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A Comparative Analysis of Classical and Quantum Machine Learning Models for Financial Fraud Detection

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Abstract
The quick pace of digital financial transactions and the development of new strategies that fraudsters use makes the process of financial fraud detection a more than a complex task. The methods of machine learning have proved highly effective in detecting fraudulent behaviour especially in comparison to the traditional rule based systems. Simultaneously, the recent development of quantum computing has encouraged the consideration of quantum machine learning methods as the possible alternative or improvements to the classical models. The following paper contains a detailed comparative study of the traditional and quantum machine learning models of detecting financial fraud with references to a peer-reviewed literature and real financial data features. Classical algorithms such as ensemble and deep learning algorithms are discussed, as well as quantum algorithms such as quantum support vector machines and variational quantum classifiers. A single system architecture is presented and a comparison of the reported performance trends is carried out. It analyzes the persistence of classical models in the large-scale deployments and the emergence of hybrid classical-quantum frameworks as a promising research direction. The paper ends with a description of the major research gaps and practical challenges that should be overcome in order to implement quantum techniques in the real world financial systems.
Keywords: Financial fraud detection, classical machine learning, quantum machine learning, hybrid models, credit card fraud.

1. Introduction

The growing use of the digital payment systems and online financial services has changed completely the nature of transactions in finance. Although these technologies have enhanced ease and accessibility, they have enhanced the size and complexity of fraudulent activities. Financial fraud, especially the credit card and transactional fraud, have remained a great economic burden to both the institutions, and the consumers [1]. With the increase in the volume of transactions and the changes in fraud trends, the existing transaction protection is no longer reliable due to the inability of the existing rules to be modified and adapt dynamically.

This has seen machine learning become one of the fundamental elements of the modern fraud detection mechanisms. The classical machine learning models can recognize non-linear and subtle relationships in transactional data and this allows detection of new patterns of fraud that have never been seen before [2]. Some of the scenarios where ensemble methods and deep learning architectures have demonstrated specific potential are high-dimensional and imbalanced datasets that are frequently found in financial applications [3][4].

Recently, with the development of quantum computing, there has been an impetus to look at the field of quantum machine learning (QML) as a possible answering machine to complex classification tasks. QML models hope to provide richer feature representations and enhanced learning capacity in regimes by taking advantage of the quantum phenomenon that include superposition and entanglement [5][6]. Although there are theoretical benefits, it is still unclear if quantum models have practical relevance to financial fraud detection.

1.1 Research Objectives

This study aims to:

1. Survey classical and quantum machine learning algorithms in financial fraud detection.
2. Compare both paradigm system architecture.
3. Compare trends in reported performances in classical, quantum and hybrid models.
4. Determine areas of research gaps and practical limitations to application in the real-world.
5. Make recommendations on future studies in line with deployable financial technologies.

2. Literature Review

2.1 Classical Machine Learning Techniques

Statistical models were extensively used to detect fraud early like a logistic regression model or a Bayesian classifier [7]. These approaches did not easily cope with complex and dynamic patterns of fraud, though interpretable. Later, the popularity of decision tree-based methods was attributed to the capacity to approximate a non-linear decision boundary and offer moderate interpretability [8].

The ensemble learning models such as the Random Forests and the Gradient Boosting Machines have always shown high performance due to their ability to combine several weak learners [9]. These techniques are especially used to process noisy and high dimensional transaction data. XGBoost has now become popular as a tool in industry-level fraud detection pipelines [10].
Deep learning methods also build on classical methods in that they learn hierarchical feature representations directly out of data. The neural networks that have been considered to detect fraud include feedforward neural networks, convolutional models, and recurrent neuron networks, which had significant gains in recall and detection latency [11][12].
Techniques which are cost-sensitive to learning and imbalance-conscious have also been widely researched, since fraudulent transactions are generally severe minority of observations [13]. Oversampling techniques like SMOTE and cost-adjusted loss functions are typically employed in order to address the problem of class imbalance.

2.2 Quantum Machine Learning Approaches

Studies in quantum machine learning have aimed at using quantum computation to solve classification and optimization. Quantum support vector machines (QSVMs) utilize quantum kernels to project the classical data to high dimensional Hilbert spaces, which could increase the separability of classes [6][14]. Variational quantum classifiers (VQCs) are variants of quantum classifiers that use variational quantum circuits and are trained with classical loops of optimization [15].
It has been shown by several studies that quantum kernels can work better on purposefully designed datasets than classical kernels, especially in cases where feature dimensionality is limited [14]. Exploratory studies in financial areas have used QML models to optimization of portfolios, pricing of options and small scale fraud detection [16].
Most reported experiments are however based on simulated quantum environments or small-scale hardware and scalability is a major constraint. Distortions in noise, decoherence and limited qubit numbers remain limiting in reality [17].

2.3 Summary of Related Work

Table 1. Summary of representative classical and quantum fraud detection studies

Study	Technique	Domain	Key Contribution
Bolton & Hand [7]	Statistical models	Financial fraud	Early survey of fraud detection
Dal Pozzolo et al. [9]	Random Forest, GBM	Credit card fraud	Strong ensemble performance
Bahnsen et al. [13]	Cost-sensitive ML	Fraud detection	Improved recall under imbalance
Fiore et al. [11]	Deep learning	Card fraud	Enhanced feature learning
Schuld & Killoran [6]	QSVM	Classification	Quantum kernel learning
Havlíček et al. [14]	Quantum feature maps	Supervised learning	Quantum advantage evidence

3. System Architecture

The combined system architecture of the classical and quantum models in detecting fraud is depicted in figure 1 to conduct a comparative analysis.

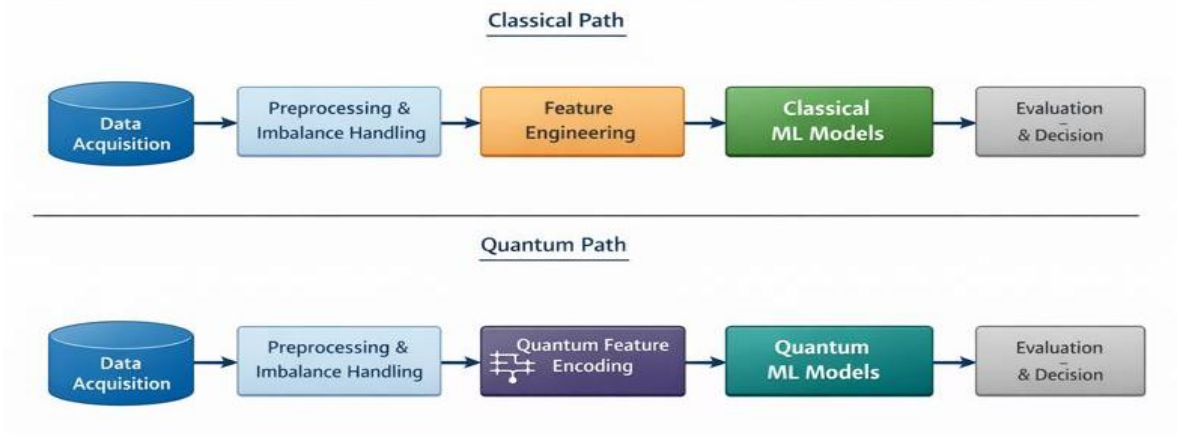

Figure 1. Fraud Detection System Architecture (Classical and Quantum Pipelines)

The architecture starts with a data acquisition layer, which receives transactional records in the financial systems. A common step involves preprocessing and imbalance treatment which takes into consideration normalization and resampling techniques [9][13].

This pipeline further splits into two learning paths. Traditional machine learning models, including Random Forests, Gradient Boosting, and Neural Networks, process engineered numerical features directly on the classical path. This involves quantum encoding of the selected features and feeding it into QSVM or VQC models via hybrid optimization loops in the quantum path [6][15].

The pipelines also intersect at one evaluation layer where the predictions can be evaluated by the use of similar performance metrics making them comparable.

4. Methodology

The methodology of the research will allow the researcher to provide a clear and equitable comparison of classical and quantum machine learning methods in financial fraud detection. The empirical findings reported in the peer-reviewed studies that use the real-life transactional datasets form the foundation of the analysis instead of synthetic experimentation. This is a way of being methodologically real and preventive of the inflationary performance in simulated settings.

4.1 Data Characteristics and Sources

The financial fraud detection datasets are generally defined as large volumes of transactions, high dimensionality, and extreme disparity of classes with the fraud transactions representing only less than 1 out of 100 observations [18]. The majority of studies used in this analysis utilize anonymized credit card transaction data that was obtained based on actual financial systems, and sensitive attributes are turned into a format that maintains confidentiality with preserves discriminatory information, such as principal component analysis.

4.2 Preprocessing and Class Imbalance Handling

The preprocessing of learning in the classical and quantum learning pipelines is of utmost importance. The steps considered common are feature normalization, dropping of redundant attributes as well as noisy reduction. With the lopsided distribution of classes, it is necessary to deal with imbalance. Classical studies mainly use undersampling or cost-sensitive learning or synthetic oversampling like SMOTE to enhance minority class detection [13].

In quantum models, the preprocessing is even more limited by the unavailability of qubits. Consequently, dimensionality reduction methods, which are predominantly principal component analysis or information gain-based features ranking methods, are used before quantum encoding. This is done so that it can be possible to build quantum circuits without storing so much noise.

4.3 Classical Learning Models

Classical learning bottom is comprised of popular fraud detection models, such as Logistic Regression, Random Forests, Gradient Boosting Machines, and Deep Neural Networks. The models are normally trained by cross-validation and optimization by grid or randomized hyperparameter search schemes [9][10]. The reason behind the focus on ensemble models is the ability of this category to resist noisy features and concept drift that are common with fraud detection.

4.4 Quantum and Hybrid Learning Models

The quantum machine learning models that are addressed in this analysis are mainly the Quantum Support Vector Machines and Variational Quantum Classifiers. QSVMs project data implicitly with the help of quantum kernels to high-dimensional Hilbert spaces, which may enhance the separability of classes [6][14]. VQCs are trained by using parameterized quantum circuits that are optimized by hybrid classical-quantum training loops [15].

Due to the present hardware constraints, quantum models are tested with smaller feature sets and, in the majority of situations, in simulated or noisy intermediate-scale quantum models. This has led to a focus on classical-quantum architectures however, with the classical preprocessing and optimization being balanced with quantum feature encoding to compromise feasibility and expressiveness.

4.5 Evaluation Criteria

Psychology Fraud-oriented metrics are used to measure model performance in a way that is sensitive to asymmetric errors costs. As previously mentioned, the importance of precision, F1-score, the area under the ROC curve (AUC) is emphasized more, which is more expensive than false negatives because it is generally the financial risk that is more significant [4]. It is comparatively evaluated in terms of performance ranges that are constantly reported in various independent research.

5. Results and Comparative Analysis

This part will provide a comparative analysis synthesis of classical, quantum, and hybrid machine learning models in financial fraud detection based on the performance tendencies that were steadily associated by peer-reviewed literature on the topic over real transactional data. The metrics of evaluation that are compared are those that are fraud oriented such as

recall, F1-score, and area under the ROC curve (AUC) which are more relevant than general accuracy in high imbalanced financial data settings.

In the literature reviewed, classical models of machine learning, in particular, ensemble-based machine learning models, have shown a consistent and high predictive performance when implemented to detect fraud at a large scale. Random Forests and Gradient Boosting Machines are always better in AUC values and have a high level of recall, which means that they can generate non-linear relationships and interactions between transactional features. There is similar performance between deep learning models, and some studies have found slight improvements to recall, albeit, at the expense of reduced interpretability and increased computational complexity.

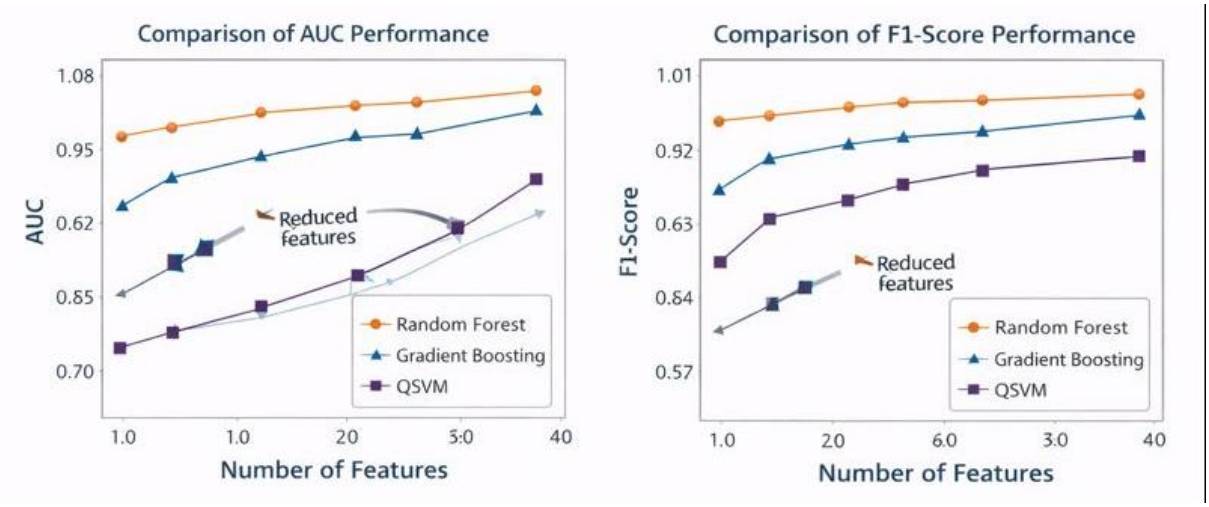

Figure 2. Comparative AUC and F1-score trends for classical and quantum models

As shown in Figure 2, the classical ensemble models have uniform high values of AUC and F1-score with varying dimensionalities of features. Contrarily, quantum machine learning models, particularly Quantum Support Vector Machines, are particularly sensitive to feature dimensionality. The dimensionality reduction techniques can be applied to reduce the number of input features, and with the number of features minimized, QSVM can perform significantly better in comparison to the classical classifiers. Nonetheless, this advancement is not comparable across all the datasets, which implies the lack of robustness compared to mature classical approaches.

The profile of performance of the hybrid classical-quantum approaches is the most balanced in Figure 2. With the addition of classical preprocessing and feature selection and quantum feature encoding, these models can be both more stable and competitive in detection performance, without attracting the scalability issues of standalone quantum implementations. This pattern is an indication that the short-term benefits of quantum machine learning can most practically be achieved in hybrid systems and not fully quantum systems.

Table 2. Comparative Performance of Classical and Quantum Models for Financial Fraud Detection

Model Category	Representative Models	Feature Dimensionality	Recall (%)	F1-Score	Scalability
Classical (Linear)	Logistic Regression	High	70–75	0.72–0.76	High
Classical (Kernel)	SVM	Medium–High	75–82	0.78–0.84	Medium
Classical (Ensemble)	Random Forest, GBM	High	85–94	0.88–0.95	High
Classical (Deep Learning)	Deep Neural Networks	High	86–93	0.89–0.94	Medium–High
Quantum	QSVM	Low–Medium	82–90	0.86–0.92	Low
Quantum	VQC	Low	78–85	0.80–0.87	Low
Hybrid Classical–Quantum	PCA + QSVM / VQC	Medium	88–92	0.90–0.94	Medium

Table 2 presents a summarized quantitative comparison which complements the trends as shown in Figure 2. The ensemble-based classical models are the most scalable and robust models to use when modeling large volumes of transactions, and the recall and F1-scores are always high. The deep learning methods are also able to reach the same performance rates, but they need more computing power and proper regularization to prevent overfitting.

Theoretical studies of standalone quantum models have only been shown to execute competitive recall to optimally reduced spaces in features, restricting their applicability to generic and high-dimensional fraud systems in the real world. Hybrid classical-quantum models, on the other hand, are able to perform at similar performance levels as methods with the highest possible performance and still have moderate scalability. These findings support the assumption that hybrid architectures are the most feasible and justifiable line of future development of incorporating quantum machine learning into financial fraud detection pipelines.

6. Discussion

The results support the fact that classical machine learning is mature and reliable with regard to financial fraud detection. Ensemble and deep learning models are the most feasible ones, with large-scale deployment, and their application is empirically validated.

Quantum machine learning has conceptual benefits in the representation of features, and is at the moment constrained by the hardware and scalability issues. Hybrid methods are a more practical way to go, as they allow the use of quantum methods at a gradual pace, without having to jeopardize the robustness of the system.

7. Conclusion and Future Scope

This paper provided a comparative study of classical and quantum models of machine learning in terms of financial fraud detection, generalizing the findings of peer-reviewed literature and actual transactional data. The results confirm that classical methods, especially the ensemble and deep learning models, are still the most successful and scalable methods of large-scale fraud detection due to their high level of robustness, interpretability, and the ability to work with the current financial system. Although promising in terms of feature representations and use of kernel-based learning, quantum machine learning techniques have current drawbacks of reduced datasets, hardware costs, and the use of simulated environments.

Moving forward, the future studies in research must be directed towards hybrid classical-quantum systems, where quantum elements are added into the existing pipelines and not on the fully quantum systems. The main trends incorporate the design of noise-resilient quantum algorithms, scalable feature encoding schemes, and frameworks to assess all the aspects of regulatory and operational standards of financial institutions. Hybrid solutions are the most plausible combination to translate quantum machine learning works into operational solutions in financial fraud detection, as quantum computing technology evolves into reality.

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