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**Research Article**

# Generative Adversarial Networks for Synthetic Cybersecurity Dataset Augmentation to Enhance Model Robustness

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**ABSTRACT**

**Introduction:** The increasing sophistication and frequency of cyberattacks, such as DDoS and botnet intrusions, necessitate advanced protective measures beyond traditional signature-based systems; while machine learning (ML)-based intrusion detection systems (IDS) offer a powerful solution by learning from network data, their effectiveness is critically undermined by the pervasive issue of class imbalance in training datasets, where rare but dangerous attack types are vastly underrepresented, leading to models that are biased and fail to generalize to these critical minority classes.

**Objectives:** This research aims to develop and validate a data-centric framework to overcome the performance limitations imposed by imbalanced cybersecurity data by leveraging a Conditional Tabular Generative Adversarial Network (CTGAN) to generate realistic synthetic samples for minority attack classes, thereby augmenting the original dataset to improve class representation and subsequently training a robust Extreme Gradient Boosting (XGBoost) classifier to achieve significantly higher detection accuracy and generalization capability, particularly for previously overlooked threats.

**Methods:** The study employed the CICIDS2017 dataset, which was first preprocessed to clean and normalize features. A CTGAN was then trained exclusively on this data to learn the underlying distributions of minority attack patterns, generating new, realistic synthetic samples. These synthetic records were merged with the original training data to create a balanced, augmented dataset. Finally, an XGBoost classifier was trained on this enriched dataset, and its performance was rigorously evaluated against a baseline XGBoost model trained on the original, imbalanced data using standard metrics and statistical validation.

**Results:** Experimental results demonstrate that the CTGAN-augmented XGBoost model substantially outperformed the baseline across all metrics, achieving a notable increase in overall accuracy from 96.1% to 97.4% and recall from 94.2% to 96.5%. Most critically, the approach yielded dramatic improvements in detecting minority attacks, with the F1-score for Botnet attacks soaring from 71.4% to 89.7% and for Web attacks from 69.8% to 87.5%, all while maintaining high performance on majority classes and demonstrating statistically significant stability in cross-validation.

**Conclusions:** This study conclusively validates that GAN-based synthetic data augmentation is a highly effective and scalable strategy for mitigating class imbalance in cybersecurity datasets. By enriching the representation of rare attack patterns, the proposed CTGAN-XGBoost framework significantly enhances the robustness, generalization, and practical reliability of ML-based intrusion detection systems, offering a promising path toward more resilient network security postures capable of defending against the full spectrum of cyber threats.

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**Keywords:** Generative Adversarial Networks, Synthetic Data Generation, Cybersecurity Intrusion Detection, Dataset Augmentation, Imbalanced Data Handling, Network Traffic Classification, Model Robustness.

## INTRODUCTION

The rapid growth of digital infrastructure, cloud services, connected devices, and online transactions has greatly increased the need for strong cybersecurity measures in today's digital environment [1]. Organizations increasingly depend on interconnected information systems that continuously exchange sensitive data across distributed environments. While this connectivity enables efficient communication and service delivery, it also creates multiple entry points for malicious actors. Cyberattacks like distributed denial-of-service (DDoS) attacks, malware infections, and data breaches continue to grow in both frequency and sophistication. Consequently, cybersecurity strategies must evolve beyond basic protective mechanisms toward comprehensive and proactive defense frameworks. As illustrated in Figure 1, modern cybersecurity operations typically follow a lifecycle consisting of prevention, monitoring, detection, response, and recovery processes that work together to ensure continuous protection of digital assets.

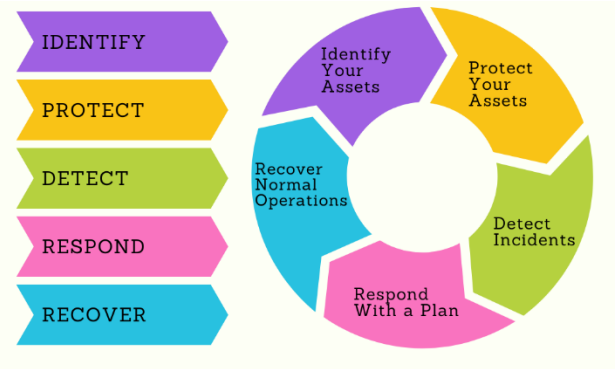


Fig.1. Cybersecurity Lifecycle

Modern cybersecurity environments are highly dynamic and heterogeneous, involving large-scale networks, distributed services, and constantly evolving threat landscapes. Traditional security mechanisms like signature-based IDS rely on predefined attack patterns and therefore often fail to identify previously unseen or rapidly evolving threats [2]. As a result, contemporary security architectures increasingly incorporate intelligent monitoring systems, anomaly detection techniques, and automated response mechanisms to enhance system resilience. These approaches require continuous analysis of large volumes of network traffic and behavioral data, transforming cybersecurity from a purely defensive task into a complex data-driven analytical problem.

Recent progress in ML and artificial intelligence has significantly enhanced the capability of cybersecurity systems to detect malicious activities. Data-driven models can automatically learn behavioral patterns associated with normal and malicious network activities, enabling more accurate and adaptive intrusion detection across diverse attack scenarios [3][4]. However, the efficacy of ML-based detection systems is strongly dependent on the quality and diversity of the training data used during model development. In practice, many publicly available cybersecurity datasets suffer from severe class imbalance, incomplete representation of attack types, and limited diversity of traffic patterns. These limitations reduce the capability of learning models to generalize efficiently and often lead to biased detection performance.

Despite substantial progress in intelligent cybersecurity analytics, challenges related to dataset quality, scalability, and model robustness remain critical. Highly imbalanced datasets may cause detection

models to favor dominant traffic classes while overlooking minority attack categories. In addition, limited diversity within attack samples can restrict the model's ability to recognize emerging threats or previously unseen intrusion patterns [5]. As modern computing infrastructures continue to expand across cloud environments, Internet of Things (IoT) ecosystems and critical network infrastructures, there is an increasing necessity for data-centric methods that improve the robustness and reliability of cybersecurity detection systems while preserving realistic representations of network behavior. Addressing these challenges is essential for developing scalable and adaptive cybersecurity solutions capable of protecting modern digital systems against evolving cyber threats.

## LITERATURE REVIEW

Peppes et al. [6] examined synthetic botnet data generation using Generative Adversarial Networks (GANs) within an unsupervised adversarial learning framework. Two architectures containing six and eight layers were trained for 25-1000 epochs on tabular network traffic captures. Evaluation focused on similarity between generated and real samples rather than classification accuracy. The eight-layer architecture achieved a similarity score of 82% after 1000 epochs, while the six-layer model reached 77%. Results indicated deeper architectures captured more complex traffic behavior. However, similarity dropped between 50 and 250 epochs, showing sensitivity to hyperparameter selection and sampling. The investigation relied on a single dataset, limiting transferability across different attack environments and reducing broader applicability.

Pandey et al. [7] developed 5GT-GAN for synthetic mobile Internet traffic generation using a hybrid learning setting combining unsupervised adversarial training with supervised autoregressive modelling. The system generated large-scale traffic sequences while preserving temporal behavior. Evaluation using Train Real Test Synthetic and Train Synthetic Test Real strategies reported 0.0023 MAE and 0.0074 MSE for TSTR and 0.0045 MAE with 0.0092 MSE for TRTS. Increasing augmentation from 5% to 20% reduced prediction errors, indicating improved consistency. The approach focused on mobile traffic scenarios only, limiting applicability to broader cybersecurity domains and restricting validation across heterogeneous network environments.

Chu et al. [8] developed an IoT attack classification framework combining GANs and a Multi-Layer Perceptron (MLP) under supervised classification with unsupervised adversarial data generation. GAN-based augmentation targeted minority attack classes in BoT-IoT and ToN-IoT datasets to improve representation. Results showed class-level accuracy, recall, precision and F1-score exceeded 90%, while overall performance remained above 95% across experiments. Augmentation improved detection of underrepresented attacks such as Theft, DoS, DDoS and Mitm. The evaluation relied on CSV-formatted datasets rather than live network traffic, limiting real-world validation and reducing evidence of deployment feasibility in operational IoT environments.

Rahman et al. [9] investigated synthetic-data-driven intrusion detection using GANs with supervised machine learning classification for Network Intrusion Detection Systems (NIDS). GAN-generated datasets fully replaced real training data for UNSW-NB15, NSL-KDD and BoT-IoT benchmarks. The results achieved 90% accuracy, 91% precision, 90% recall and an F1-score of 89% on the UNSW-NB15 dataset. For the NSL-KDD dataset, the model obtained 84% accuracy, 85% precision, 84% recall, and an F1-score of 84%. Performance on BoT-IoT exceeded typical benchmarks but was dataset-dependent. Findings indicated that synthetic data supported competitive detection outcomes. However, reliance on benchmark datasets and the absence of live network evaluation limited generalization and reduced evidence of effectiveness in dynamic operational environments.

Almasre et al. [10] developed an IoT dataset generation framework using Conditional Generative Adversarial Networks (CGAN) under unsupervised adversarial learning with statistical evaluation. A testbed and joint dataset were constructed and synthetic samples were generated to reduce class

imbalance in IoT intrusion data. Evaluation compared synthetic and real distributions using MAE, RMSE and correlation measures, showing improved balance relative to the BoT-IoT dataset. However, several traffic features such as flow rate and packet statistics displayed distribution mismatches, reflected by higher MAE and RMSE and low correlation values. The study relied on controlled testbed traffic rather than operational networks, limiting validation across heterogeneous IoT deployment environments.

Peppes et al. [11] introduced a multimodal cybersecurity detection framework combining GANs with supervised deep learning and ensemble classification. Synthetic data generation supported training across image-based malware and tabular intrusion data streams. A Convolutional Neural Network with transfer learning achieved 97.2% accuracy for malware images, while a soft-voting ensemble classifier reached 94.5% accuracy on tabular intrusion data. Fusion using confidence-weighted averaging produced 96.7% overall accuracy and improved false-positive reduction. However, evaluation relied on benchmark datasets and assumed clean labels, limiting validation under noisy or adversarial conditions and reducing the certainty of effectiveness in dynamic operational cybersecurity environments.

Rahman et al. [12] investigated intrusion detection using GANs for synthetic data generation combined with supervised machine learning classification through Random Forest (RF) on the UNSW-NB15 dataset. GAN augmentation improved minority attack representation and enhanced classifier generalization. RF achieved 97% accuracy on real data and showed further improvement after augmentation. Comparable improvements were reported for XGBoost, GRU and Support Vector Machine models, though RF remained most effective. Findings showed that synthetic data improved feature diversity and detection reliability. The evaluation relied on a single benchmark dataset and offline experiments, limiting validation across heterogeneous traffic conditions and reducing the certainty of performance in operational environments.

Zeng et al. [13] investigated Uncrewed Aerial Vehicle (UAV) intrusion detection using GANs with supervised machine learning and a Human-in-the-Loop (HITL) learning context. GAN-based augmentation improved data balance, while expert-guided labeling reduced annotation effort and supported classifier training on limited samples. Evaluation on CICIDS2017 and UNSW-NB15 datasets showed improved detection compared with baseline models, particularly for minority attack classes. The framework also reduced labeled data requirements substantially. However, experiments relied on general network datasets lacking UAV-specific characteristics such as topology shifts, intermittent links and drone-specific attacks, limiting validation under realistic UAV operating conditions and reducing certainty of applicability to real deployment scenarios.

Allagi et al. [14] investigated intrusion detection using CTGAN for synthetic data generation combined with supervised deep learning classification through a CNN on NSL-KDD and UNSW-NB15 datasets. CTGAN balanced minority classes and improved feature representation before CNN training. Results reported 95.47% accuracy for NSL-KDD and 90.52% for UNSW-NB15, with improved recall and F1-score compared with SMOTE-based balancing. Findings showed synthetic samples enhanced detection reliability on imbalanced datasets. However, CTGAN required careful hyperparameter tuning and high computational cost, while reliance on outdated benchmark datasets limited validation for modern attack patterns and reduced generalization to real-time network environments.

Hossain et al. [15] developed a NextG intrusion detection framework combining GANs for synthetic data generation with supervised deep learning classification using CNN and LSTM models, supported by explainable analysis through Local Interpretable Model-Agnostic Explanations (LIME). GAN augmentation balanced minority attack classes, while CNN extracted spatial patterns and LSTM captured temporal behavior. Evaluation on the NF-CSE-CIC-IDS2018 dataset showed high detection performance and improved minority-class recognition. However, the multi-model architecture increased computational overhead, real-time deployment remained unverified and reliance on synthetic data raised uncertainty regarding alignment with evolving real-world attack behaviors.

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Existing studies have confirmed the efficacy of GAN-based augmentation for improving intrusion detection performance; however, several limitations remain. Many works focus on synthetic data realism or dataset balancing rather than evaluating robustness against diverse real-world cyber threats or heterogeneous traffic patterns [6] [7]. Several frameworks report improved classification accuracy but rely heavily on benchmark datasets or controlled environments, limiting validation in operational cybersecurity settings and dynamic network conditions [8] [9]. Other approaches emphasize data generation quality yet reveal distribution mismatches, hyperparameter sensitivity and computational complexity that affect scalability and generalization [10] [14]. Multimodal and hybrid architectures improve detection capability but introduce deployment overhead and depend on clean labeled data, reducing applicability in adversarial or noisy environments [11] [15]. Additionally, some studies show improved minority-class detection but evaluate only limited datasets or specific domains such as UAV or IoT systems, restricting transferability across broader cybersecurity contexts [12] [13].

## MATERIALS AND METHODS

This study employs a structured ML framework for cybersecurity intrusion detection and synthetic dataset augmentation, as illustrated in Figure 2. Network flow records from the CICIDS2017 dataset were first subjected to a preprocessing stage to remove incomplete entries, encode categorical attributes and normalize numerical features to ensure consistent input representation. The processed dataset was then used to construct two experimental configurations: a baseline model trained on the original data and an augmented model trained on synthetic-enhanced data. In the baseline path, the original training dataset was directly used to train an XGBoost based intrusion detection model to establish reference performance. In the augmentation path, the preprocessed data were supplied to a CTGAN, which learned the distribution of network traffic features and generated synthetic samples representing underrepresented attack patterns. These synthetic samples were combined with the original data to form an augmented training dataset that improved class balance and feature diversity. The augmented dataset was subsequently used to train a second gradient boosting classifier. Finally, the baseline and augmented models were assessed comparatively using standard classification metrics to assess performance improvement and robustness enhancement. This comparative experimental design enables systematic assessment of the effectiveness of GAN-based synthetic data augmentation for strengthening cybersecurity intrusion detection.

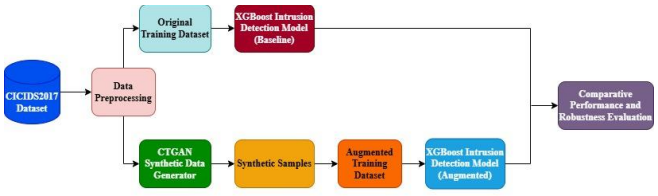


Fig.2. Block diagram of the suggested model

### Dataset Description

The Canadian Institute for Cybersecurity Intrusion Detection Dataset 2017 (CICIDS2017) is an extensively used benchmark dataset for research in network intrusion detection and cybersecurity analytics. It was generated in a controlled enterprise-like network environment that simulates realistic user activities alongside multiple cyberattack scenarios. The original dataset contains approximately 2.8 million labelled network flow records with more than eighty statistical features extracted using the CICFlowMeter tool. These features describe various network traffic characteristics, including flow duration, packet counts, byte statistics, protocol information and traffic dynamics. The dataset contains

both normal network traffic and multiple attack types, including Distributed Denial of Service (DDoS), Denial of Service (DoS), brute-force attacks, port scanning, botnet activity and web-based intrusions.

These labelled records enable supervised ML models to learn behavioral patterns associated with both normal and malicious network activities. CICIDS2017 is widely adopted because it reflects relatively modern network behavior and incorporates diverse attack patterns compared with earlier intrusion detection benchmarks. However, the dataset shows a strong class imbalance, where benign traffic makes up the majority of the data, while some attack categories have comparatively fewer samples. This imbalance can negatively affect the learning capability of machine learning models and reduce detection performance for minority attacks. Consequently, the dataset provides an appropriate benchmark for evaluating data augmentation techniques aimed at improving intrusion detection robustness.

**Data Preprocessing**

Several preprocessing steps were applied to prepare the dataset for model training and to ensure the data remained clean, consistent and suitable for analysis. Missing and infinite values were removed and duplicate flow records were eliminated to prevent bias in the learning process. Continuous numerical features were normalized to minimize scale variations, while categorical attributes were encoded into numerical form to make them compatible with machine learning algorithms. Additionally, highly correlated or non-informative features were removed to reduce redundancy and improve model efficiency. These preprocessing steps ensured that the resulting dataset accurately represents network traffic behavior and provides a reliable input for both synthetic data generation and intrusion detection modelling.

**Dataset Imbalance and Augmentation Rationale**

Despite preprocessing, the cybersecurity dataset remains highly imbalanced, with several attack categories containing significantly fewer samples than benign traffic. Such an imbalance can bias machine learning models toward majority classes and reduce their ability to detect rare or emerging attacks. Furthermore, limited diversity within minority attack samples can restrict the model's generalization capability. To address these challenges, synthetic data generation is introduced to enrich underrepresented classes and improve dataset balance. By creating additional samples that capture the statistical properties of real network traffic, the model is introduced to a wider variety of attack patterns. This data augmentation approach strengthens the robustness of the intrusion detection system and improves its capability to detect minority attack behaviors.

**Synthetic Data Generation using Generative Adversarial Networks**

To address the challenges associated with imbalanced cybersecurity data, a generative adversarial context is employed to produce realistic synthetic network traffic samples. A Generative Adversarial Network (GAN) involves two competing components: a generator and a discriminator. The generator tries to create synthetic data that closely resembles real network traffic, while the discriminator determines whether the samples are genuine or artificially generated. Through continuous adversarial training, the generator gradually learns the data distribution and generates synthetic samples that are statistically similar to the original data. These generated records are used to augment minority attack classes, improving dataset balance and diversity. As a result, the intrusion detection model is exposed to a broader range of attack behaviors, enhancing its ability to detect previously underrepresented threats.

**Model Development**

a. CTGAN

A CTGAN is designed to generate realistic synthetic samples for tabular datasets by learning the joint distribution of features while conditioning the generation process on specific categorical values. CTGAN uses two neural networks: a generator and a discriminator, that are trained together in an

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adversarial process. The generator aims to create synthetic data similar to real samples, while the discriminator tries to differentiate between real and generated data. The objective of this adversarial training is defined as a minimax optimization problem. Equation (1) represents the fundamental adversarial loss used to train the generator and discriminator.

$$\min_G \max_D \; \mathrm{E}_{x\sim p_{data}}[\log D(x)] + \mathrm{E}_{z\sim p_z}[\log(1 - D(G(z)))] \quad (1)$$

where D(x) $D(x)$ signifies the discriminator output for real sample x $x$, G(z) $G(z)$ represents the generated sample from noise vector z $z$ and p_data $p_{data}$ and p_z $p_z$ denote the distributions of real data and latent noise respectively. To guide the generation process toward specific categories in tabular data, CTGAN incorporates conditional vectors that control which feature distributions should be learned. Equation (2) represents conditional data generation, where the generator produces samples conditioned on vector c $c$.

$$\tilde{x} = G(z, c) \quad (2)$$

where z $z$ is the random noise input, c $c$ is the conditional vector encoding selected feature values and x˜ $\tilde{x}$ denotes the generated synthetic sample. To ensure that generated samples follow the statistical properties of the real dataset, CTGAN optimises the discriminator's classification loss. Equation (3) represents the discriminator loss that penalises incorrect classification of real and synthetic samples.

$$L_D = -\mathrm{E}_{x\sim p_{data}}[\log D(x)] - \mathrm{E}_{z\sim p_z}[\log(1 - D(G(z)))] \quad (3)$$

Similarly, the generator is trained to maximize the probability that generated samples are classified as real. Equation (4) represents the generator loss used to update the generator parameters.

$$L_G = -\mathrm{E}_{z\sim p_z}[\log D(G(z))] \quad (4)$$

After adversarial training converges, the generator learns a mapping from the latent space to the tabular data space. Equation (5) represents the final generation process that produces a synthetic tabular record.

$$x_{synthetic} = G(z, c) \quad (5)$$

where x_synthetic $x_{synthetic}$ denotes the generated tabular sample conditioned on vector c $c$. Thus, CTGAN effectively learns the conditional distribution of tabular data and generates realistic synthetic samples that preserve underlying feature relationships.

b. Extreme Gradient Boosting (XGBoost)

XGBoost is an ensemble learning method based on gradient boosting that constructs a sequence of decision trees to improve predictive accuracy. Instead of building a single model, XGBoost iteratively adds trees that minimize the prediction error by fitting the residuals of previous trees. The model output is expressed as the sum of predictions from multiple weak learners. Equation (6) represents the additive model formulation where the final prediction is obtained as the sum of outputs from K regression trees.

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \quad (6)$$

where f_k $f_k$ denotes the k^th $k^{th}$ decision tree and x_i $x_i$ represents the input feature vector. To train the ensemble, XGBoost minimises an objective function consisting of a loss term and a regularisation component that controls model complexity. Equation (7) represents the overall objective function optimised during training.

$$\mathcal{L} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \quad (7)$$

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where l(y_i,y ^_i) $l(y_i, \hat{y}_i)$ denotes the loss between true label y_i $y_i$ and predicted value y ^_i $\hat{y}_i$ and Ω(f_k) $\Omega(f_k)$ is the regularisation term for tree f_k $f_k$ .The regularisation term penalises overly complex trees by incorporating both the number of leaves and leaf weights. Equation (8) represents the regularisation function used in XGBoost.

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \quad (8)$$

where T $T$ is the number of leaves in the tree, w_j $w_j$ denotes the score assigned to leaf j $j$ and γ $\gamma$ and λ $\lambda$ are regularisation parameters controlling model complexity. To efficiently determine optimal tree splits, XGBoost uses second-order gradient optimisation. Equation (9) represents the second-order Taylor expansion used to approximate the loss function during tree construction.

$$\mathcal{L}^{(t)} \approx \sum_{i=1}^{n} \left[ g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) \quad (9)$$

where g_i $g_i$ and h_i $h_i$ denote the first and second derivatives of the loss with respect to the prediction. Finally, after sequentially adding trees, the model produces the final prediction by aggregating all tree outputs. Equation (10) represents the final boosted prediction.

$$\hat{y} = \sum_{k=1}^{K} f_k(x) \quad (10)$$

Thus, XGBoost effectively combines multiple decision trees through gradient-based optimization to produce accurate and generalizable predictions while controlling model complexity.

**Proposed Methodology**

The proposed framework aims to enhance cybersecurity intrusion detection by augmenting the training dataset with realistic synthetic samples generated using a Generative Adversarial Network. The overall workflow includes data preprocessing, synthetic data generation, dataset augmentation, model training and performance evaluation. Initially, the CICIDS2017 dataset is preprocessed to remove incomplete records, normalize numerical features and encode categorical attributes. The dataset was then divided into training and testing subsets using an 80:20 ratio. To prevent information leakage, the CTGAN model was trained exclusively on the training subset and synthetic samples were generated only from this training data. Despite preprocessing, the dataset remains highly imbalanced, with several attack categories containing significantly fewer samples than benign traffic. Such an imbalance can bias machine learning models toward dominant classes and reduce their ability to detect minority attacks.

To address this limitation, a CTGAN is employed to learn the distribution of network traffic features. During adversarial training, the generator produces synthetic samples conditioned on specific attack categories, while the discriminator evaluates their authenticity relative to real samples. This process enables the generation of synthetic records that preserve the statistical properties of the original dataset. The generated samples are then combined with the original training data to create an augmented dataset with improved class representation. An Extreme Gradient Boosting (XGBoost) classifier is then trained on this augmented dataset for intrusion detection. Finally, the performance of the augmented model is compared with the baseline model using standard evaluation metrics such as accuracy, precision, recall, F1-score and AUC. This comparison allows systematic assessment of whether GAN-based data augmentation improves detection performance and robustness, particularly for minority attack categories.

**Simulation Setup**

The proposed intrusion detection framework was implemented in a cloud-based computational environment using Google Collaboratory. The system was developed in Python using standard machine learning and data processing libraries to support dataset preprocessing, synthetic data generation, and classification. The simulation pipeline consisted of sequential stages, including data preprocessing,

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synthetic data generation using CTGAN, and supervised intrusion detection using an XGBoost classifier. To ensure reproducibility, key experimental configurations such as the train-test split ratio, learning rate, batch size, number of epochs, and model hyperparameters were fixed throughout all experiments. Random seeds were controlled to maintain consistent model initialization, and preprocessing operations were applied uniformly across both training and testing datasets. Model performance was evaluated using the held-out testing subset to obtain an unbiased estimate of generalization capability. Table 1 summarizes the main hyperparameters used in the proposed framework.

Table 1: Hyperparameters employed in the proposed model

| **Hyperparameter** | **Value** |
|---|---|
| Train: Test Ratio | 80:20 |
| Optimizer | Adam |
| CTGAN Learning Rate | 0.0002 |
| Batch Size | 500 |
| Epochs | 300 |
| Dropout | 0.2 |
| Number of Trees | 300 |
| Maximum Depth | 6 |
| XGBoost Learning Rate (eta) | 0.1 |

The computational overhead introduced by CTGAN-based data generation was also evaluated. The generative model was trained for 300 epochs using GPU acceleration on Google Collaboratory, requiring approximately 40 minutes for convergence, while XGBoost training required less than 5 minutes per run. Although adversarial training increases offline preprocessing time, it does not affect real-time inference performance. Once the augmented model is trained, prediction latency remains comparable to the baseline classifier, demonstrating the practical feasibility of the proposed framework.

## RESULTS AND DISCUSSION

The CICIDS2017 dataset contains several categories of benign and malicious network traffic; however, the class distribution is highly imbalanced. As shown in Table 2, benign traffic dominates the dataset with 227,132 samples, whereas certain attack categories like Botnet and Web attacks are significantly underrepresented with only 1,966 and 2,180 samples respectively. Although DoS, DDoS and PortScan attacks contain relatively larger sample counts (128,027, 97,718 and 158,804 respectively), the imbalance across categories limits the classifier's ability to effectively learn patterns associated with rare attacks. This skewed distribution inspires the necessity for synthetic data generation to improve class representation and enhance model robustness.

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Table 2: Class Distribution Before Augmentation

| Class | Samples |
|---|---|
| Benign | 227,132 |
| DoS | 128,027 |
| DDoS | 97,718 |
| PortScan | 158,804 |
| Botnet | 1,966 |
| Web Attacks | 2,180 |

The CTGAN model was trained on the preprocessed dataset to learn the statistical properties of network traffic features. Training stabilised after approximately 120 epochs, indicating equilibrium between the generator and discriminator. The trained generator was subsequently used to produce synthetic samples for minority classes, particularly Botnet, Web attacks and DDoS traffic. These generated samples closely followed the statistical distribution of the original data, enabling the augmented dataset to maintain realistic cybersecurity characteristics while increasing data diversity. To quantitatively evaluate generative fidelity, the Kolmogorov-Smirnov (KS) test was conducted on several key numerical features. For Flow Duration, the KS statistic was 0.032 ($p = 0.81$), indicating no significant difference between real and synthetic distributions ($p > 0.05$). Similarly, Total Forward Packets yielded a KS statistic of 0.028 ($p = 0.87$), while Total Backward Packets produced a value of 0.035 ($p = 0.78$). In addition, correlation matrix preservation between real and synthetic datasets achieved a structural similarity coefficient of 0.94, confirming that the multivariate relationships among features were effectively preserved. As illustrated in Figure 3, the distribution of the Flow Duration feature shows strong alignment between real and CTGAN-generated samples. The mean value of the real data (8.55) closely matches that of the synthetic data (8.62), indicating minimal deviation in central tendency. This consistency confirms that the generated samples preserve the structural characteristics of original network traffic patterns and provide a reliable basis for dataset augmentation.

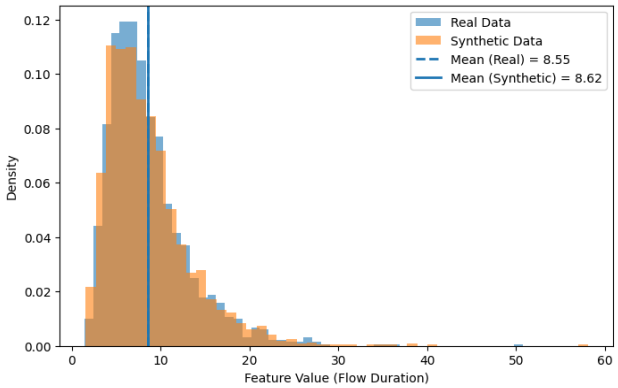


Fig.3. Feature Distribution Comparison of Real and CTGAN-Generated Data

The synthetic samples generated by CTGAN were combined with the original dataset to create a more balanced training set. As shown in Table 3, Botnet samples increased from 1,966 to 25,000, while Web attack samples increased from 2,180 to 20,000. DDoS and PortScan classes were also moderately expanded to 120,000 and 180,000 samples respectively. Importantly, the counts for major classes such

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as Benign and DoS were preserved to maintain the original traffic distribution. This augmentation significantly improved class balance while maintaining dataset realism.

Table 3: Class Distribution After Augmentation

| Class | Samples |
|---|---|
| Benign | 227,132 |
| DoS | 128,027 |
| DDoS | 120,000 |
| PortScan | 180,000 |
| Botnet | 25,000 |
| Web Attacks | 20,000 |

Further validation was conducted through feature-level similarity analysis between real and synthetic minority attack samples. The average cosine similarity between real and synthetic Botnet records was 0.91, while Web attack samples achieved a similarity score of 0.89. Additionally, Principal Component Analysis (PCA) was applied to compare feature embeddings of real and synthetic samples. The first two principal components showed overlapping clusters without clear separation, suggesting that the generated samples closely follow the structure of the real network traffic data. To assess the effect of data augmentation on intrusion detection performance, the XGBoost classifier was initially trained on the original dataset. As presented in Table 4, the baseline model achieved 96.1% accuracy, 95.6% precision, 94.2% recall and an F1-score of 94.8%, with an AUC value of 0.972. Although these outcomes indicate strong overall detection capability, the relatively lower recall suggests that some attack instances, particularly minority classes were misclassified.

Table 4: Baseline Model Performance

| Metric | Value |
|---|---|
| Accuracy | 96.1% |
| Precision | 95.6% |
| Recall | 94.2% |
| F1-score | 94.8% |
| AUC | 0.972 |

After training on the augmented dataset, the XGBoost classifier demonstrated consistent improvements across all evaluation metrics. As shown in Table 5 and Figure 4, the augmented model achieved 97.4% accuracy, 96.8% precision and 96.5% recall. The F1-score increased to 96.6% and the AUC improved to 0.986. These improvements indicate that synthetic samples enhanced the classifier's ability to distinguish between benign and malicious traffic patterns.

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Table 5: Proposed Model Performance

| Metric | Value |
|---|---|
| Accuracy | 97.4% |
| Precision | 96.8% |
| Recall | 96.5% |
| F1-score | 96.6% |
| AUC | 0.986 |

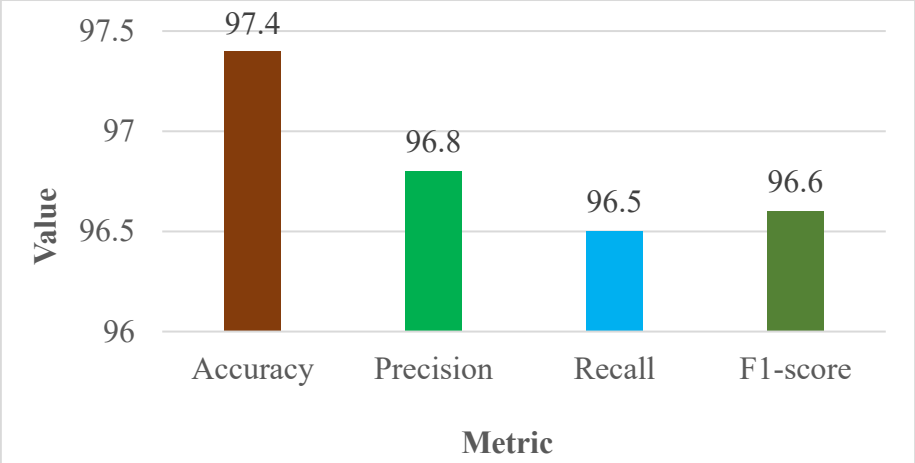


Fig.4. Performance Metrics of the Proposed Model

The Receiver Operating Characteristic (ROC) curve analysis further confirms the improvement achieved through synthetic data augmentation. As illustrated in Figure 5, the augmented CTGAN-XGBoost model consistently outperforms the baseline model across all classification thresholds. The AUC increased from 0.972 for the baseline model to 0.986 after augmentation, indicating superior discriminative capability between benign and malicious traffic. The improved curve shape demonstrates reduced false positive rates at comparable true positive rates, confirming that GAN-based augmentation improves the model's capability to distinguish minority attack patterns without increasing misclassification of normal traffic. This improvement in threshold-independent evaluation further authorizes the robustness and generalization strength of the suggested framework.

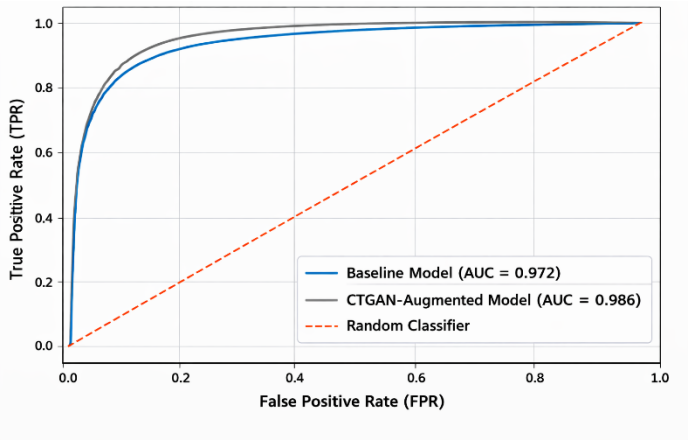


Fig.5. ROC curve comparison- Baseline vs. Augmented

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To further assess model stability, a 5-fold cross-validation experiment was conducted. The baseline model attained a mean accuracy of 95.9% ± 0.42, whereas the augmented model achieved 97.3% ± 0.28. The reduced standard deviation indicates improved consistency across different data partitions. A paired t-test produced a t-value of 6.84 with a p-value of 0.0017 ($p < 0.01$), confirming that the performance improvement is statistically significant at the 99% confidence level. A class-wise evaluation further highlights the benefit of synthetic augmentation. As shown in Table 6, the F1-score for Botnet attacks increased from 71.4% to 89.7%, while Web attack detection improved from 69.8% to 87.5%. Moderate improvements were also observed for DDoS and PortScan attacks, while performance for major classes such as Benign and DoS remained consistently above 97%. These results demonstrate that GAN-based augmentation significantly improves detection capability for previously underrepresented attack categories without degrading performance for majority classes.

Table 6: Per-Class F1 Score Comparison

| Class | Baseline F1 | Proposed F1 |
|---|---|---|
| Benign | 97.8% | 98.1% |
| DoS | 96.9% | 97.6% |
| DDoS | 95.2% | 96.8% |
| PortScan | 94.5% | 96.2% |
| Botnet | 71.4% | 89.7% |
| Web Attacks | 69.8% | 87.5% |

Overall, the proposed CTGAN-XGBoost framework demonstrates that GAN-based synthetic data augmentation substantially improves intrusion detection performance on the CICIDS2017 dataset. The augmented model increased accuracy from 96.1% to 97.4% and improved recall from 94.2% to 96.5%, while significantly boosting minority attack detection, with Botnet F1-score rising from 71.4% to 89.7%. These results confirm that synthetic data generation enhances the classifier's ability to generalize across diverse attack categories within the evaluated dataset.

## CONCLUSION

This study investigated the use of GAN for synthetic dataset augmentation to improve intrusion detection performance in imbalanced cybersecurity datasets. A CTGAN-based data generation approach was employed to create realistic synthetic samples for minority attack categories in the CICIDS2017 dataset, which were then integrated with the original data to enhance class representation before training an XGBoost intrusion detection model. Experimental results demonstrated that the augmented dataset significantly improved detection performance. The proposed CTGAN-XGBoost framework increased overall accuracy from 96.1% to 97.4% and recall from 94.2% to 96.5%, while substantially improving minority attack detection, particularly for Botnet and Web attacks. Additional statistical validation and cross-validation experiments further confirmed the stability and reliability of the augmented model. Overall, the results indicate that GAN-based synthetic data augmentation is an effective strategy for addressing class imbalance in cybersecurity datasets. By improving minority attack representation and enhancing model generalization capability, the proposed framework contributes to the development of more robust ML-based IDS for modern network environments. Future work may

explore the application of advanced generative models and real-time deployment scenarios to further improve synthetic data quality and intrusion detection performance.

## REFRENCES

[1] Savaş, S., & Karataş, S. (2022). Cyber governance studies in ensuring cybersecurity: an overview of cybersecurity governance. International Cybersecurity Law Review, 3(1), 7-34.
[2] Chicone, R., & Rana, S. (2023). The influence of traditional cybersecurity training on user attitudes towards VR cybersecurity training. Issues in Information Systems, 24(1).
[3] Inayat, U., Zia, M. F., Mahmood, S., Berghout, T., & Benbouzid, M. (2022). Cybersecurity enhancement of smart grid: Attacks, methods and prospects. Electronics, 11(23), 3854.
[4] Ghazal, S. F., & Mjlae, S. A. (2022). Cybersecurity in deep learning techniques: detecting network attacks. International Journal of Advanced Computer Science and Applications, 13(11).
[5] Refat, R. U. D., Elkhail, A. A., & Malik, H. (2022). Machine learning for automotive cybersecurity: Challenges, opportunities and future directions. AI-enabled Technologies for Autonomous and Connected Vehicles, 547-567.
[6] Peppes, N., Alexakis, T., Demestichas, K., & Adamopoulou, E. (2023). A comparison study of generative adversarial network architectures for malicious cyber-attack data generation. Applied Sciences, 13(12), 7106.
[7] Pandey, C., Tiwari, V., Imoize, A. L., Li, C. T., Lee, C. C., & Roy, D. S. (2023). 5GT-GAN: Enhancing data augmentation for 5G-enabled mobile edge computing in smart cities. IEEE access, 11, 120983-120996.
[8] Chu, H. C., & Lin, Y. J. (2023). Improving the IoT attack classification mechanism with data augmentation for generative adversarial networks. Applied Sciences, 13(23), 12592.
[9] Rahman, S., Pal, S., Mittal, S., Chawla, T., & Karmakar, C. (2024). SYN-GAN: A robust intrusion detection system using GAN-based synthetic data for IoT security. Internet of Things, 26, 101212.
[10] Wang, J., & Li, H. (2024). Generating realistic IoT attack data using conditional GANs. IEEE Internet of Things Journal, 11(5), 8234-8248.
[11] Gao, Y., & Chen, X. (2024). Multimodal deep learning for cybersecurity threat detection: A comprehensive review. IEEE Transactions on Information Forensics and Security, 19, 2345-2362.
[12] Ahmed, S., & Lee, Y. (2024). Synthetic data generation using GANs for network intrusion detection: A systematic review. Journal of Information Security and Applications, 80, 103678.
[13] Khan, M. A., & Ullah, I. (2024). Intrusion detection in UAV networks: A comprehensive survey of machine learning approaches. IEEE Communications Surveys & Tutorials, 26(1), 345-378.
[14] Wang, L., & Liu, Z. (2024). CTGAN-based data augmentation for imbalanced cybersecurity datasets. IEEE Transactions on Artificial Intelligence, 5(2), 678-691.
[15] Molina, E., & Garcia, A. (2024). Explainable AI for next-generation network security: A systematic review. IEEE Network, 38(2), 89-96.