Project Proposal: Quantum Machine Learning for Credit Card Fraud Detection

1. Project Overview

This project will investigate the potential of quantum machine learning (QML) as an alternative approach to binary fraud detection. We will propose a comparative study between classical and quantum classification models using the Quantum Support Vector Machine (QSVM) and the Variational Quantum Classifier (VQC). The goal is to assess whether quantum methods can achieve comparable or superior performance to classical models on a realistic, small-scale fraud detection problem.

Advance in quantum kernel methods (Havlíček et al., 2019) and hybrid variational classifiers (Schuld et al., 2020) suggest that quantum models may offer advantages in capturing nonlinear patterns and implicit structure in high-dimensional data.

2. Task, Experience, and Performance Metrics

* Task (T): Classify whether a given credit card transaction is fraudulent or legitimate (binary classification)
* Experience (E): Labeled transaction data with known fraud/non-fraud outcomes.
* Performance (P): Measured in terms of classification recall, F1-score, and confusion matrix. We will mostly focus on recall, as false negatives (FN) are particularly costly in fraud detection.

3. Dataset Description

We will use a Credit Card Fraud Detection dataset from Kaggle. This dataset has been widely used in fraud detection research and forms the basis of several benchmark studies. It captures European credit card transactions over a two-day period in September 2013.

* Sample Size: 284,807 transactions
* Positive Cases (Fraud): 492 transactions (0.172%)
* Features:
  + V1-V28: PCA applied to anonymize raw features
  + Time: Seconds elapsed from the first transaction
  + Amount: Monetary value of the transaction
  + Class: Binary label (1=fraud, 0=non-fraud)

\*due to confidentiality concerns, the original features were not released. Instead, PCA was used to derive 28 anonymized components to preserve the majority of the original dataset’s variance.

4. Methodology

4.1 Data Preparation

[Credit Card Fraud Detection](https://www.kaggle.com/datasets/kartik2112/fraud-detection)

We will preprocess the dataset in the following steps:

* Apply random undersampling of the majority class (non-fraud) to create a balanced subset for binary classification
* Normalize features (e.g. Amount, Time) and select a subset of V1-V28
* Use dimensionality reduction (e.g., PCA or feature selection) to reduce number of input features for quantum models, which are constrained by qubit count (typically <= 6 features for circuit encoding)
* Perform a train-test split (e.g., 70/30) while preserving class balance in both sets. During training, only input features are used. During testing, the model predicts labels which are then compared to the known class values to evaluate performance.

4.2 Classical Baselines

We will implement and evaluate several standard supervised ML models using Weka or RStudio.

* Logistic regression
* Support Vector Machine (SVM)

These models provide baseline metrics for comparison against quantum approaches.

4.3 Quantum Models

* VQC (via Pennylane or Qiskit): A hybrid quantum-classical neural network that uses parameterized quantum circuits to learn nonlinear decision boundaries. Trained using classical optimization of quantum circuit parameters. Based on Schuld et al. (2020).

5. Evaluation Strategy

Due to the highly imbalanced nature of the original dataset, accuracy is not a reliable performance metric. Instead, we will try to focus on:

* AUPRC (Area Under the Precision-Recall Curve): Recommended by the dataset creators and widely used in imbalanced classification tasks.
* F1-score: useful when false negatives and false positives are both costly
* Recall: as undetected fraud may cause significant losses
* Confusion Matrix: Will be used to visualize true / false positives and negatives

We will evaluate all models using 5-fold cross-validation on balanced subsets and report average scores. Quantum models will be compared on a basis of: Training time and inference latency, Scalability to larger sample sizes, Circuit depth and complexity (for VQC)

6. Expected Contribution/Values

The expected outcome of this project is a comparative analysis of classical and quantum classification approaches for credit card fraud detection. Although current quantum models are constrained by qubit limits and simulation overhead, this work aims to assess:

* Whether QML can match or exceed classical performance
* What role quantum classifiers might play in future fraud detection systems
* Whether quantum models offer advantages in generalization, interpretability, or training dynamics.

This project hopefully could contribute to the evolving research exploring practical applications of quantum computing in real-world fields.

7. References

* Havlíček, V., et al. (2019). *Supervised learning with quantum-enhanced feature spaces*. Nature, 567(7747), 209–212.
* Schuld, M., Bocharov, A., Svore, K. M., & Wiebe, N. (2020). *Circuit-centric quantum classifiers*. Physical Review A, 101(3), 032308.
* Carcillo, F., et al. (2018). *Streaming active learning strategies for real-life credit card fraud detection*. International Journal of Data Science and Analytics, 5(4), 285–300.