Federated Kolmogorov-Arnold Networks (F-KANs) for Biomedical Applications

Project Description

This project aims to implement and enhance Federated Kolmogorov-Arnold Networks (F-KANs) for classification tasks in the biomedical domain. The goal is to improve the performance of federated learning models while ensuring data privacy and efficiency. By leveraging federated learning, the project will explore how F-KANs can outperform traditional neural networks, particularly Multi-Layer Perceptrons (MLPs), in terms of accuracy and training efficiency.

Objectives

- Implement F-KANs using existing codebases as a foundation.
- Compare the performance of F-KANs against traditional MLPs in a federated learning setup.
- Use a biomedical dataset to evaluate model performance and demonstrate real-world applicability.
- Optimize the F-KAN architecture to achieve better classification results with fewer training rounds.

Dataset Suggestions (Choose any)

1. Federated MNIST (FEDMNIST)
    - Description: A popular benchmark dataset for federated learning that consists of handwritten digits from the MNIST dataset distributed across multiple clients.
    - Use Case: While not biomedical, it serves as a foundational dataset for implementing federated learning algorithms and can be adapted for initial testing before moving to more complex biomedical datasets.
    - Link: FEDMNIST Dataset

2. Chest X-Ray Images (Pneumonia)
    - Description: This dataset contains over 5,000 images of chest X-rays labeled with pneumonia or no pneumonia. It is widely used for image classification tasks in medical imaging.
    - Use Case: Useful for training and evaluating models that classify medical images while maintaining patient privacy through federated learning.
    - Link: Chest X-Ray Dataset

Model Implementation

Implement F-KANs inspired on existing code from:

- F-KANs GitHub Repository
- FL_KAN_x_MLP Notebook

Performance Comparison

- Compare the results of the F-KANs with traditional MLPs in terms of:
  - Accuracy achieved after a set number of communication rounds.
  - Training time taken to reach convergence.

Expected Outcomes

- The project aims to demonstrate that F-KANs can achieve comparable or superior performance to centralized MLPs while requiring fewer communication rounds between clients and the server.
- The results should highlight the benefits of using federated learning in sensitive biomedical applications where data privacy is paramount.

Setup Implementation

Mandatory: Do client simulation of model update of at least **3 epochs in 3 dummy clients**

Optional: Use Flower (flwr) framework to create a federated learning environment where multiple clients can train their local F-KAN models on their respective datasets.