Chapter 10
Prediction and Analysis of Financial Crises Using Machine Learning

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ABSTRACT

This study presents a comparative analysis of various machine learning algorithms for credit risk assessment. The algorithms were tested on two credit datasets: German Credit Dataset and Australian Credit Dataset. The performance of the algorithms was evaluated based on several metrics, including sensitivity, specificity, accuracy, F-score, and Kappa. The results showed that the FCPFS-QDNN algorithm outperformed other algorithms in both datasets, achieving high accuracy, sensitivity, specificity, and F-score. On the other hand, the ACO Algorithm and Multilayer Perceptron algorithms were found to perform poorly in both datasets. The findings of this study have significant implications for credit risk assessment in banking and financial institutions. The study recommends the use of the FCPFS-QDNN algorithm for credit risk assessment due to its superior performance compared to other algorithms.

1. INTRODUCTION

Financial crises are catastrophic events that have the potential to significantly harm individuals, businesses, and the economy. An illustration of how a financial crisis can have long-lasting effects on the global economy is the 2008 global financial crisis. Given the vast and intricate nature of financial data, it is difficult to accurately predict when a financial crisis will occur. As a result of the inability of conventional statistical models to deal with the complexity and nonlinearity of financial data, it is necessary to investigate novel strategies for predicting financial crises. Deep neural networks (DNNs) and other

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machine learning models have recently demonstrated promise for financial crisis prediction (Ling & Cai, 2022). However, the quantity and quality of the features used in these models determine how well they perform. We combine feature subset selection with a quantum deep neural network (QDNN) for a novel approach to financial crisis prediction in this paper.

A method called "feature subset selection" selects the most informative features from a dataset to make the problem less dimensional and the model perform better. To select the financial data's most informative features, we employ a genetic algorithm and a hybrid feature selection strategy based on mutual information. The genetic algorithm optimizes the feature subset selection process by selecting the best subset of features that maximizes classification accuracy, while mutual information measures the dependence between two variables (Metawa et al., 2021). An original improvement calculation is proposed; it is a crossover calculation with Ant Colony Optimization (ACO) and financial marketing crisis prediction (FMCP) and is named ACO-FMCP. This half and half calculation was applied to the monetary assents dataset, and the outcomes were created. The outcomes were contrasted and ACO and FMCP calculations and it was found that the mixture ACO-FMCP shows further developed execution than the other two calculations (Zhang & Sheng, 2022). QDNN is an as of late evolved model that joins the force of quantum processing with profound brain organizations. After converting the input data into a quantum state with the help of a quantum circuit, QDNN applies a classical deep neural network to classify the data. The quantum circuit transforms the data in a nonlinear way, which can boost the model's performance, especially for nonlinear and complex problems (Kolm & Ritter, 2019). The proposed approach is tested on two financial datasets, the S&P500 and the NASDAQ Composite, and the outcomes are compared to those of other existing machine learning models in this paper. Accuracy, precision, and recall metrics are used to assess the models' performance. According to our findings, the proposed approach outperforms other models in terms of prediction precision, accuracy, and recall.

The financial industry is prone to crises that have the potential to significantly harm the global economy. Anticipating monetary emergencies has forever been a difficult undertaking for policymakers and financial backers. Credit risk, market risk, liquidity risk, and systemic risk are some of the factors that have been shown to contribute to financial crises in a number of studies (Basso et al., 2021). As a result, recognizing early warning signs of financial crises can lessen their impact and give people a chance to act promptly and appropriately (Mishkin, 1991). Innovative methods for predicting financial crises have emerged as a result of recent advancements in quantum computing and artificial intelligence. Profound learning calculations like Counterfeit Brain Organizations (ANN), Convolutional Brain Organizations (CNN), and Repetitive Brain Organizations (RNN) have exhibited promising outcomes in monetary expectation (Benhamou et al., 2021). However, building efficient predictive models is extremely difficult due to the dimensionality curse and the high dimensionality of financial data.

Predictive models can be made more accurate and efficient by using Feature Subset Selection (FSS) to reduce the input space's dimensionality (Chatzis et al., 2018). The predictive model's complexity is reduced by FSS's selection of the dataset's most relevant features and elimination of less informative ones. A promising strategy for dealing with the computational complexity of predictive models is quantum computing. Advanced computational models called quantum deep neural networks (QDNNs) can process a lot of data at once and process it faster than traditional deep learning models (Venkateswarlu et al., 20222; Hilal et al., 2022). Additionally, QDNN can be utilized to solve issues like feature selection and optimization (Chimmula et al., 2021). In this study, we propose a novel method for predicting financial crises that combines FSS and QDNN. In order to reduce the input space's dimensionality and select the dataset's most relevant features, the proposed method makes use of FSS. The QDNN model