

Anomaly Detection in 5G Networks using Federated Learning



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INTRODUCTION



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COMPARATIVE ANALYSIS



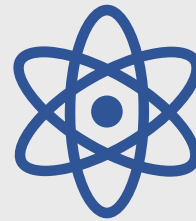
TRADITIONAL



MACHINE

LEARNING RESULT

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OUTLINE

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NON-IID RESULTS



FEDERATED

LEARNING RESULTS

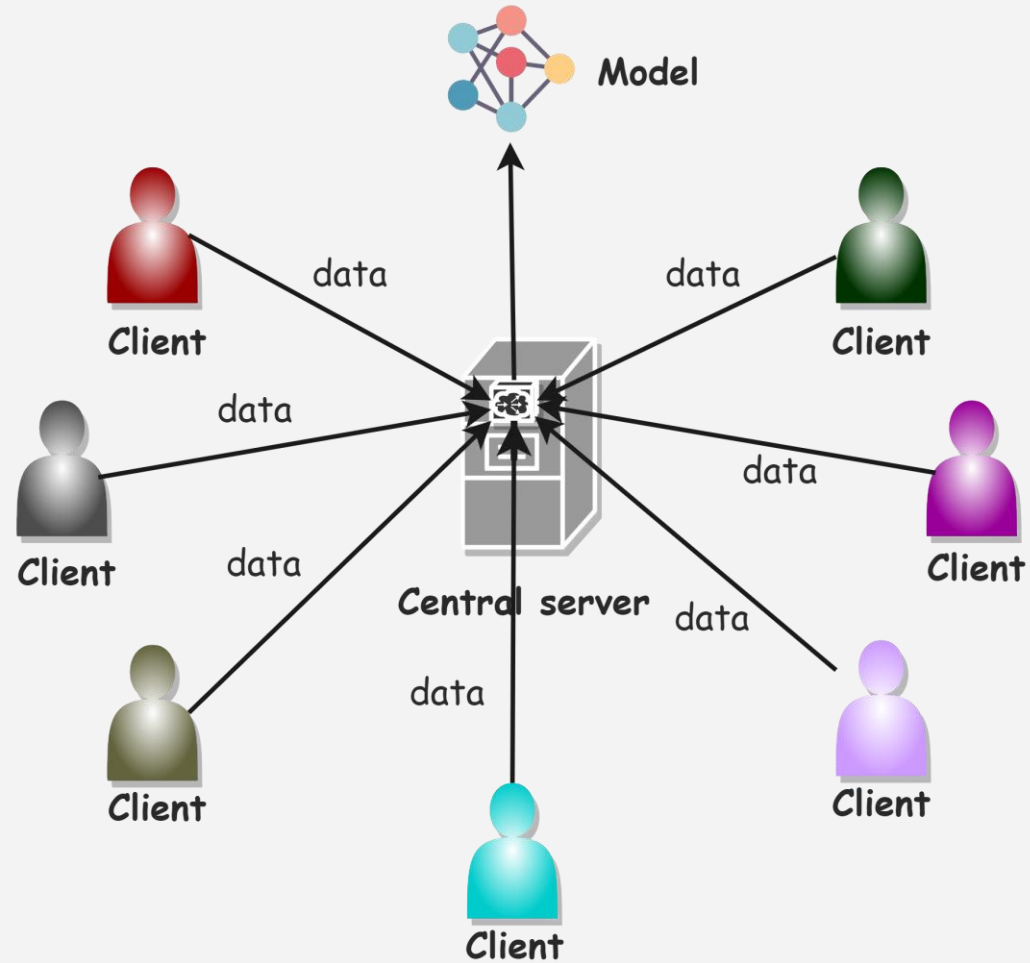
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CONCLUSION



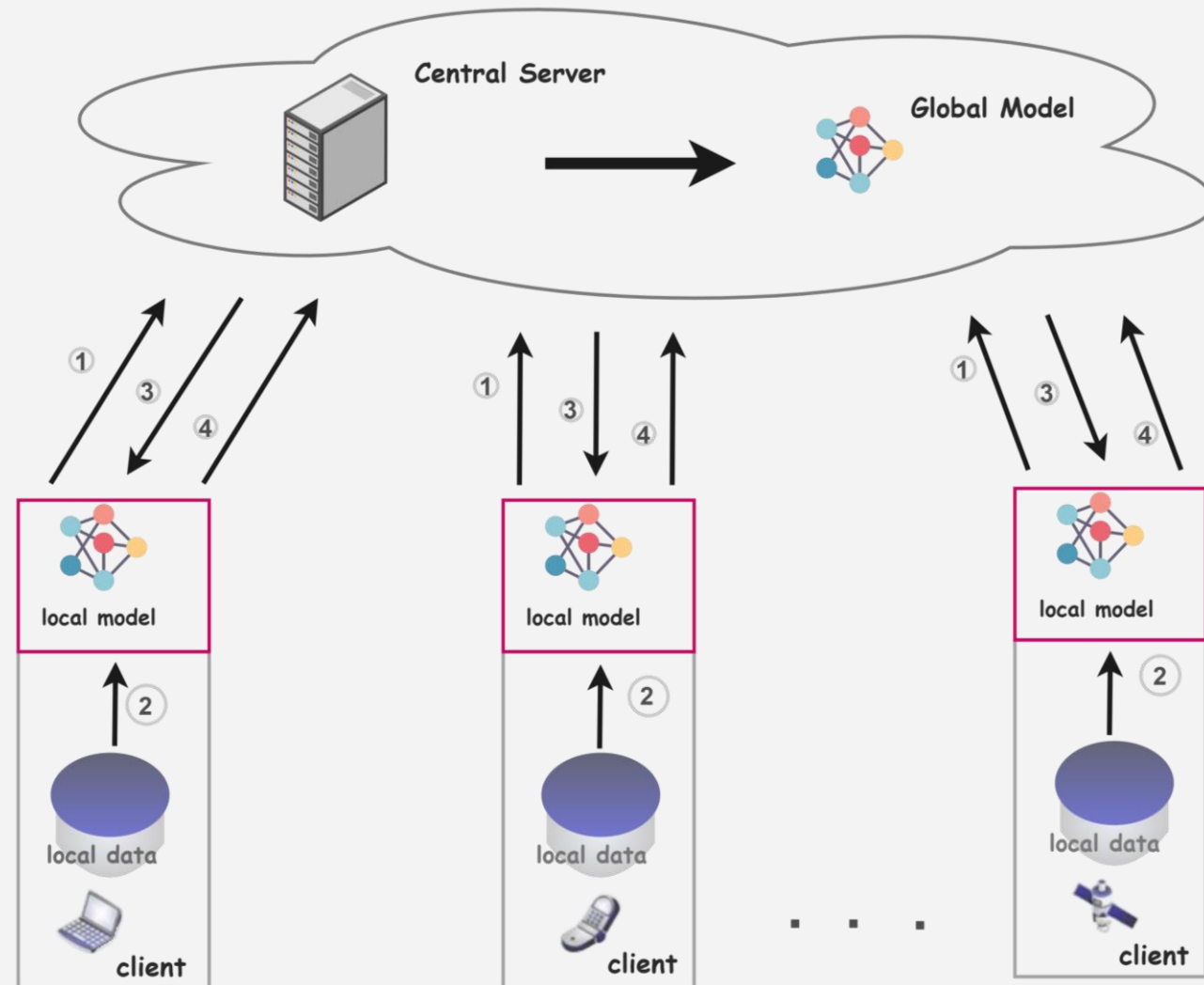
INTRODUCTION



TRADITIONAL MACHINE LEARNING



FEDERATED LEARNING



SPECIFIC OBJECTIVE ONE(1)

Evaluate the performance of the model developed by a classical deep neural network

Perform hyperparameter tuning to improve the performance of the model.



DATASET DESCRIPTION

- **CIC-IOT 2023 dataset.**
- **Size of dataset: 1177098 x 34**
- **Number of features: 33 features + 1 label**

ANOMALIES: ATTACKS

FLOODING

WEB-BASED

SPOOFING



MODEL SUMMARY



**Tensor
Flow**

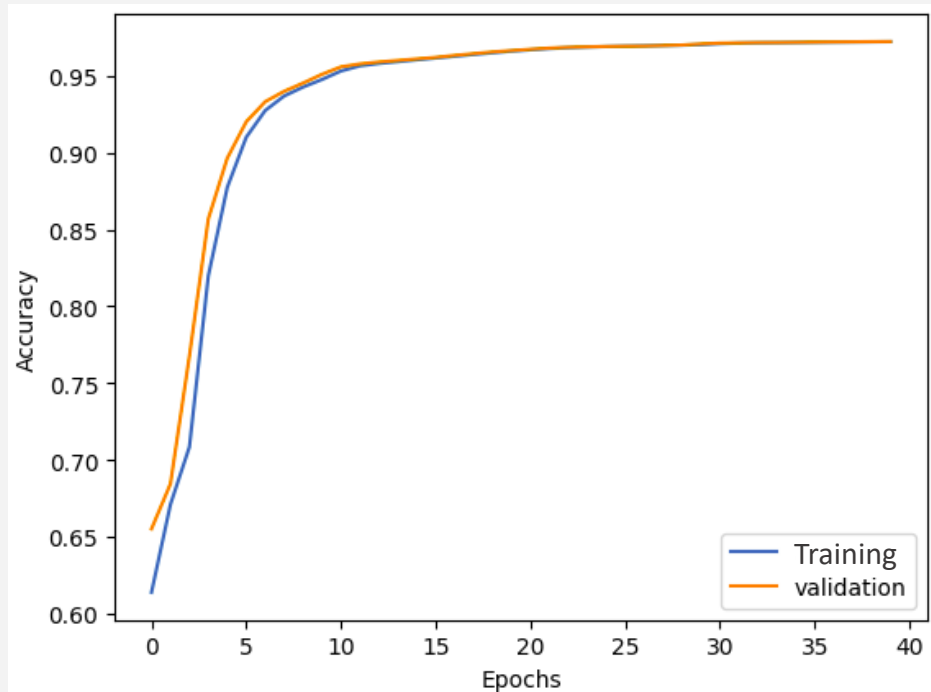


Layer (type)	Output Shape	Param #
dense_6 (Dense)	(None, 4)	136
activation_6 (Activation)	(None, 4)	0
dense_7 (Dense)	(None, 4)	20
activation_7 (Activation)	(None, 4)	0
dense_8 (Dense)	(None, 1)	5
activation_8 (Activation)	(None, 1)	0

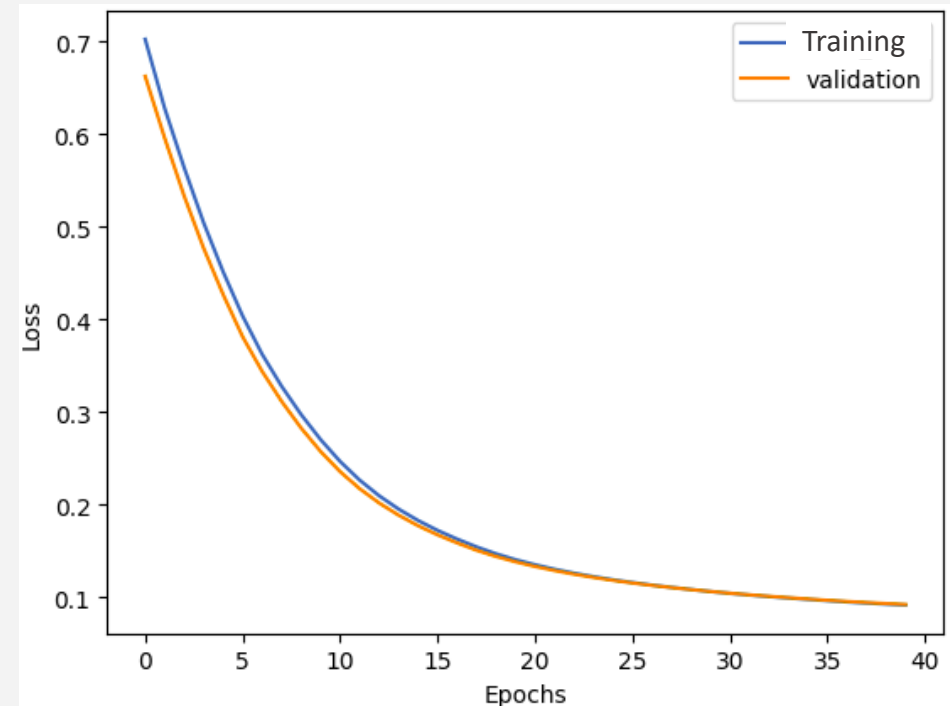
Model summary



TRADITIONAL MACHINE LEARNING RESULTS



Training and validation accuracy curves



Training and validation loss curves



TRADITIONAL MACHINE LEARNING RESULTS CONT'D

Confusion Matrixs

```
[[99893 2706]
 [ 3375 70591]]
```

Evaluation metrics

	precision	recall	f1-score	support
0	0.96732	0.97363	0.97046	102599
1	0.96308	0.95437	0.95871	73966
accuracy			0.96556	176565
macro avg	0.96520	0.96400	0.96458	176565
weighted avg	0.96554	0.96556	0.96554	176565

Model's performance on unseen data

Evaluation metrics	Values in %
Precision score	96.52
Recall	96.40
F1 score	96.46
Accuracy	96.56

Summary of the results



SPECIFIC OBJECTIVE TWO(2)

Evaluate the performance of the model developed by federated learning.

technique.

Perform hyperparameter tuning to improve the performance of the model.



FEDERATED LEARNING RESULTS

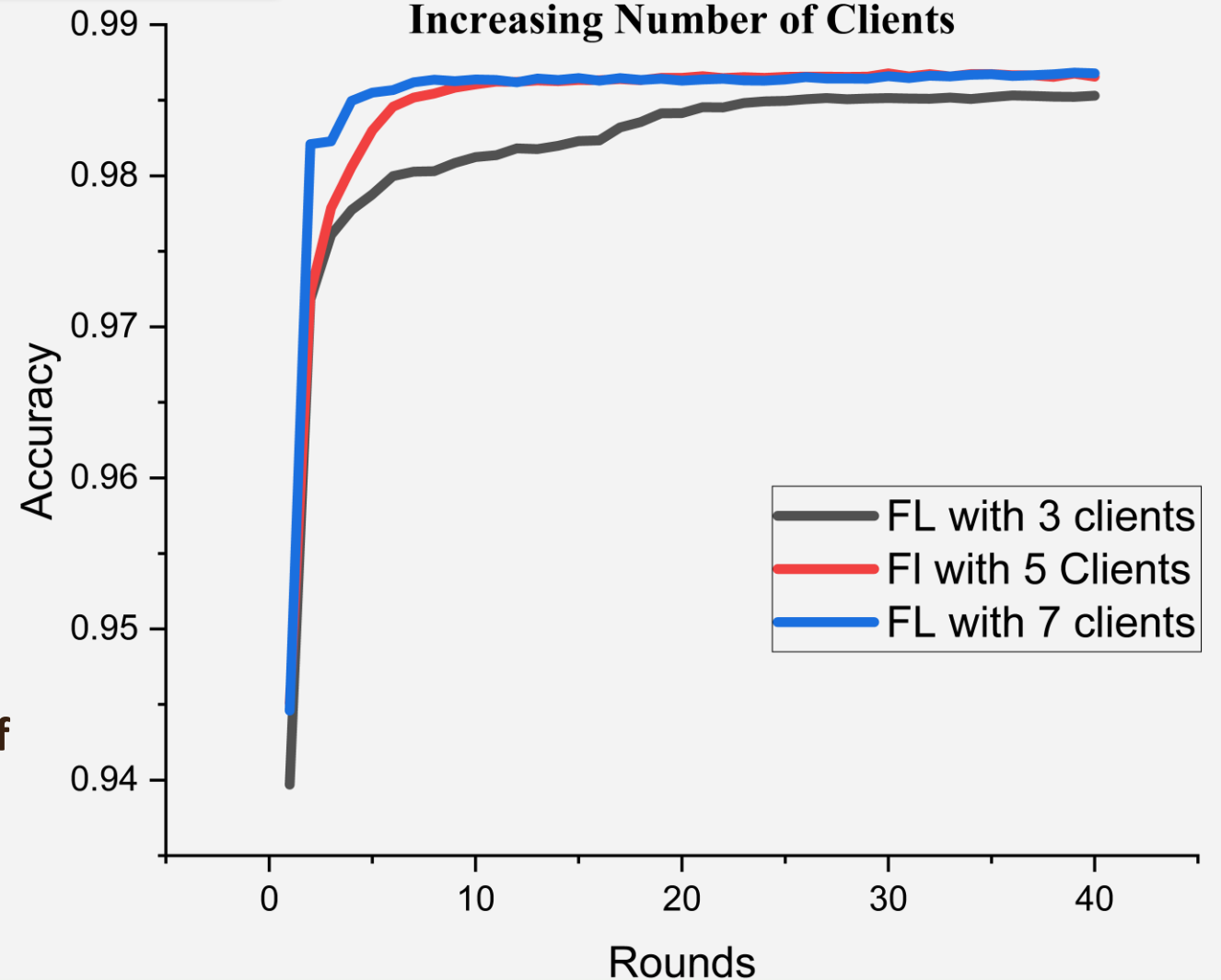
framework



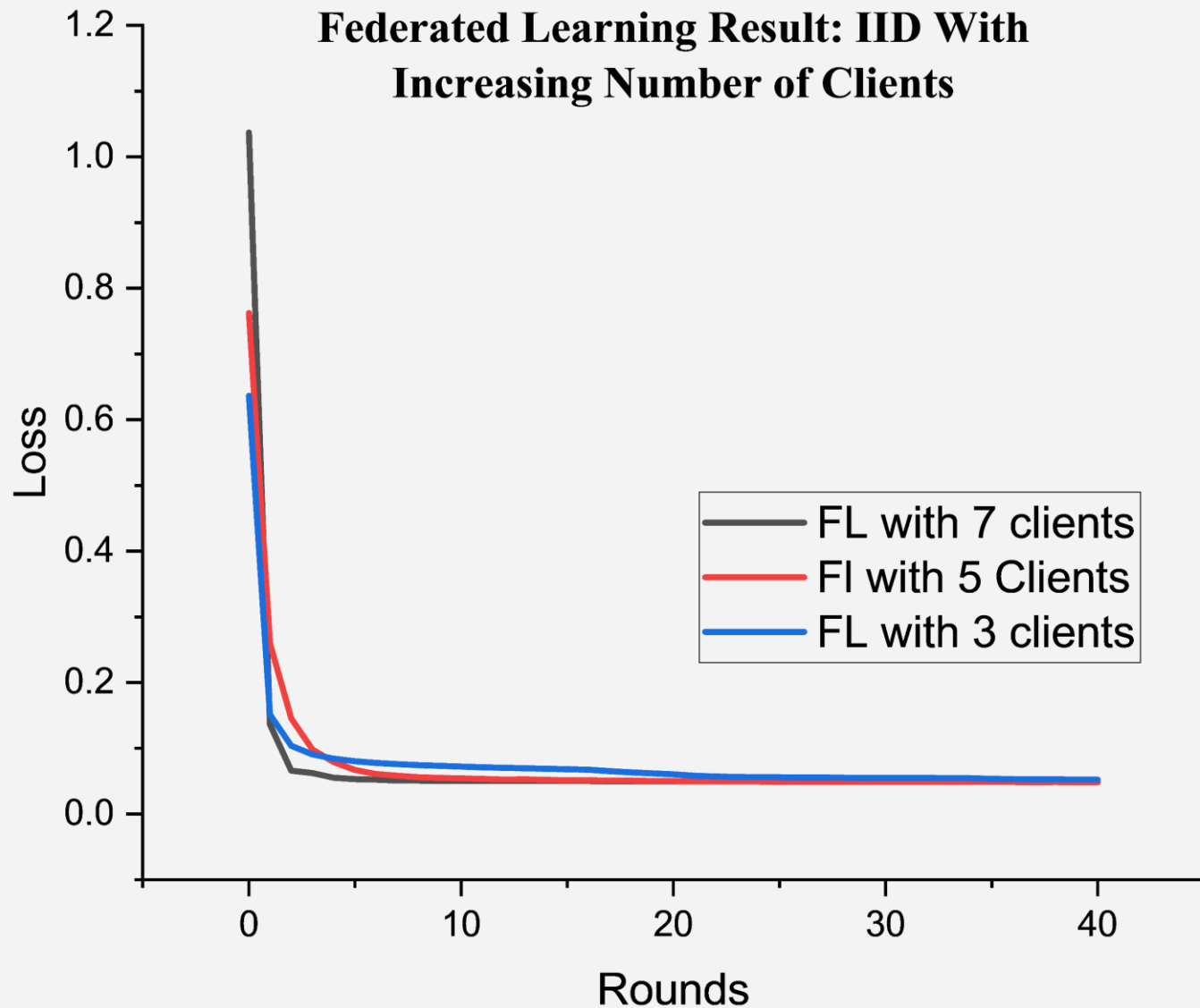
scenarios

- Impact of increased clients
- Accuracy Trend as the number of rounds is varied

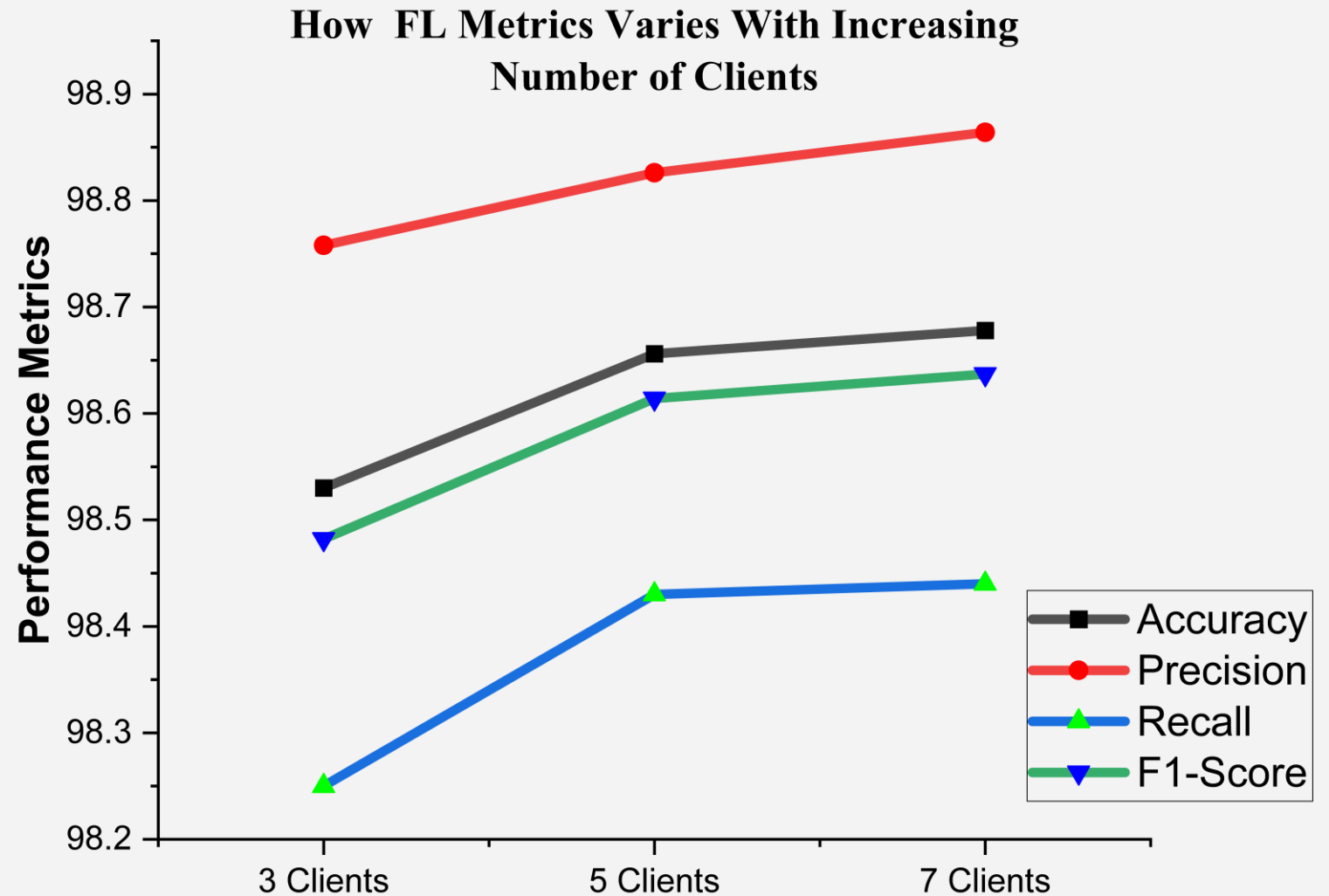
Federated Learning Result: IID With Increasing Number of Clients



FEDERATED LEARNING RESULTS



FEDERATED LEARNING RESULTS



ANALYSIS

We observed an upward trend in model performance as the number of clients increased.



Suggests that the model might benefit even further if scaled to an even larger number of devices.



The model converges in 20 rounds regardless of client count, indicating no increase in communication cost as the client base expands.

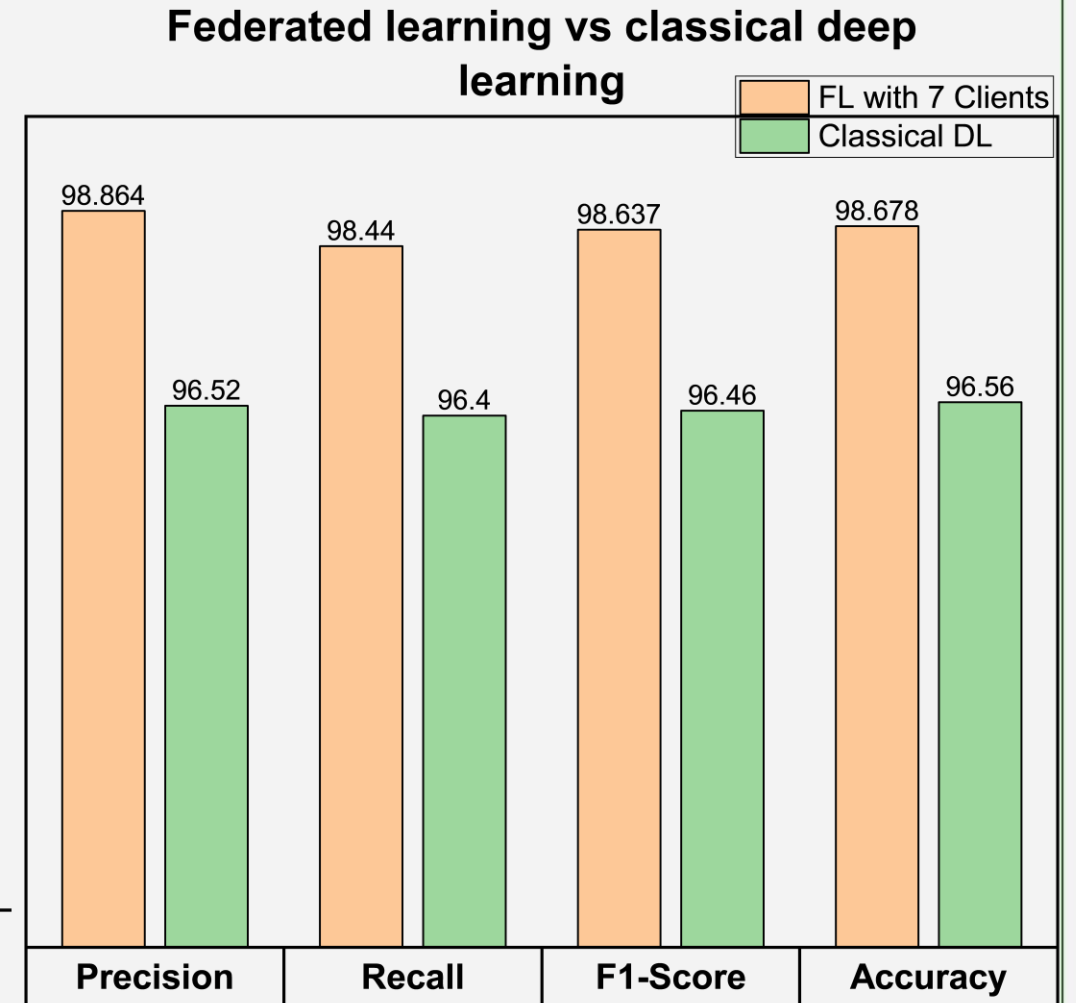
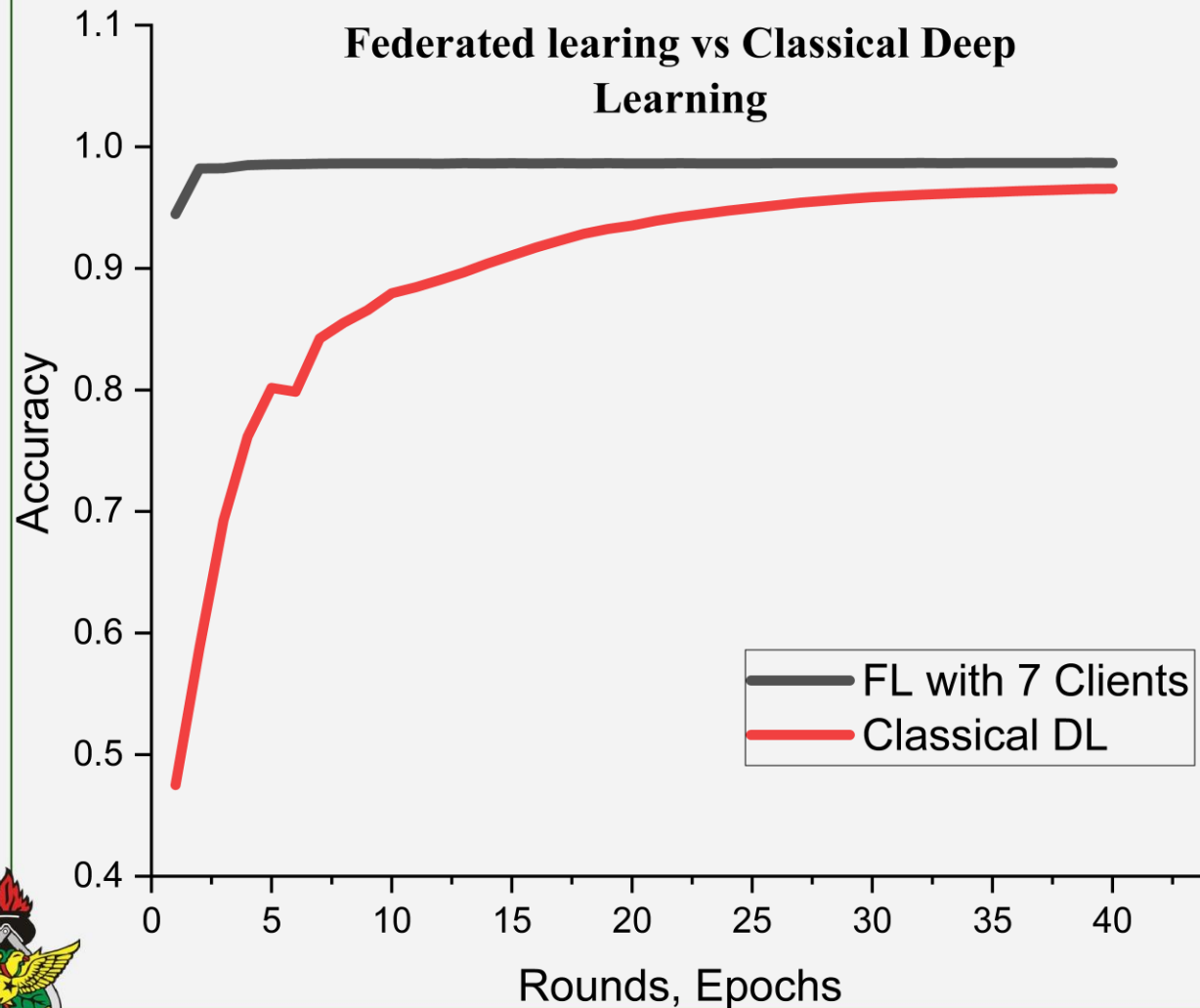


SPECIFIC OBJECTIVE THREE(3)

Comparative analysis of Classical
Deep Learning and Federated
learning techniques



COMPARATIVE ANALYSIS



ANALYSIS

In terms of the KPIs, the FL model performs better than the classical



We were able to move the model to the data rather than the data to the model.



Continual learning is made possible with federated learning than in classical deep learning



FEDERATED LEARNING RESULTS: NON-IID



PARTITIONING STRATEGIES FOR NON-IID

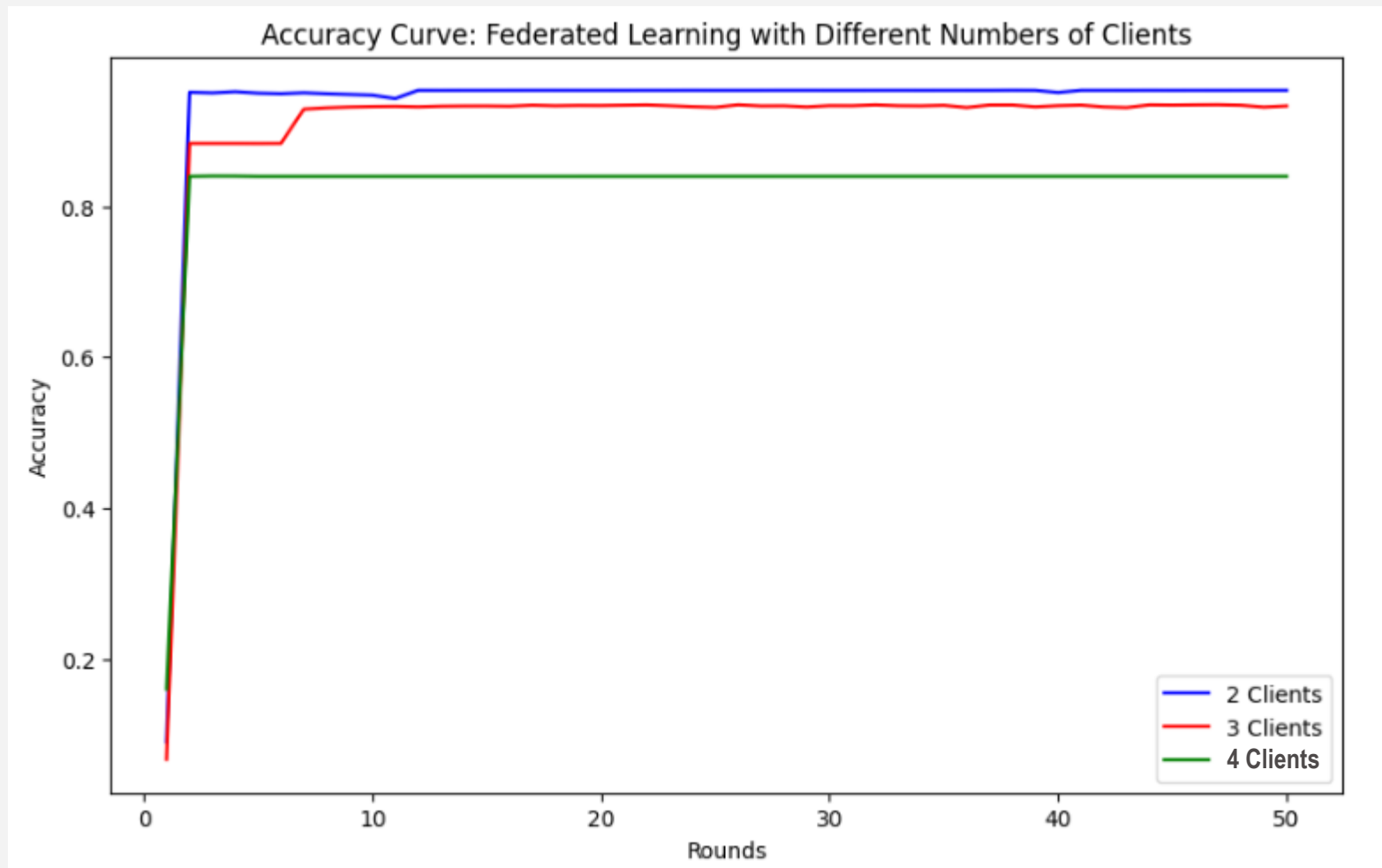
- **Label Distribution Skew**
- **Feature Distribution Skew**
- **Quantity Distribution Skew**



Number of Clients	Main Attacks	Total number of Samples	Label Ratio 0:1
CLIENT 1	DDos	519,478	2:8
CLIENT 2	Web Based	34,306	9:1
CLIENT 3	Spoofing	25,921	6:4
CLIENT 4	Dos	234,299	5:2

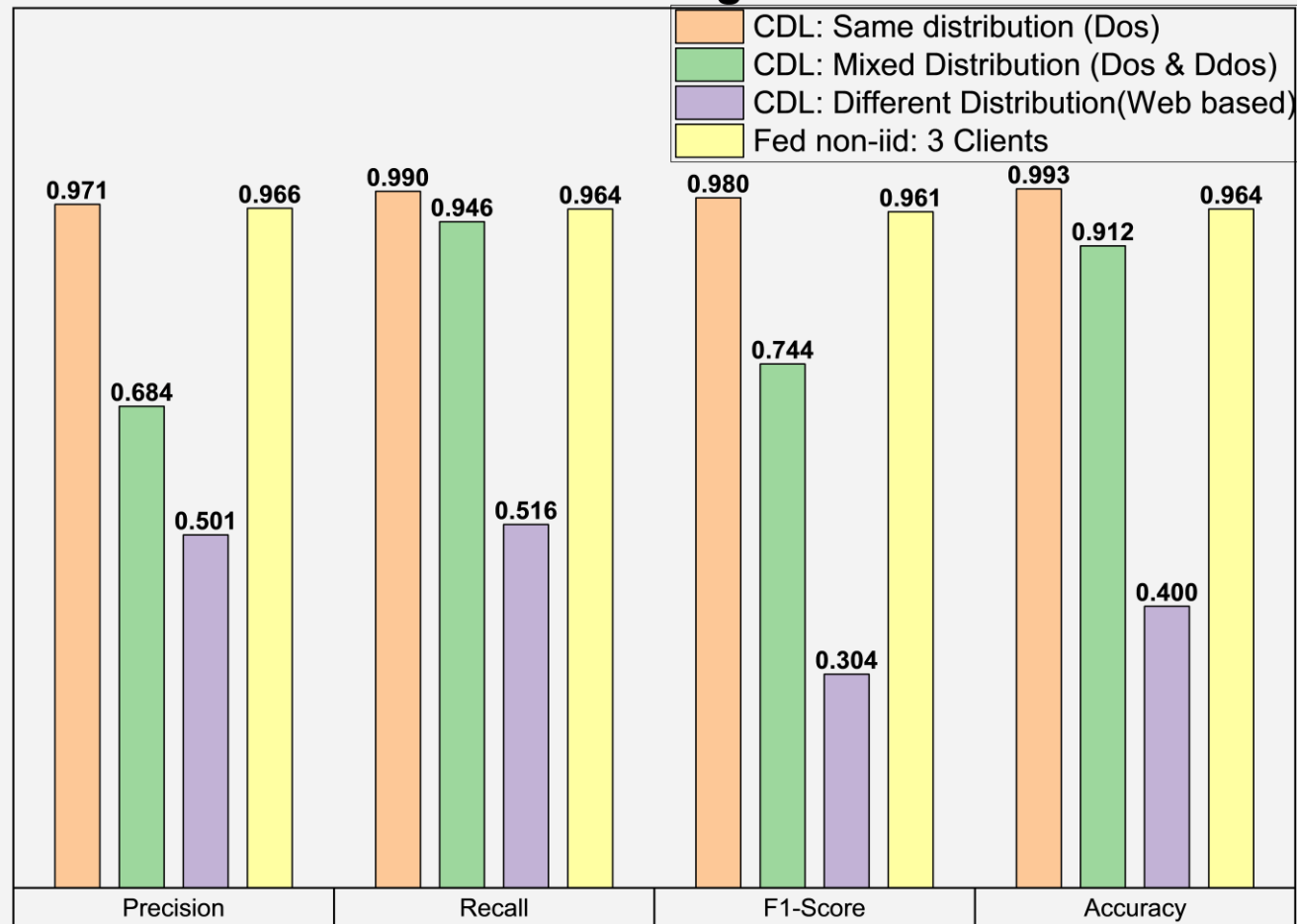


FEDERATED LEARNING RESULTS: NON-IID



FEDERATED LEARNING RESULTS: NON-IID CONT'D

Federated learning (non-iid) vs classical deep learning



CONCLUSION



We can detect network anomalies 96.56% of the time if traditional machine learning is used.



However, we can detect network anomalies 98.68% of the time and still preserve privacy if federated learning is used in an IID context.

We can detect anomalies of the same distribution 99.3% of the time, but the system's effectiveness at detecting anomalies of mixed distribution decreases to 91.2% and drops to a 40% detection rate at detecting anomalies of different distributions.

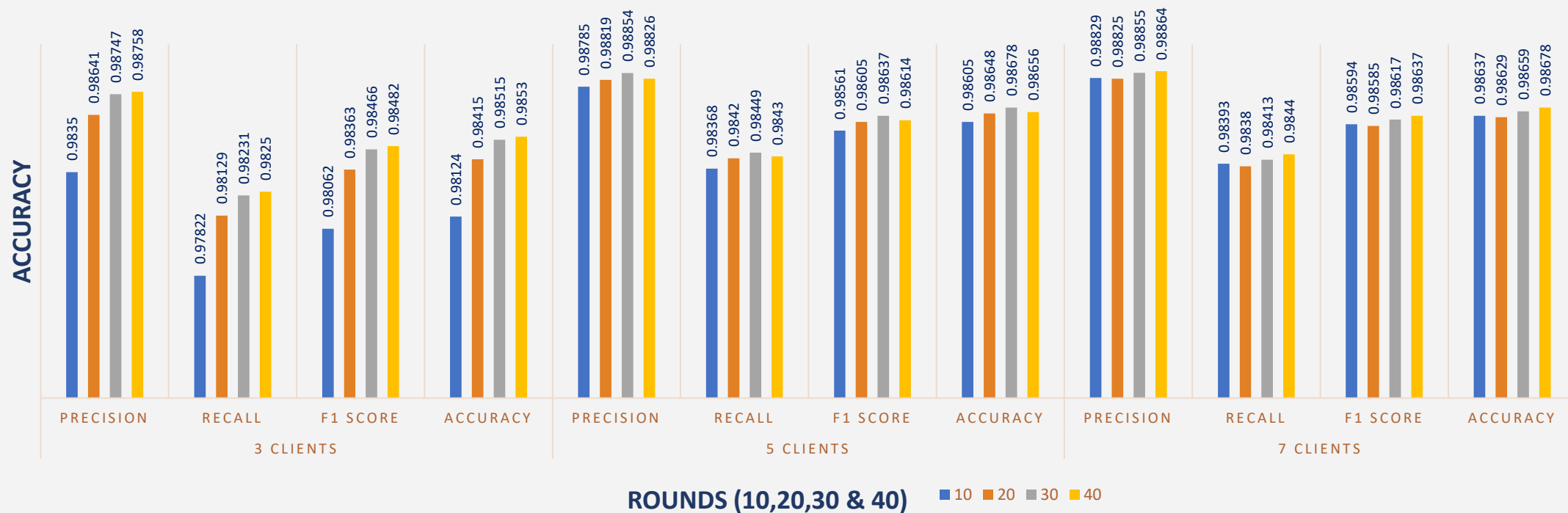


However, federated learning, irrespective of the different distributions and heterogeneity, achieves a 96.4% detection rate.



REFERENCE

FEDERATED LEARNING METRICS AFTER EVERY 10 ROUNDS



Summary of the results



THANK YOU

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