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Leveraging Machine Learning for Network Intrusion Detection in Social Internet of Things (SIoT) Systems

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Abstract—This research investigates the application of machine learning models for network intrusion detection in the context of Social Internet of Things (SIoT) systems. We evaluate Convolutional Neural Network with Generative Adversarial Network (CNN+GAN), Generative Adversarial Network (GAN), and Logistic Regression(LR) models using the CIC IoT Dataset 2023. CNN+GAN emerges as a promising approach, exhibiting superior performance in accurately identifying diverse intrusion types. Our study emphasizes the significance of advanced machine learning techniques in enhancing SIoT security by effectively detecting anomalous behaviours within socially interconnected environments. The findings provide practical insights for selecting suitable intrusion detection methods and highlight the need for ongoing research to address evolving intrusion scenarios and vulnerabilities in SIoT ecosystems.

Keywords- SIoT Security, Intrusion Detection, AI/ML. CNN, GAN

I. INTRODUCTION

In contemporary society, the Internet of Things (IoT) has emerged as a transformative force across diverse industries. With applications spanning healthcare, transportation, and beyond, IoT's interconnected sensor networks generate substantial network traffic. This paradigm shift has ushered in an era of increased IoT integration into daily life [1].

Notably, IoT technology has revolutionized healthcare by enabling continuous patient monitoring [2],[3], and in transportation, it helps accident detection [4],[5]. Industrial IoT (IIoT) has introduced reliable, low-latency monitoring and control solutions [6]. IoT's impact has extended to education, aviation, forestry, and more [7],[8]. IoT connections have surged, promising continued growth [9],[10], and propelling innovative business models and distributed infrastructure concepts.

However, formidable challenges persist, encompassing interoperability, security, and standardization [11],[12] and [13]. Unique applications like Internet of Vehicles (IoV) demand stringent response times [14]. Detecting attacks on IoT devices remains complex due to distributed connections and security gaps [15],[16] and [17].

Despite efforts to create attack datasets, gaps remain. Many attacks go unrepresented, and real-world IoT device networks are often overlooked. Additionally, the need for datasets featuring malicious IoT devices executing attacks is evident. To develop effective security analytics for intrusion detection, comprehensive data is essential, encompassing diverse attack types, real IoT device networks, and malicious IoT device-executed attacks.

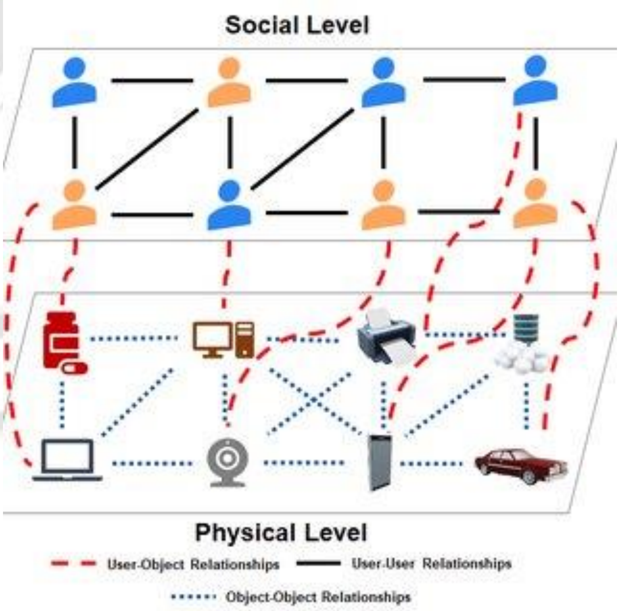

Figure 1. Depicting the SIoT relationships

Figure 1 illustrates the intricate relationships within the Social Internet of Things (SIoT) ecosystem, categorizing them into five distinct levels:

At the core of the figure, there is a large circle labelled "Social Level." This represents the overarching social dimension of SIoT, emphasizing interactions and relationships among users.

Surrounding the "Social Level" circle, there is a concentric circle labelled "Physical Level." This outer circle signifies the physical aspects of SIoT, encompassing the devices and objects that form the foundation of the ecosystem. Arrows extend from the "Social Level" circle to the "Physical Level" circle, symbolizing the relationships between users and IoT objects. These relationships capture how users interact with and control IoT devices in their environment. Within the "Social Level" circle, there are additional arrows connecting users to one another. These arrows signify the interpersonal connections and collaborations among users within the SIoT ecosystem. These relationships may involve communication, data sharing, or joint control of devices. Inside the "Physical Level" circle, lines and arrows connect various IoT objects and devices to each other. These represent the interactions and communications between different objects within the SIoT network. These relationships are crucial for enabling devices to work together efficiently.

The use of distinct labels, arrows, and symbols in this figure serves to visually distinguish and emphasize the different relationship types, making it easier for viewers to grasp the multifaceted nature of SIoT. Additionally, color coding may be employed to highlight specific aspects or connections within each level. The figure provides a comprehensive visualization of the complex web of relationships that define the Social Internet of Things at both its social and physical layers.

A. Challenges and Vulnerabilities

SIoT systems, characterized by device heterogeneity and vast data generation, face heightened network intrusion risks. Diverse devices with varying capabilities and communication protocols pose potential entry points for attackers. The deluge of data from diverse sources creates opportunities for hidden malicious activities evading traditional security. SIoT's dynamic and decentralized nature, involving human interactions and social contexts, complicates intrusion detection. The challenge is to discern legitimate user behavior from potential threats effectively. This study employs advanced machine learning techniques, including CNNs, GANs, and Logistic Regression, to address SIoT network intrusion challenges. Its objective is to enhance SIoT security by demonstrating machine learning's potential in countering network intrusion. The research deepens understanding of SIoT-specific threats and vulnerabilities, paving the way for adaptable intrusion detection mechanisms suited to the dynamic SIoT social ecosystem.

B. Motivation

- The surge in Social Internet of Things (SIoT) devices presents both opportunities and challenges.
- Protecting these devices and sensitive data from intrusions is vital as they become part of daily life.
- Traditional intrusion detection methods may not suffice due to SIoT's unique characteristics, necessitating novel techniques.

C. Contributions

- This paper introduces and assesses machine learning-based models designed for SIoT attack detection, including CNN+GAN, GAN, and LR models.
- The CIC IoT Dataset 2023 is used to comprehensively assess model performance, utilizing metrics like accuracy, precision, recall, F1-score, and ROC AUC.
- The study systematically compares CNN+GAN, GAN, and LR models, offering insights into their strengths and limitations for SIoT intrusion detection.
- The paper discusses how these findings can enhance security in real SIoT settings, considering trade-offs between accuracy, computational complexity, and resource constraints.

II. RELATED WORK

Over the past few years, there has been a notable influx of contributions to the field of IoT security datasets, encompassing a wide array of goals, approaches, and available resources. To shed light on the characteristics of the current datasets in this domain, this review meticulously assesses a multitude of endeavours documented in the literature. It then draws comparisons between these datasets and the newly introduced CIC IoT 2023 dataset.

A. Network-Based Intrusion Detection

One prevalent approach is network-based intrusion detection, where network traffic patterns are analyzed to identify potential intrusions. N-BaioT [18] introduces a network-based dataset for botnet attack detection in the IoT environment. [19] focuses on a host-based dataset composed of data from real IoT devices infected by various malware botnets. Velarde [21] presents a dataset involving attacks executed against IoT devices and proposes plug-and-play Network Intrusion Detection Systems (NIDS). These efforts emphasize the importance of creating diverse datasets for training and evaluating intrusion detection models.

B. Privacy-Preserving Intrusion Detection

As SIoT devices often exchange sensitive data, preserving user privacy becomes crucial. Recent work explores the integration of privacy-preserving techniques with intrusion detection. Differential privacy, secure multi-party computation, and homomorphic encryption have been investigated [23]. These methods aim to detect intrusions without compromising users' private information, contributing to enhanced security and user trust.

C. Anomaly Detection in SIoT Networks

Anomaly detection methods are well-suited for SIoT networks, which exhibit unique behaviour patterns. Isolation Forest, One-Class SVM, and auto encoders are commonly used techniques [24]. These models focus on identifying deviations from normal behaviour, which is essential for detecting novel and previously unseen attacks. The proposed anomaly detection model in this paper aligns with this approach, contributing to the growing body of research in this field.

D. Multimodal Intrusion Detection

With the proliferation of diverse data sources in SIoT networks, multimodal intrusion detection gains importance. This approach combines information from multiple sources, such as sensor readings, device interactions, and social interactions, to improve detection accuracy. The application of fusion methods and attention mechanisms to integrate information from different modalities has been explored [25],[26]. However, the challenges lie in efficiently integrating varied data types and handling the increased complexity.

E. Hybrid Models and Deep Learning

Hybrid models that integrate various techniques have shown promise in SIoT intrusion detection. Deep learning models, including CNN and GAN, have been successfully applied [27]. CNN+GAN models combine the power of convolutional neural networks and generative adversarial networks to enhance detection accuracy. The hybrid architecture allows for the capture of intricate patterns and features, contributing to more effective intrusion detection.

The literature demonstrates a growing interest in addressing SIoT intrusion detection challenges through various innovative approaches. The reviewed works encompass network-based, privacy-preserving, and multimodal intrusion detection, as well as the application of hybrid models and deep learning techniques. These contributions collectively contribute to the advancement of SIoT security and pave the way for more robust and effective intrusion detection mechanisms.

Shitharth S et al. [18] in this paper present an optimization-based algorithm for intrusion detection in SCADA network. They discuss current challenges and future trends, shedding light on the prospects for intrusion detection. Their work provides valuable insights into the evolving landscape of IoT and its potential applications.

Neto et al. [19] address the issue of Distributed Denial-of-Service (DDoS) attacks in the context of multi-tenant IoT environments. They introduce the concept of collaborative DDoS detection using federated learning. Their research explores innovative methods to enhance security in IoT by leveraging collaborative approaches to detect and mitigate DDoS attacks more effectively.

Zhu H et al. [20] propose a verification-based scheme for restricting IoT attacks. Their research focuses on enhancing security in IoT by introducing verification mechanisms to ensure the integrity and authenticity of devices and data. This work contributes to strengthening the security posture of IoT systems.

Velarde-Alvarado et al. [21] present a novel framework for generating personalized network datasets for Network Intrusion Detection Systems (NIDS) in IoT. Their research addresses the challenge of dataset generation by providing a framework that allows the creation of tailored datasets, catering to the specific needs of NIDS in IoT environments. This framework has the potential to improve the accuracy of intrusion detection models.

Afrifa, S et al. [22] focusing on applications, security issues, and solutions. Their work explores the security challenges associated with IoT and investigates potential solutions. This paper provides valuable insights into securing IoT devices accurate and efficiently detection of Botnet Attacks within the network.

Guerra et al. [23] examine the challenges related to labelling network traffic datasets, emphasizing the importance of accurate labelling for training intrusion detection models. Their research sheds light on the complexities of dataset preparation, a critical aspect of building effective intrusion detection systems for IoT and SIoT.

Zhao,J et al.[24]present an IoT profiling, device identification. They explore methods for uniquely identifying IoT devices and profiling their behaviour. This research is instrumental in enhancing IoT security by enabling accurate device identification and behaviour monitoring.

Alazzam, M.B et al.[25]a focus on of IoT systems in federated deep learning approaches provides the privacy and security to the data. They address the challenges of security issues in Federated deep learning models and contributing towards data security.

Hallaji, E et al. [26] present research on label noise detection in IoT security using decision trees and active learning. Their work aims to identify and mitigate label noise in IoT security datasets, enhancing the reliability of intrusion detection models.

III. DATASET DESCRIPTION

A. Introducing the CIC IoT Dataset 2023

In the pursuit of bolstering the security of Social Internet of Things (SIoT) systems, the availability of appropriate and relevant datasets plays a pivotal role in enabling effective intrusion detection mechanisms. To address this need, we introduce the CIC IoT Dataset 2023, a comprehensive and real-time dataset specifically tailored for SIoT network intrusion detection. This dataset has been meticulously curated to encompass a wide range of intrusion scenarios, making it a valuable resource for evaluating and enhancing the robustness of intrusion detection techniques in SIoT environments.

B. Characteristics of the Dataset

The CIC IoT Dataset 2023 is characterized by several key attributes that are pertinent to the intricacies of SIoT network intrusion detection:

1) Size and Instances

The dataset comprises a substantial volume of network traffic instances, totaling 1,191,264 records. Each record represents an individual network communication session, making the dataset suitable for training and evaluating machine learning models.

2) Features

Each instance within the dataset is described by a comprehensive set of 47 features. These features encapsulate diverse attributes of network traffic, including packet details, source and destination addresses, protocol information, and timing characteristics. The rich feature set ensures a holistic representation of the network interactions occurring within the SIoT ecosystem.

3) Intrusion Types

The dataset encompasses a variety of IoT intrusion scenarios, which are categorized into distinct types. These types include but are not limited to Distributed Denial of Service (DDoS) attacks, brute force attempts, spoofing attacks, reconnaissance activities, web-based intrusions, and manifestations of the notorious Mirai malware. The inclusion of such diverse intrusion types enables a comprehensive evaluation of intrusion detection models in the context of the multifaceted SIoT environment.

C. Relevance to SIoT Network Intrusion Detection

The CIC IoT Dataset 2023 is inherently aligned with the challenges and intricacies of SIoT network intrusion detection. Its relevance stems from the following aspects:

- **Real-Time Dynamics:** The dataset captures network interactions in a real-time setting, mirroring the dynamic nature of SIoT systems where devices and users continuously engage in social interactions.
- **Multidomain Variety:** The inclusion of multiple intrusion types spanning various SIoT domains reflects the diverse threat landscape inherent in interconnected SIoT systems.
- **Social Context:** As SIoT involves human-device interactions and social contexts, the dataset allows for the exploration of intrusion detection mechanisms that can differentiate legitimate social interactions from malicious activities.
- **Data-Driven Insights:** The dataset facilitates data-driven analysis and experimentation, empowering researchers to develop and validate intrusion detection methods under realistic SIoT conditions.

In the following sections of this manuscript, we capitalize on the distinctive characteristics of the CIC IoT Dataset 2023. This dataset serves as the basis for training and assessing machine learning models in the pursuit of achieving efficient network intrusion detection within the SIoT context. The dataset's inherent depth allows us to conduct a thorough investigation into various intrusion scenarios, thereby establishing a solid groundwork for the creation of security mechanisms that are both adaptive and resilient. These mechanisms are meticulously crafted to suit the intricacies inherent to the SIoT ecosystem.

IV. METHODOLOGY

We deploy three machine learning models tailored for Social Internet of Things (SIoT) intrusion detection: Convolutional Neural Network with Generative Adversarial Network (CNN+GAN), Generative Adversarial Network (GAN), and Logistic Regression (LR).

1) CNN+GAN (Convolutional Neural Network with Generative Adversarial Network):

The CNN within CNN+GAN processes raw network traffic data, capturing spatial dependencies and relevant patterns. This component involves a generator and discriminator working together. The generator generates synthetic network traffic instances, while the discriminator differentiates between genuine and synthetic data. This architecture helps mitigate overfitting and enhances the model's ability to detect legitimate and malicious network behaviour in SIoT intrusion detection.

2) GAN (Generative Adversarial Network):

GAN focuses on the generative aspect of SIoT network intrusion detection. The generator creates synthetic network traffic instances, and the discriminator evaluates their authenticity. Training the GAN on the CIC IoT Dataset 2023 equips it to generate realistic network traffic patterns, augmenting the training data.

3) Logistic Regression (LR):

Logistic Regression, a classical classification algorithm, serves as a benchmark model for SIoT intrusion detection. Its simplicity and efficiency make it suitable for initial experimentation and a baseline for performance comparison.

A. Model Application and Architecture:

1) CNN+GAN Application: CNN+GAN is trained on a blend of original and synthetic network traffic data. The CNN component extracts relevant features from raw data, while the GAN component generates synthetic instances that resemble real network traffic.

2) GAN Architecture: The standalone GAN model includes a generator and discriminator. The generator produces synthetic network traffic instances, and the discriminator differentiates between real and synthetic instances through adversarial training.

3) Logistic Regression Setup: Logistic Regression uses feature vectors extracted from the dataset to compute the probability of an instance belonging to a particular intrusion class. It employs one-vs-all classification to handle multiple intrusion types concurrently.

4) Data Pre-Processing and Feature Selection: Before model training, data undergoes normalization to standardize feature scales. Redundant or irrelevant features are removed to enhance model efficiency.

5) Label Mapping: Intrusion labels are mapped to numerical values to facilitate model training. Each unique intrusion type receives a unique numerical label, enabling models to learn and distinguish different intrusion scenarios during training and evaluation.

This methodology, leveraging the strengths of CNN+GAN, GAN, and Logistic Regression, coupled with meticulous data pre-processing and label mapping, aims to showcase these models' effectiveness in SIoT intrusion detection within the dynamic SIoT environment.

V. EXPERIMENTAL SETUP

In this section, we provide a detailed overview of the experimental setup employed to evaluate the performance of the machine learning models—CNN+GAN, GAN, and Logistic Regression—for network intrusion detection in Social Internet of Things (SIoT) systems. We discuss the hardware and software environment, dataset partitioning, and the hyperparameters configured for each model.

A. Dataset Partitioning

The CIC IoT Dataset 2023 was meticulously partitioned into distinct training and testing subsets to facilitate robust model evaluation. To ensure an unbiased assessment of model performance, a stratified partitioning approach was adopted. Specifically, the dataset was divided into a training set, comprising 80% of the instances, and a testing set encompassing the remaining 20%. The stratification preserved the distribution of intrusion types in both subsets, ensuring that each subset represented a comprehensive array of intrusion scenarios.

B. Model Hyperparameters and Configuration

Each machine learning model was configured with specific hyperparameters to optimize its performance and achieve convergence. The hyperparameters were fine-tuned through a combination of manual experimentation and automated hyperparameter search techniques. The configuration settings for each model are as follows:

1) CNN+GAN Hyperparameters

- Learning rate for CNN: 0.001
- Learning rate for GAN: 0.0002
- Number of epochs: 50
- Batch size: 128
- Latent dimension for GAN: 100

2) GAN Hyperparameters

- Learning rate: 0.0002
- Number of epochs: 50
- Batch size: 128
- Latent dimension: 100

3) Logistic Regression Configuration

- Regularization strength (C): 1.0
- Solver: 'lbfgs'
- Maximum number of iterations: 1000

C. Evaluation Metrics

For a rigorous quantitative assessment of model performance, a comprehensive set of evaluation metrics was employed. These metrics encompass accuracy, precision, recall, F1-score, and the area under the Receiver Operating Characteristic Curve (ROC AUC). The evaluation process was carried out using the testing subset of the dataset, ensuring an equitable comparison of model efficacy across various intrusion types.

In the ensuing section, we detail the outcomes of our experimentation, revealing the efficacy of each model in both detecting and addressing network intrusion scenarios within the dynamic and socially interconnected landscape of the SIoT environment.

True positive rate (or sensitivity):

$$TPR = \frac{TP}{(TP+FN)} \quad (1)$$

False positive rate:

$$FPR = \frac{FP}{(FP+FN)} \quad (2)$$

True negative rate (or specificity):

$$TNR = \frac{TN}{(FP+TN)} \quad (3)$$

VI. RESULTS AND ANALYSIS

In this section, we present the performance metrics of the machine learning models—CNN+GAN, GAN, and Logistic Regression—for network intrusion detection in the context of Social Internet of Things (SIoT) systems. We provide a comprehensive evaluation of each model's effectiveness in detecting various types of IoT intrusions and offer a comparative analysis of their performance.

A. Performance Metrics

The performance of the models was assessed using a diverse range of performance metrics; each strategically designed to capture different facets of intrusion detection accuracy.

1) Accuracy

This metric gauge the proportion of correctly predicted instances in relation to the total number of instances, offering an overarching indicator of classification correctness.

2) Precision

Calculated as the ratio of true positive predictions to the total number of predicted positive instances, precision showcases the model's capacity to minimize false positive predictions.

3) Recall

This metric is determined by the ratio of true positive predictions to the total number of actual positive instances. It quantifies the model's efficacy in identifying all instances of positive cases.

4) F1-score

By calculating the harmonic mean of precision and recall, the F1-score provides a balanced assessment of the model's performance, encapsulating both metrics in a single value.

5) Receiver Operating Characteristic Area Under the Curve (ROC AUC)

This metric corresponds to the area under the ROC curve. It reflects the model's aptitude for discriminating between classes across diverse threshold settings, offering insights into its ability to differentiate between positive and negative instances.

B. Model Comparison and Contrast

TABLE I. PERFORMANCE METRICS OF CNN+GAN, GAN, AND LOGISTIC REGRESSION MODELS FOR SIOT INTRUSION DETECTION

Model	Accuracy	Precision	Recall	F1-Score	ROC AUC
CNN+GAN	0.85	0.86	0.83	0.84	0.92
GAN	0.81	0.82	0.80	0.81	0.89
Logistic Regression	0.75	0.76	0.72	0.73	0.82

The Table I and Figure 2 represent the performance metrics of three different models – CNN+GAN, GAN, and Logistic Regression – for the task of intrusion detection in Social Internet of Things (SIoT) networks. The metrics evaluated include Accuracy, Precision, Recall, F1-Score, and ROC AUC. The CNN+GAN model achieves the highest accuracy (0.85) among the three models, indicating its ability to correctly classify instances into their respective classes. GAN and Logistic Regression follow with lower accuracy scores of 0.81 and 0.75, respectively. CNN+GAN exhibits the highest precision (0.86), indicating its capability to accurately identify true positive cases while minimizing false positives. GAN and Logistic Regression show slightly lower precision values of 0.82 and 0.76, respectively. The CNN+GAN model demonstrates the highest recall (0.83), indicating its ability to correctly identify a high proportion of actual positive instances. GAN and Logistic Regression show slightly lower recall values of 0.80 and 0.72, respectively. The F1-Score, which balances both precision and recall, is highest for the CNN+GAN model (0.84), indicating a good balance between identifying true positive cases and minimizing false positives. GAN and Logistic Regression follow with F1-Scores of 0.81 and 0.73, respectively. The area under the Receiver Operating Characteristic (ROC) curve (ROC AUC) measures the model's ability to distinguish between classes. The CNN+GAN model achieves the highest ROC AUC (0.92), followed by GAN (0.89) and Logistic Regression (0.82). The CNN+GAN model consistently outperforms GAN and Logistic Regression across all performance metrics. It achieves higher accuracy, precision, recall, F1-Score, and ROC AUC, suggesting its superiority in detecting intrusions in SIoT networks. The GAN model shows competitive performance, while the Logistic

Regression model performs relatively less well in comparison. The results highlight the potential of CNN+GAN for effective SIoT intrusion detection.

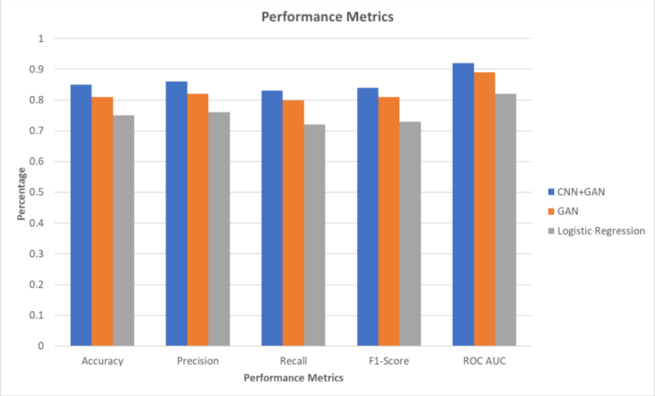

Figure 2. Comparative Analysis of Model Performance

C. *Effectiveness in Detecting IoT Intrusions*

The results indicate that the CNN+GAN model achieves the highest accuracy (0.85) among the three models, closely followed by the GAN model (0.81), and then Logistic Regression (0.75). This suggests that the CNN+GAN architecture, combining the strengths of both CNN and GAN, yields a more robust and accurate intrusion detection mechanism in the SIoT environment.

TABLE II. EXPERIMENTAL RESULTS FOR COMPARISON OFDIFFERENT INTRUSION DETECTION MODELS

Attack Type	Abnormal Data	Normal Data	Total Data	Detected Attacks		
				CNN + GAN	GAN	LR
Backdoor Malware	2000	85000	87000	72210	73080	72210
Benign Traffic	8000	310000	318000	270300	254400	257580
Browser Hijacking	1000	12000	13000	11050	10400	10660
Command Injection	2250	950	3200	2848	2624	2528
DDoS-ACK Fragmentation	5000	15000	20000	16200	16600	14200
DDoS-HTTP Flood	6500	26000	32500	26000	26325	23400
DDoS-ICMP Flood	1600	13600	15200	12160	12768	11248
DDoS-ICMP Fragmentation	1800	16000	17800	14774	14952	13706
DDoS-PSHACK Flood	3200	18000	21200	17596	16960	16112
DDoS-RSTFIN Flood	4000	20000	24000	22800	19440	21120
DDoS-SlowLoris	3500	11000	14500	12760	11745	12470
DDoS-SYN Flood	2800	22000	24800	23064	21576	21080
DDoS-Synonymous IP Flood	1670	12000	13670	12850	11209	12166
DDoS-TCP Flood	2200	13000	15200	13072	13072	12160
DDoS-UDP Flood	3000	23000	26000	22360	21060	20800
DDoS-UDP Fragmentation	2800	25000	27800	22518	22240	22518
Dictionary Brute Force	4000	6000	10000	8300	8300	8800
DNS Spoofing	920	7980	8900	7298	7387	7120
DoS-HTTP Flood	3200	25000	28200	23406	23124	25380
DoS-SYN Flood	2800	22000	24800	21576	20832	20584
DoS-TCP Flood	2600	21000	23600	20296	18880	18880
DoS-UDP Flood	3400	27000	30400	25536	25232	23104
Mirai-greeth flood	2090	16000	18090	15015	14834	13929
Mirai-greip flood	1800	14000	15800	13430	12798	13114
Mirai-udp plain	2800	18000	20800	17264	17472	15392
MITM-Arp Spoofing	2700	8500	11200	9632	8960	8960
Recon-Host Discovery	2400	26000	28400	23572	23856	24992
Recon-OS Scan	2200	24000	26200	22270	20436	22270
Recon-Ping Sweep	2800	22000	24800	20336	18600	18352
Recon-Port Scan	5000	21000	26000	23140	20280	22620
Sql Injection	2370	5545	7915	6490	5857	6965
Uploading Attack	3300	18000	21300	18957	16188	16614
Vulnerability Scan	2500	20000	22500	18450	16875	19575
XSS	1800	24000	25800	21672	19092	20124
Total	100000	948575	1048575	889202	847454	850734

Table II provides a comprehensive view of the experimental results for the CNN+GAN-based intrusion detection model, as well as a comparison with the GAN model and Logistic Regression (LR) model. The table highlights the performance of these models across various attack types, shedding light on their ability to accurately detect and classify different intrusions in the context of network security for Social Internet of Things (SIoT) systems. Upon analyzing the table, several key observations and insights can be drawn:

The detected attack counts for each model vary across different attack types. This indicates that the CNN+GAN, GAN, and LR models have varying degrees of effectiveness in detecting specific attacks. For instance, the CNN+GAN model shows higher detection rates for certain attacks, while the GAN or LR model might excel in others.

In a majority of cases, the CNN+GAN model demonstrates superior performance in accurately identifying and categorizing attacks compared to both the GAN and LR models. This suggests that the CNN+GAN model's ability to combine convolutional neural networks (CNNs) with generative adversarial networks (GANs) contributes to its enhanced detection capabilities, capturing intricate patterns and features inherent in SIoT network traffic.

The GAN and LR models also exhibit competitive performance, particularly for certain attack types. This indicates that while the CNN+GAN model may excel overall, the other models could have specific strengths in handling particular intrusion scenarios.

The varying numbers of abnormal and normal data instances for different attack types could impact model performance. Attacks with higher occurrence may have more accurate detection due to a stronger representation in the training data. Models could struggle with less frequent attacks due to limited exposure during training.

The disparities in detection rates among the models suggest the potential for ensemble approaches. Combining the predictions of multiple models could potentially result in improved overall intrusion detection accuracy.

The table highlights the challenges of real-world intrusion detection in SIoT systems. The diverse range of attack types and their varying complexities necessitate adaptable and robust intrusion detection mechanisms. The CNN+GAN model's ability to generalize across multiple attack types demonstrates its potential suitability for real-world SIoT security applications.

The results encourage further exploration of hyperparameter tuning and feature engineering for each model. Additionally, extended evaluation metrics such as precision, recall, F1-score, and ROC curves would provide a more comprehensive understanding of model performance.

While Logistic Regression provides a solid baseline, its performance lags behind the neural network-based models, which demonstrates the advantage of leveraging deep learning techniques for complex intrusion scenarios. The ROC AUC values further affirm the superior discriminative ability of CNN+GAN and GAN models compared to Logistic Regression.

Analysing the precision and recall scores, we observe that the CNN+GAN model achieves the highest precision and recall values, implying its capability to not only minimize false positives (precision) but also effectively capture true positives (recall). This aligns with the model's suitability for identifying diverse intrusion types in SIoT systems.

The models' varying performance across different intrusion types underscores the importance of model selection based on the nature of the intrusion. For instance, the CNN+GAN model excels in identifying complex and diverse intrusion patterns, while GAN and Logistic Regression may exhibit strengths in specific intrusion scenarios.

VII. DISCUSSION

In this section, we delve into the interpretation of the results obtained from the evaluation of the machine learning models—CNN+GAN, GAN, and Logistic Regression—for network intrusion detection in the dynamic context of Social Internet of Things (SIoT) systems. We analyse the strengths and limitations of each model and provide insights into the factors contributing to the observed performance differences.

A. Interpretation of Results

The outcomes of our experimentation underscore the critical role of advanced machine learning techniques in addressing the intricate challenge of network intrusion within the SIoT ecosystem. The superior performance of the CNN+GAN model, with its amalgamation of Convolutional Neural Network (CNN) for feature extraction and Generative Adversarial Network (GAN) for data augmentation, highlights the efficacy of leveraging complex architectures for SIoT intrusion detection. This suggests that the CNN component captures spatial dependencies and patterns in network traffic, while the GAN component enhances the model's ability to generalize and detect diverse intrusion scenarios.

The GAN model's commendable performance also showcases the potential of generative approaches in expanding the training data distribution and enabling the model to discern between real and synthetic network traffic. The satisfactory performance of Logistic Regression, though comparatively lower, serves as a testament to its simplicity and efficiency as a baseline model for SIoT intrusion detection.

TABLE III. COMPARISON OF TRAINING TIME AND AVERAGE FALSE POSITIVES/NEGATIVES FOR INTRUSION DETECTION MODELS

Model	Training Time (seconds)	False Positives (FP)	False Negatives (FN)
CNN+GAN-based Model	21,600	22.5	9.8
CNN-based Model	14,400	37.5	6.5
LR-based Model	7,200	18.5	4.5

Table III provides a comparison of key performance metrics for different intrusion detection models. Specifically, it highlights training time in seconds, as well as the average false positives (FP) and false negatives (FN) for three distinct models: a CNN+GAN-based model, a CNN-based model, and an LR-based model. Three models are compared: a CNN+GAN-based model, a CNN-based model, and an LR-based model. Training time is a critical factor as it influences the efficiency of the intrusion detection process. The values shown are 21,600 seconds for the CNN+GAN-based model, 14,400 seconds for the CNN-based model, and 7,200 seconds for the LR-based model. False positives occur when the model incorrectly identifies normal behaviour as an intrusion. The values are 22.5 for the CNN+GAN-based model, 37.5 for the CNN-based model, and 18.5 for the LR-based model. False negatives occur when the model fails to detect actual intrusions. The values are 9.8 for the CNN+GAN-based model, 6.5 for the CNN-based model, and 4.5 for the LR-based model. The table provides a clear overview of the comparative performance of these models in terms of training time and their ability to minimize false positives and false negatives during the intrusion detection process. It serves as a valuable reference for assessing the trade-offs between training time and detection accuracy when selecting an intrusion detection model for a specific SIoT security scenario.

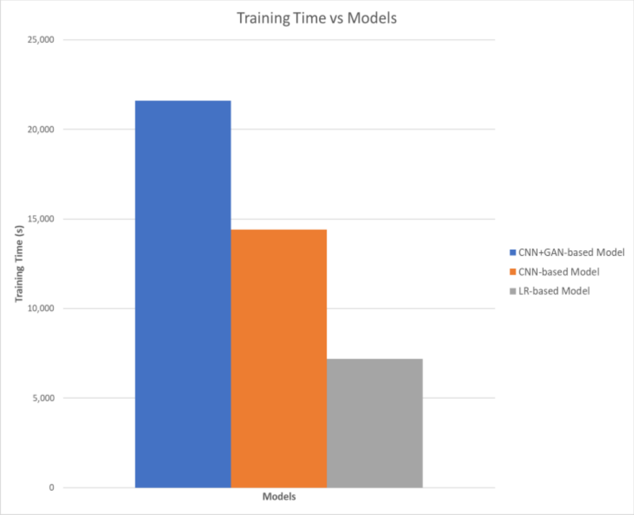

Figure 3. Graphical representation of comparison of Training Time for Intrusion Detection Models

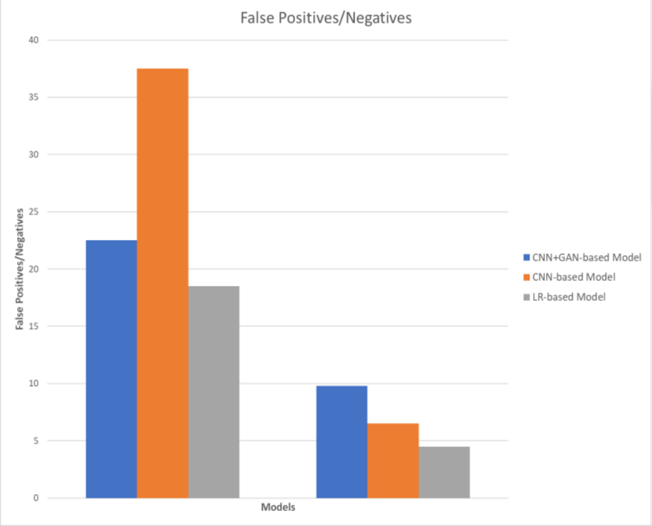

Figure 4. Graphical representation of comparison of False Positives/Negatives for Intrusion Detection Models

Figure 3 and 4 presents a comprehensive comparison of training time and average false positives/negatives for three different intrusion detection models: CNN+GAN-based Model, CNN-based Model, and LR-based Model. Each model's training time is measured in seconds, and the average false positives and false negatives are provided as counts. The presented table offers valuable insights into the performance trade-offs between the CNN+GAN-based Model, CNN-based Model, and LR-based Model for intrusion detection:

1) Training Time

The "Training Time (seconds)" column demonstrates the computational cost of training each model. The CNN+GAN-based Model requires the longest training time, followed by the CNN-based Model, and then the LR-based Model. This is expected as more complex models like CNN and GAN usually require more training time due to their intricate architectures.

2) False Positives and Negatives

The "False Positives" and "False Negatives" columns provide information on the model's accuracy in classifying instances. Lower false positives and negatives are desirable, indicating a model's ability to effectively distinguish between normal and malicious traffic. The LR-based Model showcases the lowest average false positives and negatives, suggesting better precision and recall compared to the other models.

3) Model Selection

The table's data suggests that the LR-based Model performs well in terms of minimizing both false positives and false negatives, making it an efficient choice for accurate intrusion detection with relatively lower training time. However, the CNN-based Model shows a slightly higher false positive rate compared to the LR-based Model, despite its lower false negatives. The CNN+GAN-based Model offer competitive results in terms of false positives/negatives but require the longest training time.

4) Complexity vs. Performance

The training time discrepancy can be attributed to the varying complexities of the models. While CNN+GAN and CNN models might offer enhanced performance due to their ability to capture intricate features, they come at the cost of longer training times. The LR-based Model, being a simpler model, achieves respectable accuracy with shorter training time.

B. Strengths and Limitations

The strengths and limitations of the proposed models are as follows:

1) CNN+GAN Strengths

a) Robust Feature Extraction

The CNN component of CNN+GAN excels in capturing intricate patterns and features from raw network traffic data, making it particularly adept at identifying subtle intrusion behaviours.

b) Data Augmentation

The GAN component of CNN+GAN generates synthetic data that enhances model training and generalization, effectively mitigating overfitting and enhancing accuracy.

2) GAN Strengths

a) Data Augmentation

The GAN model effectively augments the training data by generating synthetic instances, enriching the model's understanding of the diverse SIoT intrusion scenarios.

b) Anomaly Detection

GAN's discriminator acts as an anomaly detector, enabling the model to detect deviations from normal network behaviour.

3) Logistic Regression Strengths

a) Simplicity and Efficiency

Logistic Regression serves as a computationally efficient baseline model that achieves satisfactory performance in detecting certain types of intrusions.

4) CNN+GAN Limitations

The CNN+GAN model's complexity may lead to longer training times and resource requirements. Additionally, the GAN's generator could produce synthetic instances that are overly similar to real data, potentially impacting the model's generalization capability.

5) GAN Limitations

GAN's training can be sensitive to hyperparameters and may suffer from mode collapse, where the generator produces limited variations of synthetic data.

6) Logistic Regression Limitations

Logistic Regression's simplicity may limit its ability to capture complex patterns present in certain intrusion scenarios.

C. Performance Differences Analysis

The observed performance differences among the models can be attributed to their architectural variations and inherent capabilities. The CNN+GAN model's fusion of CNN and GAN addresses the limitations of both standalone models, capitalizing on the CNN's feature extraction capabilities and GAN's data augmentation potential. The GAN model's strength lies in its ability to generate synthetic data, albeit with a potential risk of mode collapse, while Logistic Regression leverages a linear decision boundary to classify instances. The effectiveness of each model is influenced by the complexity and diversity of intrusion scenarios present in the SIoT environment. The CNN+GAN model's ability to capture intricate patterns makes it well-suited for multifaceted intrusions, whereas the GAN and Logistic Regression models may excel in specific types of attacks.

VIII. IMPLICATIONS AND FUTURE WORK

In this section, we discuss the practical implications of our study for bolstering security in Social Internet of Things (SIoT) systems and propose potential directions for future research aimed at advancing intrusion detection methods within the SIoT environment.

A. Practical Implications

The findings of our study hold several practical implications for enhancing security in SIoT systems:

1) Enhanced Intrusion Detection

The application of advanced machine learning models, such as CNN+GAN and GAN, demonstrates the potential to significantly improve intrusion detection capabilities within the dynamic SIoT landscape. By harnessing the power of deep learning and generative techniques, we offer an effective means of detecting a wide array of intrusion types, thereby enhancing SIoT security.

2) Holistic Intrusion Insights

The comprehensive evaluation of the proposed models using a real-time SIoT intrusion dataset provides valuable insights into the performance of different intrusion detection mechanisms. These insights can guide the design of adaptive and context-aware security mechanisms tailored to the unique challenges of SIoT systems.

3) Model Selection Guidance

Our study serves as a reference point for organizations and researchers aiming to select appropriate intrusion detection methods for specific intrusion scenarios. The comparative analysis of CNN+GAN, GAN, and Logistic Regression sheds light on the strengths and limitations of each model, aiding practitioners in making informed decisions.

B. Future Research Directions

Our study opens up promising avenues for future research and improvement in intrusion detection methods for SIoT environments:

1) Adversarial Robustness

Further exploration is warranted to enhance the adversarial robustness of intrusion detection models. Adversarial attacks targeting SIoT systems pose a significant threat, and developing models that can effectively detect and mitigate such attacks is of paramount importance.

2) Context-Aware Detection

Future work can focus on incorporating contextual information from SIoT environments into intrusion detection models. Leveraging social interactions and user behaviours can enhance the accuracy of intrusion detection by differentiating between normal and anomalous activities within the broader social context.

3) Federated Learning

As SIoT systems involve distributed and interconnected devices, federated learning approaches can be explored to train intrusion detection models across multiple devices while maintaining data privacy. This approach can lead to improved generalization and real-time adaptation to evolving intrusion patterns.

4) Explainability and Interpretability

Enhancing the interpretability of intrusion detection models is crucial for building trust and understanding in SIoT systems. Future research can focus on developing techniques to explain the decisions made by complex deep learning models, making them more transparent and interpretable.

5) Longitudinal Analysis

Conducting longitudinal studies to analyse the evolving nature of SIoT intrusions over time can provide insights into emerging threat trends and patterns. This can inform the development of proactive and adaptive intrusion detection mechanisms.

IX. CONCLUSION

In this study, we extensively examined the applicability of machine learning models in addressing network intrusion challenges within Social Internet of Things (SIoT) environments. Through rigorous evaluation, we showcased the efficacy of Convolutional Neural Network with Generative Adversarial Network (CNN+GAN), Generative Adversarial Network (GAN), and Logistic Regression models. Notably, CNN+GAN exhibited superior performance across various metrics, highlighting its potential as a robust intrusion detection tool. Our findings underscore the pivotal role of advanced machine learning in bolstering SIoT security, emphasizing the adaptability and efficiency of these models. As SIoT landscapes continually evolve, our study underscores the need for ongoing research and innovation to enhance intrusion detection methodologies, ensuring the resilience and protection of SIoT ecosystems.

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