Chapter 13
Quantum-Enhanced Smart Computing Framework for Sustainable Credit Risk Decision Communication

Shreyansh Jain
https://orcid.org/0009-0000-1693-5829
SRM Institute of Science and Technology, Ramapuram, India

Kshitij Chaudhary
https://orcid.org/0009-0002-4313-2751
SRM Institute of Science and Technology, Ramapuram, India

Samvardhan Singh
https://orcid.org/0009-0008-4911-6035
SRM Institute of Science and Technology, Ramapuram, India

Vitri Tundjungsari
https://orcid.org/0000-0003-2185-3486
Universitas Esa Unggul, Indonesia

Akarshak Bose
https://orcid.org/0000-0003-2402-0287
National Institute of Technology, Hamirpur, India

DOI: 10.4018/979-8-3373-3541-4.ch013

ABSTRACT

Recent advancements in smart computing and intelligent decision communication systems have enabled new possibilities for sustainable financial technologies. This chapter introduces a hybrid quantum classical model for credit risk prediction that leverages superposition and entanglement to enhance complex financial data processing. Unlike traditional machine learning models that struggle with class imbalance, nonlinear relationships and high dimensional dependencies, the system combines advanced preprocessing, feature selection and quantum kernel computation within a scalable support vector framework. Trained on 33,000 loan records across 12 borrower attributes, it achieves 94.53% accuracy, outperforming logistic regression, random forests, decision trees and CNNs. By improving decision accuracy and reducing default risk, the approach contributes to economic sustainability and responsible lending. The same quantum communication architecture can extend to healthcare, logistics and cybersecurity, aligning with the wider vision of smart technology for a sustainable future.

INTRODUCTION

Credit prediction forms a critical component of financial decision-making in the contemporary world that enables the lenders to determine the creditworthiness of borrowers and reduce the risks associated with loan defaults. With the growth of digital finance, the credit risk assessment today is performed on massive data volumes, i.e. the character of various borrowers is present: demographics, financial well-being, and behavioral portrait. In this study we consider a data containing approximately 33,000 loan records that are described on 12 significant parameters, including age, loan status, length of credit history, interest rate, loan grade, annual income, loan-income ratio, default history, tenure of employment, ownership of a home, loan purpose, and the loan amount. These variables provide a holistic base of creating prognostic models that will have the capacity to cater to the individual creditors and to large financial institutions.

Despite the importance of credit prediction, the functionality of the standard machine learning (ML) models faces certain barriers. First of all, financial data is usually imbalanced in terms of the number of classes: non-default loans significantly exceed the number of defaults. This asymmetry favours models to predict the majority group thus lowering their capacity to predict actual defaults. Second, financial data is not linear and might contain many variables that depend on each other: its complexity and nonlinearity pose a challenge to traditional non-linear algorithms like logistic regression or decision trees to detect subtle effects. Third, the dimensionality of financial data is very high, which raises the probability of overfitting and lowers scalability. These problems need sophisticated preprocessing, feature selection and dimensionality reduction algorithms.

Although oversampling, under-sampling, synthetic data generation (e.g., SMOTE), or dimensionality reduction (e.g., PCA) have been used to improve prediction, the shortcomings of classical ML are not eliminated. Specifically, the conventional algorithms cannot effectively capture the nonlinear relationships and work with big and multifaceted data. In order to eliminate such obstacles, this paper examines the revolutionary nature of quantum computing. In contrast to classical computing, bits are manipulated, whether as 0 or 1, quantum computing makes use of qubits in states of superposition and entanglement, and can permit simultaneous processing of large numbers of bits. It is its special property which allows quantum algorithms to unfold complex patterns and offer computational efficiency which classical algorithms do not offer.

Our proposal is the hybrid quantum-classical model of credit risk prediction combining the newest data preprocessing, feature selection, dimensionality reduction, and quantum computational principles. The model uses quantum interference, quantum circuits and quantum annealing to the disadvantages of the conventional ML techniques, improved predictive capability and scaling the model. Other healthcare, logistics, and cybersecurity fields and finance are also welcome to use this framework. Finally, the suggested model would result in the creation of more robust financial systems as it would facilitate the adequate identification of creditworthy borrowing individuals, reduce the default rates and establish a sustainable economic growth.

LITERATURE SURVEY

You might have heard or read that credit risk assessment is one of the key components of financial decision-making - and this has been drastically transformed with the introduction of machine learning (ML) and artificial intelligence (AI) and, most recently, quantum computing and cybersecurity applications. The replacement of traditional techniques by new computational techniques has attracted considerable research interest and issues of predictive performance, scalability, interpretability and robustness have been actively studied.

Machine Learning in Credit Risk Assessment.

Bhatore et al. (2020) proposed the machine learning-based credit risk assessment model and has used decision trees, SVM and neural networks. Their studies pointed to significant improvement among creditworthiness forecasting, but also creditworthiness forecasting issues in terms of information asymmetry and missuitness. Berhane et al. (2024) has contributed to this research further by allowing more leniency in hybrid models where the traditional statistical processes are mixed with ML and are quite applicable to online lending where timely and accurate decisions should be made.

Noriega et al. (2020) and Shi et al. (2022) focus on the systematic reviews of the use of ML in credit scoring in their articles, and the algorithms in question include logistic regression, random forests, deep learning, ensemble methods, and SVMs. Their analyses had shown that the state-of-the-art ML models are more efficient than the old tools, particularly with non-linear patterns and large amounts of data, but there are also generalizability and robustness issues in other financial contexts.

Among the models studied by Bhatia et al. (2017), KNN, decision trees, and SVM model are mentioned to have the capability to improve the reliability and accuracy of credit scoring. What they discovered is that asymmetrical data distribution is performance sensitive. On the same note, Chen (2023) did evolute an ensemble machine learning approach, in which different algorithms are combined to provide a higher level of robustness and predictive accuracy, albeit not in a very computationally efficient manner.

Yang (2024) focused on the concept of applying ML to peer-to-peer (P2P) lending and demonstrated how ML algorithms improve the capability to forecast default and risk in a decentralized environment. Explainability and fairness, though, did emerge as areas for concern. Aranha and Bolar (2023) have gone further to discuss artificial neural networks (ANNs) to explain complex non-linear associations in financial data. Their results highlighted the advantages of deep learning, and also reaffirmed the issue of interpretability and the black box quality of neural models. In their comparative research, Wang et al. (2020) used ML algorithms (ensemble models, SVMs, decision trees) and ensured that ML was always more accurate and robust than other traditional statistical processes.

The innovations in fintech, the capabilities of big data, and other alternative data sources are changing, as mentioned by Espinoza and Ygnacio (2023), the way credit risk is modeled. A previous study of AI application in financial risk management (Chen, Ribeiro, and Chen, 2016) has already shown that AI models can and in fact can improve the precision of forecasts and tailoring to the specifics of the borrowers, albeit with some degree of anxiety about the biases, explainability, and ethics.

Quantum Computing in Financial Risk Modeling.

A new promising solution to the computational and dimensionality problems in credit risk assessment is quantum computing. Egger et al. (2020) were some of the first to describe quantum algorithms in the area of finance and specifically looked at the improved efficiency and accuracy of credit risk analysis. Going on that, Sri et al. (2020) proposed the schemes of introducing quantum technologies to large-scale loan appraisals, and there they believed there would be a scaling advantage.

The Adegbola et al. (2024) article discussed the prospect of quantum computing revolutionizing financial risk management and provided theoretical advantages of the speed and scalability of this system. Bova, Goldfarb, and Melko (2021) and Orus, Mugel, and Lizaso (2019) investigated the business and financial applications of quantum computing and demonstrated how the latter can solve complex datasets and optimization problems that are not accessible to the classical systems.

Egger et al. (2020) and Herman et al. (2023) talked about the application of quantum computing to determine portfolio optimum and derivative prices and in estimating credit risk and also posted hardware limitations that currently limit usability. Orus, Mugel, and Lizaso (2019) also discussed the application of quantum computing to financial crash prediction, where they demonstrated the prospects of early warning systems that heavily relied on the analytical modeling of systemic risks.

Krumnow et al. (2023) explored quantum solutions to financial risk measurement, such as Value-at-Risk (VaR) and counterparty credit risk, but also found the trade-offs between model assumptions and practical implementation on near-term quantum devices. How and Cheah (2023) suggested a hybrid quantum-classical neural network to score credit for SMEs, achieve efficiency improvements during training, and admit that it depends on simulated environments. Dri et al. (2023) generalized the existing models to multiple risk factors and real-valued loss-given-default with validation on IBM Quantum Experience.

The convergence of AI and quantum computing is a critical review proposed by Atadoga et al. (2024) and stated that this fusion will contribute to greater predictability and risk management. Nevertheless, they also added that there was no empirical robustness testing especially on heterogeneous datasets.

Cybersecurity and Cloud-Based Financial Systems

As financial risk assessment models are progressively implemented on a cloud-based system, cybersecurity is currently viewed as a critical issue. Insider threats, API vulnerabilities, and data breaches were identified by Singh and Kaushik (2023a), and real-time monitoring and AI-enabled defenses of cloud infrastructures were emphasized. Singh and Kaushik (2023b) have also revised the developments in the area of cybersecurity and presented quantum cryptographic methods, such as quantum key distribution (QKD), as safe solutions to the protection of sensitive financial information in AI- and quantum-enhanced systems.

This theme has been strengthened by complementary research. As an example, Chaudhary et al. (2024) suggested cryptographic improvements to the digital signatures, and Joshi et al. (2025) reported on security in both the IoT and multi-agent financial systems, and on the increased relevance of distributed architectures in finance.

Synthesis and Gaps

Collectively, these studies demonstrate that machine learning (ML) and artificial intelligence (AI) can enhance predictive accuracy, quantum computing holds promise for improved scalability and optimization, and cybersecurity systems play a vital role in safeguarding data-driven financial infrastructures. However, several critical gaps remain. Many approaches lack robust testing and cross-validation across diverse datasets, limiting their generalizability. Challenges related to explainability, fairness, and the ethical application of AI in financial decision-making persist. Additionally, the high computational demands and scalability issues pose barriers to real-world implementation. Furthermore, there is a noticeable lack of integration of regulatory frameworks and perspectives in the development of quantum- and AI-based financial models.

The limitations mentioned above demonstrate the importance of future studies that would combine strong validation practices, ethical and explainable AI approaches, and adherence to the updated regulatory frameworks into the next-generation credit risk assessment models.

METHODOLOGY

Methodology Overview

The methodology adopted in this study integrates quantum computing with classical machine learning in order to address the long-standing problem of credit risk prediction. Conventional statistical models such as logistic regression and decision trees, though widely applied in banking, often fail to capture the intricate, nonlinear interactions present in borrower characteristics and financial indicators. Quantum computing, in contrast, offers the ability to map classical data into a high-dimensional Hilbert space where complex relationships become more tractable.

By embedding financial attributes into quantum states and constructing a quantum kernel, we enrich the feature representation before passing it to a Support Vector Machine (SVM) classifier. The hybrid approach harnesses the representation power of quantum computing while relying on the robust optimization framework of SVMs.

The methodology is structured into three main phases. The first phase, Data Preprocessing, focuses on ensuring the quality, completeness, and normalization of the dataset to prepare it for quantum processing. In the second phase, Quantum Kernel Computation, classical features are encoded into quantum states, and a quantum similarity kernel is constructed to capture complex, high-dimensional relationships between data points. Finally, the SVM Integration phase uses this quantum-enhanced kernel within a Support Vector Machine to classify loan default risk, leveraging the expressive power of quantum feature spaces for improved predictive performance.

Dataset Description

The study utilizes a credit risk dataset comprising 32,581 loan applicant records after cleaning, with each record described by 12 attributes. The dataset, sourced from a standard financial repository, includes a mix of demographic, financial, and credit history variables. A detailed breakdown of the features is provided in Table 1.

Table 1. Dataset overview

Feature	Description	Type	Missing Values (Pre-Imputation)
person_age	Age of borrower	Numerical	0
person_income	Annual income (USD)	Numerical	0
person_home_ownership	Home ownership status	Categorical	0
person_emp_length	Employment length (years)	Numerical	895
loan_intent	Purpose of loan	Categorical	0
loan_grade	Creditworthiness grade	Categorical	0
loan_amnt	Loan amount (USD)	Numerical	0
loan_int_rate	Loan interest rate (%)	Numerical	3116
loan_status	Default flag (1 = default, 0 = non-default)	Target	0
loan_percent_income	Loan as % of income	Numerical	0
cb_person_default_on_file	Historical default (Y/N)	Categorical	0
cb_person_cred_hist_length	Credit history length (years)	Numerical	0

The dataset is representative of typical loan applications, providing a suitable testbed for exploring quantum-enhanced financial analytics.

Data Preprocessing

Importance of Preprocessing

Quantum models are highly sensitive to noise, scaling disparities, and missing entries. Unlike classical algorithms, where some robustness is inherent, quantum circuits require carefully prepared input data. Preprocessing therefore plays a critical role in ensuring model stability and fairness.

Handling Missing Values

The raw dataset contained missing entries in employment length and interest rate fields. Discarding these would reduce the dataset size by nearly 10%, potentially biasing results. Instead, mean imputation was applied using equation 1, preserving distributional properties while ensuring completeness. This yielded a cleaned dataset of 32,581 records.

$$X_{\text{imputed}} = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{1}$$

Normalization of Features

Features such as income and loan amount span vastly different ranges (e.g., \$20,000–\$200,000 vs 1–40 years of employment). To prevent dominant scaling effects, Min-Max normalization was applied using equation 2, mapping values to the [0,1] range. Normalization is particularly important for quantum embedding, where rotation angles are bounded by 2π.

$$X' = \frac{X - min(X)}{max(X) - min(X)} \tag{2}$$

Encoding of Categorical Variables

Categorical features (loan_grade, loan_intent) were transformed via one-hot encoding using equation 3. This representation avoids artificial ordinality and ensures categorical features are compatible with quantum encoding.

Loan Grade (A,B,C) = [1,0,0], [0,1,0], [0,0,1](3)

Quantum Kernel Computation

Motivation

Kernel methods are central to machine learning because they implicitly map data into higher-dimensional spaces where linear separation is possible. Classical kernels (linear, polynomial, RBF) are effective but may struggle with highly entangled, nonlinear relationships. A quantum kernel, however, naturally arises from the inner product of quantum states, enabling richer representations beyond classical capabilities.

Feature Embedding

Each borrower's feature vector was embedded into a quantum state using Angle Embedding using equation 4. Here, normalized features directly modulate the rotation angles of qubits. For example, income and loan amount become rotation parameters applied to RX and RZ gates. This ensures every classical record has a quantum representation.

$$\left|\phi\left(x\right)\right\rangle = \prod_{i=1}^{n} RX\left(x_i\right)|0\rangle \otimes n \tag{4}$$

Variational Layers and Entanglement

After embedding, the states pass through variational quantum layers composed of parameterized rotations and entangling CNOT gates using equation 5. Entanglement introduces correlations between features, allowing the circuit to capture complex interdependencies (e.g., the joint effect of income and credit history).

$$\mathrm{U}(\theta) = \prod_{i=1}^{n} \left[\mathrm{CNOT}\left(\mathrm{q_i}, \mathrm{q_{i+1}}\right) \cdot \mathrm{Rx}\left(\theta_i^x\right) \cdot \mathrm{RZ}\left(\theta_i^z\right)\right] \tag{5}$$

Kernel Matrix Construction

The similarity between two borrowers is computed as the fidelity between their quantum states, estimated by expectation values of Pauli-Z operators using equation 6. For a dataset with *m* samples, this yields an $m \times m$ kernel matrix using equation 7. Each entry measures the quantum similarity between two applicants, forming the basis for SVM classification.

$$K(x_i, x_j) = |\langle\varphi(x_i)|\varphi(x_j)\rangle|^2 \tag{6}$$

$$K_{ij} = K(x_i, x_j) \tag{7}$$

The quantum kernel was implemented using PennyLane's lightning qubit simulator, enabling efficient emulation of circuits with up to 12 qubits.

SVM Integration with Quantum Kernel

Support Vector Machines (SVMs) are highly applicable in kernel-based classification, because they are capable of identifying optimal decision boundaries in transformed feature spaces. In this scheme, training of the SVM was done with a quantum kernel matrix - representing the inner products of data in a quantum feature space. The purpose was to maximize the difference between the number of default and non-default cases by minimizing the hinge loss plus a regularization term as expressed in Equation 9. After training, the SVM classifies the new applicants using the trained hyperplane on the basis of the quantum-transformed features as given by the decision function in Equation 10.

$$\min_{w,b} \frac{1}{2} ||w||^2 + C \sum_{i=1}^{n} \max\left(0, 1 - y_i\left(w^T(s_i) + b\right)\right) \tag{9}$$

$$f\left(s\right) = \text{sign}\left(\sum_{i=1}^{m} \alpha_i y_i K\left(s, s_i\right) + b\right) \tag{10}$$

The combined workflow is such that the quantum elements supplement the feature space, whereas classical optimization stabilizes the learning process.

Ethical Considerations, Explainability, and Regulatory Challenges

Ethical implications and regulatory standards have great importance in the application of high-order AI models development in financial risk evaluation. Although this paper centers on predictive accuracy, the application of such a system needs an extensive system of fairness, transparency, and security. Algorithmic Fairness and Bias: Any credit risk model has the potential to reproduce or potentially increase the existing bias in society in historical data. Thorough bias audits are very important to make sure that the model does not discriminate against the protected groups unfairly on the basis of demographics. These risks should be addressed by introducing fairness-aware methods of machine learning in future work. Explainability and Transparency: The black box quality of complex models such as quantum kernels is a big challenge to regulatory compliance (e.g., the right to explanation in GDPR). Although the SVM component is highly interpretable, the quantum feature mapping is not theoretically interpretable. Post-hoc explanations might be adapted by methods such as SHAP (SHapley Additive explanations) or LIME (Local Interpretable Model-agnostic Explanations) to make decisions of the model more transparent to stakeholders and regulators. Data Privacy and Security: The model handles very sensitive personal and financial information and thus, solid security is absolute. All data pathways, including storage and preprocessing and calculation on a classical or quantum computer must be: kept secure from illegal use and cyber-attack to ensure integrity and confidentiality of the data, the cryptographic practices of state of the art, including the advanced encryption standard and the administration of the keys (Chaudhary et al. 2024). Quantum cryptography will be a required area. In particular, it will be important to ensure data security when quantum technologies mature (Singh and Kaushik,2023a). Further, the use of these models, particularly in cloud, requires thorough security threats and the implemented measures to counteract them (Joshi et al., 2025; Singh and Kaushik, 2023b). These ethical, explainability, and security needs can be proactively addressed so that the quantum enhanced variants of financial models can be built and applied in a responsible way, building trust and developing regulatory compliance.

Architecture Diagram

Figure 1. Workflow architecture

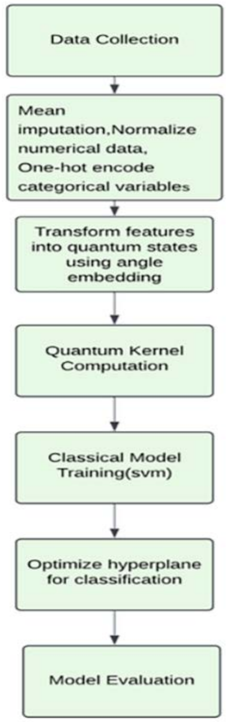
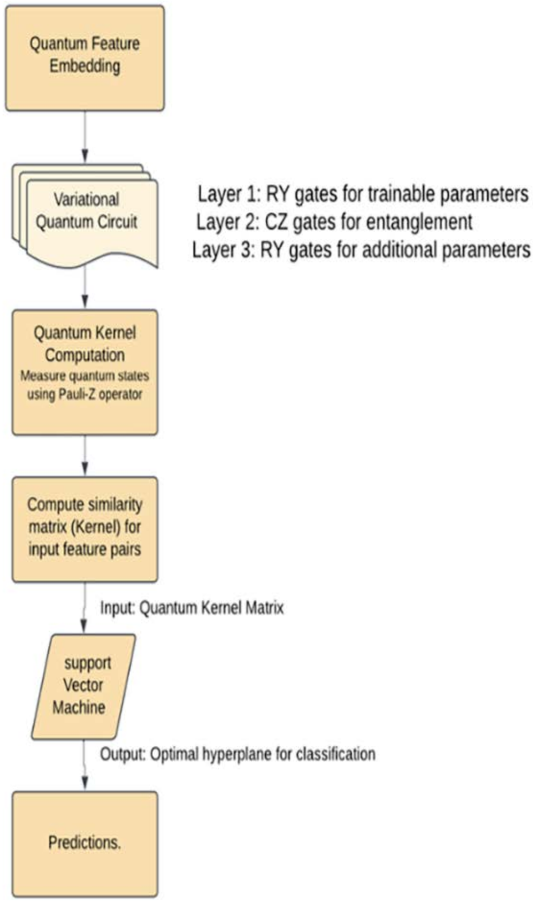


Figure 2. Flowchart of quantum architecture



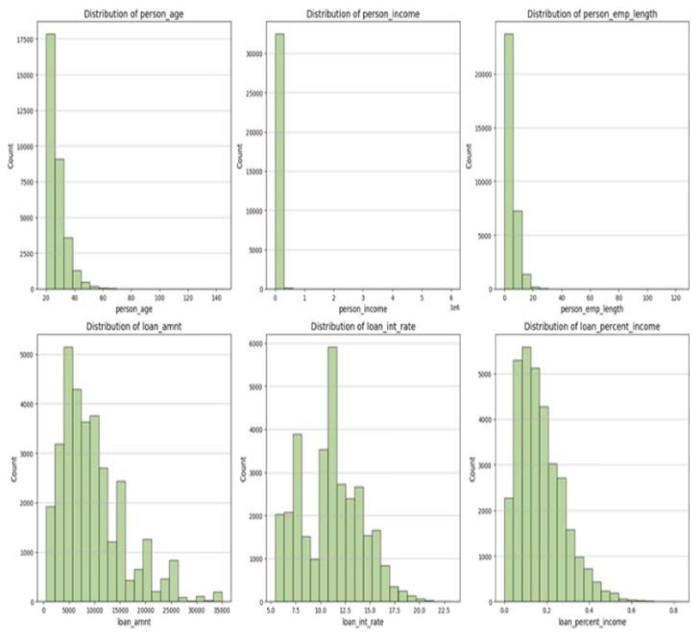
EXPERIMENTAL SETUP

One of the most important aspects to training a machine learning model is a high quality dataset with the right data points in coordination with the problem statement. For the purpose of creating a credit risk prediction model, we downloaded a full dataset from Kaggle which is a well-known source for datasets. These data points comprise a number of attributes that are vital to credit risk identification, including loan size, employment duration, interest rate, loan grade, and loan purpose that collectively determine the terms of a loan. Moreover, the length of credit history and previous default are also interesting ways of knowing risk assessment and the status of loan (1 = default, 0 = non-defaulter) and the fractions of income paid for loan repayment are direct factors of loan repayment ability. As our quantum-classical hybrid model is trained, we would assign the output feature (our variable of interest to be predicted). The loan status is important to understand and data visualization was to aid in better understanding the dataset. Techniques using some of the most popular Python packages, including Pandas, Matplotlib and Seaborn Through these tools we were able to visualize the data and derive some facts about the: structure, distributions and connectedness of what was there. Following this initial exploratory study, an Advanced preprocessing pipeline was used on the dataset that involves sophisticated high-dimensional quantum representations (HDRQRs) to find complex representations of features. This feature PennyLane helps make the process of extracting the entanglement simpler by:A quantum compatible classical data encoding was simulated for the lightning.qubit device. In order to make the dataset ready for model training, we used the train_test_split() function from the sklearn.model_selection module to divide the dataset into training and test pieces. Time consuming nature of quantum computations even on classical hardware, and lack of support of GPU acceleration in PennyLane among other significant computation constraints made training the model with the complete dataset problematic. Consequently, we have decided to only use a subset of the dataset for both the training and testing phases to control the computational needs efficiently. This limitation however did not curtail the quantum embeddings generated in preprocessing being fed into a effective classical machine learning model, SVM, using sklearn.svm.SVC() class. This classical SVM model utilized the features extracted by the quantum to provide credit risk predictions that integrated quantum feature extraction capability with the rugged features of classical machine learning.

RESULT AND DISCUSSION

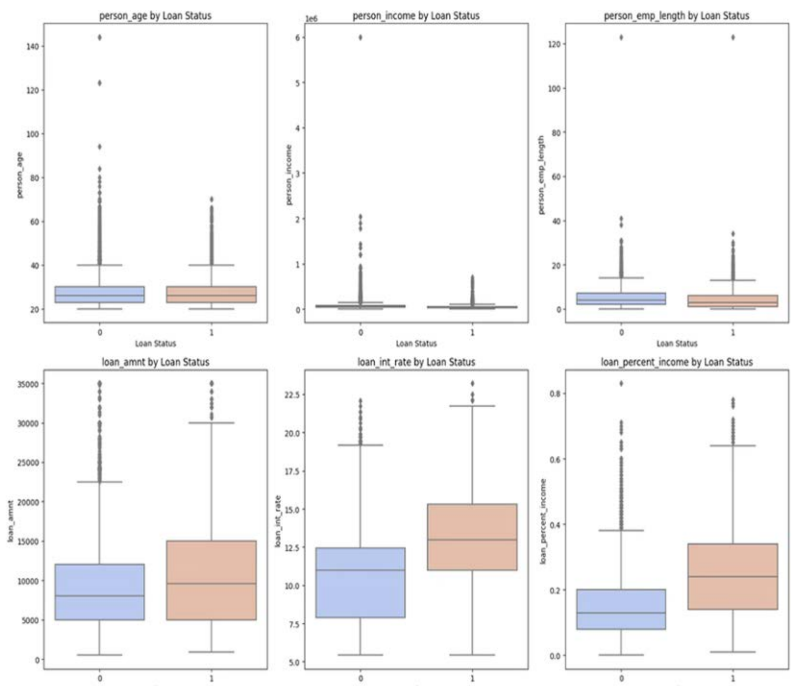
In order to estimate the efficacy of our suggested quantum-classical hybrid model, we have conducted an extensive performance evaluation concerning a group of conventional and contemporary machine learning methods. For this purpose, the dataset and its size was about 33, 000 data points, and each of these data points had 12 distinct features providing a detailed representation of the underlying data. To further visualize the dataset and show the most desirable data preparation to be employed in the modelling we start by developing a line of visuals, i.e. plots of distributions of main variables, i.e. Age, Employment Length, Income, Interest Rate, Loan Amount and Loan to Income Ratio. These visualizations had a highly significant role in identifying patterns of meaning, outliers and trends in data. Such inferences are required in solving the behavioral pattern of the borrowers as they establish significant relationships and anomalies that may affect performance of the models. As an example, the distribution plots helped us to infer the variability and skewness of the features and our preprocessing and feature engineering steps were based on this inference. To be more exact, figure 3 contains a summary of the borrower's behaviour, an overview of the most prominent sources of the borrowing patterns. These preparatory analyses have given us a good foundation to continue with the modelling step in the sense that by implementing our quantum-classical hybrid approach to our data, we were operating on well-understood data, and structured data.

Figure 3. Borrower behavior insights via plots



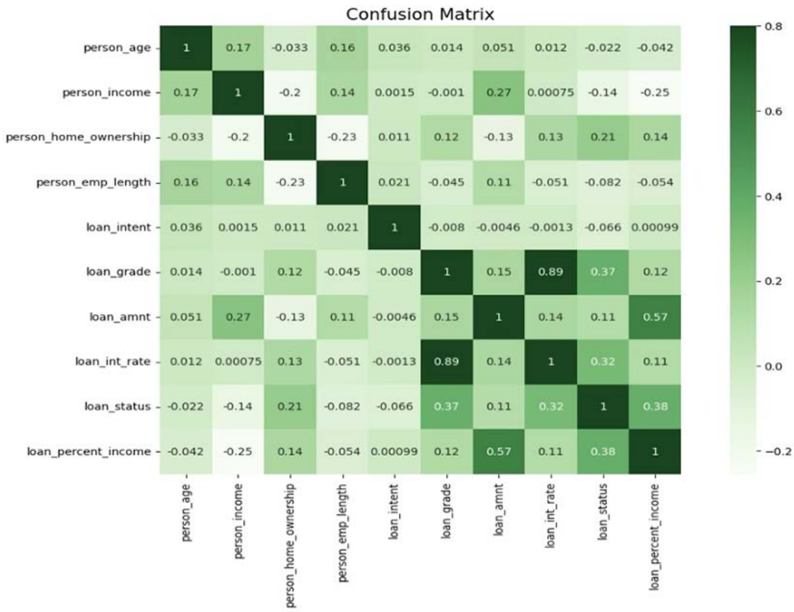
To proceed with the analysis of the dataset and identify the correlations between borrower characteristics and loan performance, the distributions of the variables, such as Age, Employment Length, Income, Loan Amount, Loan-to-Income Ratio, and Interest Rate of various loan statuses were compared using the boxplots. This trend, central tendency and possible outliers of each feature across loan status categories enabled the boxplots to help in the identification of meaningful trends, differences and outliers of the borrower characteristics. For example, they established the level to which a particular characteristic like a high income or a long tenure of employment was related to a particular outcome of a loan and these are the insights, which helped them later, to advance our modeling methodology. The full visual example of the difference in borrower attributes depending on the loan statuses is pictured in Figure 4, where these boxplots are shown: a clear and simple summary of the relations between all pairs of variables. Also, to visualize the interdependencies of all the features of the dataset, we used the heat-map to present the correlation matrix (that measure relations between all pairs of variables). This heatmap has stronger correlations between features colored in darker green, weaker or even negative correlations captured by lighter or contrasting colors. This visualization allowed the critical understanding of the degree of association between the variables according to which Income, Loan Amount or Loan-to-Income Ratio and Interest Rate are strongly correlated with one another positively or negatively. Knowledge of these interconnections is important for making appropriate feature selection because highly correlated features may lead to redundancy and weakly correlated ones may provide unique information to the model. Moreover, the insights in the correlation were used to develop our quantum-classical hybrid model since the insights could help us understand what features are most likely to influence borrower behavior and loan outcomes. The reason why the heatmap was considered a potent instrument of revealing the underlying structure of the data was to develop a more efficient model and optimization.

Figure 4. Boxplots for borrower attribute analysis



The quantum-classical hybrid model was written using the ‘ Pennylane ’ framework with particular emphasis on using the lightning.qubit device simulator of Pennylane. This simulator offered a sound and effective framework on which the quantum circuit could be created and executed successfully so as to enable the taking into account and integration of numerical information with ease with regard to a quantum computing environment. An important step of this work was the transformation of traditional data into quantum embeddings which are highly developed, which multiplied the complexity and the scope of representation of the dataset by far. These quantum embeddings, which were characterized by the ability to capture complicated non-linear relationships, which are present in the data, turned out to be excellent training material in the future of classical machine learning. In particular, the quantum embeddings were executed into a Support Vector Machine (SVM) Classifier with the help of the component sklearn.svm.SVC() of scikit-learn package. This quantum pre-processing-classical classification combination constructed a combined framework that was highly effective in detecting patterns of non linear and high dimensional data, hence enhancing the accuracy of credit risk forecasts..A heatmap, illustrated in figure 5, was applied to visualize the correlation matrix of the features of the dataset in order to further support the development process of the model. This heatmap gave a clear visual interpretation of the relationships and dependencies between the variables with colors being green, indicating strong nature of correlations, and other, weaker or negative, correlations present in lighter color tones. Such a visualization was crucial in understanding how features interact with one another and provided critical insight as to what features should be chosen for the process. With the heatmap to assign importance to useful features, the model became predictively robust and efficient, using a subset of features that was well optimized. With the lightning.qubit simulator, the quantum circuit enabled the efficient calculation of complex quantum interactions, and with SVC() module from sklearn provides a suitable, high-optimizing, and computationally low-cost way to determine the result of a loan, e.g. high and low risk. Such a combined approach could not only achieve a high predictive performance but also claimed the transformational capability of integrating quantum computing techniques with mainstream machine learning techniques.

Figure 5. Heatmap of dataset correlations



The quantum-classical hybrid algorithm seeks to find an optimal hyperplane that can effectively sort information points into distinct classes with maximum possible distance between the classes as much as possible resulting in improved classification performance. This model reached an excellent accuracy of 94.53% on the dataset, greatly exceeding multiple other general and modern machine learning techniques applied to the same data. In particular, competing models – Logistic Regression, SVM, KNN, Decision Tree, Random Forest, CNN and ANN, provided accuracies of 84.00%, 86.40%, 88.50%, 88.00%, 92.10%, 92.09% and 81.90% The outstanding performance of the quantum-classical model indicates its outstanding ability to identify complex non-linear connections in dataset mainly due to quantum-enhanced feature spaces that allow more subtle data representations. The major benefit of this hybrid method is in its novel use of quantum kernels, which significantly expand the feature space by revealing sophisticated relations between variables that many classical models tend to miss. This quantum-enhanced feature engineering enables the model to more appropriately describe the structure of data hence improving its predictions. Furthermore, the quantum model displays exceptional computing efficiency when working with high dimensional datasets thus improving both predictive accuracy and scalability significantly. Such characteristics render the hybrid model a very robust and convenient solution for real-world problems like credit risk prediction, which requires accurate and reliable classification. Table 2 shows a break-down comparison of all evaluated models' accuracy scores, in terms of percentage of correct predictions. Results clearly show the Proposed Quantum-Classical Model recorded the highest level of accuracy at 94.53%, which shows an improvement with respect to other methods. The Convolutional Neural Networks and the Random Forest models followed in second and third place respectively with maximum accuracies of 92.09% and 92.10%. Other models, Decision Tree (88.00%), KNN (88.50%), had average performance whereas Logistic Regression (84.00%) and SVM (86.40%) had relatively lower accuracies. The ANN was the most ineffective and the accuracy was 81.90%. The findings highlight the capability within quantum-classical models to take advantage of quantum computing capabilities to enable more predictive performance over classical methods and establish a new standard in credit risk assessment activities.

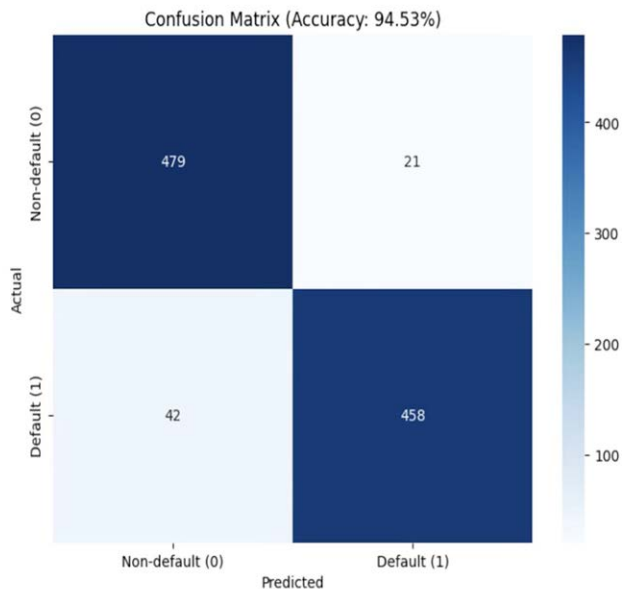
Table 2. Detailed performance comparison on accuracy basis

Model	**Accuracy(%)**
Logistic Regression	84.00
Decision Tree	88.00
Random Forest	92.10
SVM	86.40
KNN	88.50
ANN	81.90
CNN	92.09
Proposed Quantum Classical Model	**94.53**

To further evaluate the work of our quantum-classical hybrid model, detailed statistical measurements are provided in the form of classification report and the confusion matrix so that to understand its predictive capabilities better. The confusion matrix is a report on the model predictions in terms of comparing actual results and prediction results to comment more specifically on model performance in as far as the multiple classes are concerned. The model was able to predict 479 data as Non-default and was not able to predict 42 data as default. The structure identified the 458 data as Default and only 21 data points as Non-default in the case of the Default class. This failure indicates that the model could classify two classes with high levels of accuracy and also demonstrate the areas where the model misclassified and this can be utilized to improve the model.

This comparison of actual and predicted results is graphically illustrated in figure 6 in which a confusion matrix is provided which gives a simple and easy to understand overview of model performance. The confusion matrix does not just give the frequency of right predictions (or true positives and true negatives), but it gives the extent of misclassification (or false positives and false negatives) which should allow fully analyzing the strengths and weaknesses of the model.

Figure 6. Confusion matrix



Precision, Recall and F1-score provides an explicit yet subtly refined view of the model effectiveness in various classes. These measures were especially informative in terms of assessing performance of a model on the Default set, which is most important in the prediction of credit risk. We have provided a complete comparison of these performance metrics of all the models tested in Tables 2, 3 and 4, which are Logistic Regression, SVM, KNN, Decision Tree, Random Forest, CNN, and ANN. The findings clearly showed that the suggested quantum-classical hybrid model clearly outperformed all other models, based on these metrics, and thus highlights the model as having a high capacity to deal with the complexities of the dataset.

Table 2, in particular, addresses the Precision metric, which determines the correctness of the positive predictions, the percentage of the correctly recognized positive cases in comparison to the prediction of positive cases. The metric plays a very important role in the interpretation of the reliability of positive classifications of a certain model, especially in the situation of default (1) cases in credit risk modelling. The proposed Quantum-Classical Model had the highest precision scores in both classes with a score of 0.92 in the Non-Default (0) and a very impressive

0.96 in the Default (1) classes, beating all other models. Random Forest and CNN are other models that showed high scores in the aspect of precision, which depicts their strength in making positive predictions. Nevertheless, ANN and other models achieved the lowest precision scores, which implies that they carried more false positives and less predictive values. These findings, as shown in Table 3, represent the extraordinary accuracy of the quantum-classical model, which is explained by its capacity to use quantum-enhanced feature spaces to understand the characteristic data patterns, which is why it becomes an exceptional solution to credit risk prediction problems. understand characteristic data patterns, which makes it a superior solution to credit risk prediction problems.

Table 3. Detailed performance comparison on basis of precision score

Model	**Precision Score**	
	Non Default (0)	**Default (1)**
Logistic Regression	0.85	0.83
Decision Tree	0.89	0.86
Random Forest	0.91	0.94
SVM	0.86	0.86
KNN	0.88	0.87
ANN	0.80	0.81
CNN	0.91	0.93
Proposed Quantum Classical Model	**0.92**	**0.96**

Table 4 lists the comparative recall scores over two classes – Non-Default(0) and Default(1) for distinct predictive models. The Proposed Quantum-Classical Model comes as the best, recording an almost perfect recall of 0.96 for the Non-default (0) class, the model correctly predicted 479 records but incorrectly classified 42 records as Default (1). These results have shown that model superior ability to accurately classify positive cases in both classes and this is highly effective in predicting credit risks. The high recall of Non-Default cases demonstrates that the model is effective in the identification of loans, which are not at risk of default, whereas the high recall values of the Default cases help to isolate the high-risk loans that may be redirected into a safer alternative therefore helping to make sound financial decisions. Comparison of the model with other models like CNN and Random forest, they too record good values in the recall values of the two classes but fail to compete with the remaining values left behind by the Proposed Quantum-Classical Model. Conversely, the Artificial Neural Network (ANN) has the lowest Recall on both

Non-Default (0) and Default (1) classes; this implies that ANN has a weak ability of differentiating the two classes. The fact that high recall scores at both balanced and high recall proposed the Quantum-Classical Model presents high quantum embeddings and classical ML combination which can effectively extract complex data patterns justifies the fact that it is an effective technique in which financial institutions that intend to minimize the default loan risks along with maximizing the lending loans should be used. These results strongly prove the rest of the potential of hybrid quantum-classical methods to enhance the accuracy of prediction and to increase sustainable finance.

Table 4. Performance comparison on basis of recall score

Model	**Recall Score**	
	Non Default (0)	**Default (1)**
Logistic Regression	0.83	0.85
Decision Tree	0.85	0.90
Random Forest	0.94	0.91
SVM	0.86	0.86
KNN	0.87	0.88
ANN	0.81	0.80
CNN	0.93	0.91
Proposed Quantum Classical Model	**0.96**	**0.92**

Table 5. Performance comparison on basis of F-1 score

Model	**F1 Score**	
	Non Default (0)	**Default (1)**
Logistic Regression	0.84	0.84
Decision Tree	0.87	0.88
Random Forest	0.92	0.92
SVM	0.86	0.86
KNN	0.88	0.88
ANN	0.81	0.80
CNN	0.92	0.92
Proposed Quantum Classical Model	**0.94**	**0.94**

A detailed comparison of the F1 scores of Non-Default (0) and Default (1) classes of all the considered models, using which it is important to discuss the balance between precision and recall, is given in Table 5 assess the overall effectiveness of classification models in credit risk prediction. F1 score being a harmonic mean of both precision and recall provide a powerful indication of how a model can correctly classify both a positive and negative case with minimum trade-offs between false positives and false negatives. The proposed Quantum-Classical Model scored the highest in this area with the F1 score of 0.94 in both Non-default and Default classes illustrating its remarkable ability to deal with both default and non-default cases with very high levels of accuracy and reliability. The high performance of the model highlights the capabilities of the quantum-enhanced feature spaces to identify the complex patterns of data, with both classes obtaining F1 scores of 0.94 that demonstrate the high and stable results in both default and non-default cases. Other models, including Random Forest and CNN, also showed the high performance level as both classes received F1 scores of 0.92. Competitive as they were, these models were marginally outperformed by the quantum-classical hybrid model, indicating the favoritability of the latter in terms of maximizing the precision recall trade-off. On the other hand, the Artificial Neural Network (ANN) exhibited the lowest F1 scores among all the models being tested, signifying that the model is not performing well in the aspects of precision and recall, thus, making its predictions of the two classes less reliable. The results presented in Table 4 can be used to highlight the power of the quantum-classical model along with its future in terms of credit risk measurement, and the trade-off between the possibility of discovering true positives and minimizing errors is where the need to be.

CONCLUSION

In this paper we design and validate a powerful quantum classical hybrid model to overcome the issues of credit risk forecast which have been persisting. Our approach takes advantage of the principles of quantum computation, in particular the power of superposition and entanglement for navigating high dimensional and nonlinear data, to give a substantial improvement over purely classical approaches. Our quantum kernel-based approach combined with classical machine learning was very successful. Our model was able to attain a respectable predictive accuracy of 94.53%, something that is significantly better than a bunch of popular algorithms such as Logistic Regression, Random Forests, Decision Trees, or even deep learning models like CNNs. This enhanced performance is not just a minimal step up; it's a prestigious proof of quantum-boosted machine learning capability in extracting complex patterns in financial data that are unavailable to traditional systems. Overall, this research has discovered that quantum computing has the potential to transform credit risk assessment by delivering more accurate, reliable, and scalable solutions. The relevance of this work is beyond credit risk. This hybrid model serves as a conceptual framework, laying a viable path for the integration of quantum technologies into the larger landscape of financial modeling. It highlights the transformative power that quantum computing holds in improving decision-making and risk management throughout the financial sector. While these findings are promising, it's important to remember that quantum computing is still in its early stages of development. Further progress in quantum algorithms and in hardware infrastructure is required to make the practical large-scale implementation of such models feasible. However, future efforts should be devoted to breaking the current hardware bottlenecks and validating these models in more varied and larger datasets in order to ensure robustness. In conclusion, this research guarantees the great potential of hybrid quantum-classical systems as a next-generation tool for finance. By offering a bridge from theoretical quantum advantage to practical utility, this work not only increases the predictive power but also charts a path to a future where quantum computing is an invaluable tool in tackling the most difficult problems in the financial industry and beyond.

FUTURE SCOPE

Quantum computers, despite their immense computational promise, remain in an experimental stage, training of quantum or quantum-classical hybrid models on simulators like PennyLane a highly time-intensive process, particularly for large-scale datasets. The optimization of quantum circuits or kernels introduces significant computational complexity, which amplifies the time required for training quantum models. As quantum technology advances, this complexity is likely to increase, potentially leading to even longer training durations. In this study, the inherent limitations of quantum simulators restricted the research to using only a subset of the dataset, a process that still demanded over eight hours of training time. This long period needed for training implies struggles with processing sophisticated computations in quantum simulators, especially for bulky complex data sets.A drawback to PennyLane is that so far, it does not support GPU acceleration, a critical tool for parallel processing that can be useful in machine learning operations. GPU acceleration is useful to spread calculational workloads particularly in high dimension data, and its absence in PennyLane is rather restrictive. The limitation postpones the training and influences the maximum utilization of the potential of the dataset, which will influence the performance, strength, and the generalization of the model. This has forced the research to carry out a scaled-down version of data and addresses real-world challenges of application of quantum computing to real-world financial problems. Training quantum models on quantum simulators is computationally intensive, not requiring a GPU or any quantum enable hardware, and it is not simple to port quantum models to real-world, large-scale applications. These limitations diminish their capacity to compute vast amounts of data efficiently and this is important in the creation of high performing credit risk prediction models that can be readily generalized to other financial environments. Dissolving these limitations will require major upgrades in quantum computing systems. Further effort on simulator efficacy, the inclusion of parallel processing and better quantum circuit design are all notable in shortening training times reducing the time required to achieve perfect use of quantum models and massive datasets. Such advancements will also be important in carrying out effective exploitations of the quantum-classical hybrid models and achieving their transformative outcomes to challenging predictive problems. The challenges of training quantum-classical hybrid models such as long training times and lack of availability of graphics card acceleration replicates the actual world challenges of implementing the quantum computing concepts to financial uses. The technical challenges can be overcome with time as the quantum hardware and software improvement and as such, the further studies will allow increasing the scalability of the quantum-based credit risk assessment models, becoming more precise and efficient and, thus, improving the reliability and long-term sustainability of the financial decision-making.

REFERENCES

Adegbola, M. D., Adegbola, A. E., Amajuoyi, P., Benjamin, L. B., & Adeusi, K. B. (2024). Quantum computing and financial risk management: A theoretical review and implications. *Computer Science & IT Research Journal*, *5*(6), 1210–1220. DOI: 10.51594/csitrj.v5i6.1194

Aranha, M., & Bolar, K. (2023). Efficacies of artificial neural networks ushering improvement in the prediction of extant credit risk models. *Cogent Economics & Finance*, *11*(1). Advance online publication. DOI: 10.1080/23322039.2023.2210916

Atadoga, A., Ike, C. U., Asuzu, O. F., Ayinla, B. S., Ndubuisi, N. L., & Adeleye, R. A. (2024). The intersection of AI and quantum computing in financial markets: A critical review. *Computer Science & IT Research Journal*, *5*(2), 461–472. DOI: 10.51594/csitrj.v5i2.816

Berhane, T., Melese, T., & Seid, A. M. (2024). Performance evaluation of hybrid machine learning algorithms for online lending credit risk prediction. *Applied Artificial Intelligence*, *38*(1), 2358661. DOI: 10.1080/08839514.2024.2358661

Bhatia, S., Sharma, P., Burman, R., Hazari, S., & Hande, R. (2017). Credit scoring using machine learning techniques. *International Journal of Computer Applications*, *161*(1), 1–4.

Bhatore, S., Mohan, L., & Reddy, Y. R. (2020). Machine learning techniques for credit risk evaluation: A systematic literature review. *Journal of Banking and Financial Technology*, *4*, 111–138.

Bova, F., Goldfarb, A., & Melko, R. G. (2021). Commercial applications of quantum computing. *EPJ Quantum Technology*, *8*(2). Advance online publication. DOI: 10.1140/epjqt/s40507-021-00091-1 PMID: 33569545

Chaudhary, S., Singh, V., Malik, N., Sidhu, K. S., Kirola, M., & Joshi, K. (2024, October). Digital signature security enhancement: Using X-OR operation on RSA and AES with 4096 bits key length [Paper presentation]. *2024 International Conference on Computing, Sciences and Communications (ICCSC).*

Chen, N., Ribeiro, B., & Chen, A. (2016). Financial credit risk assessment: A recent review. *Artificial Intelligence Review*, *45*, 1–23. DOI: 10.1007/s10462-015-9434-x

Chen, S. (2023). A novel ensemble machine learning model for credit risk prediction. Advances in Economics. *Management and Political Sciences*, *46*, 277–281. DOI: 10.54254/2754-1169/46/20230356

Dri, E., Aita, A., Giusto, E., Ricossa, D., Corbelletto, D., Montrucchio, B., & Ugoccioni, R. (2023). A more general quantum credit risk analysis framework. *Entropy (Basel, Switzerland)*, *25*(4), 593. DOI: 10.3390/e25040593 PMID: 37190381

Egger, D. J., Gambella, C., Marecek, J., McFaddin, S., Mevissen, M., Raymond, R., Simonetto, A., Woerner, S., & Yndurain, E. (2020). Quantum computing for finance: State-of-the-art and future prospects. *IEEE Transactions on Quantum Engineering*, *1*, 1–24. DOI: 10.1109/TQE.2020.3030314

Egger, D. J., Gutiérrez, R. G., Mestre, J. C., & Woerner, S. (2021). Credit risk analysis using quantum computers. *IEEE Transactions on Computers*, *70*(12), 2136–2145. DOI: 10.48550/arXiv.1907.03044

Herman, D., Googin, C., Liu, X., Sun, Y., Galda, A., Safro, I., Pistoia, M., & Alexeev, Y. (2023). Quantum computing for finance. *Nature Reviews. Physics*, *5*(8), 450–465.

Joshi, K., Yadav, H., Gupta, S., Singh, V., Sidhu, K. S., & Kukreti, R. (2025, April). Handling security aspects in the Internet of Things: Latest challenges and measures to mitigate risks [Paper presentation]. 2025 3rd International Conference on Communication, Security, and Artificial Intelligence (ICCSAI), (Vol. 3, pp. 1434-1439).

Noriega, J. P., Rivera, L. A., & Herrera, J. A. (2020). Machine learning for credit risk prediction: A systematic literature review. *Data*, *8*(11), 169. DOI: 10.3390/data8110169

Orús, R., Mugel, S., & Lizaso, E. (2019a). Forecasting financial crashes with quantum computing. *Physical Review. A*, *99*(6), 060301.

Orús, R., Mugel, S., & Lizaso, E. (2019b). Quantum computing for finance: Overview and prospects. *Reviews in Physics*, *4*, 100028. DOI: 10.1016/j.revip.2019.100028

Shi, S., Tse, R., Luo, W., D'Addona, S., & Pau, G. (2022). Machine learning-driven credit risk: A systemic review. *Neural Computing & Applications*, *34*(17), 14327–14339. DOI: 10.1007/s00521-022-07472-2

Singh, V., & Kaushik, V. D. (2023a). A brief overview of cyber security advances and techniques along with a glimpse on quantum cryptography: Cyber security practices, advances and challenges. In Exploring cyber criminals and data privacy measures (pp. 40-64).

Singh, V., & Kaushik, V. D. (2023b). Navigating the landscape of security threat analysis in cloud computing environments. In *Security and risk analysis for intelligent cloud computing* (pp. 1–25). CRC Press.

Wang, Y., Zhang, Y., Lu, Y., & Yu, X. (2020). A comparative assessment of credit risk model based on machine learning: A case study of bank loan data. *Procedia Computer Science*, *174*, 141–149. DOI: 10.1016/j.procs.2020.06.069

Yang, R. (2024). Machine learning-based loan default prediction in peer-to-peer lending. Highlights in Science. *Engineering and Technology*, *94*, 310–318. DOI: 10.54097/qdjd8r65