Harnessing Dimensionality Reduction with Neutrosophic Net-RBF Neural Networks for Financial Distress Prediction

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Abstract

Neutrosophy is the study of neutralities and extends the discussion of the truth of opinions. Neutrosophic logic may be employed in any domain, for providing the solution for the ambiguity problems. Several real-time data experience problems such as indeterminacy, incompleteness, and inconsistency. A fuzzy set provides an uncertain solution, and intuitionistic fuzzy set handles incomplete data, but both fail to manage uncertain data. Before bankruptcy, financial distress is the early stage. Bankruptcies caused by financial problems can be seen in the financial statement of the company. The capability to predict financial problems became a crucial area of research since it provides earlier warning for the company. Moreover, predicting financial problems is advantageous for creditors and investors. In this article, we develop a new Dimensionality Reduction with Neutrosophic Net-RBF Neural Networks (DR-NSRBFNN) technique for FCP process. The DR-NSRBFNN technique concentrates on the predictive modelling of financial distress. In the DR-NSRBFNN technique, two major stages are involved. In the preliminary phase, the high dimensionality features can be reduced by the use of arithmetic optimization algorithm (AOA). In the second phase, the DR-NSRBFNN technique applies the NSRBFNN model to predict financial distress. The performance evaluation of the DR-NSRBFNN technique can be examined using distinct aspects. The widespread study stated the improved performance of the DR-NSRBFNN technique compared to other systems

Keywords: Financial Distress Prediction; Neutrosophic Set; Arithmetic Optimization Algorithm; Fuzzy Set; Intuitionistic Fuzzy Sets

1. Introduction

Bankruptcies execute enormous expenses on market participants and the economy as an entire [1]. Hence, forecasting business failure has been a topic of special trouble for numerous stakeholders, like investors, economic institutions, rating agencies, corporate managers, and shareholders [2]. An exact and effective Financial Distress Prediction (FDP) method delivers early warning signs for creditors and investors supports enterprise managers in creating effective decisions, and aids economic organizations in classifying key supervisory individuals, to uphold the economic market firmness [3]. In the past four years, methods and models for the forecast of business economic distress have concerned significant interest between practitioners and academics [4]. Economic distress prediction methods can be employed for numerous reasons such as observing the comfort of planned businesses, valuation of loan default danger and the credit derivatives, and assessing of bonds, and other safeties exposed to credit risk.

In present scenario, the neutrosophic set (NS) is merged with rough sets in order to define roughness and its space as neutrosophic rough sets [5]. The fuzzy set estimation was constructed depending upon a risp estimate that outcomes in the model of fuzzy rough sets. Therefore, the rough set model is suggested with NS in order to deliver data from many data systems [6]. The neutrosophic has been merged with rough sets to conduct vague data with estimates like lower and upper. Distinct countries have dissimilar accounting actions and rules; so, the explanation of economic distress put further by distinct scholars is not constantly similar [7]. Bankruptcy is one of the most generally utilized results of economic distress of a company. The sort of a bankrupt firm is that the owners can discard the firm and move ownership to the debt holders, and bankruptcy arises when the recognized cash flow is lesser than the debt contracts [8]. It is commonly granted that economic failure mains to fundamental weakening of viability of the company over time, but it is also practical that an economically concerned firm may not modify

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its formal condition to bankrupt [9]. Hence, in this paper, we recognize a financially troubled company as one in danger of failing, but which stays a sustainable entity at the current time. In academic research, modelling models for FDP differ from numerical methods to machine learning (ML) techniques or ensemble models. Numerous ML models and ensemble techniques have been developed in FDP for their superior analytical performance [10].

This article develops a new Dimensionality Reduction with Neutrosophic Net-RBF Neural Networks (DR-NSRBFNN) technique for FCP process. The DR-NSRBFNN technique concentrates on the predictive modelling of financial distress. In the DR-NSRBFNN technique, two major stages are involved. In the preliminary phase, the high dimensionality features can be reduced by the use of arithmetic optimization algorithm (AOA). In the second phase, the DR-NSRBFNN technique applies the NSRBFNN model to predict financial distress. The performance evaluation of the DR-NSRBFNN technique can be examined using distinct aspects.

2. Related Works

Kadkhoda and Amiri [11] present a new method for FDP by combining machine learning and network analysis approaches. This technique includes 2 company networks depends on their correlation and similarity in financial indicators. Five classification approaches are used to FDP over three scenarios. At first, model is trained by the initial features. Next, network-centric features from similarity and correlation networks are amalgamated, which enhances the prediction performance of the ML techniques. In [12], a new hybrid SA-DLSTM model is devised for predicting the simulation trading and stock market by merging an emotion LSTM, enhanced CNN (ECNN), and denoising AE (DAE) techniques. Initially, user-generated feedback on Internet complemented stock market data, and ECNN is used for extracting the sentiment representation. Next, the fundamental characteristics of stock market information are extracted with the help of DAE, improving the predictive performance. Then, the model creates a more realistic and reliable sentiment index. Lastly, the fundamental characteristics of stock data and sentiment indexes are given into LSTM for making stock market predictions. In [13], an adaptive WOA with DL (AWOADL) algorithm is employed to develop a new FDP system. A DNN named MLP based predictive and AWOA-based parameter tuning process is utilized in this work. First, the DNN receives the financial information as input and forecasts financial distress. As well, the AWOA is also used for the hyperparameters tuning of DNN approach, thus increasing the prediction accuracy.

Lee and Kim [14] present an effective technique to predict local tax delinquency using predominant DL and ML algorithms. ML and statistical approaches employ credit risk prediction, but their application to the prediction of tax arrears remains less explored. The model predicts local tax defaults in Republic of Korea via DL and ML techniques such as sequence-to-sequence (seq2seq), CNN, and LSTM models. Also, this technique integrates varied public and credit details. Alkhafaji et al. [15] developed a new Hyperparameter Tuned DRLearning based Prediction Method for Financial Crisis (HPTDRL-PFC) method. Primarily, the proposed model is used to normalize the input financial information into a uniform design. In this work, the Bayesian DQN (BDQN) method is employed for the prediction process. The artificial hummingbird optimizer (AHBO) technique implements the parameter selection for enhancing the prediction outcomes of the BQDN method. Zhang et al. [16] present a very effective methodology. First, a 3-layer lithium battery model can be used. This data is used for modelling the BPS, such as the batteries. The non-linear FE technique of the BPS can validated by means of the modal test outcomes. Next, a sensitivity analysis was implemented. Lastly, the DL model accuracy is evaluated. Moreover, the inclusion of Gaussian noise can be used for assessing the ability and robustness of the models to generalize. Kalaivani and Saravanan [17] designs Enhancing FCP with the Chimp Optimizer Algorithm using ML (EFCP-COAML) technique. This includes two primary processes namely hyperparameter tuning and classification. Initially, the model makes use of a Kernel ELM (KELM) based prediction process. Next, the COA has been used for the hyperparameter choice of the KELM technique which sequentially improves the prediction outcomes.

3. The Proposed Model

In this article, we have developed a novel DR-NSRBFNN system for FCP process. The DR-NSRBFNN technique concentrates on the predictive modelling of financial distress. In the DR-NSRBFNN technique, two major stages are involved as depicted in Fig. 1.

A. Application of AOA for Dimensionality Reduction

In the preliminary phase, the high dimensionality features can be reduced by the use of AOA. At initialization of the optimizer procedure, after the populace is prepared arbitrarily, the MOA function is utilized in order to pick the search stage among exploration stage (multiplication and division) and exploitation stage (addition and subtraction) [18]. When the value of MOA is larger than an arbitrary number r_1 formed by even distribution from zero to one, the explorative operations are nominated to upgrade every candidate's performance from the hunt space. Then, the exploitative operations are chosen. Fig. 2 illustrates the steps involved in AOA.

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During the exploration stage, the multiplication and division operators share a similar prospect to be chosen in order to compute the novel d-th dimension of nth solution $X_{n,d}^{new}$ as below:

$$X_{n,d}^{new}=\begin{cases} X_d^{best} \div (MOP+x) \times ((X_d^U - X_d^L) \times 0.5 + X_d^L), r_2 < 0.5 \\ X_d^{best} \times MOP \times \left((X_d^U - X_d^L) \times 0.5 + X_d^L\right), \text{otherwise} \end{cases} \quad (1)$$

where X_d^{best} denotes to the dth dimensional part of finest-chosen solution, where $d = 1, \dots, D$; x specifies a minor integer number; X_d^U signifies the upper bound and X_d^L represents the lower bound of d-th dimensional part; r_2 represents a number arbitrarily produced by even distribution in (0,1).

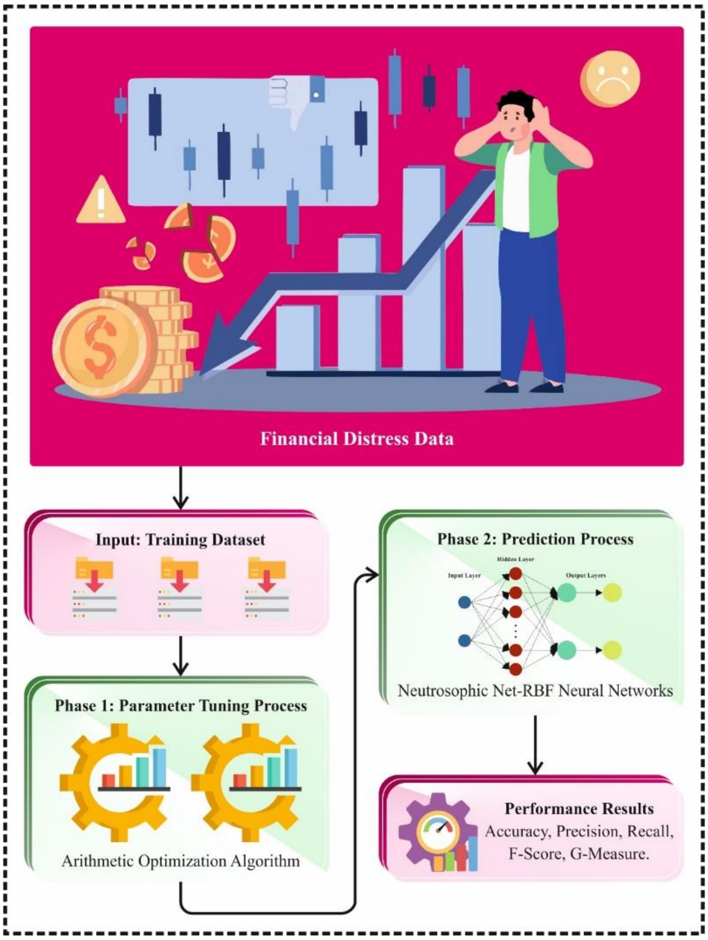

Figure 1: Overall flow of DR-NSRBFNN technique

Assumed the present fitness calculation number τ and the maximal number $\tau^{\max}$, the value of MOP has been intended as below:

$$MOP_\tau = 1 - \frac{\tau^{0.25}}{(\tau^{\max})^{0.25}} \quad (2)$$

Analogous to exploration stage, the subtraction and addition operations share a similar prospect that nominated to compute the novel dth size of nth performance $X_{n,d}^{new}$ as follow:

$$X_{n,d}^{new}=\begin{cases} X_d^{best} + MOP \times \left((X_d^U - X_d^L) \times 0.5 + X_d^L\right), r_3 < 0.5 \\ X_d^{best} - MOP \times \left((X_d^U - X_d^L) \times 0.5 + X_d^L\right), otherwise \end{cases} \quad (3)$$

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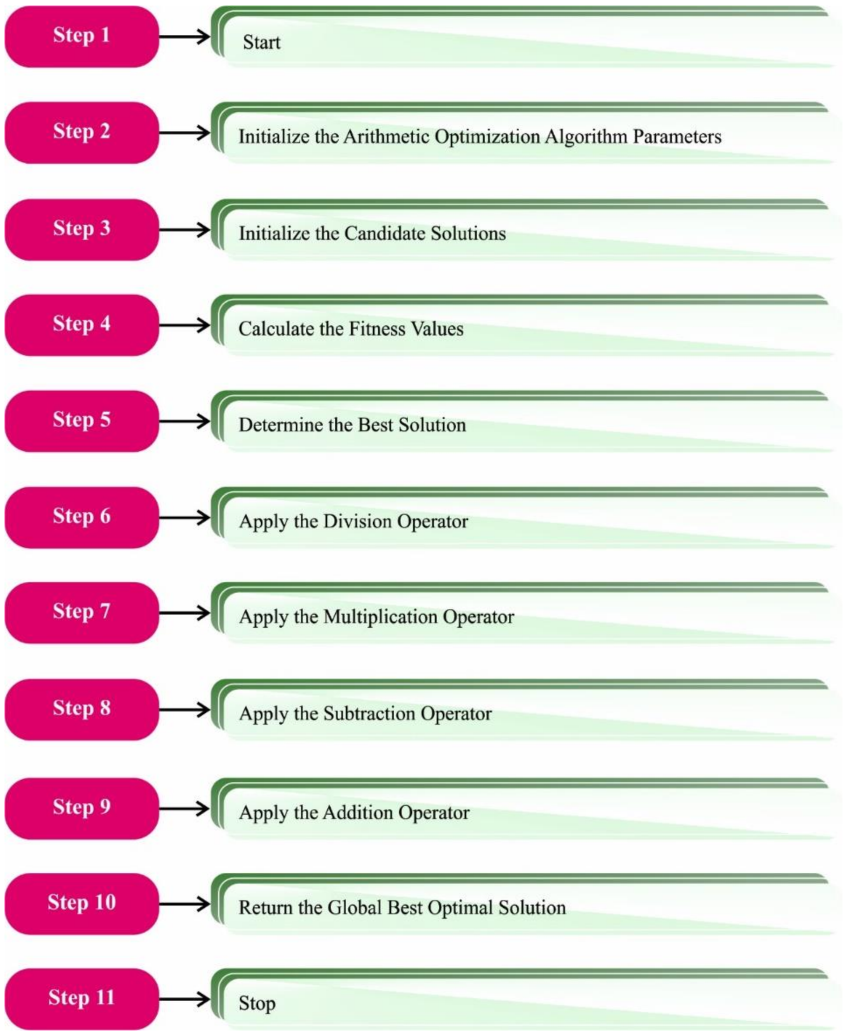

Figure 2: Steps involved in AOA

At the stage of initialization, the populace of AOA is arbitrarily produced and related fitness values (MSE) are intended. For every evaluation of fitness τ, the MOA value is initially planned to pick the phase of searching. Then, either exploration or exploitation stages are chosen in order to upgrade the solution of candidate. The optimizer procedure is repetitive till the conclusion criterion $\tau > \tau^{\max}$ is satisfied. The optimal solution attained at the conclusion of the optimizer procedure is measured as the finest mixture of biases, weights, and function of activation for FNN method in categorizing the assumed dataset.

B. Modeling of NSRBFNN

In the second phase, the DR-NSRBFNN technique applies the NSRBFNN model to predict financial distress. The transition of sets from FS to NS takes experienced several phases. Stamng by the description given by L. Zadeh in 1965 [19], whereas the FS $A = \{x, \mu_A(x) | \forall x \in X, \mu_A(x) \in [0,1]$ Goguen described the L-FS in X as a mapping $X \to L$ thus $L^*, \leq L^*$ refers to a complete lattice, whereas $L^* = \{(x_1, x_2) \in [0,1]^2, x_1 + x_2 \leq 1\}, (x_1, x_2) \leq L^*(y_1, y_2) \Leftrightarrow x_1 \leq y_1$.In 1983, Atanassanov presented the intuitionistic FS (IFS) as a generalization of FS, but all the elements of X are related to the non-membership degree (NMD) $v_A(x) \in [0,1]$ and membership degree (MD) $\mu_A(x) \in [0,1]$, thus $\forall x \in X, \mu_A(x) + v_A(x) \leq 1$. The theory of IFS presents truth and false membership degree functions and the theory uses interval as a toll for capturing ambiguity of the MD. Next, Smarandache described the NS as a tuple $< T, I, F >$ in the X_J (universe of discourse) and the component $n \in X$ is indicated as $n(T, I, F)$. T, I, and F elements are the neutrosophic logical values to handle the degree of the falsity ($\%F$), truth ($\%T$), and the indeterminacy ($\%I$). NS model depends on infinitesimal for defining the non-standard real-subset $[a, b]$. The number r is considered infinitesimal as long as for positive number n_J and the number r is described by $|r| < 1/n$. But the non-standard number is described by $-a = a - r$ and $b^+ = b + r$. The neutrosophic tuples $< T, F, I >$ are estimated by the non-standard or standard unit range.

Consider T, F, and I as non-standard or standard real subsets from zero and one with

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$$\sup T = t_{\sup};\ in\ f\ T = t_{inf}$$
$$snpF = f_{\sup};\ in\ fF = f_{inf} \tag{4}$$
$$snpI = i_{sup};\ in\ fI = i_{inf}$$

Thus, the NS $< T, I, F >$ is taken as interval, discrete, single-finite set, continuous, standard or non-standard real set, operation under union or intersection, fuzzy number, rough set, and so on.

This process is to calculate the ambiguity in the trained model of RBF-NN. This method comprises 2 kinds of uncertainty calculation depending on NSs viz., the ambiguity amongst FSs which is evaluated by estimating the fuzziness between two FSs, A_j and A_l using the overlapping coefficient. Then, the uncertainty in FS construction is related to the one-to-many relationship, viz., situation with multiple alternatives at the learning procedure of RBF-NN. The initial step is to determine the tuple $< T_i, F_i, I_i >$ in the RBF-NN taxonomy and later evaluate the related ambiguity. Next, a detection method is performed to estimate the RBF parameter.

The functional similarity among the FS and RBF-NN is established if the condition is satisfied as follows:

1. The receptive field in the HL is corresponding to the amount of FSs.
2. The MFs in all the rules are elected as a Gaussian function.
3. The T-norm operator is applied for computing firing strength of rules.
4. The FIS and the RBF-NN use the defuzzification technique, viz., weighted sum or centre of gravity to evaluate the total output.

An RBF-NN is processed as a fuzzy inference engine that maps input $U \subset R^n, k = 1, n$ considered as an MF $\mu_A(x): U \to [O, 1]$ into the non-fuzzy $Y \in R$ set. Assume, a multi- input-single-output (MISO) $f: U \subset R^n \to R$ which has n inputs $x_k \in [x_1, \dots, x_n]^T \in U_1 \times U_2 \times .. \times U_k .. \times U_n \triangleq U$ where the i^{th} rules have the form

$$\tilde{R}^i: IF\ x_1\ is\ \tilde{A}_1^i\ and\ x_2\ is\ \tilde{A}_2^i\ .and\ x_n\ is\ \tilde{A}_n^i\ THEN\ y\ is\ \tilde{B}^i \tag{5}$$

$$\mu_{A^i}(\vec{x}_p) = f_i\left(exp\left[-\frac{\|\vec{x}_p - \vec{x}\|^2}{\sigma_i^2}\right]\right) \tag{6}$$

Where $\vec{x}_p = [x_1, \dots, x_n]$ and σ_i and $\vec{x}$ are the width and the center of i^{th} FS correspondingly. The receptive field is defined as the tuple$< T_i, F_i, I_i >$where T_i is the firing strength or its normalized value.

F_i and I_i are the supplement of FS (A_I) and its uncertainties correspondingly. Thus, the T_i, F_i and I_i components are evaluated based on ambiguity and fuzziness.

Vagueness or fuzziness is commonly utilized in the FS theory since it is related to the linguistic uncertainties of FS.

$$fe_k^i(\mu_{Ov}) = \begin{cases} (1-\mu_{Ov})^\alpha e^{\mu_{Ov}} + \mu_{Ov}^\alpha e^{(1-\mu_{Ov})}, & i \neq j \\ 0, & i = j. \end{cases} \tag{7}$$

Whereas $\alpha \in [0,1]$ and μ_{Ov} are the areas that the FS (A_i) overlaps the FS $(A_j(j = 1, \dots, M))$ as follows:

$$\mu_{Ov} = \frac{Ov_{A_iA_j}}{A_i}, \mu_{Ov} \in [0,1] \tag{8}$$

The $Ov_{A_iA_j}$ overlapping coefficient calculates the area under the small of the FSs $(A_i$ and $A_j)$

$$Ov_{A_iA_j} = \int_a^b \min\left[A_i(x), A_j(x)\right]dx \tag{9}$$

Eq. (5) shows the fuzziness per dimensiona from i^{th}rules among the FSs (A_i and A_j). But the fuzziness should be average dimensional measure for each neuron at p patterns that is attained by the following equation:

$$E_i^p(fe_k^i) = \frac{1}{M \times n}\sum_{k=1}^{n}\sum_{i=1, i\neq j}^{M} f\ e_k^i(\mu_{Ov}) \tag{10}$$

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In Eq. (10), the number of rules and dimensions are M and n correspondingly. The value of local indeterminacy or uncertainty (I_k) between two FSs (A_i and A_j) defines the NSs based on the fuzziness evaluation in the FS construction.

$$\widehat{U}_{ik}^{p} = \begin{cases} \frac{1}{(1+e^{g\times fe_k^i})}, & \mu_{Ov} < \hat{t}, \\ \frac{\left(e^{g\times fe_k^j}\right) - \left(e^{g\times fe_k^i}\right)}{\left(e^{g\times fe_k^i}\right) + \left(e^{g\times fe_k^i}\right)}, & \mu_{Ov} > \hat{t}. \end{cases} \quad (11)$$

Where $i = j$ the value of $\widehat{U}_{ik}^{p}$ is 0. Whereas $\hat{t} \in [0,1]$ and $g \in R$. As a result, the local uncertainty per RU is described by

$$I_i = \frac{1}{M \times n} \sum_{k=1}^{n} \sum_{i=1, i\neq j}^{M} \widehat{U}_{ik}^{p} \quad (12)$$

Then, the network uncertainty at p pattern is given below:

$$I_p = \frac{1}{M \times n} \sum_{p=1}^{P} \sum_{k=1}^{n} \sum_{i=1, i\neq j}^{M} \widehat{U}_{ik}^{p} \quad (13)$$

Where P amount of trained patterns, T_i is described by the truth μ_{A^i} related to the receptive rule and $F_i = 1 - \mu Ov$ denotes the falsity.

Generally, in FS theory uncertainty comprises three major kinds, namely: a) non-specificity, b) dissonance, and c) confusion. The uncertainty related to non-specificity is caused by NSs representing cognitive uncertainty. Here, the uncertainty is based on the ambiguity of selecting from the normalized output in the HL while categorizing the input data. Thus, the greater the ambiguity, the superior the amount of alternatives. Here, the uncertainty is described as an indeterminacy in selecting which fuzzy rule correctly describes the input data based on the normalized output. Therefore, the tuple $< T_i, F_i, I_{ik}^{p} >$ is given by:

The truth can be measured as:

$$T_i = \frac{\mu_{A^i}(\vec{X}_p)}{\Sigma_{i=1}^{M} \mu_{A^i}(\vec{X}_p)} \quad (14)$$

The falsity can be measured as:

$$F_i = \max\,[T_i]_{i\neq j} \quad (15)$$

The indeterminacy or ambiguity is attained by the following expression:

$$I_{ik}^{p} = Ambignity_i = 1 - |T_i - F_i| \quad (16)$$

Hence, the overall neural uncertainty is measured as follows:

$$I_A = \frac{1}{M \times n} \sum_{p=1}^{P} \sum_{k=1}^{n} \sum_{i=1}^{M} I_{ik}^{p} \quad (17)$$

4. Result Analysis

The performance evaluation of the DR-NSRBFNN technique can be examined utilizing 2 datasets such as Australian and Analecta datasets are represented in Table 1.

Table 1: Details of datasets

Dataset	Source	instances	attributes	# of class	Bankrupt/Non-Bankrupt
Australian	UCI	690	14	2	383/307

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Analecta	stern	50	5	2	25/25

The financial distress prediction results of DR-NSRBFNN technique under Australian dataset are defined in Table 2. The experimental values inferred that the DR-NSRBFNN technique has suitable identification of bankrupt and non-bankrupt classes. With 70%TRAS, the DR-NSRBFNN model obtains average $accu_y$ of 94.86%, $prec_n$ of 95.16%, $reca_l$ of 94.86%, F_{score} of 94.98%, and $G_{measure}$ of 95.00%. In addition, with 30%TESS, the DR-NSRBFNN approach attains average $accu_y$ of 97.06%, $prec_n$ of 98.03%, $reca_l$ of 97.06%, F_{score} of 97.48%, and $G_{measure}$ of 97.51%.

Table 2: Financial distress prediction of DR-NSRBFNN technique under Australian dataset

Australian Dataset					
Classes	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	$G_{Measure}$
TRAS (70%)					
Bankrupt	96.93	94.05	96.93	95.47	95.48
Non-Bankrupt	92.79	96.26	92.79	94.50	94.51
Average	94.86	95.16	94.86	94.98	95.00
TESS (30%)					
Bankrupt	100.00	96.06	100.00	97.99	98.01
Non-Bankrupt	94.12	100.00	94.12	96.97	97.01
Average	97.06	98.03	97.06	97.48	97.51

In Fig. 3, the ROC curve of the DR-NSRBFNN approach under Australian dataset is studied. The outcomes inferred that the DR-NSRBFNN methodology attains improved ROC values with 2 classes, representing a significant ability to discriminate the classes. This consistent trend of enhanced values of ROC under 2 classes signifies the capable performance of the DR-NSRBFNN technique on forecasting classes, demonstrating the robust nature of classification method.

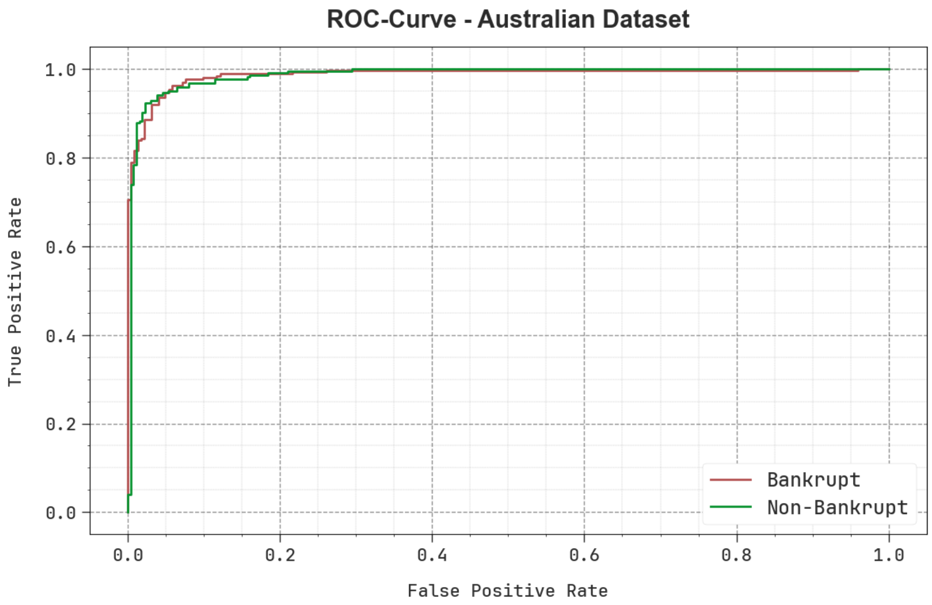

Figure 3: ROC curve of DR-NSRBFNN technique under Australian dataset

In Table 3 and Fig. 4, the comparison investigation of DR-NSRBFNN technique with existing systems on Australian dataset [13]. The outcomes stated that the DR-NSRBFNN methodology has outperformed optimum

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solution. Based on $prec_n$, the DR-NSRBFNN model has superior $prec_n$ of 98.03% while the AWOADL, TLBODL, DNN, LR, and RBFNetwork algorithms have lesser $prec_n$ of 97.65%, 96.2%, 92.43%, 65.79%, and 86.31%, respectively. Moreover, based on $accu_y$, the DR-NSRBFNN system has improved $accu_y$ of 97.06% while the AWOADL, TLBODL, DNN, LR, and RBFNetwork techniques have lesser $accu_y$ of 96.89%, 94.05%, 91.34%, 79.71%, and 85.21%, correspondingly. Finally, based on F_{score}, the DR-NSRBFNN technique has maximal F_{score} of 97.48% while the AWOADL, TLBODL, DNN, LR, and RBFNetwork methodologies have decreased` F_{score} of 95.21%, 93.15%, 89.96%, 74.26%, and 83.86%, correspondingly.

Table 3: Comparative outcome of DR-NSRBFNN technique with existing models under Australian dataset

Australian Dataset				
Methods	$Prec_n$	$Reca_l$	$Accu_y$	F_{Score}
DR-NSRBFNN	98.03	97.06	97.06	97.48
AWOADL	97.65	94.82	96.89	95.21
TLBODL	96.2	90.29	94.05	93.15
DNN Algorithm	92.43	87.62	91.34	89.96
Logistic Regression	65.79	85.23	79.71	74.26
RBFNetwork	86.31	81.53	85.21	83.86

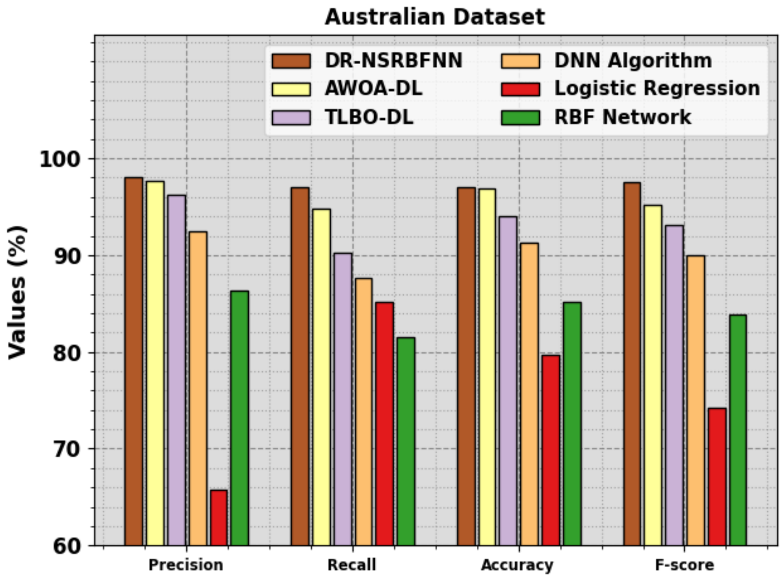

Figure 4: Comparative outcome of DR-NSRBFNN technique under Australian dataset

The financial distress prediction outcomes of DR-NSRBFNN algorithm at Analecta dataset are offered in Table 4. The simulation values stated that the DR-NSRBFNN methodology has appropriate identification of bankrupt and non-bankrupt classes. With 70%TRAS, the DR-NSRBFNN system achieves average $accu_y$ of 97.37%, $prec_n$ of 97.06%, $reca_l$ of 97.37%, F_{score} of 97.13%, and $G_{measure}$ of 97.17%. Besides, with 30%TESS, the DR-NSRBFNN technique accomplishes average $accu_y$ of 94.44%, $prec_n$ of 92.86%, $reca_l$ of 94.44%, F_{score} of 93.21%, and $G_{measure}$ of 93.43%.

Table 4: Financial distress prediction of DR-NSRBFNN technique under Analecta dataset

Analecta Dataset					
Classes	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	$G_{Measure}$
TRAS (70%)					

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Bankrupt	94.74	100.00	94.74	97.30	97.33
Non-Bankrupt	100.00	94.12	100.00	96.97	97.01
Average	97.37	97.06	97.37	97.13	97.17
TESS (30%)					
Bankrupt	100.00	85.71	100.00	92.31	92.58
Non-Bankrupt	88.89	100.00	88.89	94.12	94.28
Average	94.44	92.86	94.44	93.21	93.43

In Fig. 5, the ROC curve of the DR-NSRBFNN algorithm under Analecta dataset is examined. The outcomes define that the DR-NSRBFNN method accomplishes superior outcomes of ROC under 2 classes, signifying considerable ability to categorize the class labels. This dependable trend of superior outcome of ROC under 2 classes suggest the capable performance of the DR-NSRBFNN algorithm on predicting classes, emphasizing the robust nature of classifier method.

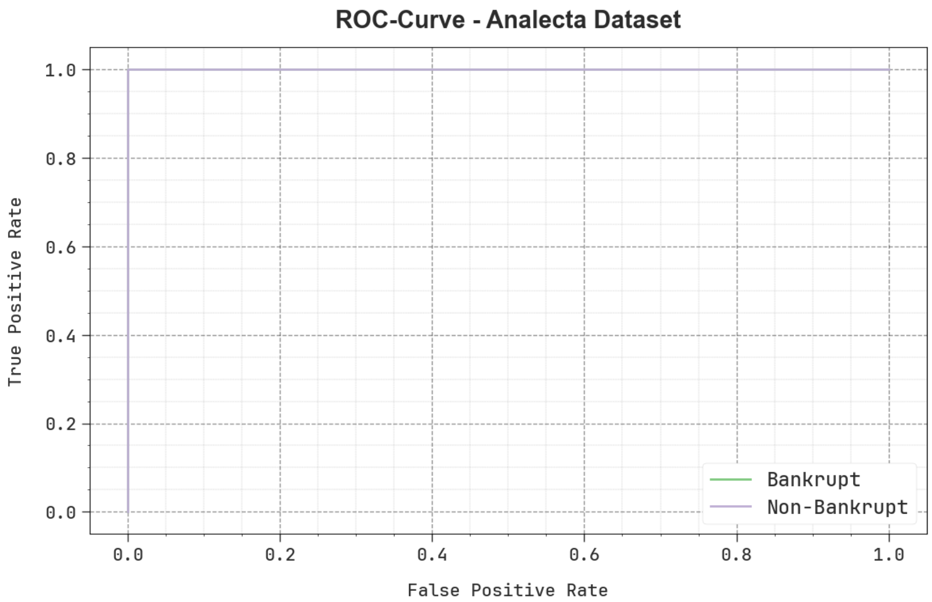

Figure 5: ROC curve of DR-NSRBFNN technique under Analecta dataset

In Table 5 and Fig. 6, the comparative outcome of DR-NSRBFNN algorithm with existing systems on Analecta dataset. The outcome defined that the DR-NSRBFNN methodology has outperformed optimum results. Based on $prec_n$, the DR-NSRBFNN technique has maximal $prec_n$ of 97.06% while the AWOADL, TLBODL, DNN, LR, and RBFNetwork methodologies have minimal $prec_n$ of 96.70%, 95.91%, 96.00%, 92.00%, and 80.00%, correspondingly.

Table 5: Comparative outcome of DR-NSRBFNN technique with existing models under Analecta database

Analact Dataset				
Methods	$Prec_n$	$Reca_l$	$Accu_y$	F_{Score}
DR-NSRBFNN	97.06	97.37	97.37	97.13
AWOADL	96.70	96.75	96.60	96.63
TLBODL	95.91	92.30	96.00	96.00
DNN Algorithm	96.00	85.00	90.00	90.56

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Logistic Regression	92.00	85.18	88.00	88.46
RBFNetwork	80.00	71.42	74.00	75.47

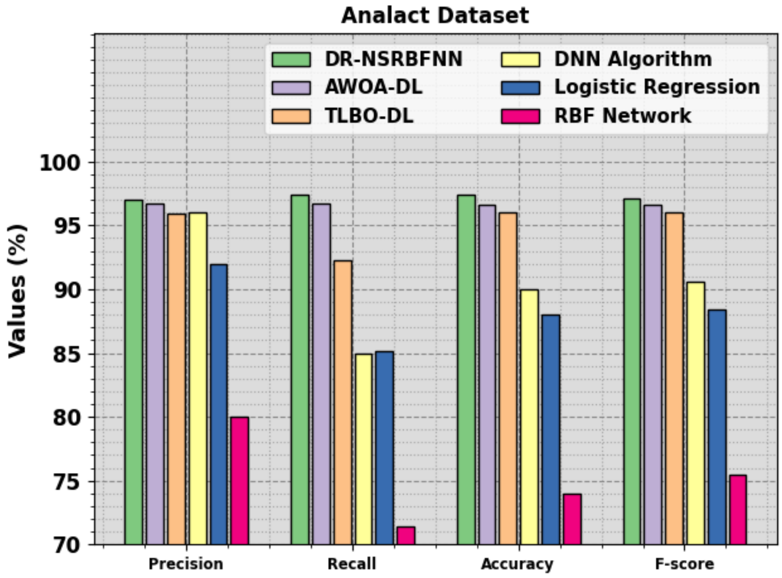

Figure 6: Comparative outcome of DR-NSRBFNN technique under Analecta dataset

Also, with respect to $accu_y$, the DR-NSRBFNN method has higher $accu_y$ of 97.37% while the AWOADL, TLBODL, DNN, LR, and RBFNetwork systems have decreased $accu_y$ of 96.60%, 96.00%, 90.00%, 88.00%, and 74.00%, correspondingly. Moroever, based on F_{score}, the DR-NSRBFNN methodology has enhanced F_{score} of 97.13% while the AWOADL, TLBODL, DNN, LR, and RBFNetwork systems have reduced F_{score} of 96.63%, 96.00%, 90.56%, 88.46%, and 75.47%, correspondingly.

5. Conclusion

In this article, we have introduced a novel DR-NSRBFNN methodology for the FCP process. The DR-NSRBFNN system concentrates on the predictive modelling of financial distress. In the DR-NSRBFNN technique, two major stages are involved. In the preliminary phase, the high dimensionality features can be reduced by the use of AOA. In the second phase, the DR-NSRBFNN technique applies the NSRBFNN model to predict financial distress. The performance evaluation of the DR-NSRBFNN technique can be examined using distinct aspects. The widespread analysis stated the improved performance of the DR-NSRBFNN technique compared to other approaches.

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