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Elevating 5G Network Security: A Profound Examination of Federated Learning Aggregation Strategies for Attack Detection

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NANCY

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Motivation

- **Rapid Growth of 5G Networks**: Significant advancements in connectivity, speed, and reliability.
- **Security Challenges**: Increased security and privacy concerns in distributed, dynamic 5G networks.
- **Dynamic and Complex Nature**: Difficulty of traditional Intrusion Detection Systems (IDS) to handle 5G's diverse devices.
- **Privacy and Data Exchange Issues**: Limitations in data sharing among devices due to privacy concerns.
- **Need for Effective IDS**: Critical for detecting cyber threats, with the balance of accuracy and privacy.

Aim and Contribution

Research Aim

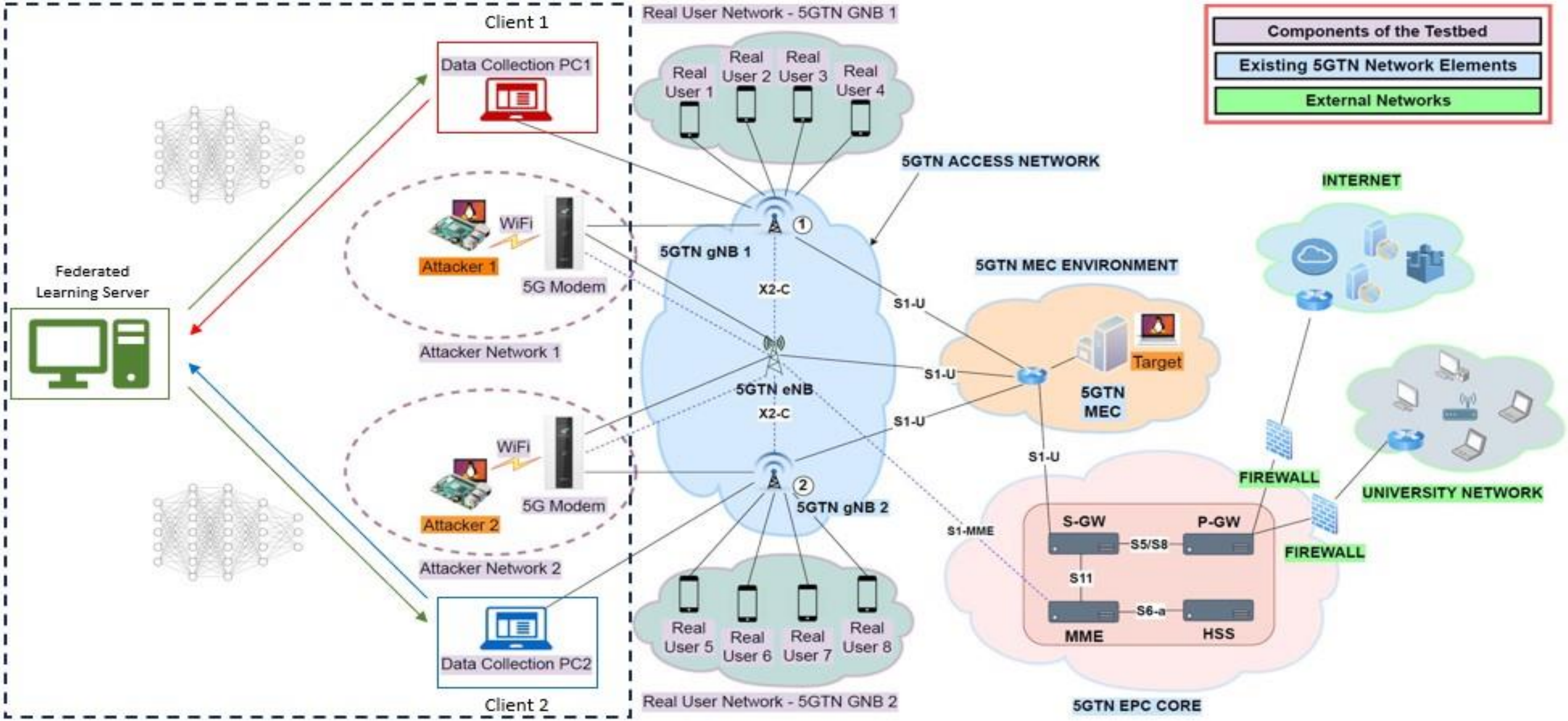
Explore the use of Federated Learning (FL)-based Intrusion Detection Systems (IDS) in 5G networks to detect 9 different types of intrusions while upholding user privacy.

Innovative Approach: Utilization of FL to train an IDS across different nodes without direct data exchange.

Contributions

- Demonstrated higher effectiveness and privacy preservation of FL-based IDS.
- Provided insights into the impact of FL aggregation strategies on IDS performance.
- Offered a scalable, adaptable solution for securing 5G networks against cyber threats.

System Architecture



S. Samarakoon, Y. Siriwardhana, P. Porambage, M. Liyanage, S.-Y. Chang, J. Kim, J. Kim, and M. Ylianttila, "5g-nidd: A comprehensive network intrusion detection dataset generated over 5g wireless network," arXiv preprint arXiv:2212.01298, 2022

Federated Learning: Model Architecture

AI/ML Model: Multi-Layer Perceptron (MLP)

- Hidden layers: 5
- Neurons/layer: 150 → 100 → 75 → 50 → 25
- Output layer's neurons: 9
- Output's layer activation function: Softmax

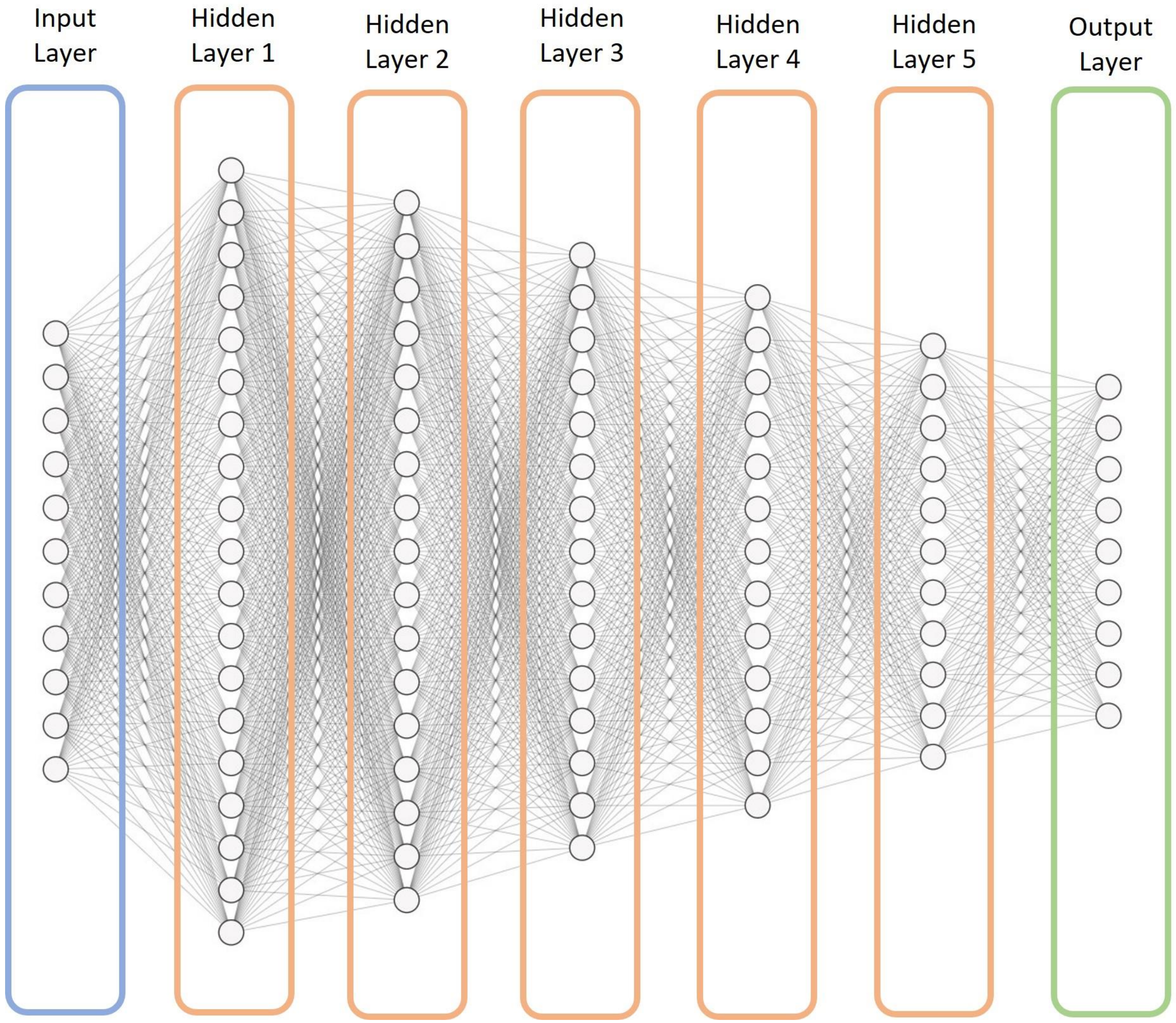
$$Softmax(x) = [e\hat{}x\_1 / sum(e\hat{}x), e\hat{}x\_2 / sum(e\hat{}x), \ldots, e\hat{}x\_9 / sum(e\hat{}x)]$$

- Optimizer: Adam

$$Adam\_update = \mathrm{lr} * \hat{m} / \mathrm{np.sqrt}(\hat{v} + 1\mathrm{e}\text{-}8)$$

- Loss function: Sparse Categorical Crossentropy

$$Sparse\_categorical\_crossentropy(y\_true, y\_pred) = \text{-sum}(\text{y\_true} * \log(\text{y\_pred}))$$



Federated Learning: FL Strategies

Aggregation

- *FedAvg*: Weighted average of local model updates. → $w_{global} = \frac{n_1}{n_1+n_2} w_1 + \frac{n_2}{n_1+n_2} w_2$
- *FedProx*: Generalization of FedAvg introducing a proximal term. Aims to reduce the impact of variable local updates. → $w_{global} = \frac{n_1}{n_1+n_2} w_1 + \frac{n_2}{n_1+n_2} w_2 + \lambda(\|w_1 - w_{prev}\|^2 + \|w_2 - w_{prev}\|^2)$

Optimization

- *FedAdam*: Introduces two decay parameters controlling historical and current model update importance. → $m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t$, $u_t = \beta_2 u_{t-1} + (1-\beta_2)\, g_t{}^2$
- *FedAdagrad*: Aggregates based on the difference between client and server models. → $g_{t,i} = \frac{1}{\eta}(\sqrt{\sum_{T=11} t\, g_{T,i}^2})$
- *FedYogi*: Considers distance from server model, direction of difference, and a decay parameter. → $g_{t,i} = g_{t-1,i} a \|\nabla F_i(w_{t-1}) - g_{t-1,i}\|$

Dataset: Description

- *Origin and Data Collection:* Generated for 5G-NIDD at University of Oulu's 5G Test Network, focusing on intrusion detection in 5G; data from Raspberry Pi attackers and live mobile traffic saved independently across two base stations.

- *Data Format and Structure:* Data collected in packet and flow formats, saved in PCAPNG, Argus, and CSV file formats, divided by base station and attack session.

- *Dataset Composition:* Focuses on BTS_1.csv (*728,316 rows*) and BTS_2.csv (*487,574 rows*), each featuring 52 features such as network packet flags, sequence numbers, runtimes, statistical measures, and TCP details.

- *Primary Study Variable:* "Attack Type" highlighted as the pivotal feature, encompassing 9 distinct categories: 1 benign and 8 varied attack types.

Dataset: Preprocessing

Consistent modifications applied to both BTS_1 and BTS_2 datasets.

- Managed missing values through sample removal or imputation.
- Eliminated duplicates.
- Applied one-hot encoding for categorical attributes.
- Stratified train-test split was done with an 80/20 ratio to maintain representation of all classes.
- Standard scaling was employed to ensure all features had consistent scale and distribution.
- SMOTE oversampling technique was implemented to address class imbalances in the "Attack Type" column, creating synthetic samples for minority classes.

Results: Evaluation Metrics

Confusion Matrix:

True label \ Predicted label		
	TP: Model correctly identifies an attack.	**FP**: Model incorrectly identifies an attack.
	FN: Model fails to identify an actual attack.	**TN**: Model correctly identifies no attack.

Predicted label

Accuracy:

$$\frac{TP+TN}{TP+TN+FP+FN}$$

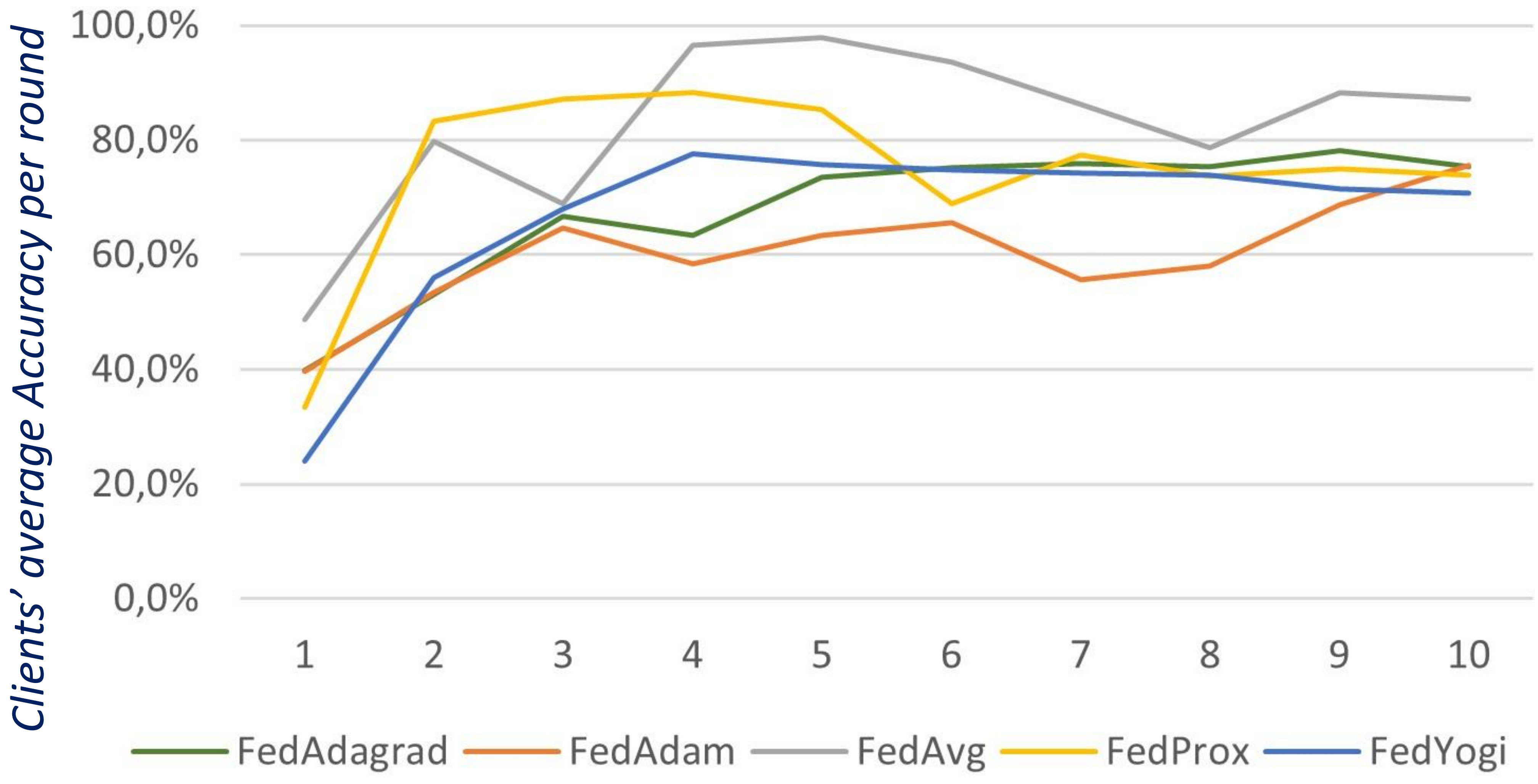
F1 Score:

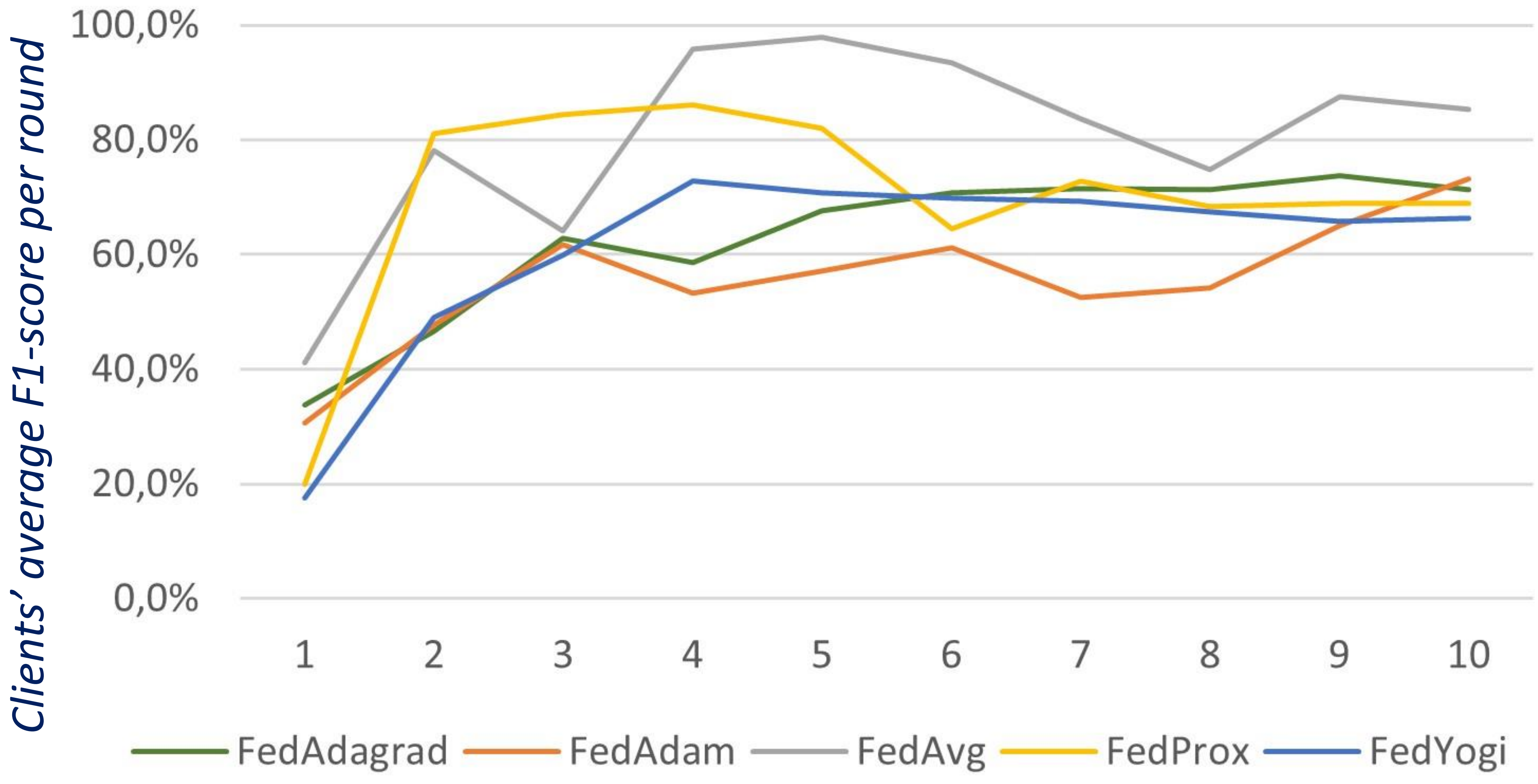
$$\frac{2\times \mathrm{TP}}{2\times \mathrm{TP}+\mathrm{FP}+\mathrm{FN}}$$

The evaluation metrics were weighted based on each client's data sample size to ensure a fair assessment.

Results: Experiments Outcomes

Strategy	Evaluation Metric	Client 1	Client 2	Average
FedAvg	Accuracy	99.45%	95.64%	**97.89%**
	F1-score	99.45%	95.55%	**97.85%**
FedProx	Accuracy	82.22%	97.18%	88.35%
	F1-score	79.01%	96.33%	86.11%
FedAdam	Accuracy	76.05%	75.12%	75.67%
	F1-score	73.47%	72.97%	73.27%
FedAdagrad	Accuracy	78.35%	77.87%	78.15%
	F1-score	73.22%	74.76%	73.85%
FedYogi	Accuracy	79.18%	75.49%	77.67%
	F1-score	74.00%	71.01%	72.77%





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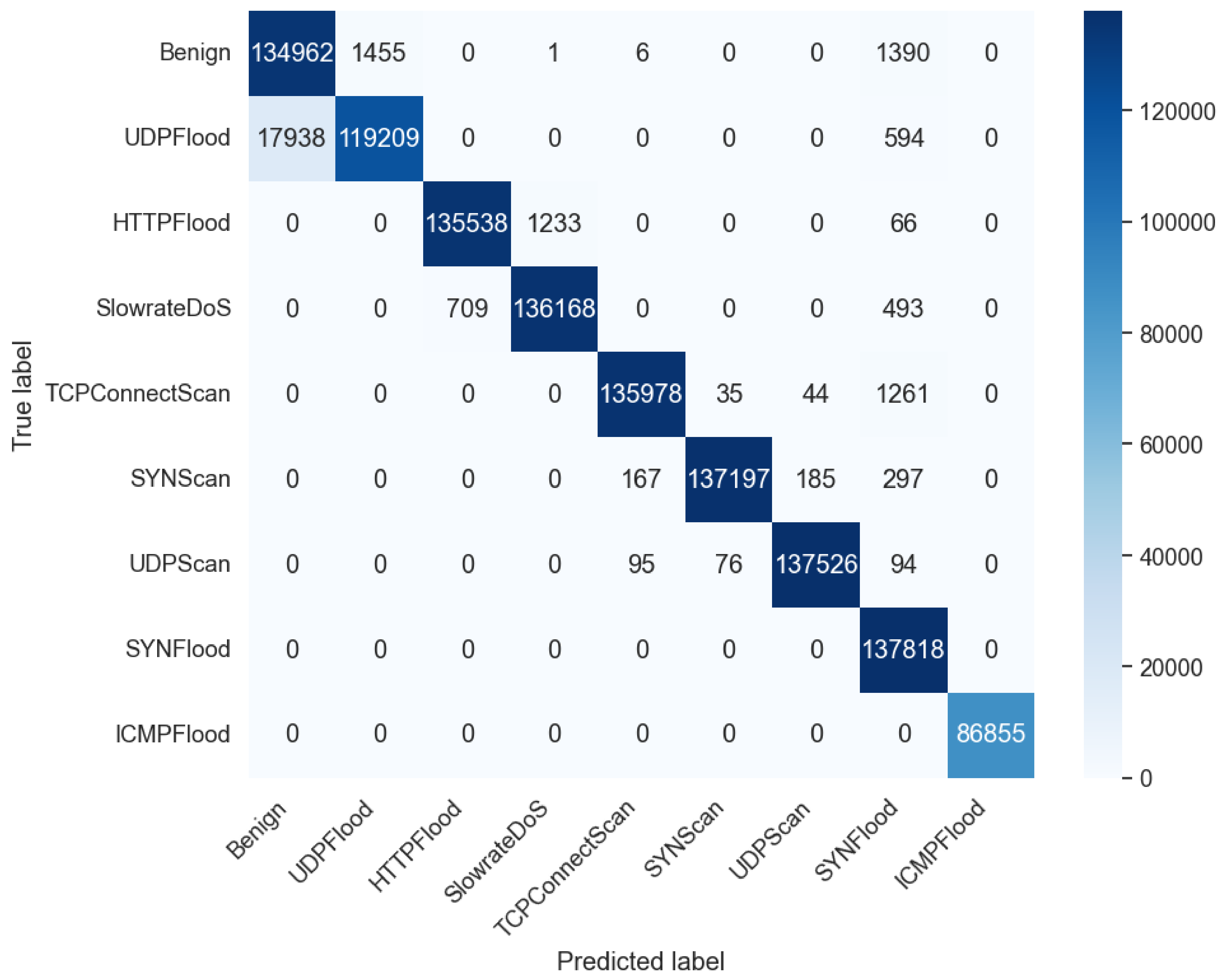
FedAvg Confusion Matrix



Conclusion and Future Work

Conclusion

- *Concluding Insight:* Federated Learning, particularly using the FedAvg aggregation strategy, proves effective for enhancing privacy and security in 5G networks by enabling base stations to collaboratively train a deep ANN for reliable intrusion detection.

Future Work

- *Aggregation Strategies:* Development of innovative, intrusion-specific federated aggregation strategies to enhance both communication and computational efficiency.

- *Real-World Testing:* Extensive testing in practical, large-scale scenarios to validate the approach's feasibility and identify any potential limitations.

Thank you for your attention!

Questions?

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