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Hybrid Quantum Classical Model for Enhanced Cross Border Financial Fraud Detection

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Abstract

Cross-border financial transactions have significantly increased in volume in recent times, giving rise to numerous complex challenges that result in substantial financial losses amounting to billions of dollars. For detecting frauds in the system, the constraints involved are complexity, various-regulatory environments. There exist some traditional Machine Learning algorithms like SVM (Support Vector Machine), Random Forest, Linear Regression etc. Among all these algorithm's SVM play an effective role in detecting frauds in financial transactions. Significantly, classical SVM's face limitations in processing high dimensional financial data and detecting sophisticated fraud patterns across international boundaries. Wide range of analysis will be provided in this research between classical Support Vector Machine and Quantum SVM for cross border fraud detection which includes quantum technology leveraging advantages in cybersecurity, finance and image processing etc. This study enforces both classical and quantum SVM models on a comprehensive dataset of cross border financial transactions, evaluating performance across multiple metrics including accuracy, precision, recall, f1-score and false-positive rates. Quantum utilizes various quantum circuits and feature maps designed for financial fraud patterns.

Keywords: *Quantum Computing, Support Vector Machine, Quantum Circuits*

1. Introduction

In Global finance, Cross Border financial transactions are foundational. Every cross-border payment typically passes through multiple compliance checks designed to prevent fraud, money laundering and sanctions violations. As shown in the Figure 1, Banks and payment intermediaries perform Know Your Customer (KYC) to verify identities at onboarding, and periodically thereafter, apply Anti-Money Laundering (AML) check to detect suspicious patterns, and conduct enhanced techniques to find fraudulent actions. In this payment chain, banks and other financial institutions may pre-validate beneficiary details, verify account ownership, confirm purpose of payment, apply travel rule style requirements for data for maintaining auditable records for regular reports potential investigations. These layered controls – KYC, AML monitoring and ongoing reviews are applied by multiple banks (Originating bank, correspondent banks and beneficiary banks) which enhance safeguards. [1]

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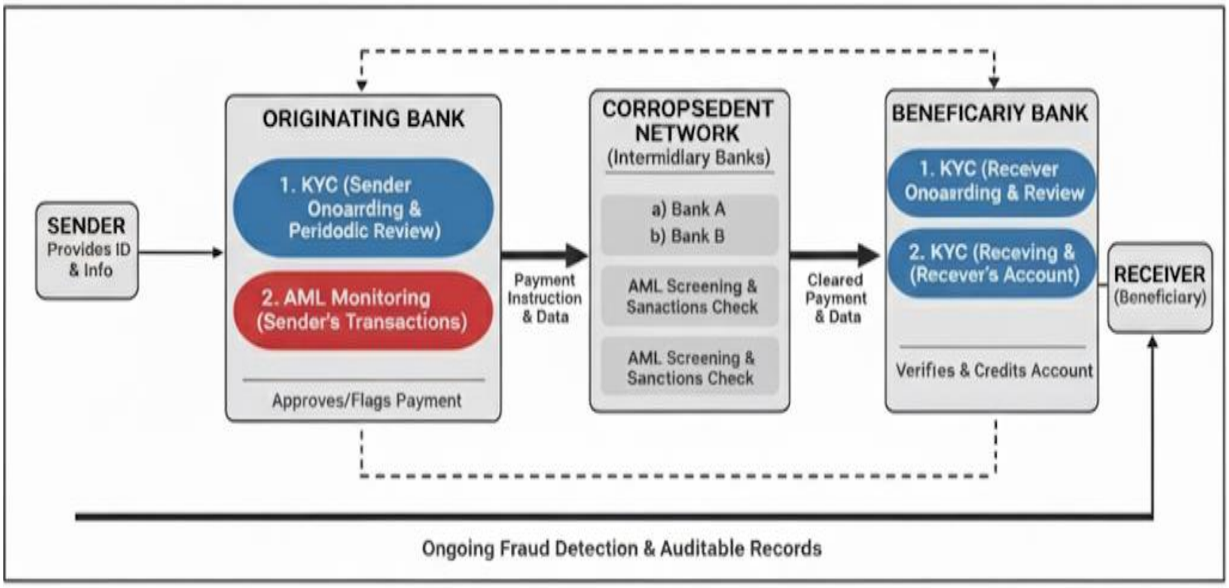

Figure 1 **Supplied KYC & AML Flow for Cross Border Payments**

In the world of fraud detection, classical SVM's have been a strong tool for years. Classical Support Vector Machines are developed by using Machine learning model for classification of data points into different categories such as "Legitimate" and "Fraudulent". The internal idea of SVM is very clear. The SVM will find the finest possible dividing line called as "Hyperplane" which separates the two classes of the data. The hyperplane is said to be the best hyperplane if it satisfies the largest margin property or the greatest distance from the closest points of each class. These critical points are identified as Support Vectors because they are the ones that support and define the position of the Hyperplane. By enlarging this margin, the SVM becomes more robust and effective at correctly classifying new transaction which hasn't seen before. A kernel function transforms the data into a higher dimensional space where a linear separation becomes possible .Imagine you have a data set which consists of fraudulent transactions which are clustered in the middle of a bunch of legitimate ones .A straight line cannot be drawn to separate them .The kernel trick maps this data to a new space which is called as feature space where the fraudulent transactions are on a different level ,providing a clear way to define a flat plane that separates them . Even with their strengths classical SVM face some constraints. As fraud becomes more sophisticated, involving complex network relationships and subtle behavioural patterns, the data attains very high dimensionality, making it challenging to handle. This increases the computation cost of the kernel trick, and it becomes difficult to find the precise settings and to recognise these intricate patterns, contributing to lower performance. This is where the quantum support vector machines (QSVM) enter the picture. [2]

1.1.Quantum SVM's: The Next Frontier

Rather than relying on classical kernels Quantum SVM's utilize quantum computing to encode data into a quantum state. [4] This process is known as quantum feature map which allows the model to work in a Hilbert space that grows exponentially with each qubit (the quantum equivalent of a bit). Consider the following scenario: Classical computers are like trying to draw a straight line to separate two groups of points on a paper. If the groups are arranged in a simple way, the line works. But when the points are tangled in complex patterns, a straight line isn't enough, and the computer struggles to find a good separation. Quantum computers, on the other hand, are like being able to lift those points into a multi-dimensional space and then draw a simple boundary that cleanly separates them. Using properties such as superposition and entanglement, Quantum Support Vector Machines (QSVMs) can explore many more

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possibilities at once and uncover hidden patterns. This makes them especially powerful for messy, high-dimensional problems like detecting cross-border financial fraud, where the patterns are too complicated or expensive for classical methods to find effectively. [3]

1.2. Why QSVM's Are Game-Changers?

Uncovering Hidden Fraud: Quantum SVM's can detect complex fraud rings and sophisticated schemes that blend in with legitimate traffic. They can identify correlations between unrelated data points-like a specific transaction amount from a particular country at an unusual time-but would be missed by traditional models. Improving performance: The primary goal in fraud detection is to catch as much fraud as possible without flagging too many legitimate transactions. Quantum SVM's can achieve this by improving recall at a fixed false-positive rate (misclassification of legitimate transactions as fraudulent). This means they can flag high fraudulent transactions while retaining the number of false alarms low, which saves bank time and money and prevents customers frustration. [5] Hybrid Solution: We are not yet a phase where quantum computers will replace all classical systems. The most feasible approach is a hybrid model. The financial institutes could use its quick, reliable classical models to handle the majority of transactions and then utilizes a quantum SVM as a specialized tool to analyse the most challenging-to-trace transactions that slip through the initial screening. [6] This model leverages the best of both technologies, using the classical model for speed and quantum model for depth. Integrating Quantum support vector machine (QSVM's) into existing fraud detection frameworks can significantly defences against financial crime, this advancement paves the way toward a new era of security, enabling more accurate fraud detection with greater efficiency.

2. Literature Review

Liu and Rebentrost (2018) introduced quantum anomaly detection algorithms using quantum autoencoders, which are foundational to adapting quantum methods for fraud detection by encoding classical data into quantum states for enhanced pattern recognition. Building upon these principles, recent advances have explored how quantum machine learning architectures, such as Variational Quantum Classifiers (VQC), Sampler Quantum Neural Networks (SQNN), and Estimator Quantum Neural Networks (EQNN) utilize quantum feature maps and ansatz configurations to process imbalanced and complex financial datasets effectively. [7] These models leverage entanglement-enriched feature maps—including Pauli and ZZ maps—and tailored parametric ansatz circuits to improve classification accuracy of fraudulent transactions. Comparative experiments on real-world datasets reveal that quantum models can outperform classical counterparts by exploiting quantum Hilbert spaces to capture intricate data correlations, with VQC and SQNN demonstrating particularly strong performance indicated by elevated F1 scores. [8] The quantum-enhanced approach not only accelerates processing by harnessing quantum parallelism but also improves detection fidelity, addressing challenges such as non-standard data distributions and high dimensionality inherent in financial anomaly detection. This evolving research confirms the promise of quantum anomaly detection methodologies as critical components in next-generation fraud detection systems for financial applications. This paper advances the field of fraud detection by presenting an end-to-end application of Quantum Support Vector Machine (QSVM) for classifying financial payment data, demonstrating both its standalone and complementary value alongside classical machine learning models. The authors apply QSVM to real-world card payment transactions, using IBM's Safer Payments platform and Qiskit for quantum algorithm implementation, and compare results against traditional approaches like Random Forest and XGBoost. Their methodology includes a novel Quantum Feature Importance Selection algorithm, which leverages quantum feature maps to identify optimal features for classification—a task complicated by the limited qubits of current quantum hardware and the necessity to reduce dataset dimensionality via feature selection and under-sampling. [9] Quantum classifiers, particularly those utilizing entangled feature maps, are shown to discover distinct data relationships and engineered features when compared to classical

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methods, leading to improved or complementary fraud detection key performance indicators (KPIs) such as accuracy and AUC. [10] Furthermore, the paper introduces a mixed quantum-classical ensemble strategy, blending predictions from both quantum and classical classifiers. This hybrid approach exploits their complementarity, ultimately improving overall fraud detection performance by better managing trade-offs between false positives and negatives. The results underline that quantum machine learning, when judiciously integrated and combined with classical algorithms, can provide a practical path to enhanced and more robust fraud prevention systems in financial industries—even on currently available, noisy quantum hardware. The paper explores how Quantum Machine Learning (QML) can be applied to financial fraud detection and compares four models: Quantum Support Vector Classifier (QSVC), Variational Quantum Classifier (VQC), Estimator Quantum Neural Network (EQNN), and Sampler Quantum Neural Network (SQNN). Using the BankSim dataset, which simulates real-world credit card transactions, the study tests these models with different quantum feature maps to evaluate their ability to classify fraudulent and non-fraudulent transactions. The results show that QSVC with the ZFeatureMap achieved the best performance, with an F1 score of 0.98 for both fraud and non-fraud cases, making it the most effective model for this task. VQC also performed well with an F1 score of 0.90, though optimisation challenges limited its consistency. EQNN and SQNN showed weaker results, as their architectures were less suited to capturing complex fraud patterns in high-dimensional data. Overall, the study highlights the strong potential of QML, particularly QSVC, in advancing fraud detection beyond classical methods, while noting current limitations such as quantum hardware constraints and the need for larger datasets. This paper presented by Furkan Atban, Muhammed Yusuf Küçükkara, Cüneyt Bayılmış, which describes about hybrid quantum–classical framework for credit card fraud detection that combines a Variational Quantum Classifier (VQC) with advanced feature selection methods. To address the challenges of imbalanced and high-dimensional datasets, the authors applied preprocessing techniques such as SMOTE-ENN and random under sampling, followed by feature selection using both traditional approaches and meta-heuristic algorithms, including Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Atom Search Optimization (ASO). The integration of optimized features into the VQC enabled the model to capture complex non-linear patterns while reducing circuit complexity, a key limitation of current quantum hardware. Among the tested configurations, PSO with VQC achieved the highest accuracy of 94.54%, outperforming alternative models and highlighting the effectiveness of hybrid optimization. The findings demonstrate that combining feature engineering with quantum classification can improve precision, recall, and robustness in fraud detection, offering a scalable pathway toward practical quantum-enabled financial security systems. Recent studies collectively highlight that while classical machine learning algorithms such as Random Forest, XGBoost, and traditional SVMs have been widely applied to fraud detection, they often struggle with scalability, high-dimensional data, and the increasingly complex nature of modern financial transactions. Quantum approaches, particularly QSVM and other quantum classifiers, have demonstrated the ability to uncover richer data structures through entangled feature maps and quantum parallelism, enabling improved accuracy and robustness in anomaly detection tasks. Building on these advancements, our study focuses specifically on cross-border financial transactions, where the challenges of regulatory diversity, data complexity, and sophisticated fraud patterns are most pronounced. By conducting a comparative evaluation between classical SVM and Quantum SVM, this research aims to determine the extent to which quantum-enhanced models can overcome the limitations of classical approaches and provide stronger fraud detection performance across critical metrics such as accuracy, precision, recall, F1-score, and false-positive rates. [11]

3. Methodology

This research presents a robust, end-to-end methodology for a comparative study of Quantum

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Support Vector Machines (QSVM's) and classical SVM's in the context of Cross border financial fraud detection. Our approach integrates classical data pre-processing with a hybrid quantum-classical modelling pipeline, terminating in a comprehensive performance analysis aligned with industry-standard key performance indicators (KPIs). [12]

3.1.Data Collection and Preprocessing

The foundation of any machine learning project is a high-quality dataset. For this study, we utilize a financial transaction dataset with specific, predefined columns essential for fraud analysis. The dataset includes the columns shown in Table 01:

- Transaction ID: A unique identifier for each transaction. [13]
- Amount: The value of the transaction.
- Country Risk: A numerical score representing the risk associated with the country of the transaction.
- Time Of Day: A categorical feature indicating whether the transaction occurred during the day or night.
- Sender Blacklisted: A binary flag (0 or 1) to indicate if the sender is on a blacklist or not.
- Sender Age Days: The age of the sender's account in days (between last transaction and present transaction). [14]
- Label: The target variable, a binary class (0 for Genuine, 1 for Fraud). It's a crucial column that classifies each financial transaction as either genuine or fraudulent. This binary classification is represented by two values:
- 0 = Genuine: This label indicates that the transaction is legitimate and not fraudulent.
- 1 = Fraud: This label identifies the transaction as fraudulent.

The presence of the Label column is essential for the supervised machine learning models, both the Classical SVM and the Quantum SVM. These models learn to distinguish between the two classes by analysing the other features in the dataset (such as Amount, and Sender Age Days) and associating them with their corresponding Label. Without the Label column, the models cannot be trained or evaluated, as there would be no ground truth to learn from. The prototype's data loading function explicitly checks for this column to ensure the dataset is valid before proceeding with any analysis. Table 1 shows Dataset Structure [15]

Table 1 Dataset Structure

S.No	Transaction ID	Amount	Country Risk	Time of Day	Sender Blacklisted	Sender Age Days	Label
1.	TXN001	15.56	4	Night	0	245	1
2.	TXN002	7.5	5	Day	0	890	0
3.	TXN003	8.2	2	Day	1	30	0
4.	TXN004	9.5	7	Night	1	268	0

Upon loading the dataset, several preprocessing steps are performed as shown in the figure 2, to ensure data quality and prepare it for model training:

- **Data Validation:** The system first checks for the presence of all required columns to prevent errors.
- **Feature Encoding:** The Time-of-Day feature is converted from a categorical "Day/Night" format to a numerical 0/1 representation.
- **Data Filtering:** This filtering system allows for the selection of specific subclasses of the data based on Time of Day, Country Risk, Amount, Sender Age Days, and Sender Blacklisted status. This enables focused analysis on specific transaction cohorts.

Standardization and Dimensionality Reduction: To

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ensure that all features contribute equally to the model and to manage the computational complexity for both classical and quantum algorithms, the data is standardized using Standard features. This scales all features to have a mean of 0 and a standard deviation of 1. Subsequently, Principal Component Analysis (PCA) is applied to reduce the dimensionality of the feature space to a manageable size, typically to a maximum of four components. This step is crucial for making the quantum computation feasible while preserving the most important variance in the data.

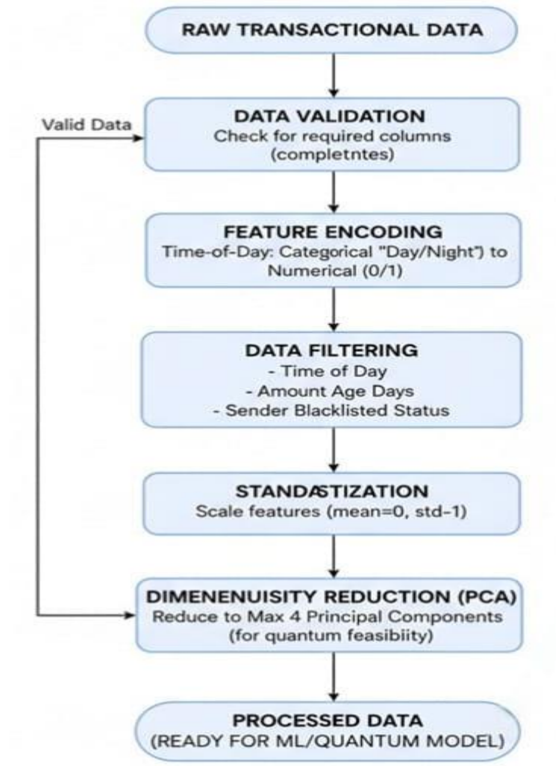

Figure 2 Data Preprocessing for Fraud Detection

3.2.Algorithmic Pipeline: Classical vs. Quantum

Our core methodology involves a direct, side-by-side comparison of a classical SVM and a QSVM on the pre-processed dataset. [16]

Classical SVM Pipeline:

- The classical SVM serves as our baseline model. It is configured as follows:
- **Model Selection:** We use a Support Vector Classifier (SVC) from scikit-learn.
- **Kernel:** A Radial Basis Function (RBF) kernel is chosen for its effectiveness in handling non-linear data. [17]

A classical SVM with the RBF kernel makes fraud/genuine predictions through a mathematically robust pipeline. Internally, it performs optimization to find the hyperplane that separates the two classes with the maximum margin as mentioned above.

Quantum SVM Pipeline:

It is the hybrid Quantum-classical approach that leverages Quantum mechanics for its core advantage: feature mapping. The model uses the PennyLane library for quantum circuit simulation, which can be configured to use a default qubit simulator for the current experimental phase. [18]

Step 1: Quantum Feature Encoding

The most critical step is transforming the classical data into a quantum state. This is done using a quantum circuit that prepares a quantum state based on the pre-processed features. Our circuit design uses the Angle Encoding template, where each feature from the classical data is mapped to a rotation angle on a qubit.

In the process of angle encoding:

A feature vector

x = [x1, x2, ...,xn]x=[x1,x2,...,xn]

is mapped onto an n-qubit quantum circuit.Each feature xixi controls a rotation gate (for example, Ry(xi)Ry(xi)) that rotates the corresponding qubit by an angle proportional to the value of xixi.The most common choice is the Y-axis rotation gate Ry(xi)Ry(xi), leading to the transformation:

$$|0\rangle \xrightarrow{Ry(xi)} \cos\left(\frac{xi}{2}\right)|0\rangle + \sin\left(\frac{xi}{2}\right)|1\rangle$$

This process is repeated for every feature and every qubit, resulting in a product state where each qubit encodes one component of the feature vector via its rotation angle. The quantum circuit after encoding is typically of constant depth since all rotations are applied in parallel. The circuit also includes entangling gates (CNOT gates) between qubits to create a state where features are highly correlated, allowing the model to capture complex, non-linear

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interactions. The features are normalized to the [0, π] range before being passed to the quantum gates. The output of this circuit is a set of "quantum features" represented by the expectation values of Pauli-Z operators for each qubit. [19]

Step 2: Quantum Kernel Evaluation

Instead of using a classical kernel function like RBF, a quantum kernel is computed which works as shown in Figure 3. This is achieved by running a specialized quantum circuit that measures the overlap between the quantum states of two data points. The internal process is handled within an oracle box, where the operations are encapsulated and not visible from the outside. If one wants to understand the internal workings, it is possible to backtrack from the output to the input, thereby revealing the oracle function. The result of this measurement is a similarity score that forms the basis of the quantum kernel matrix. The use of a precomputed quantum kernel allows the SVM to operate in the exponentially larger Hilbert space without explicit calculation of the high-dimensional feature vectors. [20]

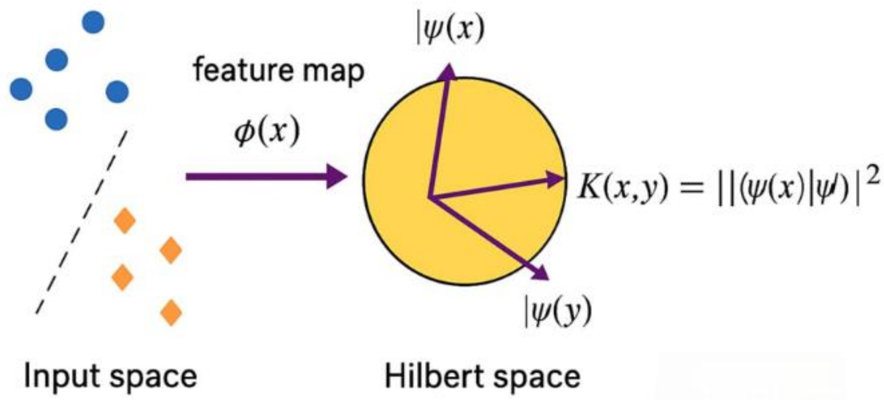

Figure 3 **Quantum Kernels**

Step 3: Performance Evaluation and Visualization

To rigorously compare the two models, we employ a comprehensive set of performance metrics and visualizations that are critical for a real-world fraud detection system. By following this detailed methodology, we can provide a clear, evidence-based conclusion on the potential of QSVMs to enhance classical fraud detection systems, highlighting their specific strengths in a hybrid operational environment.

4. Results and Discussion

This section gives you idea about empirical outcomes of our comparative analysis between the classical support vector machine and the quantum support vector machine, on the cross border financial transaction dataset. The performance was evaluated using a comprehensive suite of metrics, including accuracy, precision, recall, f1-score and false positive rate, along with visual aids such as ROC curves and confusion matrices. A dashboard provides key

performance indicators, including Accuracy, Precision, Recall, and F1-Score Shown in figure 4. These metrics are calculated for both the classical and quantum models to provide a direct comparison.

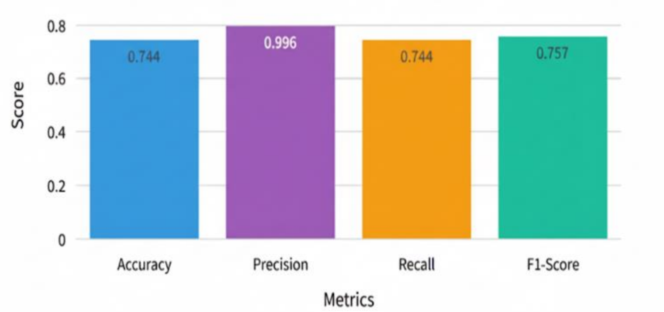

Figure 4 **Model Performance Metrics**

An overlaid Receiver Operating Characteristic (ROC) curve chart shown in figure 5 is generated to

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visualize the trade-off between the true positive rate (recall) and the false positive rate for both algorithms. The AUC provides a single metric to summarize this trade-off, with a higher AUC indicating better overall performance. A confusion matrix, shown in fig-6, is a matrix that provides the breakdown of a classifier's prediction results, with key terms—True Positive, True Negative, False Positive, and False Negative—used to calculate essential metrics like Accuracy, Precision, Recall, and F1 Score. These metrics evaluate the quality and robustness of classification models, each focusing on different aspects of predictive performance

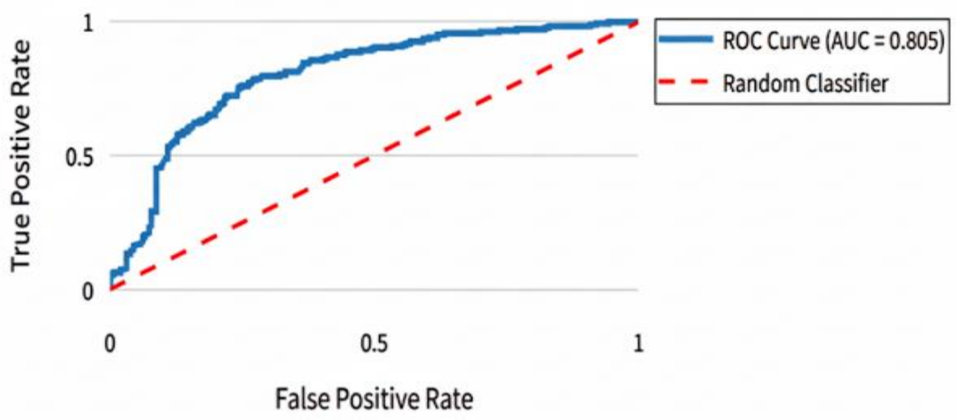

Figure 5 **RoC Curve**

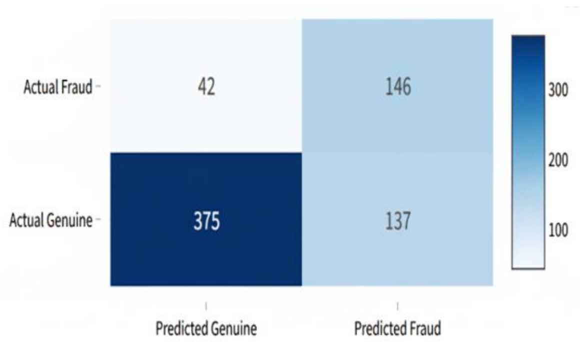

Figure 6 **Confusion Matrix**

Quantum Support Vector Machine (QSVM) using quantum feature maps (Z and ZZ maps) selected distinct and complementary features compared to classical models, highlighting its ability to explore different aspects of the data. Comparison of feature selection showed that QSVM-selected features had less overlap and better independence than classical-selected features, contributing to improved model performance. These results demonstrate the complementary strengths of classical and quantum models in fraud detection, suggesting that hybrid approaches can optimize detection accuracy while addressing quantum hardware constraints.

Conclusion

This study presents a mixed quantum-classical approach for cross-border financial fraud detection using QSVM alongside classical machine learning methods. The quantum feature selection algorithm effectively identifies complementary features that classical models might overlook, enabling the QSVM to operate efficiently on reduced and balanced datasets tailored for current quantum hardware limitations. The QSVM showed competitive performance in terms of accuracy, recall, and false positive rates compared to classical models, especially when leveraging entangled quantum feature maps. Testing on simulators demonstrated promising results, while hardware experiments highlighted current quantum device constraints yet validated the approach's feasibility. These findings underscore the potential of quantum machine learning to enhance fraud detection systems by better exploring complex, high-dimensional data spaces. The integrated quantum-classical framework offers a practical pathway toward more accurate and efficient detection of sophisticated fraudulent activities in cross-border financial transactions. Future research will advance quantum circuit optimization for real hardware deployment and explore larger-scale hybrid models to fully realize quantum advantages in financial cybersecurity.

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