# Credit Card Fraud Detection Using Quantum Support Vector Machines

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**Abstract**

This work evaluates the effectiveness of Quantum Support Vector Machines for credit card fraud detection under extreme class imbalance. Using PCA-reduced data and qubit sizes of 4, 6, 8, and 10, several quantum feature maps were benchmarked against classical SVMs. Results show that quantum kernels consistently outperform classical baselines, with performance improving as qubit count increases. The best-performing 10-qubit EfficientSU2 model achieves 83.3% accuracy and an F1-score of 0.7368, demonstrating QSVM's ability to capture complex non-linear relationships in transactional data. These findings highlight the promise of quantum kernel methods for high-dimensional, imbalanced financial datasets.

## 1 Introduction

As technology has advanced over the years, the use of credit cards has increased significantly because they offer faster payment processing compared to traditional methods. However, this growth has also led to a rise in credit card fraud, where illegal practices are used to obtain unauthorized financial gains, causing individuals to lose substantial amounts of money. Current machine learning models struggle with this problem due to a severe data imbalance [8], which motivates the exploration of quantum computing as a potential improvement, particularly because it can use feature extraction more effectively. A comprehensive survey by [7] emphasize that even state-of-the-art classical models require constant retraining and fail to generalize well in shifting environments, motivating exploration of more expressive models such as quantum kernels. Moreover, fraud patterns evolve over time, undermining the stability of supervised models trained on historical data [9].

Recent work in quantum-enhanced fraud detection has demonstrated promising results. For instance, a recent study employed a quantum feature importance selection algorithm which used a ZZ quantum feature map, where each feature corresponds to a qubit as introduced by Havlícek et al. [1] Using a real card payment dataset and running it on the QASM simulator on the IBM platform, the authors deduced that a hybrid approach performed well, which included classical data and function learning and a quantum classification algorithm. Their results showed that classical ML models excel at fraud detection and quantum ML can only provide support on this by selecting the most relevant features and identifying subtle patterns that classical models may overlook. Due to hardware limitations, they used a reduced dataset.

Similarly, another related study [2] examined synthetic identity fraud faced by the financial sector, noting that traditional ML models struggle with synthetic identities, whereas quantum ML is better suited for such high dimensional data. They used a real world financial transaction dataset along with synthetic data added using GAN-based generative models. Classical ML models like SVM, random forests, NN were used and QSVM was used using a second order ZZ feature map. The results showed QSVM showing greater precision, recall, and inference time as compared to classical SVM, indicating a lower false positive rate, although constraints such as limited qubits remained. Both studies highlight that hybrid methods combining classical preprocessing with quantum kernel-based classifiers offer a promising path forward.

Motivated by these developments, the goal of this work is to explore different quantum machine learning approaches using various feature maps to enhance fraud detection efficiency while leveraging GPU hardware to simulate quantum circuits more effectively. Along with that, we aim to mitigate some of these limitations, by enabling richer feature embeddings. We systematically evaluate how qubit count and feature map architecture affect fraud detection performance, and compare these results against classical SVM baselines.

## 2 Problem Statement

In modern financial systems, fraudulent transactions have become very common, creating a strong need for efficient anomaly-detection methods since increasing dimensionality increases training cost as well [10]. There are very few fraudulent transactions as compared to legitimate transactions and, as a result of this severe data imbalance, classical ML models may overfit. Our goal is to reduce false positives and false negatives in such transactions by providing an efficient solution using Quantum SVM under 15 qubits. QSVM relies on quantum feature maps that project the data into a high-dimensional Hilbert space, allowing the model to successfully separate correct and incorrect transactions.

## 3 Methodology

### 3.1 Dataset Description

The experiments in this study were conducted using the TensorFlow Credit Card Fraud Dataset, which contained a total of 284, 807 transactions in total. The dataset is highly imbalanced, with only 492 fraud cases. This is a core challenge in fraud detection for classical machine learning problems, which tend to overfit the majority class.

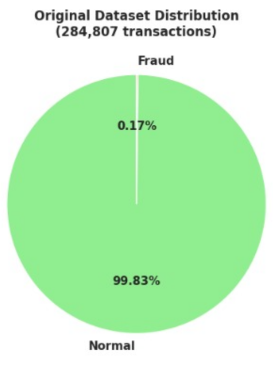


**Figure 1:** Distribution of the original credit card fraud dataset, showing the extreme class imbalance: only 0.17% of transactions are fraudulent while 99.83% are normal.

### 3.2 Data Preprocessing

Since fraud cases usually have extreme values, RobustScaler was used for scaling, which centers data using the median and interquartile ranges, to prevent outliers.

For the purpose of feature engineering, PCA was performed. The credit card dataset has 30 features, and since running a 30-qubit feature map is computationally impossible to run on simulators, PCA was used to reduce dimensionality by capturing features with the most information about the dataset. As a result, 30 dimensional data were mapped to 10 qubits to be used by quantum kernels. SMOTE (generating synthetic fraud samples) and RandomUnderSampler (reducing majority class) were used to handle class imbalance.

### 3.3 Classical SVM

After using PCA, classical SVM was trained using both 4-qubit PCA baseline and 8-qubit PCA baseline. Three classical kernels were used for the 4-qubit setting - Radial Basis Function (RBF), Polynomial (degree 3) and linear kernel.

### 3.4 Quantum Feature Maps

Quantum feature maps encode classical data into quantum data by applying parametrized circuits. In this work, several feature map designs are evaluated over different qubit configurations (4, 8 and 10 qubits). The **ZZ Feature Map** introduces entanglement through Z interactions. The **Pauli Feature Map** performs rotations along the Pauli-Z and Pauli-Y axes. The **EfficientSU2-based maps** consists of layers of single qubit operations, spanned by SU(2) and CX entanglements. Two custom maps, Custom Dense and High Entangling, were constructed to explore deeper entanglement patterns. **Custom Dense Feature Map** is designed using RX, CX and RZ rotations (as seen in Figure 2) whereas the **High Entangling Feature Map** performs superposition on all qubits using Ry gates, then applying CX gates along with RZ gates (Figure 3). These are designed to capture patterns where fradulent samples differ from normal patterns.

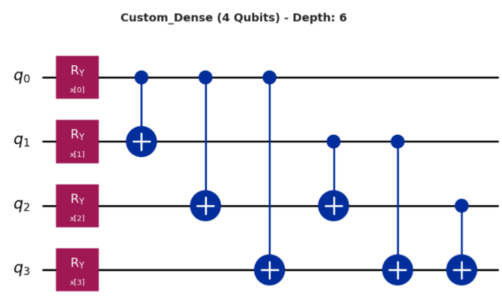


**Figure 2:** Custom Dense Feature Map: A quantum circuit that applies single-qubit $R_y$ rotations followed by multiple layers of CNOT gates, enabling strong multi-qubit correlations for capturing non-linear interactions among the features.

### 3.5 Quantum Kernel/Training

After the classical data is encoded into quantum states $\phi(x)$, the similarity between two samples is measured using the **Fidelity Quantum Kernel**,

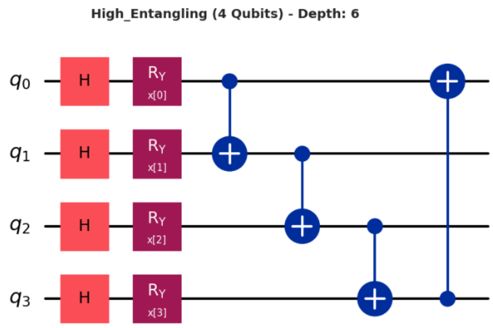


**Figure 3:** High Entangling Feature Map: A circuit that initializes all qubits in superposition using Hadamard gates, encodes inputs via $R_y$ rotations, and introduces CNOT entanglement to represent complex feature relationships within the quantum state.

which computes the squared inner product of quantum states.

$$K(x, y) = |\langle \phi(x) \mid \phi(y) \rangle|^2 . \quad (1)$$

This kernel captures the non linear relationships in high-dimensional Hilbert space.For each feature map configuration, two kernel matrices $K_{\text{train}}$ and $K_{\text{test}}$ are computed which are then passed to the SVM.

$$(K_{\text{train}})_{ij} = K(x_i, x_j), \quad x_i, x_j \in X_{\text{train}}, \quad (2)$$
$$(K_{\text{test}})_{ij} = K(x_i, x_j), \quad x_i \in X_{\text{test}},\ x_j \in X_{\text{train}}. \quad (3)$$

Due to limited hardware resources, the AER statevector simulator was used for kernel evaluation.

### 3.6 Hybrid Quantum-Classical Approach

To further evaluate quantum kernels, a hybrid model was used where instead of training a QSVM directly, quantum kernel outputs were used as inputs to a classical model SVM with an RBF kernel. This approach allows us to combine the power of quantum embeddings with the efficiency of classical models. This hybrid model was tested for each feature map architecture, calculating accuracy and F1 scores. The hybrid approach is beneficial because the learning/training phase only used classical operations whereas quantum kernels were computed only once.

## 4 Theoretical Formulation

### 4.1 Support Vector Machine (Classical)

The Support Vector Machine (SVM) aims to find a maximum-margin hyperplane that separates two classes. The optimization problem [3] is formulated as:

$$\min_{\mathbf{w},\, b,\, \boldsymbol{\xi}} \quad \frac{1}{2}\|\mathbf{w}\|^2 + C \sum_{i=1}^{n} \xi_i \quad (4)$$

subject to the constraints;

$$y_i(\mathbf{w}^\top \mathbf{x}_i + b) \geq 1 - \xi_i, \quad i = 1, \ldots, n, \quad (5)$$
$$\xi_i \geq 0, \quad i = 1, \ldots, n. \quad (6)$$

### 4.2 Quantum Kernel

In quantum machine learning, classical inputs are transformed into quantum states through an embedding process by applying a unitary operator $U_\phi(x)$ to the $|0\rangle$ qubit state, producing the following mapping as described in [5]:

$$|\phi(x)\rangle = U_\phi(x)\, |0\rangle^{\otimes n}.$$

The quantum kernel function is defined as the inner product between two embedded quantum states $|\phi(x)\rangle$ and $|\phi(y)\rangle$, which measures their similarity [4]:

$$K(x, y) = |\langle \phi(x) \mid \phi(y) \rangle|^2 .$$

Since different feature maps produce different kernel functions, the kernel matrix element

$$K_{ij} = K(x_i, x_j)$$

represents the similarity between the two data points $x_i$ and $x_j$.

### 4.3 Quantum Feature Maps

#### 4.3.1 Z Feature Map

This map applies rotations around the Z-axis of the Bloch sphere for each qubit [6].

#### 4.3.2 ZZ Feature Map

This map is an extension of the ZFeatureMap by focusing on entanglement instead of individual feature rotations leading to more feature relationships being captured. [6].

#### 4.3.3 Pauli Feature Map

The PauliFeatureMap includes rotations around multiple axes (X, Y and Z) along with focusing on entanglement [6].

#### 4.3.4 EfficientSU2 Feature Map

Efficient SU2 is a circuit applied to variational and classification algorithms. This circuit includes either single qubit rotation layers (Rx, Ry, Rz gates) or entangling layers (CNOT gates).

# 5 Results and Discussion

The experiments were conducted on four different qubit configurations - 4, 6, 8 and 10 qubits, allowing us to examine and compare performance changes with circuit size, feature map complexity and qubit count. The results obtained from these experiments demonstrate that quantum kernels can provide competitive and in several cases, superior performance compared to classical SVM baselines. The experiments conducted on 4-qubit and 6-qubit configurations show meaningful trends. Figure indicates that quantum models slightly outperformed classical models, achieving AUC scores around 0.72 compared to 0.68 for classical SVM.

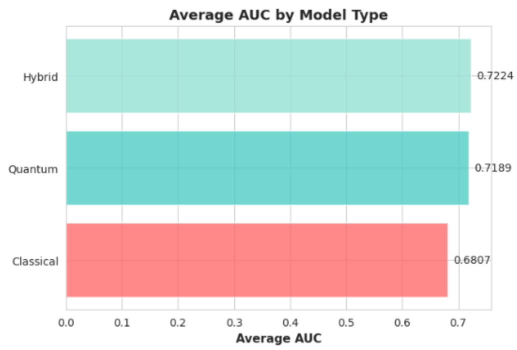


**Figure 4:** Average AUC by Model Type: Comparison of the mean AUC achieved by classical, quantum, and hybrid models on the fraud-detection task. Hybrid models obtain the highest AUC (0.7224), followed closely by quantum models (0.7189), while classical SVMs achieve slightly lower performance (0.6807).

Figure shows that more expressive circuits, particularly EfficientSU2, High-Entangling, and Custom Dense consistently achieved higher F1-scores, while simpler maps like Pauli and ZZ underperformed. This shows that circuit depth and rotation diversity play a crucial role in quantum kernel results, even before scaling to high qubit counts.

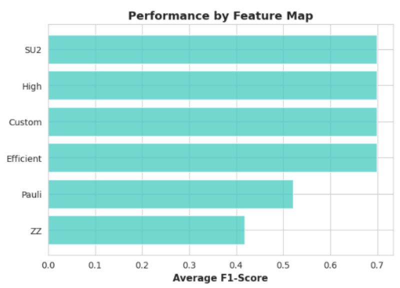


**Figure 5:** Performance by Feature Map: Average F1-scores across all quantum feature maps used in QSVM experiments. Feature maps with stronger entanglement - SU2, High Entangling, Custom Dense, and EfficientSU2 - achieve the highest performance, whereas simpler maps such as Pauli and ZZ underperform.

Moving to higher-dimensional embeddings, the performance gap between classical and quantum models became more prominent. The classical SVM with an RBF kernel achieved an accuracy of 80% and an F1 score of 0.5714 for the 8-qubit configuration. However, multiple quantum models gave a better result than this, particularly when larger feature maps and higher qubit counts were used.For the 8-qubit configuration, EfficientSU2 gave the best performance, achieving an F1 score of 0.6512, showing a noticeable improvement as compared to the classical model, indicating that quantum circuits can extract more features than classical kernels even under limited availability of qubits.

A clear pattern is demonstrated when increasing qubit count from 8 to 10 when performance improved consistently across all feature maps.The 10-qubit EfficientSU2 feature map gave the best results with an F1 score of 0.7368 and an accuracy of 83.3%, as shown in Figure 6. This improvement highlights the advantage of higher-dimensional quantum embeddings, since a larger Hilbert space allows the kernel to capture more complex data relationships compared to classical models.

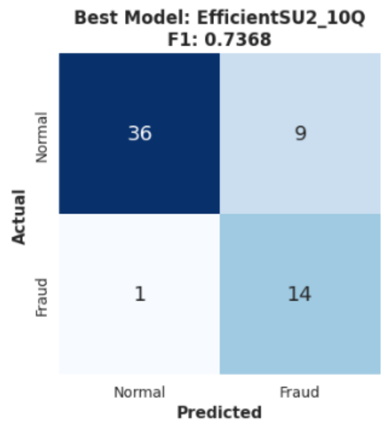


**Figure 6:** Confusion matrix of the best-performing quantum model (EfficientSU2, 10 qubits), achieving an F1-score of 0.7368. The model correctly identifies most fraud cases (14/15) and normal cases (36/45), demonstrating strong discrimination capability at higher qubit counts.

A global comparison in Figure 7 highlights that circuit design has a substantial impact on the effectiveness of QSVM's. Feature maps with stronger entanglement patterns like EfficientSU2, Custom Dense and High Entangling outperform simpler feature maps like Pauli and ZZ. This trend suggests that fraud detection relies heavily on capturing high-order correlations, which shallow circuits fail to encode due to their limited expressiveness.

While EfficientSU2 produced the highest scores, the Pauli feature map performed the weakest, suggesting that the model is unable to encode nonlinear feature interactions essential for fraud detection due to limited entanglement. These results show that both feature map selection and circuit design have a significant impact on QSVM performance.

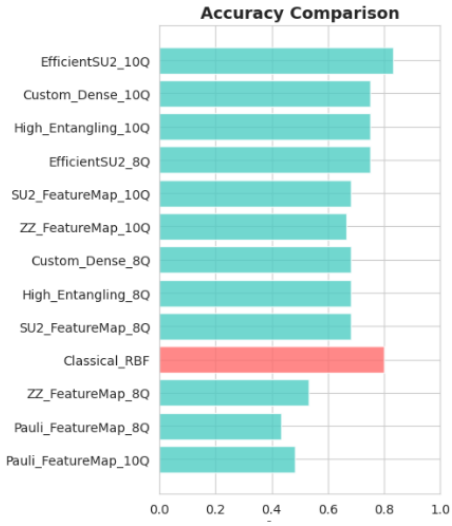


**Figure 7:** Accuracy comparison of classical, quantum, and hybrid models across different feature maps. EfficientSU2 (10 qubits) achieves the highest accuracy, while Pauli-based maps perform the weakest.

Overall, the results indicate that increasing the number of qubits improve performance, depicted in Figure 8 and the selection and design of feature map plays a crucial role in the results. Performance improvements seen in simulators indicate that QSVM's may offer meaningful benefits in domains with high-dimensional, imbalanced or structurally complex data.

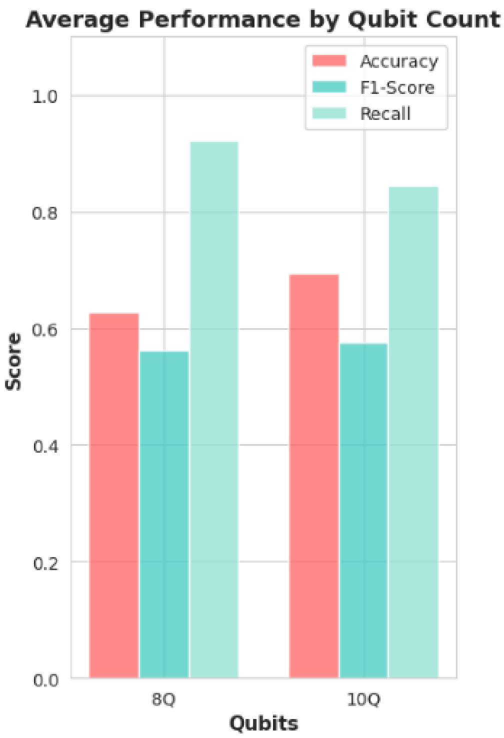


**Figure 8:** Average Performance By Qubit Count: Comparison of average Accuracy, F1-score, and Recall for 8-qubit and 10-qubit configurations. The results show that increasing the number of qubits improves overall model performance, with the 10-qubit models achieving higher accuracies and F1-scores.

# 6 Conclusion

This study evaluated the performance of Quantum Support Vector Machines for credit card fraud detection using multiple feature maps and qubit configurations. The results indicate that quantum models excel classical SVM baselines, particularly when deeper feature maps and higher qubit counts are used. As shown by the experiments, increasing the dimensionality from 4 to 6 qubits and 8 to 10 qubits consistently improved accuracy, F1-score and recall.

Among the feature maps tested, EfficientSU2 emerged as the strongest performer. Simpler maps such as Pauli and ZZ underperformed, suggesting that limited entanglement restricts the model's ability to capture non-linear relationships within the dataset. In addition to this, the comparison between classical, quantum and hybrid approaches indicated that quantum and hybrid kernels achieve higher AUC scores on average.

In conclusion, this work shows that QSVM's offer a promising direction for financial fraud detection. While current results are obtained on simulators, the observed performance suggests that quantum models may soon provide practical advantages over classical methods by improved distinction between minority classes. Future extensions could include testing on real quantum devices, using quantum feature selection methods to further enhance model efficiency.

# References


[1] M. Grossi, N. Ibrahim, V. Radescu, et al., "Mixed Quantum-Classical Method for Fraud Detection with Quantum Feature Selection," 2023. Avail able at: https://arxiv.org/abs/2208.07963

[2] L. Micheal, E. Gehrig, M. Elazar, Y. H. Lee, "Evaluating the Efficacy of Quantum Support Vector Machines in Detecting Synthetic Identity Fraud in Financial Datasets," 2024. Available at: https://www.researchgate.net/publication/391663917_Evaluating_the_Efficacy_of_Quantum_Support_Vector_Machines_in_Detecting_Synthetic_Identity_Fraud_in_Financial_Datasets.

[3] C. Cortés and V. Vapnik, "Support-Vector Networks," Machine Learning, vol. 20, no. 3, pp. 273–297, 1995.

[4] T. Yin, "Quantum support vector machines: theory and applications," in *Proceedings of CONF-MPCS 2024 Workshop: Quantum Machine Learning: Bridging Quantum

Physics and Computational Simulations*, 2024. doi:10.54254/2753-8818/51/2024CH0158.

[5] J. Schnabel and M. Roth, “Quantum Kernel Methods under Scrutiny: A Benchmarking Study,”, 2024. doi:10.48550/ARXIV.2409.04406.

[6] N. Singh and S. R. Pokhrel,”Modeling Feature Maps for Quantum Machine Learning,” doi:10.48550/arXiv.2501.08205.

[7] C. Phua, V. Lee, K. Smith and R. Gayler,”A Comprehensive Survey of Data Mining-based Fraud Detection Research”, 2010

[8] G. Kulatilleke ,”Challenges and Complexities in Machine Learning based Credit Card Fraud Detection”, 2022

[9] U. Porwal, S. Mukund ,”Credit Card Fraud Detection in e-Commerce: An Outlier Detection Approach”, 2018

[10] M. Kölle, A. Ahouzi, P. Debus, R. Müller, D. Schuman, C. Popien,”Towards Efficient Quantum Anomaly Detection: One-Class SVMs using Variable Subsampling and Randomized Measurements”, 2023