JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

DESIGN OF DEEP NEURAL DECISION TREES BASED AUTOMATED FINANCIAL CRISIS PREDICTION MODEL

[1]V. Kumaresan, [2]K. Niresh,
[1]Assistant Professor, [2]Associate Engineer,
[1]Department of Computer and Information Science, Annamalai University
[2]Attra infotech,
[1]Annamalai Nagar, [2]Bengaluru
India

Abstract: Financial crisis prediction (FCP) roles an important play in the economic phenomenon. The precise forecast of the number and probability of failing firms' performances as an index of development and strength of national economy. Usually, many approaches are projected to effectual FCP. Conversely, the classifier efficiency and forecast accuracy, and data legality were not optimum sufficient for practical applications. Besides, several developed approaches execute well for any specific dataset but are not adjustable for distinct datasets. In this view, this study develops a new deep neural decision tree based FCP (DNDT-FCP) model. Similar to the credit scoring, in this paper, we have considered FCP as a classification problem which can decide whether a financial firm is bankrupt or not. To accomplish this, the presented DNDT-FCP model involves the initial data pre-processing step to transform the actual financial data. In addition, the presented DNDT-FCP model employs the DNDT classification model to carry out the FCP process. The experimental validation of the DNDT-FCP model is tested using two benchmark datasets namely Wieslaw dataset and qualitative bankruptcy dataset. The experimental results implied a better performance of the DNDT-FCP model over recent models.

IndexTerms: **Deep learning; Intelligent models; Financial crisis prediction; Neural network; Bankruptcy**

1. Introduction

Over past few years, financial crisis of companies is rising all over the globe, the corporations had an eye on the region of financial crisis prediction (FCP) [1, 2]. For a financial institution or company, it becomes necessary to devise a dependable and prior forecasting method for predicting risk factors of the business's status of financial loss at an earlier time. FCP typically generates a binary classifier method that was resolved in a reasonable manner [3]. The result from the classifier technique is classified into 2 categories first thing it indicates the company's failure status and another indicates the company's non-failure status. The inputs to the classifier technique were always the statistic ratios gained from monetary reports in the institutions [4]. So far, lot of classifier approaches was enhanced with the help of numerous field knowledge for FCP. Finally, researchers find the artificial intelligence (AI) and machine learning (ML) approaches in search of a superior technique for forecasting economic crisis and also, for quantifying economic crisis by making use of innovative and latest technologies [5, 6].

As the analysis of monetary risks was similar to the design identification problems, techniques are utilized for the solvency sorting [7], therefore enhancing the classical methods using formerly multiple variance statistic routines such as discriminant breakdown and LR. The incorporation of ML techniques with numerous types of artificial neural networks (ANN) in economic crisis forecasting grabs more attention [8]. Currently, DL was arisen and slowly advanced as an influential method for an extensive range of applications. It reached huge achievements in natural language processing (NLP), computer vision (CV), auto-driving, voice recognition, and classifier issues in businesses namely credit scoring and bankruptcy prediction [9, 10]. The study mainly makes reviews ML and DL methods utilized in bankruptcy forecasting, for summarizing the particular procedure, features, merits, and weak zones through examining common studies.

Mai et al. [11] establish DL techniques for corporate bankruptcy predicting employing textual disclosure. But, the textual data in general, it can be rarely regarded from the financial decision support methods. DL utilizes layers of NNs for extracting features in textual data to forecast. In [12], the authors are analysing the ML or DL approaches utilize from bankruptcy forecast containing the traditional ML approaches. In [13], the authors present a new algorithmic trading approach CNN-TA utilizing a 2D CNN dependent upon image processing property. For converting financial time series to 2D images, 15 distinct technical indicators each containing various parameters chosen were employed. All the indicators sample creates data for a 15 day period. While the outcome, 15 × 15 sized 2D images are generated. All the images are then labeled as Buy, Sell or Hold depending on hill and valley of original time series. Alaminos et al. [14] introduce novel approaches for the forecast of sovereign debt and currency crises, utilizing several computational approaches that improve their precision. These techniques illustrate the superiority of computational approaches regarding statistics with respect to the level of precision.

This study develops a new deep neural decision tree based FCP (DNDT-FCP) model. Similar to the credit scoring, in this paper, we have considered FCP as a classification problem which can decide whether a financial firm is bankrupt or not. To accomplish this, the presented DNDT-FCP model involves the initial data pre-processing step to transform the actual financial data. In addition, the presented DNDT-FCP model employs the DNDT classification model to carry out the FCP process. The experimental validation of the DNDT-FCP model is tested using two benchmark datasets namely Wieslaw dataset and qualitative bankruptcy dataset.

2. The Proposed DNDT-FCP model

In this study, a new DNDT-FCP model has been developed for the classification of FCP. Primarily, we have considered FCP as a classification problem which can decide whether a financial firm under bankrupt or not. To accomplish this, the presented DNDT-FCP model involves the initial data pre-processing step to transform the actual financial data. In addition, the presented DNDT-FCP model employs the DNDT classification model to carry out the FCP process.

2.1. Data Pre-processing

Firstly, the presented DNDT-FCP model involves the initial data pre-processing step to transform the actual financial data. The Min-Max normalizing system (Eq. (1)) has been employed to normalize the data for intervals of 0 and 1:

$$x^{*}=\frac{x-x_{\min}}{x_{\max}-x_{\min}}, \tag{1}$$

In which x^{*} represents the normalization data, x defines the original data, $x_{\min}$ signifies the lesser data values in the current attribute, and $x_{\max}$ implies the maximal data value in the current attribute.

2.2. DNDT based Classification

At this stage, the presented DNDT-FCP model employs the DNDT classification model to carry out the FCP process. The DNDT is DT model implemented using deep-learning NN, in which a configuration of DNDT weighting corresponds to a certain decision tree and it can be interpretable [15]. A DNDT is much simpler, however, it finds the optimal solution in comparison with traditional DT inductor while seeking the parameter and structure of the tree using SGD. At last, traditional DT inductor uses binary division for simplifying DNDT functions by random cardinality division that could occasionally produce interpretable tree. The process starts with the implementation of a soft binning function to estimate the error rates for all the nodes which makes them feasible to take decisions separated into DNDT. Usually, the input of binning function is an actual scalar x that yields an index of container where x belongs. Assume that x is a constant variable, and group them into $n+1$ intervals. This needs n cut-off point that is trained parameters. The cut-off point is represented by $(\beta_1, \beta_2, \ldots, \beta_n)$ and are strictly ascending so that $\beta_1<\beta_2<\cdots<\beta_n$.

The activation function of DNDT process is executed according to the NN determined as follows.

$$\pi=fw,b,\tau(x)=soft\max\left(\frac{wx+b}{\tau}\right) \tag{2}$$

In Eq. (2), w denotes constant values $w = [1,2, \dots, n + 1]$, $\tau > 0$ refers to temperature factors, and b is determined as follows.

$$b = [0, -\beta_{1'} - \beta_{1'} - \beta_2, \dots, -\beta_1 - \beta_2 - \cdots - \beta_n] \tag{3}$$

The NN provides coding of binning function x. Assumed the binning function abovementioned, the major concept is to construct the DT with the Kronecker product. Assume that, it have input sample $\chi \in R^D$ using D features. Associate every feature χ_d with its individual NN $f_d(x_d)$, we define each last node of the DT, as follows.

$$z = f_1(X_1) \otimes f_2(x2) \otimes \dots \otimes f_D(xD) \tag{4}$$

In Eq. (4), z denotes a vector that represents the index of leave nodes attained using sample x. Consider that a linear classification on every leaf z categorizes the instance that reaches them. The cut point number for each feature is the complication variable of the algorithm [16]. The cut-off point value is not constraint that implies that some of them might be inactive. For instance, they are small when compared to the minimal x_d or larger when compared to maximal x_d. Fig. 1 depicts the infrastructure of DNN.

The DNDT is well-scaled using the input number owing to the trained mini-batches of NN. But the major drawback of algorithm is the usage of Kronecker product that denotes it isn't scalable interms of the amount of features. In the present execution, we presented the challenge with wide-ranging dataset, and train a forest using an arbitrary sub-space. This included presenting several trees and training them using subsets with arbitrary features.

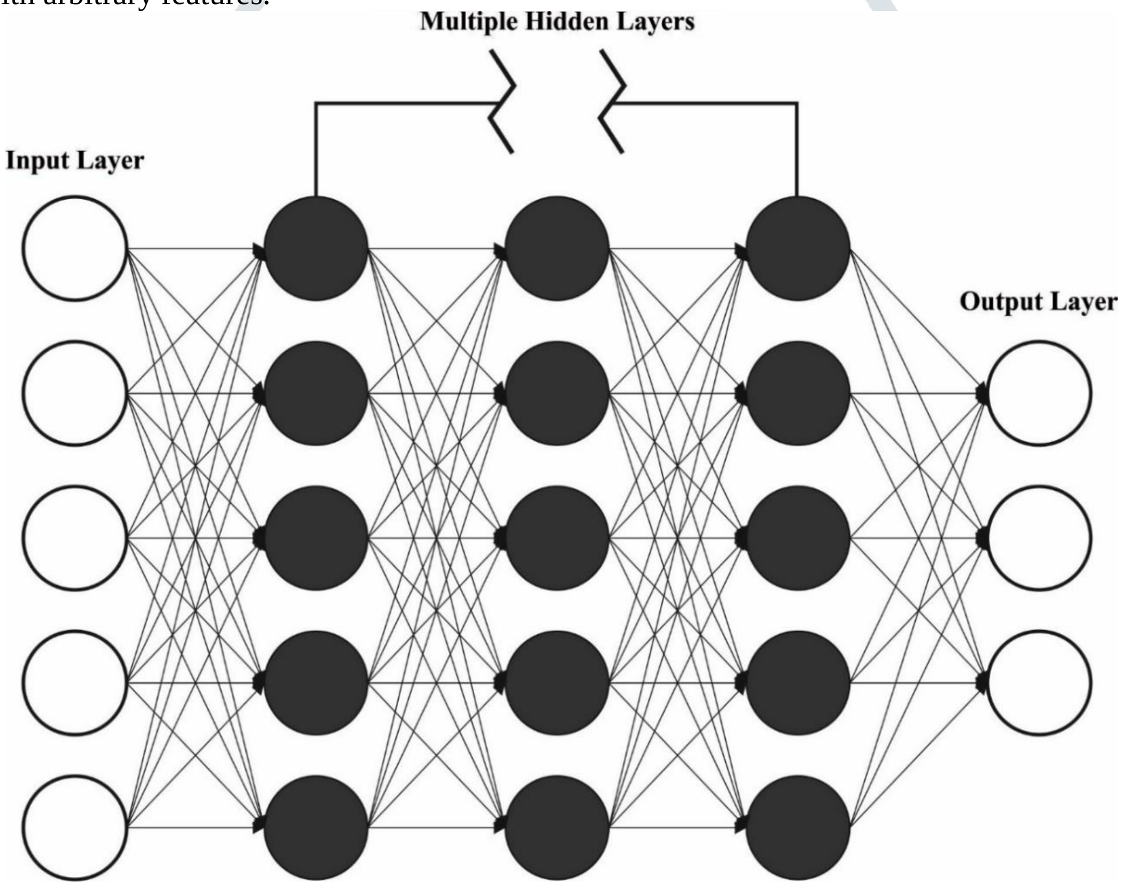

Fig. 1. Structure of DNN

3. Results and Discussion

The proposed model is simulated using two benchmark datasets namely Weislaw dataset and qualitative bankruptcy dataset. Table 1 illustrates the details of two datasets.

Table 1 Dataset details

Class	No. of Samples	
	Wieslaw Dataset	**Qualitative Bankruptcy Dataset**
Bankruptcy	112	107
Non-Bankruptcy	128	143
Total	**240**	**250**

Fig. 2 reports the confusion matrices produced by the proposed model on test datasets. With 70% of TR data on dataset-1, the proposed model has recognized 43 samples into bankrupt (BT) class and 77 samples into non-bankrupt (NBT) class. Also, with 30% of TS data on dataset-1, the proposed method has recognized 23 samples into BT class and 26 samples into NBT class. Besides, with 70% of TR data on dataset-2, the proposed system has recognized 70 samples into BT class and 99 samples into NBT class. In addition, with 30% of TS data on dataset-2, the proposed methodology has recognized 34 samples into BT class and 40 samples into NBT class.

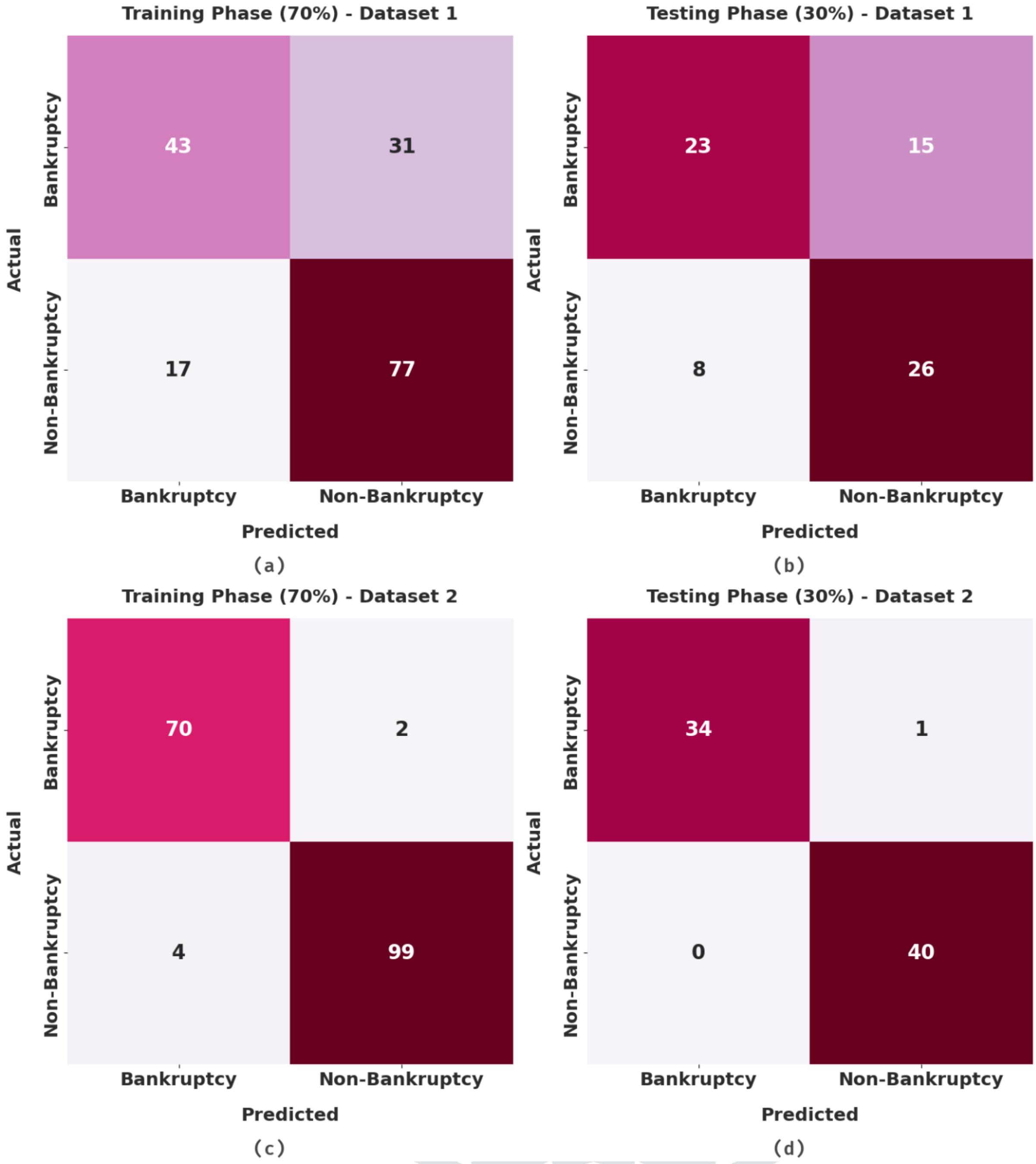

Fig. 2. Confusion matrices of proposed method (a) 70% of TR on dataset-1, (b) 30% of TS on dataset-1, (c) 70% of TR on dataset-2, and (d) 30% of TS on dataset-2

Table 2 and Fig. 3 report an overall classification output of the proposed model on Weislaw dataset. The experimental results implied that the proposed model has shown proficient results on test dataset. With 70% of TR data, the proposed model has resulted in an average $accu_y$ of 97.02%, $reca_l$ of 96.88%, $spec_y$ of 96.88%, F_{score} of 97%, and $G_{measure}$ of 97.02%. Also, with 30% of TS data, the proposed method has resulted in an average $accu_y$ of 96.57%, $reca_l$ of 96.67%, $spec_y$ of 96.67%, F_{score} of 96.47%, and $G_{measure}$ of 96.48%.

Table 2 Result analysis of proposed method with distinct measures under Weislaw dataset

Wieslaw Dataset					
Class Labels	**Accuracy**	**Recall**	**Specificity**	**F-Score**	**G-Measure**
Training Phase (70%)					
Bankruptcy	97.02	94.87	98.89	96.73	96.75
Non-Bankruptcy	97.02	98.89	94.87	97.27	97.28
Average	**97.02**	**96.88**	**96.88**	**97.00**	**97.02**
Testing Phase (30%)					
Bankruptcy	96.57	97.22	96.12	95.89	95.90
Non-Bankruptcy	96.57	96.12	97.22	97.06	97.06
Average	**96.57**	**96.67**	**96.67**	**96.47**	**96.48**

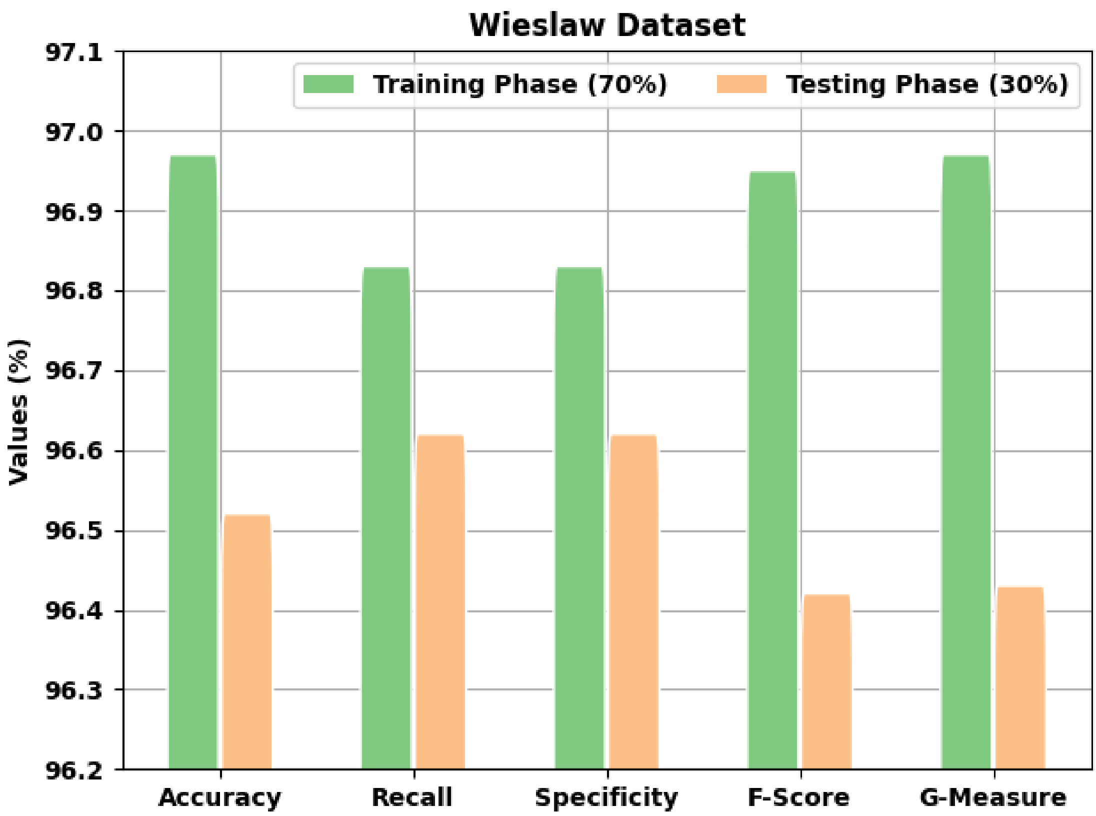

Fig. 3. Result analysis of proposed method under Weislaw dataset

Table 3 and Fig. 4 illustrate an overall classification output of the proposed system on Qualitative Bankruptcy dataset. The experimental outcomes referred that the proposed method has outperformed proficient results on test dataset. With 70% of TR data, the proposed algorithm has resulted in an average $accu_y$ of 98.61%, $reca_l$ of 98.68%, $spec_y$ of 98.68%, F_{score} of 98.61%, and $G_{measure}$ of 98.62%. Eventually, with 30% of TS data, the proposed model has resulted in an average $accu_y$ of 98.67%, $reca_l$ of 98.57%, $spec_y$ of 98.57%, F_{score} of 98.66%, and $G_{measure}$ of 98.67%.

Table 3 Result analysis of proposed method with distinct measures under Qualitative Bankruptcy dataset

Qualitative Bankruptcy Dataset					
Class Labels	**Accuracy**	**Recall**	**Specificity**	**F-Score**	**G-Measure**
Training Phase (70%)					
Bankruptcy	98.61	100.00	97.37	98.55	98.56
Non-Bankruptcy	98.61	97.37	100.00	98.67	98.68
Average	**98.61**	**98.68**	**98.68**	**98.61**	**98.62**
Testing Phase (30%)					
Bankruptcy	98.67	97.14	100.00	98.55	98.56
Non-Bankruptcy	98.67	100.00	97.14	98.77	98.77
Average	**98.67**	**98.57**	**98.57**	**98.66**	**98.67**

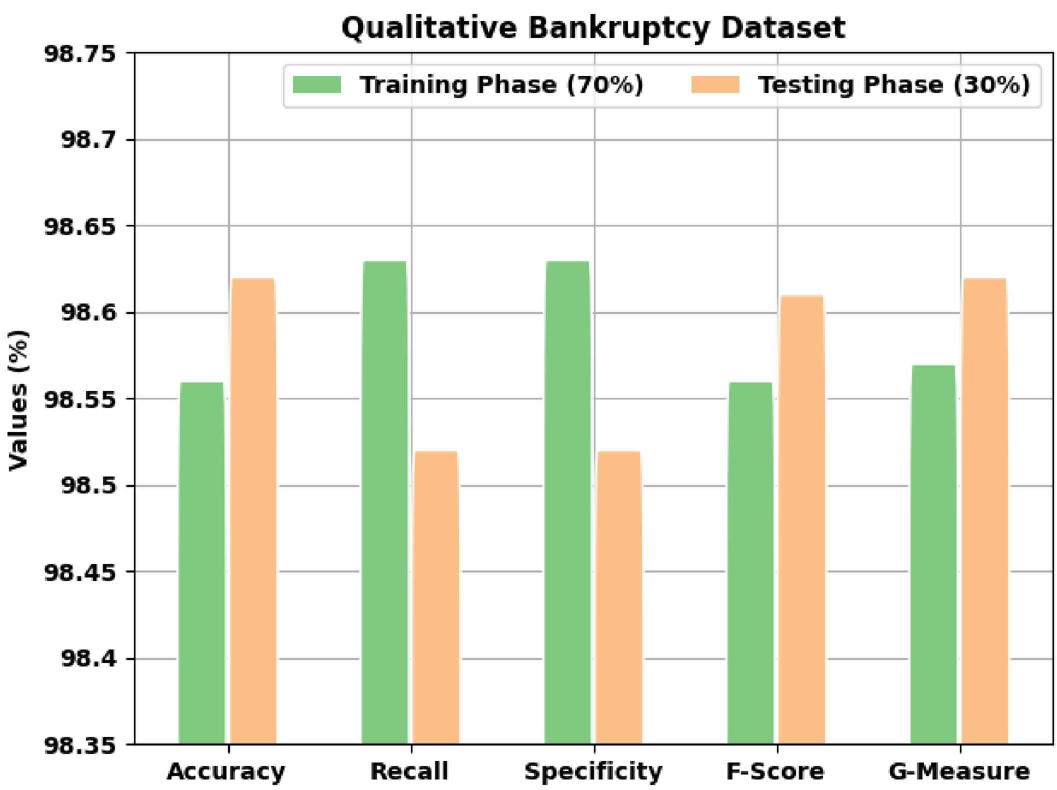

Fig. 4. Result analysis of proposed method under Qualitative Bankruptcy dataset

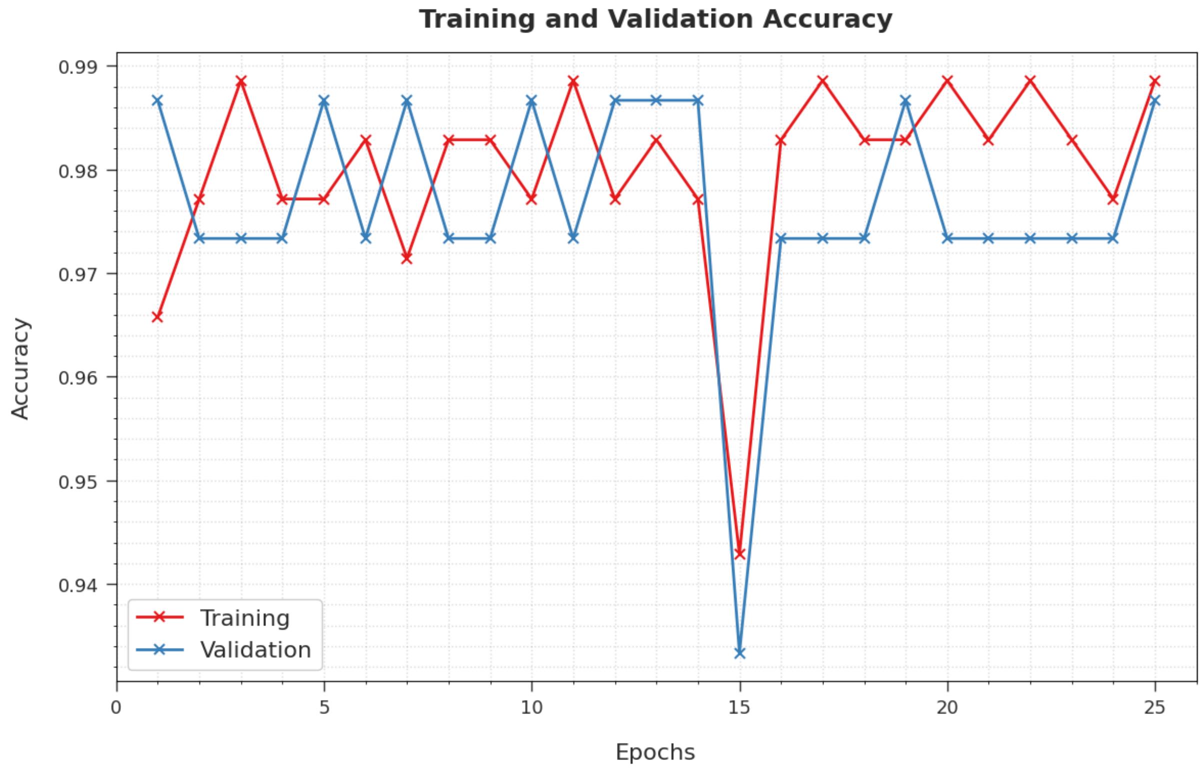

Fig. 5. TA and VA analysis of proposed methodology

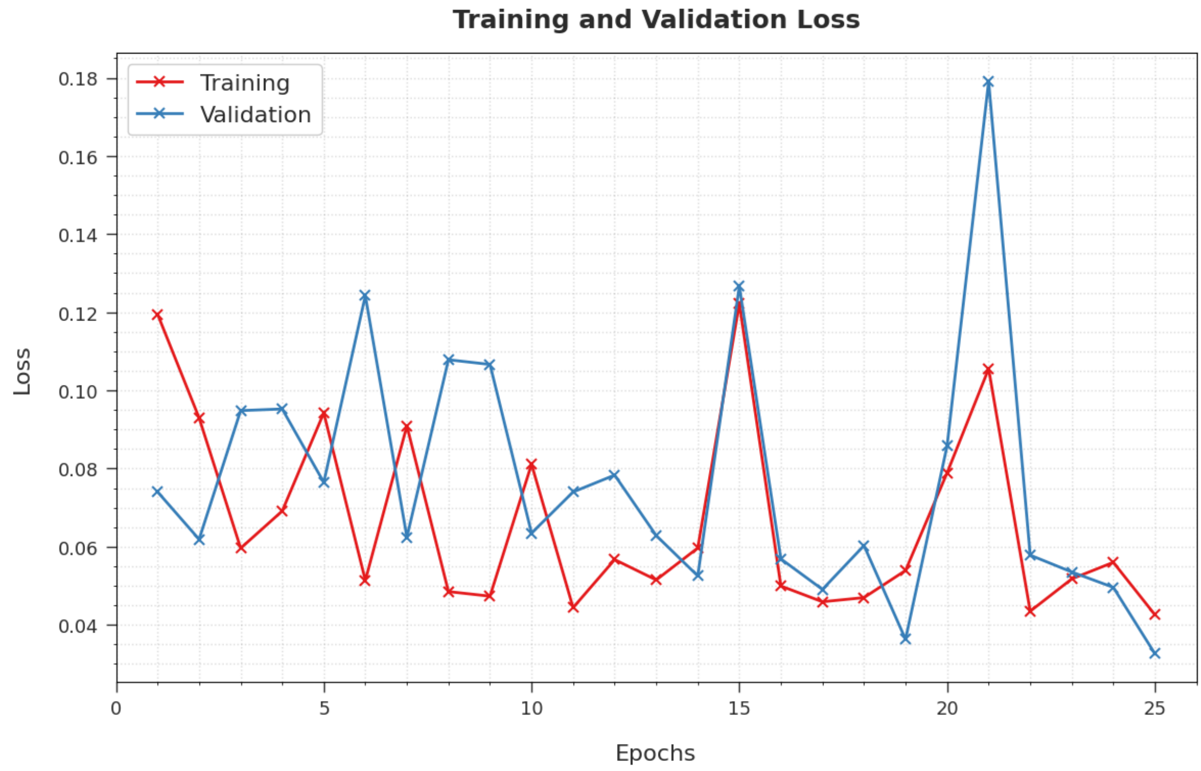

Fig. 6. TL and VL analysis of proposed methodology

The training accuracy (TA) and validation accuracy (VA) gained by the proposed method on test dataset is demonstrated in Fig. 5. The experimental outcome represented that the proposed algorithm has gained maximal values of TA and VA. In specific, the VA seemed that superior to TA.

The training loss (TL) and validation loss (VL) attained by the proposed system on test dataset are established in Fig. 6. The experimental outcome revealed that the proposed method has been able least values of TL and VL. In specific, the VL appeared to be lesser than TL.

At last, a brief comparative study is carried out between the proposed model and existing approaches in Table 4 and Fig. 7 [17, 18]. The results implied that the PSO-KELM, GA-KELM, and GS-KELM models have shown poor performance with least $accu_y$ of 82.50%, 81.67%, and 80%. At the same time, the GWO-KELM and optimal FKNN models have reported moderately closer $accu_y$ values of 84.58%

and 87.92% respectively. However, the proposed model has accomplished superior performance with improved $accu_y$ of 98.67%. So, the proposed model has accomplished enhanced FCP outcomes over other models.

Table 4 Comparative analysis of proposed algorithm with recent methodologies

Methods	Accuracy
GWO-KELM	84.58
PSO-KELM	82.50
GA-KELM	81.67
GS-KELM	80.00
Optimal FKNN	87.92
The Proposed Model	98.67

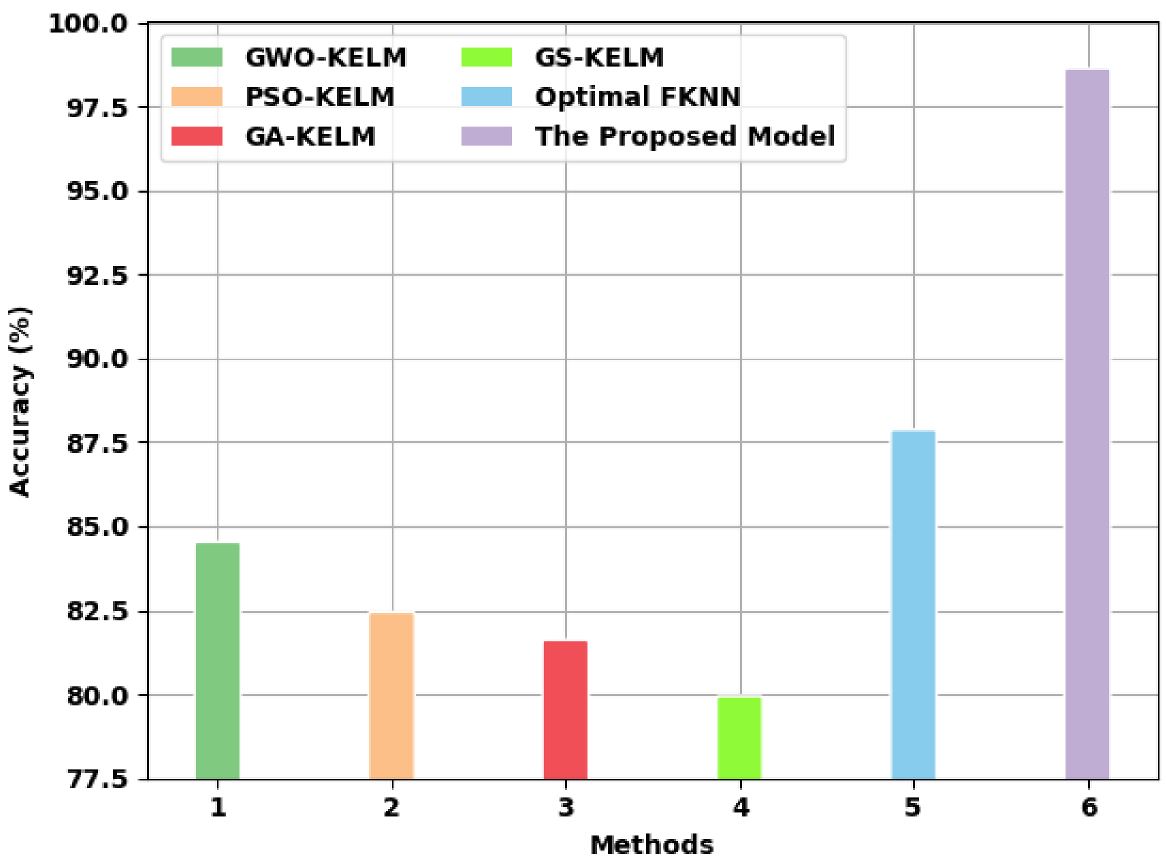

Fig. 7. Comparative analysis of proposed method with existing approaches

4. Conclusion

In this study, a new DNDT-FCP model has been developed for the classification of FCP. Primarily, we have considered FCP as a classification problem which can decide whether a financial firm is under bankruptcy or not. To accomplish this, the presented DNDT-FCP model involves the initial data pre-processing step to transform the actual financial data. In addition, the presented DNDT-FCP model employs the DNDT classification model to carry out the FCP process. The experimental validation of the DNDT-FCP model is tested using two benchmark datasets namely Wieslaw dataset and qualitative bankruptcy dataset. The experimental results implied a better performance of the DNDT-FCP model over recent models. In future, hybrid DL based FCP models can be derived to boost the overall prediction performance of the presented DNDT-FCP model.

References

[1] Ozbayoglu, A.M., Gudelek, M.U. and Sezer, O.B., 2020. Deep learning for financial applications: A survey. *Applied Soft Computing*, *93*, p.106384.

[2] Vadlamudi, S., 2020. The impacts of machine learning in financial crisis prediction. *Asian Business Review*, *10*(3), pp.171-176.

[3] Chatzis, S.P., Siakoulis, V., Petropoulos, A., Stavroulakis, E. and Vlachogiannakis, N., 2018. Forecasting stock market crisis events using deep and statistical machine learning techniques. *Expert systems with applications*, *112*, pp.353-371.

[4] Umer, M., Awais, M. and Muzammul, M., 2019. Stock market prediction using machine learning (ML) algorithms. *ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal*, *8*(4), pp.97-116.

[5] Nyman, R. and Ormerod, P., 2017. Predicting economic recessions using machine learning algorithms. *arXiv preprint arXiv:1701.01428*.

[6] Uthayakumar, J., Metawa, N., Shankar, K. and Lakshmanaprabu, S.K., 2020. Intelligent hybrid model for financial crisis prediction using machine learning techniques. *Information Systems and e-Business Management*, *18*(4), pp.617-645.

[7] Mittal, M., Goyal, L.M., Sethi, J.K. and Hemanth, D.J., 2019. Monitoring the impact of economic crisis on crime in India using machine learning. *Computational Economics*, *53*(4), pp.1467-1485.

[8] Khan, W., Ghazanfar, M.A., Azam, M.A., Karami, A., Alyoubi, K.H. and Alfakeeh, A.S., 2020. Stock market prediction using machine learning classifiers and social media, news. *Journal of Ambient Intelligence and Humanized Computing*, pp.1-24.

[9] Moumoun, L., 2022. Application of Machine Learning Techniques for Credit Risk Management: A Survey. *Advances in Information, Communication and Cybersecurity: Proceedings of ICI2C'21*, *357*, p.180.

[10] Park, J. and Shin, M., 2022. An Approach for Variable Selection and Prediction Model for Estimating the Risk-Based Capital (RBC) Based on Machine Learning Algorithms. *Risks*, *10*(1), p.13.

[11] Mai, F., Tian, S., Lee, C. and Ma, L., 2019. Deep learning models for bankruptcy prediction using textual disclosures. *European journal of operational research*, *274*(2), pp.743-758.

[12] Qu, Y., Quan, P., Lei, M. and Shi, Y., 2019. Review of bankruptcy prediction using machine learning and deep learning techniques. *Procedia Computer Science*, *162*, pp.895-899

[13] Sezer, O.B. and Ozbayoglu, A.M., 2018. Algorithmic financial trading with deep convolutional neural networks: Time series to image conversion approach. *Applied Soft Computing*, *70*, pp.525-538.

[14] Alaminos, D., Peláez, J.I., Salas, M.B. and Fernández-Gámez, M.A., 2021. Sovereign debt and currency crises prediction models using machine learning techniques. *Symmetry*, *13*(4), p.652

[15] Yang, Y.; Garcia-Morillo, I.; Hospedales, T.M. Deep Neural Decision Trees. In Proceedings of the 2018 ICML Workshop on Human Interpretability in Machine Learning (WHI 2018), Stockholm, Sweden, 14 July 2018.

[16] Alaminos, D., Salas, M.B. and Fernández-Gámez, M.A., 2021. Quantum computing and deep learning methods for GDP growth forecasting. *Computational Economics*, pp.1-27.

[17] Lu, Y., Zhu, J., Zhang, N. and Shao, Q., 2014, July. A hybrid switching PSO algorithm and support vector machines for bankruptcy prediction. In *2014 International Conference on Mechatronics and Control (ICMC)* (pp. 1329-1333). IEEE

[18] Wang, M., Chen, H., Li, H., Cai, Z., Zhao, X., Tong, C., Li, J. and Xu, X., 2017. Grey wolf optimization evolving kernel extreme learning machine: Application to bankruptcy prediction. *Engineering Applications of Artificial Intelligence*, *63*, pp.54-68.