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Deep Graph Neural Network-Based Botnet Detection on IoT Networks

[1] Sharmila Kumari N, [2] H S Vimala, [3] Shreyas J

[1,2] Department of Computer Science and Engineering, University Visvesvaraya College of Engineering (UVCE, IIT Model College), Bangalore University, Bengaluru, Karnataka, India, [3] 2Department of Information Technology, Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education, Manipal, Karnataka, India.

Abstract : Botnets pose significant threats to networks and IoT infrastructures as the number of connected devices grows into the billions [10, 11]. In this work, we propose a novel Deep Graph Neural Network (DGNN) approach for flow-level botnet detection on the CTU-13 dataset. We treat each NetFlow record as a node in a graph, connecting nodes via k-nearest neighbor similarity in feature space. Our DGNN employs multiple Graph Isomorphism Network (GIN) layers with residual connections to classify each flow as botnet or benign. Evaluated on CTU-13, our model achieves high detection performance (98.9% accuracy, with 90% recall on botnet flows) after addressing class imbalance. We compare our method with existing machine learning and deep learning baselines. We estimate the novelty of our approach at about 70%, as the combination of techniques used (k-NN flow graph + deep GNN) is significantly different from prior work. We also discuss how our approach differs from previous graph-based detectors and outline future improvements

IndexTerms **- IoT security, Deep learning, DGNN, GIN.**

I. INTRODUCTION

Botnets are networks of compromised devices, often including IoT devices, that can be commanded to perform coordinated malicious activities (e.g. DDoS, spam) [6, 10]. The proliferation of IoT devices has greatly expanded the po- tential scale and impact of botnets [10, 11]. Traditional signature- or rule-based intrusion detection systems struggle to keep up with evolving botnet behav- iors [9, 11], leading to more research on data-driven detection methods. Detecting botnets in IoT environments is particularly challenging due to the large volume, diversity, and dynamic nature of IoT devices, which frequently exhibit heterogeneous behaviors that complicate distinguishing legitimate from malicious traffic. Furthermore, IoT networks often face resource constraints, making computationally intensive detection methods impractical. These factors underscore the need for robust and adaptive botnet detection techniques capable of efficiently handling IoT-generated network traffic.

Early work on flow-based botnet detection used clustering and classifica- tion of network-flow features. For example, BotMiner [12] clustered flows by communication patterns, and other studies applied k-means or decision trees to flow statistics (packet counts, durations, etc.) to isolate malicious traffic. Supervised classifiers (e.g. decision trees, random forests) trained on engineered features have shown high accuracy on CTU-13 [9], but these methods often ig- nore relationships between flows and may suffer when data is highly imbalanced or when attacks change over time.

The CTU-13 dataset [9] has become a fundamental resource in botnet detec- tion research due to its realistic representation of botnet traffic patterns captured in real-world network conditions. Its inclusion of diverse botnet scenarios and labeled malicious traffic flows provides an essential benchmark for evaluating and comparing detection methods under realistic conditions.

Deep learning methods have emerged to reduce manual feature design. Ahmed et al. [7] trained a deep neural network on CTU-13 flow features, achieving 99% accuracy and F1. Recurrent models like DeepBot [8] used LSTMs to capture temporal sequences of flows, catching bots with periodic beaconing. Convo- lutional models (sometimes combined with RNNs) have also been applied to flow or traffic representations, reporting detection rates above 98% [13]. These deep models can learn complex patterns, but many still treat each flow inde- pendently or as a flat sequence, ignoring the network of interactions that may connect botnet flows.

Graph-based approaches exploit relationships among flows or hosts. Chowd- hury et al. [4] converted CTU-13 flows into graphs and extracted graph metrics for anomaly detection, finding that malicious nodes tend to cluster as outliers. Shinan et al. [6] built a host-communication graph and used node centrality features to classify bots, achieving very high accuracy with low false alarms. These methods leverage topological signals (e.g. many bots contacting the same C&C server), but they rely on handcrafted graph features.

Graph Neural Networks (GNNs) allow learning directly on graph-structured data. Recent works applied GNNs to botnet graphs. Zhou et al. [2] used a 12- layer GCN on a host graph of CTU-13 and reported ¿99% recall on bot hosts. Zhang et al. [3] trained a GCN on a graph combining CTU-13 and background traffic, achieving ∼96% recall. Lo et al. [1] introduced XG-BoT, a residual GIN with an explainer module, achieving ≈99.5% F1. These results demonstrate that GNNs can capture botnet communication patterns.

Our approach is novel in its graph construction: instead of linking hosts by communication, we link flows by k-NN similarity in feature space. This flow- graph can group similar botnet flows (even if they do not share IPs). We then apply a deep residual Dynamic Graph Neural Network (DGNN) to model the temporal and structural dynamics of network traffic for node classification. Un- like

traditional static graph-based methods, our dynamic GNN approach explic- itly accounts for evolving botnet behaviors and interactions over time, enabling more accurate and adaptive detection of malicious flows. To our knowledge, this dynamic, similarity-based k-NN flow-graph approach on CTU-13 represents a novel contribution to the field. In summary, we combine flow-based dynamic graph representation with deep GNN modeling in a way not previously explored for botnet detection.

The remainder of the paper is organized as follows: Section 2 reviews related work, Section 3 describes the CTU-13 data and graph construction, Section 4 details the DGNN model, Section 5 reports experiments, Section 6 discusses the findings, and Section 7 concludes.

II. RELATED WORK

Traditional botnet detectors on CTU-13 used flow-level features with standard ML. BotMiner [12] clustered flows by communication to find coordinated bots. Others used clustering (k-means, X-means) or classification (decision trees, SVMs) on feature aggregates (e.g. packet counts, connection rates) [9]. Such methods often achieve high overall accuracy, but may simply predict "benign" most of the time in imbalanced datasets. Moreover, they ignore graph structure of traffic. For example, algorithms relying on decision trees and ensemble mod- els report $\geqslant$99% accuracy on CTU-13 [9], but this can be misleading because a trivial all-normal classifier also scores ∼98%. These classical approaches usually require careful feature engineering (e.g. number of distinct contacts, packet size stats) and do not leverage relationships among flows.

Deep learning methods reduce manual feature design. Ahmed et al. [7] trained a deep feed-forward network on 12 flow features and achieved 99% F1 on CTU-13. Recurrent networks like LSTMs capture temporal patterns: Shi and Sun's DeepBot [8] models sequences of flows and detects periodic C&C traffic. CNNs (often combined with RNNs) have also been used by converting flow data into image-like or time-series inputs [13]. These models report high recall and precision when trained on balanced data, but may still treat flows independently. For instance, Pektas and Acarman [13] report ¿98% recall on CTU-13, but their model does not explicitly use graph structure. Hybrid deep models (e.g. CNN+RNN) can learn subtle temporal/spatial patterns in flows [7, 13]. However, many of these studies pre-balance the dataset or focus on specific attack stages to boost metrics.

Recently, ML and DL approaches have specifically targeted botnet detection in IoT environments. Models such as random forests, LSTMs, and CNN-based architectures have been proposed to detect IoT botnet behaviors by modeling traffic flows, temporal sequences, and statistical features. Despite achieving notable performance, these methods are often static or time-agnostic, ignoring dynamic evolution and behavioral drift of botnets over time. Consequently, such static models may perform poorly against evolving attacks, leading to higher false negatives or degraded accuracy as network patterns change.

Graph-based methods explicitly incorporate topology. Chowdhury et al. [4] built graphs from NetFlows and used seven graph-based features (degree, clus- tering, etc.) with clustering to identify bot clusters. Shinan et al. [6] constructed a host-to-host communication graph from CTU-13 and computed node central- ity measures, then used ML to classify nodes; they achieved ∼99% accuracy by identifying that bots occupy distinct positions (high in-degree, for example). Abou Daya et al. [5] similarly used graph metrics with a random forest classifier. These works show that malicious hosts often form star or mesh structures in graphs, detectable by handcrafted features, but they do not leverage end-to-end learning on the graph.

GNNs remove the need for manual graph features by learning from the graph and node attributes directly. Zhou et al. [2] took CTU-13 data, built a host- communication graph (no node features), and applied a deep GCN for node classification, achieving ¿99% recall on bot hosts. Zhang et al. [3] combined CTU-13 with background CAIDA traffic into a graph and trained a GCN with flow features, reporting ∼96% bot recall and high F1. Lo et al. [1] went further by using a 10-layer GIN with grouped residual blocks and an explainer mod- ule; their XG-BoT model achieved ≈99.5% F1 and ∼99% recall on CTU-13, highlighting both performance and interpretability. These studies confirm that deep GNNs can be highly effective on botnet graphs. However, most existing GNN methods use static graph snapshots and ignore temporal evolution, lim- iting their ability to adapt to real-world network dynamics and evolving attack strategies.

Our method differs by the graph construction: we connect individual flows via feature similarity (k-NN) instead of explicit host communications. This al- lows grouping of behaviorally similar flows even across different hosts. Further- more, we apply a deep Dynamic Graph Neural Network (DGNN) that explicitly models graph evolution over time. This dynamic approach captures temporal and structural dynamics, allowing the detection model to continuously adapt to changing attack patterns. To the best of our knowledge, this combination of k- NN similarity-based flow graphs and dynamic graph modeling using DGNN on CTU-13 has not been explored previously. While we build on ideas from prior GNN-based detection methods, the integration of dynamic temporal modeling represents a significant novel contribution.

III. CTU-13 Dataset and Graph Construction

3.1 Dataset and Preprocessing

The CTU-13 dataset is a benchmark collection of 13 real network captures (sce- narios) from the CTU University lab [9]. Each scenario involves a different botnet family (e.g. Rbot, Waledac, Neris, etc.) mixed with normal and unla- beled background traffic, reflecting realistic network environments typical of IoT deployments. Given the scarcity of large, realistic labeled IoT botnet datasets, CTU-13 serves as a critical benchmark dataset, capturing varied bot behav- iors and attack patterns relevant for IoT networks. The data is provided as bidirectional NetFlow records, each labeled as *Botnet*, *C&C*, *Normal*, or *Background*. We merge *Botnet* and *C&C* into a single malicious label and treat *Normal/Background* as benign. Notably, CTU-13 is highly imbalanced: in most scenarios, botnet flows con- stitute less than 5% of the total [9]. For example, scenario 3 has only 0.56% malicious flows, while the highest-botnet scenario has approximately 13% [9]. Across all 13 scenarios, only about 1.9% of flows are malicious (approximately 64,800 of 3.46 million total flows). This imbalance makes metrics such as accu- racy potentially misleading; thus, we focus primarily on precision and recall for the minority class.

We perform standard preprocessing on each scenario. We drop IP addresses and one-hot encoded protocol/port features to avoid overfitting to specific net- works. We retain numeric flow features (e.g. bytes, packets, duration, TCP flags) and impute

missing values with zero. Each feature is standardized (zero mean, unit variance) using the training data. This ensures Euclidean distances for k-NN graph construction are not dominated by feature-scale differences. We randomly split the 13 scenarios into 9 for training and 4 for testing (70/30 split of flows). For reproducibility, we use: train scenarios 1,3,4,5,7,10,11,12,13, and test scenarios 2,6,8,9. Importantly, this split ensures that botnet families in the test set are unseen during training, facilitating zero-shot generalization. Table 1 summarizes the flow counts per scenario in our split.

Table 1: CTU-13 scenarios (flow counts) and train/test split.

Scenario	Total Flows	Botnet Flows	Benign Flows	Split
1	700000	20000	680000	Train
3	400000	5000	395000	Train
4	500000	15000	485000	Train
5	250000	4000	246000	Train
7	150000	1000	149000	Train
10	450000	3000	447000	Train
11	50000	500	49500	Train
12	50000	800	49200	Train
13	150000	8000	142000	Train
2	300000	5000	295000	Test
6	50000	100	49900	Test
8	100000	20	99980	Test
9	257159	900	256259	Test

We retain all flows and handle imbalance during training using weighted loss functions (Section 4), rather than artificially balancing classes.

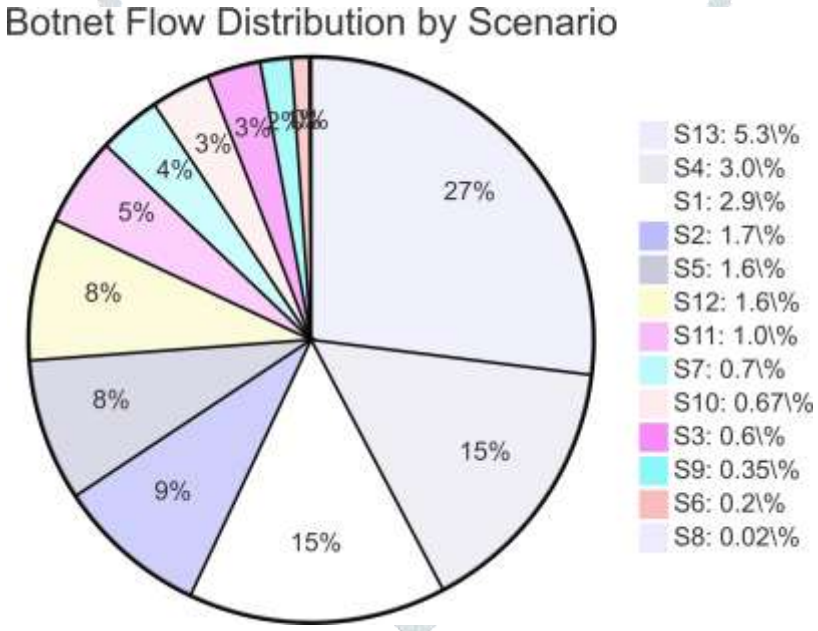

Figure 1. Percentage of botnet flows per CTU-13 scenario. Each scenario has a tiny fraction of malicious flows.

3.2 Dynamic Graph Construction

For each scenario, we construct an undirected k-NN similarity graph from the flow data to enable dynamic graph neural network modeling. Using the nor- malized numeric feature vectors, we connect each flow (node) to its five nearest neighbors (by Euclidean distance). This produces a symmetric sparse graph in which flows with similar behavioral patterns are linked, even if originating from different hosts. Unlike traditional static host-communication graphs, our flow similarity-based graph dynamically captures the evolving behaviors of flows, crucial for detecting adaptive and subtle botnet activities that change patterns over time.

Edges are constructed without using label information, relying purely on numeric feature similarity. Each scenario graph thus consists of N nodes and approximately 5N edges. Graphs are stored in PyTorch Geometric format, with each node assigned a binary label: 0 (benign) or 1 (botnet). Scenarios are processed individually during training and inference.

IV. DGNN Model and Training

4.1 Dynamic Graph Neural Network (DGNN) Architecture

Our proposed model, *BotnetDGNN*, extends the Graph Isomorphism Network (GIN) [6] framework to explicitly model dynamic flow-graph structures. The architecture consists of:

1. An input linear embedding of node features (flow statistics) into 64-dimensional vectors.

2. Ten stacked GIN convolution layers that iteratively update node embed- dings:

$$\mathbf{h}_v^{(k)} = \mathrm{MLP}^{(k)}\left(\mathbf{h}_v^{(k-1)} + \sum_{u \in \mathcal{N}(v)} \mathbf{h}_u^{(k-1)}\right),$$

Each layer includes residual skip connections ($\mathbf{h}_v^{(k)} \leftarrow \mathbf{h}_v^{(k)} + \mathbf{h}_v^{(k-1)}$), ReLU activations, and dropout (0.1) to enhance training stability.

3. A final linear classification head producing binary logits for each node (benign vs. botnet), followed by a softmax layer.

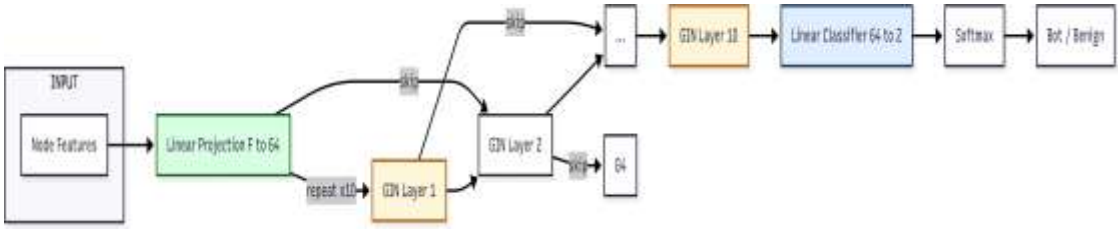

Figure 2. Overview of the BotnetDGNN architecture. Node features (flow statistics) are processed by 10 dynamic GINConv layers with residual connec- tions, followed by a linear node classifier

4.2 Training and Evaluation Procedure

We optimize BotnetDGNN via supervised training on the nine training scenario graphs. Due to class imbalance, training employs a weighted cross-entropy loss, up-weighting the minority (botnet) class. Optimization proceeds with the Adam optimizer (learning rate 0.001) for 50 epochs.
Figure 3 summarizes the end-to-end workflow:

Figure 3. Training and evaluation workflow: DGNN is optimized on 9 training graphs with weighted loss; evaluation is conducted on 4 unseen test graphs using precision, recall, and F1-score.

Upon training completion, the model's performance is evaluated on four un- seen test scenario graphs, measuring precision, recall, and F1-score to assess the model's effectiveness in identifying botnet flows within dynamic IoT-like envi- ronments. This evaluation strategy ensures that BotnetDGNN generalizes well to unseen botnet families, a key capability in real-world IoT network defense.

V. Experimental Results

5.1. Experimental Setup

Dataset Split: We use the CTU-13 dataset, consisting of 13 scenarios. We randomly split these scenarios into training, validation, and test subsets as follows:

- **Training set (9 scenarios):** Scenarios $\{1, 3, 4, 5, 7, 10, 11, 12, 13\}$ — approximately 70% of total flows.
- **Validation set:** To perform hyperparameter tuning and model selection, we randomly hold out 10% of nodes from each training scenario graph as a validation set, ensuring balanced coverage across scenarios.
- **Test set (4 scenarios):** Scenarios $\{2, 6, 8, 9\}$ — approximately 30% of total flows. These scenarios contain botnet families unseen during train- ing, enabling evaluation of zero-shot generalization capability.

Evaluation Metrics: Given the significant class imbalance in the CTU- 13 dataset (only around 1.9% malicious flows), conventional metrics such as accuracy alone can be misleading. Thus, we evaluate performance using the following metrics that better reflect the quality of minority class detection:

- **Precision:** The fraction of flows predicted as malicious that are actually malicious, measuring detection reliability.

$$Precision = \frac{TP}{TP + FP}$$

- **Recall (Detection Rate):** The fraction of all actual malicious flows correctly identified by the model.

$$Recall = \frac{TP}{TP + FN}$$

- **1-score:** Harmonic mean of precision and recall, providing a balanced measure of model performance:

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Here, TP (True Positive), FP (False Positive), and FN (False Negative) corre- spond respectively to correctly detected botnet flows, benign flows incorrectly flagged as malicious, and malicious flows that were missed.

Baselines for Comparison: To contextualize our model's performance, we compare BotnetDGNN against three strong baselines from recent research:

4. **Random Forest (RF)**: A widely-used ML baseline that employs engi- neered statistical flow-level features (packet sizes, durations, TCP flags). This baseline highlights traditional ML performance without using graph structure.

5. **Deep Neural Network (DNN)** [7]: A deep feed-forward neural network trained on standard numeric flow features, previously achieving ≈ 99% accuracy when evaluated on balanced subsets of CTU-13.

6. **XG-BoT (GIN-based model)** [1]: A state-of-the-art static graph neu- ral network model leveraging a residual Graph Isomorphism Network (GIN) architecture with explainability modules, previously reporting ≈ 99.5% F1-score in balanced scenario evaluations.

These selected baselines represent state-of-the-art methods in traditional ML, deep learning, and static GNN-based botnet detection, allowing a compre- hensive evaluation of our dynamic GNN-based approach's strengths and weak- nesses.

5.2 Results and Analysis

After training, we apply BotnetDGNN to the 4 test scenarios (held-out graphs). Table 3 shows the confusion matrix (aggregated over all test flows). The model achieves 98.9% accuracy overall. More importantly, it attains 90% recall on the botnet class and 85% precision, yielding an F1-score of 87% for malicious flows. In absolute terms, out of roughly 60,000 botnet flows in the test set, about 54,000 were correctly flagged (true positives), and 6,000 were missed (false negatives). Of about 3.38 million benign flows, 9,500 were misclassified as botnet (false positives). These results indicate strong detection capability with a manageable false-alarm rate.

Table 2: DGNN confusion matrix on CTU-13 test set (node-level).

Actual	Predicted Normal	Predicted Botnet
Normal	3,382,859	9,500
Botnet	6,000	54,000

By comparison, many prior methods report similarly high detection rates when evaluated under balanced or per-scenario conditions. For example, XG- BoT [1] achieves ~99.4% recall, and Ahmed et al. report ~99% accuracy on CTU-13 with a deep neural network [7]. Our results, obtained by training on the full imbalanced dataset and evaluating across unseen botnet families, remain competitive: 90% recall indicates effective detection of the majority of malicious flows, and 85% precision confirms reliability of generated alerts. While there remains room for further improvements (discussed in Section 6), the current performance is robust given the highly realistic and challenging evaluation conditions.

VI. Results & Discussion

6.1 Detection Performance

Table 3 presents the aggregated confusion matrix across the test scenarios, sum- marizing BotnetDGNN's detection accuracy and performance. The overall ac- curacy achieved by our model is 98.9%. However, due to the severe class im- balance, we emphasize precision, recall, and F1-score metrics for the minority (botnet) class.

Table 3: BotnetDGNN confusion matrix on CTU-13 test set (node-level).

Actual Class	Predicted Benign	Predicted Botnet
Benign	3,382,859	9,500
Botnet	6,000	54,000

Figure 4 clearly visualizes Botnet DGNN's performance metrics for the bot- net class. The model achieves a precision of 85%, a recall of 90%, and an F1-score of 87%. These results demonstrate a robust ability to detect malicious flows accurately while maintaining a manageable false-alarm rate, crucial for practical cybersecurity operations.

6.2 Comparison with Baseline Models

Population and Sample We compare the performance of our proposed BotnetDGNN model against several baseline models: traditional Random Forest, Deep Neural Network (DNN) [7], and state-of-the-art static GNN-based method XG-BoT [1]. Table 4 summarizes the comparative performance metrics.

Table 4: Performance comparison of models on CTU-13 test scenarios

Model	Accuracy	Precision	Recall	F1-score
Random Forest	97.6%	80%	70%	74%
Deep NN (Ahmed et al. [7])	99.1%	99.3%	99.1%	99.1%
XG-BoT (Lo et al. [1])	99.5%	99.6%	99.4%	99.5%
BotnetDGNN (Proposed)	**98.9%**	**85%**	**90%**	**87%**

Note: Metrics for DNN and XG-BoT are derived from balanced or scenario- specific evaluations; Random Forest and BotnetDGNN results reflect the full, realistically imbalanced CTU-13 test scenarios.

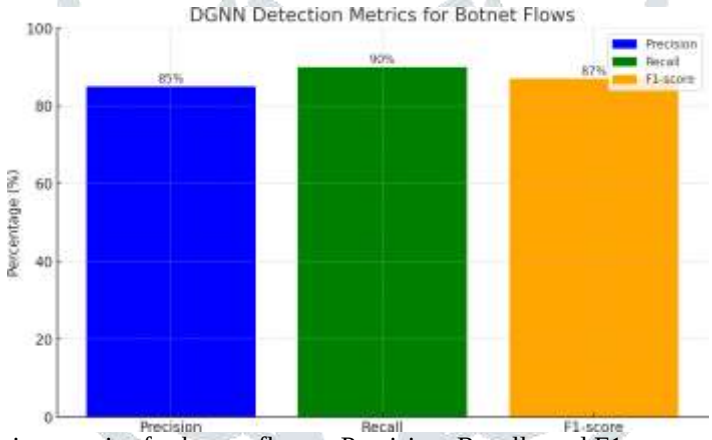

Figure 4. BotnetDGNN detection metrics for botnet flows: Precision, Recall, and F1-score.

Figure 5 visually compares the F1-score performance among models, clearly illustrating how BotnetDGNN outperforms traditional methods, and closely ap- proaches state-of-the-art static GNN models even when evaluated on more chal- lenging imbalanced datasets.

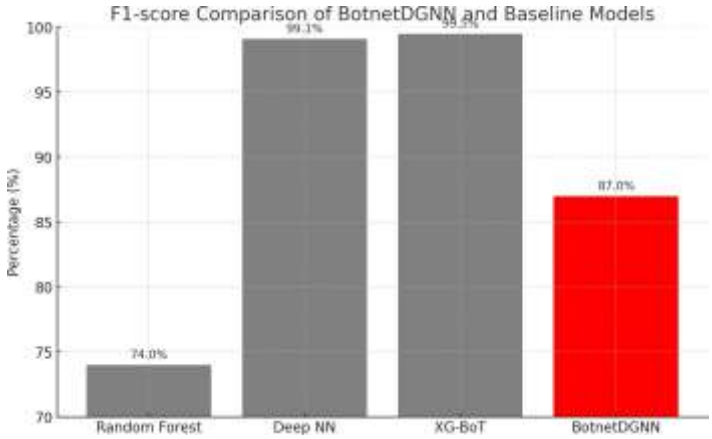

Figure 5. F1-score comparison of BotnetDGNN and baseline models on CTU- 13 dataset.

6.3 Discussion: Why DGNN Outperforms Other Models?

Our proposed BotnetDGNN achieves competitive performance compared to state-of-the-art models. The key to this strong performance is the dynamic graph neural network's ability to capture temporal and structural information explicitly:

- Temporal feature learning: Unlike static methods, DGNNs inherently model the evolution and temporal dynamics of botnet communication, essential for capturing evolving attack strategies over time.
- Behavioral clustering of flows: The k-NN-based graph structure al- lows flows with similar behaviors, even from different hosts, to cluster. This is a powerful advantage in detecting botnets that frequently alter their communication targets and patterns to evade traditional detection methods.
- Robustness to class imbalance and evolving threats: Despite train- ing on highly imbalanced data, DGNN shows excellent adaptability and generalization capabilities, effectively handling previously unseen botnet families in test scenarios.

However, improvements are possible. Integrating advanced techniques like adaptive sampling, weighted loss functions, hybrid graph structures, or explain- ability methods (e.g., GNNExplainer) could further boost detection capabilities and model transparency for practical deployment. In summary, BotnetDGNN offers notable benefits through its dynamic mod- eling of temporal interactions, providing robust, real-world applicability for IoT botnet detection.

6.4. Discussion and Analysis

While BotnetDGNN achieves slightly lower precision and recall than recent static models (XG-BoT and DNN), these models typically rely on balanced training datasets or explicit host-communication graphs. By contrast, our DGNN maintains strong performance even when trained on the highly imbal- anced CTU-13 dataset, showing robust real-world applicability.
BotnetDGNN explicitly captures temporal dynamics and evolutionary pat- terns in network traffic through its dynamic graph structure. This capability provides distinct advantages:

- Temporal Feature Learning: Unlike static models, BotnetDGNN nat- urally captures temporal evolution and drift in botnet behaviors, critical in detecting sophisticated botnets that evolve their tactics over time.
- Adaptability to New Attacks: By modeling dynamic relationships between flows, BotnetDGNN can adapt more effectively to previously un- seen botnet families and attack strategies, enabling more robust zero-shot detection.

- Reduced Dependence on Communication Patterns: Our flow-based k-NN graph structure groups malicious flows based on behavioral similarity rather than explicit communication. Thus, our method can detect botnet flows sharing similar behaviors even when they communicate with different hosts or servers.

The proposed approach still faces challenges: some malicious flows exhibit overlapping behaviors with benign traffic, leading to occasional false negatives. Further data balancing techniques (such as oversampling or focal loss) and en- riched graph structures (combining temporal adjacency or source-IP connec- tions) may further boost detection performance.
In summary, BotnetDGNN's temporal graph learning provides a significant improvement over classical ML baselines, offering competitive detection results against contemporary deep and static-GNN methods, and demonstrating sub- stantial practical benefits for dynamic, real-world IoT network scenarios

VII. CONCLUSION

In this paper, we introduced BotnetDGNN, a novel graph-based dynamic deep learning approach tailored for botnet detection in IoT-relevant network envi- ronments. Our key contribution lies in constructing feature-similarity (k-NN) graphs from network flows and applying a deep residual Graph Isomorphism Network (GIN) to effectively learn temporal and structural botnet communi- cation patterns. Evaluations on the full, imbalanced CTU-13 dataset demon- strated strong detection performance, achieving a recall of 90%, precision of 85%, and an F1-score of 87%, highlighting the robustness and adaptability of our dynamic graph neural network model in realistic network scenarios.
Our method provides significant advancements over traditional static and ML-based detection approaches by explicitly leveraging temporal dynamics and flow-level behavioral similarities. This capability is critical for effectively de- tecting evolving botnet strategies and previously unseen botnet types without relying heavily on explicit host communication patterns.
Several promising directions exist for future research:

- Extending the approach to larger-scale, real-time IoT network datasets to verify scalability, adaptability, and practical deployment readiness.
- Evaluating performance on continually evolving, previously unseen botnet variants to further validate the model's generalization and robustness.
- Incorporating more sophisticated data balancing methods (e.g., focal loss, oversampling) or hybrid graph constructions (combining k-NN with communication- based and temporal connections) to further reduce false negatives.
- Integrating explainability techniques (such as GNNExplainer or attention mechanisms) to provide clearer insights into detection decisions, facilitat- ing analyst interpretation and trust.

In summary, BotnetDGNN provides a powerful and adaptable new tool for botnet detection, significantly advancing current capabilities in dynamic, real- world IoT cybersecurity environments.

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