

Intelligent Feature Selection with Deep Learning Based Financial Risk Assessment Model

Thavavel Vaiyapuri¹, K. Priyadarshini², A. Hemlathadhevi³, M. Dhamodaran⁴, Ashit Kumar Dutta⁵, Irina V. Pustokhina^{6,*} and Denis A. Pustokhin⁷

¹College of Computer Engineering and Sciences, Prince Sattam bin Abdulaziz University, Al-Kharj, 16278, Saudi Arabia

²Department of Electronics and Communication Engineering, K.Ramakrishnan College of Engineering, Tiruchirappalli, 621112, India

³Department of Computer Science and Engineering, Panimalar Engineering College, Chennai, 600 123, India

⁴Department of Electronics and Communication Engineering, M. Kumarasamy College of Engineering, Karur, 639113, India

⁵Department of Computer Science and Information System, College of Applied Sciences, AlMaarefa University, Riyadh, 11597, Kingdom of Saudi Arabia

⁶Department of Entrepreneurship and Logistics, Plekhanov Russian University of Economics, 117997, Moscow, Russia

⁷Department of Logistics, State University of Management, 109542, Moscow, Russia

*Corresponding Author: Irina V. Pustokhina. Email: ivpustokhina@yandex.ru

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Abstract: Due to global financial crisis, risk management has received significant attention to avoid loss and maximize profit in any business. Since the financial crisis prediction (FCP) process is mainly based on data driven decision making and intelligent models, artificial intelligence (AI) and machine learning (ML) models are widely utilized. This article introduces an intelligent feature selection with deep learning based financial risk assessment model (IFSDL-FRA). The proposed IFSDL-FRA technique aims to determine the financial crisis of a company or enterprise. In addition, the IFSDL-FRA technique involves the design of new water strider optimization algorithm based feature selection (WSOA-FS) manner to an optimum selection of feature subsets. Moreover, Deep Random Vector Functional Link network (DRVFLN) classification technique was applied to properly allot the class labels to the financial data. Furthermore, improved fruit fly optimization algorithm (IFFOA) based hyperparameter tuning process is carried out to optimally tune the hyperparameters of the DRVFLN model. For enhancing the better performance of the IFSDL-FRA technique, an extensive set of simulations are implemented on benchmark financial datasets and the obtained outcomes determine the betterment of IFSDL-FRA technique on the recent state of art approaches.

Keywords: Financial risks; intelligent models; financial crisis prediction; deep learning; feature selection; metaheuristics



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1 Introduction

Financial crisis prediction (FCP) is the most challenging requirement for the enterprise in making financial decisions. Artificial intelligence (AI) and Statistical techniques were utilized for recognizing the important aspects of FCP [1]. During this method, AI technique was utilized for performance validation and forecasts if the system faces a problem or not. The primary goal of this method is for extracting the financial parameter in a wide-ranging economical statement like financial features using maximal data with FCP [2]. Commonly, FCP takes a binary classification method that has been resolved in an efficient manner. The result from the classification algorithm could be classified into two kinds: failure and non-failure status of enterprises [3]. So far, a greater amount of classification methods has been proposed with several domain knowledge for FCP [4]. In general, the proposed predictive method could be separated into artificial intelligence (AI) or statistical methods.

In FCP, data mining (DM) methods have been employed by decision-making and primary detection modules [5]. On the other hand, financial risk could be evaluated by using Machine Learning (ML) algorithms, which are capable of extracting nonlinear relationships amongst the financial data contained in the balance sheet [6]. In a typical data science life cycle, model is selected for optimizing the prediction accuracy. In highly regulated areas, such as medicine or finance, model needs to be selected balancing accuracy with explainability. Enhance the choice selecting model-based prediction accuracy, and employs a posteriori a model attains explainability [7]. It doesn't limit the selection of the optimally executing methods. Therefore, it is appropriate to make decision in removing financial failures. In the event of imbalanced data, the data extraction method is extremely challenging [8]. Hence, the extraction of massive number of information is significant to detect financial errors; particularly in FCP. In this architecture, many arithmetical methods and estimations were applied for the management of FCP [9]. It can be accountable for removing the redundant and unwanted features in new information. Furthermore, FS has been employed to extract highly possible information through minimal feature subset and potential properties such as computation time, noise removal [10], minimization of impure feature, and decreased cost that is crucial to implement an estimated technique. Moreover, it is used to process the feature set under the applications of fixed value instead of utilizing elected features [11]. The most significant challenge in this model is discovering an optimum feature from existing feature named an NP-hard problem.

1.1 Recent State of Art Financial Risk Assessment Models

This section performs a detailed review of existing FCP techniques available from the literature. Uthayakumar et al. [12] proposed a clustering-based classification method, includes: fitness-scaling chaotic genetic ant colony algorithm (FSCGACA) and improved K-means clustering based classification technique. Firstly, an enhanced K-means method is introduced to remove the inaccurately clustered data. Subsequently, a rule-based method is elected for designing the offered dataset. Lastly, FSCGACA was used for seeking the ideal parameter of rule-based method. Tyagi et al. [13] presented a smart IoT assisted FCP method with meta-heuristic algorithm. The presented FCP model includes feature selection (FS), classification, pre-processing, and data acquisition. In the beginning, the financial information of the enterprises is accumulated by utilizing IoT gadgets like laptops, smartphones, and so on. Then, the quantum artificial butterfly optimization (QABO) method to FS was employed for choosing an optimum subset of features. Later, LSTM using RNN technique is exploited for categorizing the gathered financial data.

Metawa et al. [14] designed a novel FS with EHO using MWWO technique based on DBN to FCP. The EHO approach was employed as a feature selector, and MWWO-DBN is applied to the classifier model. The application of MWWO algorithms assist in tuning the parameter of DBN algorithm, and the selection of optimum feature set in the EHO model results in better classification accuracy. Ivanyuk et al. [15] resolved the problems of creating a weighted-average prediction that comprises numerous individual predictions. Original prediction models are utilized in the grouping include gradient boosting, Arima, and FC-FFNN models. NN is becoming more prominent nowadays since they allow prediction in the case of uncertainty and crisis. Wang et al. [16] created a novel index assessment scheme to supply chain finance dependent upon hesitant fuzzy linguistic PROMETHEE methodology, and the advantages and effectiveness of the models were established. To some extent, the SME financing the assessment model and enhanced PROMETHEE technique could assist financial institutions to decrease the survival threat of financial institutions as well as decrease the risk in certain financial transactions. Zheng et al. [17] presented architecture of privacy-preserving credit risk modelling based adversarial learning (PCAL). The presented model focus on masking the secret data within the original data set, when preserving the significant utility data for the target predictive performances, through (iteratively) weighing among utility oriented loss and privacy-risk loss.

1.2 Paper Contributions

The major contribution of this study is summarized here. This article introduces an intelligent feature selection with deep learning based financial risk assessment model (IFSDL-FRA). The proposed IFSDL-FRA technique derives a novel water strider optimization algorithm based feature selection (WSOA-FS) approach to an optimum selection of feature subsets. Also, Deep Random Vector Functional Link network (DRVFLN) classification method was applied to properly allot the class labels to the financial data. Eventually, improved fruit fly optimization algorithm (IFFOA) based hyperparameter tuning procedure was implemented. In order to make sure the enhanced predictive outcomes of the IFSDL-FRA technique, a wide range of experiments were performed on benchmark financial datasets.

1.3 Paper Organization

The residual sections of the paper are arranged as follows. Section 2 offers a brief discussion of the IFSDL-FRA approach. Section 3 provides a detailed experimental analysis and Section 4 draws the concluding remarks of the study.

2 The Proposed Model

In this study, a novel IFSDL-FRA technique has been presented to determine the financial crisis of a company or enterprise. The proposed IFSDL-FRA technique comprises different major processes such as pre-processing, WSOA based optimal feature subset selection, DRVFLN based classification, and IFFOA based hyperparameter tuning. The utilization of WSOA to elect optimum features and IFFOA to select hyperparameters to help considerably boost the overall performance. [Fig. 1](#) illustrates the overall process of IFSDL-FRA approach. The processes involved in these modules are elaborated in the succeeding sections.

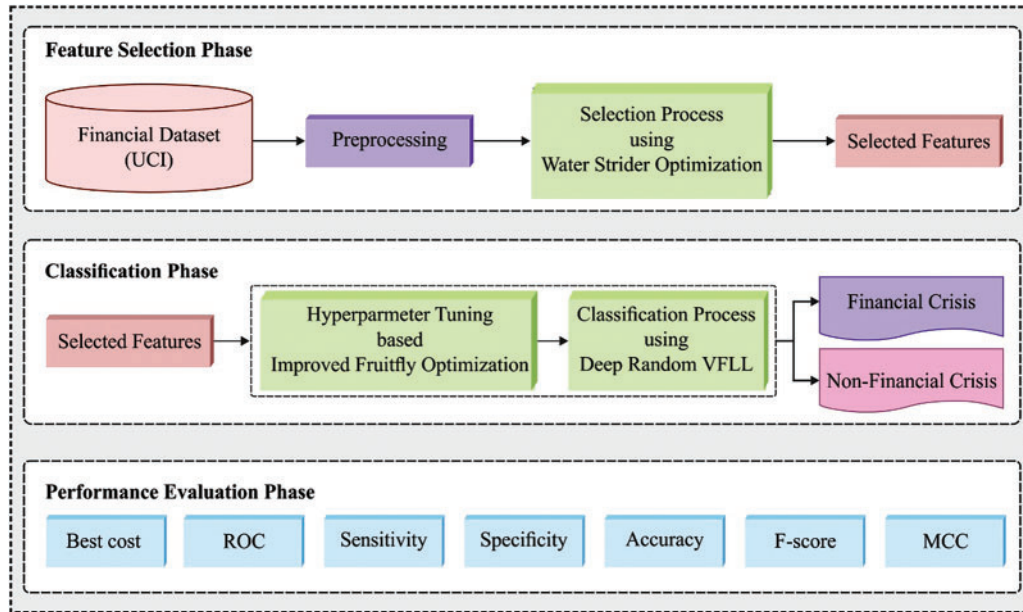


Figure 1: Overall process of IFSDL-FRA technique

2.1 Preprocessing

To begin with, the dataset has appropriately normalization utilizing min-max normalized. In this procedure, the minimal and maximal values of data were attained and changed with utilizing in Eq. (1).

$$\bar{L} = \frac{l - \min(X)}{\max(X) - \min(X)}(new_{\min(X)} - new_{\max(X)}) + new_{\min(X)} \quad (1)$$

where X refers the parameter that exists from the data, $\min(X)$ and $\max(X)$ signifies the lower as well as upper levels of attribute values, \bar{L} implies the upgrade values of entries, l stands for the previous value from the data and $new_{\min(X)}$ and $new_{\max(X)}$ denotes the value of minimal and maximal restricts correspondingly.

2.2 Design of WSOA-FS Technique

Next to data pre-processing, the preprocessed data is fed as input to WSOA-FS technique to choose optimal features. The WSOA is a meta-heuristic algorithm which is simulated as the nature of territorial, intellectual ripple interaction, mating style, feeding, and progression of water striders (WSs) bugs [18]. The mathematical modeling of the WSOA is given in the following. The WSs or candidate solutions can be arbitrarily produced in the searching area using Eq. (2):

$$WS_i^0 = Lb + rand.(Ub - Lb); i = 1, 2, \dots, nws \quad (2)$$

where WS_i^0 denotes the starting locations of the i th WS in the lake (searching area). Lb and Ub denote minimum and maximum bounds of parameters. $rand$ indicates an arbitrary number lies between 0 to 1, and nws represent the population size. The starting locations of the WS_s can be determined using an objective function for calculating the fitness value (FV). For creating a set of nt regions, the WS_s gets arranged to depend upon the FV and $\frac{nws}{nt}$ group counts are sorted. The j th member of all the groups is allocated to the j th region, where $j = 1, 2, \dots, nt$. So, the number of WS_s alive in every region is

equivalent to $\frac{mws}{nt}$. The locations in all regions with the minimum and maximum FV are treated as male and female correspondingly.

The male WS transmits the ripple to the female ones in mating process. As the reply of the female WS s remains unknown, a likelihood (p) is determined to identify attractive or repulsive responses. The location of the male WS can be upgraded using Eq. (3):

$$\begin{cases} WS_i^{t+1} = WS_i^t + R.rand; & \text{if mating happens (with probability of } p) \\ WS_i^{t+1} = WS_i^t + R.(1 + rand); & \text{otherwise} \end{cases} \quad (3)$$

The length of R can be computed using Eq. (4):

$$R = WS_F^{t-1} - WS_i^{t-1} \quad (4)$$

where WS_i^{t-1} and WS_F^{t-1} denotes the male and female WS s in the $(t - 1)^{th}$ cycle, correspondingly.

Mating spends massive quantity of energy for WS and the male ones start foraging process next to mating process. The objective function can be assessed for checking the existence of food. When the FV exceeds the earlier FV, the male WS has identified food in new location, and vice versa. Then, the male WS starts moving in the direction of optimal WS of the lake for determining the food based on Eq. (5):

$$WS_i^{t+1} = WS_i^t + 2rand*(WS_{BL}^t - WS_i^t) \quad (5)$$

When the WS exist in newly generated location, the male WS could not identify the food, it gets dead and a new WS gets replaced to it using Eq. (6):

$$WS_i^{t+1} = Lb_j^t + rand*(Ub_j^t - Lb_j^t) \quad (6)$$

where Ub_j^t and Lb_j^t denotes the upper and lower values of the WS 's location inside the j^{th} region.

When the stopping criteria are unsatisfied, the WSOA returns the mating process for a new loop and highest number of FV determinations is treated as the ending criteria. The overall process of the WSOA is given in Algorithm 1.

In feature selection, when the size of the feature vector is N , the amount of distinct feature combination tends to be 2^N , that is a large space for comprehensive search. The proposed method is utilized for searching the feature space dynamically and produces the accurate integration of features. Feature selection falls within multiobjective problem since it should fulfill one or more objectives for getting optimal solution, that reduces the set of features selected and simultaneously, maximize the accuracy of the output for a provided classification. Fig. 2 showcases the flowchart of WSA.

In this study, the fitness function to determine solution in this scenario was constructed to attain a balance among the two objectives is given as follows.

$$fitness = \alpha \Delta_r(D) + \beta \frac{|Y|}{|T|} \quad (7)$$

Whereas $\Delta_r(D)$ represent the classifier error rate. $|Y|$ denotes the size of the subset that selects and $|T|$ indicates the overall amount of the feature contains in the existing data set. α illustrates a variable $\in [0, 1]$ that relates to the weight of the error rate of classification, correspondingly and $\beta = 1 - \alpha$ indicates the fine reduction. The classification performance is given a weight instead of number of features selected. When the calculation function takes the classification accuracy into account, the effects will be the neglect of solution which might contain the similar accuracy but have less selected feature which serves as most important factors in decreasing the dimensionality problem.

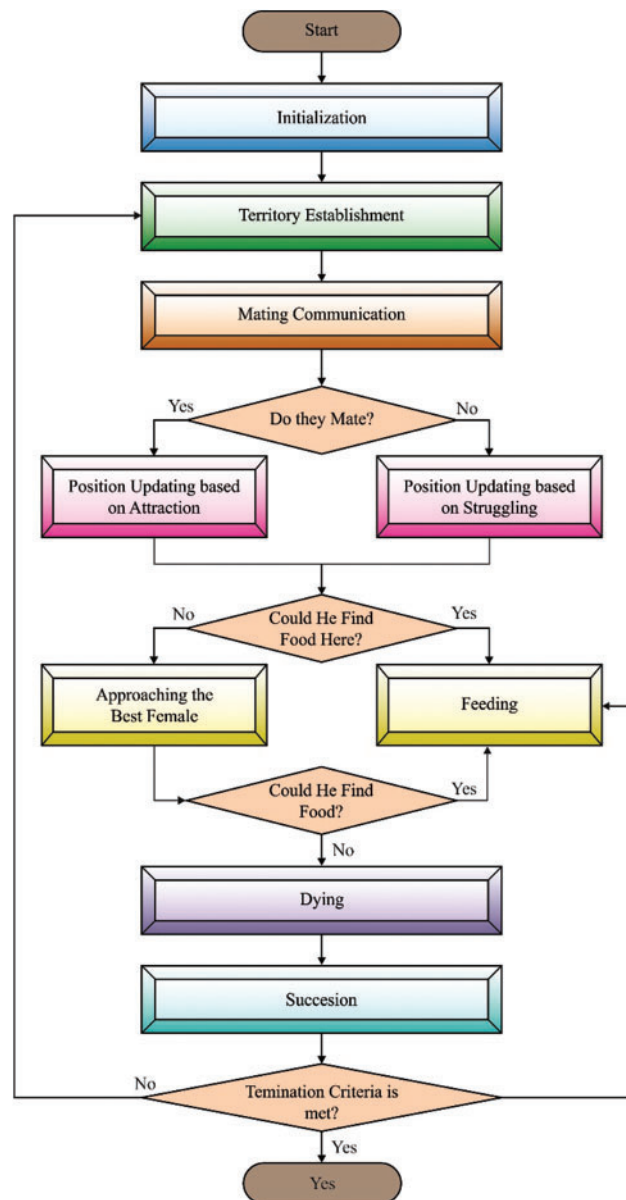


Figure 2: Flowchart of WSA

2.3 Process Involved in Optimal DRVFLN Based Classification

During classification process, the chosen subset of features is passed into the DRVFLN based classifier to allot proper class labels. The DRVFLN network is extensive of shallow RVFL network regarding deep or representation learning. The input to all the layers in the stack is the outcome of previous layer where all the layers build an internal representation of input data. Now assume a stack of L hidden layers all of them have a similar amount of hidden nodes N . For ease of representation, neglect the bias term from the formula. Then, the outcome of initial

hidden layer was determined by Eq. (8):

$$H^{(1)} = g(XW^{(1)}) \quad (8)$$

For each layer $l > 1$ it is determined by Eq. (9):

$$H^{(l)} = g(H^{(l-1)}W^{(l)}) \quad (9)$$

In which $W^{(1)} \in \mathbb{R}^{d \times N}$ and $W^{(l)} \in \mathbb{R}^{N \times N}$ represent the weight matrices among the input-first and inter hidden layers correspondingly. Such variables (biases and weights) of hidden neurons are formed arbitrarily within an appropriate range and kept set in the trained phase. g indicates the nonlinear activation function [19]. Then, the input to the output layers is determined by Eq. (10):

$$D = [H^{(1)} H^{(2)} \dots H^{(L-1)} H^{(L)} X]. \quad (10)$$

This model framework is equivalent to RVFL network. Where input to output the layers consist of nonlinear features under stacked hidden layer and the novel feature. Then, the outcome can be determined by Eq. (11):

$$Y = D\beta_d \quad (11)$$

The resultant weight $\beta_d \in \mathbb{R}^{(NL+d) \times K}$ (K : the amount of classes) was resolved. From Eqs. (10) and (11), DRVFLN exist a linear integration among the features as well as resultant layer weight matrix β_d that is weighted amount of features under the hidden layer includes the input layer. During the trained phase, this directly allows the system to differently weigh the support of all types of feature making in distinct layers.

To optimally tune the hyperparameters of the DRVFLN technique, the IFFOA technique is employed. The fundamental FOA is simulated as the foraging performance of fruit flies (FFs) naturally is presented by Pan [20]. The foraging performance of FF are separated as to 2 phases: the olfactory search phase and visual search phase. In olfactory foraging, the FF search and locate food sources nearby the populations, next estimates the odor focus equivalent to all feasible food sources. During the visual foraging stage, an optimum food source with maximal smell focus value was initiated, afterward, the FF group flies near it. The process of FOA has outlined as follows:

Step 1: Initialization parameters are containing the maximal amount of rounds and size of population.

Step 2: Initialization of the FF swarm place.

Step 3: Olfactory foraging stage: make various FF arbitrarily close to the present FF swarm place for constructing a population:

Step 4: Estimate the population for obtaining the fitness value of all FF.

Step 5: Visual foraging stage: determine the FF with optimum fitness values, later the FF group flies near optimum one.

Step 6: Once the maximal count of rounds is attained, this technique was ended; else, go back to Step 3.

Before creating novel solution with altering every decision variable of population place as the original FOA, IFFOA makes novel solution with arbitrarily chosen indexes for enhancing the search from the growth phase.

$$\lambda = \lambda_{\max} \cdot \exp \left(\log \frac{\lambda_{\min}}{\lambda_{\max}} \right) \cdot \frac{Iter}{Iter_{\max}} \quad (12)$$

In Eq. (1), λ implies the search radius of FF from all iterations, λ_{\max} refers the maximal search radius, and λ_{\min} signifies the minimal search radius. $Iter$ stands for the present iteration number, and Max_Iter defines the maximal iteration number.

$$x_{i,j} = \begin{cases} \delta_j \pm \lambda \cdot rand() & \text{if } j = d \\ \delta_j & \text{otherwise, } j = 1, 2, \dots, n \end{cases} \quad (13)$$

$d \in \{1, 2, \dots, n\}$ stands for the index arbitrarily chosen in uniformly distributed decision variable, n refers the dimensional of solution [21], $rand()$ demonstrated the arbitrary number from the range of zero and one, and the place of $x_{i,j}$ is upgraded in Eq. (13). δ_j denotes the value of better solution from the j^{th} dimension.

The fitness function performs an important part in optimized problems. It computes a positive integer for specifying a better candidate outcome. During this work, classification error rate is considered as a minimalizing fitness function. The poor solution has maximum fitness score (error rate) and better solution is minimum fitness score (error rate).

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{\text{number of misclassified documents}}{\text{Total number of documents}} * 100 \quad (14)$$

3 Performance Validation

The performance validation of the IFSDL-FRA technique is performed against 3 benchmark datasets like Qualitative [22], Polish [23], and Weislaw datasets. The former qualitative dataset contains 250 samples with 6 attributes and 2 classes. The second Polish dataset has 43405 samples with 64 attributes and 2 classes. The last Weislaw dataset includes 240 instances with 30 features.

The FS result analysis of the WSOA-FS technique takes place in Tab. 1. The results demonstrated that WSOA-FS technique has chosen an optimal number of features on all datasets. Tab. 2 offers the best cost (BC) analysis of the WSOA-FS technique under three datasets. The results show that the WSOA-FS technique has gained lower BC under all datasets. For instance, with qualitative dataset, the WSOA-FS technique has offered least average BC of 0.0320 whereas the GSO-FS, DFO-FS, and FFO-FS techniques have obtained increased average BC of 0.0520, 0.0810, and 0.0972.

Table 1: Selected features of proposed WSOA-FS algorithm on applied dataset

Dataset	Selected features
Qualitative	1, 3, 5, 6
Polish	1, 3, 7, 8, 9, 10, 11, 14, 15, 16, 18, 22, 24, 26, 27, 28, 30, 32, 34, 35, 37, 40, 42, 43, 45, 47, 50, 55, 60, 61
Weislaw	1, 4, 7, 8, 9, 10, 13, 17, 18, 20, 22, 23, 26, 28

Table 2: BC analysis of WSOA-FS technique with different count of iteration

No. of iterations	Qualitative dataset			
	WSOA-FS	GSO-FS	DFO-FS	FFO-FS
Iteration 1	0.0326	0.0520	0.0810	0.0972
Iteration 2	0.0315	0.0525	0.0744	0.0876
Iteration 3	0.0321	0.0500	0.0744	0.0868
Iteration 4	0.0337	0.0508	0.0755	0.0893
Iteration 5	0.0301	0.0487	0.0638	0.0746
Average	0.0320	0.0508	0.0738	0.0871
No. of iterations	Polish dataset			
	WSOA-FS	GSO-FS	DFO-FS	FFO-FS
Iteration 1	0.1501	0.1643	0.1776	0.1811
Iteration 2	0.1491	0.1626	0.1697	0.1849
Iteration 3	0.1527	0.1621	0.1694	0.1648
Iteration 4	0.1518	0.1633	0.1683	0.1645
Iteration 5	0.1464	0.1548	0.1721	0.1643
Average	0.1500	0.1614	0.1714	0.1719
No. of iterations	Weislaw dataset			
	WSOA-FS	GSO-FS	DFO-FS	FFO-FS
Iteration 1	0.0632	0.0862	0.0970	0.1027
Iteration 2	0.0627	0.0891	0.0967	0.1041
Iteration 3	0.0617	0.0882	0.0988	0.1026
Iteration 4	0.0609	0.0876	0.0964	0.1017
Iteration 5	0.0505	0.0855	0.0949	0.0989
Average	0.0598	0.0873	0.0968	0.1020

Likewise, with Polish dataset, the WSOA-FS technique has provided minimal average BC of 0.1500 whereas the GSO-FS, DFO-FS, and FFO-FS techniques have resulted in maximum average BC of 0.1614, 0.1714, and 0.1719 respectively. Moreover, with Weislaw dataset, the WSOA-FS system has offered average BC of 0.0598 but the GSO-FS, DFO-FS, and FFO-FS techniques have obtained increased average BC of 0.0873, 0.0968, and 0.1020.

Fig. 3 illustrates the set of confusion matrices produced by the IFSDL-FRA technique. On the test qualitative dataset, the IFSDL-FRA technique has identified the 107 instances into financial crisis (FC) class and 142 instances into non-financial crisis (NFC) class. Besides, on the test Polish

dataset, the IFSDL-FRA technique has identified the 2086 instances into FC class and 431294 instances into NFC class. In addition, on the test Weislaw dataset, the IFSDL-FRA technique has identified the 111 instances into FC class and 128 instances into NFC class.

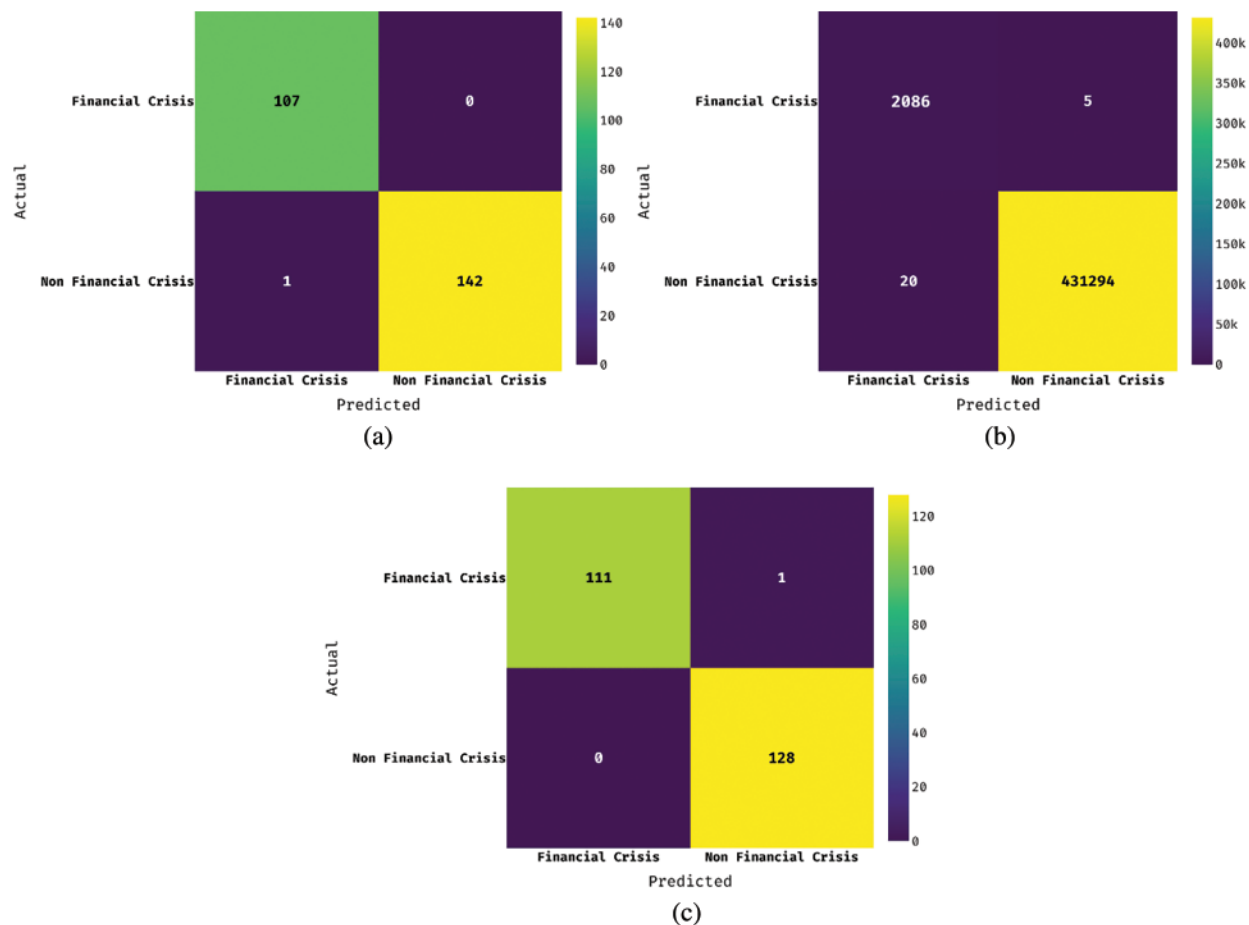


Figure 3: a) Qualitative dataset b) Polish dataset c) Weislaw dataset

Tab. 3 and Fig. 4 provide a detailed classification results analysis of the IFSDL-FRA technique on the qualitative bankruptcy dataset. The results show that the OlexGA model has shown worse classification results than the other techniques. At the same time, the Improved GACO and Genetic Ant Colony models have obtained slightly enhanced classification results. Followed by, the optimal SAE and ant colony techniques have reached reasonable classification performance.

However, the presented IFSDL-FRA technique has showcased maximum classifier results with the $sens_y$, $spec_y$, $accu_y$, F_{score} , and MCC of 1.0000, 0.9930, 0.9960, 0.9953, and 0.9919 respectively.

Table 3: Result analysis of various classifiers on qualitative bankruptcy dataset

Methods	$Sens_y$	$Spec_y$	Acc_y	F_{score}	MCC
IFSDL-FRA	1.0000	0.9930	0.9960	0.9953	0.9919
Optimal SAE	0.9995	0.9900	0.9900	0.9900	0.9900
Ant colony method	0.9976	0.9900	0.9900	0.9914	0.9800
Improved GACO	0.9636	0.9924	0.9793	0.9769	0.9500
Genetic ant colony	0.8909	0.9318	0.9132	0.9032	0.8200
Olex-GA	0.6666	0.7578	0.7148	0.6877	0.4300

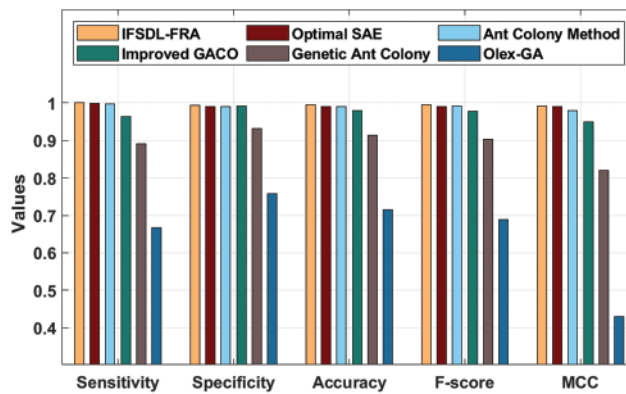


Figure 4: Result analysis of IFSDL-FRA technique on qualitative bankruptcy dataset

Fig. 5 offers a clear accuracy graph analysis of the IFSDL-FRA technique on the test qualitative bankruptcy dataset. The results revealed that the IFSDL-FRA technique has gained increased values of training and validation accuracies on the applied qualitative bankruptcy dataset.

A loss graph analysis of the IFSDL-FRA technique on the test qualitative bankruptcy dataset is offered in Fig. 6. The results showcased that the IFSDL-FRA technique has resulted in minimal values of training and testing loss on the applied qualitative bankruptcy dataset.

Tab. 4 and Fig. 7 demonstrate a comparative results analysis of the IFSDL-FRA technique on the Polish bankruptcy dataset. The experimental results demonstrated that the OlexGA model has depicted poor classification results over the other techniques. Along with that, the Improved GACO and Genetic Ant Colony models have gained moderately closer classification results. In line with, the optimal SAE and ant colony techniques have tried to accomplish somewhat improved classification performance. However, the presented IFSDL-FRA technique has outperformed the other techniques with the increased $sens_y$, $spec_y$, $accu_y$, F_{score} , and MCC of 0.9976, 1.0000, 0.9999, 0.9940, and 0.9940 respectively.

Fig. 8 gives a clear accuracy graph analysis of the IFSDL-FRA approach on the test Polish bankruptcy dataset. The outcomes depicted that the IFSDL-FRA approach has gained improved values of training and validation accuracies on the applied qualitative bankruptcy dataset. A loss graph analysis of the IFSDL-FRA system on the test Polish bankruptcy dataset is offered in Fig. 9. The outcomes outperformed that the IFSDL-FRA manner has resulted in minimal values of training and testing loss on the applied qualitative bankruptcy dataset.

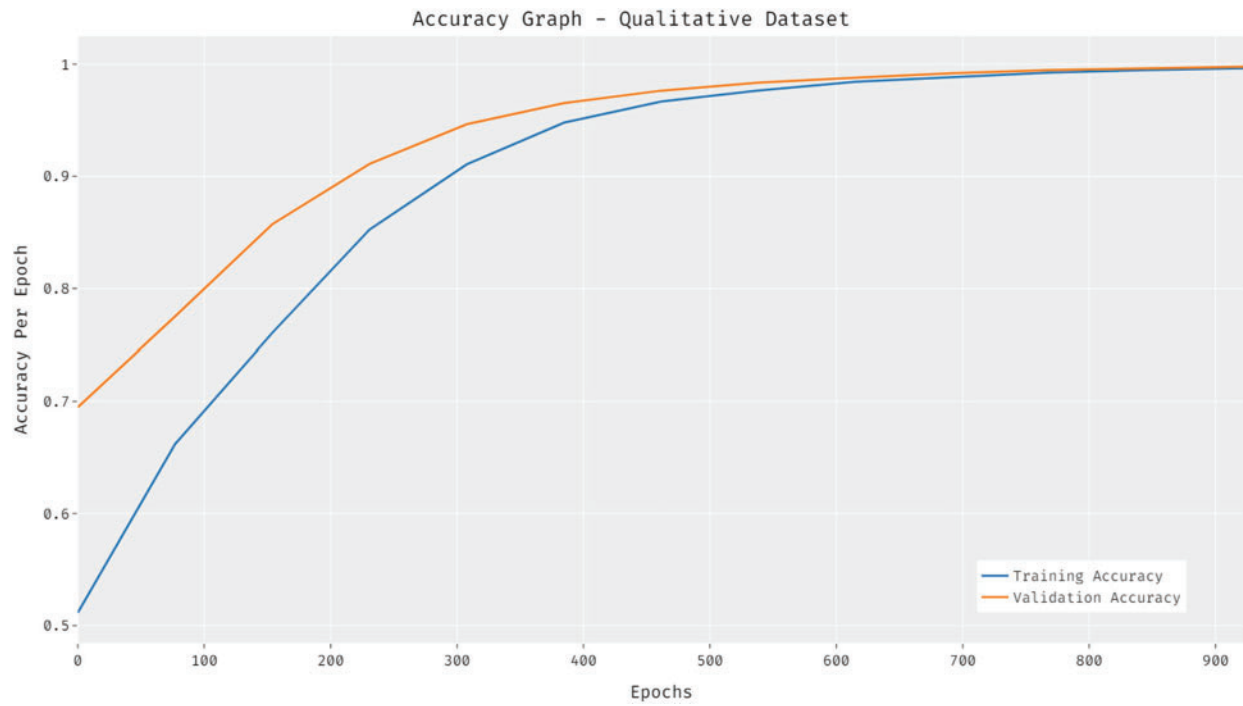


Figure 5: Accuracy analysis of IFSDL-FRA technique on qualitative bankruptcy dataset

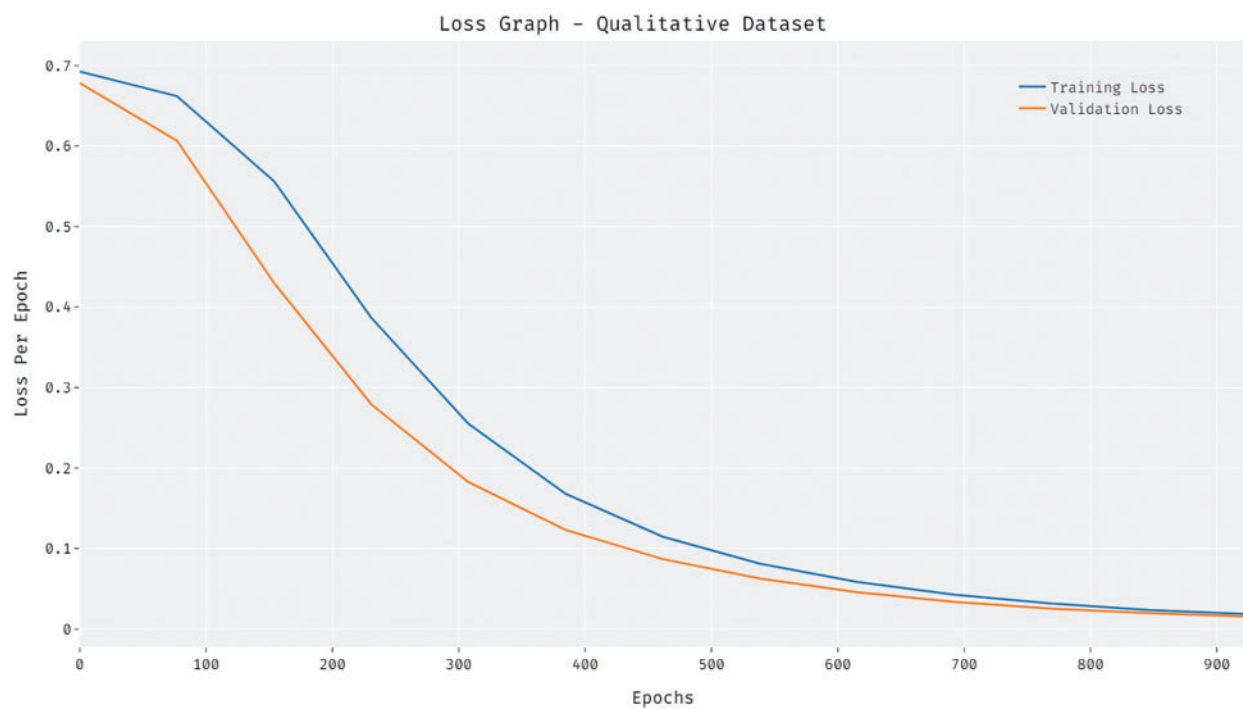


Figure 6: Loss analysis of IFSDL-FRA technique on qualitative bankruptcy dataset

Table 4: Result analysis of various classifiers on polish bankruptcy dataset

Methods	$Sens_y$	$Spec_y$	Acc_y	F_{score}	MCC
IFSDL-FRA	0.9976	1.0000	0.9999	0.9940	0.9940
Optimal SAE	0.9876	0.9993	0.9899	0.9897	0.9600
Ant colony method	0.9763	0.9990	0.9769	0.9880	0.7100
Improved GACO	0.4791	0.9989	0.9472	0.6439	0.6600
Genetic ant colony	0.3155	0.9948	0.8998	0.4684	0.5000
Olex-GA	0.1499	0.9806	0.7946	0.2464	0.2500

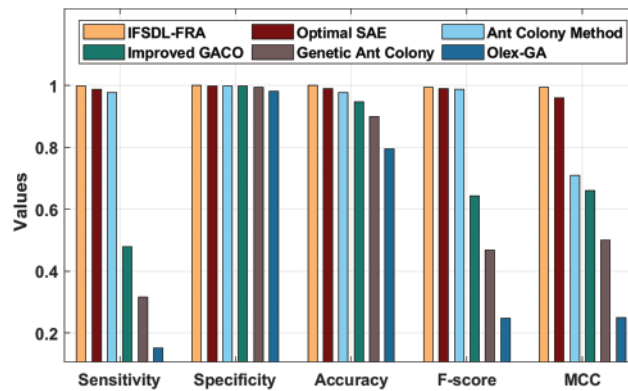


Figure 7: Result analysis of IFSDL-FRA technique on polish bankruptcy dataset

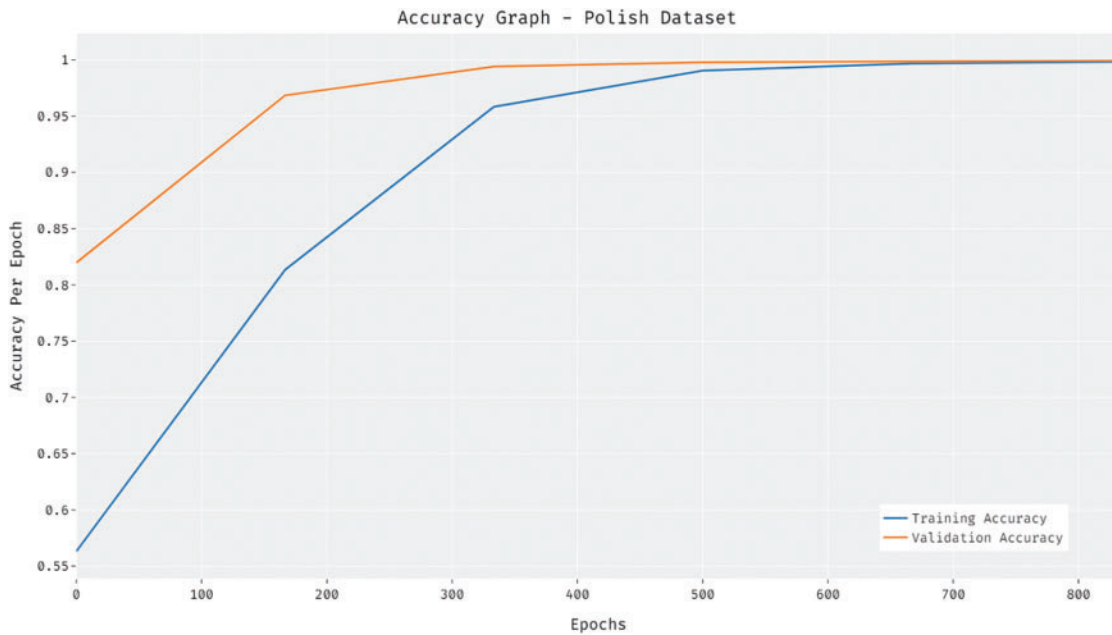


Figure 8: Accuracy analysis of IFSDL-FRA technique on polish bankruptcy dataset

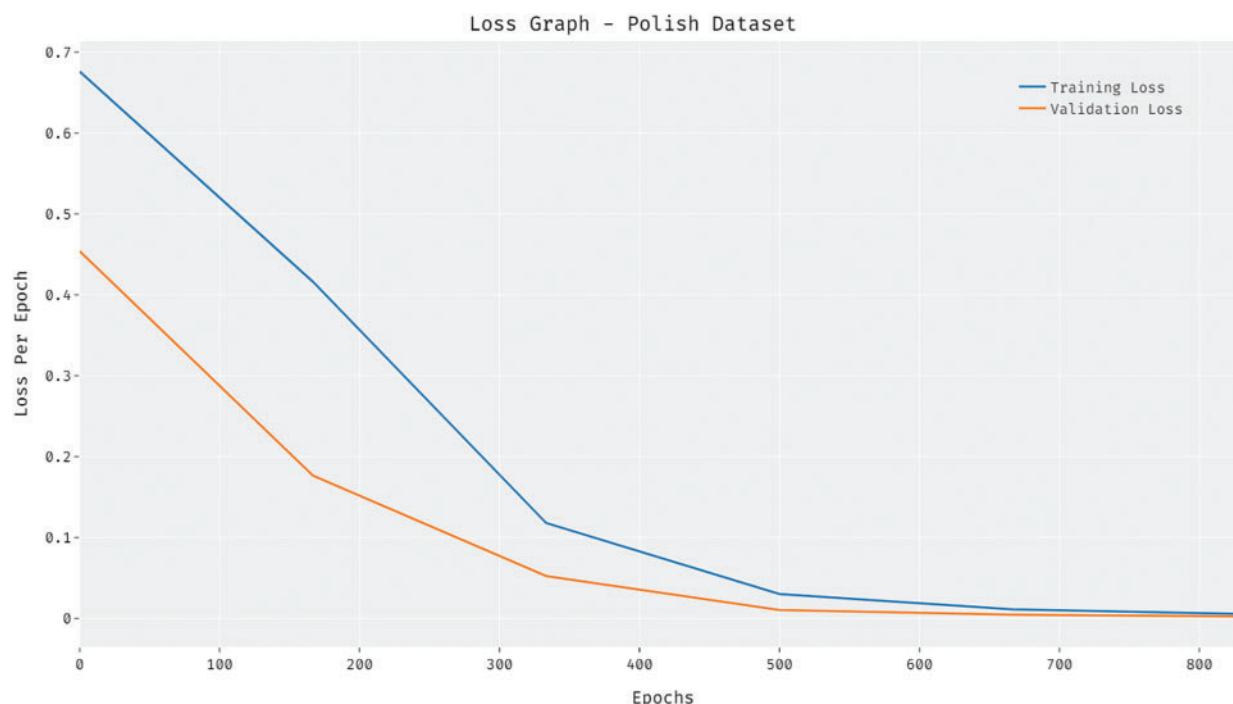


Figure 9: Acc_y analysis of IFSDL-FRA technique on polish bankruptcy dataset

Tab. 5 and Fig. 10 offer a comprehensive performance validation of the IFSDL-FRA technique on the Weislaw bankruptcy dataset [24]. The experimental results demonstrated that the OlexGA model has reported reduced efficiency over the other techniques. Eventually, the Improved GACO and Genetic Ant Colony models have resulted in somewhat improved classifier outcomes. Next to that, the optimal SAE and ant colony techniques have accomplished acceptable classifier performance. But the presented IFSDL-FRA technique has demonstrated superior results over the other techniques with the higher $sens_y$, $spec_y$, acc_y , F_{score} , and MCC of 0.9911, 1.0000, 0.9958, 0.9955, and 0.9917 respectively.

Table 5: Result analysis of various classifiers on weislaw bankruptcy dataset

Methods	$Sens_y$	$Spec_y$	Acc_y	F_{score}	MCC
IFSDL-FRA	0.9911	1.0000	0.9958	0.9955	0.9917
Optimal SAE	0.9856	0.9939	0.9878	0.9875	0.9700
Ant colony method	0.9789	0.9912	0.9798	0.9834	0.9600
Improved GACO	0.9639	0.9892	0.9755	0.9772	0.9500
Genetic ant colony	0.8729	0.9417	0.9074	0.9115	0.8100
Olex-GA	0.8135	0.8605	0.8333	0.8496	0.6700

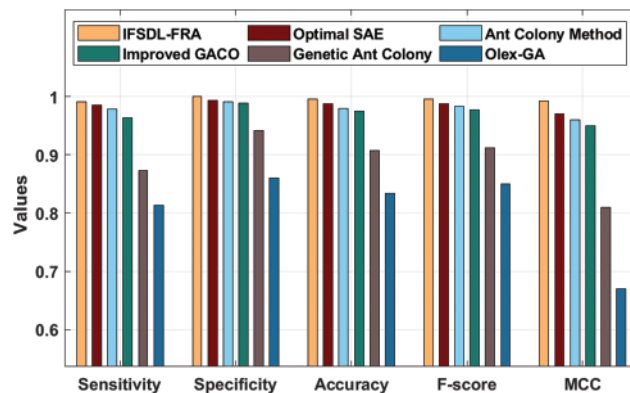


Figure 10: Result analysis of IFSDL-FRA technique on weislaw bankruptcy dataset

4 Conclusion

In this study, a novel IFSDL-FRA approach has been presented to determine the financial crisis of a company or enterprise. The proposed IFSDL-FRA technique comprises different major processes such as pre-processing, WSOA based optimal feature subset selection, DRVFLN based classification, and IFFOA based hyperparameter tuning. The utilization of WSOA to elect optimum features and IFFOA to select hyperparameters to help considerably boost the overall performance. In order to ensure the enhanced predictive outcomes of the IFSDL-FRA technique, a wide range of experiments were carried out on benchmark financial datasets and the obtained outcomes depict the betterment of the IFSDL-FRA technique over the recent state of art approaches. Therefore, the IFSDL-FRA technique was applied as proficient tools for predicting the financial condition of a firm. In future, outlier detection and clustering techniques can be integrated into the IFSDL-FRA technique to further improve the classification performance.

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