AIMS Mathematics

AIMS Mathematics, 9(7): 17555–17577.
DOI: 10.3934/math.2024853
Received: 23 March 2024
Revised: 25 April 2024
Accepted: 29 April 2024
Published: 21 May 2024

https://www.aimspress.com/journal/Math

Research article

Modeling of extended osprey optimization algorithm with Bayesian neural network: An application on Fintech to predict financial crisis

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Abstract: Accurately predicting and anticipating financial crises becomes of paramount importance in the rapidly evolving landscape of financial technology (Fintech). There is an increasing reliance on predictive modeling and advanced analytics techniques to predict possible crises and alleviate the effects of Fintech innovations reshaping traditional financial paradigms. Financial experts and academics are focusing more on financial risk prevention and control tools based on state-of-the-art technology such as machine learning (ML), big data, and neural networks (NN). Researchers aim to prioritize and identify the most informative variables for accurate prediction models by leveraging the abilities of deep learning and feature selection (FS) techniques. This combination of techniques allows the extraction of relationships and nuanced patterns from complex financial datasets, empowering predictive models to discern subtle signals indicative of potential crises. This study developed an extended osprey optimization algorithm with a Bayesian NN to predict financial crisis (EOOABNN-PFC) technique. The EOOABNN-PFC technique uses metaheuristics and the Bayesian model to predict the presence of a financial crisis. In preprocessing, the EOOABNN-PFC technique uses a min-max scalar to scale the input data into a valid format. Besides, the EOOABNN-PFC technique applies the EOOA-based feature subset selection approach to elect the optimal feature subset, and the prediction of the financial crisis is performed using the BNN classifier. Lastly, the optimal parameter selection of the BNN model is carried out using a multi-verse optimizer (MVO). The simulation process identified that the EOOABNN-PFC technique reaches superior accuracy outcomes of 95.00% and 95.87% compared with other existing approaches under the German Credit and Australian Credit datasets.

Keywords: financial crisis prediction; financial technology; multi-verse optimizer; Bayesian neural network; metaheuristics
Mathematics Subject Classification: 68T07

1. Introduction

Recently, avoiding and managing financial risks has become increasingly essential because of increased macroeconomic pressure, improved regulatory necessities, intensified business competitiveness, and enhanced criminal activities, among others [1]. Retail banks serve as both risk managers and participants in their activity as financial mediators. The business landscape for commercial banks has become increasingly challenging and risky as the financial system becomes more complex and global financial incorporation develops rapidly [2]. The capability of commercial banks to get comparative benefits in this new landscape relies on their proficiency to avoid and control risk [3]. Wide-ranging risk control and preventive actions, dependent upon big data, biometrics, and artificial intelligence (AI), have become essential tools for financial researchers and professionals. Internet of things (IoT) experts support banks and other financial organizations by getting real-time data based on individual and user resources, enhancing the financial risk assessment efficiency [4]. Currently, with the undergoing financial crisis worldwide, businesses have focused on financial crisis prediction (FCP). Businesses or financial organizations require dependable predictive models for predicting the possible risks of financial failure [5]. FCP typically produces a dual classification method; the outcomes are considered as enterprises' non-failure or failure grades. Numerous classification techniques have been presented for FCP. Generally, the developed predictive techniques are divided into statistical or AI methods [6].

Regarding the concept of unpredictability in the e-commerce industry, constructing a FCP system to systematically analyze and predict a particular financial indicator from extensive corporate data becomes a requirement to maintain the presence and development of the enterprises [7]. Nevertheless, the vast and heterogeneous quantity of corporate financial data and its continuous modifications make it challenging to analyze. Currently, with the expansion of big data and machine learning (ML), artificial neural networks (ANN) have been extensively implemented due to their higher capability to resolve nonlinear mapping issues [8]. In the ANN model, a financial risk system dependent upon ML will be achieved through the training and testing of higher-dimensional economic data to gain more efficient analysis outcomes [9]. Remarkably, ML techniques can not only resolve the timeliness prediction problem but retain the inherent correlation among previous time series (financial data) and existing financial indicators, attaining more precise FCP outcomes. Several researchers have performed advanced studies on financial risk, employing ML to get more relevant FCP systems. However, a generalizable model that efficiently predicts financial crises of enterprises still needs to be developed [10]. This section accentuates the growing significance of averting and administering economic risks in the context of enhanced macroeconomic pressure and convolutional economic systems. It also highlights the dependencies on big data, biometrics, and AI, specifically in the FCP context. ML exhibits promise for FCP but lacks a universally applicable model, which requires further study for robust and generalizable predictive models.

This study develops an extended osprey optimization algorithm with a Bayesian neural network (NN) to predict financial crisis (EOOABNN-PFC) technique. The EOOABNN-PFC method uses metaheuristics and the Bayesian model to predict a financial crisis. In preprocessing, the EOOABNN-PFC technique uses a min-max scalar to scale the input data into a valid format and applies the EOOA-based feature subset selection approach to elect optimal feature subsets. Moreover, the prediction of a financial crisis is performed using the BNN classifier. Lastly, the optimal parameter selection of the BNN model is carried out using a multi-verse optimizer (MVO). The performance validation of the EOOABNN-PFC approach is tested under a benchmark financial dataset.

The remaining sections of the article are arranged as follows: Section 2 offers the literature review, and Section 3 represents the proposed method. Then, Section 4 elaborates on results evaluation, and Section 5 completes the work.

2. Literature review

Muthukumaran and Hariharanath [11] considered the development of an optimal deep learning (DL)-based FCP (ODL-FCP) technique for small and medium-sized enterprises (SMEs) that integrated two stages: Archimedes optimization algorithm-based feature selection (FS) (AOA-FS) technique and deep-CNN (DCNN) with long short-term memory (LSTM)-based data classification. Muthukumaran et al. [12] introduced an innovative multi-verse optimization (MVO)-based FS with optimum variational autoencoder (OVAE) technique for the FCP. The developed technique mainly targeted FCP, developing a subsets FS process employing the MVOFS method. Then, the VAE method was implemented to classify financial data, and the differential evolution (DE) technique was used to tune the VAE method. Kalaivani and Saravanan [13] enhanced FCP by employing a chimp optimization algorithm with machine learning (ML) (EFCP-COAML) technique. The primary target was to forecast an automatic and precise FCP using a kernel extreme learning machine (KELM)-based prediction process. In [14], the authors designed a unique DL-based method, introducing an innovative credit decision support system with CNN and gated recurrent unit (GRU) that employed extensive series of financial data requiring some resources. Metawa and Elhoseny [15] proposed a new harmony search algorithm with the optimum LSTM (HSA-OLSTM) method in FCP for better predicting enterprises' financial conditions. Vaiyapuri et al. [16] presented an intelligent FS with a DL-based financial risk assessment (IFSDL-FRA) method. The method included the development of a new water strider optimizer technique-based FS (WSOA-FS) technique for optimal FS subsets. Likewise, the deep random vector functional link network (DRVFLN) classification algorithm was implemented. Additionally, an improved fruit fly optimization algorithm (IFFOA) model was used for the hyperparameter tuning process.

Park and Chai [17] developed a technique for the application of ML methods for forecasting information asymmetry. The authors also overcame the requirement of modifying XGBoost to predict data asymmetry by obtaining the significant aspects impacting it. That study also scientifically evaluated earlier researchers under data asymmetry in the financial market. Katib et al. [18] presented a hybrid hunter-prey optimization with DL-based FCP (HHPODL-FCP) method that used the HHPO method for the FS method. Furthermore, the algorithm utilized the gated attention recurrent network (GARN) system for detection and classification. The model used a sparrow search algorithm (SSA)-based hyperparameter tuning method to increase system effectiveness. Liu et al. [19] presented a model utilizing multi-objectivization, particularly reformulating the issue of crafting autoencoders (AEs) as a multi-objective optimizing issue. An evolutionary model called HydraText has also been efficiently employed. In [20], an effectual local search (LS) technique was proposed. The study established the initial provable approximation for resolving the general cases issue. Huang et al. [21] proposed a survey of automated hyperparameter tuning models for metaheuristics, giving a new classification depending on their structure into three categories: simple generate-evaluate, iterative generate-evaluate, and high-level generate-evaluate methods. The authors in [22] portrayed the universal best accomplishment estimator in a theoretical context and subsequently set theoretical borders on the analysis errors, considering both finite and infinite configuration spaces for parameter settings. Liu et al. [23] introduced a technique incorporating instance generation and portfolio construction in an adversarial procedure.

3. The proposed method

This study develops an EOOABNN-PFC technique, which uses metaheuristics and a Bayesian model to predict a financial crisis. To accomplish that, it contains the following major preprocessing processes: EOOA-based feature subset selection, BNN-based classifier, and MVO-based hyperparameter tuning. Figure 1 represents the working procedure of the EOOABNN-PFC technique.

3.1. Preprocessing

Initially, the EOOABNN-PFC technique uses a min-max scalar to scale the input data into a valid format. To remove the magnitude effect of the distinct dimensional datasets on the predictive method [24], the study implements min-max deviation normalization that linearly changes new data toward the solution that can be mapped among [0.0,1.0] to enhance the convergence rate and predictive outcomes, as expressed in Eq (1).

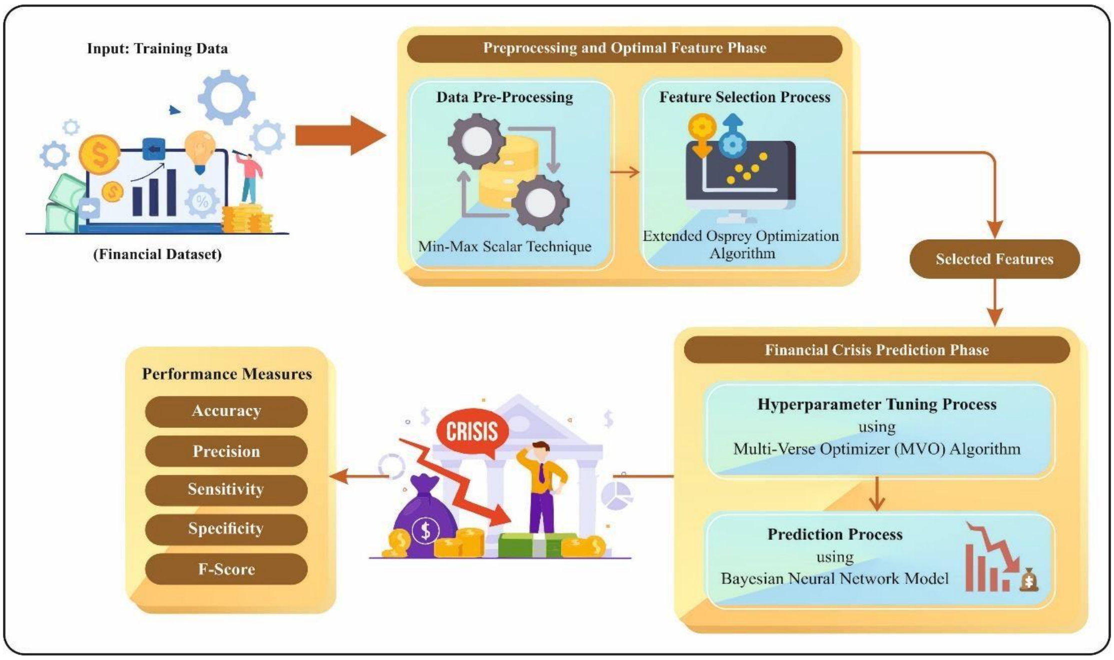

Figure 1. Overall flow of the EOOABNN-PFC technique.

$$X_{norm} = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}}. \tag{1}$$

In Eq (1), Xi signifies the ith measurement, $x$max represents the maximal measurement values, and $Xnorm$ denotes the normalized measurement.

3.2. EOOA-based feature subset selection

The EOOABNN-PFC technique applies the EOOA-based feature subset selection approach to elect optimal feature subsets. This study intends to use an osprey optimization algorithm (OOA), a meta-heuristic approach [25], to execute the searching method in both local and global problem-resolving spaces to give a pleasing solution. Generally, there are dual phases, such as exploitation and exploration. The ability of the method to find the main appropriate area and evade local goals is amended by uniting the global searching stage and incorporating the notion of exploration. The technique can attain more possible choices in promising areas and upsurges as an outcome of the search procedure utilizing the prospect of exploitation. The OOA defines the optimum way, which is dependent upon parameters.

$$C_{ij} = \lambda_1 LQ_{ij} + \lambda_2 X_{ij} + \lambda_3 S_{ij}. \tag{2}$$

Whereas C_{ij} signifies link stability from i and j, X_{ij} specifies safety degree, λ_1, λ_2, and λ_3 denote weighting vector, LQ_{ij} embodies link quality, and S_{ij} means factor for forecasting mobility

$$V(Y) = \left(\sum_h \frac{Y_h^2}{n}\right) - \left(\sum_h \frac{Y_h}{n}\right)^2. \tag{3}$$

Here, (Y) signifies the variance, Y_h denotes the level of message attained from each adjacent node, and h represents the entire number of nodes. The value of fitness is attained by utilizing Eq (4),

$$fitness\ value = max(Node\ stability\ degree\ +\ Link\ stability\ degree). \tag{4}$$

3.2.1. Initialization

The OOA defines a population-based tactic that uses the advantage of the searching capability in the region of problem-resolving to classify a potential solution through the replication-based model. Each searching agent defines the range of variables connected to the exact position within the exploration area. Thus, each searching agent is probably responsible for the issue by the vector. Every searching agent includes an OOA population assumed in Eq (5). Equation (6) is employed to set searching agents' positions in the search area randomly.

$$p = \begin{bmatrix} p_1 \\ \cdots \\ p_2 \\ \cdots \\ p_n \end{bmatrix}_{N\times M} = \begin{bmatrix} p_{1,1} & \cdots & p_{1,j} & \cdots & p_{1,m} \\ \vdots & \ddots & \vdots & ⋰ & \vdots \\ p_{i,1} & \cdots & p_{i,j} & \cdots & p_{i,m} \\ \vdots & ⋰ & \vdots & \ddots & \vdots \\ p_{N,1} & \cdots & p_{Nj} & \cdots & p_{N,M} \end{bmatrix}_{N\times M}, \tag{5}$$

$$p_{i,j} = lb_j + r_{ij}.\left(ub_j - lb_j\right), i = 1,2,\dots,N. j = 1,2,\dots,m. \tag{6}$$

Here, p designates the locations of searching agents; pi embodies the ith searching agents, $p_{i,j}$ directs the jth dimension, M represents the variable of the problem, lb_j denotes the lower bound, N signifies the number of searching agents, ub_j specifies the upper bound, and r_{ij} refers to a randomly produced variable in the interval among [0 and 1]. Equation (7) signifies the function as a set of vectors.

$$G = \begin{bmatrix} G_1 \\ \vdots \\ G_i \\ \vdots \\ G_N \end{bmatrix}_{N\times M} = \begin{bmatrix} G(P_1) \\ \vdots \\ G(P_i) \\ \vdots \\ G(P_N) \end{bmatrix}_{N\times M}. \tag{7}$$

Here, G_i signifies the objective function of ith searching agent, and G indicates the array.

3.2.2. Exploration phase

This initial state of the OOA population-upgrading method has been created by pretending to search agents' performance. The OOA discovers the ability to permit the classification of the perfect location while evading the local optimal. The locations of dissimilar searching agents delivering an advanced objective function score were less dignified. Equation (8) is employed to recognize every search agent's range of features exclusively.

$$GL_i = \{P_h | h \in \{1,2,\dots,N\} \wedge G_h < G_i\} \cup \{P_{besi}\}. \tag{8}$$

GL_j signifies the feature positions of the ith searching agent, and P_{besi} specifies the finest search agents' locations. The related search agent's novel location is originated by a replication that includes the search agent's future features. The function's value is delivered in Eq (9), amplified by the searching agent's novel position.

$$p_{i,j}^{L_i} = p_{i,j} + r_{i,j}.\left(SG_{i,j} - R_{i,j}.p_{i,j}\right). \tag{9}$$

$$p_{i,j}^{L_1} = \begin{cases} p_{i,j}^{L_1}, lb_j \leq p_{i,j}^{L_1} \leq ub_j, \\ lb_j, p_{i,j}^{L_1} < ub_j, \\ ub_j, p_{i,j}^{L_1} > ub_j. \end{cases} \tag{10}$$

$$P_i = \begin{cases} P_{i'}^{L_1} G_i^{L_1} < G_i; \\ P_i, else, \end{cases} \tag{11}$$

where p_i^{L1} specifies the novel position of the ith search agents in the early phase, $p_{i,j}^{L1}$ denotes the jth vector, G_i^{L1} indicates the rate of objective function, SG_i specifies an optimum feature of the ith searching agent, SGi,j denotes the jth vector, and $R_{i,j}$ is the randomly generated variable interval of [0 and 1].

3.2.3. Exploitation phase

The second phase in the OOA depends upon an arithmetical replication of the usual actions of searching agents. Then, the model affects the feature to the precise place and changes the location of the searching agent. The search region improves the OOA exploitation latent to better potentials that beat the known methods through integration. As per the OOA model, a correct position for recognizing features is randomly nominated for all individuals utilizing Eq (12).

$$p_{i,j}^{L_2} = p_{i,j} + \frac{lb_j + r.(ub_j - lb_j)}{t}, i = 1,2, \ldots, m,\ k = 1,2, \ldots, K, \tag{12}$$

$$P_{i,j}^{L_2} = \begin{cases} p_{i,j}^{L_2}, lb_j \leq p_{i,j}^{L_2} \leq ub_j, \\ ib_j, p_{i,j}^{L_2} < lb_j, \\ ub_j, p_{i,j}^{L_2} < ub_j. \end{cases} \tag{13}$$

This is employed to upsurge the score of objective functions in the existing location, which alters the correlated places of the searching agents, allowing Eq (14),

$$P_i = \begin{cases} P_i^{L_2}, G_i^{L_2} < G_{i;} \\ P_i, else. \end{cases} \tag{14}$$

Whereas p_i^{L2} signifies the position of the ith searching agents, and p_i^{L2} embodies the jth vector, G_i^{L2} shows the value of the objective function, K represents the iteration count, ri,j denotes a randomly produced variable in the interval [0 and 1], and k means iteration area. The projected method regularly yields training faults. This is because the hyperparameters were very complex to acquire. Therefore, to solve the above problem, the opposition-based learning (OBL) model employs the extended OOA (Ex-OOA) technique to improve the hyperparameter of the planned technique. The OBL approach employs the fitness function (FF) f value to define whether the existing selection is superior. For the true value $p \in [v, l]$, a dissimilar value p has been accepted in the vital description of OBL. The value can originate utilizing the below-mentioned formulation:

$$\overline{p} = v + l - p. \tag{15}$$

The explanation is protracted to n sizes utilizing the below-given formulation:

$$\overline{p}_i = v_i + l_i - p_i, i = 1,2, \ldots, N. \tag{16}$$

Here, $p \in Rn$ signifies the opposite vector, $p \in Rn$ represents the vector of real. The binary responses p and $\overline{p}$ are also contrasted during the optimizer stage. The enhanced dual selections are kept, and the other is removed from the assessment of fitness function.

The FF considers the classifier outcome and the amount of attributes chosen. It increases the classifier outcomes and reduces the set size of the attributes selected. As a result, the following FF is used for assessing the individual solution, as follows:

$$Fitness = \alpha * \ ErrorRate + (1-\alpha) * \frac{\#SF}{\#All\_F}. \tag{17}$$

In Eq (17), $ErrorRate$ implies the classifier error rate and is evaluated as the number of incorrect classifieds to the number of classifiers made within [0,1]. $ErrorRate$ refers to the complement of the classifier accuracy, indicating the number of selected features and the total number of attributes in the original data are $\#SF$ and $\#All\_F$. α controls the importance of classifier quality and subset length and is fixed to 0.9.

3.3. FCP using the BNN model

The financial crisis prediction is performed using a BNN classifier at this stage. Bayes theorem is a vital concept in statistics, depending on the fact that data were employed to evaluate the probability of occurrence outcomes [26]. Integrating the Bayesian model and ML implies that uncertainty can be restricted in typical ML approaches. Kendall and Gal separated uncertainty into epistemic and aleatoric. The former mentions that the uncertainty classified in the database can come from several logical explanations. However, epistemic uncertainty, also called classic uncertainty, can be reduced with the development of input data in the method. Once this method removes data from any database, it will create undependable decisions depending on the databases trained earlier. Then, epistemic uncertainty directly represents the consistency of the forecast and is employed to observe the method's strength to boost.

By changing the biased and weighted parameters of typical NNs as ANNs, BNNs measure epistemic uncertainty. The subsequent derivations express a probabilistic method, and this model, variational inference, is employed to execute a practical and effective BNN. Figure 2 exhibits the architecture of the BNN model.

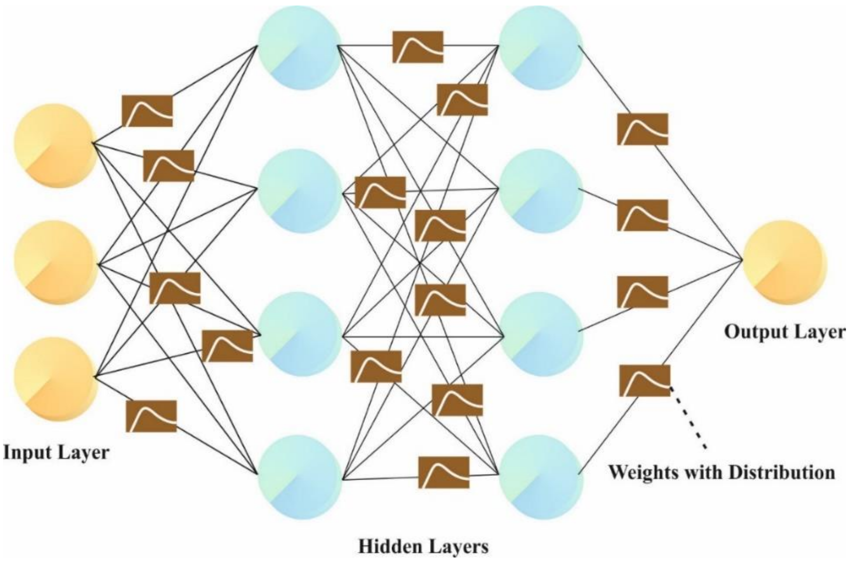

Figure 2. Framework of BNN.

3.3.1. Probabilistic model

An NN is assumed as a probabilistic model $P(y|x,z)$ whereas x signifies the input data and z refers to the parameters within the network. To classifier tasks, y implies a group of class labels, and, correspondingly, $P(y|x, and\ z)$ supports a categorical distribution. To provide a database with n trained points as $D = \{x_i, y_i\}$: Whereas $|D| = n$, they simply make the probability function:

$$P(D|z) = \prod_{i=1}^{n} P\left(y_i|x_{i,}z\right). \tag{18}$$

The maximum likelihood estimate of parameter w is attained and, generally, the negative log probability can be elected to improve purposes that suggest the cross entropy of $softmax$ loss to probability distribution is expressed as:

$$z_{MLE} = \arg\max_{z}\ \sum_{i}^{n} \log P(y_i|x_i, z). \tag{19}$$

However, the MLE can be utilized in CNN and can be inclined to over-fitting under the training. To resolve the over-optimization, regularization is established by multiplying the probability with the previous distribution $P(z)$:

$$P(z|D) \propto P(D|z)P(z). \tag{20}$$

Maximized $P(D|z)P(z)$ offers the maximum a posteriori (MAP) evaluation of z. The learning process for probability distribution encompasses the $softmax$ loss along with a regularized term derived from the logarithm of the prior:

$$z_{MAP} = \arg\max_{z} \sum_{i}^{n} \log P(y_i|x_i, z) + \log P(z). \tag{21}$$

Either MLE or MAP offer point evaluations of w that could not be continuously depended on. Bayesian inference aims to estimate the posterior distribution of the weighted parameter dependent on trained data $P(z|D)$, for the uncertainty parameters measured.

3.3.2. Variational inference

It can be difficult to acquire analytical performances to $P(z|D)$. Thus, an estimate method can be assumed. A variational distribution can be determined as $q(z|\theta)$ to estimate the posterior distribution. The similarity among $q(z|\theta)$ and $P(zD)$ is evaluated by the Kullback-Leibler (KL) divergence, expressed as:

$$KL[q(z|\theta)P(z|D)] = E_{q(z|\theta)} \log \frac{q(z|\theta)}{P(z|D)}. \tag{22}$$

Next, executing the Bayes hypothesis to the posterior distribution $P(zD)$ and creating any operations, the cost function is provided as follows:

$$KL[q(z|\theta)P(z|D)] = KL[q(z|\theta)P(z)] - E_{q(z|\theta)} \log P(D|z) + \log P(D). \tag{23}$$

To reduce the KL divergence among $q(z|\theta)$ and $P(z|D)$, the divergence-free energy needs to be diminished:

$$F(D,\theta) = KL[q(z|\theta)P(z)] - E_{q(z|\theta)}\ \log\ P(D|z). \tag{24}$$

By reordering the KL term, the overhead formula is demonstrated as:

$$F(D,\theta) = E_{q(z|\theta)}\log q(z|\theta) - E_{q(z|\theta)}\log P(z) - E_{q(z|\theta)}\log P(D|z). \tag{25}$$

Note that all three terms in Eq (25) comprise the probability of $q(z|\theta)$. Then, by sampling $z^{(i)}$ from variational distribution $q(z|\theta)$, this appearance is estimated, and the last cost function is provided as:

$$F(D,\theta) \approx \frac{1}{M}\sum_{i=1}^{M}\left[\log q\left(z^{(i)}\middle|\theta\right) - \log P\left(z^{(i)}\right) - \log P\left(D\middle|z^{(i)}\right)\right], \tag{26}$$

whereas M denotes the size of batches. Usually, not all data is inputted into the network in the training model (epoch) because of inadequacy. As an alternative, the entire database can be separated into smaller batches, which are then fed into the network; this allows the processing of huge-scale data.

3.4. Hyperparameter tuning process

Finally, the optimal parameter selection for the BNN is carried out using MVO. The new metaheuristic MVO algorithm is based on the cosmological concepts of black holes, white holes, and wormholes [27]. Exploration, exploitation, and local search are performed using an analytic model based on these concepts. The objects of the universe serve as solution variables for the problem, as the algorithm and the universe are parallel. A roulette wheel mechanism is used to exchange objects between universes and determine the optimal result for the analytical models of black and white holes. A randomized representation of the universe found in the solution space is as follows:

$$U = \begin{bmatrix} x_1^1 & x_1^2 & \dots & x_1^n \\ x_2^1 & x_2^2 & \dots & x_2^n \\ \vdots & \vdots & \vdots & \vdots \\ x_n^1 & x_n^2 & \dots & x_n^n \end{bmatrix}. \tag{27}$$

In Eq (27), n indicates the frequency of the search component, U represents the world, X_i^j denotes the j^{th} variable of i^{th}world, and d shows the measurement of control parameters.

$$x_i^j = \begin{cases} x_k^j & r_1 < NI(U_i), \\ x_i^J & r_1 > NI(U_i). \end{cases} \tag{28}$$

In Eq (28), X_k^j refers to the j^{th} variables of k^{th} worlds, selected by applying the roulette wheeling mechanism. U_i indicates the i^{th} world, NI indicates the normalized inflation rate, and r_1 shows the random integer within $[0,1]$,

$$x_i^j = \begin{cases} \begin{cases} x_j + TDR \cdot \left[\left(ub_j - lb_j\right) \cdot r_4 + lb_j\right] & r_3 < 0.5, \\ x_j - TDR \cdot \left[\left(ub_j - lb_j\right) \cdot r_4 + lb_j\right] & r_3 \geq 0.5, \end{cases} & r_2 < WEP, \\ x_i^j, & r_2 \geq WEP. \end{cases} \tag{29}$$

In Eq (29), X_j indicates the j^{th} variable of the optimum world, TDR (traveling distance rate) and WEP (wormhole existence probability) are coefficients, the upper and lower limitations of j^{th} variables are ub_j and lb_j, x_i^j shows the j^{th} parameter of the i^{th} world, and r_4, r_3, and r_2 are random integers within $[0,1]$.

$$WEP = \min + t \times \left(\frac{\max - \min}{T_{\max}}\right). \tag{30}$$

In Eq (30), the maximal and minimal numbers of controlled variables are indicated by max and min, and t and $T_{\max}$ are the existing and maximum iteration counters.

$$TDR \ = 1 - \frac{t^{\left(\frac{1}{p}\right)}}{T_{\max}^{\left(\frac{1}{p}\right)}}. \tag{31}$$

In Eq (31), p denotes the exploitation accuracy through the iteration; as p improves, quicker local search and more precise exploitation take place. The MVO algorithm derives an FF to achieve better classifier results. It determines a positive integer to embody the superior performance of the solution candidate. Now, the reduction of the classifier error is defined as the FF.

$$\begin{aligned} fitness(x_i) &= ClassifierErrorRate(x_i) \\ &= \frac{No.of \ \ misclassified \ \ samples}{Total \ \ No.of \ \ samples} * 100. \end{aligned} \tag{32}$$

4. Result analysis and discussion

This section inspects the performance of the EOOABNN-PFC technique on two datasets: The German Credit [28] and the Australian Credit [29] database, containing 1000 and 690 samples, respectively, as described in Table 1.

Table 1. Details on German Credit and Australian Credit databases.

Dataset	# of instances	# of attributes	# of class	Financial crisis/ non-financial crisis
German Credit	1000	24	2	300/700
Australian Credit	690	14	2	383/307

Table 2 and Figure 3 show the average best cost (ABC) results of the EOOABNN-PFC method for the two datasets. These experimental outcome values highlight that the GWO-FS, QABO-FS, and ACO-FS models have poorer performance with increased ABC values. Meanwhile, the HHPODL-FCP model has slightly improved results with moderate ABC values. However, the EOOABNN-PFC technique demonstrates superior performance with the least ABC of 0.099 and 0.042 in the German and Australian Credit databases, respectively.

Table 2. Average best cost (ABC) outcome of EOOABNN-PFC model for the two datasets.

	Average best cost	
Method	**German Credit database**	**Australian Credit database**
EOOABNN-PFC	0.099	0.042
HHPODL-FCP	0.139	0.071
QABO-FS	0.160	0.093
ACO-FS	0.185	0.097
GWO-FS	0.200	0.108

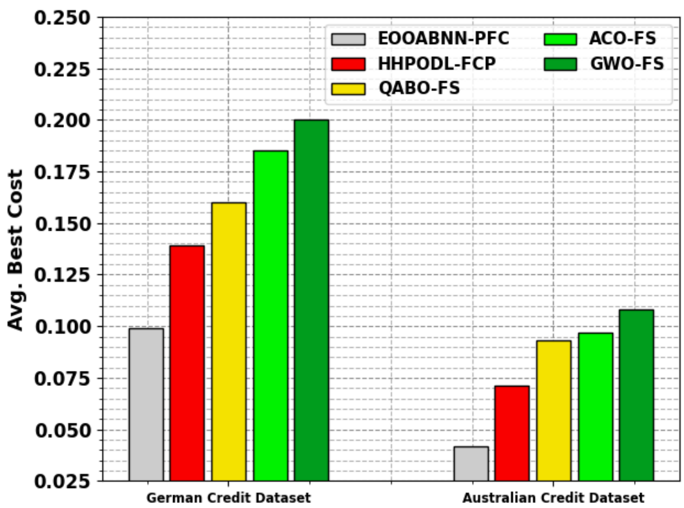

Figure 3. Average best cost (ABC) outcome of EOOABNN-PFC method for the two datasets.

Figure 4 examines the classifier outcomes of the EOOABNN-PFC method in German Credit data. Figure 4(a),(b) showcases the confusion matrices acquired by the EOOABNN-PFC method with 70% TRAS and 30% TESS. This figure shows that the EOOABNN-PFC technique can correctly identify and classify the financial crisis and non-financial crisis class labels. Meanwhile, Figure 4(c) illustrates the PR effectiveness of the EOOABNN-PFC method, showing that the EOOABNN-PFC algorithm offers maximal PR results with each class. In conclusion, Figure 4(d) showcases the ROC result of the EOOABNN-PFC technique, showing that the EOOABNN-PFC system gives effective outcomes with improved ROC values with two classes.

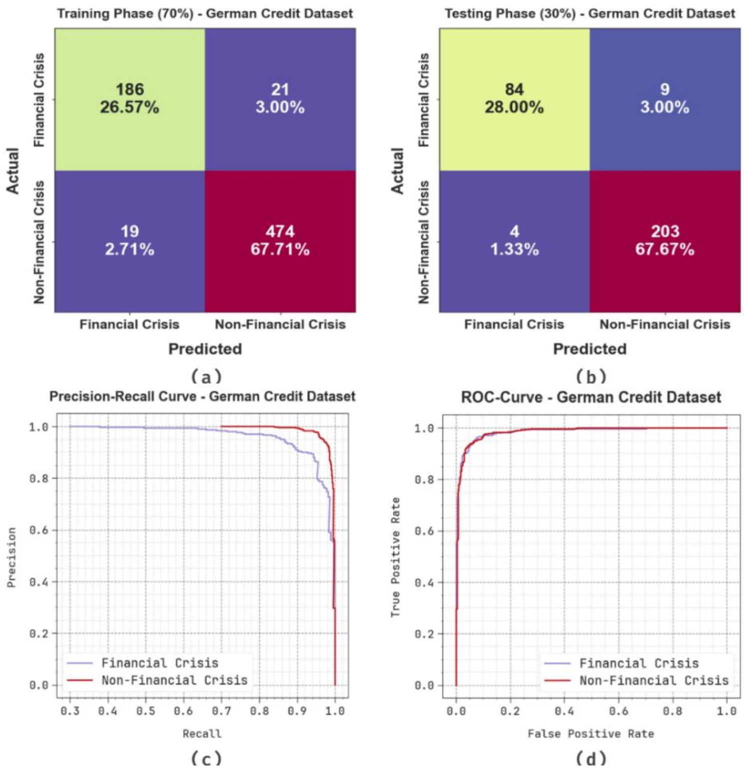

Figure 4. (a) German Credit database, (b) confusion matrices, (c) PR curve, and (d) ROC curve.

In Table 3 and Figure 5, the FCP results of the EOOABNN-PFC model are provided for the German Credit database. These outcome results emphasize that the EOOABNN-PFC technique was able to predict financial and non-financial crisis. Based on 70% TRAS, the EOOABNN-PFC technique gained an average $accu_y$ of 92.83%, $prec_n$ of 93.95%, $sens_y$ of 92.83%, $spec_y$ of 92.83%, and F_{score} of 93.22%. Also, based on 30% TESS, the EOOABNN-PFC method acquired average $accu_y$ of 95%, $prec_n$ of 95.21%, $sens_y$ of 95%, $spec_y$ of 95%, and F_{score} of 95.10%

Table 3. FCP outcomes of the EOOABNN-PFC method for the German Credit database.

Class	$Accu_y$	$Prec_n$	$Sens_y$	$Spec_y$	F_{score}
TRAS (70%)					
Financial crisis	97.76	90.97	97.76	87.91	94.24
Non-financial crisis	87.91	96.92	87.91	97.76	92.20
Average	92.83	93.95	92.83	92.83	93.22
TESS (30%)					
Financial crisis	96.52	94.87	96.52	93.48	95.69
Non-financial crisis	93.48	95.56	93.48	96.52	94.51
Average	95.00	95.21	95.00	95.00	95.10

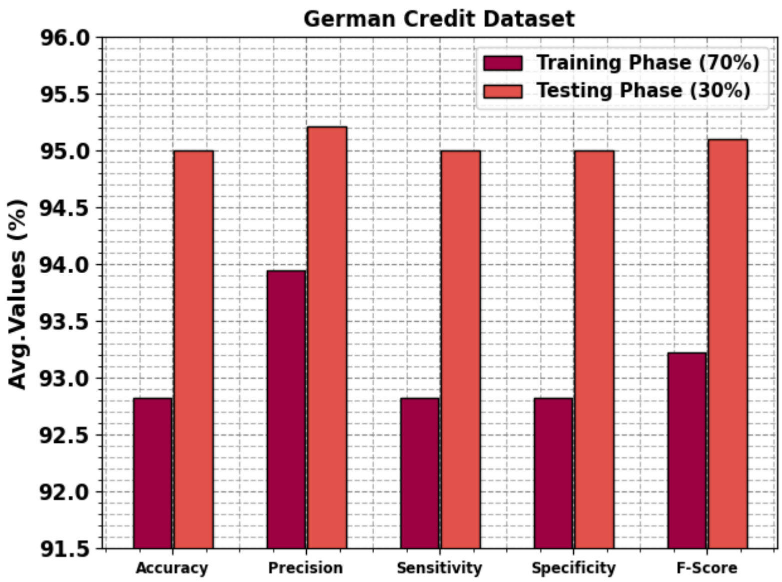

Figure 5. Average of the EOOABNN-PFC system on the German Credit database.

The effectiveness of the EOOABNN-PFC system for the German Credit database is demonstrated in Figure 6 in the form of training accuracy (TRAA) and validation accuracy (VALA) curves. The figure displays the useful analysis of the behavior of the EOOABNN-PFC method over varying epoch counts, representing its generalization and learning development proficiencies. Mostly, the figure denotes a constant development in the TRAA and VALA with an improvement in epochs. It ensures the adaptive aspect of the EOOABNN-PFC system in the pattern recognition process under TRA and TES data. The increased trends in VALA outline the ability of the EOOABNN-PFC technique to adjust to the TRA data and also to provide correct classification on undetected data, showing capabilities for robust generalization.

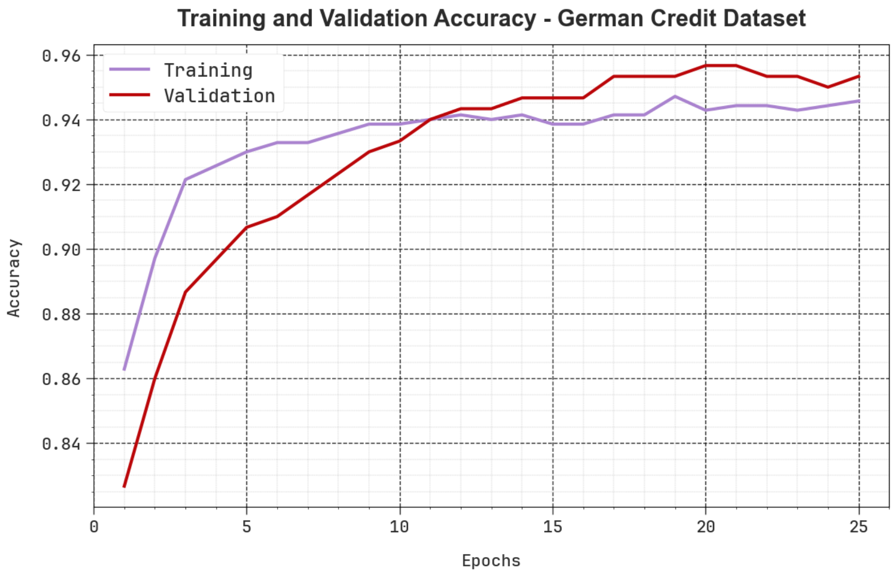

Figure 6. $Accu_y$ curve of the EOOABNN-PFC method for the German Credit database.

Figure 7 illustrates a wide-ranging representation of the training loss (TRLA) and validation loss (VALL) outcomes of the EOOABNN-PFC method for the German Credit database at distinct epochs. The progressive minimization in TRLA points out that the EOOABNN-PFC method improved the weights and diminished the classification error at TRA and TES data. The figure specifies a better understanding of the EOOABNN-PFC techniques related to the TRA data, underlining its capability to capture patterns. Mainly, the EOOABNN-PFC algorithm incessantly boosts its parameters in decreasing the variances between the prediction and real TRA class labels.

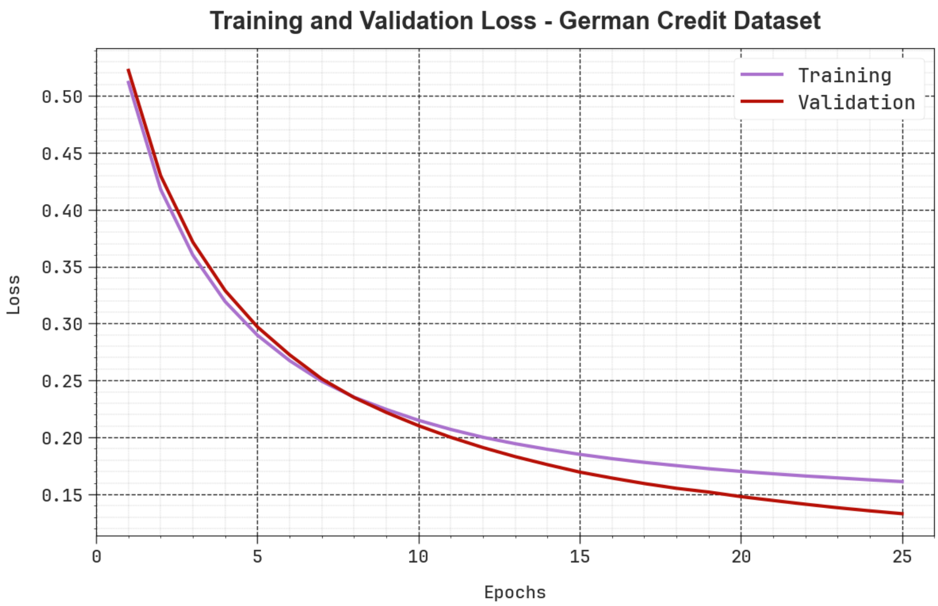

Figure 7. Loss curve of the EOOABNN-PFC technique for the German Credit database.

In Table 4 and Figure 8, the comparison analysis of the EOOABNN-PFC technique is given for the German Credit database [18]. The results highlight that the LSTM-RNN, MLP, and ACO techniques have the lowest performance. Meanwhile, the HHPODL-FCP and QABO-LSTM-RNN models have accomplished closer results. However, the EOOABNN-PFC technique exhibits better performance with maximum $sens_y$ of 95.00%, $spec_y$ of 95.00%, $accu_y$ of 95.00%, and F_{score} of 95.10%.

Table 4. Comparative outcomes of the EOOABNN-PFC model with other recent algorithms for the German Credit database.

German Credit database				
Classifiers	$\boldsymbol{Sens_y}$	$\boldsymbol{Spec_y}$	$\boldsymbol{Accu_y}$	$\boldsymbol{F_{score}}$
EOOABNN-PFC	95.00	95.00	95.00	95.10
HHPODL-FCP	93.54	93.99	94.89	93.70
QABO-LSTM-RNN	87.21	93.56	91.94	90.08
LSTM-RNN	82.16	88.53	84.56	88.71
ACO	78.29	69.28	75.74	85.38
MLP	73.84	66.86	70.93	75.10

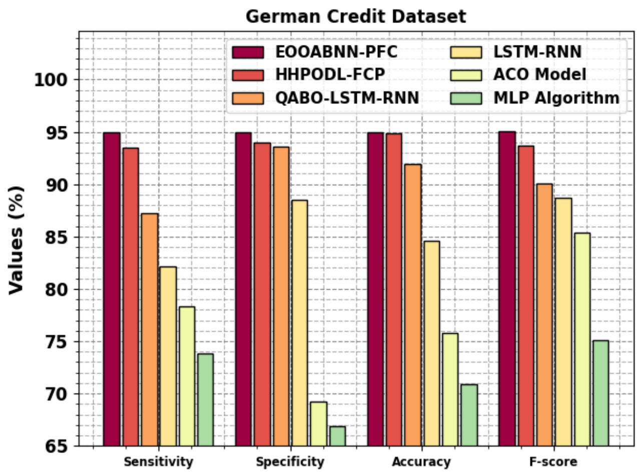

Figure 8. Comparative outcomes of the EOOABNN-PFC technique for the German Credit database.

Figure 9 displays the classifier outcomes of the EOOABNN-PFC method for the Australian Credit database. Figure 9(a),(b) examines the confusion matrices obtained by the EOOABNN-PFC model at 70% TRAS and 30% TESS and shows that the EOOABNN-PFC method can correctly identify and categorize the financial crisis and non-financial crisis labels. Moreover, Figure 9(c) displays the PR effectiveness of the EOOABNN-PFC system, showing that the EOOABNN-PFC algorithm gains higher PR results with every class. Also, Figure 9(d) indicates the ROC result of the EOOABNN-PFC method, showing that the EOOABNN-PFC method provides effective outcomes with maximum ROC values with two classes.

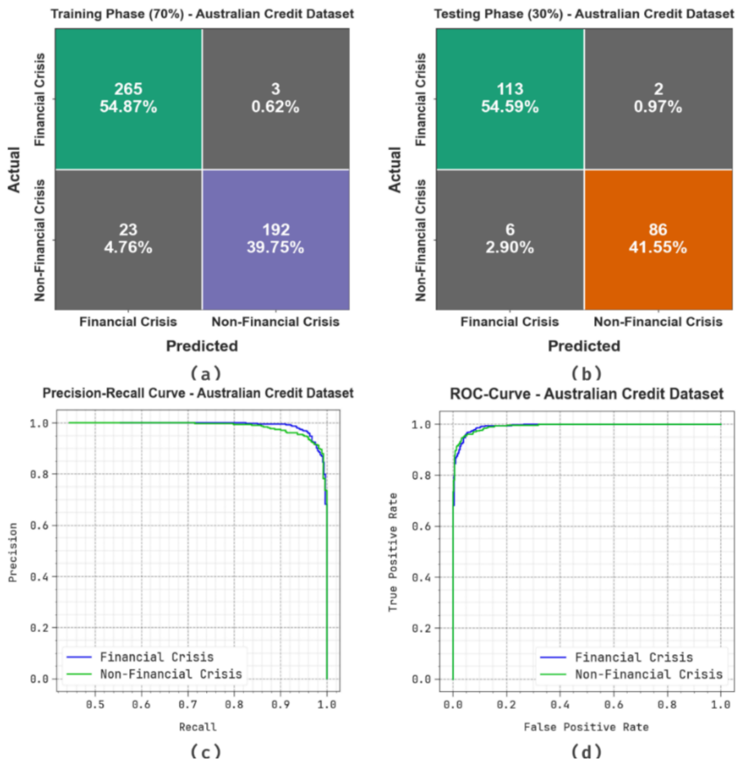

Figure 9. (a) Australian Credit database, (b) confusion matrices, (c) PR curve, and (d) ROC curves.

In Table 5 and Figure 10, the FCP outcomes of the EOOABNN-PFC system are reported for the Australian Credit database. These outcomes show that the EOOABNN-PFC method predicted the financial and non-financial crisis. According to 70% TRAS, the EOOABNN-PFC system obtained an average $accu_y$ of 94.09%, $prec_n$ of 95.24%, $sens_y$ of 94.09%, $spec_y$ of 94.09%, and F_{score} of 94.49%. Meanwhile, based on 30% TESS, the EOOABNN-PFC algorithm got an average $accu_y$ of 95.87%, $prec_n$ of 96.34, $sens_y$ of 95.87%, $spec_y$ of 95.87%, and F_{score} of 96.07%.

Table 5. FCP outcomes of the EOOABNN-PFC technique for the Australian Credit database.

Classes	$Accu_y$	$Prec_n$	$Sens_y$	$Spec_y$	F_{score}
TRAS (70%)					
Financial crisis	98.88	92.01	98.88	89.30	95.32
Non-financial crisis	89.30	98.46	89.30	98.88	93.66
Average	94.09	95.24	94.09	94.09	94.49
TESS (30%)					
Financial crisis	98.26	94.96	98.26	93.48	96.58
Non-financial crisis	93.48	97.73	93.48	98.26	95.56
Average	95.87	96.34	95.87	95.87	96.07

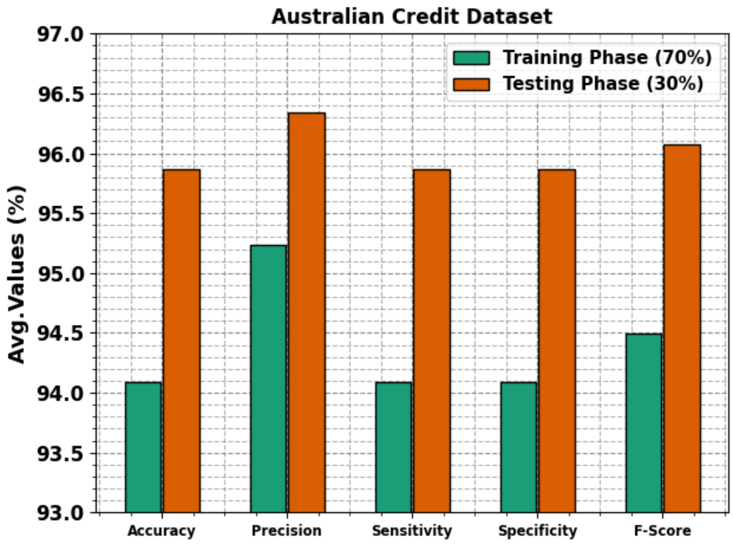

Figure 10. Average of the EOOABNN-PFC model at the Australian Credit database.

The efficiency of the EOOABNN-PFC system at the Australian Credit database is graphically examined in Figure 11 with respect to TRAA and VALA curves. The figure shows a beneficial analysis of the behavior of the EOOABNN-PFC method over multiple epoch counts, signifying its learning process and generalization abilities. Primarily, the figure shows a continual improvement in the TRAA and VALA with progress in epochs. It confirms the adaptable aspects of the EOOABNN-PFC algorithm in the pattern recognition method with TRA and TES data. The greater trends in VALA outline the proficiency of the EOOABNN-PFC technique in modifying the TRA data and surpassing to give exact classification on unnoticed data, displaying the capabilities of robust generalization.

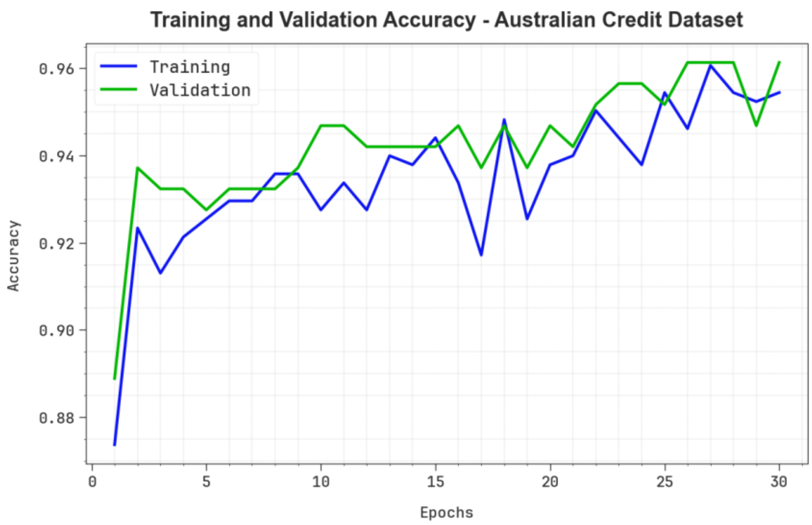

Figure 11. $Accu_y$ curve of the EOOABNN-PFC method for the Australian Credit database.

Figure 12 illustrates a comprehensive representation of the TRLA and VALL results of the EOOABNN-PFC method for the Australian Credit database over distinct epochs. The gradual minimization in TRLA points out the EOOABNN-PFC model boosting the weights and lessening the classification error at the TRA and TES data. The figure shows a greater understanding of the

EOOABNN-PFC algorithm relevant to the TRA data, emphasizing its proficiency in capturing patterns. Significantly, the EOOABNN-PFC technique constantly increases its parameters in minimizing the variances among the prediction and real TRA class labels.

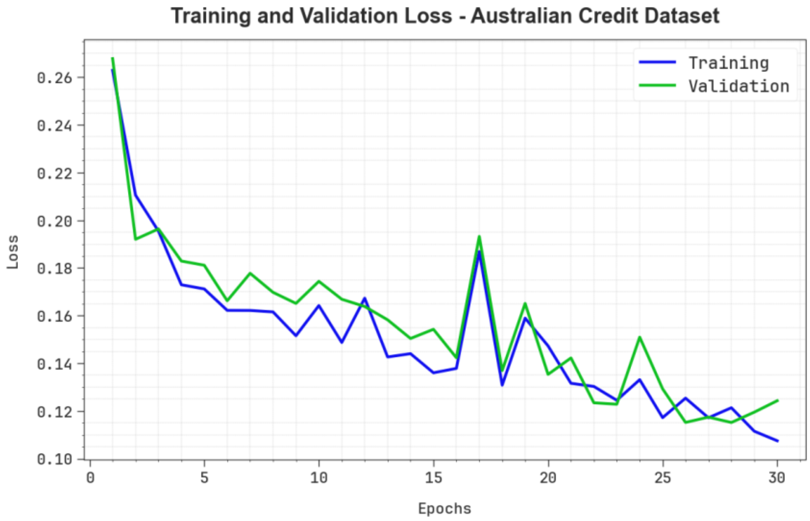

Figure 12. Loss curve of the EOOABNN-PFC model for the Australian Credit database.

In Table 6 and Figure 13, a comprehensive comparative analysis of the EOOABNN-PFC method is reported for the Australian Credit database. These outcomes show that the LSTM-RNN, MLP, and ACO algorithms provide the lowest performance. On the other hand, the HHPODL-FCP and QABO-LSTM-RNN methods achieved remarkable outcomes. Nevertheless, the EOOABNN-PFC system indicates excellent performance with a boosted $sens_y$ of 95.87%, $spec_y$ of 95.87%, $accu_y$ of 95.87%, and F_{score} of 96.07%.

Table 6. Comparative outcomes of the EOOABNN-PFC system with other algorithms for the Australian Credit database.

Australian Credit database				
Classifiers	$\boldsymbol{Sens_y}$	$\boldsymbol{Spec_y}$	$\boldsymbol{Accu_y}$	$\boldsymbol{F_{score}}$
EOOABNN-PFC	95.87	95.87	95.87	96.07
HHPODL-FCP	94.34	94.58	95.06	94.65
QABO-LSTM-RNN	90.92	93.18	93.33	94.67
LSTM-RNN	85.99	93.04	93.05	91.63
ACO	79.75	89.34	89.68	81.94
MLP	76.50	84.43	84.42	78.70

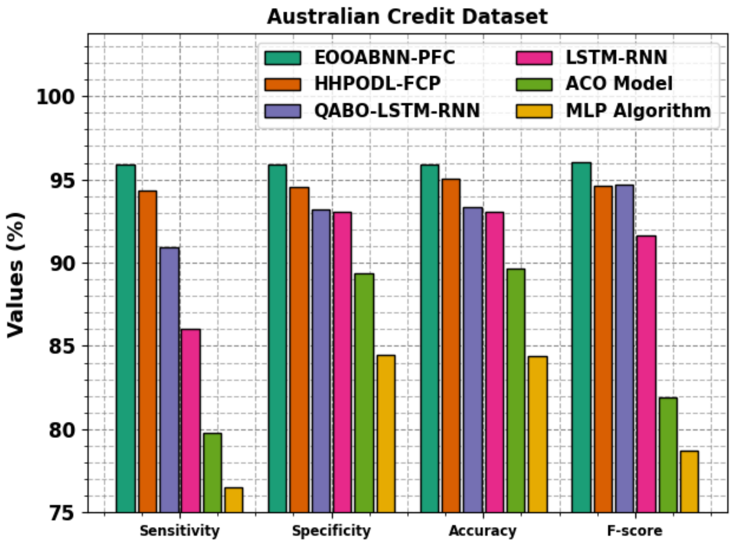

Figure 13. Comparative outcomes of the EOOABNN-PFC technique under the Australian Credit database.

In Table 7 and Figure 14, a comparative assessment of extensive computational time (CT) for all methods is shown for the German Credit and Australian Credit databases. These experimentation outcomes indicate that the LSTM-RNN, MLP, and ACO techniques offer poorer performances. Moreover, the HHPODL-FCP and QABO-LSTM-RNN algorithms show considerable results.

Table 7. Computational time (CT) outcomes for the EOOABNN-PFC model and other algorithms under two databases.

Computational time (s)		
Classifiers	German Credit database	Australian Credit database
EOOABNN-PFC	0.13	0.26
HHPODL-FCP	0.25	0.43
QABO-LSTM-RNN	1.26	1.43
LSTM-RNN	2.29	3.38
ACO	1.32	1.39
MLP	3.25	2.40

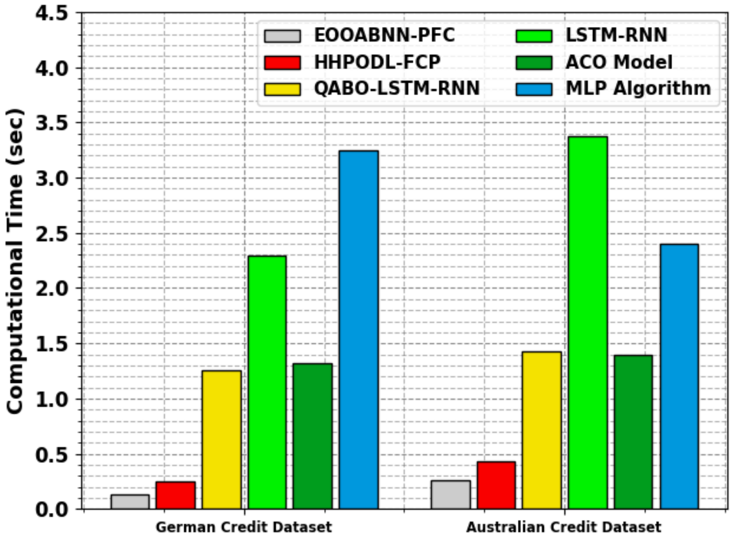

Figure 14. CT outcomes for the EOOABNN-PFC technique compared with other systems for the two databases.

However, the EOOABNN-PFC method shows higher performance with minimized CT of 0.13 s and 0.26 s. Hence, the EOOABNN-PFC technique is found to be effective for predicting financial crises.

5. Conclusions

In this study, we established an EOOABNN-PFC method that aims to predict the presence of a financial crisis using metaheuristics and the Bayesian model. In the preprocessing stage, the EOOABNN-PFC technique uses min-max scalar for scaling the input data into a useful format. Besides, the EOOABNN-PFC technique applies the EOOA-based feature subset selection approach to elect optimal feature subsets. The prediction of financial crisis is performed by using the BNN classifier, and the optimal parameter selection of the BNN model is carried out using MVO. The performance validation of the EOOABNN-PFC algorithm was tested for a benchmark financial dataset. The simulation outcomes identified that the EOOABNN-PFC technique reaches better predictive outcomes compared with other existing techniques.

Author contributions

Ilyos Abdullayev: conceptualization, methodology, formal analysis, writing-original draft preparation; Elvir Akhmetshin: methodology, software, validation, formal analysis; Irina Kosorukova: investigation, data curation, visualization; Elena Klochko: software, validation, visualization, formal analysis; Woong Cho: validation, supervision, project administration, resources; Gyanendra Prasad Joshi: validation, writing-review and editing, resources, supervision, project administration. All authors have read and approved the final version of the manuscript for publication.

Data availability statement

The data that support the findings of this study are two datasets: German Credit at https://archive.ics.uci.edu/ml/datasets/statlog+(german+credit+data) and Australian Credit at http://archive.ics.uci.edu/ml/datasets/statlog+(australian+credit+approval), reference number [23, 24].

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare that they have no conflict of interest.

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