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Enhancing Bankruptcy Prediction with White Shark Optimizer and Deep Learning: A Hybrid Approach for Accurate Financial Risk Assessment

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Abstract: Bankruptcy prediction is the process of measuring the possibility of a company facing bankruptcy or financial distress in the future. An accurate bankruptcy prediction model is valuable for creditors, investors, and financial institutions to assess credit risk, make informed investment decisions, and take appropriate risk management measures. Various methods have been built to contemplate bankruptcy, involving more advanced machine learning (ML) methods and traditional statistical techniques. Typically, this method utilizes financial ratios, accounting data, market performance indicators, and other related variables as input features for predicting the probability of bankruptcy. There has been a growing interest in leveraging the power of neural networks for anticipating the bankruptcy with the emergence of deep learning (DL) methods. With this motivation, this article introduces a new white shark optimizer with deep learning-based bankruptcy prediction for financial risk assessment (WSODL-BPFCA) technique. The presented WSODL-BPFCA technique utilizes a hyperparameter-tuned DL model to predict the existence of bankruptcy. To obtain this, the WSODL-BPFCA technique utilizes min-max normalization to transform the input data into a uniform format. For bankruptcy prediction, the WSODL-BPFCA technique introduces an attention-based long short-term memory (ALSTM) approach. Lastly, the hyperparameter tuning of the ALSTM model was carried out by employing of WSO approach. To exhibit the enhanced performance of the WSODL-BPFCA technique, a widespread set of simulations were performed. The comprehensive comparison study highlighted the improved results of the WSODL-BPFCA technique as 97.61% in terms of different metrics.

Keywords: Bankruptcy prediction, Financial risk assessment, Machine learning, White shark optimizer, Deep learning.

1. Introduction

Bankruptcy prediction is considered a data classification difficulty that signifies the user as "default" or the user is denoted as "non-default" once they can return the loan. Bankruptcy prediction is generally a classification issue which implies can be dealt with by classifying algorithms [1]. Generally, the tasks of bankruptcy prediction are used for predicting whether the enterprise can have bankrupt or not, which is a binary classification difficulty. We have to apply the techniques to train the databases like the financial data from the firm's financial declarations in conducting the prediction accurately [2]. The advanced techniques can assist the data distribution on the organization's risk condition in different approaches, like professional agencies and mass media [3]. The reasons for loss of enterprise and bankruptcy are based on the aspects, namely, economic, financial, disaster, and scam. The financial factors contain weakness of industry, poor location, and economic issues involving massive responsibilities in bankruptcy [4]. Consequently, accurate bankruptcy prediction is an increasingly important issue in financial and management complications [5]. Bankruptcy prediction is a binary classification issue, which comprises two categories such as non-bankrupt and bankrupt [6]. Various bankruptcy elements are property elimination, repayment, protected responsibilities, and more. Thus, numerous existing approaches utilized for predicting financial collapse and bankruptcy should be constantly enhanced. The major challenge of the prediction of bankruptcy begins with selecting the prediction technology.

Starting at the beginning of the year 1960s, various research has been performed on the classification of bankruptcy. Recently, traditional methods are used in mathematical functions for predicting the financial crisis that distinguishes financial organizations from sturdier and feebler ones [7]. In 1990, the focal point moved to artificial intelligence (AI) and ML supported professional systems namely the neural networks and support vector machines (SVM) [8]. Newly, AI systems can be suitable to develop conventional classification approaches. But, the existence of different factors from the high-dimensional economic data performance in diverse challenges. There is over-fitting higher computational complexity, and less interoperability [9]. The accessible method to determine this problem was decreasing the obtainable quantity of features with the feature selection (FS) technique [10].

This article introduces a new white shark optimizer with a deep learning-based Bankruptcy prediction for financial risk assessment (WSODL-BPFCA) technique. The presented WSODL-BPFCA technique utilizes a hyperparameter-tuned DL model to predict the existence of bankruptcy. To obtain this, the WSODL-BPFCA technique utilizes min-max normalization to transform the input data into a uniform format. For bankruptcy prediction, the WSODL-BPFCA technique introduces an attention-based long short-term memory (ALSTM) approach. Lastly, the hyperparameter tuning of the ALSTM model was carried out by employing of WSO approach. To exhibit the enhanced performance of the WSODL-BPFCA technique, a widespread set of simulations were performed.

The remaining sections of the article is arranged as: section 2 and 3 represents the literature review and proposed model. Then, section 4 elaborates the results evaluation and section 5 completes the work.

2. Literature review

In [11], a greater FS-XGBoost approach depends on FS can be projected. FS-XGBoost was comparable to 7 ML approaches depending on 3 FS methods commonly exploited in anticipating bankruptcy: stepwise LR, partial least squares discriminant analysis (PLS-DA), and step-wise discriminant evaluation. The authors [12] examine a novel DL-based method termed as BSM-SAES method. This method mixes the borderline synthetic minority (BSM) oversampling method and SAE depending on the Softmax classifier. The drive is to establish a correct and dependable anticipation of bankruptcy approach that involves the features extraction method. Al-Milli et al. [13] examined a dynamic controller for the most popular population diversity controller-GA (PDC-GA) method presented as a new FS method for reducing the searching space but creating ML classifiers. The PDC-GA was presented by integrating GA with k-mean clustering for controlling the diversity of the population by the exploration procedure.

Soui et al. [14] present a new DL-based algorithm that contains either feature extraction or classification stage as one model for bankruptcy prediction of economic companies. This approach integrates SAE with softmax classification. Primarily, the SAE can be utilized for extracting optimum features in the training database. Secondarily, the softmax classification layer has been trained for predicting the classes. In [15], 2 meta-heuristics approaches like magnetic optimizer algorithm (MOA) and PSO are improved by hybridization for proposing a novel MOA-PSO approach. The hybrid methods are recognized that able of resolving optimizer problems faster with optimum accuracy.

In [16], a hybrid system combining the DT with DNN has been presented to offer a compromise performance for investors. The DT was implemented as an initial method for providing explainable capability, but the DNN is selected for improving predictive accuracy. The hybrid method can be executed by integrating the DNN to the selected DT branches that carry out worse forecast accuracy under the trained method. Jain et al. [17] introduce a novel approach to enhance the bankruptcy prediction efficiency of several ML approaches. Initially, the authors convert the imbalanced database comprising bankrupt and non-bankrupt data into a stable database by executing oversampling method. Afterwards, the appropriate and non-duplicate factors can be created dependent upon the fuzzy rough FS approach using evolutionary search.

3. The Proposed model

In this article, a new WSODL-BPFCA technique is presented for accurate prediction of bankruptcies.

The presented WSODL-BPFCA technique utilized the hyperparameter-tuned DL model to predict the bankruptcy. In the presented WSODL-BPFCA technique, three major procedures are involved such as data normalization, ALSTM-based prediction, and WSO-based tuning. Fig. 1 illustrates the overall flow of the WSODL-BPFCA approach.

3.1 Data normalization

At the preliminary stage, the WSODL-BPFCA technique makes use of a min-max normalization

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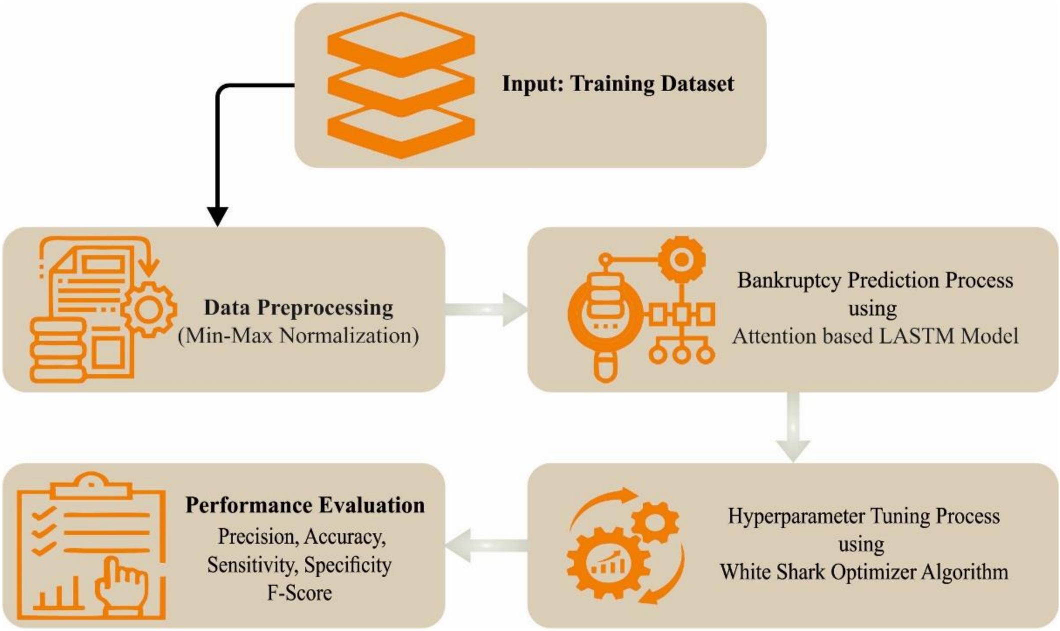

Figure. 1 Overall flow of WSODL-BPFCA approach

process. Min-max normalized also called feature scaling or min-max scaling, is a general approach employed for transforming numerical data as a standardization range. The drive of min-max normalized is to rescale the values of the variable to a certain range, naturally between zero and one, but maintaining the comparative connections among the data points. This equation for min-max normalized is as follows:

$$Normalized\ value = \frac{(X - X\_min)}{(X\_max - X\_min)} \quad (1)$$

whereas X, X_min, and X_max refers to the original value, the minimal value, and the maximal value.

3.2 Bankruptcy prediction using ALSTM

For the data classification process, the WSODL-BPFCA technique employs the ALSTM model. LSTM is an enhanced RNN architecture with special units (viz., memory module) along with the RNN that is adaptable with dams' processing time sequences data [18]. In the process of hydraulic buildings, the monitoring data generated are organized time sequence data. The LSTM approach extracts the data correlation with a huge span on the time sequences while learning the existing data to accomplish lasting memory and decrease the rate of information loss. Its efficient utilization in dam security observation and better solution in long-time sequences data anticipation was evaluated by an extensive investigation. LSTM model comprises the following gates: forget (f_t^l), input (i_t^l), and output (0_t^l), and the decision to discard or update data was developed by 3 elements. Initially, the forget gate decides with specific probability if maintain the cell state at the prior moment and chooses the data proportion that is maintained by using the output $(h_t - 1)$ of the Hidden Layer (HL) in the prior and the input (x) at existing time steps, and the 2 parameters are given as sigmoid function (σ) for obtaining the output of forget gate(f_t). f_t and σ are evaluated as follows:

$$f_t = \sigma\left(W_f \cdot \left(h_{t-1}, x_j\right) + b_f\right) \quad (2)$$

$$\sigma(x) = \frac{1}{1-e^{-x}} \quad (3)$$

Where the input and the output vector at t and $t-1$ time are characterized as x_i and h_{t-1}, correspondingly. w_f denotes the weight matrix of the forget gate, σ shows the logistic sigmoidal function, and b_f indicates the deviation vector. The forget gate output f_t controls to what extent the unit data in the prior time step is forgotten, and its values range from zero to one. $f_t = 0$ complete forgetting and $f_t = 1$ denotes the complete retention.

The input gate filters the input at the existing moment to define the data needed that is kept as novel data from the cell state. The beginning of novel data can be defined by the σ (sigmoid layer) and $tanh$ layer, where σ (sigmoid) layer defines the degree of novel data entry it and the $tanh$ layer produces the count of novel data candidates $\tilde{a}$ required for storing. The mathematical expression can be given as follows:

$$i_t = \sigma(W_i \cdot (h_{t-1}, x_i) + b_i) \quad (4)$$

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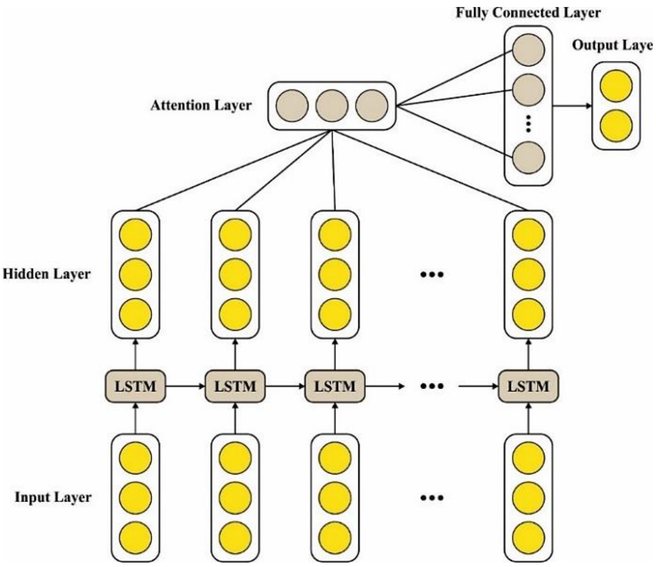

Figure. 2 Architecture of ALSTM

$$\tilde{a} = \tanh(W_c \cdot (h_{t-1}, x_i) + b_c) \tag{5}$$

$$\tanh x = \frac{(1-e^{-x})}{1+e^{-x}} \tag{6}$$

Where W_i, W_c denotes the weight matrix of $sigmoid$ and tanh layers and b_i, b_c shows the deviation vector of $sigmoid$ and tanh layers, correspondingly.

The cell state can be upgraded by fusing the prior cell state time step and the existing input data time steps through forget and input gates. The updated equation can be given as follows:

$$C_t = f_t C_{t-1} + i_t a_t \tag{7}$$

The output gate chooses and extracts appropriate data in the existing cell state for generating a novel HL. First, the cell state' output part can be defined by the sigmoid function (σ), and later can be handled by t he tanh function, and lastly a novel HL h_t is produced. The computation equation can be expressed as follows:

$$h_t = 0_t \tanh C_t \tag{8}$$

$$o_t = \sigma(W_o \cdot (hx) + b_0) \tag{9}$$

Where W_0 refers to the weight matrix of the output gate, and b_f shows the deviation vector.

In summary, the existing HL output h_t and cell state $C_t$of LSTM are impacted by the prior HL output h_{t-1} and cell state C_{t-1}, along with the existing input x_t at the provided moment. The LSTM model comprises multiple HLs which could better train the complex non-linear relationships between impact and dam deformation factors.

ALSTM refers to a NN structure, which integrates the strengths of the LSTM network and attention mechanisms [19]. Fig. 2 represents the structure of ALSTM. LSTM networks are effectual in modelling consecutive data and capturing long-term dependency, making them appropriate for tasks like NLP and time sequence investigation. Conversely, attention mechanisms permit the network to concentrate on important parts of input sequences, allowing optimum interpretation and understanding of data. During the framework of ALSTM, the attention mechanism has been combined with the LSTM structure to improve its capability to procedure sequential data. The attention mechanism allocates weights to distinct parts of input sequences dependent upon their relevance and significance to the present stage of classification or prediction. These weights guide the LSTM network concentration on significant data, permitting it to choose to attend to particular elements of sequences. The attention mechanism in the ALSTM is generally separated into 2 elements like context vector and attention weights. The context vector suggests the aggregated data in the input series, weighted by attention weights.

The attention weights can be computed depending on the similarity or relevance among all the input elements and the present context. Distinct approaches are employed for computing attention weighted namely additive attention, dot product attention, or multiplicative attention. The major benefit of ALSTM is its capability to capture essential patterns or features in the input order. Typical LSTM approaches give the complete sequence uniformly, but ALSTM is selectively concentrated on significant parts of the sequences, providing further weight to elements that are additional informative or influential for the task. This adaptive attention mechanism permits the method for allocating resources efficiently and creating more correct forecasts and classification.

3.3 WSO-based hyperparameter tuning

To improve the detection results of the ALSTM model, the WSO algorithm can be employed for the optimal hyperparameter selection process. WSO algorithm has been presented as dependent upon the performance of white sharks (WS) through foraging [20]. A great WS in the ocean seizes its prey by affecting the waves and other factors for seizing its prey reserved in the deep ocean. While the WS catching the prey depends on 3 performances such as

(i) the shark velocity from the prey catch, (ii) exploring for an optimum food source, and (iii) the other shark's movement nearby the shark that is towards an optimum food source. A primary WS population was defined as:

$$W_q^p = lb_q + r \times \left(up_q - lb_q\right) \tag{10}$$

whereas W_q^p denotes the primary parameters of p_{th} WS from the q_{th} dimensional. The upper and lower bounds from the q_{th} dimensional are represented by up_q and lb_q, correspondingly. Where r implies the arbitrary number from the range of zero and one.

The WS's velocity to place the prey depends on the sea waves motion was defined as:

$$vl_{s+1}^p = \mu\left[vl_s^p + F_1\left(W_{gbest_s} - W_s^p\right) \times C_1 + F_2\left(W_{best}^{vl_s^p} - W_s^p\right) \times C_2\right] \tag{11}$$

whereas $s = 1,2, \ldots., m$ denotes the index of WSs with the size of populations m. A novel velocity of p_{th} shark was represented by vl_{s+1}^p in $(s+1)_{th}$ step. The primary speed of the p_{th} shark from the s_{th} step is represented by vl_s^p. The global optimum position attained by some p_{th} sharks in $the\, s_{th}$ step is demonstrated by W_{gbest_s}. A primary position of $the\, p_{th}$ shark in the s_{th} step is represented by W_s^p. An optimum position of $the\, Pth$ shark and the index vector on accomplishing a better position is implied by $W_{best}^{vl_s^p}$ and vc^i. Whereas, C_1 and C_2 in the formula are determined as the formation of uniform arbitrary numbers from the range of one and zero. F_1 and F_2 denote the force of sharks for controlling the outcome of W_{gbest_s} and $W_{best}^{vl_s^p}$ on $W_s^p . \mu$ defines the examine the converging aspect of the sharks. The index vector of WS was defined as:

$$vc = [t \times rand(1, t)] + 1 \tag{12}$$

whereas $rand\,(1, t)$ denotes the arbitrary numbers vector acquired with uniform distribution from the range of zero and one. The forces of the shark to manage the outcomes are defined as:

$$F_1 = F_{\max} + (F_{\max} - F_{\min}) \times e^{-(4u/U)^2} \tag{13}$$

$$F_2 = F_{\min} + (F_{\max} - F_{\min}) \times e^{-(4u/U)^2} \tag{14}$$

A primary and maximal sum of iterations is represented by u and U, in which the WS's present and sub-ordinate velocities are defined by $F_{\min}$ and $F_{\max}$. The convergence aspect is written as:

$$\mu = \frac{2}{\left|2-\tau-\sqrt{\tau^2-4\tau}\right|} \tag{15}$$

In which, τ refers to the acceleration coefficient. This approach for upgrading the WS position is expressed as:

$$W_{s+1}^p = \begin{cases} W_s^p . \neg \oplus W_o + up.c + lo.d; rand < MV \\ W_s^p + vl_s^p / fr; rand \geq MV \end{cases} \tag{16}$$

A novel position of p_{th} shark in $(s+1)$ iteration, $\neg$ implies the negation operator c and d denotes the binary vectors. W_0 and fr represent the logical vector and frequency of the movement of the shark. The searching space lower as well as upper bounds are signified by lo and ub. The binary and logic vectors can be formulated as:

$$c = sgn\left(W_s^p - up\right) > 0 \tag{17}$$

$$d = sgn\left(W_s^p - 1\right) > 0 \tag{18}$$

$$W_o = \oplus\,(c, d) \tag{19}$$

The frequency in which the WS moves is defined as:

$$fr = fr_{\min} + \frac{fr_{\max} - fr_{\min}}{fr_{\max} - fr_{\min}} \tag{20}$$

$fr_{\max}$ and $fr_{\min}$ indicate the maximal and minimal frequency rates. An improvement in force at all the iterations has been demonstrated as:

$$MV = \frac{1}{\left(c_0 + e^{(s/2-S)/c_1}\right)} \tag{21}$$

whereas MV stands for the weighted terms from the document.

An optimum solution is demonstrated as:

$$W_{s+1}^{\prime p} = W_{gbest_s} + r_1 \vec{D}is_W sgn(r_2 - 0.5) r_3 < Str_{sns} \tag{22}$$

In which, the position upgrade then the food source of p_{th} the WS is represented by $W_{s+1}^{\prime p}$. The $sgn(r_2 - 0.5)$ creates 1 or -1 to adapt the searching direction. The distance between the shark and food source $\vec{D}is_w$, the WS power, and then other sharks

Table 1. Database details

Class	Sample Numbers
Financial Crisis	383
Non-Financial Crisis	307
Total Samples	690

nearby the food source Str_{sns} is expressed as:

$$\vec{D}is_W = |rand \times (W_{gbest_s} - W_s^p| \quad (23)$$

$$Str_{sns} = \left|1 - e^{(c_2 \times s/S)}\right| \quad (24)$$

A primary optimum solution is held constant, and other shark's location is upgraded based on these 2 constant optimum performances. The fish school performance of sharks is written as:

$$W_{S+1}^P = \frac{W_s^p + W_{s+1}'^p}{2 \times rand} \quad (25)$$

The weighted factor j_{we} is defined as:

$$p_{we} = \frac{1}{m-1} \times \left(\frac{\sum_{Y=,Y\neq j}^{\rho} q_{fit}}{\sum_{Y=1}^{\rho} q_{fit}}\right) \quad (26)$$

In, q_{fit} implies the fitness of all the terms from the text document. The development of the formula is written as:

$$p_{we} = \frac{1}{m-1} \times \frac{[{}^1fit + {}^2fit + \cdots + {}^{q+1}fit + \cdots + {}^{m-1}fit + {}^mfit]}{1fit + {}^2fit + \ldots {}^{q-1} + {}^qfit + + {}^{q+1} + \cdots + {}^{m-1}fit + {}^mfit} \quad (27)$$

The incorporation of Hybrid Mutation (HM) was utilized in the WSO for rapid converging method. So, the HM executed with the optimizer is defined as:

$$HM =^{t+1} GM +^{t+1} CM \quad (28)$$

$$t + 1GM = W_q^{new} + D_1 . G_a(\mu, \sigma) \quad (29)$$

$$\tau + 1CM = W_q^{new} + D_2 . C_a(\mu', \sigma') \quad (30)$$

In which, $G_a(\mu, \sigma)$ and $C_a(, \sigma)$, and (μ, σ) and (μ', σ') indicates the arbitrary number, and mean and variance function of either Gaussian or Cauchy dispersals. D_1 and D_2 imply the coefficients of Gaussian $t + 1GM$ together with Cauchy $(t + 1)CM$ mutation. On executing these 2 hybrid mutation functions, a novel solution was created that are demonstrated as:

$$[W_q^{new}]_{new} = W_q^{new} +^p we(HM) \quad (31)$$

$$p_{we} = \sum_{y=1}^{PS} \frac{W_q^{new}}{PS} \quad (32)$$

In which, p_{we}, PS implies the weighted vector and the population size. The FS from the feature extraction is defined as $(p = 1,2, \ldots m)$. The WSO output is stated as $(sel) = \{sel^1, sel^2, \ldots .. sel^m\}$ that is a novel terms sub-group in the database. Concurrently, m refers to the noel count of all the same features. Finally, the FS step offers a database document with optimum features. The fitness choice is a key aspect of the WSO method. An encoding result was employed to develop the optimum candidate outcomes. Presently, the accuracy value is the major condition employed to strategy a FF.

$$Fitness = \max(P) \quad (33)$$

$$P = \frac{TP}{TP + FP} \quad (34)$$

In which, TP and FP denote the true and false positive values.

4. Results and discussion

The performance validation of the WSODL-BPFCA technique is examined on the Australian credit dataset (available at http://archive.ics.uci.edu/ml/datasets/statlog+(australian+credit+approval). It has 690 samples and two classes as defined in Table 1.

Fig. 3 shows the classifier analysis of the WSODL-BPFCA approach under test dataset. Fig. 3 (a) illustrates the confusion matrix obtainable by the WSODL-BPFCA approach on 70% of the TR set. The figure showed that the WSODL-BPFCA technique has determined 256 and 192 instances under FC and NFC. Moreover, Fig. 3 (b) portrays the confusion matrix on 30% of the TS set. The figure signified that the WSODL-BPFCA technique has detected 111 instances under FC and 91 instances under NFC. Likewise, Figs. 3 (c), and (d) exhibits the total classifier results at 70:30 of the TR set /TS set. The observational values specify that the WSODL-BPFCA model correctly identified two class labels.

Table 2 report the overall outcomes on 70 and 30% the TR and TS set. The experimental values depict that the WSODL-BPFCA technique properly recognized two classes. With 70% of TR set, the WSODL-BPFCA approach offers average $accu_{bal}$ of 92.44%, $prec_n$ of 92.87%, $sens_y$ of 92.44%, $spec_y$ of 92.44%, and F_{score} of 92.62%. Likewise, with 30% of TS set, the WSODL-BPFCA approach

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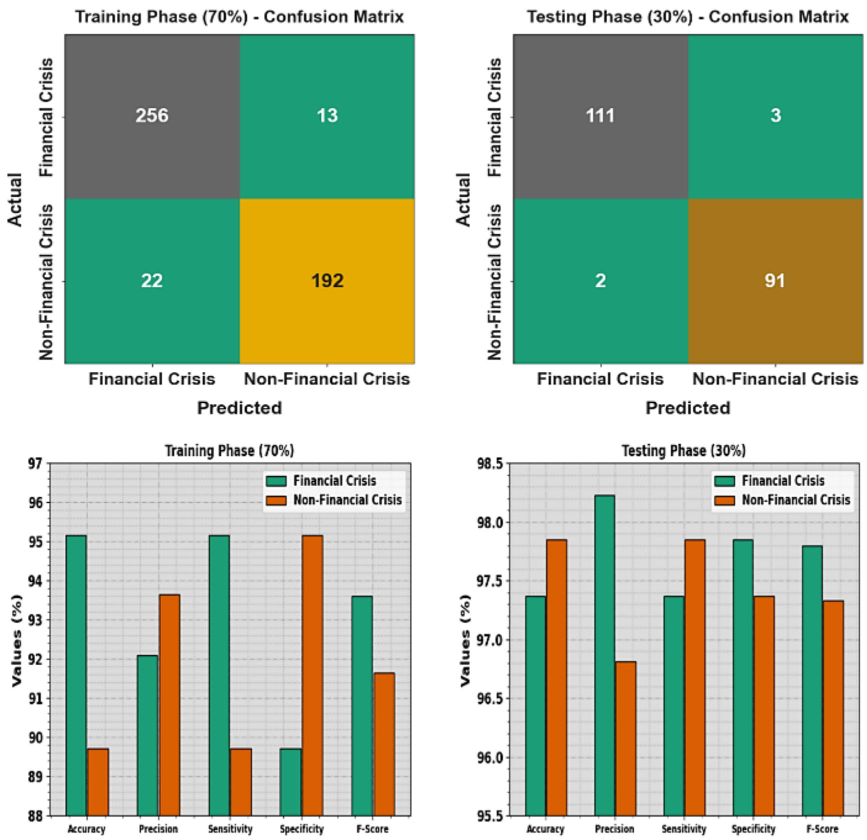

Figure. 3 Performance output of confusion matrices and overall outcome on 70:30 of TR set/TS set

Table 2. Classifier output of WSODL-BPFCA model on 70:30 of TR set/TS set

Class	$Accu_{bal}$	$Prec_n$	$Sens_y$	$Spec_y$	F_{Score}
Training Phase (70%)					
FC	95.17	92.09	95.17	89.72	93.60
NFC	89.72	93.66	89.72	95.17	91.65
Average	92.44	92.87	92.44	92.44	92.62
Testing Phase (30%)					
FC	97.37	98.23	97.37	97.85	97.80
NFC	97.85	96.81	97.85	97.37	97.33
Average	97.61	97.52	97.61	97.61	97.56

Table 3. Comparative outcome of WSODL-BPFCA model with other methodologies

Techniques	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}
RBF Algorithm	74.00	71.42	77.27	75.47
Random Forest	86.00	84.61	87.50	86.27
MLP Algorithm	90.90	90.56	83.33	90.90
DBN Model	91.29	90.67	90.54	90.65
CNN Model	90.08	91.13	91.50	90.64
GRU Model	91.16	91.26	90.95	91.43
WSODL-BPFCA	97.61	97.61	97.61	97.56

Table 4. CT outcome of WSODL-BPFCA model with other methodologies

Techniques	Computational Time (sec)
RBF Algorithm	4.80
Random Forest	3.52
MLP Algorithm	5.80
DBN Model	7.75
CNN Model	4.83
GRU Model	3.82
WSODL-BPFCA	1.97

gives an average $accu_{bal}$ of 97.61%, $prec_n$ of 97.52%, $sens_y$ of 97.61%, $spec_y$ of 97.61%, and F_{score} of 97.56%.

The classification results of the WSODL-BPFCA technique are compared with other models in Table 3 [21].

The obtained values portrayed the ineffectual performance of the RBF and RF models. Then, the MLP, DBN, CNN, and GRU models have reported slightly enhanced results. But, the WSODL-BPFCA technique exhibited superior performance with maximum $accu_y$, $sens_y$, $spec_y$, and F_{score} of 97.61%, 97.61%, 97.61%, and 97.56% respectively.

The CT results of the WSODL-BPFCA technique are compared with other models in Table 4. The outcomes exhibit that the DBN model results in a worse CT of 7.75s. Concurrently, the RBF, MLP, and CNN models exhibit moderate CT values of 4.80s, 5.80s, and 4.83s respectively. Although the RF and GRU models accomplish reasonable CTs of 3.52s and 3.82s, the WSODL-BPFCA technique exhibits better performance with minimal CT of 1.97s. Therefore, the WSODL-BPFCA technique can be employed for accurate bankruptcy prediction.

5. Conclusion

In this article, a new WSODL-BPFCA technique for accurate prediction of bankruptcies is designed and developed. The presented WSODL-BPFCA technique utilized the hyperparameter-tuned DL model to predict the existence of bankruptcy. In the proposed WSODL-BPFCA algorithm, three major procedures are contained such as data normalization, ALSTM-based prediction, and WSO-based hyperparameter tuning. In this work, the tuning process of the ALSTM model is accomplished by utilizing of WSO system. To exhibit the enhanced performance of the WSODL-BPFCA technique, a widespread set of simulations were performed. The comprehensive comparison study highlighted the improved results of the WSODL-BPFCA technique in terms of different metrics. Therefore, the WSODL-BPFCA technique can be exploited for accurate financial risk assessment.

Conflict of interest:

The authors hereby confirm no conflict of interest.

Author contributions:

Conceptualization, Gunita Arun Chandok and Arul Mary Rexy; methodology, Gunita Arun Chandok, Arul Mary Rexy, Anwer Basha, and Selvi; software, Gunita Arun Chandok and Arul Mary Rexy; validation, Gunita Arun Chandok and Arul Mary Rexy; formal analysis, Gunita Arun Chandok, Arul Mary Rexy, Anwer Basha, and Selvi; investigation, Gunita Arun Chandok, Arul Mary Rexy, Anwer Basha, and Selvi; resources, Gunita Arun Chandok, Arul Mary Rexy, Anwer Basha, and Selvi; data curation, Gunita Arun Chandok and Arul Mary Rexy; writing-original draft preparation, Gunita Arun Chandok and Arul Mary Rexy; writing-review and editing, Gunita Arun Chandok, Arul Mary Rexy, Anwer Basha, and Selvi; supervision, Gunita Arun Chandok, Arul Mary Rexy, Anwer Basha, and Selvi; project administration, Gunita Arun Chandok and Arul Mary Rexy; funding acquisition, Gunita Arun Chandok, Arul Mary Rexy, Anwer Basha, and Selvi. All authors have recited and accepted the final manuscript.

References

[1] T. K. Chen, H. H. Liao, G. D. Chen, W. H. Kang and Y. C. Lin, "Bankruptcy Prediction Using Machine Learning Models with the Text-based Communicative Value of Annual Reports", *Expert Systems with Applications*, p. 120714, 2023, doi: 10.1016/j.eswa.2023.120714.

[2] G. Lombardo, M. Pellegrino, G. Adosoglou, S. Cagnoni, and P. M. Pardalos *et al.*, "Machine Learning for Bankruptcy Prediction in the American Stock Market: Dataset and Benchmarks", *Future Internet*, Vol. 14, No. 8, p. 244, 2022.

[3] B. Siswoyo, Z. A. Abas, A. N. C. Pee, R. Komalasari and N. Suyatna, "Ensemble machine learning algorithm optimization of bankruptcy prediction of bank", *IAES International Journal of Artificial Intelligence*, Vol. 11, No. 2, p. 679, 2022.

[4] V. Abrol, P. Singh, R. Subhashini, A. S. Kumar, K. Singh, and B. R. Mannar, "Bankruptcy Prediction using Emperor Penguin Optimizer with Deep Learning Model on Qualitative Dataset", In: *Proc. of 2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT)*, Tirunelveli, India, pp. 1028–1033, Jan. 2023.

[5] Y. Cao, X. Liu, J. Zhai and S. Hua, "A two-stage Bayesian network model for corporate bankruptcy prediction", *International Journal of Finance & Economics*, Vol. 27, No. 1, pp. 455-472, 2022.

[6] J. A. Adisa, S. Ojo, P. A. Owolawi, A. Pretorius and S. O. Ojo, "Application of an Improved Optimization Using Learning Strategies and Long Short Term-Memory for Bankruptcy Prediction", *IAENG International Journal of Computer Science*, Vol. 50, No. 2, 2023.

[7] S. Begum, "A detailed study for bankruptcy prediction by machine learning technique", *Intelligent Sustainable Systems: Selected Papers of WorldS4 2021*, Vol. 2, pp. 201-213, 2022.

[8] S. H. Cho and K. S. Shin, "Feature-Weighted Counterfactual-Based Explanation for Bankruptcy Prediction", *Expert Systems with Applications*, Vol. 216, p. 119390, 2023.

[9] H. U. R. Siddiqui, B. S. D. Abajo, I. D. L. Torre Díez, F. Rustam, and A. Raza *et al.*, "Predicting bankruptcy of firms using earnings call data and transfer learning", *PeerJ Computer Science*, Vol. 9, 2023, doi: 10.7717/peerjcs.1134/table-13.

[10] C. Thilakarathna, C. Dawson and E. Edirisinghe, "Using Financial Ratios with Artificial Neural Networks for Bankruptcy Prediction", In: *Proc. of 2022 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA)*, Dalian, China, pp. 55-58, 2022.
[11] S. B. Jabeur, N. Stef and P. Carmona, "Bankruptcy prediction using the XGBoost algorithm and variable importance feature engineering", *Computational Economics*, Vol. 61, No. 2, pp. 715-741, 2023.
[12] S. Smiti and M. Soui, "Bankruptcy prediction using deep learning approach based on borderline SMOTE", *Information Systems Frontiers*, Vol. 22, pp. 1067-1083, 2020.
[13] N. A. Milli, A. Hudaib and N. Obeid, "Population diversity control of genetic algorithm using a novel injection method for bankruptcy prediction problem", *Mathematics*, Vol. 9, No. 8, p. 823, 2021.
[14] M. Soui, S. Smiti, M. W. Mkaouer and R. Ejbali, "Bankruptcy prediction using stacked auto-encoders", *Applied Artificial Intelligence*, Vol. 34, No. 1, pp. 80-100, 2020.
[15] A. Ansari, I. S. Ahmad, A. A. Bakar and M. R. Yaakub, "A hybrid metaheuristic method in training artificial neural network for bankruptcy prediction", *IEEE Access*, Vol. 8, pp. 176640-176650, 2020.
[16] T. N. Chou, "An Explainable Hybrid Model for Bankruptcy Prediction Based on the Decision Tree and Deep Neural Network", In: *Proc. of 2019 IEEE 2nd International Conference on Knowledge Innovation and Invention (ICKII)*, Seoul, Korea (South), pp. 122-125, 2019, doi: 10.1109/ICKII46306.2019.9042639.
[17] P. Jain, A. K. Tiwari and T. Som, "Improving financial bankruptcy prediction using oversampling followed by fuzzy rough feature selection via evolutionary search", *Computational Management: Applications of Computational Intelligence in Business Management*, pp. 455-471, 2021, doi: 10.1007/978-3-030-72929-5_21.
[18] J. Madiniyeti, Y. Chao, T. Li, H. Qi and F. Wang, "Concrete Dam Deformation Prediction Model Research Based on SSA–LSTM", *Applied Sciences*, Vol. 13, No. 13, p. 7375, 2023.
[19] S. Xiong, L. Zhou, Y. Dai and X. Ji, "Attention-based long short-term memory fully convolutional network for chemical process fault diagnosis", *Chinese Journal of Chemical Engineering*, Vol. 56, pp. 1-14, 2023.
[20] N. Parveen, P. Chakrabarti, B. T. Hung and A. Shaik, "Twitter sentiment analysis using hybrid gated attention recurrent network", *Journal of Big Data*, Vol. 10, No. 1, pp. 1-29, 2023.
[21] J. Uthayakumar, T. Vengattaraman and P. Dhavachelvan, "Swarm intelligence based classification rule induction (CRI) framework for qualitative and quantitative approach: An application of bankruptcy prediction and credit risk analysis", *Journal of King Saud University-Computer and Information Sciences*, Vol. 32, No. 6, pp. 647-657, 2020.