Anomaly-Flow: A Multi-domain Federated Generative Adversarial Network for Distributed Denial-of-Service Detection

Leonardo Henrique de Melo, Gustavo de Carvalho Bertoli, Michele Nogueira, Aldri Luiz dos Santos, Lourenço Alves Pereira Junior

***Abstract*—Distributed denial-of-service (DDoS) attacks remain a critical threat to Internet services, causing costly disruptions. While machine learning (ML) has shown promise in DDoS detection, current solutions struggle with multi-domain environments where attacks must be detected across heterogeneous networks and organizational boundaries. This limitation severely impacts the practical deployment of ML-based defenses in real-world settings.**

This paper introduces Anomaly-Flow, a novel framework that addresses this critical gap by combining Federated Learning (FL) with Generative Adversarial Networks (GANs) for privacy-preserving, multi-domain DDoS detection. Our proposal enables collaborative learning across diverse network domains while preserving data privacy through synthetic flow generation. Through extensive evaluation across three distinct network datasets, Anomaly-Flow achieves an average F1-score of 0.747, outperforming baseline models. Importantly, our framework enables organizations to share attack detection capabilities without exposing sensitive network data, making it particularly valuable for critical infrastructure and privacy-sensitive sectors.

Beyond immediate technical contributions, this work provides insights into the challenges and opportunities in multi-domain DDoS detection, establishing a foundation for future research in collaborative network defense systems. Our findings have important implications for academic research and industry practitioners working to deploy practical ML-based security solutions.

***Index Terms*—Multi-domain, DDoS, Federated Learning, GAN, Network Attacks, Anomaly Detection**

I. Introduction

Learning across multiple domains remains challenging for machine learning (ML) applications [1], particularly in network environments with diverse segments and heterogeneous participants. This segmented characteristic creates vulnerability, as adversaries can launch attacks without detection across all segments due to the limited global network visibility. Federated Learning (FL) offers a solution by enabling collaborative attack detection while preserving privacy [2].

Among various network attacks, Distributed Denial of Service (DDoS) stands out as particularly impactful, denying services by flooding computational resources with numerous requests.

Recent research has introduced FL-based mechanisms to detect DDoS attacks across different networks and distributed targets [3]–[5]. However, researchers rarely evaluate their proposals from a multi-domain perspective [6], contributing to the ineffectiveness of ML techniques for DDoS detection in operational environments [7]. We assume multi-domain as multiple heterogeneous network environments with distinct traffic patterns and attack characteristics. ML algorithms generally struggle with cross-domain performance, limiting practical deployment [8]. Although data sharing could enhance cross-domain generalization [1], it also introduces privacy and availability challenges.

To improve multi-domain DDoS detection, we propose Anomaly-Flow, which leverages FL for detecting network attacks across diverse domains [9] while integrating Generative Adversarial Networks (GANs) to generate synthetic network data that can be shared without compromising privacy [10]. This approach addresses both privacy constraints and domain generalization challenges.

Our evaluation demonstrates that Anomaly-Flow improves DDoS detection across multiple networks using different datasets. The framework's integrated GANs generate synthetic data that facilitates learning DDoS patterns across domains, while enabling the sharing of heterogeneous models with external entities not participating in the FL scheme. To our knowledge, Anomaly-Flow is the first method for multi-domain DDoS detection that integrates three key components: FL-based detection, synthetic data generation, and heterogeneous model sharing.

The remainder of this paper is organized as follows: Section II explores ML for DDoS detection and multi-domain generalization. Section III details our proposed Anomaly-Flow framework. Section IV presents our experimental results, followed by discussions of challenges and opportunities in Sections V and VI. Finally, Section VII concludes the paper and outlines future work.

II. DDoS Detection and Multi-domain Evaluation

This section reviews previous applications of ML – particularly GANs and FL – to DDoS detection, focusing explicitly on their evaluation across multiple domains. Such multi-domain evaluations typically involve cross-dataset validation to assess the generalization capabilities of ML solutions. Overall, multi-domain DDoS detection has received limited attention in the literature. Then, we discuss related works that present multi-domain detection when applying ML to flow-based network data for security-related tasks.

GANs have been applied to network flow analysis, notably in the Netshare framework [10], which generates synthetic data

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of IP headers and network flow attributes. The authors' proposed solution has three aspects: "fidelity", "scalability-fidelity tradeoff" and "privacy-fidelity tradeoffs." They stated that the proposed framework, considering proximity metrics between synthetic and actual data, obtained 46% more fidelity than the baseline. Furthermore, the authors showed that GAN presents the best tradeoff between scalability and fidelity among all their baselines. Despite their seminal contribution of applying GANs to network flow data, the discussion about anomaly detection and the experiments conducted are superficial, which can hinder the reproducibility of the results. Additionally, no specific considerations for DDoS are presented.

Regarding FL applied to DDoS detection, [3] proposed FLDDoS as a federated recurrent neural network (RNN) model to detect malicious network activities and maintain privacy. The authors proposed hierarchical clustering to aggregate local models using the k-means algorithm and a method to balance the number of benign and attack samples among the clients. Furthermore, the authors used an Autoencoder (AE) to extract features automatically during the training rounds. However, the authors did not evaluate the detection across multi-domains and the model's capability to identify DDoS on unseen data. Thus, the evaluation of FLDDoS in a multi-domain scenario is not presented.

Also applying FL for DDoS, [11] presented FL for DDoS detection in a multi-tenant scenario. This scenario represents the challenge of DDoS attacks against a specific tenant going unnoticed by other tenants. To overcome this challenge, they proposed the use of FL. Although the multi-tenant scenario resembles a multi-domain setting, the approach evaluates only a single dataset divided among tenants, limiting the generalizability of their results. A truly multi-domain evaluation should ideally encompass distinct datasets reflecting different network environments.

The work [5] also focused on FL applied to DDoS detection. It presented a form of aggregation based on the performance of federated clients. The authors validated the proposed architecture using an MLP model to detect multiple classes of DDoS attacks in a dataset. Compared with FLDDoS [3] and traditional FedAvg, the results demonstrated better convergence time and performance considering ML learning metrics. Furthermore, the authors evaluated the traffic classification of unseen data using the model. However, similar to [11], the presented approach evaluated different attacks from the exact origin without considering a multi-domain evaluation. Additionally, the authors did not explore strategies for multi-domain performance through information sharing or training heterogeneous models with external entities.

Addressing evaluations in a multi-domain setting, [6] presented the XeNIDS framework for cross-evaluation between multiple datasets. The authors highlighted the challenges of deploying anomaly-based NIDS in real-world networks, noting that while many studies achieve near-perfect results, these outcomes often do not translate well into practical applications due to this lack of multi-domain evaluation. The authors proposed a methodology for training and testing models with various attack types. They identified ten contexts for cross-evaluation based on the presence or absence of attack types and benign data during the training and testing phases. This multi-context approach can aid in generating augmented data. However, there are significant concerns regarding data privacy, as different data compositions can lead to data leaks or make practical implementation challenging due to privacy issues between multiple parties.

Then, [12] proposed the Energy-based Flow Classifier (EFC) algorithm for identifying malicious network flow data. The authors tested the model's generalization capability using three datasets: CIDDS-001, CICIDS-2017, and CIC-DDoS2019. The binary classification task involves determining whether flows are benign or anomalous. The algorithm, used to identify anomalies in graph structures, demonstrated promising results in a cross-evaluation analysis between two datasets involving the same attack type, representing a multi-domain setting. However, the evaluation is limited to similar datasets and does not focus on DDoS. The authors suggested extending it to assess performance across distinct datasets.

Lastly, [8] employed different ML algorithms for anomaly detection, including Principal Component Analysis (PCA), Isolation Forest (IF), AE, and One-Class Support Vector Machine (oSVM). The authors conducted cross-evaluation between two different datasets containing similar types of attacks. The results showed that the anomaly detection models performed poorly in this multi-domain setting, highlighting the need for adaptable and robust models. Additionally, it is a limitation evaluating closely related datasets as [12], no focus on DDoS was given, and the work did not discuss the performance degradation in diverse network topologies with more heterogeneous flows.

In summary, we identified gaps in DDoS detection research involving FL and GANs, including limited use of GANs for DDoS-specific synthetic data [10], FL approaches [3], [5], [11] lacking multi-domain generalization and sharing beyond participants, and insufficient privacy consideration in multi-domain settings [6] and [12]. Anomaly-Flow addresses these gaps by (1) integrating FL and GANs for multi-domain DDoS detection across heterogeneous networks while preserving privacy, (2) generating shareable synthetic network flows, and (3) enabling external entities to benefit from collaborative learning via heterogeneous model sharing without compromising data. This is the first framework to combine these features for practical multi-domain DDoS detection.

III. Generative Model to Detect DDoS Attacks: A Use Case

This section presents a use case that narrows the detection task, focusing on a binary task between network flows representing benign network communication versus DDoS attacks.

We use the terminology *flow* as the five-tuple (Source IP, Source Port, Destination IP, Destination Port, and Protocol) and the respective network packets in a given period. Our experiments use network flows from NetFlow-based datasets Bot-IoT, CICIDS-2018, and TON-IoT [13]. These datasets comprise DDoS attacks that involve large-scale UDP, TCP, and HTTP requests. Our primary goal in this study is to develop a technique for identifying attacks in a multi-domain scenario

represented by various network environments. The chosen datasets capture distinct contextual nuances for this goal while sharing a common feature set [13]. Our focus is on identifying potential DDoS attacks across this multi-domain scenario. Furthermore, we exclusively trained the models using benign data representing an anomaly detection setting, which, from an operational perspective, would be simpler for deployment.

Thus, we propose a method called Anomaly-Flow that allows the classification of anomalous flows and the generation of synthetic data. It permits information exchange with other entities through external models trained with this synthetic data.

The Anomaly-Flow training is presented in Fig. 1. In the first stage ①, an FL scheme is used to create a model capable of obtaining information from different data sources (participants' silos) with privacy.

Participants communicate with an aggregation server during the federated model's training phase. The models are trained locally by FL clients for several epochs in each training round. In our study, each client trains for 50 epochs during each round. After local training, each client sends only the model weights to the aggregation server. In turn, the server combines all the weights received from participants through an aggregation function, generating a global model.

Finally, all local models are updated using the weights of the aggregated model, and the following rounds repeat the process until the specified number of rounds is reached. Furthermore, we use FedAvg as the aggregation algorithm.

We use the GANomaly [14] algorithm as the federated model. This model uses a modified version of a GAN to identify image anomalies. However, this algorithm is also suitable for anomaly detection in different domains. A converged GANomaly model generates synthetic data resembling real samples by minimizing adversarial and contextual losses, which enforce feature consistency and contextual alignment with the training data. While theoretical alignment is achieved, further validation remains a potential direction for future work.

This work proposes changes for a network intrusion detection system (NIDS) based on network flows. Those changes are from the original GANomaly's convolutional layers to dense layers, aligned with the tabular format of network flows as input. Additionally, the *generator* has decoder-dense layers with the structure of $256 : 512 : 1024$ and an encoder of the structure $1024 : 512 : 256$ — the *discriminator* with layers of $1024 : 512 : 256$ and using a sigmoid function as output.

A semi-supervised GAN network is suitable for this work, as it leverages anomaly detection principles by training exclusively on benign data. This is advantageous for practical deployment scenarios in NIDS, where obtaining representative attack data can be challenging. Network administrators and cybersecurity experts typically have easier access to benign traffic, aligning our approach with real-world constraints. However, we acknowledge a limitation of our current methodology, which is partially dependent on attack samples as part of the validation set to determine the classification threshold. Alternative threshold determination techniques that rely solely on benign data can be incorporated into the framework as a future improvement. For instance, approaches based on statistical properties of benign traffic or directly employing GANomaly's threshold metric could improve the Anomaly-Flow's real-world applicability and robustness.

Hyperparameters were initially selected through manual tuning. While automated strategies like Bayesian optimization or grid search could be applied, we opted for incremental trial-and-error adjustments suitable for practical network administration. Administrators can progressively adapt parameters based on real-time system performance and resource constraints, starting from our recommended default settings. Although attack samples were methodologically used in validation to set the classification threshold, the hyperparameter tuning relies only on benign data, minimizing computational costs during real-world deployment.

In addition, dataset-specific rescaling information was calculated and kept local during training for each participant in the trained model. Thresholds based on anomaly scores were used to classify examples: values below the threshold were labeled benign, while higher values indicated DDoS samples.

Next, we propose generating synthetic data with the collaboratively trained GAN in the method's second stage ② – referred to as *Generator* on Fig 1. This synthetic data aims to train heterogeneous models (diverse ML algorithms), allowing information sharing even to entities outside the FL scheme. Synthetic data enables the sharing of network context while preserving privacy, as the generated data, though related to actual data, represents non-existent flows. As the models are trained only with benign data, synthetic data consequently also represents a scenario of benign behavior. Furthermore, it should be noted that we consider that all use of synthetic data will be within a trustful perimeter and that it will not be externally accessible.

Finally, in the third ③ and last stage of the proposed method, heterogeneous ML models can be trained with this synthetic data, simultaneously sharing the context of distinct participants. Besides, when using the synthetic data, we allow the training of models that are different from the one used in the FL setup. Therefore, external models become more flexible, enabling, for example, the use of lightweight models that are more suitable for resource-constrained devices. Moreover, we can share these models with external entities, maintaining the sensitive data within a trusting perimeter. For instance, a less complex algorithm like a tree-based model, which is simpler than a GAN, can be trained on this synthetic data and shared with third parties.

A. Data Processing

We preprocess the datasets for model training to remove inconsistencies and improve data organization. Initially, we split columns representing specific data protocol flags into multiple columns, each representing a particular value. Furthermore, the data pre-processing step removes attributes that bias training, such as IP address information and ports, resulting in 50 features. Moreover, we remove examples containing outliers and null values. Following this, we divide samples from the datasets into three subsets: training (80 percent), testing (18 percent), and validation (2 percent). We filter only benign

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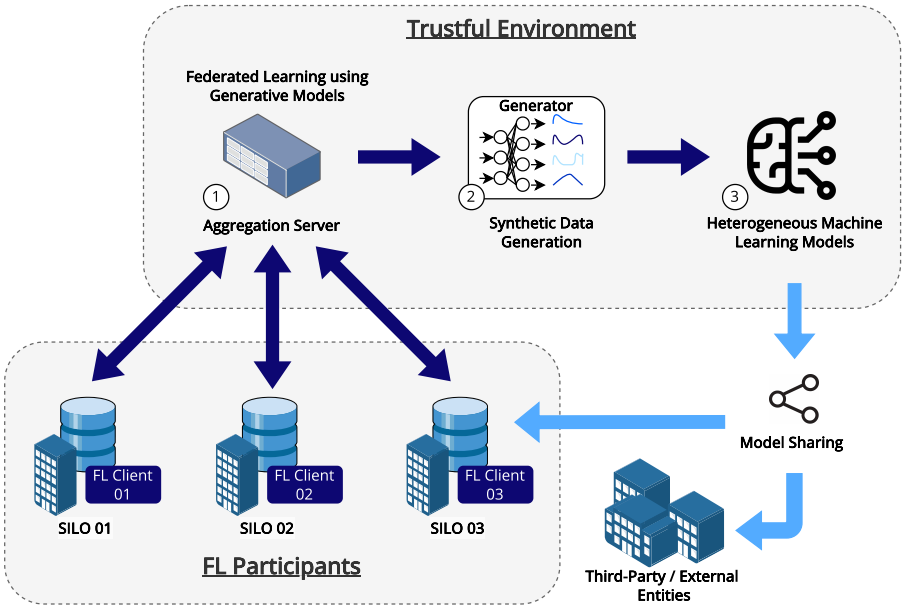


Fig. 1: Use Case Training Diagram using Generative models in a FL schema ① FL using large datasets and the GANomaly model; ② Generation of synthetic data using the global model trained in the FL schema; ③ Use the synthetic data generated by the generative model to train heterogeneous models that the FL participants and third-party entities can use.

samples for the training subset and use the validation subset determined the classification threshold using anomaly scores combining benign and attack data, which were then applied to evaluate the model during the test phase.

B. Evaluation Metrics

Our experiments evaluate the models' performance using two learning metrics: Area Under the Curve of the Receiver Operation Curve (ROC-AUC) and F1-score. Such metrics are due to the characteristic of the problem that presents an imbalanced number of samples in the classes (benign and DDoS, as reported in Fig. 2) and the strategy using an anomaly score from GANomaly for each sample (continuous real value between zero and one), which allows the threshold evaluation to compose the ROC curve. GANomaly computes an anomaly score as the distance between two latent vectors extracted from the input and its reconstructed version. Our experiments use a dynamic threshold based on the Youden-Index for the validation dataset. The strategy for obtaining the threshold considers the presence of benign and attack data. However, it is emphasized that this was a decision for the experiments carried out in this work. Furthermore, the Anomaly-Flow framework can integrate other methods to calculate the threshold according to the requirements of network operators.

C. Cross-Evaluation

We employ a cross-evaluation methodology to comprehensively assess the model's performance and multi-domain capabilities, as shown in Fig. 3. Initially, the model undergoes local assessment, training, and testing on the same dataset

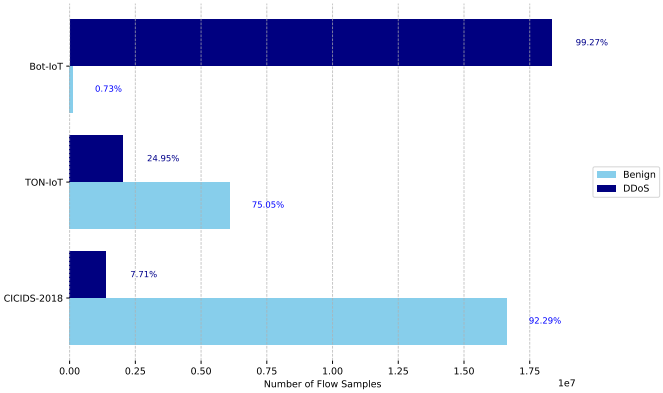
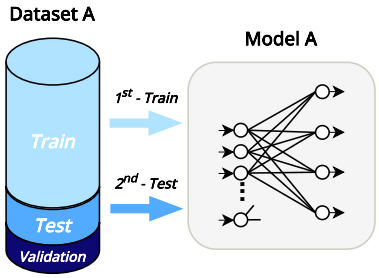


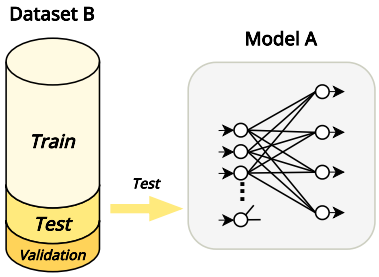
Fig. 2: Class distribution and imbalance across analyzed datasets for DDoS detection, highlighting the skewness in class proportions and sample quantities. The benign class dominates in CICIDS-2018 and TON-IoT, whereas DDoS traffic overwhelmingly prevails in Bot-IoT, illustrating significant disparities in data distribution across datasets.

(Fig. 3a). After that, a cross-evaluation is conducted, entailing training the model on one dataset and testing it on another (Fig. 3b).

This cross-evaluation is paramount in discerning the model's ability to identify previously unseen attacks and gauging the variations in its performance across different datasets representing a multi-domain setting. The initial local evaluation is a comparative baseline for the subsequent federated evaluation. Subsequently, a single FL model is evaluated in multiple contexts to assert the generalization of the proposed model.



(a) Training Model / Testing Model Locally



(b) Cross-Evaluation Test

Fig. 3: (a) The diagram presents the structure of the data split for the training and test. Initially, model A is trained on the train split of dataset A and then evaluated with the test set from the same dataset used in training, referred to as local evaluation. Next, (b) presents the cross-evaluation procedure, in which model A, previously trained on dataset A, is evaluated with data from a different dataset, in this example, dataset B.

IV. Results and Discussion

This section presents the results obtained during the execution of the experiments to evaluate Anomaly-Flow. We present the results and discussion in three steps: developing a GAN model in an FL setup to learn in a cross-domain setting (generalization capability), generating synthetic flows using GAN, and evaluating the sharing of GAN's synthetic data for external model training.

We present the results related to ① regarding the generalization capability. Then, we present the results of ② and ③ about synthetic data generation and training different models using the generated examples. Furthermore, we present a discussion along with the results.

A. Multi-domain DDoS Detection

The performance of the models and the generalization capability in a multi-domain scenario used the learning metrics ROC-AUC and F1-score. Our evaluation follows a structured approach consisting of key analyses:

1) Local vs. Cross-Evaluation Performance: We present the evaluation results for each test dataset in Table I. A GANomaly-based model was trained on each dataset listed in the Model column. Then, the trained models were assessed using their data (test split) and against the other datasets with the same features (i.e., cross-evaluation). Lastly, in a horizontal FL setup and after ten training rounds, the global GANomaly-based model was evaluated against the three datasets, and its metrics are also present in Table I representing ①.

2) Comparison with State-of-the-Art Methods: Table II compares Anomaly-Flow with baselines for multi-domain DDoS detection. Given AE's applicability for anomaly detection, we opt for AE as one of the baselines. Then, we used the architecture of [9], excluding the proposed stacking architecture and dual-threshold mechanism. We evaluated the AE solely for benign versus DDoS anomaly detection. However, this simple AE did not achieve satisfactory performance, as indicated by the reported F1-score. A basic logistic regression model within an FL framework for multi-domain DDoS detection is proposed in [15]. Nevertheless, its performance in multi-domain evaluations is lower than that of Anomaly-Flow, based on the same reference datasets. FLAD [5] aims to improve convergence in FL-based DDoS detection but does not explicitly evaluate multi-domain detection. In this study, we extend FLAD's evaluation to the same multi-domain detection scenario as proposed by Anomaly-Flow, but FLAD still underperforms relative to Anomaly-Flow. We did not explore FLAD's client-specific optimization, as this is not part of the Anomaly-Flow methodology.

3) Baseline Comparison with Traditional ML Algorithms: Furthermore, to establish a baseline for comparison with other models, we performed experiments using various ML algorithms under the same data processing and separation conditions described in Section III-A. We cross-evaluated these various ML algorithms as presented in Fig. 3. We only considered the average F1-score as a reference for these baselines. In Fig. 4, we have reported the average F1-score metric values obtained for each baseline model.

4) Key Findings and Analysis: The results in different contexts using the cross-evaluation, compared with similar studies conducted previously, demonstrate the robustness of the GANomaly models. Comparatively, using the average F1-score, it is possible to compare the performance of this work using GANomaly, which was 0.615 (averaging the six cross-evaluation metrics from CICIDS-2018, Bot-IoT and TON-IoT), representing a considerable result in the ability to classify DDoS attacks. This result is 5.1% lower than the best baseline obtained with the EFC algorithm (Fig. 4).

However, the EFC algorithm needs to be trained with all the data each time, so if the models need to be trained with new data, the previous training data must be recovered, thus making incremental training of the models cumbersome.

Considering the FL task for GANomaly – GANomaly on an FL setup from Table I – the metrics' average demonstrates that after 10 rounds, it can detect DDoS better than the previous approaches using GANomaly on each dataset without FL. The average F1-score obtained is 0.747, based on the evaluation of each of the participants (CICIDS-2018, Bot-IoT, TON-IoT). Although the model presented reaches a sub-optimal point, it can reasonably identify attacks. Considering a real scenario, this result represents a mitigation of DDoS attacks in a multi-domain setting, assuming the application of the same model to different contexts.

TABLE I: Performance Measurement for Local and Cross-Evaluation of GANomaly Models vs. GANomaly on a FL setup after 10 rounds, considering no data shared among silos. The first three models in the first column represent "trained on" (CICIDS-2018, Bot-IoT, TON-IoT), and the same dataset name in the Evaluation Dataset column means the evaluation in the same dataset (no cross-evaluation), and the other two datasets (cross-evaluation representing a multi-domain setting). Lastly, the FL result after ten rounds.

Model	Evaluation dataset	ROC-AUC	F1-score
GANomaly trained on CICIDS-2018	CICIDS-2018	0.924	0.615
	Bot-IoT	0.892	0.989
	TON-IoT	0.885	0.751
GANomaly trained on Bot-IoT	Bot-IoT	0.808	0.998
	CICIDS-2018	0.419	0.062
	TON-IoT	0.474	0.743
GANomaly trained on TON-IoT	TON-IoT	0.891	0.867
	Bot-IoT	0.691	0.998
	CICIDS-2018	0.764	0.147
GANomaly on a FL setup	CICIDS-2018	0.926	0.493
	Bot-IoT	0.994	0.968
	TON-IoT	0.866	0.781

TABLE II: Comparison of Anomaly-Flow and baselines in a federated learning setting, focusing on multi-domain DDoS detection by average F1-score. The baselines are evaluated in a cross-evaluation setting, with CICIDS-2018, Bot-IoT, and TON-IoT representing the multi-domain scenario.

Reference	Scope	Average F1-score
Autoencoder	Multi-domain detection with FL (excluding [9] changes, adapted for DDoS)	0.451 ± 0.329
Logistic Regression [15]	DDoS multi-domain detection with FL	0.496 ± 0.097
FLAD [5]	Improving FL Convergence for DDoS	0.694 ± 0.336
Anomaly-Flow	DDoS multi-domain detection and Pre-trained Models using Synthetic Data	0.747 ± 0.195

Using models trained on a specific context data yields good results within that context. However, performance significantly degrades when evaluated in other contexts, as reported in Fig. 4 for most algorithms. For example, in Table I, consider evaluating the GANomaly trained with the Bot-IoT dataset: within its context (its test set), it achieved an F1-score of 0.998. However, when assessed in a different context, such as CICIDS-2018, its performance dropped to 0.062. This demonstrates the model's limited effectiveness from a multi-domain perspective.

Considering the ROC-AUC values in Table I, the GANomaly trained on CICIDS-2018 and TON-IoT datasets obtained a better cross-evaluation result than the Bot-IoT case. A factor in this difference is the amount of benign and DDoS data in each dataset; this measure is presented in Fig. 2. In this way, the Bot-IoT dataset is highly imbalanced, containing a low percentage of samples referring to benign flows. This factor may have influenced the training of the models and, consequently, its cross-evaluation performance.

B. External Models Evaluation

The external models' evaluation analysis uses an additional dataset (UNSW-NB15) representing an external entity. Our analysis follows a structured approach examining how pre-trained models can be shared and adapted for external use.

1) Model Training and Sharing Methodology: We trained different heterogeneous models using synthetic data ② and shared those models ③ with the external entity without taking data outside the trustful environment (Fig. 1). Thus, sharing a model instead of synthetic data adds another layer of privacy. The shared model ③ was trained with benign synthetic network data, which enables the external entity to start from this previous knowledge. Then, the external entity can fine-tune this shared model with its data to adapt to its domain.

2) Performance Analysis in External Domain: Our analysis is two-fold: how this shared model performs on the external entity and whether this external entity identifies anomalous DDoS samples never seen before.

We considered as external models the algorithms capable of incremental learning: Random Forest, Isolation Forest, XGBoost, and MLP – EFC and LR are unfeasible for incremental learning. The models were trained using 100,000 synthetic samples. Next, the models were trained in this new domain incrementally based on UNSW-NB15 data. Then, we evaluated the model's capability to detect attacks on this new domain. On the one hand, the algorithms Isolation Forest (F1-score: 0.018) and XGBoost (F1-score: 0.076) performed insufficiently. On the other hand, the algorithms Random Forest (F1-score: 0.965) and MLP (F1-score: 0.940) obtained reasonable results in the new domain data after fine-tuning.

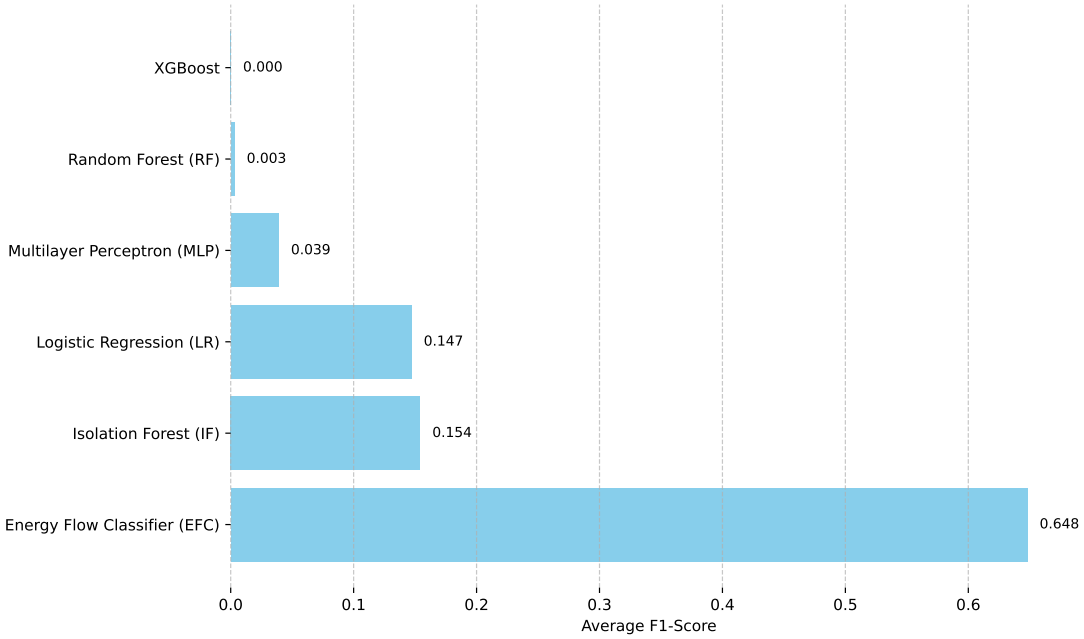


Fig. 4: Average F1-score for baseline algorithms, showing their generalization performance when trained on one dataset and tested on the other two in the context of DDoS detection. The results reveal significant variability in performance across models, with most algorithms achieving low scores, indicating poor cross-dataset generalization. Notably, the Energy Flow Classifier (EFC) substantially outperforms others, suggesting its robustness in diverse network scenarios. These findings emphasize the challenges of deploying machine learning models in multi-domain – multiple heterogeneous environments – and underscore the importance of designing algorithms capable of handling such variability.

3) Cross-Domain Detection Capabilities: Subsequently, we used TON-IoT, CICIDS-2018, and Bot-IoT test data to evaluate this model's performance when facing DDoS samples that were never seen before in its domain (UNSW-NB15). The results obtained in this analysis were the following: the MLP algorithm is the most promising, detecting DDoS samples from TON-IoT and Bot-IoT, achieving an F1-score of 0.750 and 0.989, respectively. However, CICIDS-2018 achieved an F1-score of 0.024, a possible reason for which is that the synthetic data could be statistically distant from the CICIDS-2018 domain. When synthetic flows deviate statistically from actual network characteristics, model performance degrades substantially, as seen with the CICIDS-2018 results. Overall, the external model could identify DDoS attacks from other domains.

4) Summary of Findings: The results of sharing synthetic data as a pre-trained model were behind expectations. However, when sharing synthetic data, the model began to identify previously unseen DDoS samples from other domains. This result highlights challenges that still need to be overcome, such as the semantic quality of the data generated by GAN networks. It is also noteworthy that sharing attacks and benign data could improve the models' performance. Furthermore, by refining the presented proposal, other methods can be applied to enhance the performance of models trained with synthetic data. Future work should focus on techniques to maintain statistical fidelity between synthetic and real network traffic distributions.

V. Challenges

Using machine learning for NIDS and techniques to enhance generalization capabilities still pose challenges. The following are challenges identified regarding the approach to those topics.

Generalization across domains: Different networks exhibit varying types of traffic during use. For instance, IoT networks have significant differences compared to corporate networks. Furthermore, DDoS attacks also have specific traits depending on the tool used to generate the attacks. Considering the datasets analyzed in this work, different DoS attack tools exist in each dataset on which the models were trained. Each dataset involved a range of DDoS tools, highlighting the diversity of attack generation methods.

Data sharing privacy: Sharing information between multiple networks can be a way to identify a greater variety of attacks. However, information sharing must consider several factors, such as sharing sensitive information or corporate secrets. The use of FL contributes to sharing information relating only to machine learning models. However, there are still concerns regarding attacks on the FL system. We propose sharing synthetic data via a pre-trained model to enable collaborative NIDS while preserving privacy, though it demands extra effort.

Data Quality, Availability, and Updates: It becomes challenging for the developer to identify whether the data used for training has all the valid information and also for the synthetically generated data. Given this uncertainty, the

models can be trained incorrectly and represent a behavior different from the applications' regular use.

For instance, during our evaluation of Anomaly-Flow's synthetic generated data, initial findings about the feature *protocol*, which would be expected to range between 0 and 255, for some synthetic flows this feature assumed values above 4000, which reinforces this challenge. Furthermore, data drift in network data is intense, as factors such as seasonal operations, new applications, and obsolete detection systems require constant retraining with new information.

Regarding quality, datasets must contain information from attacks that have a substantial impact. Therefore, providing the ability to update data and models is an open challenge for NIDS research. Furthermore, network traffic patterns evolve rapidly, introducing data drift and requiring continuous model updates, making static detection approaches quickly obsolete without regular retraining.

Deployment and use of ML NIDS in real-world: Many works present solutions based on ML, but adopting the tools in a corporate environment is still a long way off. Application in practice requires that models be capable of identifying attacks without generating many false alarms. Erroneous attributions result in time-consuming analyses and generate unnecessary costs for operators. It still becomes an even more significant challenge to explain the identification quickly and generate information to facilitate future studies. Furthermore, the computational overhead of complex ML approaches like GANs and FL presents considerable practical challenges. Training generative models require substantial resources, while inference time can introduce critical latency in attack detection. Optimizing these models for resource-constrained environments without sacrificing accuracy remains an open research problem, as does addressing energy consumption implications of continuous operation across distributed networks.

VI. Opportunities

Identifying DDoS attacks in a multi-domain setting presents opportunities for improvement concerning the challenges presented. Attacks can be identified through anomalies but without the use of fixed thresholds. The use of adaptive thresholds or even the composition with machine learning systems can contribute to improving the performance of models, taking into account differences in the data in each context.

From a research perspective, cross-evaluation between different datasets should be an essential component of future research to validate whether reported results generalize across scenarios and to document limitations explicitly. This rigorous evaluation approach would help bridge the gap between theoretical advances and practical implementations. Additionally, it would provide more precise insight into which detection methods are genuinely effective across different network environments.

Researchers can explore techniques to enhance the semantic quality of synthetic data by evaluating it with domain experts and implementing constraints that prevent inconsistent conditions (e.g., negative time measurements) while preserving the data's utility for detection tasks. Creating a method to identify new DDoS attack tools and techniques is necessary regarding data quality, availability, and updates. When placing new participants, applying a technique capable of grouping attack examples with benign samples is essential, thus creating datasets that represent potentially harmful samples. Finally, developing a tool capable of simulating environments as closely as possible to reality is critical. Including experts' feedback to ensure that using the NIDS system becomes practical is also an opportunity.

VII. Conclusions

This work demonstrated how GAN networks configured in an FL scheme can help identify DDoS in a multi-domain setting. The proposed GAN system can generate synthetic data based on FL participants. We presented that heterogeneous models trained using this synthetic data can identify previously unseen DDoS attacks.

However, the solution's performance requires more effort to implement and use in practice by network operators. Thus, we report several challenges encountered during our tests. The first challenge is that generalization across domains remains an open issue despite the advancements achieved through our approach.

Furthermore, the performance of heterogeneous models is highly dependent on the data generated synthetically, so the distribution of the generated data must be as close to reality as possible. Moreover, the operational aspects of the models must be considered, such as the implementation of the system, stages of updating training data, and the models' ability to support decision-making.

Finally, we list research opportunities for overcoming these challenges, serving as future directions for research in the area.

The code to reproduce the experiments is available in the repository https://github.com/c2dc/anomaly-flow.

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