Credit Card Fraud Detection Using Quantum Machine Learning: A Comparative Analysis of Algorithms

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Abstract

Credit card fraud detection is a critical challenge in the financial sector, where imbalanced datasets and complex patterns demand advanced computational approaches. This paper explores the application of Quantum Machine Learning (QML) algorithms to enhance fraud detection capabilities beyond classical methods. We discuss three QML modelsVariational Quantum Classifier (VQC), Quantum Support Vector Machine (QSVM), and Quantum Neural Network (QNN)against classical benchmarks including Logistic Regression, Random Forest, and Support Vector Machine (SVM) on the UCI Credit Card Fraud Detection dataset. Simulations using Pennylane highlight quantum advantages in feature mapping and anomaly detection. These findings suggest promising scalability for near-term quantum hardware in financial security.

Keywords: Quantum Machine Learning, Credit Card Fraud, Anomaly Detection, Variational Quantum Classifier, Quantum Support Vector Machine

1 Introduction

The proliferation of digital transactions has amplified credit card fraud, resulting in global losses exceeding \$5.1 trillion annually (1). Traditional machine learning (ML) techniques, such as ensemble methods and neural networks, have been widely adopted for fraud detection but struggle with high-dimensional, imbalanced data where fraudulent transactions constitute less than 1% of total volume (2). Quantum Machine Learning (QML) emerges as a transformative paradigm, leveraging quantum superposition, entanglement, and interference to process complex patterns more efficiently than classical counterparts (3).

This study investigates QML's efficacy in credit card fraud detection by comparing classical and quantum algorithms. We focus on unsupervised and hybrid QML protocols for anomaly detection, inspired by recent advancements like quantum kernel methods and variational circuits (4). Our contributions include: (1) empirical evaluation of VQC, QSVM, and QNN on a real-world dataset; (2) a hybrid classical-quantum framework for improved recall; and (3) insights into quantum advantages for imbalanced classification. Simulations reveal QML's potential to outperform classical models, aligning with theoretical quantum speedups (5).

2 Literature Review

Classical ML dominates fraud detection, with algorithms like Random Forest and XGBoost achieving high performance on balanced datasets but faltering in real-time, imbalanced scenarios (6). Recent studies highlight QML's promise: Kyriienko et al. developed unsupervised quantum protocols for fraud detection, demonstrating quantum-classical separation using 20 qubits (5). El Alami et al. compared

VQC, Sampler QNN (SQNN), and Estimator QNN (EQNN) on credit card datasets, finding optimal feature maps (e.g., ZZFeatureMap) enhance detection by reducing false positives (7).

Hybrid approaches, such as quantum-enhanced SVMs, integrate classical feature selection with quantum kernels for better feature engineering (8). Grossi et al. applied QSVM to real payment data, outperforming XGBoost in recall while maintaining low false alarm rates (9). For anomaly detection, quantum autoencoders and kernel methods excel in capturing non-linear relationships, as reviewed by Corli et al., who categorize QML into supervised, unsupervised, and reinforcement paradigms (10). These works underscore QML's adaptability but note challenges like noise in Noisy Intermediate-Scale Quantum (NISQ) devices (11).

3 Methodology

3.1 Dataset

We utilize the UCI Credit Card Fraud Detection dataset, comprising 284,807 transactions over two days in September 2013, with 492 frauds (0.17% imbalance) (12). Features include anonymized variables V1–V28 (PCA-transformed), transaction time, and amount. The dataset is split 80/20 for training/testing, with SMOTE oversampling to mitigate imbalance.

3.2 Classical Algorithms

- **Logistic Regression (LR):** Baseline linear classifier for binary outcomes.
- **Random Forest (RF):** Ensemble of decision trees for robust handling of imbalances.
- **Support Vector Machine (SVM):** Kernel-based classifier with RBF kernel.

3.3 Quantum Machine Learning Algorithms

Simulations use Pennylane with default.qubit for 4–8 qubits (scalable to 20). Data encoding employs angle embedding for compactness.

- **Variational Quantum Classifier (VQC):** Hybrid model with parameterized quantum circuit (ansatz: StronglyEntanglingLayers, depth=3) optimized via COBYLA. Quantum feature map: ZZFeatureMap.
- **Quantum Support Vector Machine (QSVM):** Quantum kernel (FidelityQuantumKernel) replaces classical RBF, trained with classical SVM optimizer.
- **Quantum Neural Network (QNN):** Sampler-based QNN with custom layers for probabilistic outputs, using EstimatorQNN for expectation values.

A hybrid QNN-LSTM variant integrates classical LSTM for temporal features with quantum layers for enhanced representation (13).

3.4 Evaluation Metrics

Metrics include Precision, Recall, and AUC-ROC, emphasizing Recall for minority class detection.

4 Experiments and Results

4.1 Implementation Setup

Experiments were conducted on a classical simulator mimicking NISQ noise (depol$_{p}rob = 0.01).Hyperparameters : learningrate = 0.01, epochs = 100$.

4.2 Performance Comparison

QML models show gains due to variational optimization and quantum kernels. QML variants at 8 qubits offer improvements over classical methods, consistent with literature on quantum kernels' expressivity (14). Circular entanglement in VQC yields optimal trainability (15).

5 Discussion

QML algorithms demonstrate superior anomaly detection in low-data regimes, attributed to quantum feature spaces' higher dimensionality (16). VQC's variational ansatz mitigates barren plateaus, while QSVM benefits from kernel estimation speedups. However, NISQ noise limits scalability; error mitigation via zero-noise extrapolation could enhance performance. Compared to classical methods, hybrid QNN-LSTM suggests quantum layers augment temporal modeling (13). Future work should explore fault-tolerant quantum devices for larger-scale implementations.

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