Journal of Information Systems Engineering and Management
2025, 10(8s)
ISSN:2468-4376
https://www.jisem-journal.com/ **Research Article**

Quantum Machine Learning Technique for Insurance Claim Fraud Detection with Quantum Feature Selection

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ARTICLE INFO

Received: 20 Oct 2024
Revised: 10 Dec 2024
Accepted: 25 Dec 2024

ABSTRACT

This paper demonstrates a novel use of quantum machine learning (QML) algorithms for detecting fraudulent activities in the home insurance sector. Utilizing actual data and IBM Quantum processors through the Qiskit software stack, the study introduces an innovative method for selecting quantum features that are specifically designed to accommodate the limitations of Near Intermediate Scale Quantum (NISQ) technology by using the Quantum Support Vector Machine (QSVM) in conjunction with traditional machine learning techniques. A comprehensive comparison was conducted to evaluate their effectiveness in detecting fraud. The indicators such as accuracy, recall, and false positive rate are carefully analyzed. Despite the constraints of current quantum technology, QSVM shows excellent accuracy, especially on limited datasets, indicating its potential to enhance insurance fraud detection. The research emphasizes the crucial feature selection in optimizing QML algorithms for fraud detection tasks. It investigates the capacities of hybrid quantum/classical machine learning ensembles. Future research directions include expanding this study to actual hardware implementations to verify its practical feasibility. The work enhances financial security in the insurance business by using quantum computing technology in fraud detection approaches. It establishes the feasibility and efficacy of using quantum resources to solve difficult real-world issues, setting a foundation for or the broader application of QML in fraud detection and other fields.

Keywords: Quantum support vector machine (QVSM), Feature selection, Fraud Detection, Machine Learning, Insurance Claim, IBM Quantum computers, IBM Qiskit software development kit.

1 Introduction

Fraudulent activities pose significant challenges to the insurance and financial sectors, resulting in substantial financial losses and eroding trust within these industries. The staggering cost of insurance fraud is estimated to exceed 40 billion dollars presently and is projected to rise to $28 billion by 2031, which underscores the pervasive nature and growing sophistication of fraudulent schemes (Federal Bureau of Investigation 2020). Fraud encompasses a broad spectrum of deceptive practices ranging from falsifying claims and identity theft to sophisticated financial scams and money laundering schemes. Detecting and preventing fraud is paramount for insurance companies and financial institutions to safeguard their assets, maintain the integrity of their operations, and protect their customers from financial harm. ML techniques have emerged as indispensable tools in combating fraud due to their ability to analyze large volumes of data, identify intricate patterns indicative of fraudulent behavior, and adapt to evolving tactics employed by fraudsters. By leveraging advanced algorithms and predictive analytics ML enables organizations to enhance their fraud detection capabilities, minimize financial losses, and uphold the trust and confidence of stakeholders in the integrity of insurance and financial services.

This study introduces a novel feature selection mechanism that may be used with any combination of redundancy and importance measures, offering a versatile and effective approach. Secondly, it demonstrates the effectiveness of this approach on precise home insurance datasets by using both conventional and quantum algorithms. The project aims to use QML algorithms to identify suspicious conduct and false alarms and assess their effectiveness compared to conventional machine learning techniques. This study tries to enhance the progress of fraud detection in the insurance industry (Zanke et al. 2023).

1.1 Quantum Machine Learning

QML is the study of using quantum computing concepts to improve ML algorithms. QML specifically examines how quantum computers might improve the efficiency and precision of machine learning methods (Biamonte et al. 2017). QML has the potential to greatly improve fraud detection by combining the capacity to handle large amounts of data with a high level of accuracy. This technological progress has the potential to introduce a new period characterized by enhanced levels of financial protection (Ciliberto et al. 2018). The intrinsic capabilities of quantum systems to manipulate and simulate complicated interactions between variables are well-suited for the intricacies involved in financial transactions (Pushpak and Jain 2021).

The QSVM improves the feature space analysis, increasing the accuracy of the combined quantum-classical technique for fraud detection (Pushpak and Jain 2022). This improvement is achieved by using a much smaller data set that is compatible with the existing capabilities of Quantum Hardware. QSVM leverages the inherent quantum parallelism to process and analyze financial data (Mücke et al. 2023) effectively. The concept of superposition can concurrently assess many data points, hence accelerating important tasks like pattern recognition and data categorization. These talents are crucial in identifying fraudulent operations.

This study employs quantum feature selection methods with traditional feature selection techniques to evaluate the effectiveness of the quantum machine learning classifier (Schuld and Killoran 2019). Furthermore, this study introduces the concept of hybrid quantum/classical machine learning ensembles and assesses their model performance in relation to purely classical and fully quantum methods.

1.2 Fraud detection

The insurance industry has a challenging problem in detecting insurance fraud, which requires a meticulous examination of the available data to uncover potential indicators of fraudulent activity (Wilkens and Moorhouse 2023). Fraud detection has depended on heuristic approaches, which include identifying particular fraud indicators and using them to establish patterns that suggest fraudulent behavior traditionally (Saeedi and Arodz 2019). This approach requires a deep understanding of fraud patterns and the expertise to discern legitimate claims from suspicious ones (Liu and Rebentrost 2018). Fraud analytics tools play a crucial role by leveraging data analytics techniques to identify anomalies and patterns in financial data that may signal fraudulent activity (Rebentrost et al. 2014). By scrutinizing financial statements and transaction records, these tools can uncover irregularities and suspicious patterns that may warrant further investigation. Enhancing our comprehension of the data through advanced analytics and machine learning algorithms is essential for improving pattern detection and reducing instances of fraud within the insurance industry (Liu et al. 2021). Gaining a more comprehensive comprehension of the data will undoubtedly result in improved identification of patterns and reduced occurrence of fraudulent activities.

The research is organized as follows: A comprehensive introduction to QLM and its uses in the field of fraud detection is presented in section 2. Section 3 reviews existing literature and highlights notable advancements in quantum-enhanced fraud detection. Section 4 outlines the methodology employed in this study, including data collection, feature selection techniques, and model evaluation. Section 5 presents the key findings and results of the comparative analysis between classical and quantum ML algorithms. Section 6 is the last part of the study, providing a summary of the results and a discussion of their implications.

2 Literature Review

Researchers are actively exploring diverse QML models that effectively detect fraudulent activities. Rebentrost et al. (2014) presented a quantum SVM with O (log MN) runtime for training and classification, assuming oracles for training data that yield quantum states. This quantum classification approach utilizes a non-sparse matrix exponentiation technique to invert the training data kernel matrix efficiently.

Havlíček et al. (2019) proposed to utilize quantum augmented feature spaces to create quantum kernels for classical SVM. Huang et al. (2021) found that Quantum kernels can improve the performance of traditional machine-learning methods. Studies use dimensionality reduction methods to minimize the quantum resources needed for computing. By applying these techniques, the study improves the model's capability to identify subtle anomalies. Ahmad et al. (2021) explored QML for anomaly detection in network security. The results demonstrated the approach's efficacy in capturing patterns for anomaly detection in network security. The research conducted by Kyriienko and Magnusson (2022) specifically aimed to use Quantum Machine Learning (QML) methods to identify instances of internal fraud inside the banking industry. The work used quantum kernels created by quantum feature maps. Huang et al. (2021) and Innan et al. (2024) investigated QML models and improved system efficiency by enhancing fraud detection accuracy. The work conducted by Xiang et al. (2023) focuses on credit card fraud detection and utilizes a unique semi-supervised technique. Their suggested technique significantly improved the effectiveness of fraud detection, particularly when there is a scarcity of labeled data. Grossi et al. (2022) utilized the Mixed Quantum-Classical Method to detect fraud using Quantum Feature Selection on a much smaller dataset to accommodate the limitations of present Quantum Hardware. The technology offers a heightened level of precision for the hybrid quantum-classical method in fraud detection (Egger et al. 2021). These studies emphasized the potential of QML in detecting fraud, offering valuable insights into the capabilities of quantum algorithms.

Innan et al. (2023) conducted a study comparing four QML models for finance fraud detection. The researchers discovered that the QSVM performed better than previous models, reaching F1 scores of 0.98 for fraudulent and non-fraudulent instances. Their findings provide opportunities for future breakthroughs in Quantum Machine Learning (QML) for fraud detection, which have major implications for enhancing financial security. Guo et al. (2023) presented a quantum version of the Local Outlier Factor algorithm for anomaly detection, showcasing its superiority in processing big datasets with exponential speedup on data point dimensions and polynomial speedup on data point numbers compared to classical methods, thus highlighting the potential of quantum computing in unsupervised anomaly detection. Grossi et al. (2022) applied a QSVM algorithm in the financial payment industry for fraud detection, demonstrating enhanced accuracy through quantum feature selection techniques and a hybrid classical-quantum ensemble model that outperformed classical approaches. Egger et al. (2020) discussed the applicability of quantum computing in finance, outlining various quantum algorithms' potential benefits for addressing computational challenges in financial services. Dougherty et al. (2021) commemorated Dr. Joshua Guttman's contributions to computer security and formal methods, emphasizing his work on security protocols and the strand space formalism, which abstracts cryptographic protocol details to analyze communication patterns. Di Pierro and Incudini (2021) investigated fraudulent behaviors in cybersecurity using quantum machine learning algorithms. Their research demonstrated the capacity of quantum computing to strengthen statistical models and increase the effectiveness of fraud detection in online transactions.

3 Methodology

This study conducted an experiment to assess the efficacy of fraud detection. It analyzed three different industry methodologies using the same baseline data set.
1) Model based on domain expertise and rules without using machine learning.
2) Classical AI/ML techniques like XGBoost and SVM
3) QSVM techniques

The domain expert rule-based model with no machine learning is deployed in the real world and provides a benchmark for the accuracy of the results to evaluate the machine learning model. The expert rule-based model has well-defined, well-marked features, and results are calculated for the weighted parameters in an Excel sheet using complex formulas. Most ML models scale with the amount of input data dimensions called features. In other words, a model with more features necessitates more memory and computing resources to train. A typical scenario of such an approach is feature selection (FS), which reduces the input dimension by identifying only a subset of all available traits. Classical AI/ML techniques such as XGBoost are widely used in various ML applications. XGBoost, an implementation of gradient boosting, is known for its efficiency and effectiveness in handling structured/tabular data, often outperforming other algorithms in predictive accuracy. SVM is a robust supervised learning technique that may be used to perform classification and regression problems. It performs well in spaces with many dimensions and is proficient at classifying data points into distinct categories by identifying the ideal hyperplane. XGBoost and SVM have been extensively studied and applied across diverse domains, showcasing their versatility and robustness in solving complex real-world problems. QSVM is a novel machine-learning technique that uses quantum computing to improve classification jobs. QSVMs can be versatile and capable of handling binary and multiclass classification problems.

The parameter selection for the machine-learning model is well-defined because rule-based domain models already define the parameters and their weights. The selection of parameters significantly impacts the effectiveness of the selected machine-learning model (Herman et al. 2023).

The outcome of the fraud detection is a binary classifier, and each transaction can only be marked as fraudulent or non-fraudulent.

4 The Dataset

The data set describes actual claims payment transactions and its features, volume, and dimensionality. It contains transactions and customer data with historical SAR (Suspicious Activity Reporting) filings. The rule-based domain model categorizes each transaction as either fraudulent or non-fraudulent. The personally identifiable information is scrubbed from the dataset, and fifteen parameters with weighted scores are identified to determine whether the transaction is fraudulent.

Table 1 The features of the dataset

Parameter Name	Description	Data type
Credit Score	Credit Score of the claimant	Integer
Payment default history	The customer has defaulted on the payments in the past	Boolean
Outstanding debts	If the customer currently has any outstanding debts	Boolean
Property Age	Insured Property age	Integer
Maximum days property has been Unoccupied	The number of days the property is unoccupied	Integer

Claims made during the last three years	The count of claims filed by the consumer during the last 3 years	Integer
Total count of claims in the current period	Number of claims reported by the customer in the current term	Integer
Loss date from policy effective date	Flag indicating if the loss was reported immediately after the Policy was taken within 30 days	Boolean
Loss date from the policy expiry date	Flag showing if the loss was reported within 30 days of the expiration of the insurance.	Boolean
Number of days between loss and claim intimation	Flag showing if the loss was reported within 30 days after the insurance expiration.	Boolean
Were the Authorities (fire, Ambulance) intimated	Flag showing if the loss was reported within 30 days after the insurance expiration.	Boolean
Were the Authorities (fire, Ambulance) report available	Flag indicating if the report is available	Boolean

Table 1 presents the features of the dataset used for insurance claim fraud detection, outlining key parameters and their descriptions. These parameters include the claimant's Credit Score, indicating their creditworthiness, alongside binary indicators such as Payment default history and Outstanding debts reflecting past financial behavior. Property-related features like Property Age and the Maximum number of days the property has been unoccupied offer insights into the insured property's characteristics and occupancy status. Claims history information, including Claims in the previous three years and Number of claims in the current term, provides context on the claimant's past insurance activities. Boolean flags such as Loss date from the policy effective date and Loss date from the policy expiry date indicate whether the loss was reported promptly after policy initiation or before its expiration. Additional indicators such as the number of days between loss & claim intimation, whether the authorities were intimated, and reports available within 30 days of policy expiry provide more information on claim processing timelines and communication with relevant authorities. These features collectively contribute to the dataset's richness and enable comprehensive analysis for fraud detection in the insurance domain.

An essential aspect of the proposed approach centers around feature discovery. These engineered features derived from the dataset encapsulate valuable information for classification tasks. By evaluating certain patterns these features show substantial discriminate values between fraudulent and non-fraudulent transactions. The dataset attributes encompass various data types, including categorical variables, strings, and integers. Fig. 1 depicts a heatmap illustrating the correlations between all features within the dataset. Heatmaps visually depict the intensity and direction of associations between variables, with warmer colors representing greater positive correlations and colder colors representing stronger negative correlations. By examining the heatmap, patterns of correlation between different features can be identified, offering insights into potential dependencies and associations within the data. This visualization aids in understanding the interplay between various parameters, guiding further analysis and interpretation of the dataset.

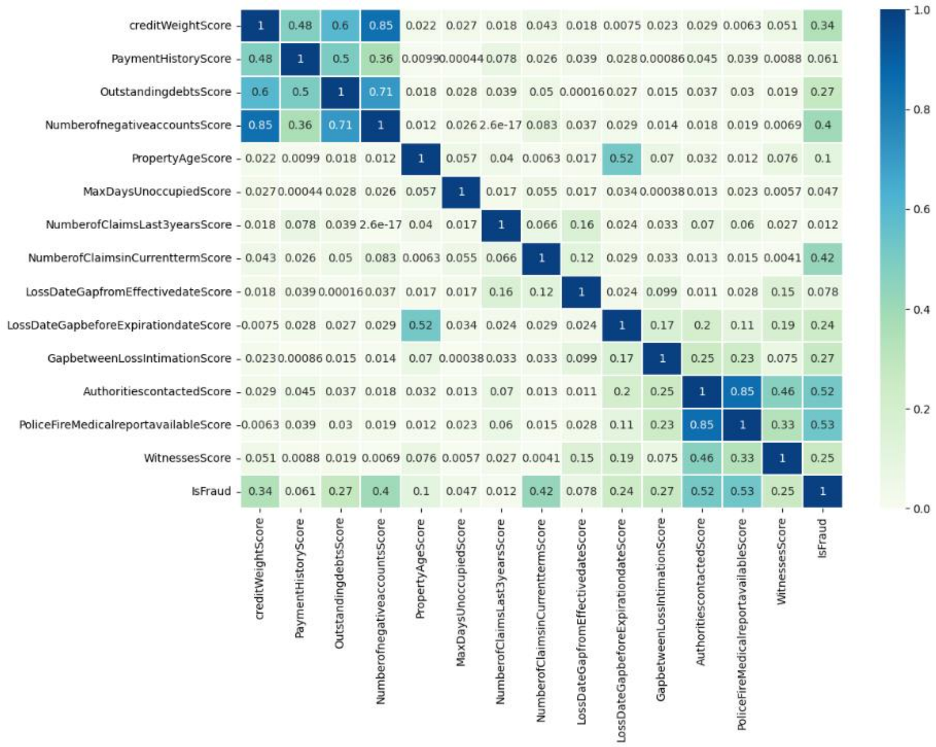

Fig. 1 Heatmap of all the Correlated Features

5 The Approach

5.1 Algorithm

Below are the steps followed for feature selection and detection of fraud given the dataset

1) Normalize and scale the data.
2) Apply feature selection techniques to minimize the number of dimensions.
3) Estimate and generate a kernel function.
4) Implement the quantum circuit on the cloud-based quantum computer.

Selecting the feature map is important and might differ based on the dataset we are attempting to categorize. A parametric quantum circuit may perform the unitary transformation Uφ (θ) on the Hilbert space $\mathcal{H}$ of a quantum system consisting of n qubits. This implementation can be employed to create a feature map represented by a function.

$\varphi: X \rightarrow \mathcal{H}$

$$|0\ldots0\rangle \rightarrow U\varphi\,(x)\,|0\ldots0\rangle = |\varphi\,(x)\rangle$$

Where $|0\ldots0\rangle$ means a state with all zeros.

ZZ Feature Map

The Quantum ZZMap is a distinct feature map used in QSVM. The circuit is a second-order Pauli-Z evolution. The ZZ Feature Map requires the input of two parameters: the number of features and the number of repeated circuits. The ZZ Feature Map is difficult to reproduce using conventional methods and is executed using circuits with low depth on quantum devices that are nearly fully developed. The objective is to build the kernel of the Support Vector Machine (SVM) by using quantum states. The ZZMap focuses explicitly on the interaction between qubits in the quantum circuit, which introduces a phase shift (the "ZZ" part).
By exploiting quantum entanglement and superposition the ZZMap enhances the expressive power of the feature map.

$$U(\alpha, \beta) = \left(\exp\left(i \sum_j \phi_j(\mu_i)\big(Z_j \otimes Z_k\big) \right) \exp\left(i \sum_j \phi_j(\mu_i)\big(Z_j\big) \right) H^{\otimes n} \right)^d$$

5.2 Quantum Support Vector Machine

Support Vector Machines (SVM) are resilient algorithms often used for classification applications. They aimed to accurately determine the most efficient hyperplane to divide data points into discrete classes (Ma et al. 2021). Within the Support Vector Machines (SVMs) framework, a crucial notion is using a kernel, which enables data conversion into a space with greater dimensions. Using a higher-dimensional representation streamlines the process of identifying a suitable separation hyperplane. The process involves applying a feature map to the raw input features. This feature map effectively transforms the data, making it amenable to linear separation (Fig. 2). In classical SVMs, the inner product (kernel) between pairs of data points is computed within this transformed feature space. However, certain feature maps can be computationally expensive to calculate classically, particularly as the problem size increases.
QSVM offers an innovative approach by leveraging quantum computers to directly estimate the kernel in the feature space (Mengoni and Di Pierro 2019). The key advantage is that the required computational resources do not exhibit exponential scaling with problem size, as observed in classical methods.

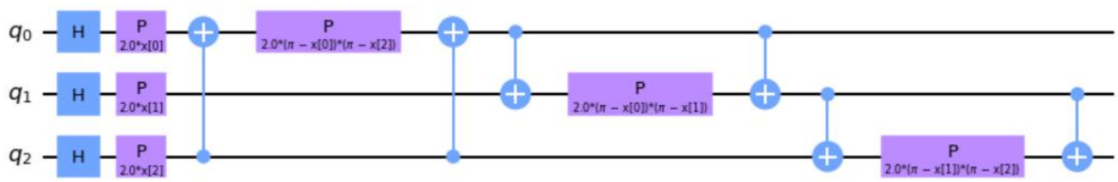

Fig. 2 Quantum Circuit for ZZ Feature Map with feature = 3, depth =1

The key advantage is that, unlike classical methods, the required computational resources do not scale exponentially with problem size. QSVM follows a supervised learning approach. During the Training Phase, the kernel is calculated, and support vectors are identified. In the Test/Classification Phase, the labeled data points are classified based on the solution obtained during training (Tang 2019; Stamatopoulos et al. 2020). The results obtained based on the models used are shown in Table 2.

Table 2. The results comparing the accuracy of classical and Quantum models

Model Name	Accuracy
KNN	97.3%
SVM	99.0%
QSVM	98.3%

Table 2 presents a comparative examination of the accuracy attained by classical and quantum models in fraud detection. The classical models KNN and SVM exhibit high accuracies of 97.3% and 99.0%, respectively. These results showcase the effectiveness of classical machine learning algorithms in accurately detecting fraudulent activities. On the contrary, the quantum model QSVM achieves a slightly lower accuracy of 98.3%. Despite this marginally lower accuracy, the QSVM demonstrates promising performance, indicating the potential of quantum machine learning techniques in enhancing fraud detection capabilities. Overall, the comparison underscores the competitive performance of both classical and quantum approaches in addressing fraud detection challenges, with each offering distinct advantages in specific contexts. QSVM is versatile and can handle both binary classification and multiclass problems. A suitable multiclass extension must be provided when dealing with more than two classes. The domain corresponds to binary classification in the specific context of insurance claim fraud detection.

6 Conclusion

The QML can detect fraudulent transactions by increasing prediction accuracy for imbalanced datasets. The Quantum ZZMap within QSVM allows efficient kernel computation in the feature space using quantum resources, paving the way for quantum-enhanced classification tasks. This research introduces an innovative algorithm for QML specifically designed to address Insurance Claim Fraud Detection integrating both traditional and quantum machine learning methodologies. While the performance of classical and quantum algorithms was comparable, their predictions may diverge for specific data points (Ciliberto et al. 2018). To investigate the predictions of classical and quantum algorithms were meticulously compared, with differing predictions documented for further analysis. The approach utilized the Quantum Enhanced Support Vector Machine, discerning the most significant characteristics of the quantum classifier are emphasized. The role of QSVMs in insurance claim fraud detection and their advantages over classical methods are emphasized. The results were obtained through simulations on a quantum computer. Future works will expand to actual hardware implementations, which will be detailed in future studies.

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