Predicting Financial Crises with an Intelligent Decision-Making System

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Abstract

predicting financial crises, (FCP) is essential for financial institutions to assess firm failure risks. Traditional FCP models fall short in achieving high prediction accuracy across diverse datasets. This paper introduces an intelligent decision-making system for FCP using a deep neural network (DNN) model, optimized through a quasi-oppositional Jaya optimization algorithm (QOJOA). The model distinguishes between financial crises (FC) and non-crises (NFS) based on financial data. QOJOA employs a quasi-oppositional based learning (QOBL) technique to accelerate convergence. Experiments on benchmark datasets—Anal cat Data, German Credit, and Australian Credit—demonstrate that the QOJOA-DNN model outperforms recent approaches across various evaluation metrics.

Keywords: Financial crisis prediction; Parameter tuning; Deep neural network; optimization algorithm.

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1.Introduction

Financial Crisis Prediction (FCP) is a well-known and significant model, which is applied by numerous economical organizations to minimize future crisis and loss. It determines the risks and eliminates novel credit methods when a general problem is greater than the previous acceptance level. Also, it is designated as a credit default classification operation, which is named as “non-default” if a user returns the loan amount, or the user is called “default”. Here, the accurateness of the FCP model is responsible for computing the production and profit of an economical firm. For sample, even a small change in the accuracy level of trustworthy users leads to a reduction in the future loss of financial organization (Ala'raj & Abbod, 2016). Classification is defined as a supervised learning operation in Machine Learning (ML) that acquires a correlation between features and classes. Traditionally, previous models used numerical functions for detecting financial problems, which distinguishes the financial institution among robust and vulnerable modalities (Rao, 2016). In the last decades, Artificial Intelligence (AI) related expert methods such as Neural Network (NN) and Support Vector Machine (SVM) has been presented. In recent times, AI models have been applied for the refinement of classical classifiers (Hinton & Salakhutdinov, 2006).

Distinct approaches were employed to identify the incomplete solutions with specific duration. Only a few ML schemes namely Ant Colony Optimization (ACO) and Genetic Algorithm (GA) are used for the selection of required features, and it is not applicable for the business sector, especially FCP (Uthayakumar, Metawa, Shankar, & Lakshmanaprabu, 2020). Green (2019) implied an SVM-based ensemble framework for FCP and related it to the conventional SVM model. Finally, the attained simulation performance has depicted that the SVM ensemble approach has outperformed SVM performance. Y. Lin, Guo, and Hu (2013) applied SVM with previous approaches and highlighted that grading a model varied based on accuracy. A detailed examination of FCP is deployed on 107 Chinese organizations using data mining (DM) schemes (Geng, Bose, & Chen, 2015). The outcome showcases that NN is optimal when compared with Decision Tree (DT) and SVM. In recent times, bio-inspired approaches are applied in resolving the problems involved in the classification task.

Ant miner is applied for the classification of finance data to Qualitative and Quantitative modules in Uthayakumar, Vengattaraman, and Dhavachelvan (2020). A novel enhanced boosting technique using feature selection (FS) is presented in Wang, Ma, and Yang (2014). The employment of FS in boosting outcomes has accomplished an optimal detection rate with a huge variety. The new approach of FS F. Lin, Liang, Yeh, and Huang (2014) combines the knowledge of the user with the wrapper method. In the initial stage, features of economical data are categorized into 7 sets, and wrapper application is adopted for the FS task. The resultant outcome demonstrates that projected approach is referred to as conventional FS approaches interms of accuracy. Under the application of various FCP models, the performance of FCP approaches is identified.

This paper presents a novel intelligent decision making tool for FCP using a parameter tuned deep neural network (DNN) model. The proposed model involves the quasi oppositional Jaya optimization algorithm (QOJOA) based parameter tuning technique to optimize the hyperparameters of DNN. The goal of the presented model is to identify the financial crisis (FC) and non-financial crisis (NFS) of the firms based on financial data. Besides, quasi oppositional based learning (QOBL) scheme is employed to improve the convergence rate of JOA. To examine the prediction performance of the QOJOA-DNN model, a set of experiments were carried out using three benchmark dataset namely AnalcatData, German Credit, and Australian Credit dataset.

2. The Empirical methodology

Figure 1 shows the working principle of the QOJOA-DNN model. The figure stated that the presented model initially performs pre-processing in two stages namely format conversion and data transform. Besides, the QOJOA-DNN model is executed to carry out the data classification, as discussed in the subsequent sections.

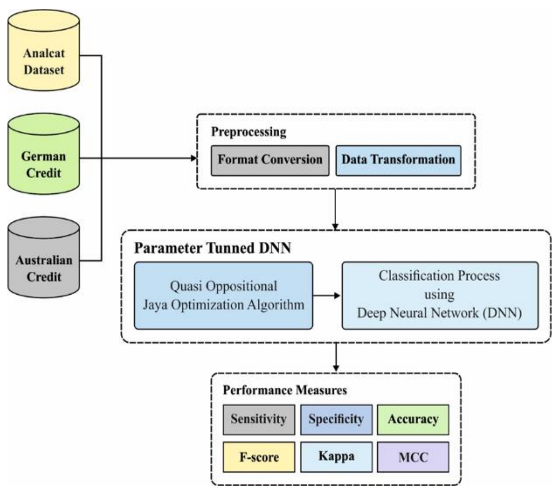

Figure 1: Overall Process of QOJOA-DNN model

DL models are applicable for accomplishing high dimension features from the input data. Therefore, the features gathered from DNN are used for enhancing the performance of classifiers (Aswathy et al., 2022). In general, DL approach is evolved from the DNN classifier which is deployed by integrating the stack of auto encoder (AE) framework by applying the SM classifier. AE contains a set of input, hidden, and output layers. The AE is trained in an unsupervised manner for generating the equivalent input at a resultant stage in the least error. Hence, the outputs as well as input are nearly identical. Moreover, AE is trained to embed the input to feature spaces, which is composed of a limited dimension than input space. Hence, the dimensions of a code space are decided on the input space to improve the efficiency of classification in specific actions. Here, the AE intends to offer the best representation of the input vector through the replacement of the proper codes.

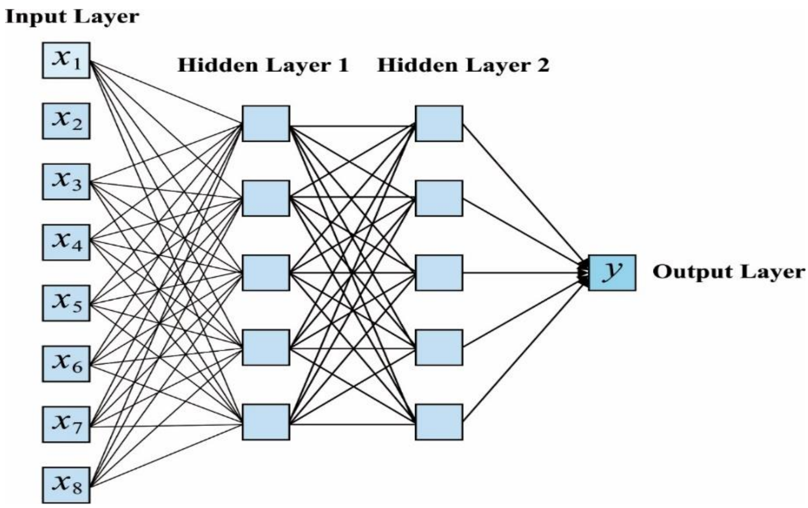

Figure 2: Representation of DNN

Figure 2 depicts the DNN system where the neuron count from the resultant layer is identical to input values. The left part of AE is named as an encoder, where input is referred as an input of AE, and the output is a consequence of the hidden layer. The encoder converts the input vector into the code that has to be proficient for the input vector

3. Experimental Validation

The proposed QOJOA-DNN model is simulated using MATLAB tool. The performance of the QOJOA-DNN model is tested using AnalcatData, German Credit, and Australian Credit dataset (Aswathy et al., 2022). A detailed comparative analysis of the QOJOA-DNN model takes place with the recently presented models in terms of sensitivity, specificity, accuracy, F-score, Mathew correlation coefficient (MCC), and kappa coefficient.

3.1. Dataset details

The details of the benchmark dataset used for the evaluation of the QOJOA-DNN model. The first Analcat dataset comprises 50 samples, 5 features with 2 class labels. Similarly, the second German Credit dataset includes 1K samples, 24 features, and 2 class labels. Finally, the Australian Credit dataset has 690 samples, 14 features with 2 class labels.

3.2. Analysis of QOJOA-DNN Model on AnalcatData Dataset

Table 1 and Figs. 4-5 analyzes the results of the QOJOA-DNN model on the applied AnalcatData dataset. Fig. 4 shows the examination of the QOJOA-DNN model in terms of different performance measures. The figure portrayed that the AdaBoost approach has shown poor performance with the sensitivity of 0.650, specificity of 0.670, MCC of 0.643 and Kappa of 0.642. At the same time, the SVM model has offered a slightly higher sensitivity of 0.760, specificity of 0.790, MCC of 0.751 and Kappa of 0.750. In addition, the MLP model has exhibited slightly manageable results with a sensitivity of 0.780, specificity of 0.800, MCC of 0.773 and Kappa of 0.772. Simultaneously, the ACO algorithm has showcased even better results with the sensitivity of 0.880, specificity of 1.0, MCC of 0.880 and Kappa of 0.880. Moreover, the DNN model has tried to showcase closer results to the proposed method with the sensitivity of 0.9111, specificity of 1.0, MCC of 0.927 and Kappa of 0.929. Furthermore, the QOJOA-DNN model has showcased the effective outcome with the sensitivity of 0.947, specificity of 1, MCC of 0.944 and Kappa of 0.948.

Table 1: Result Analysis of Proposed QOJOA-DNN on AnalcatData Dataset

Classifiers	Sens.	Spec.	Accu.	F-score	MCC	KAPPA
QOJOA-DNN	0.947	1.000	0.989	0.969	0.944	0.948
DNN	0.911	1.000	0.967	0.959	0.927	0.929
ACO	0.880	1.000	0.940	0.936	0.880	0.880
MLP	0.780	0.800	0.799	0.795	0.773	0.772
SVM	0.760	0.790	0.774	0.764	0.751	0.750
AdaBoost	0.650	0.670	0.658	0.658	0.643	0.642

the ACO framework has exhibited moderate results with the accuracy of 0.940 and F-score of 0.936. Furthermore, the DNN approach has managed to display identical outcomes to the presented scheme with the accuracy of 0.967 and F-score of 0.959. Moreover, the QOJOA-DNN technology has surpassed the traditional schemes with the accuracy of 0.989 and F-score of 0.969.

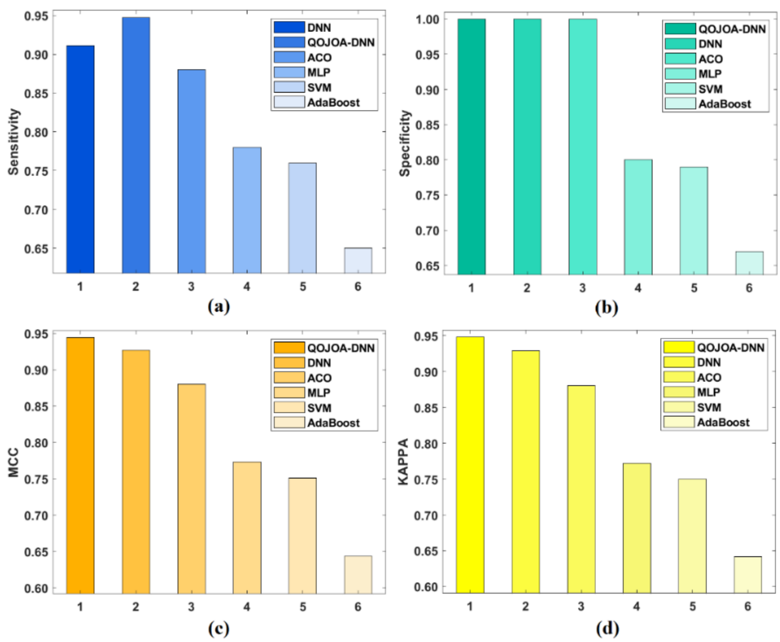

Fig. 3. Comparative Classification Results of QOJOA-DNN on German Credit Dataset

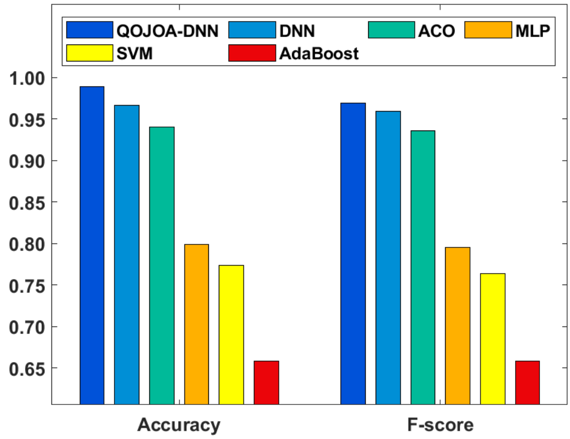

Figure 4: QOJOA-DNN vs. Existing Methods Accuracy & F-score on AnalcatData

4. Conclusion

This study has successfully introduced an advanced intelligent decision-making framework for **Financial Credit Prediction (FCP)** by leveraging the **QOJOA-DNN model**, which integrates the strengths of Deep Neural Networks (DNN) and the Quantum-Optimized Jellyfish Optimization Algorithm (QOJOA). The proposed model employs a two-stage preprocessing strategy—**format conversion** followed by **data transformation**—to ensure the quality and consistency of the input financial data.

A key innovation of this approach lies in its **optimized parameter tuning process**, where QOJOA is utilized for both **parameter initialization** and **population update**, thus enhancing the learning efficiency and predictive capability of the DNN. By effectively distinguishing between **Financially Capable (FC)** and **Non-Financially Stable (NFS)** firms, the QOJOA-DNN model demonstrates its potential as a robust financial assessment tool.

The model's performance was rigorously validated on three benchmark datasets: **AnalcatData, German Credit, and Australian Credit datasets**. Experimental results revealed that the proposed framework consistently achieved superior outcomes, recording **maximum accuracy rates of 0.989, 0.896, and 0.937**, respectively. These results underscore the model's ability to handle diverse financial datasets and to deliver reliable predictions, making it a valuable asset for financial institutions and decision-makers seeking to evaluate organizational financial health.

Looking forward, the predictive performance of the QOJOA-DNN model can be further enhanced through the integration of **feature selection** and **clustering techniques**, which are expected to refine data representation and reduce computational complexity. Such improvements could lead to more precise financial risk assessments and broader applicability across various economic and industrial domains.

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Conflict of Interest

The authors declare no conflict of interest.

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