Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.18576/amis/180626

Optimized Deep Fuzzy Neural Network for Financial Risk Evaluation in Fintech Model

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Received: 2 Aug. 2024, Revised: 12 Sep. 2024, Accepted: 22 Oct. 2024
Published online: 1 Nov. 2024

Abstract: FinTech has evolved and invented rapidly in recent years. It uses a variety of services and technologies to improve economic processes, disrupt banks, and offer new solutions to clients and enterprises. Today, fintech refers to technology companies that directly serve consumers via mobile and online platforms, bypassing traditional financial institutions. The importance of banks in the economic model requires recognition of FinTech's opportunities and threats for banks and their main roles as economic intermediaries in present economic services systems. Big data analytics, machine learning (ML), and artificial intelligence (AI) can improve risk assessment by providing real-time supplier economic health perceptions, influencing loan decisions and reducing defaults. This study proposes an Intelligent Multi-Criteria Decision Making Using a Deep Fuzzy Neural Network on Financial Risk Evaluation Enabled Fintech Model. The MDMDFNN-FREFM strategy uses deep learning and optimization to improve financial risk management decision-making. The MDMDFNN-FREFM method initially normalizes input data within a range using min-max normalization. To accurately quantify risk, the feature selection-based snake optimization (SO) model is used to determine the most important variables. Additionally, the deep fuzzy neural network (DFNN) model predicts financial risk. Finally, the dung beetle optimization (DBO) model is used to tune the DFNN model's hyperparameters to reduce prediction errors and enhance accuracy. To improve MDMDFNN-FREFM performance, many simulation analyses are used. Under German credit and Polish companies bankruptcy datasets, MDMDFNN-FREFM performed well with 96.03% and 99.38% accuracy.

Keywords: Financial Risk; Fintech; Deep Fuzzy Neural Network; Decision Making; Snake Optimization; Financial Forecasting

1 Introduction

The financial services business is enduring a great alteration derived from technical developments. Efficient and enhanced client knowledge is drifting away users from traditional payment approaches to FinTech [1]. FinTech is a significant dimension of the economic services industry owing to constant novelties. Fintech businesses are at the lead of this modification, providing new solutions, that improve effectiveness, access to economic services, and customer experience [2]. But the fast proliferation of fintech solutions also presents new threats, like fraud, data breaches, regulatory compliance tasks, and cyber threats. These threats can interrupt economic steadiness and establish substantial tasks for financial institutions and regulatory authorities. Fintech advances have extensively changed the landscape for economical modeling, specifically in predictive analytics [3]. Predictive economic modeling depends on advanced models and huge databases to predict future economic trends, risks, and results. Usually, economic institutions utilize historical data and statistical models to create such predictions. Nevertheless, evasion endeavor works in a stochastic way, economic information is created to be used for constructing or developing the Financial Crisis Prediction (FCP) method [4]. Professionals and Researchers have tried to improve the performance of FCP theoretic stereotypes through the application of diverse quantifiable models. The FCP technique is immensely needed for determining a reliable, accurate, and earlier forecast approach to predict the critical danger of the firm's economic situation [5]. In general, the FCP is the dual classification model which is resolved reasonably. The classification approach results undertake classification into dual kinds like non-failing and failing situations of a company. Nowadays, several classification

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approaches are presented by utilizing diverse areas of interest for FCP [6,7]. These tools assist risk management, banking, investing, and insurance decision-making by providing deeper market insights [8, 9] Using DL, AI, and ML to handle risks enhances how economic organizations assess, moderate, and identify them.

This study presents an Intelligent Multi-Criteria Decision Making Using a Deep Fuzzy Neural Network on Financial Risk Evaluation Enabled Fintech Model (MDMDFNN-FREFM). The main intention of the MDMDFNN-FREFM approach is to enhance decision-making processes in financial risk management by utilizing sophisticated deep learning and optimization techniques. At first, the MDMDFNN-FREFM approach utilizes min-max normalization to standardize the input data within a specified range. A wide range of simulation analyses are implemented to ensure the enhanced performance of the MDMDFNN-FREFM technique.

2 Review of Literature

Abikoye et al. [10] develop a complete structure for integrating risk and operations management performances between classical fintech companies and financial institutions. By leveraging developed technologies like ML and AI, this structure intends to guarantee effective and consistent risk assessment. The variance of risk management and operational model methods makes a security, fragmented risk landscape, and poses important tasks to the economic method stability. Zheng et al. [11] utilizing the Conditional Value-at-risk (?CoVaR) risk metrics, the comprehensive auto-regressive conditional heteroscedasticity, the forecast error variance decomposition (Tvpdy), and Structural Vector Auto-regression with Stochastic Volatility (SV-TVP-SAVR) method. Morales et al. [12] provide visions on economic risk assessment by relating ML methods and classical econometric modeling to recognize tasks related to the investigation of time series in the economical context and enclosed in the US FinTech segment. The major conclusions exposed an absence of substantial divergences among the Non- and FinTech companies in the stock markets. Chang et al. [13] present an incorporated Multiple Criteria Decision-Making (MCDM) method across a rough set concept to assist administrators attain a strategic impact relational map. This method includes 3 stages the rough number is employed to describe group views that consider the specialist?s real experiences. This paper employs the rough altered VIKOR control to examine the gap between the value of performance and the aspirated stage.

The study presents an adaptive neuro-fuzzy-based K-Nearest Neighbors (KNN) method for the banking sector, enhancing it with the chaotic improved foraging optimizer algorithm (IFOA) [14]. It also uses the rolling window auto-regressive lag modeling method to analyze FinTech development [15]. A new decision-making method incorporates spherical fuzzy sets, facial action coding system, and M-SWARA quantum theory methods to reduce hesitation. The study also explores the impact of AI-aided FinTech on sustainable models [16].

3 Methodology

In this study, an Intelligent MDMDFNN-FREFM approach is presented. The main intention of the MDMDFNN-FREFM approach is to enhance decision-making processes in financial risk management by utilizing advanced DL and optimization techniques. Fig. 1 demonstrates the overall flow of the MDMDFNN-FREFM model.

3.1 Data Normalization: Min-Max Normalization

At first, the MDMDFNN-FREFM approach utilizes min-max normalization to standardize the input data within a specified range.Data normalization is vital to safeguard comparison

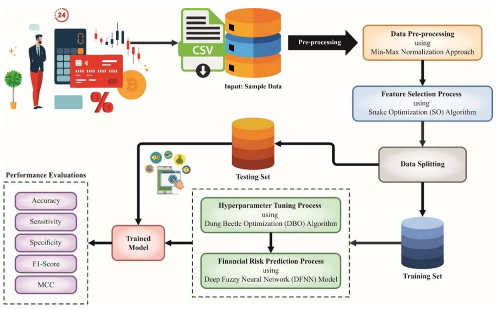

Fig. 1: Overall process of MDMDFNN-FREFM model

among indicators with theoretically different arithmetic ranges[17]. This procedure standardizes the information by measuring it to a precise, narrower period. In this paper, an equivalent mapping to the interval $[1,1]$ was used. Normalization provides various advantages: it quickens the convergence of the model and enhances accuracy while modifying the danger of gradient explosion. Eq. (1) denotes the normalization model, while X signifies the value to be transformed,x' denotes the transformed outcome, x_{max}, and x_{min} represents the maximum and minimum borders of the feature values, respectively.

$$x' = 2 * \frac{x - x_{\min}}{x_{\max} - x_{\min}} - 1 \tag{1}$$

3.2 Feature Selection Process using SO

Besides, the feature selection-based SO technique is employed to effectively identify the most relevant variables for accurate risk assessment. The SO model is stimulated by the snake?s novel mating behavior [18]. The SO approach is a new metaheuristic optimizer method that mimics the dissimilar behavior patterns of snakes in various food and temperature conditions to hunt for the optimum value.

$$X_i = X_{(i,min)} + rand \times X_{(i,max)} - X_{(i,min)}, \quad (2)$$

Whereas X_i characterizes the location of individual i, rand denotes randomly generated numbers among $(0,1)$, and$X_{(i,max)}$ and $X_{(i,min)}$ represent upper and lower limits of the issues, correspondingly. Afterward, the populations of snakes have been arbitrarily initialized in the search area, the population is separated equally into dual clusters: female and male. The number of females and males is characterized by the next dual equations, correspondingly:

$$N_m \approx \frac{N}{2}$$

$$N_f = N - N_m' \quad (3)$$

Here N characterizes the size of the entire population, Nm and Nf denote the amount of male and female individuals. The individual of the best male, female, and food, represented as $f_{best,m}$,$f_{best,f}$, and f_{food}, correspondingly. The temperature explanation is as shown:

$$\text{Temp} = \exp\left(\frac{-t}{T}\right) \quad (4)$$

Now t and T characterize the present and maximal iteration count. The quantity of food is described as:

$$Q = c_1 \times \exp\left(\frac{t-T}{T}\right) \quad (5)$$

Whereas c_1 denotes constant, considered as 0.5. This exploration stage defines the ecological conditions of cold areas and food, while snakes inactively pursue food in their nearby locations. When $Q <$ Threshold whereas Threshold=0.25, the individual snake hunts for food by arbitrarily choosing locations and upgrading their locations consequently. The exploration stage of the population of the snake is pretended as shown:

$$x_{i,m(f)}(t+1) = x_{\text{rand },m(f)}(t) \pm c_2 \times A_{m(f)} \times ((X_{\max} - X_{\min}) \times \text{ rand }) + X_{\max} \quad (6)$$

Here:$x_{i,m(f)}$ signifies a female or male individual, rand denotes a randomly generated number in the interval of $[0,1]$, c_2 is considered as 0.05; and $A_{m(f)}$ symbolizes the capability of females or males to hunt for food, which is provided by the succeeding Eq. (7):

$$A_{m(f)} = \exp\left(\frac{-f_{\text{rand },m(f)}}{f_{i,m(f)}}\right) \quad (7)$$

Here, $f_{rand,m(f)}$ refers to fitness value$x_{rand,m(f)}$, and $f_{i,m(f)}$ stands for the fitness value of an individual i;$x_{i,m(f)}$ is the female or male population.

In the exploitation stage, food is presented, for example, $Q >$ Threshold . When the temperature is great, signified by temperature $>$ threshold (0.6), snakes simply hunt for food, and the updated location equation is as demonstrated:

$$X_{i,j}(t+1) = x_{food} \pm c_3 \times \; Temp \; \times \; rand \; \times \left(x_{food} - X_{i,j}(t)\right) \quad (8)$$

Now $X_{i,j(t)}$ characterizes the location and the optimal location, the snake individual is denoted by x_{food}, where c_3 is fixed as 2. When the temperature is below the threshold, for example; $temperature¡Thresgold$, signifying a cool atmosphere, an individual snake would access both combat and mating manner. The location updated equation in combat manner is as shown:

$$x_{i,m(f)}(t+1) = x_{i,m(f)}(t) \pm c_3 \times FM(F) \times \text{rand} \times \left(Q \times x_{\text{best },f(m)} - x_{i,m(f)}(t)\right) \quad (9)$$

Now, $x_{\text{best },f(m)}$ signifies the optimal location within the male or female cluster, and FM(F) symbolizes the fighting capability of females or males. It is computed as shown:

$$FM(F) = \exp\left(\frac{-f_{best \;,f(m)}}{f_i}\right) \quad (10)$$

Here, $f_{best,f(m)}$ characterizes the fitness value, whereas the present f_i denotes the fitness value of a snake individual. During mating manner, replace $x_{best,f(m)}$ with $X_i f(m)$, which characterizes the location of the ith male or female individuals. Moreover, replacing FM(F) using $M_{m(f)}$ to characterize the mating capability of female and male. It is computed below:

$$M_{m(f)} = \exp\left(\frac{-f_{i,f(m)}}{f_{i,m(f)}}\right) \quad (11)$$

When snake eggs were accessed, the female and male with poor fitness were nominated to substitute their locations. Its mathematical formulation is expressed below:

$$x_{\text{worst },m(f)} = X_{\min} + \text{ rand } \times (x_{\max} - X_{\min}) \quad (12)$$

The fitness function (FF) employed in the SO model is constructed to have a balance among the sum of nominated features in every solution (least) and the classification accuracy (greatest) achieved by utilizing these nominated features, Eq. (13) denotes the FF to compute solutions.

$$\text{Fitness } = \alpha\gamma_R(D) + \beta\frac{|R|}{|C|} \tag{13}$$

Here, $\gamma_R(D)$ signifies the classifier rate of error of an assumed classifier.$|R|$ refers to the cardinality of the selected sub-set, and $|C|$ signifies the overall sum of features. α and β are dual parameters related to the position of the classification feature and sub-set length. $\in$ [1,0] and $\beta = 1-\alpha$.

3.3 Prediction Process: DFNN Model

The DFNN technique is utilized for predicting financial risk. The DFNN approach is derived from the FNN model, which integrates an artificial neural network (ANNs) with a fuzzy inference system (FIS) [19]. Particularly, the Takagi?Sugeno?type FIS has been applied to increase computational complexities by neglecting the defuzzification procedure at the output phase. The fuzzy rules (FR) are stated in Eq. (14); this represents the outcome of ith FR for sth data samples.

If $x_1(s)$ is $M_{i1}(s),\cdots,x_m(s)$ is $M_{im}(s)$, then

$$\hat{y}(s) \text{ is } f_i(x_1(s),\cdots,x_m(s)) \tag{14}$$

Whereas x_1, x_m denotes input variables in the FNN approach, m refers to input variable counts,$M_{i1},\ldots,M_{im}$ represents fuzzy sets (FS) of ith FR, and $\hat{y}_i$ stands for output variable of the ith FR. Additionally, the DFNN model handles every FNN as a component and was built by loading these components in a layer formation. The six layers are demonstrated below:

Layer1:Input layer:$x_1(s),\ldots,x_m(s)$
Layer2: Membership function layer: $M_{i1},\ldots,M_{im}$
Layer3: Weight layer: $w_1,\ldots,w_n$
Layer4: Normalization layer: $\bar{w}_1,\ldots,w\bar{w}_n$
Layer5: Multiplication layer:
$\bar{w}_1 f_1(x_1(s),\ldots,x_m(s)),\ldots,\bar{w}_n f_n(x_1(s),\ldots,x_m(s))$
Layer6: Output layer: y

Initially, the input layer has the responsibility of taking $x_1(s)$ and $x_m(s)$ and giving them to the subsequent layers. Then, the layer of membership function captures the values from an input and computes membership values by Eq. (15).

$$M_{ij}(x_j(s)) = e^{-\left(x_j(s)-c_{ij}\right)^2/2d_{ij}^2} \tag{15}$$

Here c_{ij} refers to the midpoint of the SGF and d_{ij} means a value that defines the SGF width. Thirdly, the layer of weight multiplies each of the membership values from the preceding layers that is computed for every FR, as exposed in Eq. (16).

$$w_i(s) = \prod_{j=1}^{m} M_{ij}(x_j(s)) \tag{16}$$

Fourth, the layer of normalization captures the value from the preceding layer and standardizes them. Its mathematical formulation is presented in Eq. (17).

$$\bar{w}_{\mathrm{i}}(s) = \frac{w_i(s)}{\sum_{i=1}^{n} w_i(s)} \tag{17}$$

Fifth, the layer of multiplication multiplies every standardized weight by the FR outputs, which is directed to the following layer. Lastly, the layer of output encapsulates every outcome from the former layer to give the value of the output, as displayed in Eq. (18).

$$\hat{y}(s) = \sum_{i=1}^{n} \overline{w_i}(s) y_i(s) = \sum_{i=1}^{\mathrm{n}} \overline{w_{\mathrm{i}}}(s) f_i(x_1,\ldots,x_m) \tag{18}$$

The DFNN model believes the stacked architecture of FNN components, equivalent to DL techniques. Specifically, the DFNN approach locations the FNN modules sequentially. The FIS at the initial modules of FNN is provided by Eq. (14), while the FIS at the g th modules of FNN has been provided as:

If $x_1(s)$ is $M_{i1}^{(g)}(s),\ldots,x_m(s)$ is $M_{im}^{(g)}(s)$, and $y_{(g-1)}(s)$ is $M_{i(m+1)}^{(g)}(\mathrm{s})$, then $\hat{y}_{\mathrm{g}}(s)$ is $f_g\left(x_1(s),\cdots,x_m(s),\hat{y}_{(g-1)}(s)\right)$

Here g represents modules of FNN number for the DFNN approach. Fig. 2 depicts the DFNN framework.

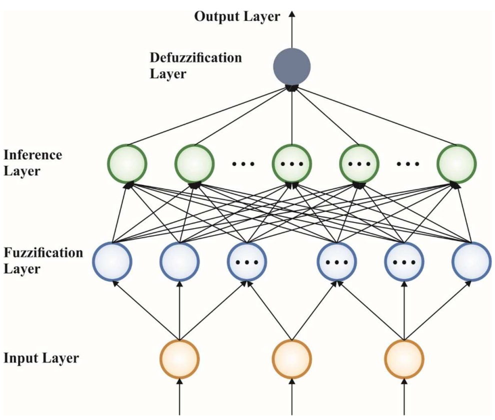

Fig. 2: DFNN structure

The DFNN model is considered through the succeeding features:
1) The input variables were moved into the initial modules of FNN for giving the value of the output.
2) The next modules of FNN have been accompanied by

input values and variables of the output of the initial modules of FNN, and the value of output is transferred into the 3rd modules of FNN.
3) This process has been reiterated till the final modules of FNN, which can attain a higher performance of the estimation.
The structural properties of the DFNN approach allow improved performance of the estimation; still, the overfitting risk occurs due to its structural difficulty. The DFNN technique utilizes a rule?dropoutodel and genetic approaches to avoid overfitting.

3.4 Parameter Optimizer: DBO

The hyperparameter tuning of the DFNN model is conducted with the DBO method to reduce prediction errors and enhance overall accuracy. The DBO approach is a sophisticated swarm intelligence optimization model inspired by the natural behavior of dung beetles (DBs) [20] It primarily encompasses four components: breeding behavior, rolling behavior, thieving behavior, and foraging behavior.
1. Ball-Rolling Behavior In the forward action, in the lack of difficulties, the DB upgrades its location by rolling a ball, as illustrated in Eq. (19). In contrast, in the presence of difficulties, DB helps a dance habit to improve its location.

$$x_i^{k+1} = \begin{cases} x_i^k + \alpha \cdot e \cdot x_i^{k-1} + b \cdot \left(\left|x_i^k - X^{\omega}\right|\right) & \text{if there is an obstacle} \\ x_i^k + \tan(\theta) \cdot \left(\left|x_i^k - x_i^{k-1}\right|\right) & \text{if there is no obstacle} \end{cases} \tag{19}$$

In the above-mentioned calculation, k denotes the present iteration coefficient; x_i^k signifies the location of the ith DB throughout the kth iteration; $x_i^{(k-1)}$ refers to the location of the ith DB throughout the $(k-1)th$ iteration; $x_i^{(k+1)}$ represents the location of ith DB at $(k+1)th$ iteration; α denotes coefficient with a value of either 1 or -1, whereas 1 specifies no deviation, and -1 directs deviation; e denotes the defection coefficient, within the range of $(0, 0.2]$;b refers to a constant in the range of $(0, 1)$;X^{ω} embodies the global worst location; θ is the angle of defection in the interval of $[\theta, \pi]$, when θ takes a value of $[\theta, \pi/2]$ or π, the location of the DB is not upgraded, whereas θ refers the location of DB is upgraded.

2. Reproductive Behavior
The tactic imitates the selection procedure by which scarab beetles recognize optimum areas for oviposition, so guaranteeing that their young are protected and nurtured in an environment beneficial to their endurance and growth. The mechanism of boundary selection shows the oviposition site determination, which is expressed in Eq. (20) as given below:

$$\begin{cases} L_* = \max(X^* \cdot (1-R), L) \\ U_* = \max(X^* \cdot (1+R), U) \end{cases} \tag{20}$$

Here U_* and L_* indicate the upper and lower limits, correspondingly; U is the upper limit; L refers to a lower limit; X^* indicates the present local optimum location; and R refers to the intermediate variable, which is defined as $R = 1 - k/K_{max}$, here K_{max} is the maximum iteration count. As per the selection of boundary, it is apparent that the DB's eggs-laying region adapts actively with the iteration count. Therefore, the location of the egg ball also varies, as denoted in Eq. (21):

$$B_i^{k+1} = X^* + r_1 \cdot (B_i^k - L_*) + r_2 \cdot (B_i^k - U_*) \tag{21}$$

While B_i^{k+1} indicates the location of ith egg ball at the kth iteration; r_1 and r_2 are independent randomly generated vectors of dimension $1 \times D$;D signifies the dimension.

3. Behavior of foraging Depend upon achieving appropriate adulthood DBs search for food resources. By determining an optimum foraging region, adult DBs are instructed to search. The explanation of the optimum foraging boundary region is shown in Eq. (22):

$$\begin{cases} L_b = \max(X^b \cdot (1-R), L) \\ U_b = \max(X^b \cdot (1+R), U) \end{cases} \tag{22}$$

Here, L_b and U_b indicate the lower and upper limits, correspondingly; X^b indicates the global optimum location.
4. Behavior of thief In the population, particular DBs employ the thieving action of dung balls from their conspecifics; this kind of behavior is assigned as thief DBs. The position upgrade mathematical formulation is expressed in Eq. (23).

$$x_i^{k+1} = X^b + s \cdot g \cdot \left(\left|x_i^k - X^*\right| + \left|x_i^k - X^b\right|\right) \tag{23}$$

While s denotes a constant, and g represents a randomly generated vector of dimension $1 \times D$, which is generally spread. The fitness selection is the substantial factor persuading the efficiency of the DBO model. The hyperparameter range method contains the solution-encoded model to estimate the effectiveness of the candidate solution. Here, the DBO model uses accuracy as the primary metric to evaluate the FF model. Its mathematical expression is expressed below:

$$Fitness = \max(P) \tag{24}$$

$$P = \frac{TP}{TP + FP} \tag{25}$$

Here, TP and FP imply the positive value of true and false, correspondingly.

4 Result Analysis and Discussion

The experimental investigation of the MDMDFNN-FREFM technique is studied under dual

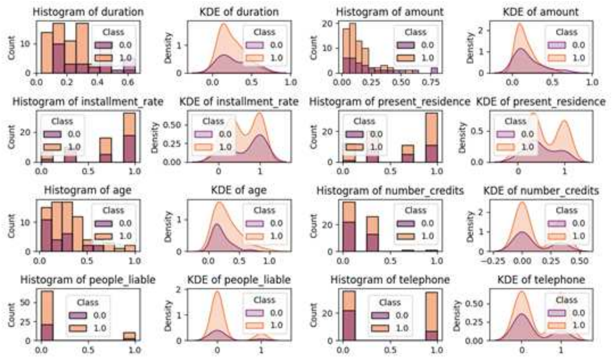

Fig. 3: Histogram analysis of various attributes on the German credit database

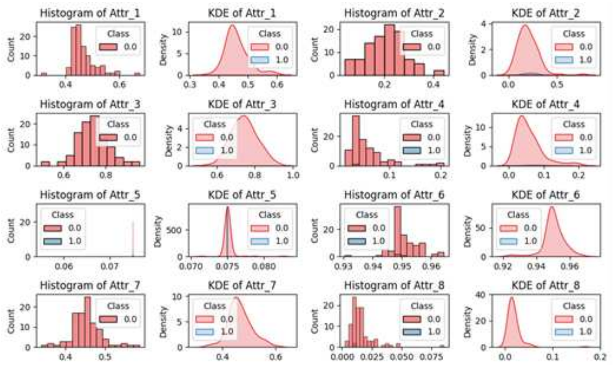

Fig. 4: Histogram analysis of various attributes on Polish companies? bankruptcy database

databases such as German Credit [21] and Polish Companies Bankruptcy [22]. The German Credit database contains 1000 instances under dual classes. The selected number of features for this database is 14. The Polish Companies Bankruptcy database contains 7027 instances under dual classes. The selected number of features for this database is 26. The complete details of both databases are shown in Table 1. Fig. 3 represents the histogram analysis of various attributes on the German credit database.

Fig. 4 represents the histogram analysis of various attributes on the Polish Companies Bankruptcy database.

Fig. 5 delivers the classifier results of the MDMDFNN-FREFM method under the German credit database. Figs. 5a–5b illustrate the confusion matrix of overall classes under 70% TRPH and 30% TSPH. Fig. 5c shows the PR study which indicates higher performance through all classes

Finally, Fig. 5d portrays the ROC study, signifying proficient outputs with higher ROC values under distinct classes. Table 2 demonstrates the classifier result of the MDMDFNN-FREFM approach under the German credit

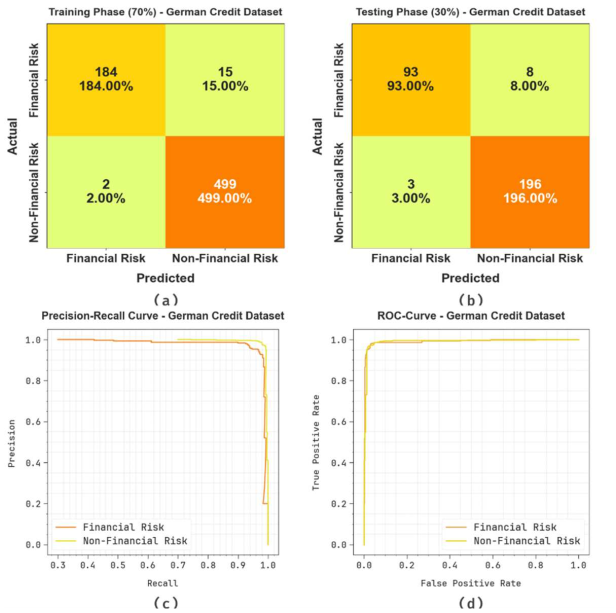

Fig. 5: German credit database (a-b) confusion matrices, (c-d) PR and ROC curves

database. The outcomes illustrate that the MDMDFNN-FREFM approach properly identified the samples. With 70% TRPH, the MDMDFNN-FREFM model delivers average accu$_y$, sens$_y$, spec$_y$, $F1_{\text{score}}$, and MCC of 96.03%, 96.03%, 96.03%, 96.95%, and 94.01%, respectively. Furthermore, with 30% TRPH, the MDMDFNN-FREFM model delivers average accu$_y$, sens$_y$, spec$_y$, $F1_{\text{score}}$, and MCC of 95.29%, 95.29%, 95.29%, 95.84%, and 91.75%, correspondingly.

Table 2 demonstrates the classifier result of the MDMDFNN-FREFM approach under the German credit database. The outcomes illustrate that the MDMDFNN-FREFM approach properly identified the samples. With 70% TRPH, the MDMDFNN-FREFM model delivers average accu$_y$, sens$_y$, spec$_y$, $F1_{\text{score}}$, and MCC of 96.03%, 96.03%, 96.03%, 96.95%, and 94.01%, respectively. Furthermore, with 30% TRPH, the MDMDFNN-FREFM model delivers average accu$_y$, sens$_y$, spec$_y$, $F1_{\text{score}}$, and MCC of 95.29%, 95.29%, 95.29%, 95.84%, and 91.75%, correspondingly

In Fig. 6, the training (TRA) $accu_y$ and validation (VAL) $accu_y$ outcomes of the MDMDFNN-FREFM approach under the German credit database is exposed. The $accu_y$ values are computed through an interval of 0-50 epochs. The figure shows that the TRA and VAL $accu_y$ values exhibit a growing trend, indicating the proficiency of the MDMDFNN-FREFM technique with enhanced performance through multiple iterations. Moreover, the TRA and VAL $accu_y$ values remain close over the epochs notifying lesser overfitting and exhibiting

Table 1: Dataset description

Database	No. of instances	No. of attributes	No. of classes	Financial Risk/Non-Financial Risk
German Credit	1000	20	2	300/700
Polish Companies Bankruptcy	7027	64	2	271/6756

Table 2: Classifier outcome of MDMDFNN-FREFM method under German credit database

Class Labels	$Accu_y$	$Sens_y$	$Spec_y$	$F1\_score$	MCC
TRPH (70%)					
Financial Risk	92.46	92.46	99.60	95.58	94.01
Non-Financial Risk	99.60	99.60	92.46	98.33	94.01
Average	96.03	96.03	96.03	96.95	94.01
TSPH (30%)					
Financial Risk	92.08	92.08	98.49	94.42	91.75
Non-Financial Risk	98.49	98.49	92.08	97.27	91.75
Average	95.29	95.29	95.29	95.84	91.75

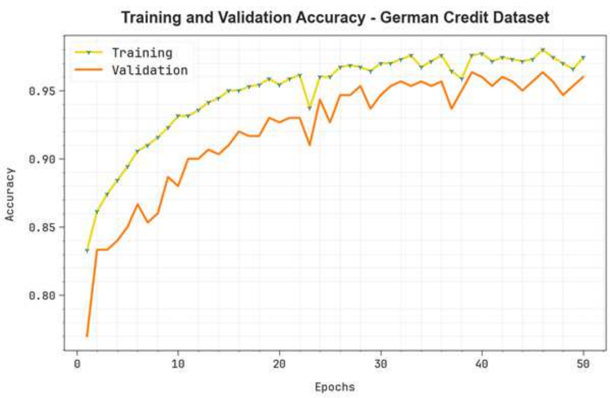

Fig. 6: $Accu_y$ curve of MDMDFNN-FREFM method under German credit database

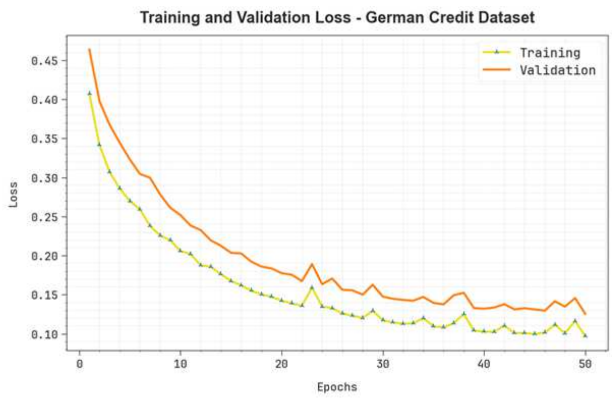

Fig. 7: . Loss curve of MDMDFNN-FREFM method under German credit database

superior performance of the MDMDFNN-FREFM method, ensuring consistent prediction on unseen samples

In Fig. 7, the TRA loss (TRALOS) and VAL loss (VALLOS) graph of the MDMDFNN-FREFM technique under the German credit database is exhibited. The values of loss are computed across an interval of 0-25 epochs. It is depicted that the TRALOS and VALLOS values represent a decreasing trend which notifies the competency of the MDMDFNN-FREFM technique in harmonizing an equilibrium among generalization and data fitting. The steady lessening in values of loss furthermore securities the higher performance of the MDMDFNN-FREFM approach and tunes the prediction results over time.

Fig. 8 presents the classifier performance of the MDMDFNN-FREFM technique under the Polish dataset. Figs. 8a–8b display the confusion matrix of overall classes under 70% TRPH and 30% TSPH. Fig. 8c shows the PR inspection which indicates improved performance through all classes. Eventually, Fig. 8d depicts the ROC inspection which illustrates proficient outputs with higher ROC values under distinct classes.

Table 3 reveals the classifier performance of the MDMDFNN-FREFM method under the Polish database. The outcomes indicate that the MDMDFNN-FREFM method accurately identified the samples. With 70% TRPH, the MDMDFNN-FREFM technique presents average accu$_y$, sens$_y$, spec$_y$, $F1_{\text{score}}$, and MCC of 99.33%, 95.03%, 95.03%, 95.38%, and 90.76%, correspondingly. Additionally, with 30% TRPH, the MDMDFNN-FREFM technique delivers average accu$_y$, sens$_y$, spec$_y$, $F1_{\text{score}}$, and MCC of 99.38%, 98.54%, 98.54%, 96.17%, and 92.46%, respectively.

In Fig. 9, TRA $accu_y$ and VAL $accu_y$ outcomes of the MDMDFNN-FREFM method under the Polish database are showcased. The $accu_y$ values are computed through a range of 0-50 epochs. The figure illustrated that the TRA and VAL $accu_y$ values showed an increasing trend,

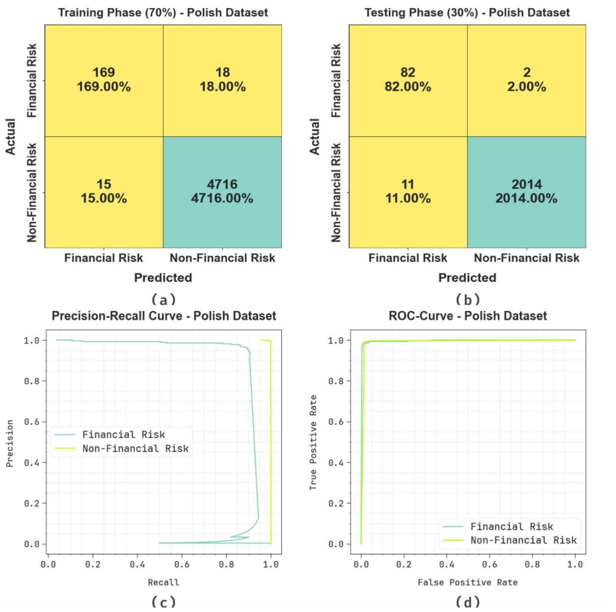

Fig. 8: German credit database (a-b) confusion matrices, (c-d) PR and ROC curves

Table 3: Classifier outcome of MDMDFNN-FREFM method under Polish database

Class Labels	*Accu_y*	*Sens_y*	*Spec_y*	*F1_score*	MCC
TRPH (70%)					
Financial Risk	99.33	90.37	99.68	91.11	90.76
Non-Financial Risk	99.33	99.68	90.37	99.65	90.76
Average	99.33	95.03	95.03	95.38	90.76
TSPH (30%)					
Financial Risk	99.38	97.62	99.46	92.66	92.46
Non-Financial Risk	99.38	99.46	97.62	99.68	92.46
Average	99.38	98.54	98.54	96.17	92.46

indicating the proficiency of the MDMDFNN-FREFM technique with superior performance above various iterations. In addition, the TRA and VAL $accu_y$ values remain close through the epochs notifying diminished overfitting and displaying the maximum performance of the MDMDFNN-FREFM technique, ensuring consistent prediction on unseen samples.

In Fig. 10, the TRALOS and VALLOS graph of the MDMDFNN-FREFM method under the Polish database is demonstrated. The values of loss are computed across a range of 0-25 epochs. It is signified that the TRALOS and VALLOS values represent a reducing trend which indicates the proficiency of the MDMDFNN-FREFM technique in balancing an equilibrium among data fitting and generalization. The constant decrease in values of loss moreover securities the maximal performance of the MDMDFNN-FREFM technique and tune the prediction results over time.

Table 4 studies the comparison results of the MDMDFNN-FREFM approach under the German credit

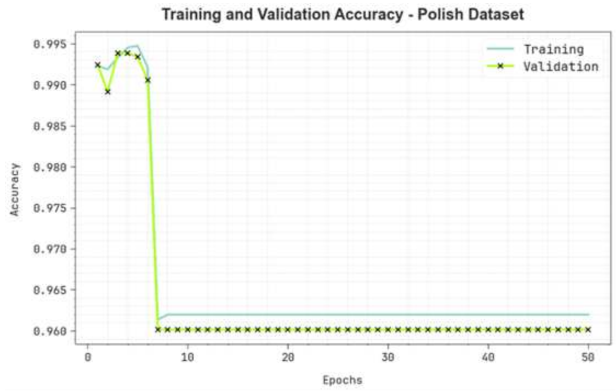

Fig. 9: $Accu_y$curve of MDMDFNN-FREFM method under Polish database

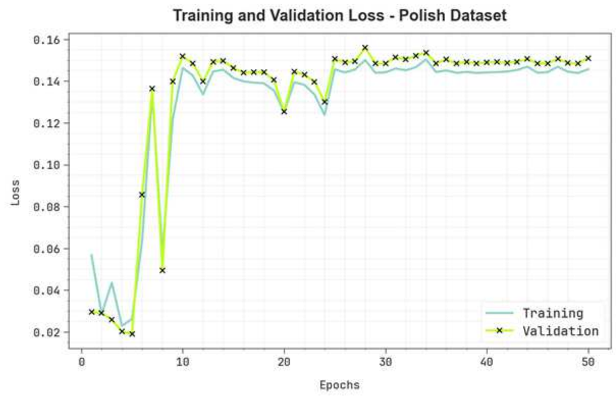

Fig. 10: Loss curve of MDMDFNN-FREFM method under Polish database

Table 4: Comparative analysis of the MDMDFNN-FREFM approach under German credit database

German Credit Database				
Classifiers	Accu_y	Sens_y	Spec_y	F1_score
MDMDFNN-FREFM	96.03	96.03	96.03	96.95
EOOABNN-PFC	95.15	95.17	95.18	95.27
HHPODL-FCP	95.05	93.71	94.17	93.88
LSTM-RNN	84.71	82.34	88.69	88.87
ACO Approach	75.90	78.46	69.45	85.54
MLP Algorithm	71.10	74.01	67.02	75.26
LDA Method	76.03	88.89	78.13	83.88
AugBoost-ELM	76.32	92.61	78.79	84.61

database with the existing methodologies??25, 26, and 27].

Fig. 11 delivers the comparative study of the MDMDFNN-FREFM technique under the German credit database with existing models in terms of $accu_y$, and $F1_{score}$.
The simulation result identified that the

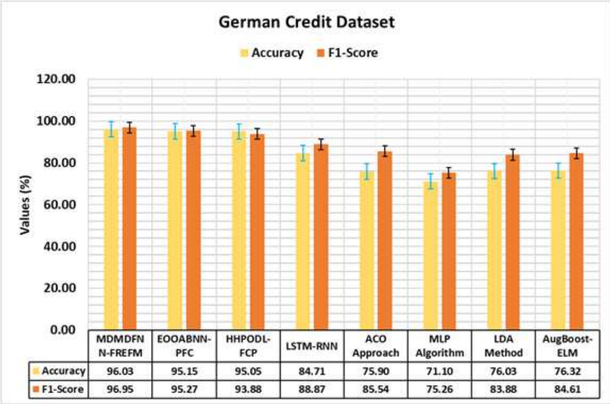

Fig. 11: $Accu_y$, and $F1_{score}$ analysis of MDMDFNN-FREFM model under German credit database

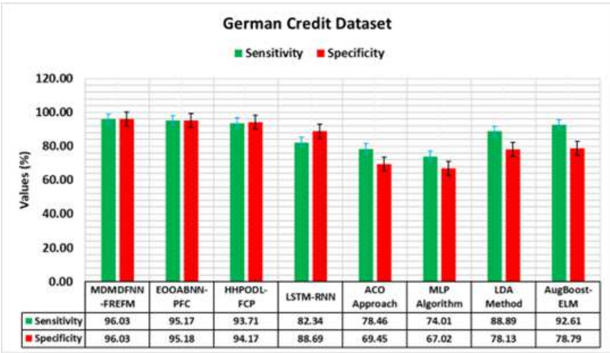

Fig. 12: $Sens_y$, and $Spec_y$ analysis of the MDMDFNN-FREFM model under the German credit database

MDMDFNN-FREFM technique outperformed greater performances. Based on accu$_y$, the MDMDFNN-FREFM technique has superior accu$_y$ of 96.03% whereas the EOOABNN-PFC, HHPODL-FCP, LSTM-RNN, ACO, MLP, LDA, and AugBoost-ELM models have minimal accu$_y$ of 95.15%, 95.05%, 84.71%, 75.90%, 71.10%, 76.03%, and 76.32%, respectively. Similarly, based on $F1_{\text{score}}$, the MDMDFNN-FREFM technique has a higher $F1_{\text{score}}$ of 96.95% while the EOOABNN-PFC, HHPODL-FCP, LSTM-RNN, ACO, MLP, LDA, and AugBoost-ELM models have lower $F1_{\text{score}}$ of 95.27%, 93.88%, 88.87%, 85.54%, 75.26%, 83.88%, and 84.61%, subsequently.

Fig. 12 presents the comparative outcome of the MDMDFNN-FREFM model under the German credit database in terms of sens$_y$ and spec$_y$. The simulation analysis indicated that the MDMDFNN-FREFM model outperformed greater performances. Based on sens$_y$, the MDMDFNN-FREFM technique has an enhanced sens$_y$ of 96.03% whereas the EOOABNN-PFC, HHPODL-FCP,

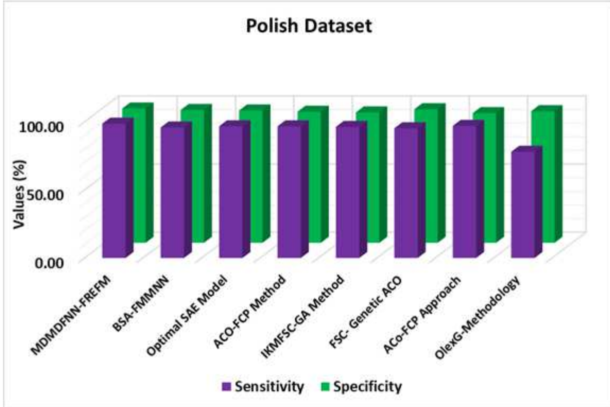

Fig. 13: $Sens_y$, and $Spec_y$ analysis of MDMDFNN-FREFM model under the Polish database

LSTM-RNN, ACO, MLP, LDA, and AugBoost-ELM models have minimal sens$_y$ of 95.17%, 93.71%, 82.34%, 78.46%, 74.01%, 88.89%, and 92.61%, respectively. Also, based on spec$_y$, the MDMDFNN-FREFM method has maximum spec$_y$ of 96.03% whereas the EOOABNN-PFC, HHPODL-FCP, LSTM-RNN, ACO, MLP, LDA, and AugBoost-ELM models have minimum spec$_y$ of 95.18%, 94.17%, 88.69%, 69.45%, 67.02%, 78.13%, and 78.79%, respectively

Table 5 examines the comparison outputs of the MDMDFNN-FREFM model under the Polish Companies Bankruptcy database with the existing methodologies.

Fig. 13 provides the comparative study of the MDMDFNN-FREFM method under Polish Companies Bankruptcy database in terms of sens$_y$ and spec$_y$. The simulation performance stated that the MDMDFNN-FREFM approach outperformed better performances. Based on sens$_y$, the MDMDFNN-FREFM approach has higher sens$_y$ of 98.54% while the BSA-FMMNN, Optimal SAE, ACO-FCP, IKMFSC-GA, FSC-Genetic ACO, ACO-FCP, and OlexG approaches have lesser sens$_y$ of 95.77%, 96.60%, 96.59%, 96.19%, 95.15%, 96.90%, and 77.89%, respectively. Furthermore, based on spec$_y$, the MDMDFNN-FREFM approach has higher spec$_y$ of 98.54% while the BSA-FMMNN, Optimal SAE, ACO-FCP, IKMFSC-GA, FSC-Genetic ACO, ACO-FCP, and OlexG approaches have lesser spec$_y$ values.

Fig. 14 provides the comparative analysis of the MDMDFNN-FREFM technique under the Polish Companies Bankruptcy database with existing approaches in terms of accu$y$ and Fscore. The simulation outcome stated that the MDMDFNN-FREFM approach outperformed better performances. Based on accu$y$, the MDMDFNN-FREFM approach has a higher accu$y$ of 99.38 while the BSA-FMMNN, Optimal SAE, ACO-FCP, IKMFSC-GA, FSC-Genetic ACO, ACO-FCP, and OlexG approaches have lesser accu$y$ of 99.28, 98.33, 97.30,

Table 5: Comparative analysis of MDMDFNN-FREFM approach under the Polish database

Polish Database				
Methods	Sens_y	Spec_y	Accu_y	F_score
MDMDFNN-FREFM	98.54	98.54	99.38	96.17
BSA-FMMNN	95.77	97.44	99.28	95.59
Optimal SAE Model	96.60	97.08	98.33	95.65
ACO-FCP Method	96.59	96.18	97.30	95.49
IKMFSC-GA Method	96.19	95.66	96.75	94.57
FSC- Genetic ACO	95.15	98.00	97.10	94.79
ACo-FCP Approach	96.90	95.17	94.24	94.65
OlexG-Methodology	77.89	96.59	93.63	93.15

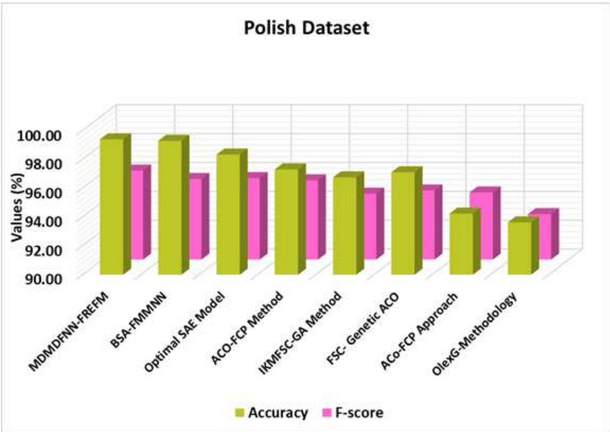

Fig. 14: $Accu_y$ and F_score analysis of MDMDFNN-FREFM model under Polish database

96.75, 97.10, 94.24, and 93.63, respectively. Also, based on the Fscore, the MDMDFNN-FREFM approach has a higher Fscore of 96.17 while the BSA-FMMNN, Optimal SAE, ACO-FCP, IKMFSC-GA, FSC-Genetic ACO, ACO-FCP, and OlexG approaches have lesser Fscore of 95.59, 95.65, 95.49, 94.57, 94.79, 94.65, and 93.15, respectively

Conclusion

In this study, an Intelligent MDMDFNN-FREFM is presented. The main intention of the MDMDFNN-FREFM approach is to enhance decision-making processes in financial risk management by utilizing advanced DL and optimization techniques. At first, the MDMDFNN-FREFM approach utilized min-max normalization to standardize input data within a specified range. Likewise, the feature selection-based SO model is employed to effectively recognize the most relevant variable for precise risk assessment. In addition, the DFNN model is employed for predicting financial risk. Eventually, the hyperparameter tuning of the DFNN model is performed by using the DBO model to minimize prediction errors and improve overall accuracy. A wide range of simulation analyses are implemented to ensure the enhanced performance of the MDMDFNN-FREFM technique. The performance validation of the MDMDFNN-FREFM method portrayed a superior accuracy value of 96.03% and 99.38% under German credit and Polish Companies Bankruptcy datasets

Data Availability Statement

The data that support the findings of this study are openly available at https://archive.ics.uci.edu/ml/databases/ statlog+ (german+credit+data)
and
https://archive.ics.uci.edu/ database/365/ polish+ companies +bankruptcy+data, reference number [23, 24].

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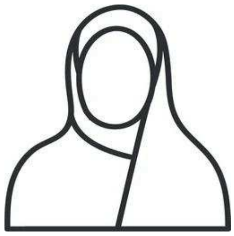

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