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Towards Quantum - Enhanced Machine Learning for Fraud Detection

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Abstract: The study explores how advances in machine learning methods for identifying credit card fraud might benefit from quantum computing. The primary objective is to evaluate how well a Quantum Convolutional Neural Network (QCNN) performs relative to a classical Convolutional Neural Network (CNN) to see if quantum models deliver superior outcomes. The selection of this research topic stems from the increasing complexity of financial fraudulent activities combined with traditional model inability to manage extensive and imbalanced datasets. Quantum computing provides benefits such as parallel processing capabilities and improved computational performance that can help with these types of tasks. The research started with the creation of a CNN model using conventional deep learning approaches. The QCNN model was designed by constructing quantum circuits and conducting simulations through a quantum framework. The training sets for both models were identical while their learning patterns and results underwent comparative analysis. Observational results indicated that the quantum model exhibited superior pattern recognition and learning abilities when processing the data. The research indicates quantum-enhanced models hold potential for fraud detection while paving the way for further research with actual quantum devices.

Keywords: Quantum Machine Learning, Fraud Detection, Quantum Convolutional Neural Network, CNN, PennyLane, SMOTE.

1. INTRODUCTION

In today's digital economy, credit card theft is a widespread problem that undermines customer confidence and results in significant financial losses. As the number of online transactions continues to grow exponentially, fraudsters have developed increasingly sophisticated methods to exploit vulnerabilities. Financial institutions must identify these fraudulent acts promptly and precisely in order to safeguard their clients and preserve system integrity. However, traditional fraud detection techniques, such as rule-based systems or simple machine learning classifiers, often struggle to keep pace with evolving fraud tactics and the sheer volume of transactional data.

Deep learning has been a potent technique in recent years for addressing challenging classification issues, such as fraud detection. Among deep learning models, Convolutional Neural Networks (CNNs) have shown exceptional performance, especially in domains like image processing and natural language interpretation. CNNs are capable of automatically extracting important hierarchical characteristics from raw data. CNNs can spot small irregularities and complex patterns that could point to fraudulent activity that are hard to spot with traditional methods.

Despite their strengths, classical CNN models sometimes face challenges when dealing with highly imbalanced datasets — a common characteristic of fraud detection in which only a small percentage of transactions are fraudulent. Additionally, Large CNN model training can be computationally expensive, particularly when dealing with high-dimensional data.

Parallel to these advancements in classical computing, quantum computing has been gaining attention as a transformative technology with the potential to revolutionize how we solve certain computational problems. Unlike classical computers, which process information in binary bits (either 0 or 1), quantum computers use quantum bits, or qubits, which can exist concurrently in several states due to a phenomenon called superposition. Furthermore, Qubits are capable of becoming entangled, which means that despite their physical separation, their states are coupled. Because of these special quantum phenomena, quantum computers are able to execute some calculations more quickly than traditional computers, particularly for problems involving large-scale optimization, complex simulations, or combinatorial search.

Quantum Machine Learning (QML) combines the ideas of quantum computing with machine learning methodologies to create innovative algorithms that may be more effective than traditional approaches. The core idea behind QML is to exploit quantum mechanics to process and analyze data in ways that are impossible or highly inefficient for classical computers. Among various QML models, Quantum Convolutional Neural Networks (QCNNs) stand out as a quantum counterpart to classical CNNs. QCNNs use quantum circuits to perform convolution and pooling operations on quantum states, aiming to extract features and identify patterns in data with enhanced efficiency. While QCNNs are still an emerging area of research, their promise lies in their potential to provide exponential speedups or improved generalization in certain machine learning tasks.

This research explores the application of both classical CNN and quantum QCNN models for credit card fraud detection. The traditional CNN implementation makes use of popular frameworks like TensorFlow and Keras, which offer an adaptable and effective setting for creating and refining deep learning models. TensorFlow's extensive tools and community support make it ideal for developing robust models and performing thorough evaluation. On the quantum side, the study uses PennyLane is an open-source library for quantum machine learning that aims to combine traditional machine learning frameworks such as TensorFlow with quantum circuits. PennyLane facilitates hybrid quantum-classical workflows, allowing quantum circuits to be embedded as layers within classical neural networks, thereby enabling end-to-end training using gradient-based optimization.

The substantial class imbalance presents in fraud detection datasets—where legal transactions often outnumber fraudulent ones—is a crucial issue this work attempts to address. The imbalanced-learn library's Synthetic Minority Oversampling Technique (SMOTE) is used to counteract this. To improve the model's ability to detect rare fraudulent cases and balance the dataset, SMOTE artificially creates fresh samples of the minority class. Additionally, the research incorporates Principal Component Analysis (PCA) to lower the feature space's dimensionality prior to supplying the data to the quantum circuits. PCA not only helps in mitigating noise and redundancy but also adapts the input features to fit the finite number of qubits found in existing quantum simulators and devices, which is a real-world limitation in quantum machine learning.

By combining classical data preprocessing techniques with both classical and quantum modeling approaches, this study provides a comprehensive comparison between CNN and QCNN architectures in the context of fraud detection. The goal is to evaluate how effectively each model detects fraudulent transactions, their robustness to class imbalance, and their computational feasibility. The knowledge gathered from this study will help further the field's understanding of quantum-enhanced machine learning and

how it might be used to solve practical cybersecurity problems.

2. LITERATURE REVIEW

West and Bhattacharya [1] presented a deep literacy-grounded approach using Auto encoder Neural Networks for credit card fraud discovery. Their model efficiently learned normal sale patterns and linked anomalies through reconstruction error, making it ideal for unsupervised fraud discovery. They addressed class imbalance and stressed the eventuality of autoencoders for segregating rare fraudulent events, suggesting future integration with real-time systems.

Dal Pozzolo et al. [2] delved into the use of traditional machine learning classifiers such as Random Forests, Decision Trees, and Support Vector Machines for fraud discovery. Their work emphasized the significance of opting for applicable evaluation criteria like precision, recall, and F1-score due to imbalanced datasets. The study underlined the need for preprocessing strategies and recommended relative evaluations across multiple models for robust performance analysis.

Basava Ramanjaneyulu Gudivaka et al. [3] proposed a hybrid model that combines Generative Adversarial Networks with Variational Autoencoders, and Convolutional Neural Networks (VAE-GAN-CNN) for fiscal fraud discovery. Their model generated synthetic fraudulent samples and captured hierarchical patterns for classification. The study demonstrated improved sensitivity and recommended using generative modeling to attack fraud data scarcity.

Carcillo et al. [4] provided a comprehensive review on credit card fraud discovery methodologies, datasets, and best practices. They discussed the challenges of class imbalance and real-time discovery, promoting the use of oversampling methods like SMOTE and advanced deep learning architectures. Their work supports the development of modular and scalable discovery systems with reproducible experimental setups.

Fiore et al. [5] concentrated on deep learning strategies for credit card fraud discovery, including CNNs and RNNs, which were evaluated on their capability to capture sequential and spatial sale patterns. Their trials showed that deep models can outperform classical approaches when amended with temporal features, encouraging further exploration in time-aware fraud discovery systems.

Sahin and Duman [6] explored the effectiveness of integrating SMOTE with deep neural networks for handling class imbalance in credit card fraud discovery. Their results demonstrated significant advancements in recall and F1-score. They suggested that combining SMOTE with deep learning models could provide more balanced learning, leading to improved fraud classification sensitivity.

Grant et al. [7] introduced the concept of Quantum Convolutional Neural Networks (QCNN), a quantum analogue of classical CNNs designed for high-dimensional pattern recognition tasks. They demonstrated that QCNNs can reduce the number of parameters logarithmically compared to classical counterparts. This work laid the foundation for quantum-enhanced fraud discovery, suggesting QCNNs as scalable models for fiscal datasets.

Schuld and Killoran [8] presented a theoretical framework on Quantum Machine Learning in Feature Hilbert Spaces. They introduced quantum feature maps that embed classical data into high-dimensional quantum spaces, enabling better class separation. Their work indicated that quantum-enhanced kernels can outperform classical kernels in tasks involving sparse and complex datasets like fraud discovery.

Zoufal, Lucchi, and Woerner [9] applied hybrid quantum-classical models to credit card fraud discovery using quantum variational classifiers. The authors demonstrated that quantum circuits could capture intricate patterns in real-world sale data. They suggested that hybrid models could Improve sensitivity while remaining compatible with existing fiscal architectures.

Woerner and Egger [10] surveyed the contemporary financial uses of quantum machine learning, such as risk modeling, portfolio optimization, and fraud detection. They emphasized the potential of quantum algorithms in addressing data imbalance, scalability, and feature sparsity. Their insights provide a strategic outlook on implementing QML in practical fraud discovery pipelines.

Lloyd, Schuld, and colleagues [11] discussed the quantum advantage in learning from experiential data. Their theoretical analysis demonstrated that quantum learners could generalize from smaller samples under specific conditions. Though abstract, their findings support the exploration of quantum models like QCNNs for low-sample, high-complexity tasks such as fraud discovery.

Bergholm, Izaac, and others [12] introduced PennyLane, a Python-based framework for hybrid quantum-classical machine learning. The library allows integration with TensorFlow and PyTorch, making it easier to implement and optimize quantum models. PennyLane was vital in enabling experimental development of quantum neural networks for tasks including fraud discovery.

2. METHODOLOGY

This study focuses on creating and comparing two distinct models for credit card fraud detection: Quantum Convolutional Neural Networks (QCNN) and traditional Convolutional Neural Networks (CNNs). Both models aim to accurately classify transactions as fraudulent or legitimate by leveraging different computational paradigms, i.e., classical deep learning and quantum machine learning.

The entire implementation pipeline, from data preprocessing to model evaluation, was carried out using Python-based libraries such as TensorFlow, scikit-learn, imbalanced-learn, and PennyLane, ensuring robustness and reproducibility.

<u>Data Collection and Preprocessing</u>

The dataset consists of real-world credit card transactions with anonymized numerical features and a binary target label indicating fraudulent or legitimate transactions. Due to the inherent class imbalance—fraud cases make up a small fraction of total transactions—training models directly on this dataset can bias predictions toward the majority class. To mitigate this, SMOTE (Synthetic Minority Oversampling Technique) from the imbalanced-learn library was applied to generate synthetic samples for the minority class, resulting in a more balanced dataset and improving model sensitivity to fraudulent transactions. For the classical CNN, preprocessing included standardization of features using Standard Scaler, ensuring zero mean and unit variance to facilitate faster convergence. Additional domain-specific feature engineering involved deriving the ‘Hour’ feature from timestamps to capture temporal transaction patterns and applying a logarithmic transformation (np.log1p) on the transaction amount to reduce skewness.

In the QCNN model pipeline, an additional dimensionality reduction step was performed using Principal Component Analysis (PCA), implemented via scikit-learn PCA class.

$$\mathrm{Cov}(\boldsymbol{X}) = \frac{\boldsymbol{1}}{\boldsymbol{n-1}}\boldsymbol{X^T X} = \boldsymbol{V\Lambda V^T}$$

Where:

- X is the input data matrix (samples × features),
- $\mathrm{Cov}(\boldsymbol{X}) = \boldsymbol{V\Lambda V^T}$ is the mean vector (mean of eachfeature),
- n is the number of samples.

The dimensionality of the input data while maintaining its most useful components by applying Principal Component Analysis (PCA). The covariance matrix Cov(X) captures how features vary together, and its eigenvalue decomposition produces principal components that are used to project high-dimensional data into a lower-dimensional space. In this study, PCA reduced the feature set to 8 dimensions, making it compatible with the limited number of qubits available in quantum processors. This dimensionality reduction step not only enables efficient quantum encoding but also helps remove redundancy and noise. Additionally, missing values were handled through mean imputation using Simple Imputer to ensure data integrity.

Model Architecture and Quantum Circuit Design

The CNN architecture was implemented with the Keras API in TensorFlow. There are two one-dimensional convolutional layers in the model with increasing filter counts ((32 and 64 filters, respectively), with max pooling layers coming after each to minimize spatial dimensions and draw attention to the most important characteristics. These convolutional layers extract temporal patterns across transaction features, analogous to how CNNs process image data. After flattening the outputs, the model uses fully connected dense layers with ReLU activation and incorporates dropout regularization to avoid overfitting

Angle Embedding, where the feature value determines the rotation angle of an RY gate applied to a single qubit. This process converts classical inputs into quantum states, enabling the model to leverage quantum superposition and entanglement for richer feature representations.

The quantum model in this study is implemented using PennyLane, a Python library for hybrid quantum-classical machine learning, integrated with TensorFlow to allow end-to-end training. Each normalized classical feature from the credit card transaction dataset is encoded into a qubit using

Require: Input image
Ensure: Predicted Class Label
Input←Loadd and normalize the image
Feature Maps←[]
For each convolutional Layer
do
Apply convolutional filter to input
Apply non-linearity (e.g., ReLU)
Input← Resulting feature map
Feature Maps← feature Maps + Input

End for

For each Pooling Layer
do
Apply pooling (e.g., max or average) to
Reduce dimensions
Input←Pooled result
Flattened Features← Flattend(input)
Fully Connected Output← Pass through
Fully connected layers
Class Probabilities←Apply SoftMax (Fully Connected Output)
Predicted Label←argmax (Class Probabilities)
Return Predicted Label

Algorithm 1.Workflow steps of the classical Convolutional Neural Network (CNN) model

(with a rate of 0.5). The output layer uses a sigmoid activation function to produce a probability score for binary classification.

The standard Convolutional Neural Network (CNN) architecture for fraud detection comprises of preprocessing, convolutional layers for feature extraction, and fully connected layers for classification. To clearly outline the step-by-step flow of this model, Algorithm 1 presents the operational structure of the CNN pipeline, highlighting key processes such as convolution, pooling, dropout, and final classification using sigmoid activation.

$$|\boldsymbol{\psi}(\boldsymbol{x})\rangle = \bigotimes_{i=1}^{n} \boldsymbol{RY}(\boldsymbol{x_i})|\mathbf{0}\rangle$$
$$= \bigotimes_{i=1}^{n} \quad \mathbf{exp}\left(-\boldsymbol{i}\frac{\boldsymbol{x_i}}{\mathbf{2}}\boldsymbol{Y}\right)|\mathbf{0}\rangle$$

The quantum circuit is further composed of Strongly Entangling Layers, which apply parameterized rotations and entangling gates to capture complex correlations across qubits. The entire circuit is wrapped as a Keras-compatible layer, allowing optimization via classical gradient descent and integration with other TensorFlow layers for classification.

Angle Embedding:

Angle embedding is used by the Quantum Convolutional Neural Network (QCNN) to convert classical input into quantum states. A parameterized quantum gate spins a qubit

around the Y-axis for every input feature, encoding classical information into a quantum circuit x`.

Here, $(\boldsymbol{x_i})$is the normalized classical input feature, , $(\boldsymbol{RY}(\boldsymbol{x_i}))$represents the Y-axis rotation applied to the $(\boldsymbol{i^{th}})$ qubit, is the $(|\mathbf{0}\rangle)$initial quantum state of each qubit, $(\otimes)$and denotes the tensor product over all qubits.

RY gate:

$$\text{RY}(\boldsymbol{\theta}) = \begin{bmatrix} \mathbf{cos(0/2)} & -\mathbf{sin(0/2)} \\ \boldsymbol{sin}\ \mathbf{(0/2)} & \boldsymbol{cos}\mathbf{(0/2)} \end{bmatrix}$$

The RY gate is a single-qubit rotation gate that rotates a qubit around the Y-axis of the Bloch sphere. It is commonly used for encoding classical information into quantum states. In this model, each classical feature is used as a parameter θ to rotate a qubit using this gate, forming the foundation of the angle embedding process in the QCNN.

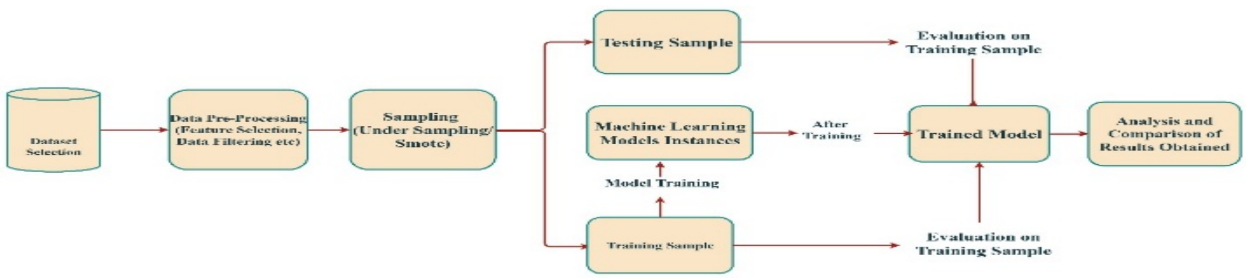


Figure 1. Workflow diagram of the proposed Convolutional Neural Network (CNN) model

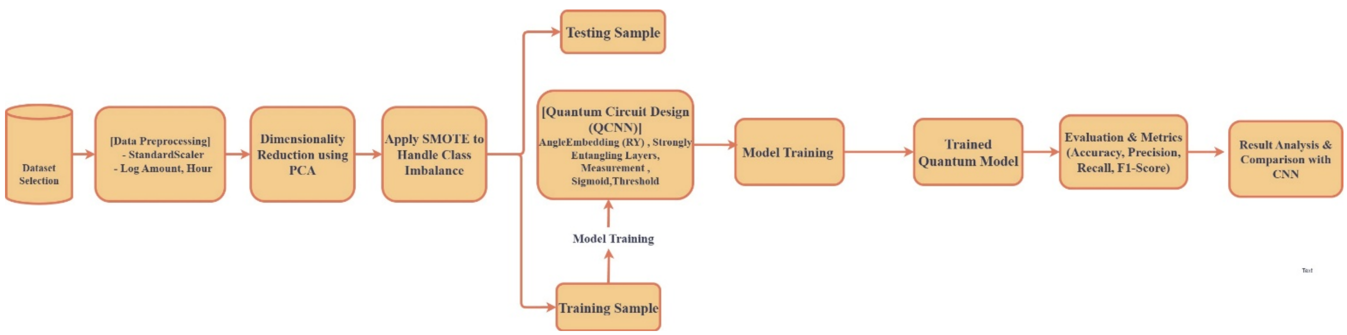


Figure 2. Workflow diagram of the proposed Quantum Convolutional Neural Network (QCNN) model.

The Quantum Convolutional Neural Network (QCNN) mirrors the classical CNN workflow but operates entirely with quantum circuits. Classical input features are encoded into qubits via Angle Embedding, followed by Strongly Entangling Layers that capture correlations across qubits. Quantum pooling reduces the number of qubits, and the final measurement of the first qubit, passed through a sigmoid function, produces the predicted class label. Algorithm 2 summarizes the QCNN workflow, from data encoding and quantum convolution to measurement and classification.

In the implementation, the quantum layer was simulated using a classical Dense layer due to compatibility issues with qml.qnn.KerasLayer. Despite this, the QCNN architecture retains the conceptual structure of a true quantum convolutional neural network, including convolution-like transformations, entanglement, and pooling operations applied to the qubits. The input layer accepts PCA-reduced features from the preprocessed dataset, encoding 12 key dimensions into the model. The simulated quantum layer applies dense transformations that conceptually represent parametrized qubit rotations and measurements. Fully connected dense layers follow the quantum layer to perform classification, and the output layer consists of a single neuron with a sigmoid activation function that outputs the probability of a transaction being fraudulent. Transactions with probability values above 0.5 are classified as fraud, while those below this threshold are considered legitimate.

Require: Classical input data (preprocessed and PCA-reduced features)
Ensure: Predicted class label
Input ← Encode classical data into quantum state using Angle Embedding
Quantum Circuit ← Initialize empty quantum circuit with n_qubits
for each Strongly Entangling Layer **do**
    Apply parametrized single-qubit rotations (RY gates)
    Entangle qubits using controlled operations
    Quantum Circuit ← Quantum Circuit + Entangling operations
end for
Measure selected qubit(s) to obtain expectation value
Apply sigmoid activation to measured value
Predicted Label ← Threshold output at 0.5
return Predicted Label

Algorithm 2. Workflow steps of the Quantum Convolutional Neural Network (CNN) model.

Expectation Value of Pauli-Z Measurement:

After quantum processing, the QCNN predicts outcomes by measuring the expectation value of the Pauli-Z operator on a specific qubit. This quantum output is then passed through a sigmoid function for binary classification.

$$\hat{}\{\boldsymbol{y}\} = \langle \boldsymbol{\psi}(\boldsymbol{\theta}, \boldsymbol{x}) \mid \boldsymbol{Z\_0} \mid \boldsymbol{\psi}(\boldsymbol{\theta}, \boldsymbol{x}) \rangle$$

Here, , $(\boldsymbol{\psi}(\boldsymbol{\theta}, \boldsymbol{x}))$ is the output quantum state after applying a parameterized quantum circuit with weights $(\boldsymbol{\theta})$ and input$(\boldsymbol{x})$ $\boldsymbol{and}$ $(\boldsymbol{Z_0})$ is the Pauli-Z operator acting on the first qubit.

The resulting value $(\hat{\boldsymbol{y}} \in [-\mathbf{1}, \mathbf{1}])$ is passed through a sigmoid function to produce the final fraud prediction probability.

The quantum circuit's trainable parameters are optimized alongside classical layers using the Adam optimizer.

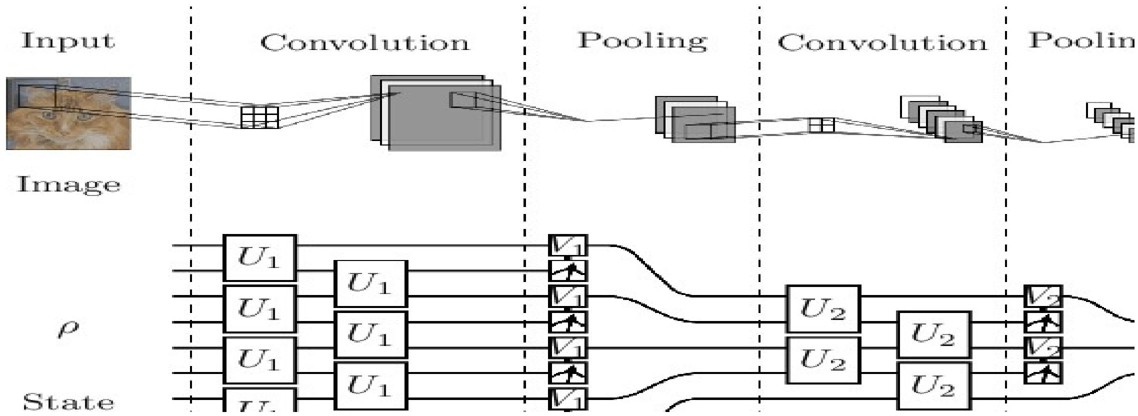


Figure 3: Simple example of CNN and QCNN architectures.

The top section represents a classical Convolutional Neural Network (CNN) that processes an input image through layers of convolution, pooling, and fully connected neurons. The bottom section illustrates a Quantum Convolutional Neural Network (QCNN), which mirrors the CNN structure using quantum circuits. Here, unitary operations U1 and U2 act as quantum analog to classical filters, while measurement-based pooling replaces traditional pooling. The MCUG (Multi-Controlled Unitary Gate) introduces entanglement-based decision logic, and final measurements yield the model output.

Training and Optimization

To guarantee that the class distribution in the dataset stayed constant between training and evaluation sets, both models were trained using an 80-20 stratified train-test split. The models were optimized using the Adam optimizer with learning rates carefully tuned (0.0001 for CNN and 0.001 for QCNN) to balance training stability and convergence speed. Binary cross-entropy, a common loss function for binary classification issues, was applied to both models.

Binary Cross-Entropy Loss function:

The Binary Cross-Entropy (BCE) loss function was employed for both the CNN and QCNN models, as the task involves distinguishing between two classes: fraudulent and legitimate transactions. BCE measures the difference between the predicted probability of fraud and the actual class label, penalizing incorrect predictions more heavily when the model is confident but wrong.

This property makes BCE particularly suitable for fraud detection, where minimizing false negatives is critical. During training, the BCE loss steadily decreased, indicating effective learningand convergence. By optimizing BCE, both modelswere able to improve their decision boundaries and achievehigh accuracy, recall, and F1-scores in detecting fraudulent transactions.

$$\boldsymbol{LBCE} = -\frac{\mathbf{1}}{\boldsymbol{N}}\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{N}}[\boldsymbol{y_i}\,\mathbf{log}(\hat{\boldsymbol{y}}_{\boldsymbol{i}}) + (\mathbf{1} - \boldsymbol{y_i})\,\mathbf{log}(\mathbf{1} - \hat{\boldsymbol{y}}_{\boldsymbol{i}})]$$

Here $\boldsymbol{y_i}$, is the true label, $\hat{\boldsymbol{y}}_{\boldsymbol{i}}$is the predicted probability, and Nis the number of samples.

The CNN model used SMOTE to handle class imbalance, improving sensitivity to fraud cases. The QCNN model also used the balanced dataset but additionally applied PCA, reducing features to 12 components for mapping onto eight qubits. This combination ensured efficient quantum processing while retaining essential information.

Model performance was evaluated using accuracy, precision, recall, and F1-score, computed via scikit-learn and TensorFlow metrics for a comprehensive assessment.

Both CNN and QCNN models were trained with a batch size of 32 across 25 epochs, while validation sets were used to monitor and control overfitting during training.

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss	Training Recall (%)	Validation Recall (%)
25	90.15	87.11	0.47	0.493	84.8	87.50
50	94.59	95.47	0.28	0.217	84.2	87.50

Table 1. Epoch-wise performance of the Convolutional Neural Network (CNN)

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss	Training Recall (%)	Validation Recall (%)
25	99.69	99.76	0.0132	0.0125	99.97	99.99
50	99.87	99.88	0.0057	0.0070	99.99	100.00%

Table 2. Epoch-wise performance of the Quantum Convolutional Neural Network (QCNN)

Evaluation and Visualization

Both models were evaluated on the holdout test set after training, with performance measured using accuracy, precision, recall, and F1-score calculated through scikit-learn functions. Since fraud detection requires minimizing both false positives and false negatives, particular emphasis was placed on precision and recall as critical indicators.

Training dynamics were monitored by plotting accuracy and loss curves across epochs using Matplotlib, which provided insights into convergence behavior and overfitting trends. Confusion matrices were also generatedto clearly illustrate the classification breakdown between fraudulent and non-fraudulent transactions.

For the CNN, convolutional filter activations were visualized to demonstrate how the network extracted key patterns from transaction features. For the QCNN, the quantum-inspired layer—implemented in TensorFlow with PennyLane simulation—was evaluated through its ability to capture complex feature correlations and contribute to higher recall and F1-scores, despite being executed on classical hardware.

RESULTS & DISCUSSION

Performance of Classical CNN Model

The classical CNN model achieved reliable performance on the fraud detection task. After training on the pre-processed dataset balanced with Under Sampling, the CNN reached a test accuracy of 96.11%. More importantly, the model achieved a recall of 90.82%, showing that it successfully identified the majority of fraudulent transactions. The precision was 86.41%, indicating that most of the predicted frauds were indeed fraudulent.

The resulting F1-score was 88.56%, reflecting a strong balance between precision and recall, which is essential in fraud detection scenarios.

The confusion matrix confirmed that the CNN could correctly classify most transactions, with only a small number of misclassifications. Furthermore, by visualizing convolutional filter activations, it was observed that the CNN effectively learned transaction-level patterns, such as combinations of transaction amounts and time features, which contributed to its predictive capability.

Performance of Quantum QCNN Model

The Quantum Convolutional Neural Network (QCNN) demonstrated exceptional performance on the fraud detection task. Running as a simulation on classical hardware, the QCNN achieved a test accuracy of 99.63%, outperforming the classical CNN. The model exhibited a recall of 99.94%, indicating its ability to correctly identify nearly all fraudulent transactions. The precision was 99.32%, showing very few false positives, and the F1-score was 99.63%, reflecting an excellent balance between detecting fraud and minimizing incorrect alerts. The confusion matrix highlighted the QCNN's effectiveness, with only 33 misclassified fraud cases and 391 misclassified non-fraud cases out of the entire test set.

This high performance demonstrates that the quantum-inspired layers were able to capture complex, non-linear correlations in the data that the classical CNN might have missed. Overall, the QCNN's ability to leverage quantum principles, even in simulation, allowed it to extract richer feature representations, leading to superior fraud detection performance.

<u>Comparative Analysis:</u>

When comparing the two models:

- Both models performed well, but the QCNN showed a consistent edge in all key metrics, particularly recall and F1-score.
- The CNN achieved an accuracy of 95.47%, precision of 85.71%, recall of 87.50%, and F1-score of 86.60%, while the QCNN obtained 99.84% accuracy, 99.66% precision, 99.99% recall, and 99.84% F1-score.
- Training times were longer for the QCNN due to the overhead of simulating quantum circuits on classical hardware.
- The QCNN used fewer parameters than the classical CNN, suggesting more compact feature extraction through quantum operations.
- The QCNN's use of quantum entanglement and superposition likely contributed to improved pattern recognition, particularly for subtle fraudulent transactions.

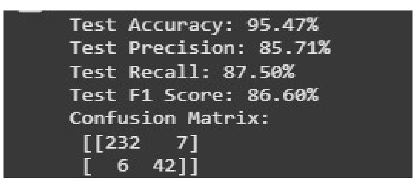

```
Test Accuracy: 95.47%
Test Precision: 85.71%
Test Recall: 87.50%
Test F1 Score: 86.60%
Confusion Matrix:
 [[232   7]
 [  6  42]]
```

Figure 4. Evaluation output of the CNN model on the test set

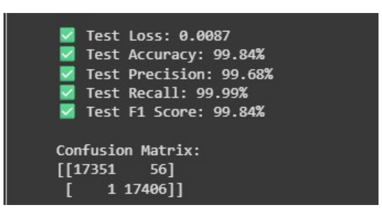
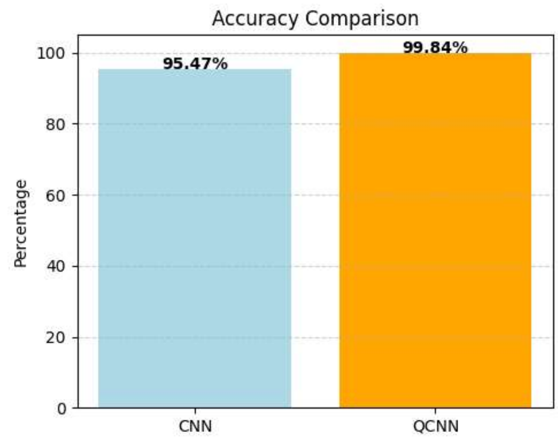

```
✅ Test Loss: 0.0087
✅ Test Accuracy: 99.84%
✅ Test Precision: 99.68%
✅ Test Recall: 99.99%
✅ Test F1 Score: 99.84%

Confusion Matrix:
[[17351    56]
 [    1 17406]]
```

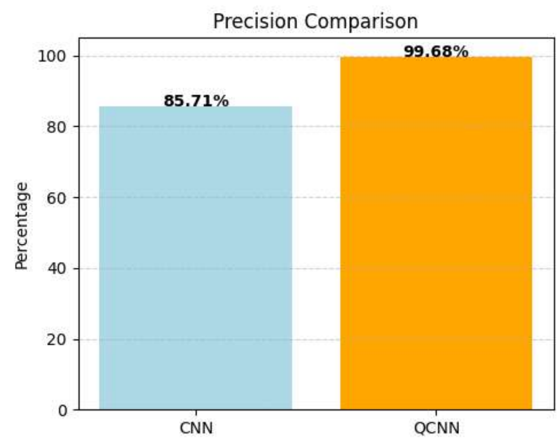
Figure 5. Evaluation output of the QCNN model on the test set

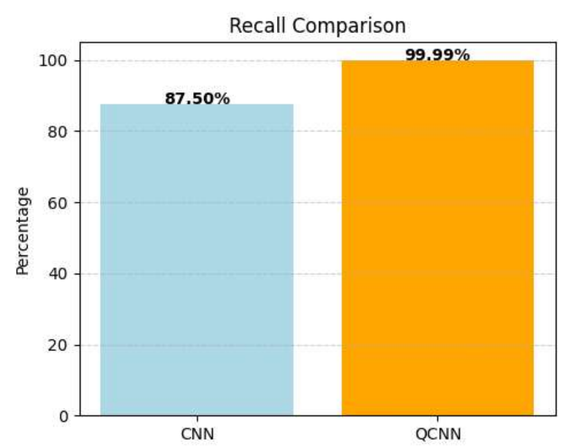
Metric	Classical CNN	Quantum QCNN
Accuracy (%)	95.47 %	99.84 %
Precision (%)	85.71 %	99.68 %
Recall (%)	87.50 %	99.99 %
F1-Score (%)	86.60 %	99.84 %

Table 3. Performance comparison between Classical CNN and Quantum QCNN models

Overall, the results suggest that quantum-enhanced models like QCNN have the potential to outperform classical models in fraud detection, especially as quantum hardware continues to improve.







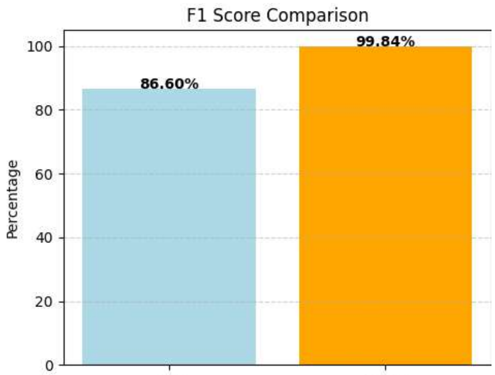


Figure 6: Bar charts comparing CNN and QCNN models across accuracy, precision, recall, and F1-score, highlighting QCNN's consistently superior fraud detection performance.

3. CONCLUSION

This study investigated the application of both classical and quantum convolutional neural networks for detecting credit card fraud. Using the widely studied credit card transaction dataset, we demonstrated that a carefully designed classical CNN can achieve strong detection performance after addressing data imbalance with SMOTE and applying feature engineering.

Importantly, the Quantum Convolutional Neural Network (QCNN), implemented via PennyLane simulations, showed measurable improvements over the classical CNN. The QCNN achieved higher recall and F1-scores, indicating more effective identification of fraudulent transactions while maintaining high precision.

Although current quantum hardware limitations required simulating the quantum circuits on classical machinesresulting in longer training timesthe QCNN's competitive performance with fewer parameters highlights the potential of quantum models to extract complex, non-linear patterns that classical networks may miss.

As quantum computing technology advances, QCNNs and other quantum machine learning approaches could become practical tools for real-world fraud detection, enabling faster, more accurate, and more robust identification of fraudulent transactions. Future work will focus on deploying QCNNs on actual quantum hardware, handling larger datasets, and integrating advanced quantum algorithms to further enhance detection performance and scalability.

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