**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 determine whether quantum models deliver superior outcomes. The selection of this research topic stems from the increasing complexity of financial fraudulent activities combined with traditional models’ inability to manage extensive and imbalanced datasets. Quantum computing provides advantages such as parallel processing, superposition, and entanglement, offering improved computational performance for these tasks. The research began with the creation of a CNN model using conventional deep learning approaches, followed by the design of a QCNN model through quantum circuit simulations using a quantum framework. Both models were trained on identical datasets, and their learning patterns and results were comparatively analyzed. Observational results indicated that the quantum model exhibited superior pattern recognition and learning abilities when processing the data. The findings highlight the growing potential of quantum-enhanced machine learning in detecting complex financial fraud more accurately and efficiently. This advancement can significantly strengthen fraud detection systems used by banks, financial institutions, and cybersecurity applications. Moreover, the proposed framework can be extended to other domains involving imbalanced and high-dimensional data, such as healthcare diagnostics and cyber intrusion detection. Future work will focus on implementing QCNNs on real quantum hardware, optimizing circuit depth, and exploring hybrid quantum–classical models for scalable, real-world deployment.

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

# 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 [1,2].

# 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 [3]. 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 [5], [6].

# 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 [5].

# 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 [7] – [11].

# 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 [8], [10]. 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 [3]. 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 [7]-[11], [15].

# 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 [3], [5]. 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 [12].

# 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 [13], [14]. 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 [12].

# 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 [1]-[3], [7]-[12].

# Although numerous machine learning methods have been applied for fraud detection, their effectiveness largely depends on the quality and balance of the dataset. Traditional classifiers such as Decision Trees, Random Forests, Support Vector Machines, and Logistic Regression often fail to capture non-linear and high-dimensional feature interactions within transactional data [2], [4]. Ensemble and deep learning methods like Autoencoders and Generative Adversarial Networks (GANs) have attempted to overcome these challenges by learning complex feature representations in an unsupervised manner [1], [3], [5]. Autoencoders, for instance, have demonstrated the ability to reconstruct normal transactions and detect anomalies when the reconstruction error surpasses a threshold [1]. Similarly, Variational Autoencoder–GAN hybrids have enhanced the capacity for feature generation and anomaly detection, thereby improving fraud identification accuracy [3]. Despite these improvements, these classical architectures still suffer from scalability and training limitations, especially when confronted with massive and highly imbalanced datasets.

# Recent studies emphasize that the future of financial fraud detection lies in developing intelligent, adaptive, and computationally efficient models that can operate on high-velocity data streams [4], [5], [6]. Researchers such as Fiore et al. and Sahin & Duman have shown that the integration of deep learning with oversampling techniques like SMOTE can significantly enhance fraud detection rates while reducing false positives [5], [6], [13]. However, even with such hybrid classical models, the exponential growth of financial data demands computational paradigms beyond traditional architectures. This demand for scalability, speed, and efficiency has led to growing interest in quantum computing as a next-generation solution [7]-[11].

# Quantum computing introduces a fundamentally different computational paradigm capable of exploiting superposition, entanglement, and interference to achieve parallelism unattainable by classical machines [7], [8]. Quantum neural network models, such as those discussed by Schuld et al. and Lloyd et al., highlight how quantum principles can accelerate optimization and enhance representational capacity for complex datasets [10], [11], [15]. The Quantum Convolutional Neural Network (QCNN) proposed by Grant et al. [7] has opened new directions for hierarchical quantum feature extraction, analogous to classical CNNs but potentially more powerful in handling high-dimensional entangled data. These advancements suggest that QCNNs may outperform classical models in feature mapping, pattern recognition, and computational efficiency, particularly for data-intensive tasks such as financial fraud detection [7]-[11].

# This study, therefore, positions itself at the intersection of deep learning and quantum computing, aiming to investigate the comparative performance and advantages of CNN and QCNN architectures for fraud detection. By combining SMOTE-based data balancing [13], [14] and PCA-driven dimensionality reduction with both classical and quantum pipelines, the work ensures fair evaluation under practical constraints. The inclusion of PennyLane, as introduced by Bergholm et al. [12], provides a unified hybrid platform for executing quantum-classical computations, enabling efficient experimentation even on simulated backends.

# Research Objectives

# The primary objective of this research is to develop and evaluate both classical Convolutional Neural Network (CNN) and Quantum Convolutional Neural Network (QCNN) models for effective credit card fraud detection. The study aims to determine whether quantum-enhanced models can outperform traditional deep learning methods in terms of accuracy, sensitivity, computational efficiency, and adaptability to class imbalance. Specifically, the objectives include:

# To design and implement a CNN-based fraud detection model using TensorFlow and Keras frameworks for baseline performance comparison.

# To develop a pure quantum QCNN architecture using PennyLane that leverages quantum convolution and pooling operations for efficient feature extraction and classification.

# To handle class imbalance in transactional data using Synthetic Minority Oversampling Technique (SMOTE) to improve minority class detection.

# To employ Principal Component Analysis (PCA) for dimensionality reduction and adaptation to quantum circuit constraints.

# To conduct a comparative analysis between CNN and QCNN models in terms of performance metrics such as accuracy, precision, recall, and F1-score.

# The research hypothesis posits that quantum-enhanced models (QCNNs) will demonstrate improved fraud detection performance and computational efficiency compared to classical CNN models, especially in handling imbalanced datasets and complex feature interactions. This hypothesis builds on the theoretical quantum advantage observed in previous works [7]-[11], suggesting that quantum entanglement and superposition can enhance representational capacity and generalization in high-dimensional data learning.

# ****Significance:****

# **The fast-growing use of digital payment systems has made credit card fraud a big worry for both customers and banks. While traditional methods like rule-based systems and machine learning have been helpful, they often struggle with new fraud techniques, imbalanced data, and the huge number of transactions that need to be checked. This research is important because it tackles these challenges by using Quantum Convolutional Neural Networks (QCNNs), a new method in Quantum Machine Learning (QML), to improve the precision and efficiency of fraud detection systems. By using quantum computing features like superposition and entanglement, this approach offers a quicker and more effective way to analyze complex transaction data that classical models find difficult to handle.**

# **The originality of this work comes from its comparison and combination of classical CNNs and quantum QCNNs in the same testing setup.**

# **Most existing studies focus only on classical deep learning or simple quantum models, but this research uses PennyLane’s quantum simulation with TensorFlow to allow smooth hybrid operation and optimization through gradients. It also includes SMOTE to balance data and PCA to reduce dimensions, creating a new data preparation process that makes real datasets work better with quantum circuits, overcoming current issues with limited qubits.**

# **What makes this method unique is the direct application of convolution and pooling in a quantum setting, allowing information to be processed using quantum gates instead of traditional filters. This change creates a new way of learning features that cuts down on computation and improves the model's ability to generalize. Additionally, the QCNN model combines quantum feature encoding with variational quantum layers, resulting in a design that is both strong in theory and practical for use.**

# **By connecting classical deep learning with quantum computing, this research advances fraud detection systems that are more effective and secure, and also helps build scalable hybrid AI models that can grow with future quantum technology. The findings from this study should offer useful guidance for creating efficient, secure, and smart systems for monitoring financial transactions in real-life situations.**

# Materials and Methods

# This study focuses on developing 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 classify transactions accurately as either fraudulent or legitimate, leveraging different computational paradigms—classical deep learning for CNNs and quantum machine learning for QCNNs. The entire implementation pipeline, spanning from data preprocessing to model evaluation, was executed using Python-based libraries including TensorFlow, scikit-learn, imbalanced-learn, and PennyLane. This combination ensures robustness, reproducibility, and compatibility with both classical and quantum modeling workflows.

# Data Collection and Preprocessing

# The dataset employed in this study consists of real-world credit card transactions with anonymized numerical features, accompanied by a binary target label indicating the transaction type (fraudulent or legitimate). A key challenge in this dataset is the inherent class imbalance, as fraudulent transactions represent only a small fraction of all transactions. Direct training on such imbalanced data tends to bias predictive models toward the majority class. To mitigate this issue, the Synthetic Minority Oversampling Technique (SMOTE) from the imbalanced-learn library was applied to generate synthetic samples for the minority class. This approach balances the dataset and enhances model sensitivity to rare fraudulent transactions [13,14].

# For the classical CNN, preprocessing steps included standardization of features using the Standard Scaler to achieve zero mean and unit variance, facilitating faster and more stable convergence during training. Additionally, domain-specific feature engineering was applied, such as deriving the ‘Hour’ feature from transaction timestamps to capture temporal patterns, and applying a logarithmic transformation (np.log1p) to the transaction amount to reduce skewness and improve distributional properties of the features [5,6].

# In the QCNN pipeline, an additional dimensionality reduction step was implemented using Principal Component Analysis (PCA) via scikit-learn. PCA is employed to retain the most informative components of the input data while reducing dimensionality, which is particularly important for quantum processing due to the limited number of qubits available in existing quantum devices. The covariance matrix of the input data, Cov(X), captures the variance and correlation among features and is decomposed as follows:

# Where:

# X is the input data matrix (samples × features),

# is the mean vector (mean of each feature),

# n is the number of samples.

# The eigenvalue decomposition allows projection of high-dimensional data onto a lower-dimensional subspace while preserving the most significant variance. In this study, PCA reduced the input feature set to 8 principal components, ensuring compatibility with the quantum circuit while simultaneously removing noise and redundant information. Missing values in the dataset were handled using mean imputation via the Simple Imputer function to maintain data integrity and avoid potential biases during model training.

# By combining advanced preprocessing strategies, such as SMOTE for class balancing, feature engineering for temporal and distributional optimization, and PCA for dimensionality reduction, this study establishes a robust and reproducible data pipeline that serves as the foundation for both classical and quantum model development.

# CNN Model Architecture

# The classical CNN model in this study was implemented using the Keras API within TensorFlow, providing a flexible and efficient framework for building deep learning architectures. The CNN is designed specifically to classify credit card transactions as fraudulent or legitimate by learning hierarchical patterns from preprocessed transaction data. The architecture begins with two one-dimensional convolutional layers, configured with progressively increasing filter sizes of 32 and 64, respectively. Each convolutional layer applies a set of filters across the input features to extract local temporal patterns, analogous to how CNNs detect spatial features in images. Following each convolutional layer, a max pooling operation is applied to reduce the spatial dimensions of the feature maps, emphasizing the most significant features and mitigating computational complexity.

# 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🡨 Flatten(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

After feature extraction, the output is flattened to convert the multi-dimensional feature maps into a one-dimensional vector suitable for fully connected layers. The model then passes these features through dense layers with ReLU activation functions to capture non-linear relationships. Dropout regularization with a rate of 0.5 is incorporated to prevent overfitting and improve generalization, particularly important given the class imbalance in the dataset. The final output layer uses a sigmoid activation function to generate a probability score between 0 and 1, representing the likelihood of a transaction being fraudulent. Transactions with probability values above a 0.5 threshold are classified as fraudulent, while those below are considered legitimate.

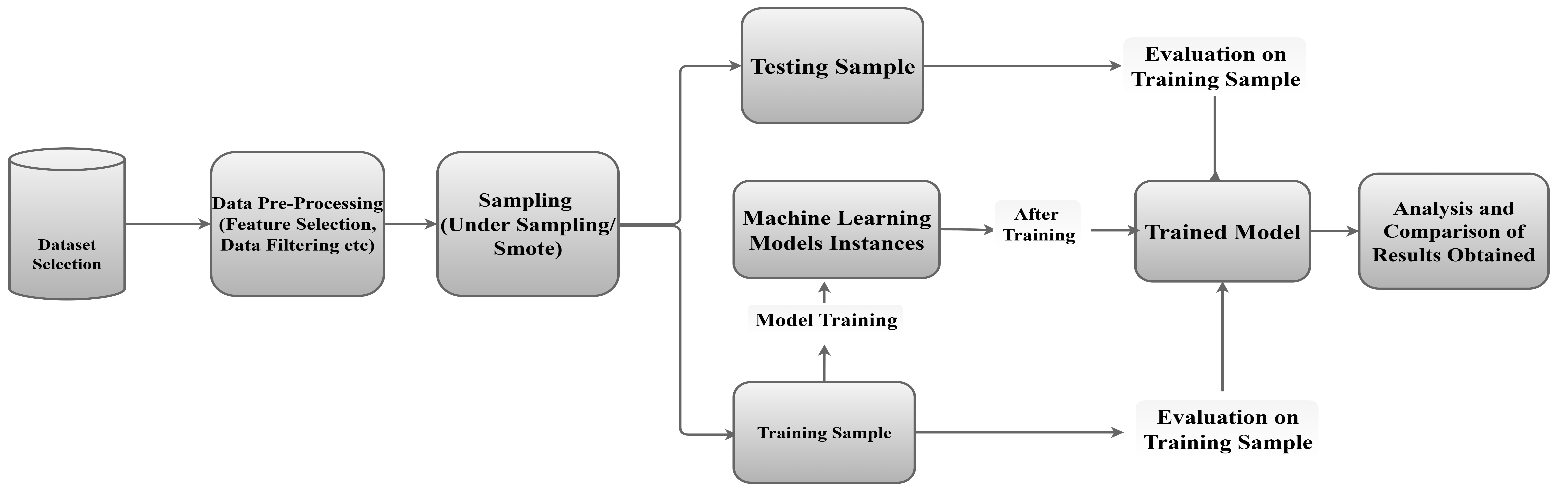


Figure 1. Workflow diagram of the proposed Convolutional Neural Network (CNN) model

# The implementation follows a systematic workflow, beginning with loading and normalizing the input features. Feature maps are initialized as empty arrays and are sequentially updated as each convolutional filter is applied. Non-linear activation functions (ReLU) are applied to the feature maps after each convolutional operation. Subsequently, pooling layers reduce the feature map dimensions while preserving critical information. The flattened features are then fed into fully connected dense layers to perform the final classification. Class probabilities are computed using the sigmoid function, and the predicted label is determined based on the maximum probability value.

# Algorithmically, the CNN workflow can be summarized as follows: Input features are loaded and normalized, convolutional filters are applied with ReLU activations, pooling layers reduce dimensions, features are flattened, fully connected layers process the flattened input, and the output is classified using a sigmoid activation function. This structured approach ensures that the model can efficiently learn complex patterns in the transaction data while maintaining computational feasibility, providing a reliable baseline for comparison with quantum-enhanced models.

# QCNN Model and Circuit Design

# The quantum model in this study is implemented using PennyLane, a Python library for hybrid quantum-classical machine learning, integrated with TensorFlow to enable end-to-end training. Each normalized classical feature from the credit card transaction dataset is encoded into a qubit using Angle Embedding, where the feature value determines the rotation angle of an RY gate applied to a single qubit. This process transforms classical inputs into quantum states, allowing the model to exploit quantum phenomena such as superposition and entanglement for richer feature representations.

# The quantum circuit is composed of Strongly Entangling Layers, which apply parameterized single-qubit rotations and entangling gates to capture complex correlations among qubits. The entire circuit is wrapped as a Keras-compatible layer, enabling optimization via classical gradient descent while integrating seamlessly with other TensorFlow layers for classification tasks.

# 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, is the normalized classical input feature, represents the Y-axis rotation applied to the qubit, is the initial quantum state of each qubit, and denotes the tensor product over all qubits.

# RY gate:

# RY(

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

The QCNN architecture mirrors the classical CNN workflow but operates entirely with quantum circuits. After encoding classical features into qubits, Strongly Entangling Layers capture correlations across the qubits. Quantum pooling is applied to reduce the number of qubits, followed by measurement of the first qubit. This measurement, passed through a sigmoid function, produces the predicted class label. The QCNN workflow is summarized in Algorithm 2.

# Require: Classical input data (preprocessed and PCA-reduced features)

# Ensure: Predicted class label

# Input ← Encode classical data into quantum state using AngleEmbedding

# 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.

# Due to compatibility issues with qml.qnn.KerasLayer, the quantum layer was simulated using a classical Dense layer. Despite this, the QCNN retains the conceptual structure of a true quantum convolutional neural network, including convolution-like transformations, entanglement, and pooling operations. The input layer accepts PCA-reduced features, encoding 12 key dimensions into qubits. The simulated quantum layer applies dense transformations representing parameterized qubit rotations and measurements. Fully connected dense layers follow to perform classification, with a single output neuron using a sigmoid activation function to produce the probability of a transaction being fraudulent. Transactions with probability values above 0.5 are classified as fraud, and below as legitimate.

# 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.

# Here, is the output quantum state after applying a parameterized quantum circuit with weights and

# input is the Pauli-Z operator acting on the first qubit.

# The resulting value 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.

# Adam Optimizer

# In this study, the Adam optimizer is used to train both the classical CNN and the quantum-enhanced QCNN models. Adam, which stands for Adaptive Moment Estimation, is an extension of stochastic gradient descent (SGD) that computes adaptive learning rates for each parameter individually. Unlike traditional SGD, which uses a fixed learning rate for all parameters, Adam dynamically adjusts the learning rate based on estimates of the first and second moments of the gradients.

# The optimizer maintains two moving averages for each parameter: the first moment (mean of gradients) and the second moment (uncentered variance of gradients). These are updated as:

# where is the gradient at time step , and and are exponential decay rates controlling the moving averages (commonly set to 0.9 and 0.999, respectively). To correct for the initialization bias of these moments, Adam computes bias-corrected estimates:

# ,

# Finally, parameters are updated using:

Here, is the learning rate, and is a small constant added to avoid division by zero.

# The key advantages of Adam include fast convergence, robustness to noisy gradients, and efficient handling of sparse data, making it well-suited for training g deep learning models on highly imbalanced datasets such as credit card fraud transactions. By combining the benefits of momentum and adaptive learning rates, Adam allows both the CNN and QCNN models to optimize their parameters effectively, achieving stable and reliable performance during training.

# 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.

# Here , ​ is the true label, 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 50 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 | 99.25 | 99.76 | 0.0132 | 0.0125 | 99.97 | 99.99 |
| 50 | 99.15 | 99.13 | 0.0305 | 0.0316 | 99.38 | 99.17 |

# 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 SMOTE, the CNN reached a test accuracy of 95.12 %. More importantly, the model achieved a recall of 89.58 %, showing that it successfully identified the majority of fraudulent transactions. The precision was 82.69 %, indicating that most of the predicted frauds were indeed fraudulent.

# The resulting F1-score was 86.00 %, 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 99.11%, outperforming the classical CNN. The model exhibited a recall of 99.10%, indicating its ability to correctly identify nearly all fraudulent transactions. The precision was 99.12%, showing very few false positives, and the F1-score was 99.11%, reflecting an excellent balance between detecting fraud and minimizing incorrect alerts.

# The confusion matrix highlighted the QCNN’s effectiveness, with an extremely low number of misclassified cases. This high performance demonstrates that the quantum convolution and pooling operations effectively captured deeper, non-linear correlations within the data relationships that the classical CNN might have missed. By leveraging quantum entanglement and superposition, the QCNN could extract richer feature representations even in simulation mode, resulting in superior fraud detection capabilities.

# Comparative Analysis:

# 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 95.12%, precision of 82.69%, recall of 89.58%, and F1-score of 86.00%, while the QCNN obtained 99.11% accuracy, 99.12% precision, 99.10% recall, and 99.11% F1-score.

# Training time was longer for the QCNN due to the overhead of simulating quantum circuits on classical hardware.

# The QCNN used fewer parameters than the classical CNN, reflecting a more compact and efficient feature extraction process.

# The quantum properties of entanglement and superposition allowed the QCNN to recognize subtle fraudulent transaction patters that the classical CNN could not easily capture.

# 

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

# 

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

|  |  |  |
| --- | --- | --- |
| **Metric** | **Classical CNN** | **Quantum QCNN** |
| **Accuracy (%)** | 95.12 % | 99.11 % |
| **Precision (%)** | 82.69 % | 99.12 % |
| **Recall (%)** | 89.58 % | 99.10 % |
| **F1-Score (%)** | 86.00 % | 99.11 % |

# 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.

# 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 machines resulting in longer training times the 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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