# Towards Federated Learning in ML Models

**Team:** Salva Umar, Karan Khubdikar, Hina Bandukwala, Prabhjit Thind
**Mentor:** Quan Nguyen
**Capstone Partner:** ALS GoldSpot Discoveries Ltd.

# Team Members

Karan Khubdikar

Salva Umar

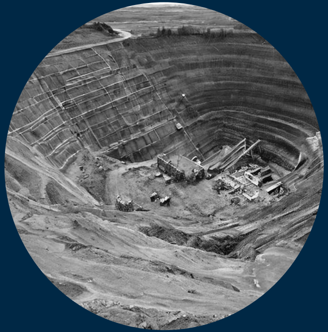
Prabhjit Thind

Hina Bandukwala

Quan Nguyen
(Mentor)

ALS GoldSpot Discoveries Ltd.
(Partner)

# Capstone Partner: ALS GoldSpot Discoveries Ltd.



## Who are they?

- Geoscience expertise with AI and data science for mineral exploration & mining

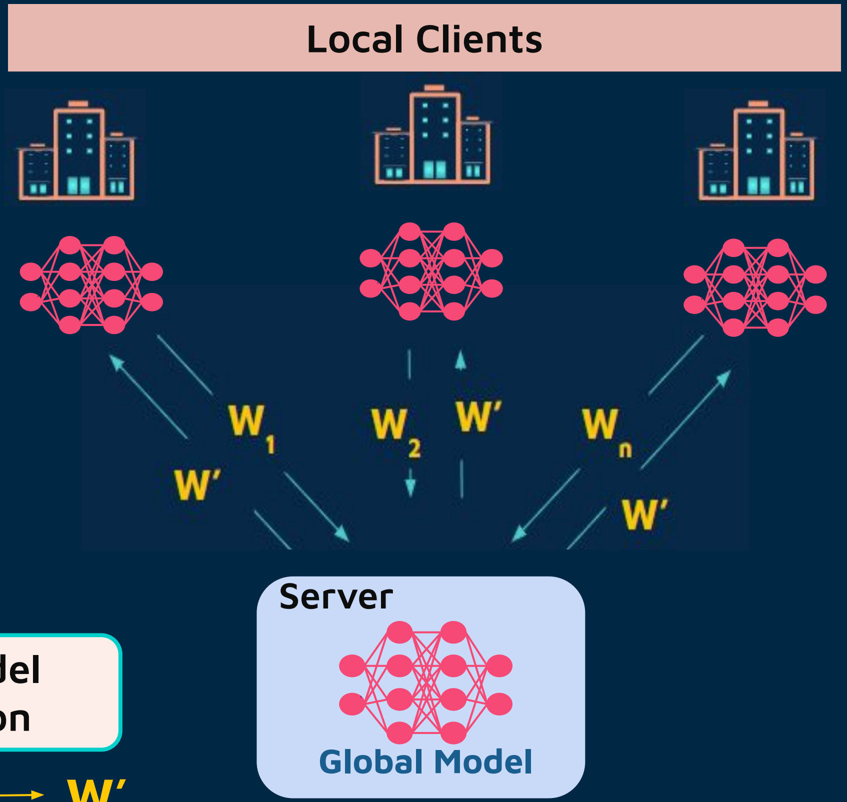
## Why is it important?

- Enhances decision-making in mining operations
- Ensuring sustainable and profitable resource extraction.

# Introduction

01

# Federated Learning Model Overview




Train local models

Global model aggregation

$(W_1, W_2, \dots W_3) \longrightarrow W'$

# What are the capstone partner's needs?

## What issues are they facing?

- Communication Efficiency: data is distributed across clients
- Data Heterogeneity: Managing different client data distributions
- Model Training Efficiency: Improving accuracy of ML models in decentralized framework

# Scientific Objective

- Investigating effectiveness of decentralized training approaches.

- Creating a federated learning framework to solve business problems in the mining industry.

# Data Science Workflow

02

# Data Product

Successful Project Delivery will entail:

- ★ **A report:** covering objectives, methodology, experiments, results.
- ★ **A Git repository:** with reproducible code, documentation, experiment configurations.
- ★ **A data pipeline:** processes and tools needed to simulate the federated learning framework.

# Data Source

Osteosarcoma dataset:

- Bone cancer images
- Open source dataset is used for testing the applicability of the decentralised framework

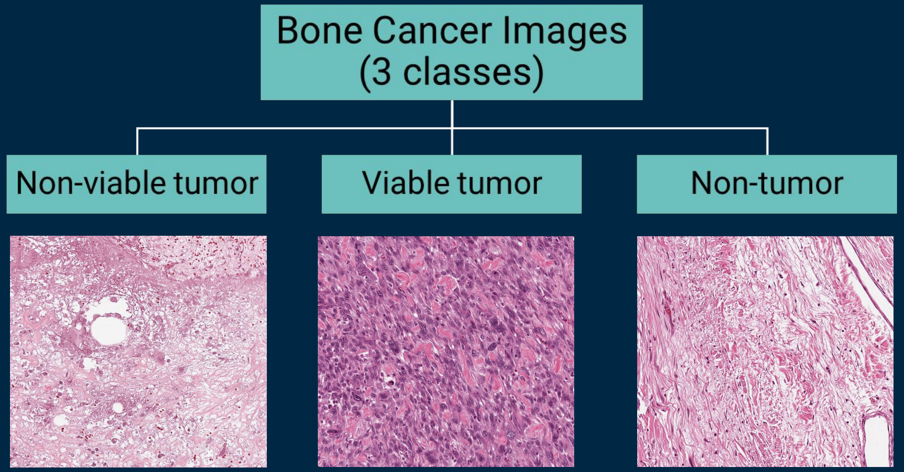
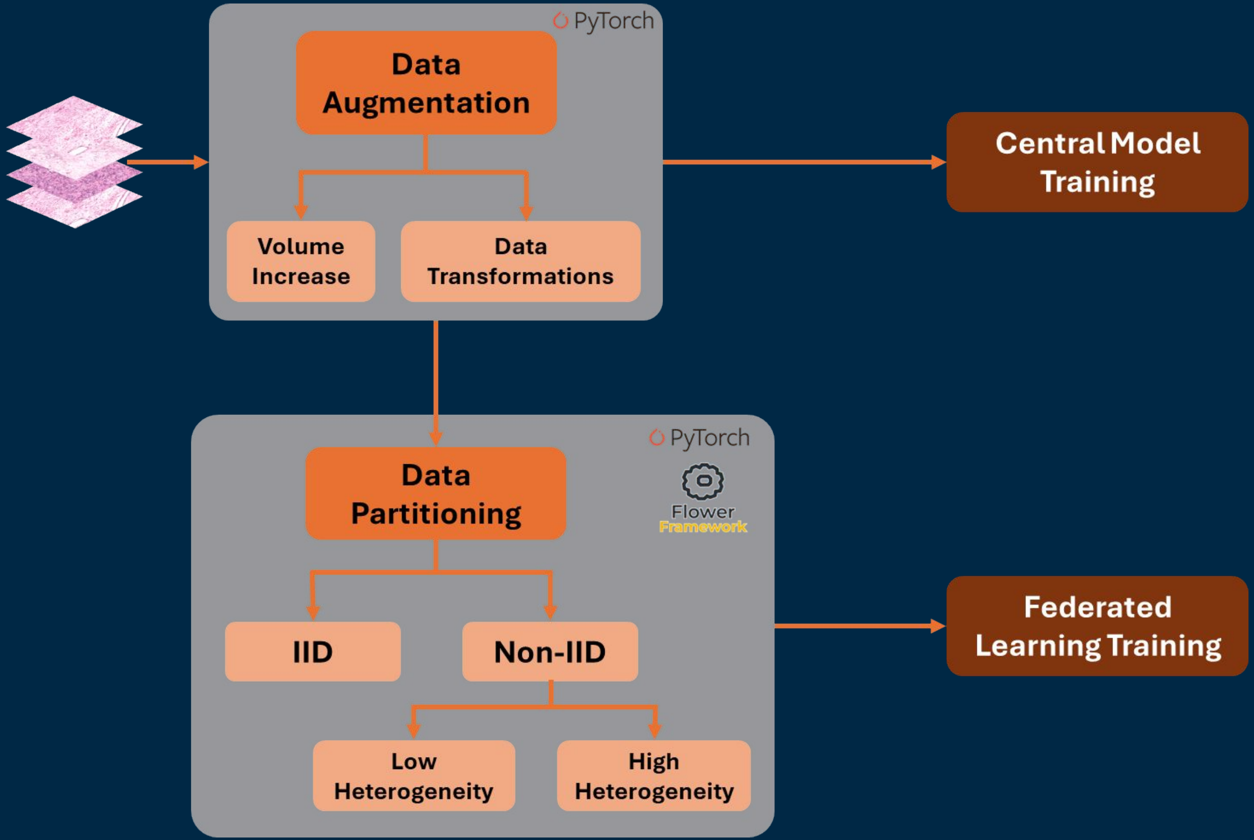



Image specifications

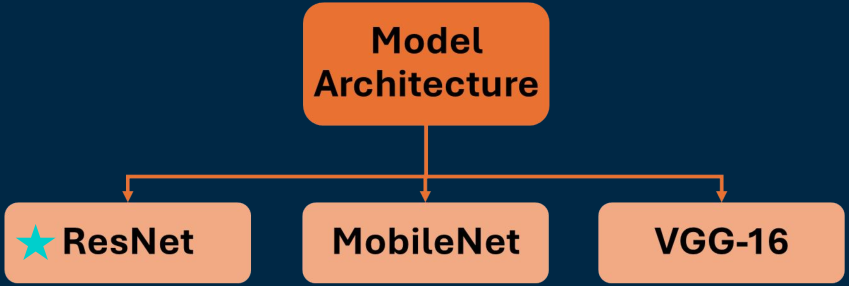
- ❑ 1,144 images
- ❑ 1024 x 1024 at 10X resolution

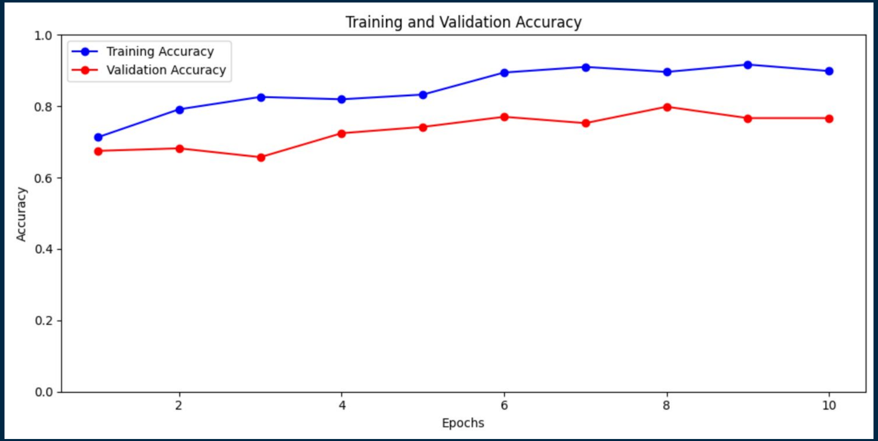
# Dataflow Pipeline



# Central Model

- ★ Multi-Class Classification task
- ★ Unfreeze last few layers for fine tuning



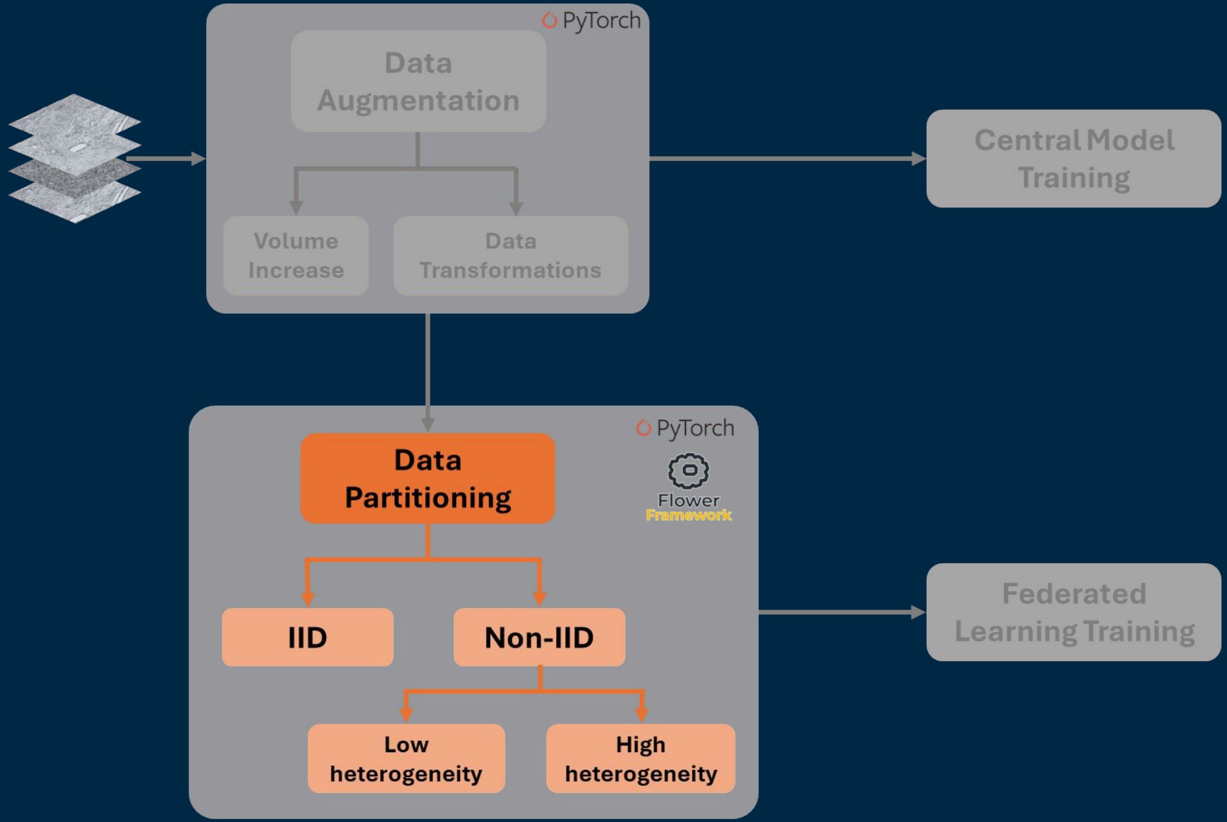




| Metric | Value |
|---|---|
| Balanced Accuracy | 0.77 |
| F1 Score | 0.81 |
| Precision | 0.77 |
| Recall | 0.77 |

# Federated Training

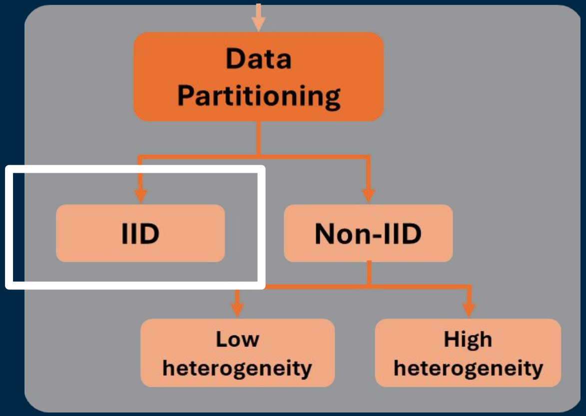
03

# Data Partitioning



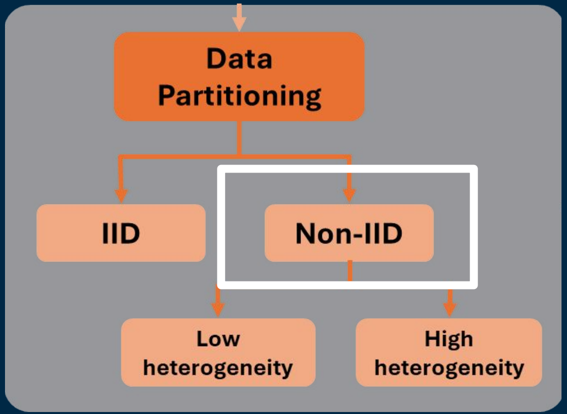
# Data Partitioning: IID

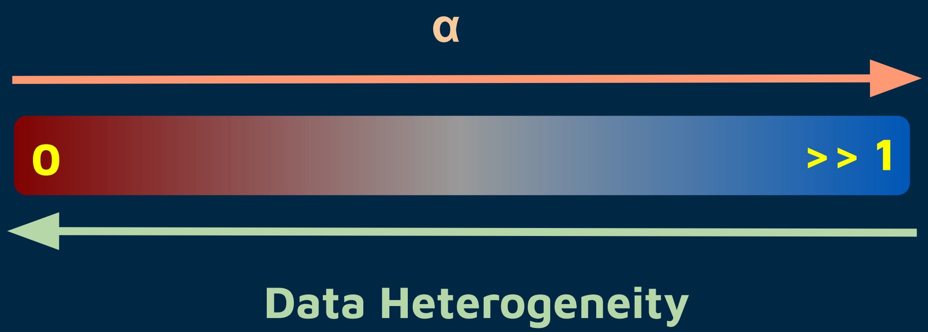
- ★ PyTorch *random_split* function
- ★ Each client receives a random sample from the training set
- ★ Minimal heterogeneity between clients



# Data Partitioning: Non-IID

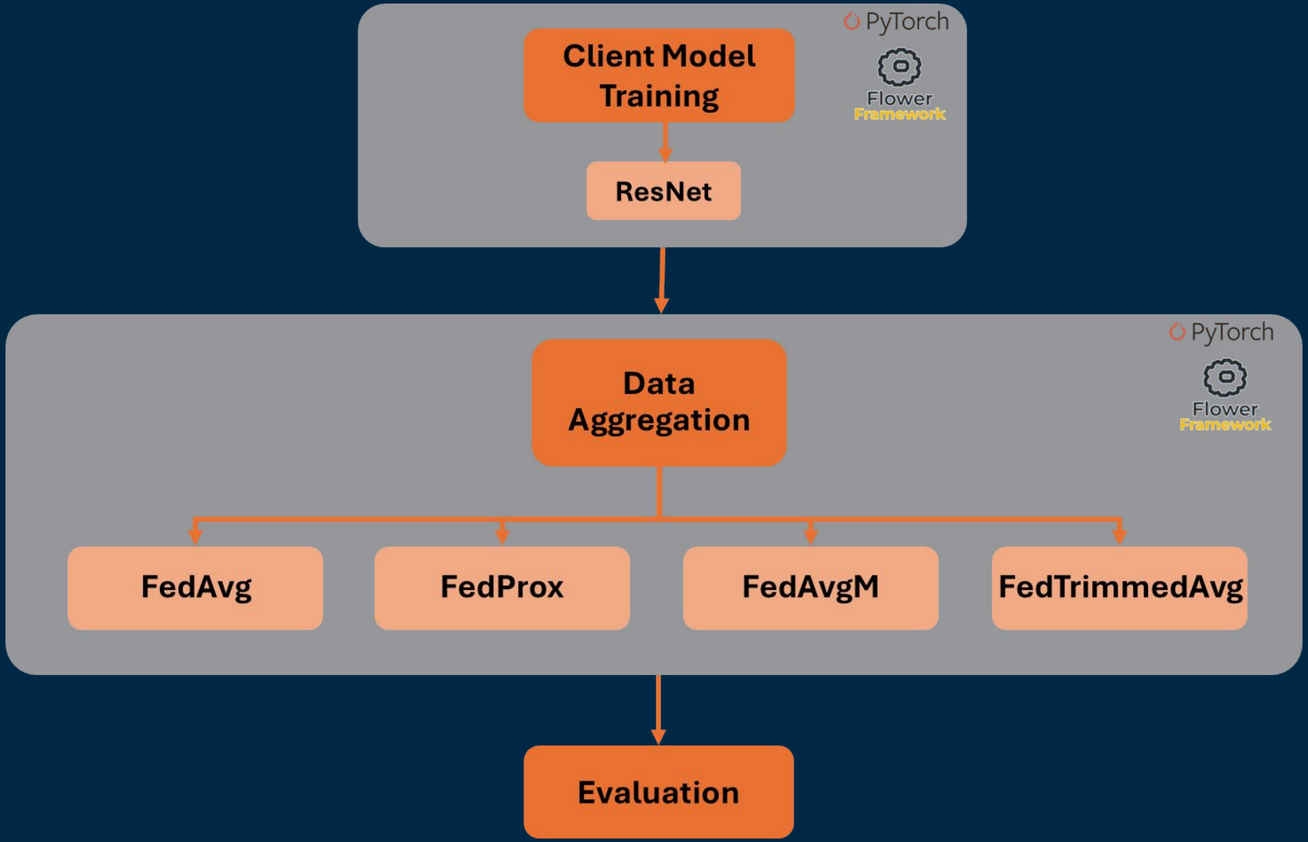
- Dirichlet Distribution:
- Controlled by α (Concentration Parameter)
  - Multivariate generalization of beta distribution
- Used to split a dataset among multiple clients
- Exhibit heterogeneity in their class distributions




0
>> 1
α = 0.1
α = 0.5
More skewed
Less skewed
Client 1
Client 2
Client 3
Client 4
0
Proportion
1
0
Proportion
1

# Client Training



# Results

04

# Experimental Setup & Evaluation

- ★ We carried out 12 experiments where we tested the following:
  - Data Partitioning:
    - *Iid*
    - *Non-iid* ($\alpha$ = *0.5 and 0.1)*
  - Aggregation strategies:
    - FedAvg, FedProx, FedAvgM,FedTrimmedAvg

- ★ All experiments were conducted with:
  - 4 clients
  - 5 rounds of FL
  - Learning rate = 0.002
  - Momentum = 0.9

Evaluation Metrics:

**BALANCED ACCURACY**

**F1 -SCORE**

**RECALL**

**PRECISION**

# Server Aggregation Methods

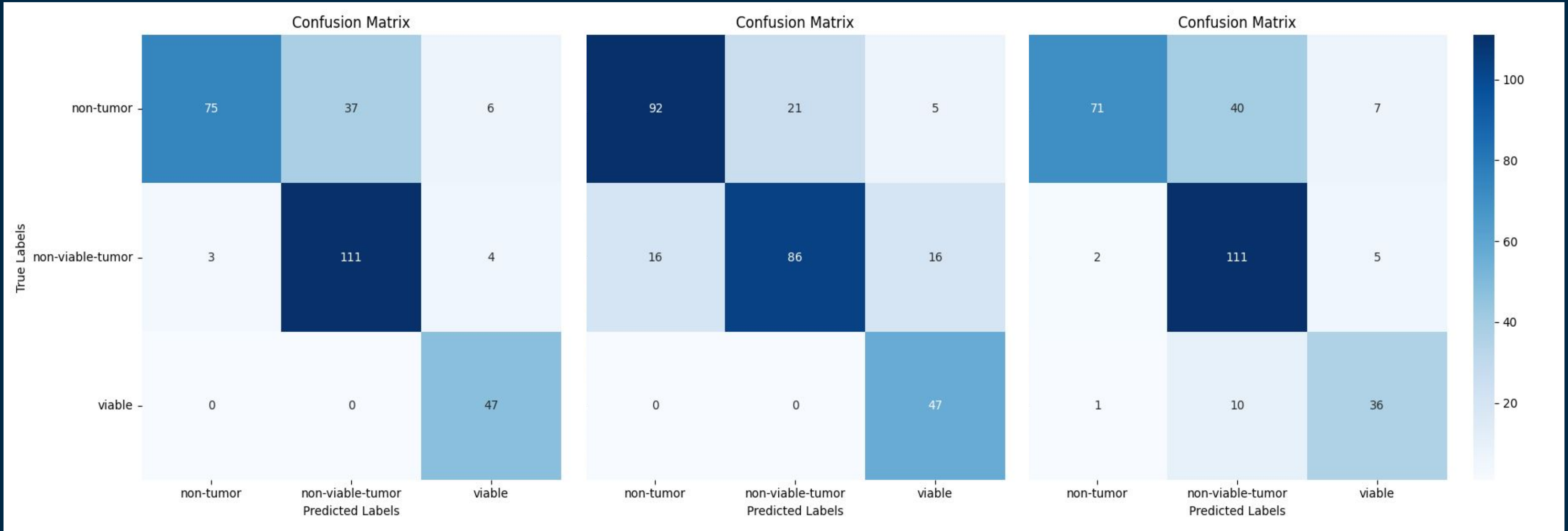
| Strategy | Description |
| --- | --- |
| **FedAvg** | Computes a **weighted average** of the local updates from each client. |
| **FedAvgM** | Builds on FedAvg by incorporating momentum parameter, to accelerate convergence by considering past gradients |
| **FedProx** | Builds on FedAvg by introducing a **proximal term** to handle heterogeneity |
| **FedTrimmedAvg** | Aggregates model updates by **averaging the central 80%** of updates |

# Experiments: Confusion Matrices

IID

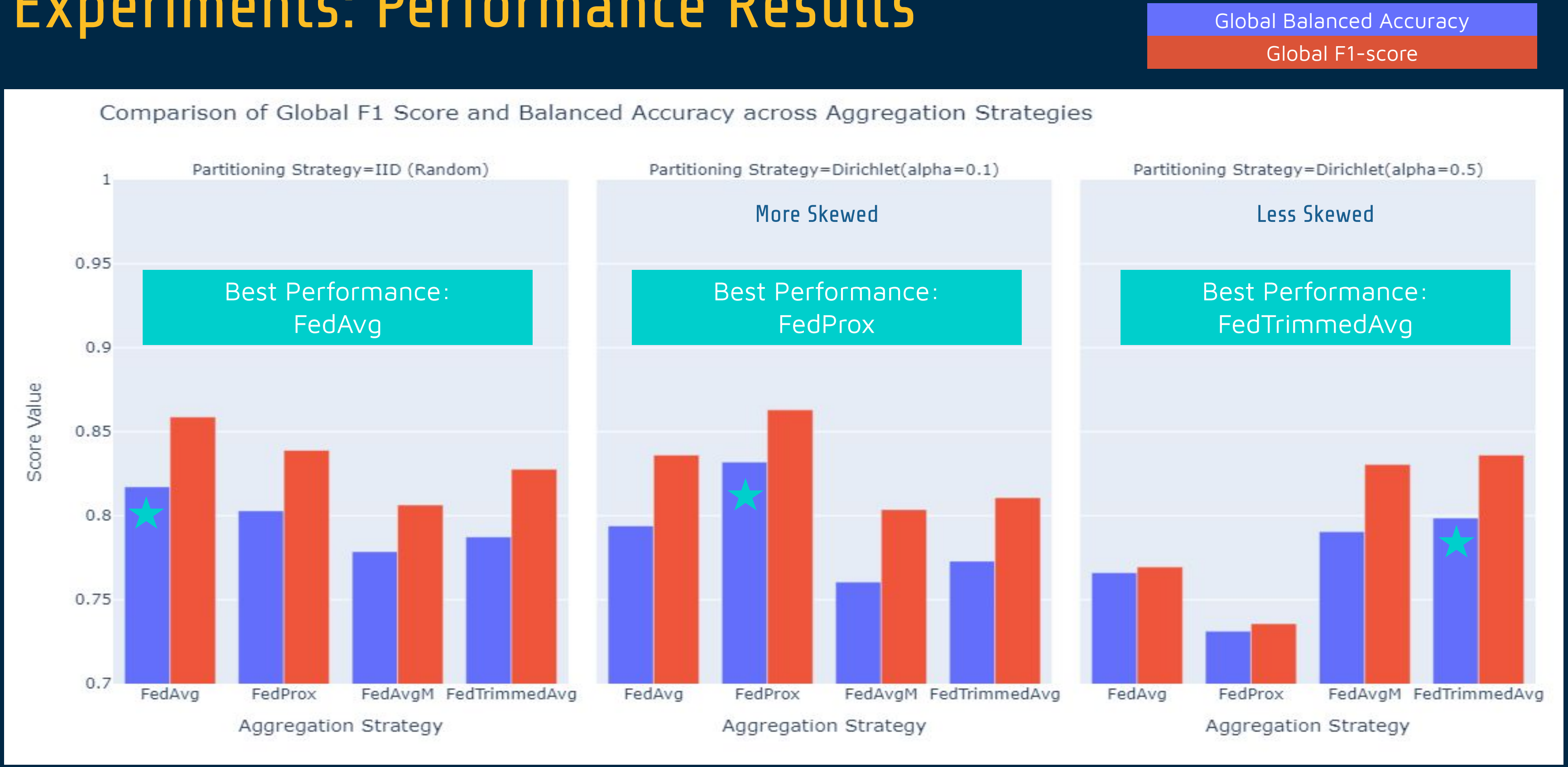
Dirichlet (α = 0.1)
More Skewed

Dirichlet (α = 0.5)
Less skewed




*Note: FedAvg Results*

# Experiments: Performance Results



# Experiments: Non-IID Observations

**Best Strategy: Dirichlet (α = 0.1)**
More Skewed

**Best Strategy: Dirichlet (α = 0.5)**
Less Skewed

| **FedAvg** | **FedProx** | **FedAvgM** | **FedTrimmedAvg** |
| --- | --- | --- | --- |
| - High variability data<br>- Focus on balanced accuracy<br>- General robustness | -Highly non-IID data<br>- Regularization focus<br>- Consistency across metrics | - Moderate data imbalance<br>- High recall requirements<br>- Balanced performance | - Moderate non-IID data<br>Outlier robustness<br>- High precision requirements |
| Balanced Accuracy: 0.84<br>F1 Score: 0.80<br>Precision: 0.81<br>Recall: 0.80 | Balanced Accuracy: **0.86**<br>F1 Score: 0.83<br>Precision: 0.85<br>Recall: 0.83 | Balanced Accuracy: 0.83<br>F1 Score: 0.79<br>Precision: 0.82<br>Recall: 0.80 | Balanced Accuracy: **0.86**<br>F1 Score: 0.84<br>Precision: 0.85<br>Recall: 0.83 |

# Design Features

## 1. Customising Model Parameters: Hydra framework

- Configuration manager
- To efficiently evaluate across different datasets and parameters
- Important Parameters:
  - No of clients
  - Rounds of training
  - Path to data directory
  - Partition type
  - Strategy type

  … many more

# Design Features

## 1. Configurability: Hydra

```yaml
data_dir: "./data/combined"


batch_size: 4
class_names: ["non-tumor", "non-viable-tumor", "viable"]
input_size: 224

num_clients_per_round_fit: 4
num_clients_per_round_eval: 4
num_rounds: 5
num_clients: 4


num_cpus_per_client: 4
gpu_usage_per_client: 0.2
strategy_name: "FedAvg"

config_fit:
  lr: 0.002
  momentum: 0.9
  local_epochs: 5
  batch_size: 4
  decay_rate: 0.1
  step_size: 5
  gamma: 0.1

data_partition:
  strategy: "dirichlet"
  alpha: 0.1
```

## Start Simulation: python main.py

```
[2024-06-04 21:45:32,092][flwr][INFO] - Starting Flower simulation, config: num_rounds=5, no round_timeout
[2024-06-04 21:45:37,647][flwr][INFO] - Flower VCE: Ray initialized with resources: {'object_store_memory': 16165516492.0, 'memory': 32331032987.0,
'node:__internal_head__': 1.0, 'GPU': 1.0, 'node:172.28.0.12': 1.0, 'CPU': 8.0}
[2024-06-04 21:45:37,651][flwr][INFO] - Optimize your simulation with Flower VCE: https://flower.ai/docs/framework/how-to-run-simulations.html
[2024-06-04 21:45:37,654][flwr][INFO] - Flower VCE: Resources for each Virtual Client: {'num_cpus': 4, 'num_gpus': 0.2}
[2024-06-04 21:45:37,671][flwr][INFO] - Flower VCE: Creating VirtualClientEngineActorPool with 2 actors
[2024-06-04 21:45:37,675][flwr][INFO] - [INIT]
[2024-06-04 21:45:37,679][flwr][INFO] - Requesting initial parameters from one random client
[2024-06-04 21:45:46,428][flwr][INFO] - Received initial parameters from one random client
[2024-06-04 21:45:46,431][flwr][INFO] - Evaluating initial global parameters
[2024-06-04 21:45:49,939][flwr][INFO] - initial parameters (loss, other metrics): 1.263537882919043, {'test_bal_accuracy': 0.3949993989662219, 'test_f1':
0.25517252023721754, 'test_precision': 0.6158703968694331, 'test_recall': 0.3286219081272085}
[2024-06-04 21:45:49,942][flwr][INFO] -
[2024-06-04 21:45:49,946][flwr][INFO] - [ROUND 1]
[2024-06-04 21:45:49,949][flwr][INFO] - configure_fit: strategy sampled 4 clients (out of 4)
[2024-06-04 21:46:31,147][flwr][INFO] - aggregate_fit: received 4 results and 0 failures
[2024-06-04 21:46:33,089][flwr][WARNING] - No fit_metrics_aggregation_fn provided
[2024-06-04 21:46:36,289][flwr][INFO] - fit progress: (1, 1.9769039609417005, {'test_bal_accuracy': 0.39716312056737585, 'test_f1': 0.3044097497656307,
'test_precision': 0.3456449408062727, 'test_recall': 0.44876325088339225}, 46.34703543399996)
[2024-06-04 21:46:36,292][flwr][INFO] - configure_evaluate: no clients selected, skipping evaluation
[2024-06-04 21:46:36,295][flwr][INFO] -
[2024-06-04 21:46:36,298][flwr][INFO] - [ROUND 2]
[2024-06-04 21:46:36,301][flwr][INFO] - configure_fit: strategy sampled 4 clients (out of 4)
[2024-06-04 21:47:17,407][flwr][INFO] - aggregate_fit: received 4 results and 0 failures
[2024-06-04 21:47:22,543][flwr][INFO] - fit progress: (2, 1.2887797025261893, {'test_bal_accuracy': 0.6638418079096046, 'test_f1': 0.4902542299442604,
'test_precision': 0.7598527912401012, 'test_recall': 0.5795053003533569}, 92.60115222599984)
[2024-06-04 21:47:22,546][flwr][INFO] - configure_evaluate: no clients selected, skipping evaluation
[2024-06-04 21:47:22,549][flwr][INFO] -
[2024-06-04 21:47:22,552][flwr][INFO] - [ROUND 3]
[2024-06-04 21:47:22,556][flwr][INFO] - configure_fit: strategy sampled 4 clients (out of 4)
[2024-06-04 21:48:00,008][flwr][INFO] - aggregate_fit: received 4 results and 0 failures
[2024-06-04 21:48:05,160][flwr][INFO] - fit progress: (3, 5.701338005366954, {'test_bal_accuracy': 0.3333333333333333, 'test_f1': 0.24539358317985954,
'test_precision': 0.17385658454968847, 'test_recall': 0.4169611307420495}, 135.2184447489999)
[2024-06-04 21:48:05,164][flwr][INFO] - configure_evaluate: no clients selected, skipping evaluation
[2024-06-04 21:48:05,168][flwr][INFO] -
[2024-06-04 21:48:05,172][flwr][INFO] - [ROUND 4]
[2024-06-04 21:48:05,176][flwr][INFO] - configure_fit: strategy sampled 4 clients (out of 4)
[2024-06-04 21:48:45,489][flwr][INFO] - aggregate_fit: received 4 results and 0 failures
[2024-06-04 21:48:50,568][flwr][INFO] - fit progress: (4, 1.770318077618444, {'test_bal_accuracy': 0.7188965019834114, 'test_f1': 0.6016802052989247,
'test_precision': 0.7822973272040019, 'test_recall': 0.6537102473498233}, 180.62626229900002)
[2024-06-04 21:48:50,571][flwr][INFO] - configure_evaluate: no clients selected, skipping evaluation
[2024-06-04 21:48:50,575][flwr][INFO] -
[2024-06-04 21:48:50,578][flwr][INFO] - [ROUND 5]
[2024-06-04 21:48:50,582][flwr][INFO] - configure_fit: strategy sampled 4 clients (out of 4)
[2024-06-04 21:49:30,664][flwr][INFO] - aggregate_fit: received 4 results and 0 failures
[2024-06-04 21:49:36,162][flwr][INFO] - fit progress: (5, 0.47380182282716266, {'test_bal_accuracy': 0.8559322033898304, 'test_f1': 0.8197952885501935,
'test_precision': 0.8339563319566574, 'test_recall': 0.8197879858657244}, 226.22070998499998)
[2024-06-04 21:49:36,166][flwr][INFO] - configure_evaluate: no clients selected, skipping evaluation
```

# Design Features

2. **Parallel Programming: Ray**

    - Enhances scalability
    - Manages client model training concurrently
    - Resource Optimization

3. **Addressing Class Imbalance in Federated Models**

    - Addition of a decaying learning rate to address overfitting
    - Running 5 rounds of training for each client ( within each round 10 epochs per local model are run)
    - Data Augmentation techniques to increase robustness of the local models

# Limitations of current work

| | | |
|---|---|---|
| 01 | **Limited Data** | • ~2k images after augmentation<br>• Limit on the maximum no of clients to test without increasing overfitting |
| 02 | **Data Quality and Consistency** | • Variability in data quality and heterogeneity across clients impacts model performance |
| 03 | **Resource Constraints at Client level** | • Decentralized training can be resource-intensive, and some clients may not have all available across all nodes |

# Final Product: Big Picture!