Zaiku Quantum Federated Hackathon (Brain Tumor Classification using Quantum Federated Learning)

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Problem Statement

Precise detection and classification of brain tumors from MRI scans are crucial for timely diagnosis and effective treatment planning. Traditional diagnostic methods rely heavily on manual interpretation, which can be time-consuming and prone to human error. the variability in tumor characteristics necessitates robust classification techniques capable of distinguishing between different tumor types, such as meningioma, glioma, and pituitary tumors.
Current machine learning approaches have shown promise in automating tumor detection and classification tasks. However, challenges persist in achieving consistently high accuracy, especially across diverse patient populations and imaging conditions. the integration of advanced computing technologies, such as quantum computing-inspired algorithms, presents an opportunity to enhance the precision and efficiency of tumor classification models.
This project aims to leverage quantum-inspired algorithms and classical machine learning techniques to address these challenges. By analyzing MRI data from patients diagnosed with various brain tumors, the goal is to develop and optimize machine learning models capable of accurately identifying tumor types and delineating tumor boundaries from imaging data. Additionally, the project explores federated learning methodologies to ensure privacy and security while improving model robustness across different medical institutions and patient demographics.

Introduction

The accurate identification and classification of brain tumors are critical tasks that often rely on advanced imaging techniques. Traditional methods, while effective, can benefit significantly from the integration of cutting-edge technologies like quantum computing and machine learning. This project aims to harness the power of quantum-inspired algorithms and classical machine learning to enhance the automated detection and classification of brain tumors from MRI images.

- The dataset used comprises MRI scans of patients with different types of brain tumors—meningioma, glioma, and pituitary tumors—gathered from medical archives.
- Leveraging quantum-inspired algorithms such as Variational Quantum Circuits (VQC) and classical machine learning models, the project seeks to develop robust classifiers capable of accurately distinguishing between these tumor types. This not only facilitates quicker and more precise diagnosis but also aids in personalized treatment planning tailored to the specific characteristics of each tumor type.

Motivation

The motivation for choosing the quantum federated learning approach for brain tumor classification stems from several key factors.

- Brain tumors are among the most severe medical conditions due to their complexity and the delicate nature of the brain. Accurate classification of brain tumors is essential for:
- Diagnosis: Proper diagnosis is the first step toward effective treatment and patient management.
- Treatment Planning: Different types of tumors require different treatment approaches, including surgery, radiation therapy, and chemotherapy.
- Prognosis: Accurate classification helps predict the disease progression and the patient's prognosis

Challenges in Traditional Methods

Traditional methods for brain tumor classification often face challenges such as:.

- Data Privacy: Sharing medical imaging data across institutions can raise privacy concerns.
- Data Imbalance: The number of available samples for different types of tumors may be unequal, affecting the model's performance.
- Computational Resources: Training advanced models on large datasets requires significant computational resources.

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Solution

Problem Formulation:. **Problem Formulation**
Given a dataset $\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N}$, where $\mathbf{x}_i$ represents MRI images and y_i denotes the corresponding tumor type labels (meningioma, glioma, pituitary tumor), the objective is to train a classification model that accurately predicts the tumor type from new MRI images.
Classical Preprocessing
Data Preprocessing:

- MRI images are preprocessed to enhance features relevant to tumor classification.
- Images are normalized and resized as necessary for input to machine learning models.

Feature Extraction:

- Classical feature extraction techniques are employed to capture relevant patterns from the MRI images.
- These features serve as inputs to both classical and quantum machine learning models.

Solution

Quantum Machine Learning
Feature Mapping:

- Quantum machine algorithms typically begin with a feature map $\Phi(\mathbf{x}_i)$ that transforms classical data into quantum states.
- A common feature map used in Quantum Machine Learning is the ZZ Feature Map:

$$\Phi(\mathbf{x}_i) = \exp\left(-i \sum_{p<q} \theta_{pq} Z_p Z_q\right) \mid \mathbf{x}_i\rangle$$

  where Z_p denotes the Pauli-Z operator acting on qubit p, and θ_{pq} are trainable parameters.

Quantum Circuit (Ansatz):

- The quantum circuit, or ansatz $U(\theta)$, is designed to prepare a quantum state that depends on the features extracted by $\Phi(\mathbf{x}_i)$.
- Real Amplitudes Ansatz is commonly used in QML:

$$U(\theta) = \prod_{j=1}^{L} R_z(\theta_{2j-1}) R_y(\theta_{2j})$$

  where $R_z(\theta)$ and $R_y(\theta)$ are rotation operators around the Z and Y axes, respectively.

Training and Optimization:

- The model parameters θ are optimized using quantum-classical hybrid optimization algorithms like COBYLA.

Solution

Feature Map (FM): The quantum circuit that encodes classical input data into a quantum state. A typical choice is the ZZFeatureMap, which calculates pairwise interactions between input features:

$$U_{FM}(\vec{x}) = e^{-i \sum_{i<j} \theta_{ij} Z_i Z_j}$$

Here, $\vec{x}$ represents the input features and θ_{ij} are the variational parameters.
Ansatz: Represents the variational form of the quantum circuit. RealAmplitudes is commonly used, allowing flexibility in parameterized rotations:

$$U_{Ansatz}(\vec{\theta}) = \prod_{l=1}^{L} e^{-i\theta_l H_l}$$

H_l are local Hamiltonians defined by gates such as RX, RY, and RZ.
Quantum Circuit Training: The training process involves optimizing the parameters $\vec{\theta}$ of the quantum circuit using a classical optimizer such as COBYLA.

Solution

Federated Learning Approach: To maintain privacy and utilize decentralized data, federated learning is employed.
Objective Function: Defined to minimize the difference between predicted and actual labels:

$$\min_{\vec{\theta}} L(\vec{\theta}) = \sum_i \left(1 - \langle \psi(\vec{\theta}) | Y_i | \psi(\vec{\theta}) \rangle \right)^2$$

Here, Y_i represents the target labels and $|\psi(\vec{\theta})\rangle$ is the quantum state output by the circuit.
Client-Server Architecture: Multiple clients (medical institutions) each hold local datasets. They train their models locally on their data without sharing it centrally.
Global Model Aggregation: After local training epochs, clients send model updates (weights) to a central server. The server aggregates these updates using averaging techniques like Simple Averaging:

$$\vec{\theta}_{avg} = \frac{1}{N} \sum_{i=1}^{N} \vec{\theta}_i$$

Global Model Deployment: The server broadcasts the updated global model back to clients for further local training. This iterative process continues until convergence or a predefined criterion.

Solution

Plotting Train and Test Scores for Federated Learning Clients:
For each averaging technique indexed by $technique\_idx$ in the array $clients\_array\_2d$, the following plots are generated:

1. Train Scores Plot:

- Each plot shows the training scores over epochs for all clients under a specific averaging technique.
- The x-axis represents the epochs, and the y-axis represents the train score.
- For each client indexed by $client\_idx$ in $clients\_list$, a line plot is generated using $client.train\_scores$.
- The label for each line plot is denoted as 'Client $client\_idx + 1$'.
- The plot is titled as "Train Scores for All Clients ($technique\_name$)" where $technique\_name$ is the name of the averaging technique.
- Each plot is displayed using `plt.figure()`, with a figure size of 8×6 inches, and then shown using `plt.show()`.

2. Test Scores Plot:

- Similar to the train scores plot, each plot shows the test scores over epochs for all clients under a specific averaging technique.
- The x-axis represents the epochs, and the y-axis represents the test score.
- For each client indexed by $client\_idx$ in $clients\_list$, a line plot is generated using $client.test\_scores$.
- The label for each line plot is denoted as 'Client $client\_idx + 1$'.
- The plot is titled as "Test Scores for All Clients ($technique\_name$)" where $technique\_name$ is the name of the averaging technique.
- Each plot is displayed using `plt.figure()`, with a figure size of 8×6 inches, and then shown using `plt.show()`.

Technical Architecture

Technical Architecture

The optimization process aims to adjust the parameters $\vec{\theta}$ of the quantum circuits to minimize a cost function, typically using classical optimizers like COBYLA:

$$\min_{\vec{\theta}} \mathcal{L}(\vec{\theta})$$

where $\mathcal{L}$ denotes the loss function measuring classification error.

Federated Learning Integration

In a federated learning setup, multiple clients (hospitals or institutions) maintain their data locally, enhancing privacy and scalability. Each client performs local QML training on their datasets, utilizing Quantum Variational Circuits (QVCs) tailored to local distributions. After each local epoch, client models synchronize their updates through averaging mechanisms such as Simple Averaging:

$$\vec{\theta}_{\text{global}}(t+1) = \frac{1}{N} \sum_{i=1}^{N} \vec{\theta}_{\text{local}}(t+1)$$

This averaging stabilizes the global model while preserving data privacy across clients.

Evaluation and Deployment

The global model's accuracy is evaluated iteratively across epochs, ensuring convergence and performance improvements over time. Once trained, the model is deployed for inference on new brain tumor MRI data, providing accurate classification results crucial for clinical decision-making.

Figure: Test accuracy

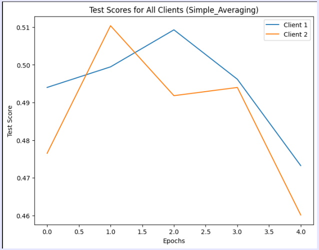

Figure: Train accuracy

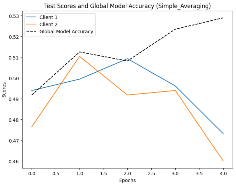

Figure: Global Model accuracy

Results

performance of a federated learning setup using Simple Averaging across multiple epochs. Each epoch involves training models on multiple clients (two in this case) and averaging their parameters to update the global model.
Epoch 0 Client 0:
Train Score: 0.45 Test Score: 0.49398907103825135 Training took approximately 89 seconds.
Client 1:
Train Score: 0.48 Test Score: 0.47650273224043715 Training took approximately 14 seconds.
Global Model:
Accuracy: 0.4918032786885246 Epoch 1 Client 0:
Train Score: 0.60 Test Score: 0.4994535519125683 Training took approximately 14 seconds.
Client 1:
Train Score: 0.52 Test Score: 0.5103825136612021 Training took approximately 14 seconds.
Global Model:
Accuracy: 0.512568306010929 Epoch 2 Client 0:
Train Score: 0.52 Test Score: 0.5092896174863388 Training took approximately 15 seconds.
Client 1:
Train Score: 0.47 Test Score: 0.4918032786885246 Training took approximately 19 seconds.
Global Model:
Accuracy: 0.5081967213114754 Epoch 3 Client 0:
Train Score: 0.51 Test Score: 0.4961748633879781 Training took approximately 13 seconds.
Client 1:
Train Score: 0.55 Test Score: 0.49398907103825135 Training took approximately 13 seconds.
Global Model:
Accuracy: 0.5234972677595628 Epoch 4 Client 0:
Train Score: 0.44 Test Score: 0.473224043715847 Training took approximately 14 seconds.
Client 1:
Train Score: 0.51 Test Score: 0.4601092896174863 Training took approximately 15 seconds.
Global Model:
Accuracy: 0.5289617486338798

Future Work

- Increase the Number of Clients: Incorporate more clients (e.g., hospitals or institutions) to increase the diversity of training data and improve the generalizability of the global model. Geographical Diversity: Include clients from different geographical regions to capture a wider variety of data, potentially leading to a more robust model.
- Enhance Model Architecture Advanced Quantum Circuits: Explore more complex quantum variational circuits to potentially improve the learning capacity and accuracy of the models. Hybrid Models: Develop and integrate hybrid quantum-classical models that leverage the strengths of both quantum and classical machine learning techniques.
- Optimization Techniques Advanced Optimizers: Implement more sophisticated optimization algorithms (e.g., Adam, L-BFGS) to potentially enhance the training efficiency and model performance. Adaptive Learning Rates: Use adaptive learning rates to improve convergence speed and prevent overfitting.
- Federated Learning Enhancements Federated Averaging Algorithms: Explore alternative federated averaging techniques such as Federated Averaging with Momentum or Federated Stochastic Gradient Descent (FedSGD) to potentially enhance the global model's performance. Secure Aggregation: Implement secure aggregation techniques to ensure data privacy and security during the model parameter synchronization process.

Future Work

- Performance Evaluation and Metrics Comprehensive Metrics: Expand the set of evaluation metrics to include precision, recall, F1-score, and area under the ROC curve (AUC) for a more comprehensive assessment of model performance. Cross-Validation: Implement cross-validation techniques to more reliably estimate model performance and generalization capabilities.
- Scalability and Efficiency Distributed Computing: Utilize distributed computing resources to handle larger datasets and more clients efficiently, potentially leveraging cloud computing platforms. Parallel Processing: Implement parallel processing techniques to speed up training and evaluation processes.

Bonus Tasks Done

- The model can handle high dimensional data sets such as MRI images
- The Federated Framework is multimodal i.e. it can handle more than one data modality during the training: we have trained the model on a different dataset Pulsar Dataset-The notebook is available in the repository .

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