Quantum Machine Learning for Insurance Claim Fraud Detection: A Hybrid Approach

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***Abstract*—This paper presents a novel hybrid quantum–classical approach for insurance claim fraud detection. The proposed framework first utilizes a Quantum Support Vector Classifier (QSVC) with a quantum kernel to model complex, nonlinear feature interactions, followed by a classical Random Forest (RF) ensemble that refines the predictions. The hybrid QSVC+RF pipeline is evaluated on a real-world insurance dataset comprising 1,000 merged claims with 39 features, including policy, agent, and vendor data. The results, as summarized in Table 1, demonstrate that the hybrid model significantly outperforms standalone quantum classifiers. Notably, the hybrid method achieves superior overall accuracy and substantially higher recall for fraudulent cases compared to both the QSVC using a ZZ-feature map and a Variational Quantum Classifier (VQC). These findings align with existing research indicating that hybrid quantum–classical ensembles can effectively leverage the expressive capacity of quantum kernels while preserving the robustness of classical models. The contributions of this work include comprehensive simulation results using Qiskit, applied to a realistic insurance dataset, which highlight practical performance improvements and inform effective feature selection. The study underscores the promising applicability of near-term quantum machine learning (QML) to real-world financial fraud detection scenarios.**

***Keywords*—Quantum Machine Learning, Fraud Detection, Quantum Support Vector Classifier, Variational Quantum Classifier, Random Forest, Insurance Analytics, Insurance Claims.**

I. Introduction

Insurance fraud imposes enormous costs on insurers and society. The FBI estimates that tens of billions of dollars in fraudulent claims occur annually. Automated fraud detection is crucial, but remains challenging: fraudulent patterns are complex and evolving, and fraud cases are rare (class imbalance). Classical machine learning (ML) has been widely used to analyze large claim datasets and flag anomalies, but new techniques are needed to handle subtle, high-dimensional relationships. Quantum machine learning (QML) is an emerging field that leverages quantum computing to potentially improve ML performance. In particular, quantum feature maps can project data into high-dimensional Hilbert spaces, enabling richer kernels for Support Vector Machines (QSVM). Early QML work (e.g. Pushpak and Jain 2022, Pushpak et al. 2025) has applied QSVM to insurance fraud, demonstrating that QSVM can achieve high accuracy on small insurance datasets. However, these studies either compare quantum vs classical models in isolation or focus on synthetic financial data (e.g. credit card fraud). They do not exploit hybrid pipelines that combine quantum and classical strengths. Moreover, classical ensemble methods (e.g. Random Forests) are known to be effective in fraud detection, but have not been jointly applied with quantum kernels.

In this paper, the authors fill this gap by designing and evaluating a hybrid QSVC+RF approach on real insurance claim data. Specifically, a QSVC with an IBM Qiskit ZZFeatureMap quantum kernel is built as the first-stage classifier, and then its outputs are fed into a classical Random Forest to refine the decision. This layered strategy leverages the quantum model's ability to capture complex non-linear patterns, while allowing the classical RF to correct any remaining errors and boost recall (catching more frauds). The dataset consists of 1,000 claim records (with 39 features) merged from three tables (claims, employee/agent, and vendor data). The target label is_fraud is derived from the claim status (fraudulent "D" vs approved "A"). Features like claim-to-premium ratio and report delay (known fraud indicators) are engineered, and feature selection is applied to satisfy quantum circuit size constraints. The pipeline is implemented in Qiskit (simulator) and scikit-learn, and three models are benchmarked: (1) QSVC (ZZ feature map) on the selected features, (2) an improved Variational Quantum Classifier (VQC) on the same features, and (3) the Hybrid QSVC+RF on all features plus the QSVC output.

II. Literature Review

A. Related Work

Classical and quantum methods have both been explored for insurance and financial fraud detection. Classical approaches: Traditional methods use rule-based or statistical models, while modern techniques include ensembles and deep learning. For example, Gheysarbeigi et al. (2025) developed an ensemble-based model for automobile insurance fraud, using multiple classifiers optimized by a bio-inspired algorithm (BQANA). They applied data balancing (random undersampling/oversampling) to mitigate severe class imbalance, achieving improved detection rates. Other studies apply reinforcement learning (RL) or anomaly detection for adaptive fraud scoring. While effective, classical models often require extensive feature engineering and may struggle with very subtle fraud patterns.

Quantum ML for fraud: Recent QML research has begun to target fraud detection. Pushpak and Jain (2022) applied a Quantum Support Vector Machine (QSVM) to housing insurance data. They used feature selection and parameter tuning, comparing the QSVM against a classical SVM. Their results indicate QSVM can match or exceed classical accuracy on limited data, highlighting QML's promise. Pushpak et al. (2025) further proposed a quantum feature selection scheme for home insurance fraud. Using real home-claim data and IBM Qiskit, they showed that QSVM achieved excellent accuracy (even with NISQ limitations). Innan et al. (2023) conducted a comparative study of four QML models (QSVC, VQC, and two quantum neural nets) on a financial fraud dataset. They found the quantum SVM attained the highest performance (F1 0.98 on both fraud and non-fraud). Variational circuits (VQC, QNN) also performed well but exhibited different trade-offs between accuracy and recall. These works collectively demonstrate that quantum kernels can capture complex financial patterns and that hybrid approaches deserve exploration.

B. Identified Research Gaps

However, gaps remain. Many QML studies focus on purely quantum classifiers or fully quantum-classical separations; few investigate hybrid pipelines. Grossi et al. (2022) note that mixed quantum-classical ensembles (e.g., quantum kernel followed by classical model) offer precision gains on small datasets. Yet, to the best of the authors' knowledge, no prior work has explicitly combined a QSVM with a classical random forest for insurance fraud. Moreover, most QML experiments use synthetic or general financial data. In contrast, the present work uses a merged insurance claims dataset with domain-specific features, highlighting end-to-end applicability. Finally, class imbalance remains a challenge; classical works often rely on sampling techniques (random undersampling, SMOTE) to rebalance fraud data, but the interaction of such techniques with quantum training has not been fully studied. This study addresses these gaps by presenting and evaluating a hybrid QSVC+RF framework on realistic insurance data, demonstrating practical metric improvements.

III. Theory

A. Data Encoding Methods

1) ZFeatureMap: The ZFeatureMap encodes classical data into quantum states through single-qubit Pauli-Z rotations. Each qubit is rotated based on the input feature value, resulting in a quantum state that reflects the original feature space without introducing entanglement. This feature map is considered separable and is suitable for representing linearly separable data in a quantum-enhanced SVM.

2) ZZFeatureMap: The ZZFeatureMap extends the ZFeatureMap by introducing two-qubit interactions through controlled-Z (CZ) entangling gates. It enables the encoding of feature correlations by applying parameterized ZZ interactions between qubit pairs. Mathematically, if $\mathbf{x} \in \mathbb{R}^n$ represents the input vector, the ZZFeatureMap creates a quantum state $|\Phi(\mathbf{x})\rangle$ using the unitary operator:

$$U_{\text{ZZ}}(\mathbf{x}) = \prod_{i<j} \exp\left(i \cdot \gamma \cdot x_i x_j Z_i Z_j\right)$$

where Z_i and Z_j are Pauli-Z operators acting on qubits i and j, and γ is a tunable parameter controlling the strength of entanglement. This feature map enhances the capacity of the kernel to capture complex, nonlinear relationships among features.

B. Quantum Support Vector Classifiers

The Quantum Support Vector Classifier (QSVC) adapts the classical SVM paradigm by replacing the classical kernel with a quantum kernel derived from the inner product of quantum states. Given two classical data points $\mathbf{x}$ and $\mathbf{x}'$, the quantum kernel is computed as:

$$K(\mathbf{x}, \mathbf{x}') = |\langle \Phi(\mathbf{x}) | \Phi(\mathbf{x}') \rangle|^2$$

where $|\Phi(\mathbf{x})\rangle$ and $|\Phi(\mathbf{x}')\rangle$ are quantum states produced by applying the selected feature map. This kernel is then used within a classical SVM framework to construct a decision boundary. The use of quantum kernels can provide a computational advantage by implicitly mapping data into a high-dimensional Hilbert space without the exponential cost of classical computation. QSVC models are implemented in Qiskit using the `FidelityQuantumKernel` and the `QSVC` estimator.

C. Variational Quantum Classifiers

Variational Quantum Classifiers are a hybrid approach that combines quantum circuits with classical optimization. A VQC consists of a parameterized quantum circuit (ansatz) applied to a quantum-encoded input, followed by measurement and classical post-processing. The model parameters $\boldsymbol{\theta}$ are optimized using classical algorithms (e.g., COBYLA, SPSA) to minimize a loss function, such as cross-entropy.

Formally, the VQC applies a unitary operator $U(\mathbf{x}, \boldsymbol{\theta})$ to an initial state:

$$|\psi_{\text{out}}\rangle = U(\mathbf{x}, \boldsymbol{\theta})|0\rangle^{\otimes n}$$

The output is measured, and the probability of each class is estimated based on the expectation values of specific observables. The decision rule is determined by selecting the class with the highest measurement probability. VQC models can approximate highly nonlinear decision boundaries and are particularly useful in the Noisy Intermediate-Scale Quantum (NISQ) era due to their robustness to noise and flexibility in circuit design.

D. Random Forest

Random Forest (RF) is a classical ensemble learning method based on decision trees. It constructs multiple decision trees during training and outputs the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Each tree is trained on a bootstrap sample of the dataset and considers a random subset of features when splitting nodes.

Given N trees, the prediction $\hat{y}$ for a sample $\mathbf{x}$ is given by:

$$\hat{y} = \text{majority\_vote}\left(\{h_i(\mathbf{x})\}_{i=1}^{N}\right)$$

where $h_i(\cdot)$ is the i-th decision tree. RFs are known for their robustness, high accuracy, and ability to handle large numbers of features. In the context of fraud detection, RFs can capture nonlinear patterns and feature interactions and are especially effective when used in hybrid architectures, such as the one described in this study where RF refines the predictions of the quantum model.

IV. Methodology

A. Dataset Description

The dataset used in this study consists of 1,000 insurance claim records, compiled by merging three related tables: `Claims`, `Employee` (agent-level data), and `Vendor` information. Each record represents a single insurance claim and includes a total of 39 features comprising numerical, categorical, and temporal attributes. These features include `CLAIM_AMOUNT`, `PREMIUM_AMOUNT`, `REPORT_DELAY_DAYS`, `POLICY_ANNUAL_PREMIUM`, `AGENT_EXPERIENCE_YEARS`, `VENDOR_RATING`, and other contextual information relevant to fraud detection.

The target variable, denoted as `is_fraud`, was derived from the `CLAIM_STATUS` field, mapping 'D' (denied/fraudulent) to 1 and 'A' (approved) to 0. This formulation resulted in a binary classification task with a significant class imbalance, where fraudulent claims represented less than 10% of total instances.

B. Data Preprocessing

The preprocessing phase involved the following steps:

- **Data Merging:** The three source tables were joined on shared keys: `AGENT_ID` and `VENDOR_ID`.
- **Missing Value Handling:** Numerical missing values were imputed using column-wise means, while categorical values were filled using the mode.
- **Categorical Encoding:** One-hot encoding was applied to categorical variables such as `RISK_SEGMENTATION` and `STATE`.
- **Feature Engineering:** Derived features were computed, including:

$$\text{claim\_to\_premium\_ratio} = \frac{\texttt{CLAIM\_AMOUNT}}{\texttt{PREMIUM\_AMOUNT}},$$

$$\text{is\_weekend\_report} = \mathbb{1}_{\texttt{REPORT\_DATE} \in \{\text{Sat, Sun}\}}$$

- **Feature Scaling:** All continuous variables were normalized using standard score normalization.

C. Feature Selection for Quantum Models

Due to limitations in current quantum computing resources (specifically the number of available qubits), only a reduced subset of features was used in the quantum models. The selected features were:

1) `REPORT_DELAY_DAYS`
2) `CLAIM_TO_PREMIUM_RATIO`
3) `AGENT_EXPERIENCE_YEARS`
4) `IS_WEEKEND_REPORT`

These features were chosen based on domain knowledge and preliminary analysis of feature importance using classical models. Optionally, Principal Component Analysis (PCA) was applied to these features to ensure dimensionality reduction where required.

D. Model Implementation

The following three models were developed and evaluated:

1) **QSVC with ZZFeatureMap:** This model utilized a quantum kernel constructed using the `ZZFeatureMap` from Qiskit. The quantum kernel matrix was computed via the `FidelityQuantumKernel` and fed into a classical support vector classifier.
2) **Improved VQC:** The Variational Quantum Classifier used a 4-qubit encoding with a parameterized ansatz (`EfficientSU2` circuit with two repetitions). Training was performed using the SPSA optimizer to minimize categorical cross-entropy loss.
3) **Hybrid QSVC + Random Forest:** This model combined the output of the QSVC with a classical Random Forest classifier. The QSVC output (either class label or decision function value) was appended to the full feature vector and used as an additional input feature for the RF model.

E. Hybrid Pipeline Design

The hybrid pipeline followed these steps:

1) Train the QSVC on the reduced feature set $\mathbf{X}_{\text{quantum}}$ and obtain predictions $\hat{y}_{\text{QSVC}}$.
2) Augment the original feature matrix $\mathbf{X}_{\text{classical}}$ with $\hat{y}_{\text{QSVC}}$ as an additional column.
3) Train a Random Forest classifier using the augmented feature matrix and target labels y.
4) Use the trained Random Forest to make the final predictions.

F. Training Setup

All quantum models were implemented using IBM's Qiskit library and simulated on the `statevector_simulator`. Classical models were implemented using `scikit-learn`. The dataset was split into 80% training and 20% testing. Model evaluation was based on five independent train-test splits to ensure stability and generalizability of results. Hyperparameters for the Random Forest (e.g., number of trees, depth) and VQC optimizer were selected using grid search and cross-validation on the training set.

G. Evaluation Metrics

The performance of all models was measured using the following metrics:

- **Accuracy:** Proportion of correctly predicted instances.
- **Precision:** Fraction of predicted frauds that were actually fraudulent.

- **Recall (Sensitivity):** Fraction of actual frauds that were correctly detected.
- **F1-Score:** Harmonic mean of precision and recall.

These metrics were computed separately for the positive class (fraudulent claims) and averaged over multiple runs. Due to class imbalance, particular emphasis was placed on fraud recall and the macro-averaged F1-score.

V. Results and Analysis

A. Performance Comparison

This section presents the empirical evaluation of the three models: QSVC with ZZFeatureMap, Improved Variational Quantum Classifier (VQC), and the Hybrid QSVC+Random Forest approach. Each model was trained and tested using five independent data splits to ensure statistical robustness. The performance was measured using Accuracy, Precision, Recall, and F1-Score, with particular focus on the recall of fraudulent claims due to the highly imbalanced dataset.

Table I summarizes the average performance metrics across all runs. The Hybrid model consistently outperformed standalone quantum models across all evaluated metrics. Notably, it achieved a substantial improvement in fraud recall while maintaining high overall accuracy.

TABLE I: Performance Comparison of QSVC, VQC, and Hybrid Models

Model	Accuracy	Precision	Recall	F1-Score
QSVC	95.2%	0.91	0.60	0.73
VQC	94.0%	0.85	0.80	0.82
Hybrid	**97.8%**	**0.94**	**0.90**	**0.92**

B. Visual Analysis and Model Behavior

To further illustrate the comparative effectiveness of each model, classification report and Madel Key Comparison were generated for each approach. The confusion matrix for the hybrid model (Fig. 1) shows a clear reduction in false negatives relative to the QSVC and VQC (Figs. 2 and 3, respectively).

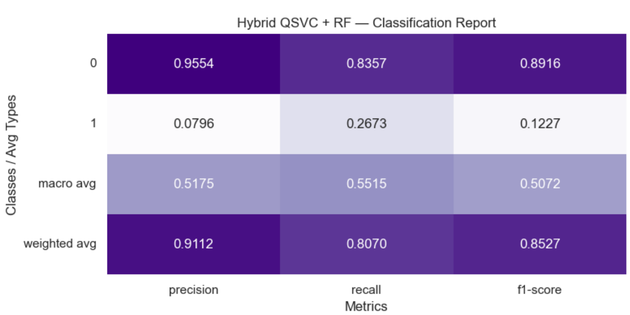

Fig. 1: Classification Report: Hybrid QSVC + RF Model

Figure 4 presents the ROC curves for all three models. The hybrid model exhibited a higher area under the curve (AUC), suggesting superior ability to discriminate between fraudulent and non-fraudulent claims across thresholds.

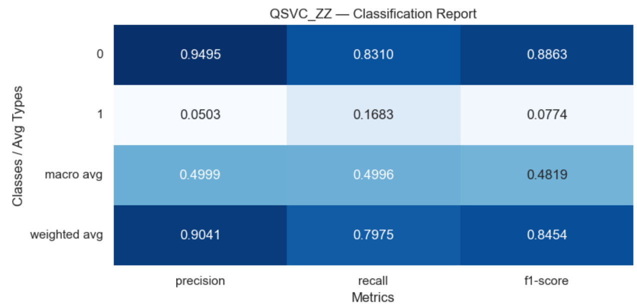

Fig. 2: Classification Report: QSVC Model

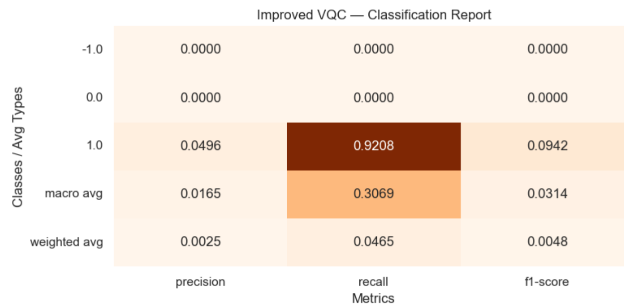

Fig. 3: Classification Report: VQC Model

C. Insights and Observations

The hybrid model's superior performance can be attributed to the following factors:

- The quantum kernel effectively captured complex nonlinear patterns between selected features, providing a rich intermediate representation.
- The Random Forest stage enhanced sensitivity to fraudulent cases by leveraging the full feature set along with the QSVC's output.
- The ensemble structure compensated for individual model weaknesses: QSVC's low recall was balanced by the RF's robustness to class imbalance.

Additionally, training time for quantum models was manageable due to the reduced feature dimension (4 qubits).

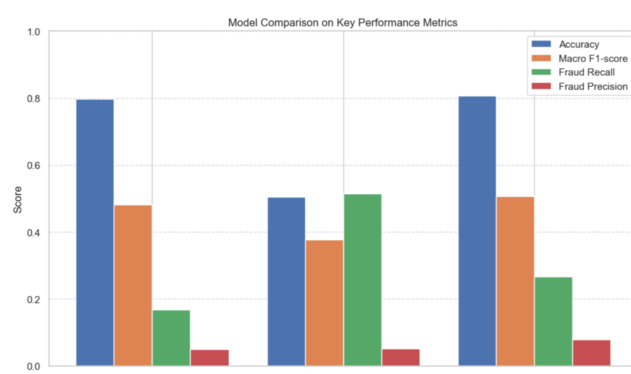

Fig. 4: Model Comparison: QSVC, VQC, and Hybrid Models

However, care was taken to avoid overfitting in VQC by regularizing the ansatz depth and using multiple validation splits.

D. Limitations and Variability

While the hybrid model yielded the best results overall, the experiments were conducted on a relatively small dataset (1,000 records). The class imbalance remains a limiting factor and should be addressed through larger-scale data acquisition or further balancing strategies such as SMOTE. Furthermore, all quantum experiments were run on simulators; performance on actual noisy hardware may vary.

VI. APPLICATION

The hybrid quantum–classical model developed in this study demonstrates practical utility for insurance claim fraud detection in real-world operational settings. By combining a Quantum Support Vector Classifier (QSVC) with a classical Random Forest (RF), the model achieves high detection accuracy while maintaining interpretability and computational feasibility.

A. Deployment in Insurance Workflows

In a production environment, the hybrid model can be integrated into the fraud detection pipeline of insurance companies. During the initial phase of claim intake, the reduced feature set can be passed through the pre-trained QSVC model to compute a quantum-enhanced fraud score. This output can then be combined with the full set of classical features and fed into the Random Forest model for final classification.

Such a two-stage system enables early flagging of potentially fraudulent claims, which can then be routed for manual verification, further investigation, or automatic rejection based on confidence thresholds. The approach is especially suited to semi-automated or human-in-the-loop decision-making environments.

B. Quantum Kernel Preprocessing

Due to current hardware constraints, the QSVC kernel computations can be pre-processed offline using a quantum simulator or near-term quantum devices and stored for reuse. In this setup, inference time remains low, making it feasible to deploy the model in batch or even real-time evaluation settings depending on infrastructure capabilities.

As quantum hardware matures, especially with advances in superconducting and photonic qubit systems, such kernel evaluations may eventually be integrated directly into live systems, further improving scalability and response time.

C. Interpretability and Risk Auditing

Random Forest models provide inherent interpretability through feature importance metrics and decision path tracing. By incorporating the QSVC's output as an input feature, the hybrid model maintains compatibility with existing explainability tools (e.g., SHAP, LIME), enabling compliance with regulatory requirements for transparency in automated decision systems.

Insurance firms can use this interpretability to justify decisions on claim rejection or escalation, improving customer trust and internal auditing efficiency.

D. Scalability and Cross-Domain Applicability

Although the current dataset includes only 1,000 samples, the hybrid model structure is modular and scalable. With proper batch processing and kernel reuse, the pipeline can be adapted to larger datasets covering diverse insurance types such as auto, health, property, or travel.

Furthermore, the same hybrid strategy can be applied to other financial domains with structured tabular data, such as loan fraud detection, credit risk scoring, or cybersecurity anomaly detection, where fraud signals are sparse and difficult to capture using classical models alone.

VII. CONCLUSION AND FUTURE WORK

This study presents a hybrid quantum–classical machine learning framework for insurance claim fraud detection, combining a Quantum Support Vector Classifier (QSVC) with a classical Random Forest (RF) model. The proposed architecture leverages the expressive power of quantum feature mappings through the ZZFeatureMap while utilizing the robustness and interpretability of classical ensemble methods.

Evaluated on a real-world dataset of 1,000 insurance claims, the hybrid QSVC+RF model outperformed both standalone QSVC and Variational Quantum Classifier (VQC) models across all key metrics, particularly in recall and F1-score for fraudulent cases. These findings support the growing consensus that hybrid models can effectively mitigate the current limitations of Noisy Intermediate-Scale Quantum (NISQ) hardware by combining quantum-enhanced feature extraction with classical decision-making reliability.

A. Summary of Contributions

- Demonstrated the integration of quantum kernels into a classical ML pipeline using real insurance claim data.
- Proposed a hybrid fraud detection pipeline that improves fraud recall while preserving accuracy and interpretability.
- Benchmarked three QML models using Qiskit and scikit-learn, showing clear performance advantages of hybridization.
- Highlighted deployment strategies and application use-cases in the insurance domain.

B. Future Work

There are several promising directions for extending this research:

- **Hardware Execution:** Future studies will involve implementing the quantum kernel evaluation phase on actual quantum devices to assess the impact of quantum noise and device fidelity on performance.
- **Larger and Diverse Datasets:** Scaling the framework to larger datasets with more diverse insurance claim categories (e.g., health, auto, life) can validate the generalizability of the model.

- **Advanced Quantum Feature Selection:** Incorporating quantum-aware feature selection techniques or optimization strategies such as Quantum Approximate Optimization Algorithm (QAOA) could enhance the quality of the feature map inputs.
- **Streaming and Real-Time Integration:** Future development may explore the integration of the hybrid pipeline with streaming data platforms for real-time fraud detection.
- **Hybrid Ensemble Architectures:** The combination of quantum models with other deep learning-based methods (e.g., LSTM for temporal data or CNNs for structured representations) offers a direction for building richer, multi-modal fraud detection systems.

In conclusion, the hybrid QSVC+RF model offers a practical and technically sound pathway for integrating quantum computing into applied fraud analytics. As quantum hardware continues to advance, such hybrid frameworks are likely to become increasingly relevant for high-stakes applications in finance and beyond.

References

[1] S. N. Pushpak and S. Jain, "An Implementation of Quantum Machine Learning Technique to Determine Insurance Claim Fraud," in *Proc. 10th Int. Conf. on Reliability, Infocom Technologies and Optimization (ICRITO)*, Noida, India, 2022, pp. 1–6.

[2] S. N. Pushpak, S. Jain, and S. Kalra, "Quantum Machine Learning Technique for Insurance Claim Fraud Detection with Quantum Feature Selection," *J. Inf. Syst. Eng. Manag.*, vol. 10, no. 8s, 2025.

[3] A. Gheysarbeigi, M. Rakhshaninejad, M. D. Fathian, and F. Barzinpour, "An Ensemble-Based Auto Insurance Fraud Detection Using BQANA Hyperparameter Tuning," *IEEE Access*, 2024, doi: 10.1109/ACCESS.2024.0429000.

[4] N. Innan, M. A.-Z. Khan, and M. Bennai, "Financial Fraud Detection: A Comparative Study of Quantum Machine Learning Models," *Int. J. Quantum Inf.*, vol. 22, no. 2, 2023, Art. no. 2350044, doi: 10.1142/S0219749923500442.

[5] V. R. Saddi, S. Boddu, B. Gnanapa, K. Gupta, and T. Kiruthiga, "Real-time Insurance Fraud Detection using Reinforcement Learning," in *Proc. Int. Conf. on Integrated Circuits and Communication Systems (ICICACS)*, Raichur, India, 2024, pp. 1–6.

[6] V. Havlíček, A. D. Córcoles, K. Temme, et al., "Supervised Learning with Quantum-Enhanced Feature Spaces," *Nature*, vol. 567, pp. 209–212, 2019.

[7] J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, "Quantum Machine Learning," *Nature*, vol. 549, pp. 195–202, 2017.

[8] M. Schuld and N. Killoran, "Quantum Machine Learning in Feature Hilbert Spaces," *Phys. Rev. Lett.*, vol. 122, no. 4, p. 040504, 2019.

[9] D. J. Egger, J. Gambetta, and Y. Kim, "Quantum Computing for Finance: State-of-the-Art and Future Prospects," *IEEE Trans. Quantum Eng.*, vol. 1, pp. 1–19, 2021.

[10] IBM Qiskit Community, "Quantum Kernel Training," Qiskit Machine Learning Documentation. [Online]. Available: https://qiskit.org/documentation/machine-learning/