An Intelligent Bankruptcy Prediction Model based on an Enhanced Sparrow Search Algorithm

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Abstract

Bankruptcy detection becomes one of the major subjects in finance. Indeed, for apparent reasons, several actors like shareholders or managers show more attention to the possibility of a firm's bankruptcy. Subsequently, various researches are being conducted on the matter of bankruptcy prediction. Recently numerous research works have explored the application of machine learning (ML) techniques to bankruptcy prediction by having financial ratios as predictors. This article devises an Enhanced Sparrow Search Optimization with Deep Learning Enabled Bankruptcy Prediction (ESSODL-BP) model. The proposed ESSODL-BP technique involves the forecasting of the bankruptcy of a financial firm. To accomplish this, the ESSODL-BP technique primarily follows the Z-score normalization approach. Followed by, the bidirectional long short-term memory (BLSTM) model is designed to predict the bankruptcy status of a financial firm. Then, the ESSO algorithm is utilized for optimally tuning the hyperparameters related to the BLSTM model and also boosts the prediction performance to a maximum extent. The performance validation of the ESSODL-BP technique is tested using a benchmark dataset. The experimental outcomes reported better performance of the ESSODL-BP technique over other approaches.

Keywords: Intelligent Systems; Bankruptcy prediction; Deep learning; Sparrow search optimization

1. Introduction

Business failure was generally examined, attempting to distinguish the several determinants that could affect the (Non) presence of companies. Particularly because of the new changes in the economy and as additional organizations, small and large, appear to fail now like never before [1]. Bankruptcy prediction is very important. In the major research, bankruptcy prediction can be considered a binary classification issue. The target (yield) variable of the models is regularly a dichotomous variable where "firm sought financial protection" is set to 1 and "firm remains dissolvable" is set to 0. The reference (input) variables were financial ratios derived from financial reports and incorporate measures of profitability, liquidity, and leverage. Bankruptcy was unwanted peculiarity. It adversely affects business proprietors, managers, stakeholders, workers, manufacturers, providers, customers, and the government [2]. Subsequently, the bankruptcy prediction was highly important in financial analysis and has generally been concentrated on in late decades. Concentrates on prediction of bankruptcy fall under several trains like business management accounting, finance.

In the recent past, bankruptcy prediction is one of the critical issues faced by decision makers in the field of finance [3]. Bankruptcy causes various failures affecting economics, stockholders, customers, management, and so on. The main focus of bankruptcy prediction is to find out whether a financial firm or organization will go bankrupt or not [4]. Bankruptcy or financial concern is a position that proceeds when a financial firm verifies its financial obligations. The development of technology supports the acquisition of information on the risk condition of an organization in various manners, such as mass media and professional agencies [5]. The causes of bankruptcy and loss of business are based on factors, such as financial, economic, disaster, and fraud. In

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bankruptcy, the economic factors consist of poor location, weakness of industry and financial factors consist of enormous obligations [6]. Therefore, the accurate prediction of bankruptcy is a more important problem in financial and management problems [7]. The prediction of bankruptcy is a binary classification problem, which includes two classes namely bankrupt and non-bankrupt [8]. Different elements of bankruptcy are secured obligations, repayment, property elimination, etc. Therefore, many of the current techniques used to predict financial failure and bankruptcy must be continuously improved. The primary challenge of bankruptcy prediction starts with the selection of the prediction technique. Several recent and advanced techniques for predicting bankruptcy have been developed [9]. Statistical and machine learning techniques are the two broad categories used to predict bankruptcy.

Machine learning (ML) was a sub-domain of computer science. It permits PCs to assemble analytical methods of data and find stowed away experiences automatically, lacking being unequivocally coded [10]. It was implied to various prospects in present day culture, extending from DNA groupings classification, credit card fraud identification, robot locomotion, to NLP. It very well may be utilized to settle many sorts of tasks like classification. ML was brought into the world from pattern acknowledgment.

This article devises an Enhanced Sparrow Search Optimization with Deep Learning Enabled Bankruptcy Prediction (ESSODL-BP) model. The proposed ESSODL-BP technique involves the forecasting of the bankruptcy of a financial firm. To accomplish this, the ESSODL-BP technique primarily follows Z-score normalization approach. Followed by, the bidirectional long short term memory (BLSTM) model is designed to predict the bankruptcy status of a financial firm. Then, the ESSO algorithm is utilized for optimally tuning the hyperparameters related to the BLSTM model and also boosts the prediction performance to a maximum extent. The performance validation of the ESSODL-BP technique is tested using benchmark dataset.

2. Related works

In [11], a hybrid method integrating the DT with the DNN was suggested to give a trade-off answer for investigators. The DT was adopted as the primary method to give explainable ability, while the DNN decided to work on prescient accuracy. The decision combination of two methods was planned with the compensatory and non-compensatory methods approaches. The hybrid model was carried out by concatenating the DNN to the chosen branches of DT that perform poor prescient accuracy during model training. Mai et al. [12] present DL models for corporate bankruptcy forecasting utilizing textual revelations. Although textual data are normal, it was rarely viewed in the financial decision support techniques. At the point when textual data are utilized related to traditional market-related variables and accounting-related ratios, DL models can additionally further develop prediction accuracy.

In [13], an enhanced XGBoost process based on feature selection (FS-XGBoost) was suggested. FS-XGBoost was made a comparison with seven ML techniques based on three notable FS strategies that are oftentimes utilized in bankruptcy prediction: partial least squares discriminant analysis (PLS-DA) stepwise discriminant analysis, and stepwise LR. In [14], an original method based on deep genetic cascade ensemble of various SVM classifiers was implied to the Statlog Australian data. The suggested technique is a hybrid method which blends the advantages of ensemble learning, DL, and evolutionary computation. The proposed approach contains an original 16-layer genetic cascade ensemble of classifiers, has two sorts of feature extraction strategies, SVM classifiers, normalization approaches, three kinds of kernel capacities, parameter optimizations, and stratified 10-crease cross validation (CV) strategy.

Soui et al. [15] suggest a new DL -based method which incorporates both feature extracting and classification stage into single method for forecasting bankruptcy of financial firms. This method consolidates SAE with softmax classifier. In the primary stage, the SAEs are utilized for extracting the best features from the trained data. Secondly, a softmax classification layer was well-trained to foresee the class label. Oliveira et al. [16] aim to foster a different criteria framework to foresee bankruptcy in small-and medium-sized enterprises (SMEs). It joins mental mapping with the measuring attractiveness by a categorical based evaluation technique (MACBETH), bringing about a comprehensive and transparent cycle for assessing SMEs and their risk of bankruptcy. In [17], a hybrid design integrating statistical hypothesis and computational intelligence method was created using GA having statistical dimensions and FL based fitness capacities for key ratio selection. A fuzzy clustering procedure was utilized for the classifier plan. In the analyses, two financial ratio sets, one derived from the ideas of different examinations and the other gained by utilizing the GA tool stash in the SAS statistical software packages, are implied to scrutinize the suggested ratio selection plans.

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3. The Proposed Model

In this article, a new ESSODL-BP model has been introduced for forecasting the bankruptcy of a financial firm. To accomplish this, the ESSODL-BP technique primarily follows Z-score normalization approach. Followed by, the bidirectional long short term memory (BLSTM) model is designed to predict the bankruptcy status of a financial firm. Then, the ESSO algorithm is utilized for optimally tuning the hyperparameters related to the BLSTM model. Figure 1 depicted the overall process of ESSODL-BP approach.

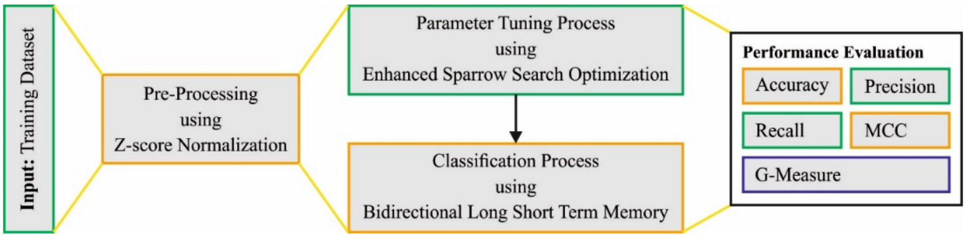

Figure 1. Overall process of ESSODL-BP algorithm

3.1 Stage I: BLSTM based Classification

In this study, the BLSTM model is designed to predict the bankruptcy status of a financial firm. The Bi-LSTM methodology receives the feature vector as input and implements the detection technique [18]. The LSTM indicates a diverse RNN technique that overcomes the vanishing gradient problem of RNN through offering a memory unit and threshold method. But v signifies the weighted input in HL to the output layer, x represents the network input at diverse times, h refers to the hidden layer (HL), u denotes the weighted input to HL, y denotes the network result, and$w$ demonstrates the weighted input of the previous node HL to the existing node HL.

In the effective enforcement of the LSTM method, the LSTM unit was upgraded at t time using the following equation:

$$i_t = \sigma(W_i h_{t-1} + U_i x_t + b_t) \tag{1}$$

$$f_t = \sigma\left(W_j h_{t-1} + U_f x_t + b_f\right) \tag{2}$$

$$\tilde{c} = tanh(W_c h_{t-1} + U_c x_t + b_c) \tag{3}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{4}$$

$$o_t = \sigma(W_o h_{t-1} + U_o x_t + b_o) \tag{5}$$

$$h_t = o_{t-1} \odot tanh(c_t) \tag{6}$$

From the equations, σ denotes the sigmoid function, and $\odot$ stands for the equal product of elements. h_t refers to the HL vector named as the output vector and the storage of each dataset at t time and the preceding time. x_t signifies the input vector at t time. W_i, W_f, W_c, W_o implies the weight of various gates to the HL vector h_t. b_t, b_f, b_c, b_o demonstrates the offset vector. x_t denotes the input, forgotten, unit, and output gates. U_i, U_f, U_c, U_o stands for the weighted input vector. Applying the three-gate architecture, the LSTM lets the recurrent architecture for maintaining the advantageous dataset of the task from the memory unit in the trained model, consequently evade the RNN vanishing problem however, it reaches all information. Figure 2 depicts the infrastructure of LSTM.

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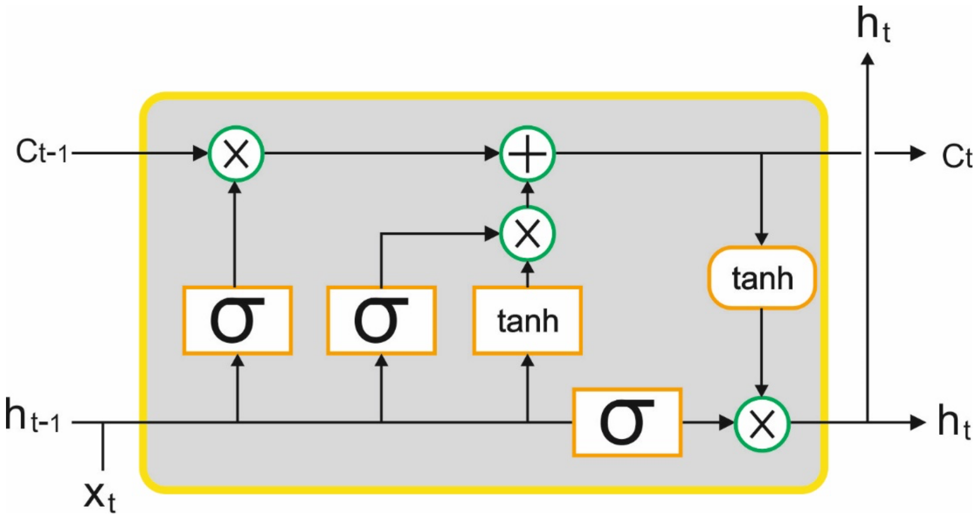

Figure 2. Framework of LSTM

Besides processing the data sequence, the BLSTM presents backward approximation procedure, as an example of dissimilar LSTM instance. This procedure applies the succeeding sequence data. Eventually, the forward and reverse approximations are implemented. The value was subsequent to the output layer at the same time; accordingly, each series dataset is accomplished in $2 * 2$ directions that are exploited for completing an NLP task.

3.2 Stage II: ESSO based Hyperparameter Tuning

Then, the ESSO algorithm is utilized for optimally tuning the hyperparameters related to the BLSTM model. SSA accomplishes the optimum solution by imitating definite behavior of sparrows [19]. Primarily, the discoverer–joiner sparrow population model is determined, following the sparrow is chosen in a random manner as a guard. The joiner seizes food from the discoverer, observes the discoverer, and follows the discoverer for food. The discoverer is responsible for providing foraging direction and area for the sparrow population. When the vigilante realizes the threat, the population immediately implements anti-predation behaviors. At last, with different iterations of the position of the joiner and discoverer, the adoptive location for the whole population is determined. The sparrow population in the space of $N \times D$, wherever D characterizes the spatial dimension, N specifies the total amount of sparrows. Following, x_{id} symbolizes the place of $i\text{-}th$ sparrows in d-dimension and the position of $i\text{-}th$ sparrows in space characterizes $X_i = (x_{i1}, x_{i2}, \cdots, x_{id})$, $i \in [1, N]$, $d \in [1, D]$. The location upgrade formula of the discoverer is demonstrated as follows.

$$x_{id}^{t+1} = \begin{cases} x_{id}^{t} \cdot exp.(\dfrac{-i}{\alpha \cdot T}) & R_2 < ST \\ x_{id}^{t} + Q \cdot L, & R_2 \geq ST \end{cases} \tag{7}$$

From the expression, T signifies the highest iteration count; t denotes the present iteration count; Q denotes an arbitrary number using normal distribution; L indicates a matrix in that element is 1 and its size is $1 \times d$; α indicates an arbitrary integer lies between zero and one; $ST \in [0.5,1]$ denotes the safety values, $R_2 \in [0,1]$ signifies the warning values. When $R_2 \geq ST$, the vigilante discovered the predator and instantly delivered an alarm to the others. When $R_2 < ST$, the population is not at risk and the discoverer continues searching. The sparrow population immediately executes anti-predation behavior to a safe area for food. The updating location formula of the joiner is demonstrated as follows.

$$x_{id}^{t+1} = \begin{cases} Q \cdot exp(\dfrac{x_{worstd}^{t} - x_{id}^{t}}{i^2}) & i > \dfrac{N}{2} \\ x_{best\,d}^{t+1} + \dfrac{1}{D}\displaystyle\sum_{d=1}^{D}(rand(-1,1) \cdot |x_{id}^{t} - x_{best\,d}^{t+1} & i \leq \dfrac{N}{2} \end{cases} \tag{8}$$

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At this point, x_{bestd}^{t+1} signifies the global optimal location at the tth iteration; x_{worstd}^{t} signifies the global worst place in tth iteration. When $i \leq \frac{N}{2}$, then $i\text{-}th$ joiner is close to the optimum place and is arbitrary foraging around. When $i > \frac{N}{2}$, then $i - th$ joiner has not accomplished food and needs to fly towards other place for finding food. The upgrade location of vigilant equation can be given in the following:

$$x_{id}^{r+1} = \begin{cases} x_{worst\ d}^{t} + \beta(x_{id}^{t} - x_{worst\ d}^{t}), & f_i \neq f_g \\ x_{id}^{t} + K\left(\dfrac{x_{id}^{t} - x_{worst\ d}^{t}}{|f_i - f_w| + e}\right) & f_i = f_g \end{cases} \quad (9)$$

In Eq. (9), K indicates the direction motion of sparrow, and arbitrary integer lies between [1, 1];β indicates the step length control variables i.e., an arbitrary value subjected to a normal distribution with means value of 0 and a variance of 1; f_i symbolizes the fitness of $i\text{-}th$ sparrow; e specifies a constant with smaller value; f_w symbolizes the worst fitness of existing population; f_g indicates the finest fitness of the existing population. When $f_i = f_g$, then $i\text{-}th$ sparrows are within center of population, and it is aware of danger; it repositions nearby to other sparrows for decreasing the threat of being captured. When $f_i \neq f_g$, then $i\text{-}th$ sparrows are at the edge of population and are easily attacked by the predator. As well as a global optimal sparrow neighborhood in each iteration, the searching capability of SSA is improved. Furthermore, this might help the sparrow group in accomplishing the optimal position via the searching procedure. The chaotic local searching method is exploited during the iteration procedure of SSA to improve the ability of exploitation and maintain the best harmony amongst the core searching procedure. Furthermore, the logical chaotic function is exploited for calculating chaotic SSA and it is attained by.

$$\rho_{k+1} = \mu\rho_k(1 - \rho_k),\ \ \mathrm{k} = 1,2, \dots, N - 1 \quad (1)$$

Alternatively, $\rho_1 \in (0,1)$ and $\rho_1 \neq 0.25, 0.5, 0.75$, and 1 if the control variable μ is fixed as 4, and the logistic function is transformed to a chaotic state. As a result, it is expressed in the following.

$$P_i = b + \rho_i \times (b - a), i = 1,2, \dots, N \quad (2)$$

Now, $[a, b]$ denotes the searching region, and the chaotic function was generated through mapping chaotic variables ρ_i into the chaotic vector P_i. Moreover, chaotic vector P_i was linearly incorporated to TP targeted position for producing CL candidate location that is formulated by.

$$CL = (1 - SC) \times TP + SC \times P_i \quad (3)$$

$$SC = (T - t + 1)/T \quad (13)$$

The CSSA technique solves an FF to obtain high classifier performance. It determines a positive integer to represent the optimum efficiency of solution candidate.

4. Performance Validation

This section examines the performance of the ESSODL-BP method using a dataset containing 690 samples with two class labels as depicted in Table 1.

Table 1: Dataset details

Australian credit Dataset	
Class	**No. of Samples**
Good case	307
Bad case	383
Total Number of Samples	**690**

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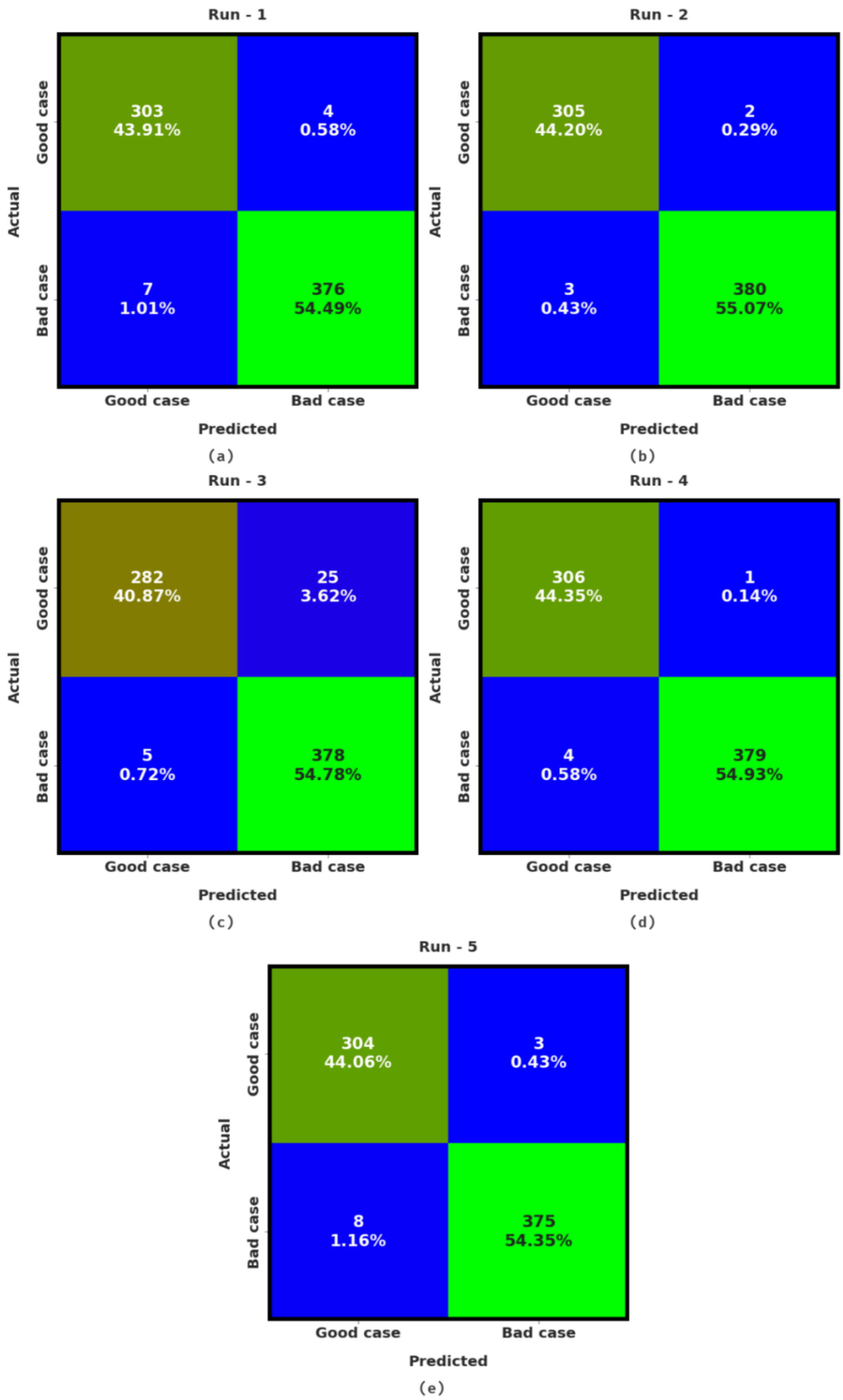

Figure 3. Confusion matrices of ESSODL-BP approach (a) Run-1 (b) Run-2, (c) Run-3, (d) Run-4, and (e) Run-5

Figure 3 displays the confusion matrix generated by the ESSODL-BP technique on distinct runs. With run-1, the ESSODL-BP approach has recognized 303 samples into good cases and 376 samples into bad cases. Additionally, with run-3, the ESSODL-BP model has recognized 282 samples into good cases and 378 samples into bad cases. Furthermore, with run-5, the ESSODL-BP technique has recognized 304 samples into good cases and 375 samples into bad case

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Table 2 and Figure 4 summarize the classification results of the ESSODL-BP technique under distinct runs. On run-1, the ESSODL-BP method has gained average $accu_y$ of 98.41%, $prec_n$ of 98.34%, $reca_l$ of 98.43%, F_{score} of 96.78%, and MCC of 98.39% correspondingly. Besides, on run-3, the ESSODL-BP algorithm has acquired average $accu_y$ of 95.65%, $prec_n$ of 96.03%, $reca_l$ of 95.28%, F_{score} of 91.30%, and MCC of 95.61% correspondingly. Meanwhile, on run-5, the ESSODL-BP approach has reached average $accu_y$ of 98.41%, $prec_n$ of 98.32%, $reca_l$ of 98.47%, F_{score} of 96.79%, and MCC of 98.39% correspondingly.

Table 2: Result analysis of ESSODL-BP approach with various measures and runs

Labels	Accuracy	Precision	Recall	MCC	G-Measure
Run-1					
Good case	98.41	97.74	98.70	96.78	98.22
Bad case	98.41	98.95	98.17	96.78	98.56
Average	**98.41**	**98.34**	**98.43**	**96.78**	**98.39**
Run-2					
Good case	99.28	99.03	99.35	98.53	99.19
Bad case	99.28	99.48	99.22	98.53	99.35
Average	**99.28**	**99.25**	**99.28**	**98.53**	**99.27**
Run-3					
Good case	95.65	98.26	91.86	91.30	95.00
Bad case	95.65	93.80	98.69	91.30	96.21
Average	**95.65**	**96.03**	**95.28**	**91.30**	**95.61**
Run-4					
Good case	99.28	98.71	99.67	98.54	99.19
Bad case	99.28	99.74	98.96	98.54	99.35
Average	**99.28**	**99.22**	**99.31**	**98.54**	**99.27**
Run-5					
Good case	98.41	97.44	99.02	96.79	98.23
Bad case	98.41	99.21	97.91	96.79	98.56
Average	**98.41**	**98.32**	**98.47**	**96.79**	**98.39**

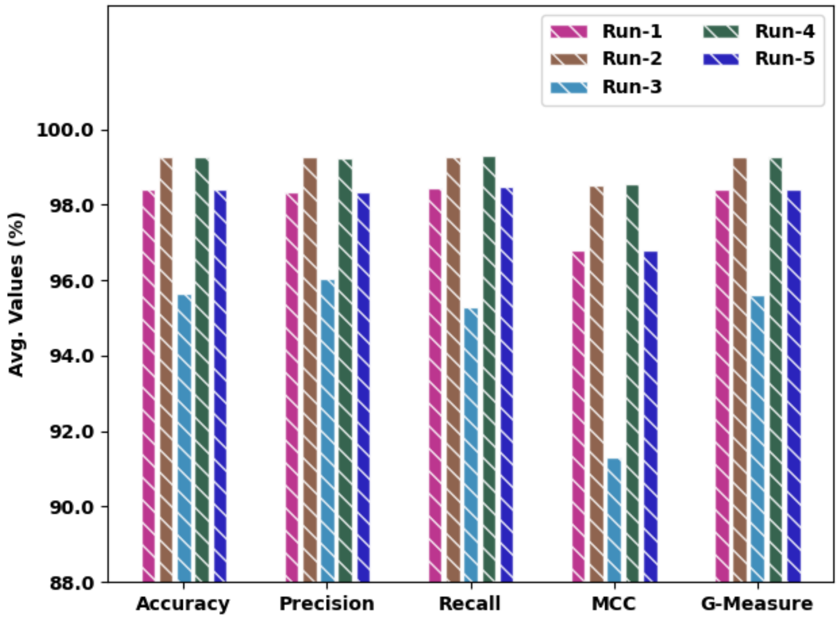

Figure 4. Average analysis of ESSODL-BP approach with various measures and runs

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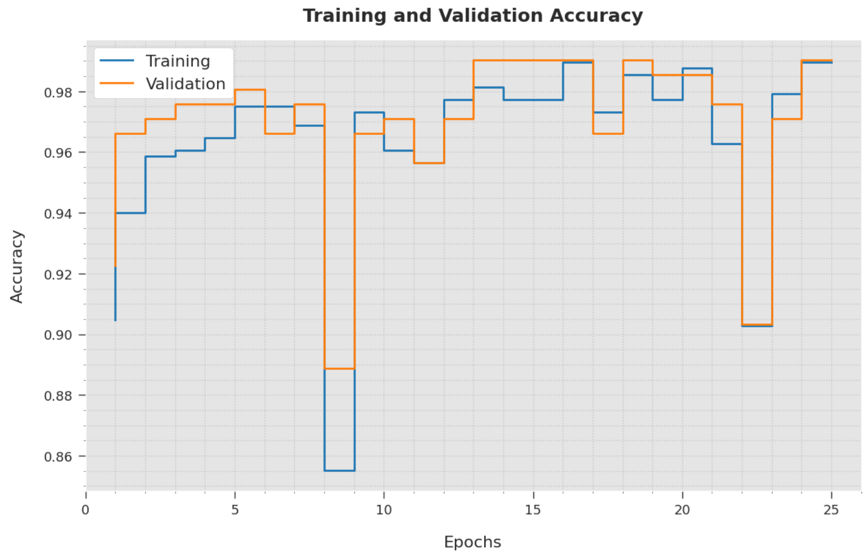

Figure 5. TA and VA analysis of ESSODL-BP approach

The training accuracy (TA) and validation accuracy (VA) attained by the ESSODL-BP approach on test dataset is demonstrated in Figure 5. The experimental outcome denoted the ESSODL-BP model has reached maximum values of TA and VA. In Particular, the VA seemed to be superior to TA.

The training loss (TL) and validation loss (VL) achieved by the ESSODL-BP approach on test dataset are established in Figure 6. The experimental outcome represented that the ESSODL-BP methodology has accomplished least values of TL and VL. Specifically, the VL is lesser than TL.

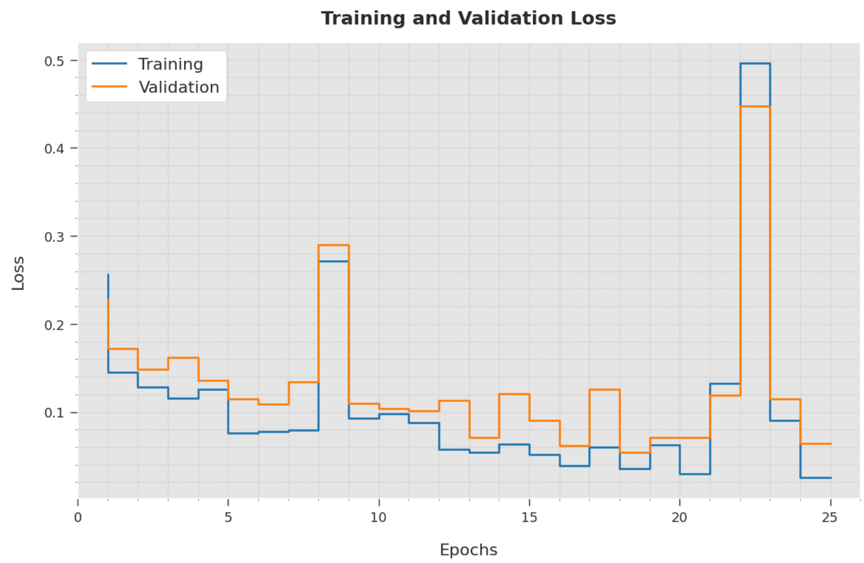

Figure 6. TL and VL analysis of ESSODL-BP approach

Table 3 and Figs. 7-8 offers a brief study of the ESSODL-BP approach with recent models. Based on $accu_y$, the ESSODL-BP technique has rendered improved $accu_y$ of 99.28% whereas the KNN, Bagging, MobileNet v2, RestNet, and DNN algorithms have reached reduced $accu_y$ of 94.90%, 93.64%, 94.63%, 95.51%, and 96.99% correspondingly.

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Table 3: Comparative analysis of ESSODL-BP approach with existing methodologies

Methods	Accuracy	Precision	Recall
ESSODL-BP	99.28	99.22	99.31
KNN Model	94.90	94.27	93.20
Bagging Model	93.64	95.00	95.97
MobileNet v2	94.63	93.60	96.81
RestNet	95.51	96.72	95.70
DNN Model	96.99	96.76	95.16

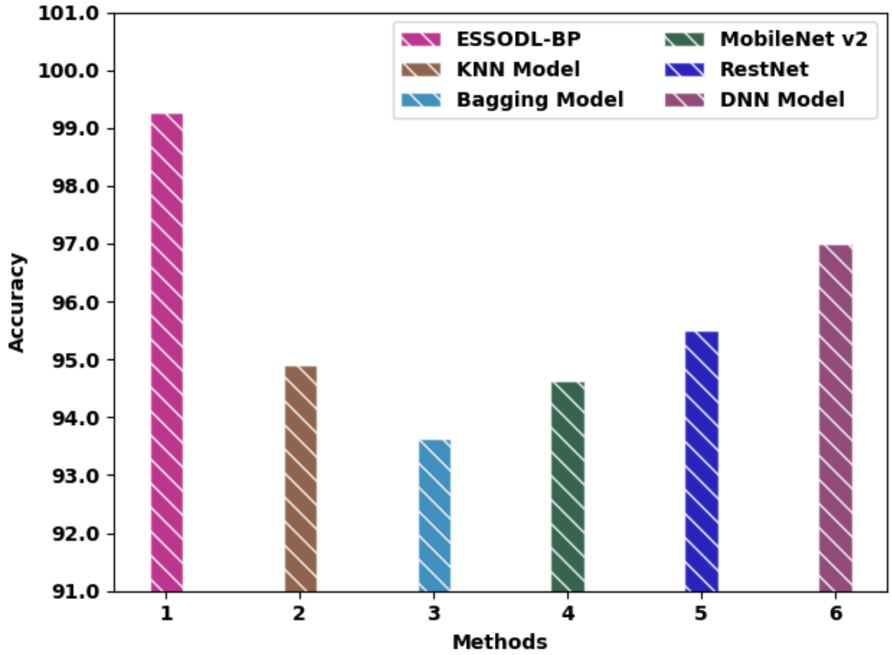

Figure 7. $\boldsymbol{Accu_y}$ analysis of ESSODL-BP approach with existing methodologies

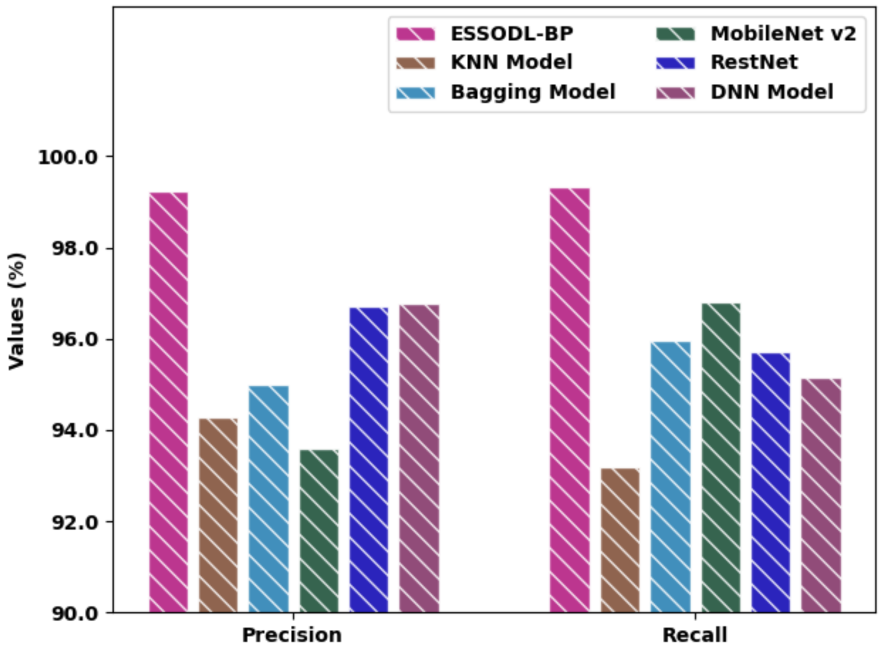

Figure 8. $\boldsymbol{Prec_n}$ and $\boldsymbol{reca_l}$ analysis of ESSODL-BP approach with existing methodologies

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Also, based on $prec_n$, the ESSODL-BP method has rendered improved $prec_n$ of 99.22% whereas the KNN, Bagging, MobileNet v2, RestNet, and DNN algorithms have acquired reduced $prec_n$ of 94.27%, 95%, 93.60%, 96.72%, and 96.76% correspondingly. At last, based on $reca_l$, the ESSODL-BP method has presented improved $reca_l$ of 99.31% whereas the KNN, Bagging, MobileNet v2, RestNet, and DNN models have attained minimal $reca_l$ of 93.20%, 95.97%, 96.81%, 95.70%, and 95.16% correspondingly.

5. Conclusion

In this article, a new ESSODL-BP model has been introduced for forecasting the bankruptcy of a financial firm. To accomplish this, the ESSODL-BP technique primarily follows Z-score normalization approach. Followed by, the bidirectional long short term memory (BLSTM) model is designed to predict the bankruptcy status of a financial firm. Then, the ESSO algorithm is utilized for optimally tuning the hyperparameters related to the BLSTM model and also boosts the prediction performance to a maximum extent. The performance validation of the ESSODL-BP technique is tested using benchmark dataset. The experimental outcomes reported better performance of the ESSODL-BP technique over other approaches.

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