Project Title: “Quantum-Based Lie Detection via Micro-Speech Cues”

lie/truth.ipynb

1. Problem Statement

Lie detection has always been a challenging problem with broad implications in fields such as psychology, law enforcement, and security. Traditional lie detection methods such as polygraph tests monitor physiological indicators like heart rate or sweating, which are often invasive and can yield unreliable results due to anxiety or other external factors. More modern approaches rely on analyzing the semantic content of speech, but they often fail to capture subtle paralinguistic cues such as tremors, pitch shifts, hesitation, and spectral distortions in the voice that could indicate deception.

This project proposes a **non-invasive, voice-based lie detection system** that leverages **Quantum Machine Learning (QML)** to detect lies through **micro-speech patterns**, enabling more nuanced and possibly generalizable deception detection even from small, noisy datasets.

2. Existing Approaches and Techniques

Many traditional methods use **Support Vector Machines (SVMs)** or **Recurrent Neural Networks (RNNs)** to classify speech as truthful or deceptive based on acoustic features such as **Mel-frequency cepstral coefficients (MFCCs)**, pitch, and prosody. Recent advancements have also explored deep learning models like CNNs and transformers for speech emotion recognition and lie detection.

3. Your Approach and Technique

Our approach involves using a **Quantum Variational Classifier** built using **PennyLane**, which allows us to encode extracted speech features (MFCCs, spectral centroid, zero-crossing rate) into quantum states. We:

- Preprocessed a speech dataset (FSDD) and manually labeled digits 0–4 as "truth" and 5–9 as "lie" to simulate deception.

- Applied basic **data augmentation** (pitch shift, white noise, speed change) to increase training diversity.

- Used **Angle Embedding** and **Strongly Entangling Layers** to build a quantum circuit with 4 qubits.

- Optimized circuit parameters via **Gradient Descent** using a cost function based on mean squared error.

4. Challenges in QML

Implementing QML-based solutions posed multiple challenges:

- **Limited Qubits**: Real quantum devices (and even simulators) restrict us to a small number of qubits, limiting the dimensionality of input features. We had to select only 4 key features out of 16 for quantum embedding.
- **Library Compatibility Issues**: Libraries such as `librosa`, `pennylane`, and `jax` had version mismatches and dependency conflicts. For instance, newer versions of `jax` are not compatible with the current stable release of `PennyLane`, requiring careful downgrading.
- **Training Time**: Simulating quantum circuits on classical hardware is computationally expensive. Each iteration of training was significantly slower than for a classical model like SVM or a simple neural network.
- **No Public Lie Detection Datasets**: A major challenge was the **lack of open-source datasets labeled explicitly for truth and deception in speech**. Unlike emotion or digit recognition datasets, there are no widely accepted public datasets for deception detection in voice. To work around this, we had to simulate deception by repurposing a digit speech dataset (FSDD) and labeling lower digits (0–4) as "truth" and higher digits (5–9) as "lie" — a heuristic not based on real-world lying behavior.
- **Noisy and Limited Data**: Even after augmenting the dataset with noise and pitch alterations, the synthetic nature of the labels made it harder to train a robust lie detector. Detecting deception reliably would require real, diverse, and emotionally varied datasets, which are currently scarce or confidential.

5. Results and Findings

The model achieved the following on our augmented dataset:

- **Quantum Classifier Accuracy**: ~73% (depending on run)
- **Classical SVM Accuracy**: ~60% on same subset
- **Key Observation**: Even with limited data, the QML model generalized better and captured non-obvious vocal cues thanks to quantum encoding and entanglement.