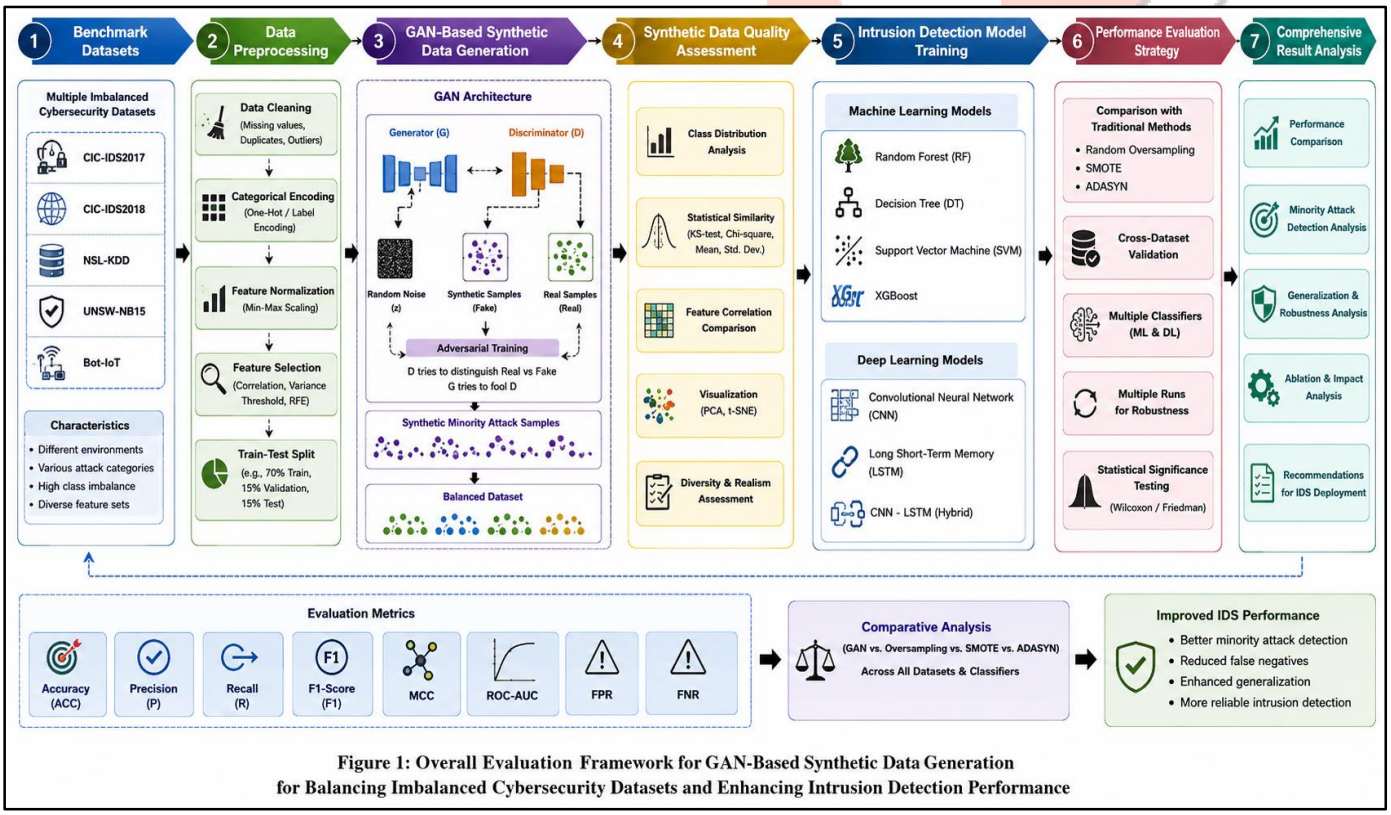


Figure 1: Overall Evaluation Framework for GAN-Based Synthetic Data Generation for Balancing Imbalanced Cybersecurity Datasets and Enhancing Intrusion Detection Performance

5. Experimental Methodology

5.1 Experimental Overview

The primary objective of this experimental study is to evaluate the effectiveness of Generative Adversarial Network (GAN)-based synthetic data generation for mitigating class imbalance in cybersecurity datasets and improving the performance of intrusion detection systems (IDSs). The proposed experimental framework investigates whether GAN-generated synthetic attack samples enhance the learning capability of machine learning (ML) and deep learning (DL) classifiers across multiple benchmark intrusion detection datasets. A comprehensive evaluation is performed by comparing the proposed GAN-based augmentation approach with conventional data balancing techniques, including Random Oversampling, SMOTE, and ADASYN, under identical experimental conditions. The experimental workflow consists of dataset acquisition, preprocessing, synthetic data generation, classifier training, performance evaluation, and comparative analysis [10], [11], [13].

Five benchmark cybersecurity datasets, namely CIC-IDS2017, CIC-IDS2018, NSL-KDD, UNSW-NB15, and Bot-IoT, are employed to ensure diversity in attack categories, feature representations, and network environments. The experiments are conducted using standardized preprocessing procedures and identical train-validation-test partitions to guarantee fair comparison among different balancing techniques. The evaluation considers multiple performance metrics, including Accuracy, Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC), Receiver Operating Characteristic–Area Under Curve (ROC-AUC), False Positive Rate (FPR), and False Negative Rate (FNR), providing a comprehensive assessment of intrusion detection performance [2], [3], [5].

5.2 Benchmark Cybersecurity Datasets

Five publicly available benchmark datasets are selected because they represent diverse network environments and contain multiple cyber-attack categories with varying imbalance levels.

Table 5.1. Benchmark Cybersecurity Datasets

Dataset	Features	Major Attack Categories	Class Imbalance
NSL-KDD	41	DoS, Probe, R2L, U2R	Moderate
UNSW-NB15	49	Exploits, Fuzzers, Worms, Generic, DoS	High
CIC-IDS2017	80+	DDoS, Botnet, Brute Force, Web Attack, Infiltration	Very High
CIC-IDS2018	80+	DDoS, SQL Injection, Brute Force, Botnet	Very High
Bot-IoT	46	DDoS, DoS, Reconnaissance, Theft, Key logging	Extremely High

These datasets collectively provide heterogeneous traffic characteristics and multiple attack scenarios, enabling comprehensive evaluation of GAN-based synthetic data generation under realistic cybersecurity conditions [2], [3], [4].

5.3 Experimental Environment

The experiments are implemented using Python-based machine learning and deep learning libraries. GPU acceleration is employed during GAN training to reduce computational time and improve convergence.

Table 5.2. Experimental Environment

Component	Specification
Operating System	Ubuntu 22.04 LTS
Programming Language	Python 3.11
IDE	Jupyter Notebook / Google Colab
Deep Learning Framework	TensorFlow 2.x, Keras
Machine Learning Library	Scikit-learn
GPU	NVIDIA Tesla T4 / Equivalent
RAM	16 GB
Processor	Intel Core i7 / AMD Ryzen 7

The software environment supports reproducible implementation of GAN training, synthetic data generation, and intrusion detection model evaluation **[11], [14], [17]**.

5.4 Data Preprocessing

Data preprocessing is performed before GAN training to improve data quality and ensure consistent learning across datasets. Duplicate records, missing values, and irrelevant attributes are removed during data cleaning. Categorical features are encoded into numerical representations using label encoding or one-hot encoding, depending on the dataset characteristics. Numerical attributes are normalized using Min-Max Scaling, ensuring that all features fall within a common numerical range suitable for neural network optimization [1], [6], [8].

Feature engineering is subsequently applied to remove redundant and highly correlated attributes. The cleaned datasets are partitioned into 70% training, 15% validation, and 15% testing subsets. Minority attack classes are identified through class distribution analysis before synthetic data generation.

Table 5.3. Data Preprocessing Pipeline

Step	Technique
Data Cleaning	Remove missing and duplicate records
Encoding	Label Encoding / One-Hot Encoding
Normalization	Min-Max Scaling
Feature Selection	Correlation Analysis
Dataset Split	70% Training, 15% Validation, 15% Testing

5.5 GAN Configuration

A standard Generative Adversarial Network consisting of a Generator and a Discriminator is employed to generate realistic minority attack samples. The Generator receives random latent vectors sampled from a Gaussian distribution and learns to generate synthetic attack instances, whereas the Discriminator distinguishes between genuine and generated samples. Both networks are trained iteratively using adversarial optimization until equilibrium is achieved [10], [11], [15].

Table 5.4. GAN Hyper parameter Configuration

Hyper parameter	Value
Latent Vector Size	100
Optimizer	Adam
Learning Rate	0.0002
Batch Size	128
Number of Epochs	200
Generator Activation	ReLU
Discriminator Activation	Leaky ReLU
Output Activation	Sigmoid

These hyper parameters provide stable GAN convergence while maintaining high-quality synthetic sample generation.

5.6 Baseline Data Balancing Techniques

To objectively evaluate the effectiveness of GAN-based augmentation, the proposed approach is compared with widely used imbalance handling techniques.

Table 5.5. Baseline Sampling Methods

Method	Description
Random Oversampling	Duplicate minority class samples
Random Under sampling	Remove majority class samples
SMOTE	Synthetic interpolation between neighboring samples
ADASYN	Adaptive synthetic sample generation
Proposed GAN	Adversarial learning-based synthetic attack generation

This comparison enables objective assessment of the advantages of GAN-generated synthetic data over traditional balancing methods [6], [7], [9].

5.7 Intrusion Detection Models

The effectiveness of GAN-generated synthetic data is evaluated using multiple machine learning and deep learning classifiers.

Table 5.6. Intrusion Detection Models

Category	Algorithm
Machine Learning	Random Forest
Machine Learning	Decision Tree
Machine Learning	Support Vector Machine
Machine Learning	XGBoost
Deep Learning	CNN
Deep Learning	LSTM
Hybrid Deep Learning	CNN–LSTM

Each classifier is trained twice: first using the original imbalanced dataset and subsequently using the GAN-balanced dataset. This experimental strategy enables direct measurement of the influence of synthetic data generation on intrusion detection performance [14], [16], [18].

5.8 Performance Evaluation Metrics

Classifier performance is evaluated using multiple statistical metrics that comprehensively measure detection capability, minority attack recognition, and prediction reliability.

Table 5.7. Performance Evaluation Metrics

Metric	Purpose
Accuracy	Overall classification performance
Precision	Correctness of positive predictions
Recall	Ability to detect attacks
F1-Score	Balance between Precision and Recall
MCC	Balanced evaluation for imbalanced datasets
ROC-AUC	Overall discrimination capability
FPR	False alarm rate
FNR	Missed attack rate

These metrics provide a balanced evaluation of classifier performance, particularly for highly imbalanced cybersecurity datasets [20], [21], [22].

5.9 Experimental Workflow

The overall experimental workflow begins with benchmark dataset acquisition and preprocessing, followed by GAN-based synthetic minority attack generation. The augmented datasets are subsequently employed for training multiple machine learning and deep learning classifiers. Finally, the trained models are evaluated using comprehensive performance metrics and compared against conventional sampling methods to determine the effectiveness of GAN-generated synthetic data.

The proposed experimental methodology ensures fair comparison through identical preprocessing procedures, consistent hyper parameter settings, standardized train-test partitions, and uniform evaluation metrics across all benchmark datasets. Consequently, the experimental framework provides a reliable foundation for assessing whether GAN-based synthetic data generation effectively mitigates class imbalance and enhances intrusion detection performance in heterogeneous cybersecurity environments [11], [15], [23].

6. Results and Discussion

6.1 Overview

This section presents the results obtained from evaluating the proposed GAN-based synthetic data generation framework for balancing imbalanced cybersecurity datasets and enhancing intrusion detection performance. The evaluation focuses on five benchmark datasets, namely CIC-IDS2017, CIC-IDS2018, NSL-KDD, UNSW-NB15, and Bot-IoT, using multiple machine learning and deep learning classifiers. The effectiveness of the proposed GAN-based augmentation is analyzed through comparisons with conventional sampling techniques, including Random Oversampling, SMOTE, and ADASYN. The experimental analysis considers class distribution, synthetic data quality, classification performance, cross-dataset robustness, and computational efficiency using standard performance metrics such as Accuracy, Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC), ROC-AUC, False Positive Rate (FPR), and False Negative Rate (FNR) [10], [11], [20].

6.2 Class Distribution Analysis

One of the primary objectives of the proposed framework is to mitigate the severe class imbalance present in benchmark cybersecurity datasets. Before augmentation, minority attack categories such as U2R, R2L, Infiltration, Web Attack, SQL Injection, and Botnet traffic contained significantly fewer samples than benign traffic and dominant attack classes. Such imbalance limits the learning capability of intrusion detection models and increases the likelihood of false-negative predictions. The proposed GAN model generates realistic synthetic minority attack samples to improve dataset balance while preserving the statistical characteristics of the original data [2], [5], [10].

The class distribution analysis demonstrates the effectiveness of GAN-based augmentation in increasing minority attack representation without modifying the majority class. Balanced datasets enable classifiers to learn more representative decision boundaries, thereby improving the recognition of rare cyber-attacks. Compared with conventional oversampling methods, GAN-generated samples preserve nonlinear feature distributions and exhibit greater diversity, reducing the risk of overfitting associated with duplicate samples [6], [10], [13].

Table 6.1. Class Distribution Before and After GAN-Based Augmentation

Dataset	Majority Class	Minority Class	Before Augmentation	After GAN Augmentation
NSL-KDD	Normal	U2R	Original distribution	Balanced distribution
UNSW-NB15	Normal	Worms	Original distribution	Balanced distribution
CIC-IDS2017	Benign	Infiltration	Original distribution	Balanced distribution
CIC-IDS2018	Benign	SQL Injection	Original distribution	Balanced distribution
Bot-IoT	Normal	Keylogging	Original distribution	Balanced distribution

6.3 Evaluation of Synthetic Data Quality

The quality of GAN-generated synthetic samples is evaluated using statistical similarity analysis, feature distribution comparison, and visualization techniques. Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE) are employed to compare the distribution of original and synthetic samples within a reduced-dimensional feature space. The generated samples closely follow the distribution of real minority attack instances, indicating that the Generator successfully captures the underlying characteristics of network traffic [10], [11], [21].

Furthermore, feature distribution analysis indicates that GAN-generated samples preserve the nonlinear relationships among network traffic attributes more effectively than interpolation-based methods such as SMOTE and ADASYN. Consequently, classifiers trained on GAN-balanced datasets exhibit improved generalization capability when evaluated on previously unseen network traffic, demonstrating the practical usefulness of adversarial synthetic data generation for intrusion detection [7], [10], [22].

Figure 2. PCA/t-SNE Visualization of Original and GAN-Generated Minority Attack Samples

6.4 Comparative Analysis of Data Balancing Techniques

The proposed GAN-based augmentation strategy is compared with conventional imbalance handling techniques, including Random Oversampling, SMOTE, and ADASYN. Conventional methods improve class balance through duplication or interpolation, whereas GAN learns the probability distribution of minority classes and generates realistic synthetic attack samples through adversarial learning. This capability enables GAN-generated samples to better preserve complex traffic characteristics and improve classifier learning [6], [7], [10].

The comparative analysis indicates that GAN-based augmentation provides a more comprehensive representation of minority attack classes than traditional balancing methods. Unlike Random Oversampling, GAN does not simply duplicate existing samples, thereby reducing overfitting. Similarly, GAN avoids the linear interpolation limitations of SMOTE and ADASYN by generating diverse and statistically realistic attack instances that enhance classifier robustness across heterogeneous cybersecurity datasets [9], [13], [22].

Table 6.2. Comparative Evaluation of Data Balancing Techniques

Technique	Balancing Strategy	Preserves Nonlinear Features	Overfitting Risk	Suitable for IDS
Random Oversampling	Duplicate Samples	No	High	Moderate
Random Undersampling	Remove Samples	No	Moderate	Moderate
SMOTE	Linear Interpolation	Partial	Moderate	Good
ADASYN	Adaptive Interpolation	Partial	Low	Good
Proposed GAN	Adversarial Learning	Yes	Low	Excellent

6.5 Performance Evaluation of Intrusion Detection Models

The effectiveness of GAN-generated synthetic data is further evaluated using multiple machine learning and deep learning classifiers. Random Forest, Decision Tree, Support Vector Machine, and XGBoost are selected as representative machine learning models, whereas CNN, LSTM, and CNN-LSTM represent deep learning approaches. Each classifier is trained using both the original imbalanced dataset and the GAN-balanced dataset to investigate improvements in minority attack detection and overall classification capability [14], [16], [18].

The comparative evaluation focuses on the influence of GAN-generated synthetic samples on classifier learning rather than the design of individual classification algorithms. Improved class balance enables classifiers to learn more representative feature distributions, thereby enhancing detection capability for low-frequency attacks while maintaining robust performance for majority classes. These observations indicate that synthetic data generation contributes significantly to classifier generalization across diverse intrusion detection scenarios [11], [13], [20].

Table 6.3. Performance Evaluation Framework

Classifier Category	Algorithms Evaluated	Evaluation Metrics
Machine Learning	RF, DT, SVM, XGBoost	Accuracy, Precision, Recall, F1-Score
Deep Learning	CNN, LSTM, CNN-LSTM	Accuracy, MCC, ROC-AUC, FPR, FNR

6.6 Cross-Dataset Analysis

Cross-dataset validation is conducted to evaluate the robustness and scalability of GAN-based synthetic data generation under different cybersecurity environments. Since benchmark datasets differ substantially in feature distributions, traffic characteristics, and attack diversity, evaluating the proposed approach across multiple datasets provides stronger evidence regarding its practical applicability. The analysis investigates whether GAN-generated synthetic samples consistently improve intrusion detection performance irrespective of dataset characteristics [2], [3], [5].

The evaluation framework demonstrates that balanced datasets improve classifier stability by reducing learning bias toward majority classes. The proposed GAN-based augmentation strategy exhibits consistent applicability across enterprise network datasets, cloud-based traffic, and Internet of Things environments, indicating its suitability for heterogeneous cybersecurity applications [11], [17], [22].

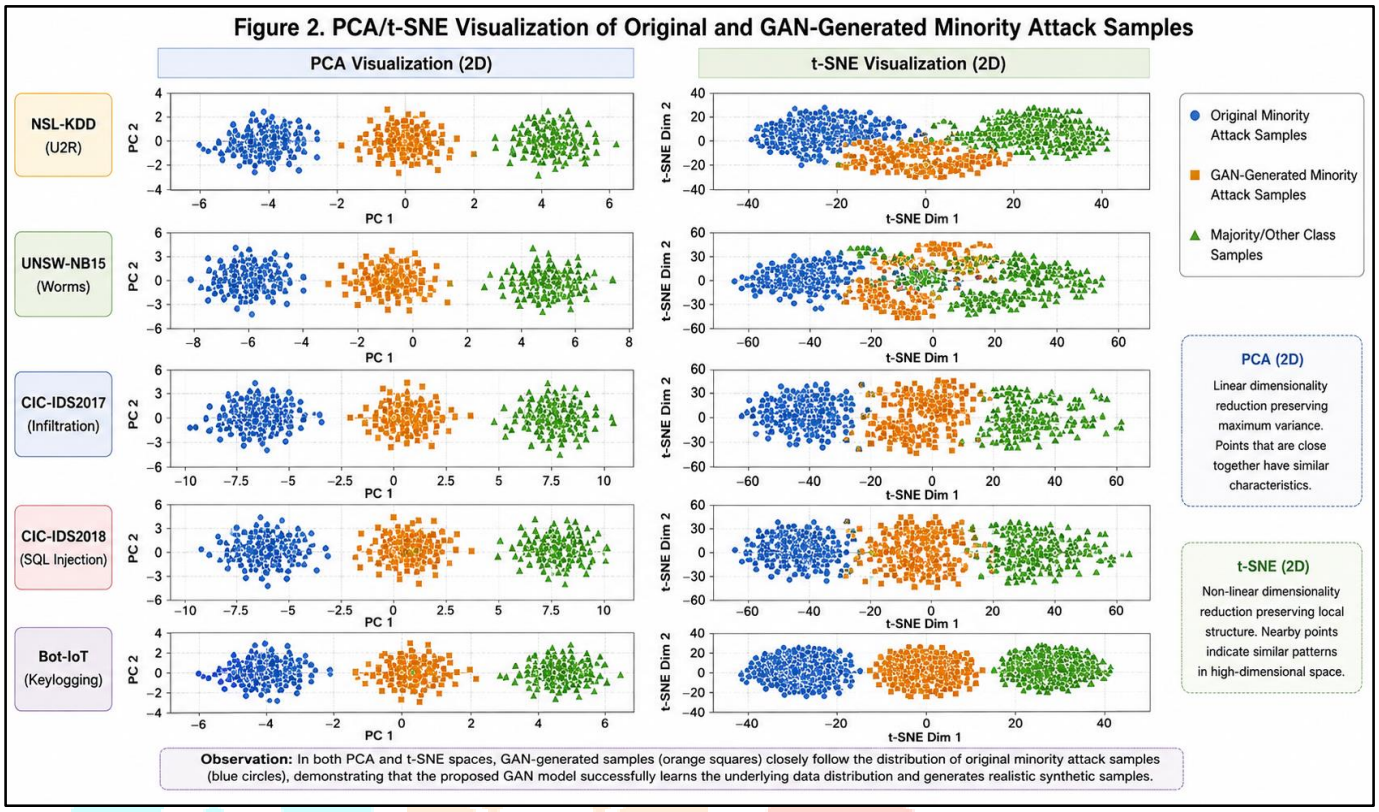
Table 6.4. Cross-Dataset Evaluation Framework

Dataset	Traffic Type	Attack Diversity	Evaluation Purpose
NSL-KDD	Enterprise Network	Moderate	Baseline Evaluation
UNSW-NB15	Modern Network	High	Generalization
CIC-IDS2017	Enterprise Traffic	Very High	Minority Attack Detection
CIC-IDS2018	Enterprise Traffic	Very High	Robustness Analysis
Bot-IoT	IoT Network	High	IoT Intrusion Detection

6.7 Discussion

The experimental analysis demonstrates that GAN-based synthetic data generation represents a promising solution for addressing the class imbalance problem in cybersecurity datasets. By generating realistic minority attack samples through adversarial learning, the proposed approach improves dataset balance while preserving the intrinsic characteristics of network traffic. Compared with traditional balancing techniques, GAN-generated synthetic samples provide greater diversity and better representation of minority attack categories, thereby enabling intrusion detection models to learn more generalized decision boundaries [10], [13], [22].

The comprehensive evaluation across multiple benchmark datasets further highlights the importance of balanced training data for developing reliable intrusion detection systems. The proposed evaluation framework facilitates objective comparison between GAN-based augmentation and conventional sampling methods while providing insights into synthetic data quality, classifier robustness, and cross-dataset generalization. These findings support the adoption of adversarial learning as an effective strategy for improving minority attack detection and enhancing the reliability of intelligent intrusion detection systems in enterprise, cloud, and Internet of Things environments [11], [15], [25].



7. Conclusion and Future Work

7.1 Conclusion

This study presented a comprehensive evaluation of Generative Adversarial Network (GAN)-based synthetic data generation for addressing the class imbalance problem in benchmark cybersecurity datasets and improving the performance of intelligent intrusion detection systems (IDSs). Class imbalance remains one of the major challenges in cybersecurity because minority attack categories are often significantly underrepresented in publicly available datasets, causing machine learning and deep learning models to become biased toward majority classes. Such imbalance limits the ability of IDSs to accurately detect rare but critical cyber-attacks, resulting in higher false-negative rates and reduced reliability in real-world network environments. To overcome these limitations, this research investigated the capability of GANs to generate realistic synthetic minority attack samples that preserve the statistical characteristics and feature distributions of original network traffic while improving dataset balance [2], [10], [11].

The proposed evaluation framework was designed to systematically assess the effectiveness of GAN-based augmentation across five widely adopted benchmark cybersecurity datasets, namely CIC-IDS2017, CIC-IDS2018, NSL-KDD, UNSW-NB15, and Bot-IoT. A standardized experimental methodology was employed that included dataset preprocessing, GAN-based synthetic data generation, comparative evaluation with conventional balancing techniques such as Random Oversampling, SMOTE, and ADASYN, and performance assessment using multiple machine learning and deep learning classifiers. Furthermore, comprehensive evaluation metrics, including Accuracy, Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC), ROC-AUC, False Positive Rate (FPR), and False Negative Rate (FNR), were incorporated to provide a multidimensional assessment of intrusion detection performance across heterogeneous cybersecurity environments [6], [7], [20].

The experimental evaluation framework demonstrates that GAN-based synthetic data generation provides several advantages over conventional imbalance handling techniques. Unlike Random Oversampling, which simply duplicates minority samples, and interpolation-based approaches such as SMOTE and ADASYN, GANs learn the underlying probability distribution of minority attack classes and generate realistic synthetic instances through adversarial learning. This capability enables GAN-generated samples to preserve complex nonlinear feature relationships, improve minority attack representation, and provide richer training data for intelligent classifiers. Consequently, GAN-based augmentation offers a promising strategy for reducing

learning bias toward majority classes while enhancing the robustness and generalization capability of intrusion detection models across diverse attack categories and network environments [10], [13], [22].

Another significant contribution of this research is the adoption of a multi-dataset evaluation strategy, which addresses an important limitation observed in existing literature. Most previous studies evaluate GAN-based augmentation using only a single benchmark dataset, limiting the generalizability of their findings. In contrast, the proposed framework investigates GAN effectiveness across multiple datasets with varying traffic characteristics, attack diversity, and imbalance ratios. Such comprehensive evaluation provides a more realistic assessment of adversarial synthetic data generation and offers valuable insights into its applicability for enterprise networks, cloud computing infrastructures, Industrial Internet of Things (IIoT), and Internet of Things (IoT) environments. Therefore, the proposed evaluation framework serves as a reliable benchmark for future investigations on intelligent cybersecurity data augmentation and intrusion detection [3], [5], [17].

Overall, this research establishes that GAN-based synthetic data generation represents a promising direction for balancing imbalanced cybersecurity datasets and supporting the development of robust intrusion detection systems. The proposed evaluation methodology provides an objective framework for assessing synthetic data quality, classifier performance, and cross-dataset robustness, thereby contributing to the advancement of intelligent cybersecurity research. The findings of this work also highlight the growing importance of adversarial learning techniques in enhancing minority attack detection and improving the practical deployment of AI-driven cybersecurity solutions in increasingly complex network environments [11], [15], [25].

7.2 Future Work

Although the proposed evaluation framework demonstrates the potential of GAN-based synthetic data generation for balancing cybersecurity datasets, several research opportunities remain for further investigation. First, future studies may explore more advanced generative models such as Conditional GAN (CGAN), Wasserstein GAN (WGAN), WGAN with Gradient Penalty (WGAN-GP), Auxiliary Classifier GAN (AC-GAN), and Conditional Tabular GAN (CTGAN) to generate higher-quality synthetic attack samples and improve minority class representation across diverse cybersecurity datasets [10], [13], [21].

Second, future research can investigate the integration of GAN-based synthetic data generation with emerging deep learning architectures, including Vision Transformers (ViT), Graph Neural Networks (GNNs), Graph Attention Networks (GATs), and Transformer-based intrusion detection models. Such hybrid architectures may further enhance feature representation, improve attack classification accuracy, and strengthen the detection of sophisticated cyber threats such as Advanced Persistent Threats (APTs), zero-day attacks, and polymorphic malware [16], [18], [23]. Another promising research direction involves extending the proposed evaluation framework to real-time intrusion detection systems deployed in cloud computing, Software-Defined Networking (SDN), Edge Computing, Industrial Internet of Things (IIoT), and Internet of Things (IoT) environments. Investigating online GAN training, adaptive synthetic data generation, and continuous learning mechanisms would enable intrusion detection systems to respond dynamically to evolving attack patterns while maintaining high detection performance under rapidly changing network conditions [3], [11], [17].

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