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Article

Bird Swarm Algorithm with Fuzzy Min-Max Neural Network for Financial Crisis Prediction

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Abstract: Financial crisis prediction (FCP) models are used for predicting or forecasting the financial status of a company or financial firm. It is considered a challenging issue in the financial sector. Statistical and machine learning (ML) models can be employed for the design of accurate FCP models. Though numerous works have existed in the literature, it is needed to design effective FCP models adaptable to different datasets. This study designs a new bird swarm algorithm (BSA) with fuzzy min-max neural network (FMM-NN) model, named BSA-FMMNN for FCP. The major intention of the BSA-FMMNN model is to determine the financial status of a firm or company. The presented BSA-FMMNN model primarily undergoes min-max normalization to transform the data into uniformity range. Besides, k-medoid clustering approach is employed for the outlier removal process. Finally, the classification process is carried out using the FMMNN model, and the parameters involved in it are tuned by the use of BSA. The utilization of proficient parameter selection process using BSA demonstrate the novelty of the study. The experimental result analysis of the BSA-FMMNN model is validated using benchmark dataset and the comparative outcomes highlighted the supremacy of the BSA-FMMNN model over the recent approaches.

Keywords: Financial crisis; predictive model; machine learning; outlier removal; clustering; metaheuristics

1 Introduction

The financial community, management organizations, and lending organizations are longing to build a theoretical framework or an instrument that would assist in examining the possibility of current avoidance; that is to predict when a business succeeds or fail within a required time [1]. Notwithstanding, avoidance activity works in a stochastic manner, financial data produced is utilized for developing or constructing financial crisis prediction (FCP) system. For instance, it is stated that employing the different variance piece of information methods, discriminative study for classifying bankrupt corporations and funds by working financial data [2]. Financial distress arises because of corrupting responsibility along with insolvent rankings of credit-based assets [3]. Notwithstanding circumvention practice has been employed applied, financial crises guiding the operation FCP method using maximal priority [4]. At the same time, Wang and his co-workers suggested that there are no theories or typical stereotypes that arise for a company's FCP method. The absence of theories or stereotypes to investigate financial distress for investigative activity for the documentation of extrapolation replicas and discriminative potentials applying error and trial [5]. Researchers and professionals have been attempted to enhance the performance of FCP theoretical stereotypes by the application of distinct quantifiable replicas.

The procedure of FCP is extremely required for demonstrating an early, trustworthy, and accurate prediction method to forecast the important risk of the company's economic condition [6]. Generally, The FCP is taken into account as the binary classification method that is solved in reasonable way. The outcomes of the classification method undertake classification into two types such as failing and non-failing conditions of an organization [7]. Now, various classification methods were introduced by using distinct areas of interest for FCP. machine learning (ML), and Statistics-based methods are widely employed for finding the significant factor of the FCP. In the field of FCP, the ML model is employed in different ways [8]. It is utilized for the structure procedure to validate the methods for the recognition of financial crises. The key assumption is that the financial parameter extracting in the open-accessing financial stamen such as financial ratio includes huge number of information connecting the financial detail and is useful for the FCP method [9]. The FCP is a difficult method for utilizing the connected economic detail and other data regarding the company strategy affordability for active information for constructing a new method. As well as the AI and dataset concept, data mining technique is commonly employed in different fields. In FCP, data mining method is widely accessible in two different ways such as decision-making and early warning systems. It is useful to take appropriate measures for eliminating the financial loss of the organization [10].

This study designs a new bird swarm algorithm (BSA) with fuzzy min-max neural network (FMM-NN) model, named BSA-FMMNN for FCP. The presented BSA-FMMNN model primarily undergoes min-max normalization to transform the data into uniformity range. In addition, k-mediod clustering approach is employed for the outlier removal process. Also, the classification process is carried out using the FMMNN model and the parameters involved in it are tuned by the use of BSA. The experimental result analysis of the BSA-FMMNN model is validated using benchmark dataset.

2 Related Works

Junyu [11] employed the information on credit default using an overall sample of 1,000 comprising Germany credit default record and private data. Random forest, XGboost, and Logistic regression have been employed for discovering helpful data behindhand this information. Faris et al. [12] presented a hybrid model which integrates the synthetic minority oversampling method using ensemble models. Furthermore, we applied 5 distinct FS techniques for finding the important characteristics of bankruptcy calculation. The presented method is estimated according to real data gathered from Spanish company. Shetty et al. [13] applied different ML approaches for predicting bankruptcy with simply attainable financial statistics of 3728 Belgian Small and Medium Enterprises (SME) in 2002–2012. With the abovementioned ML approaches, we predicted bankruptcy using a total precision of 82%–83% with three simply attainable financial ratios.

Kim et al. [14] investigated that corporate bankruptcy prediction is enhanced by using the recurrent neural network (RNN) and long short term memory (LSTM) approaches that could process consecutive information. Applying the LSTM and RNN methods enhances bankruptcy predictive efficiency related to other classifier methods including techniques. The authors in [15] developed a DL-based method. This technique integrates Stacked AutoEncoder (SAE) and Borderline Synthetic Minority oversampling approach (BSM) depending upon the Softmax classification. The goal is to propose a reliable and accurate bankruptcy predictive system that involves the feature extraction method. Chen et al. [16] address bankruptcy predictive issue from the perception of learning with label proportion, whereas the unlabelled trained information is given in various bags and gives the bag-level proportion of instance belongs to a certain class. Next, contributed support vector machine (SVM) enabled two predictive systems named Boosted-pSVM and Bagged-pSVM, depending on proportion SVM and ensemble strategy includes boosting and bagging. Muneer et al. [17] introduced a multi-objective squirrel search optimization method using stacked autoencoder (MOSSA-SAE) for FCP in IoT. The aim is to describe the region of nearest neighbors and oversampling rate. Moreover, SAE method is employed as a classifier method for determining the class label of financial information. Simultaneously, the presented approach has been employed for properly selecting the 'weight' and 'bias' values of the SAE.

3 The Proposed Model

This study has developed a new BSA-FMMNN model is to determine the financial status of a firm or company. The presented BSA-FMMNN model involves several subprocesses namely preprocessing, k-medoid clustering based outlier removal, FMMNN based classification, and BSA based parameter optimization. The utilization of proficient parameter selection process using BSA helps to accomplish maximum performance. Fig. 1 illustrates the working process of BSA-FMMNN technique.

3.1 Pre-processing

To design a proper and effective learning model, it is needed to primarily normalize the input data. In this work, min-max normalization approach is employed as defined in the following.

$$a_m^{'} = c + \frac{(a_m - \min(a))\,(q - p)}{(\max(a) - \min(a))} \tag{1}$$

where $a_m^{'}$ denotes new attribute value at row m, a_m, min(a), and max (a) represents the input, minimal, and maximum attributes at row m, and [p, q] is the scaling range.

3.2 K-medoid Clustering Based Outlier Removal

The K-medoid clustering is a statistical technique, used for the removal of outliers existing in the financial data [18]. The traditional K-means technique computes and exploits the mean value of the data points in computation, specifically sensible to the existence of outliers in the financial data. For resolving these issues, a concept of medoid is utilized rather than the mean values in the cluster. Though k-Medoid approach exhibits high computation complexity, the k-medoid clusters are insensitive to the existence of clusters. It can be employed on continuous as well as discrete data domains. It reduces the total of the dissimilarity among the objects that exist in the cluster with the reference objects chosen for the clusters. In general, the input provided is the k value which denotes total cluster count involved in the data. For every individual k clusters, k reference points can be chosen. The rest of the points can be grouped into a cluster of reference points thereby the total dissimilarity among the reference objects and points in the cluster can be reduced. By the use of various initial medoids chosen, the clusters can be distinct. The variation among the K-means and K-medoid techniques is that the k-Means considered the mean value in a cluster to be a reference point and k-Medoids considered the points as reference objects for clusters.

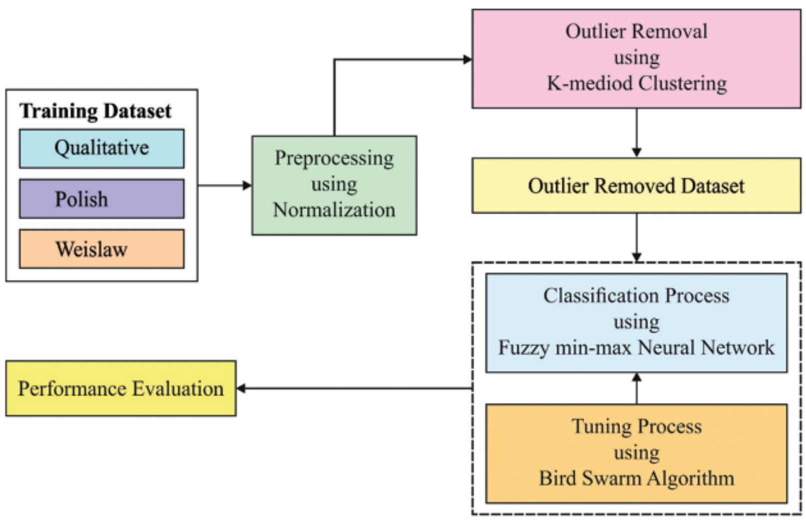

Figure 1: Working of BSA-FMMNN model

3.3 Data Classification Using FMMNN Model

For classification process, the FMMNN model can be employed for data classification. The FMM network contains 3 states of nodes such as F_A refers the input state, F_B signifies the hidden state, and F_C represents the output state [19]. An input and output states comprise nodes equivalent from number to the amount of dimensional of the input pattern and the amount of target classes correspondingly. The hidden state is recognized as hyperbox state, which comprises nodes which are generated incrementally. All the F_B nodes signify a hyperbox fuzzy set (HFS). F_A to F_B connection comprises the minimal and maximal points of hyperboxes, referred to as matrices V and W correspondingly. F_B and F_C linking are binary values, and are saved from matrix U. Eq. (2) has been utilized for assigning the values amongst F_B and F_C connection, for instance,

$$u_{jk} = \begin{cases} 1 & \textit{if } b_j \textit{ is a hyperbox for class } C_k \\ 0 & \textit{otherwise}, \end{cases} \tag{2}$$

where b_j refers the j^{th} nodes and C_k is k^{th} node. All the F_C nodes signify the class. The outcome of F_C node signifies the degree to that h^{th} input pattern, $A_h = (a_{h1}, a_{h2}, \ldots, a_{hn}) \in I^n$, fits in the class k. The transfer function to all F_C nodes carry out the fuzzy union of suitable HFS value and has determined as:

$$c_k = \max_{j=1}^{m} b_j u_{jk} \tag{3}$$

where the membership function (MF) to j^{th} hyperbox, $b_j(A_h)$, $0 \leq b_j(A_h) \leq 1$, has utilized for measuring the extents to that h^{th} input pattern, A_h, decreases outside hyperbox B_j. The resultant of the F_C class nodes are utilized from 2 distinct approaches. During the analysis of soft decisions, the resultants were utilized directly. During the case of hard decision, the F_C node with maximum value are selected, and their node value has set to 1 for indicating that it can be neighboring pattern class, but other F_C node value is fixed to 0, for instance, the rule of winner- takes-all. The HFSs was the essential element of FMM networks. The parameter called expansion co-efficient, $\theta \epsilon [0, 1]$ has been utilized for controlling the hyperbox size. The smaller value of θ causes to formation of huge amount of hyperboxes, and conversely. In order to n dimensional input pattern, unit cube, I^n has determined, and the explanation of all the HFSs B_j is:

$$B_j = \left\{X, V_j, W_j, f\left(X, V_j, W_j\right)\right\} \forall X \in I^n, \tag{4}$$

where $V_j = (v_{j1}, v_{j2}, \ldots.., v_{jn})$ refers to the minimal point of B_j and $W_j = (w_{j1}, w_{j2}, \ldots., w_{jn})$ signifies the maximal point of B_j. Fundamentally, the MF has calculated interms of the minimal and maximal points of hyperbox, and for extending to that the input pattern fits as to the hyperbox. The integrated fuzzy set classifications the k^{th} pattern class, C_k, is:

$$C_k = \bigcup_{j \in K} B_j, \tag{5}$$

where K implies the group of hyperboxes connected to class k. The FMM trained model was concentrated on establishing and fine-tune the class boundary. In FMM, hyperboxes in a similar class were allowable for overlapping one another. But, the overlapped region of hyperboxes in various classes requires that removed. The MF to j^{th} hyperbox, $b_j(A_h)$, has been utilized for measuring the extent all components of input patterns are superior (or lesser) than the maximal (or minimal) point along all dimensions which decreases outside the minimal and maximal boundaries of hyperbox. While $b_j(A_h)$ develops quicker than 1, the point has said that "more" controlled from the respective hyperbox. The MF condition is the sum of 2 complements, namely, the average of maximal and minimal point violations. The resultant MF is:

$$\left[\max\left(0, 1 - \max\left(0, \gamma \min\left(1, a_{hi} - w_{ji}\right)\right)\right) \max\left(0, 1 - \max\left(0, \gamma \min\left(1, v_{ji} - a_{hi}\right)\right)\right)\right], \tag{6}$$

where γ refers the sensitivity parameter which controls the speed the connection value reduces if the distance amongst A_h and B_j improves. Fig. 2 depicts the framework of FMMNN technique.

3.4 Parameter Tuning Using BSA

In order to tune the parameter values involved in the FMMNN model, the BSA can be employed. The BSA is a biological heuristic technique simulated in bird foraging, vigilance, and flight performance naturally [20].

Foraging behavior: All the birds feed food on the fundamental of personal experiences or group experiences. When the arbitrary number is uniformly distributed amongst zero and one, afterward the bird is foraging for food. Then, the bird is vigilant. As demonstrated by Eq. (7):

$$x_{i,j}^{t+1} = x_{i,j}^{t} + \left(p_{i,j} - x_{i,j}^{t}\right) \cdot C.rand\,(0, 1) + \left(g_j - x_{x,j}^{t}\right) \cdot S.rand\,(0, 1) \tag{7}$$

where $x^t_{i,j}$, · indicates the j^{th} dimension place of i^{th} bird from the t^{th} generation populations. $j \in [1, \ldots D]$, C and s are learning co-efficient that is correspondingly named as cognitive and social accelerated co-efficient. $rand(0, 1)$ refers the independent uniformly distributed number from zero and one, g_j represents the optimum preceding place shared with the swarm and $p(i, j)$ denotes the optimum preceding place of birds.

Vigilance behavior: The birds are attempt for moving to center of groups, and it is inevitably competing with everyone. Their performance is explained by the subsequent equations:

$$x^{t+1}_{i,j} = x^t_{i,j} + A1\left(mean_j - x^t_{i,j}\right).rand\left(0, 1\right) + A2\left(p_{k,j} - x^t_{i,j}\right).rand\left(-1, 1\right) \tag{8}$$

$$A1 = a1 \cdot \exp\left(-\frac{pFit_i}{sumFit + \varepsilon} \cdot N\right) \tag{9}$$

$$A2 = a2 \cdot \exp\left[\left(\frac{p_{Fiti} - p_{Fiti}}{|p_{Fit} - p_{Fit}| + \varepsilon} \cdot N\right)\frac{N \cdot p_{Fitk}}{sumFit + \varepsilon}\right] \tag{10}$$

where $k(k \neq i)$ indicates the positive integer that is arbitrarily chosen amongst 1 and N. a_1 and a_2 refers the 2 positive constants from zero and two. sumFit signifies the sum of swarm's optimum fitness values. $pFit_j$ indicates the i^{th} bird's optimum fitness value. $\mathcal{E}$ represents the minimum constant from the computer, for avoiding zero-division error. $mean_j$ stands for the component of average places of the entire bird's swarm.

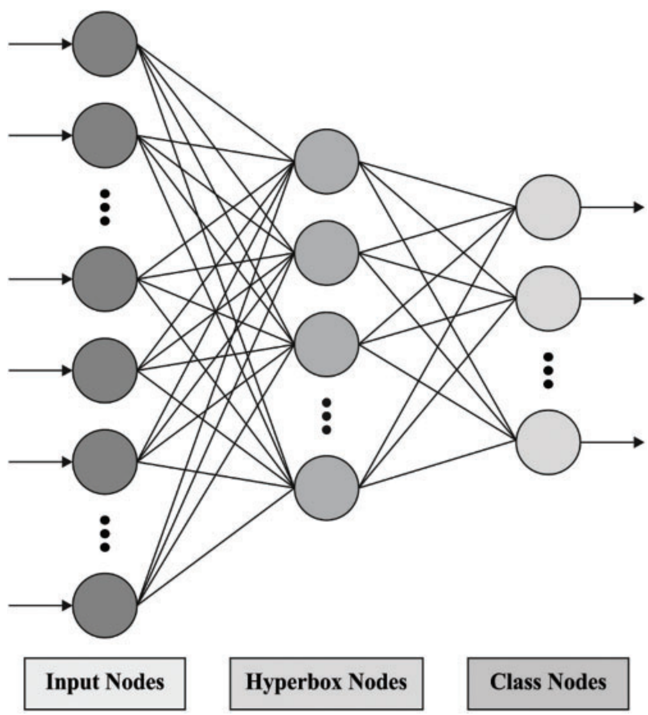

Figure 2: Structure of FMMNN model

Flight behavior: Because of the threat of predators or other reasons, birds are flying to another location for searching for food. In several birds performing as producers, however the other need for getting food from producer. Based on Rule (4), the performance of producers and scroungers are explained in mathematical process that is as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + randn\,(0,1) \times x_{i,j}^{t} \tag{11}$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + \left(x_{k,j}^{t} - x_{i,j}^{t}\right) \times FL \times randn\,(0,1) \tag{12}$$

where $randn(0,1)$ refers the arbitrary number of Gaussian distributions as 0, the standard deviation is 1. $k(k \neq i).FL \in (0,2)$ implies the scrounger is followed that producer for finding food. It can be supposing the flight frequency is FQ, Where FQ has a positive integer. The BSA is applied to tune the parameters contained in the FMMNN model. The BSA derives an objective function with the minimization of classification error rate.

4 Performance Validation

This section inspects the performance validation of the proposed model against three benchmark datasets such as qualitative, Polish, and Weislaw datasets (available at https://archive.ics.uci.edu/ml/datasets.php).

Tab. 1 reports the FCP outcomes of the BSA-FMMNN technique with recent techniques on Qualitative Bankruptcy dataset [21]. Fig. 3 depicts the $sens_y$ and $spec_y$ inspection of the BSA-FMMNN technique with existing techniques on qualitative bankruptcy dataset. The results indicated that the ant colony optimization (AC)-FCP and OlexG algorithms have obtained lower values of $sens_y$ and $spec_y$. At the same time, the FSC-Genetic ACO and Genetic ACO algorithms have obtained slightly increased values of $sens_y$ and $spec_y$. Along with that, the Optimal SAE, ACO-FCP, and IKMFSC-GA methods have reached reasonably closer values of $sens_y$ and $spec_y$. However, the BSA-FMMNN technique has accomplished improved $sens_y$ and $spec_y$ values of 99.960% and 99.985% respectively.

Table 1: FCP Results Investigation of BSA-FMMNN model on Qualitative Bankruptcy Dataset

Methods	Sensitivity	Specificity	Accuracy	F-score	Mathew Correlation Coefficient (MCC)
BSA-FMMNN	99.960	99.985	99.964	99.962	99.420
Optimal SAE Model	99.663	99.721	99.714	99.673	98.702
ACO-FCP	99.533	99.632	99.504	98.874	97.771
IKMFSC-GA Model	98.143	99.946	99.642	99.472	95.735
FSC- Genetic ACO Algorithm	92.505	94.985	92.885	92.966	84.704
Genetic ACO Algorithm	89.865	93.931	93.054	91.111	82.706
ACo-FCP Model	80.185	87.875	83.842	83.014	66.785

(Continued)

Table 1: Continued

Methods	Sensitivity	Specificity	Accuracy	F-score	Mathew Correlation Coefficient (MCC)
OlexG-Algorithm	67.381	76.503	72.223	69.481	53.773

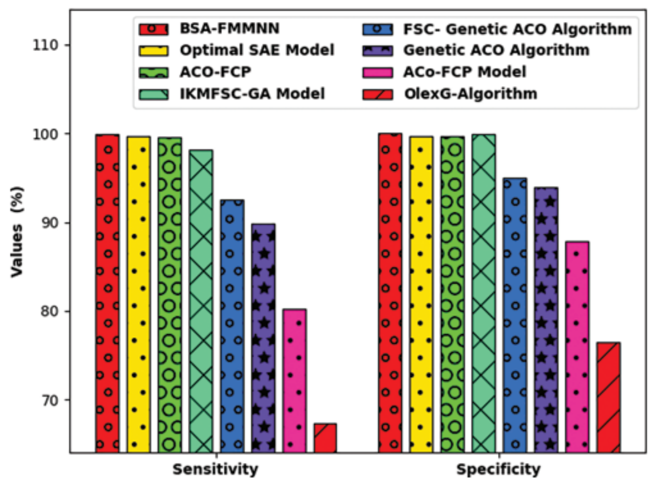

Figure 3: Comparative $sens_y$ and $spec_y$ analysis of BSA-FMMNN model on qualitative dataset

Fig. 4 portrays the $accu_y$, F_{score} and MCC examination of the BSA-FMMNN technique with recent techniques on qualitative bankruptcy dataset. The experimental results denoted that the ACo-FCP and OlexG algorithms have obtained lower values of $accu_y$, F_{score} and MCC. In line with, the FSC-Genetic ACO and Genetic ACO algorithms reached somewhat improved values of $accu_y$, F_{score} and MCC. Besides, the Optimal SAE, ACO-FCP, and IKMFSC-GA methods have reached sensibly closer values of $accu_y$, F_{score} and MCC. But the BSA-FMMNN technique has resulted in better $accu_y$, F_{score} and MCC values of 99.964%, 99.962%, and 99.420% respectively.

Fig. 5 demonstrates the accuracy inspection of the BSA-FMMNN model on the qualitative bankruptcy dataset. The results reported that the BSA-FMMNN model has the ability to obtain improved values of training and validation accuracies. It is observable that the validation accuracy values are slightly higher than training accuracy.

A brief training and validation loss offered by the BSA-FMMNN model are reported in Fig. 6 on the test qualitative dataset. The results portrayed that the BSA-FMMNN model has accomplished least values of training and validation losses on qualitative dataset.

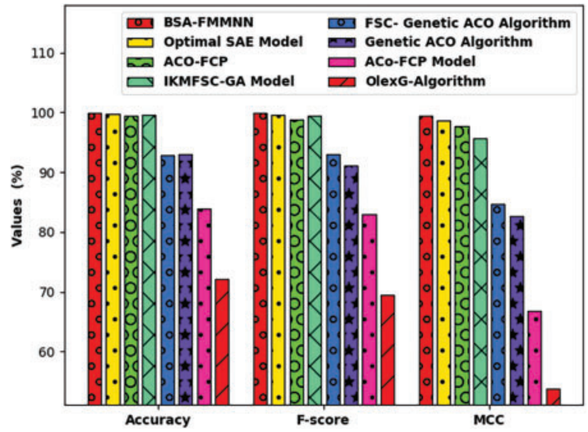

Figure 4: Comparative $accu_y$, F_{score} and MCC analysis of BSA-FMMNN model on qualitative dataset

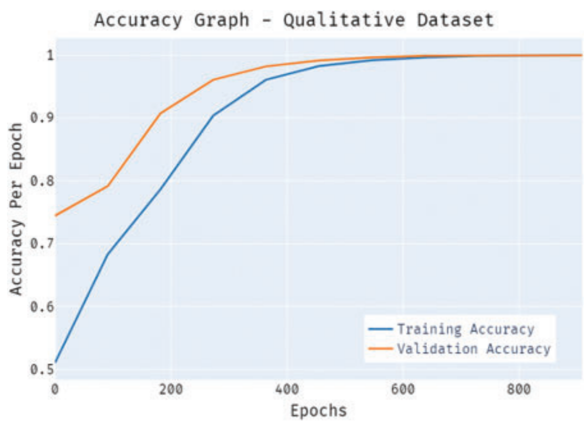

Figure 5: Accuracy graph of BSA-FMMNN model on qualitative dataset

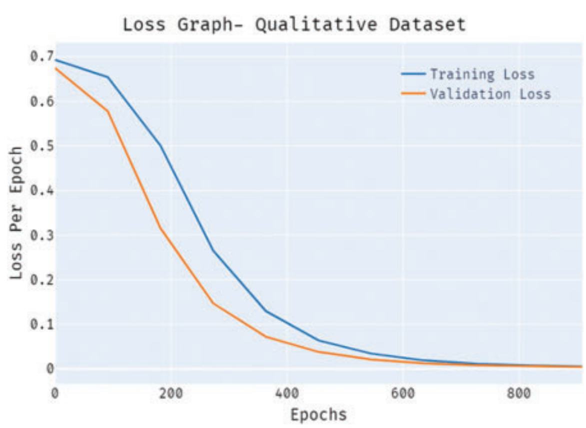

Figure 6: Loss graph of BSA-FMMNN model on qualitative dataset

Tab. 2 highlights the comparative study of the BSA-FMMNN technique on Polish dataset. Fig. 7 depicts the $sens_y$ and $spec_y$ assessment of the BSA-FMMNN technique with existing techniques on Polish bankruptcy dataset. The table values demonstrated that the ACo-FCP and OlexG algorithms have obtained lower values of $sens_y$ and $spec_y$. Additionally, the FSC-Genetic ACO and Genetic ACO algorithms have reached certainly enhanced values of $sens_y$ and $spec_y$. Moreover, the Optimal SAE, ACO-FCP, and IKMFSC-GA methods have reached considerably increased values of $sens_y$ and $spec_y$. But the BSA-FMMNN technique has outperformed other methods with maximum $sens_y$ and $spec_y$ values of 99.216% and 99.954% respectively.

Table 2: FCP results investigation of BSA-FMMNN model on Polish dataset

Methods	Sensitivity	Specificity	Accuracy	F-score	MCC
BSA-FMMNN	99.216	99.954	99.182	99.075	98.895
Optimal SAE Model	98.265	99.564	98.764	98.621	95.683
ACO-FCP	97.241	99.692	97.494	98.327	70.536
IKMFSC-GA Model	49.682	98.194	93.247	62.996	64.326
FSC- Genetic ACO Algorithm	37.037	98.077	89.694	49.434	52.405
Genetic ACO Algorithm	33.313	97.806	88.367	45.413	48.447
ACo-FCP Model	31.172	97.672	87.996	42.586	44.391
OlexG-Algorithm	36.574	96.586	77.885	33.152	33.604

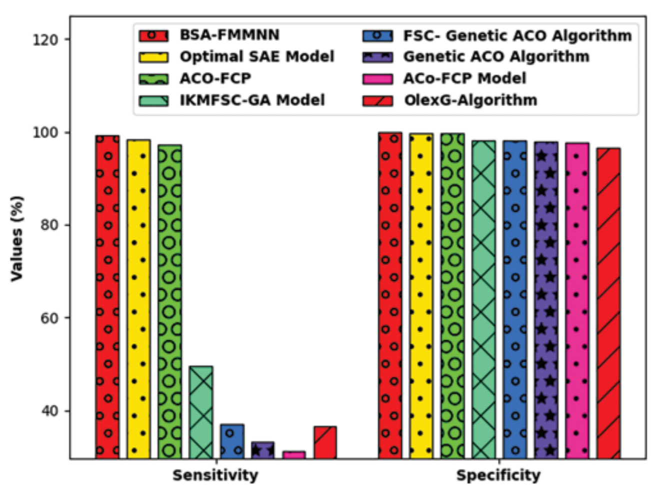

Figure 7: Comparative $sens_y$ and $spec_y$ analysis of BSA-FMMNN model on polish dataset

Fig. 8 reveals the $accu_y$, F_{score} and MCC analysis of the BSA-FMMNN technique with recent techniques on Polish bankruptcy dataset. The results indicated that the ACo-FCP and OlexG algorithms have obtained lower values of $accu_y$, F_{score} and MCC. Followed by, the FSC-Genetic ACO and Genetic ACO algorithms reached somewhat improved values of $accu_y$, F_{score} and MCC. In line with, the Optimal SAE, ACO-FCP, and IKMFSC-GA methods have reached sensibly closer values of $accu_y$, F_{score} and MCC. But the BSA-FMMNN technique has resulted in better $accu_y$, F_{score} and MCC values of 99.182%, 99.075%, and 98.895% respectively.

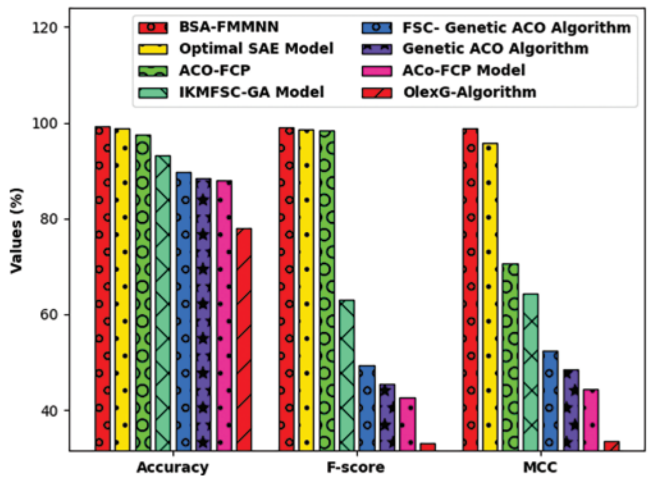

Figure 8: Comparative $accu_y$, F_{score} and MCC analysis of BSA-FMMNN model on polish dataset

Fig. 9 validates the accuracy assessment of the BSA-FMMNN model on the Polish bankruptcy dataset. The results described that the BSA-FMMNN model has the aptitude of gaining improved values of training and validation accuracies. It is visible that the validation accuracy values are slightly higher than training accuracy.

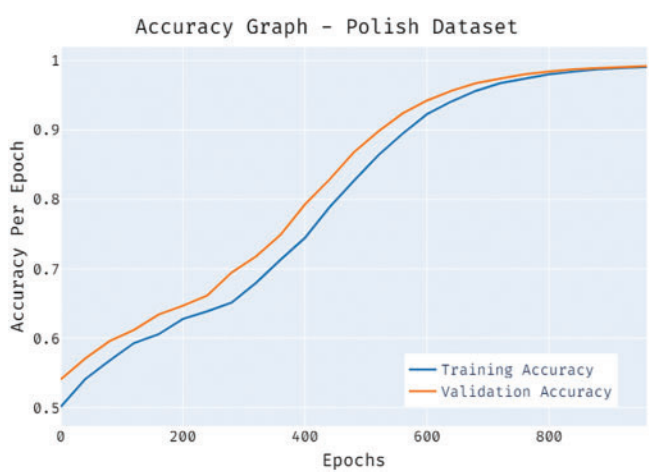

Figure 9: Accuracy graph of BSA-FMMNN model on polish dataset

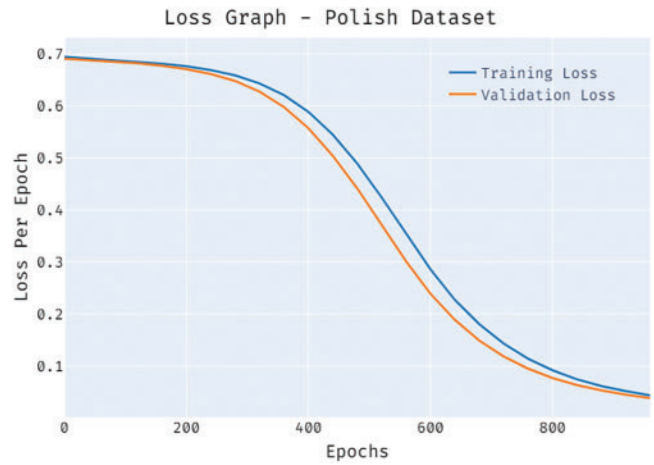

Figure 10: Loss graph of BSA-FMMNN model on polish dataset

A brief training and validation loss offered by the BSA-FMMNN model are reported in Fig. 10 on the test Polish dataset. The results revealed that the BSA-FMMNN model has accomplished minimum values of training and validation losses on Polish dataset.

Fig. 11 represents the $sens_y$ and $spec_y$ valuation of the BSA-FMMNN technique with existing techniques on Weislaw bankruptcy dataset. The table values established that the ACo-FCP and OlexG algorithms have gained lower values of $sens_y$ and $spec_y$. Furthermore, the FSC-Genetic ACO and Genetic ACO algorithms have gotten certainly boosted values of $sens_y$ and $spec_y$. Also, the Optimal SAE, ACO-FCP, and IKMFSC-GA methods have extended to noticeably better values of $sens_y$ and $spec_y$. But the BSA-FMMNN technique has outdone other methods with supreme $sens_y$ and $spec_y$ values of 99.146% and 99.563% respectively.

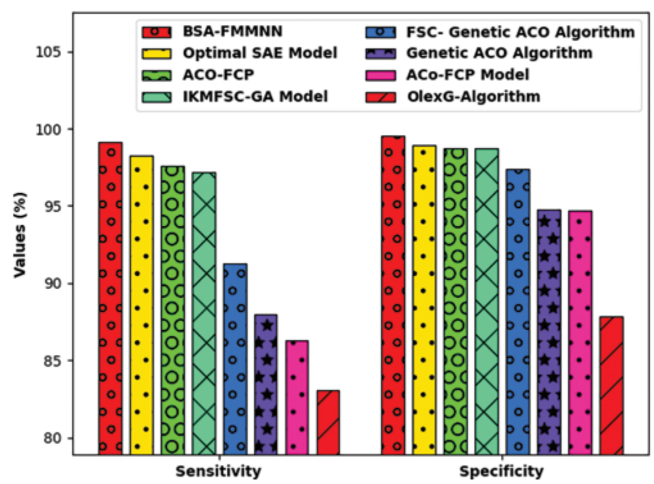

Figure 11: Comparative $sens_y$ *and* $spec_y$ analysis of BSA-FMMNN model on weislaw dataset

Fig. 12 exposes the $accu_y$, F_{score} and MCC analysis of the BSA-FMMNN technique with recent techniques on Weislaw bankruptcy dataset. The results designated that the ACo-FCP and OlexG algorithms have obtained lower values of $accu_y$, F_{score} and MCC. After that, the FSC-Genetic ACO and Genetic ACO algorithms reached slightly enhanced values of $accu_y$, F_{score} and MCC. In line with, the Optimal SAE, ACO-FCP, and IKMFSC-GA methods have reached sensibly closer values of $accu_y$, F_{score} and MCC. But the BSA-FMMNN technique has resulted in superior $accu_y$, F_{score} and MCC values of 99.313%, 99.025%, and 98.722% respectively.

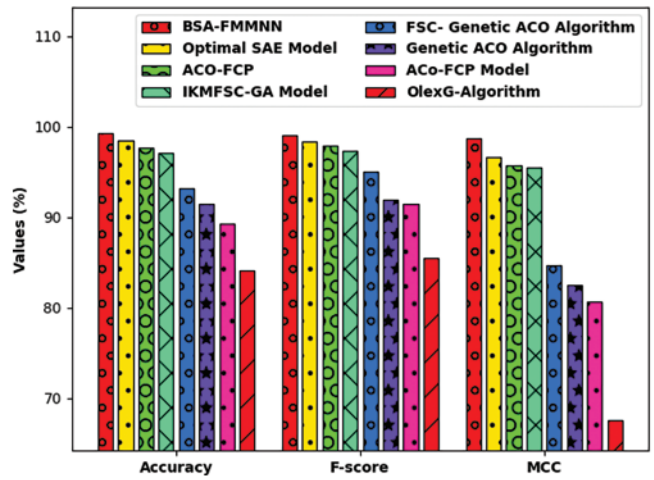

Figure 12: Comparative $accu_y$, F_{score} and MCC analysis of BSA-FMMNN model on weislaw dataset

Fig. 13 demonstrates the accuracy inspection of the BSA-FMMNN model on the Weislaw dataset. The results reported that the BSA-FMMNN model has the ability to obtain improved values of training and validation accuracies. It is observable that the validation accuracy values are slightly higher than training accuracy.

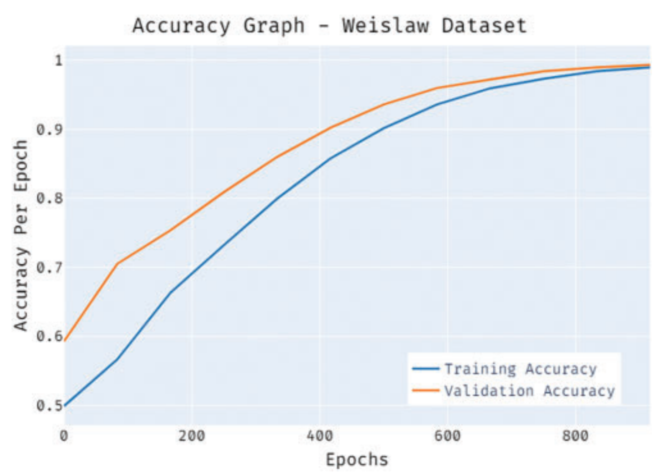

Figure 13: Accuracy graph of BSA-FMMNN model on weislaw dataset

A brief training and validation loss offered by the BSA-FMMNN model are reported in Fig. 14 on the Weislaw dataset. The results portrayed that the BSA-FMMNN model has accomplished least values of training and validation losses on Weislaw dataset. The above mentioned results ensured the supremacy of the BSA-FMMNN model over the recent models.

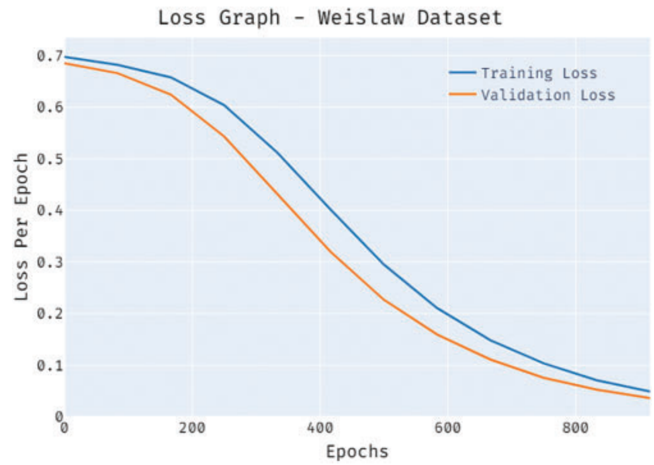

Figure 14: Loss graph of BSA-FMMNN model on weislaw dataset

5 Conclusion

This study has developed a new BSA-FMMNN model is to determine the financial status of a firm or company. The presented BSA-FMMNN model involves several subprocesses namely preprocessing, k-medoid clustering based outlier removal, FMMNN based classification, and BSA based parameter optimization. The classification process is carried out using the FMMNN model and the parameters involved in it are tuned by the use of BSA. The utilization of proficient parameter selection process using BSA helps to accomplish maximum performance. The experimental result analysis of the BSA-FMMNN model is validated using benchmark dataset and the comparative outcomes highlighted the supremacy of the BSA-FMMNN model over the recent approaches. In future, metaheuristics based feature selection models can be developed for improving the classification performance of the FMMNN model.

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