Arithmetic Optimization Algorithm with Adaptive Neuro-Fuzzy Interference System for Predicting Financial Crisis

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Abstract

Financial technology (Fintech) is paramount in driving advanced technologies, economies, society, and several other sectors. Smart Fintech is the new-generation Fintech, primarily stimulated and endowed by compuational technology. Smart Fintech syndicates DSAI and renovates economies and finance for dynamic, smart, customized, automated services and systems, economies and financial companies, and the industry. The strength and development of the country's economies are assessed by the correct forecasting. Financial crisis prediction (FCP) has the substantial consequence on the economies. Previous studies mainly emphasise statistical, DL, and ML methodologies for predicting the financial well-being of the business. Therefore, this article develops a new Arithmetic Optimization Algorithm with Adaptive Neuro-Fuzzy Interference System (AOA-ANFIS) technique for Predicting Financial Crisis. The presented AOA-ANFIS technique aims to predict the presence of financial crises or not. The model incorporates three major elements: Arithmetic Optimization Algorithm (AOA) for feature selection, Adaptive Neuro-Fuzzy Inference System (ANFIS) as the classification algorithm, and Bat Optimization Algorithm (BOA) for parameter tuning. The AOA feature selection model effectively detects the important attributes from a large proportion of financial indicators, augmenting the model's prediction capability while decreasing computational difficulty. Subsequently, the ANFIS classifier exploits the features selected for capturing the intricate non-linear relations intrinsic in financial data, permitting accurate crisis calculation. Additionally, the BOA parameter tuning model augments the ANFIS model's parameters, ensuring robustness and optimum performance. Experimental outcomes on varied financial databases validate the higher efficiency of the AOA-ANFIS technique over underlying processes, demonstrating its effectiveness in forecasting financial crises with great reliability and precision.

Keywords: Financial Crisis Prediction; Arithmetic Optimization Algorithm; Fintech; ANFIS; Deep Learning; Machine Learning

1. Introduction

The global financial disaster has highlighted the portion of economic connectedness as a latent resource of systemic risk and macroeconomic instability [1]. This disaster has also emphasized the necessity to better recognize whether an upsurge in connectedness mains to a greater possibility of an economic crisis. The authors indicated that contagion is a major upsurge in market relations afterwards a large shock to a network of economy [2]. Particularly, contagion denotes the state where we detect the extent of economic conflicts from one state to others or after an exact channel of finances to others. Traditional models can be separated into quantitative and qualitative forecasting [3]. In most situations, time series prediction is employed to measure the effect of contagion. Yet, recent enlargement in econometrics and Artificial Intelligence presented modern models like Machine Learning (ML) and Deep Learning (DL) [4]. Present literature displays that this family of predicting models are more trustworthy and capable of procedure huge amounts of data when equated to traditional models such as time series analysis and they deliver promising outcomes in predicting accuracy.

Doi: https://doi.org/10.54216/IJNS.230435
Received: August 15, 2023 Revised: January 21, 2024 Accepted: March 21, 2024

Furthermore, an early warning method may also be beneficial in defining the exposure of a cluster of countries, which might be more challenging to estimate [5]. By recognizing which countries are more exposed in a period of global economic disasters, policymakers might be capable of concentrating their attention on the states that need fundamental policy changes to avert a disaster [6]. Therefore, early warning methods can support policymakers and regulators to safeguard their markets from financial crises. Experimental studies on emerging early warning methods have been comparatively novel. While there are a range of dissimilar models which can be employed to forecast the future economic crisis, owing to the difficulty of factors, forecast of economic crisis is a complex case till now [7]. Generally, the researcher's advantage is from a range of dissimilar statistical models to analyse data, create methods and make decisions dependent upon their assessments to perform their research. In past few years, as research work intended at forecasting the economic crisis has become more general, ML has also been commonly utilized by researchers to recognize this objective [8]. With the arrival of Artificial Neural Networks (ANN), the researchers had opportunity to analyse numerous issues in finance like forecasts of potential economic crises. ANNs have been commonly utilized in the area of finance. Presently, they have become common tools to help economic decision-making [9]. There are numerous dissimilar regions of study in finance in which ANN are employed like credit risk assessment, credit authorization and screening, project management, financial forecasting, forecast of default and bankruptcy, fixed income savings, and credit card manipulations [10]. Moreover, ANN applications can considerably enhance subsequent corporate economics applications like investor behavior forecast, financial simulation, financial evaluation pricing initial public offerings, portfolio management, defining optimum capital structure, and credit approval.

This study develops a new Arithmetic Optimization Algorithm with Adaptive Neuro-Fuzzy Interference System (AOA-ANFIS) technique for Predicting Financial Crisis. The presented AOA-ANFIS technique aims to predict the presence of financial crises or not. The AOA feature selection model effectively detects the important attributes from large proportion of financial indicators, augmenting the model's prediction capability while decreasing computational difficulty. Subsequently, the ANFIS classifier exploits the features selected for capturing the intricate non-linear relations intrinsic in financial data, permitting accurate crisis calculation. Additionally, the BOA parameter-tuning model augments the ANFIS model's parameters, ensuring robustness and optimum performance. Experimental outcomes on varied financial databases validate the higher efficiency of the AOA-ANFIS technique over underlying processes, demonstrating its effectiveness in forecasting financial crises with great reliability and precision.

2. Related Works

Wu et al. [11] developed a new DL model, the user-response-guided deep attention network (URGDAN) approach. In this method, a DL structure is built to combine economic indicators, user responses and present report texts. URGDAN influences the consumer responses to present reports to conduct the representation of semantic feature reports; it also recognizes event data which contain a major association with company economic distress. The authors [12] proposed the hybrid HPO with the DL-based FCP (HHPODL-FCP) approach. This proposed approach uses HHPO system for the FSS procedure. The proposed system abuses a SSA-based hyperparameter tuning procedure. Muthukumaran and Hariharanath [13] concentrate on the strategy of optimal DL-based FCP technique for the SMEs. The developed system consists of dual stages: Archimedes optimizer algorithm-based FS (AOA-FS) technique and optimum deep CNN-LSTM-based data identification. The proposed system includes a sailfish optimizer (SFO) system for the hyperparameter optimizer.

Rostamian [14] examined the realism of a DL CNN-LSTM method within the Directional Change structure to forecast major DC events. Also, the possibility of AE and variational AE to improve economic predicting accuracy and eliminate noise from economic time-series data was discovered. Leveraging their capability within economic time series, these techniques presented promising ways for enhanced data representation and subsequent prediction. To further give to financial forecast abilities, a deep multi-model was projected. In [15], a design science technique is applied to progress DeepVoice, a new non-verbal analytical analysis method for economic risk forecast. DeepVoice forecasts economic danger by exploiting what managers say (spoken language signs) and how managers say it (verbal signals) throughout the conference call. The technique also suggests a dual-stage DL technique to efficiently combine managers' verbal cues and sequential vocals.

HongXing et al. [16] projected a DNN-based multivariate regression method (DNN-MRM). For robustness assessment, this work contains structural-based Bayesian model with PC technique and generalized least square-random effect (GLS-RE) regression method in order to discover the join prospect distribution. Ren et al. [17] developed a new gated graph neural network (GGNN) early warning technique dependent upon data spillover systems. The approach also offers a dual-classification disaster early warning technique based on GGNN, which

Doi: https://doi.org/10.54216/IJNS.230435
Received: August 15, 2023 Revised: January 21, 2024 Accepted: March 21, 2024

can mechanically remove features from inter-industry risk spillover systems. In the application of empirical, the method built dual kinds of data (volatility and risk) spillover networks.

3. Proposed Methodology

In this work, we have established a novel AOA-ANFIS model for predicting financial crises. The presented AOA-ANFIS technique aims to predict the presence of financial crises or not. The model incorporates three major elements AOA for feature selection, ANFIS as the classification algorithm, and BOA for hyperparameter fine-tuning. Fig. 1 demonstrates the working flow of AOA-ANFIS model.

A. AOA-based Feature Selection

For feature selection, the AOA can be utilized. AOA is a metaheuristic technique recently presented by Laith Abualigah et al in 2021 [18]. This method mostly utilizes 4 operators of division, addition, subtraction, and multiplication for seeking and slowly methods the better performance. During the running procedure of the system, initialization is performed first, and a primary solution X has been created 7arbitrarily.

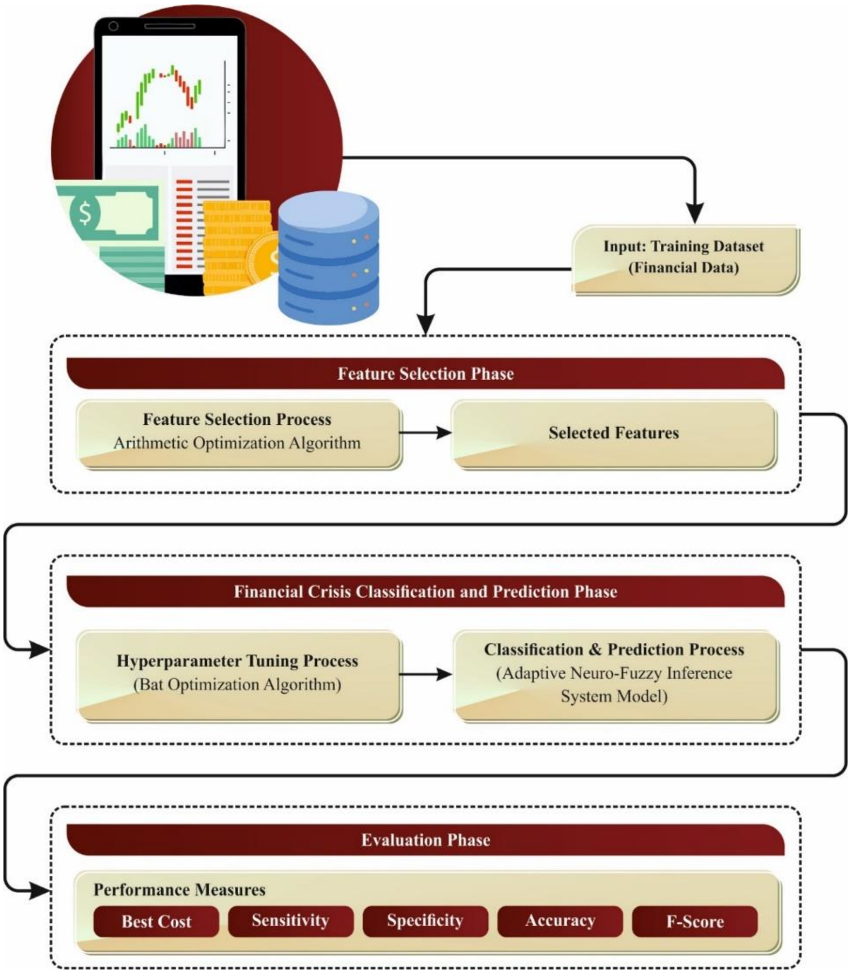

Figure 1: Overall flow of AOA-ANFIS technique

$$X = \begin{bmatrix} x_{1,1} & \cdots & \cdots & x_{1,n\text{-}1} & x_{1,n} \\ x_{2,1} & \cdots & \cdots & x_{2,n\text{-}1} & x_{2,n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{N,1} & \cdots & \cdots & x_{N,n\text{-}1} & x_{N,n} \end{bmatrix} \tag{1}$$

Afterwards, math optimization acceleration (MOA) function was utilized for controlling this method's chosen search stage. MOA can be related to $r1$ ($r1$ implies the random number from [0-1]).

Doi: https://doi.org/10.54216/IJNS.230435
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Once MOA is superior to $r1$, the AOA enters the exploration phase. Once MOA is lesser than $r1$, the AOA enters the exploitation phase. Eq. (2) is the computation equation of MOA. The math optimization probability (MOP) function is a vital parameter for controlling the method position upgrade, as depicted in Eq. (3).

$$MOA(C\_Iter) = \text{Min} + C\_Iter \times \left(\frac{\text{Max} - \text{Min}}{M\_Iter}\right) \tag{2}$$

$$MOP(C\_Iter) = 1 - \frac{C\_Iter^{\frac{1}{\alpha}}}{M\_Iter^{\frac{1}{\alpha}}} \tag{3}$$

Whereas, $MOA(C\_iter)$ and $MOP\ (C\_iter)$ denotes the MOA and MOP values correspondingly. α stands for the parameter that affects the searching accuracy, $\alpha = 5$.

If MOA is superior to $r1$, AOA can optimized utilizing division or multiplication operators. The exploration phase has been searched widely. Eq. (4) signifies the position upgrade expression of AOA exploration phase. Once MOA is lesser than $r1$, this method enters the exploitation step. Now, AOA utilizes addition and subtraction operators for updating the position that is searched more correctly and effortlessly method the optimum performance. Eq. (5) defines the exploitation phase place upgrade equation as:

$$x_{ij}(C\_lter) = \begin{cases} best(x_j) \div (MOP{+}\epsilon) \times \left((UB_j - LB_j) \times \mu + LB_J\right), r2 < 0.5 \\ best(x_j) \times MOP \times \left((UB_j - LB_j) \times \mu + LB_j\right), \ \ otherwise \end{cases} \tag{4}$$

$$x_{ij}(C\_lter) = \begin{cases} best(x_j) - (MOP{+}\epsilon) \times \left((UB_j - LB_j) \times \mu + LB_J\right), r2 < 0.5 \\ best(x_j) + MOP \times \left((UB_j - LB_j) \times \mu + LB_j\right), \ \ otherwise \end{cases} \tag{5}$$

Whereas, $best(x_j)$ denotes the j^{th} position of better performance attained. $x_{i.j}(C\_\ lter)$ refers the j^{th} position of i^{th} performance. $r2$ and $r3$ stands for the random integers within $[0,1]$. UB_j and LB_j defines the up and low boundary values. $\in$ is A smaller integer, μ refers to the parameter that controls the searching of the method, $\mu = 0.5$.

The FF utilized in the AOA is intended to strike the balance between the classifier accuracy and the amount of features chosen in all the solutions obtained through the features selected, Eq. (6) shows the FF to estimate the solution.

$$Fitness = \alpha\gamma_R(D) + \beta\frac{|R|}{|C|} \tag{6}$$

In Eq. (6), $\gamma_R(D)$ refers to the classifier error rate. $|R|$ signifies the cardinality of chosen subset and $|C|$ shows the total quantity of attributes in the datasets, both α and β parameters are corresponding to the significance of classifier quality and subset length. $\in [1,0]$ and $\beta = 1 - \alpha$.

B. Classification using ANFIS

Next, the ANFIS classifier exploits the features selected for capturing the intricate non-linear relations intrinsic in financial data, permitting accurate crisis calculation. The structure of the ANFIS proves that it encompasses NNs and FL in the five layers. In the year of 1965, FL and fuzzy inference systems (FIS) were developed by L. Zadeh [19]. The main objective of this technique is to overcome problems that occur when regarding decision-making methods that include data to be inconsistent, unreliable, and ambiguous. In 1943, Walter Pitts and Warren McCulloch, representing motivation from the brain neuron's functions, designed NNs. It can be generally described as "connectionism," comprising the usage of interlinked neurons for simulating intelligence. Afterwards, ANFIS was extensively utilized to match various global complexities and developed enormously because of its ability to integrate FS features with artificial neural networks (ANNs). Jang et al. presented the hybrid neural network in 1993 which is called ANFIS by integrating FL and NNs. Meanwhile, it has been advanced and robust ANN that incorporated FL and IF-THEN rule execution for making interconnections among outputs and inputs and then learning abilities. Fig. 2 represents the infrastructure of ANFIS. The illustration of ANFIS has input and output layers. The next is a detailed explanation of the layers. The 1st layer nodes called a membership function. Fuzzy clusters have been produced by employing input values and membership functions. The inputs of the 1st

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layer can be adapted into fuzzy inputs by applying sigmoid membership functions. The arithmetical equation for producing fuzzy inputs in 1st layer:

$$O_j^{l_1} = \mu_{A_j}(y_1), j = 1,2 \tag{7}$$

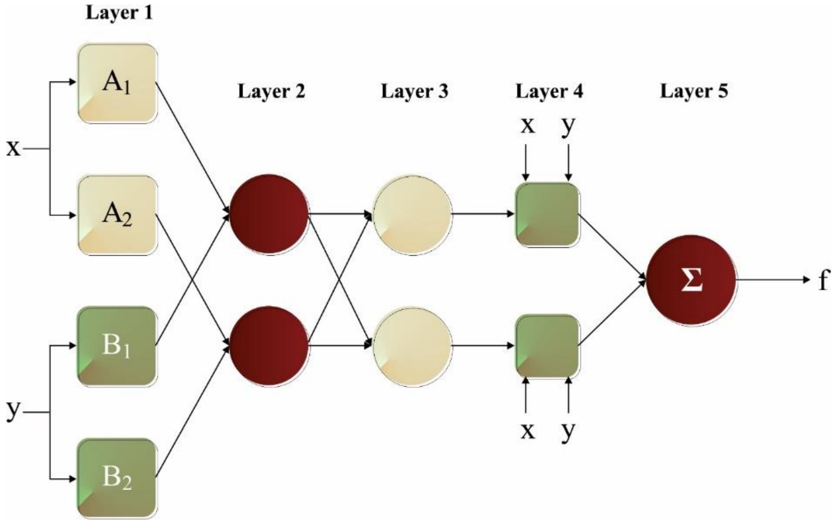

Figure 2: Structure of ANFIS

We know that,

$$Sigmoid(y_j, a, c) = \mu(y_j) = \frac{1}{1 + e^{-a(y_j - c)}} \; j = 1,2,3, \ldots \tag{8}$$

At 2nd layer, the output can be calculated through multiplication of the received signals. Generally, the inaccurate AND operation was utilized for computing the firing strong point of nodes dependent upon the membership value of the preceding layer.

$$O_j^{l_2} = w_j = \mu_{A_j}(y_1) \times \mu_{B_{j-2}}(y_2) \tag{9}$$

In 3rd layer, all the nodes are static and utilize the output of 2nd layer fire potential to find the normalized values for all the rules. The ratio of existing firing potential to the firing ability and standardized output will be acquired by Eq. (10).

$$O_j^{l_3} = \overline{w_j} = \frac{w_j}{\sum_{j=1}^{2} w_j} \tag{10}$$

Generally, 4th layer is described as a defuzzification layer with an adaptable node. A linear formula should be applied for calculating the output of such layer through multiplication of the output of prior layer as given below:

$$O_j^{l_4} = \overline{w_j} f_j = \overline{w_j}(p_j y_1 + q_j y_2 + r_j) \tag{11}$$

Now f_j signifies the linear equation included the factors p_j, q_j and r_j.

The last stage is to find the ANFIS output that will be shown in the summation of every preceding node output in Eq. (12).

$$O^{l_5} = \sum_j \overline{w_j} f_j = \frac{\sum_j w_j f_j}{\sum_j w_j} \tag{12}$$

C. BOA-based Parameter Tuning

At last, the BOA parameter tuning model augments the ANFIS model's parameters, ensuring robustness and optimum performance. BOA emulates the hunting strategy of bats using natural echolocation capabilities as a new metaheuristic optimization technique [20]. This approach has received significant interest for its capability to effectively resolve optimization problems through different fields. The basic notion behind BOA is simulated by

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the bat echolocation, where bat produces ultrasonic waves to localize and capture target. This helps bats measure the quality and distance of the target. In this work, the positions within the search range, and the solution quality can be measured as a function to be maximized or minimized. Some of the essential components of the BOA are:

Initialization: the algorithm initializes the random population of candidate solution, which represents potential solution.

Echolocation: Bats produce pulses, and emulates this procedure by enabling bats to examine the search range. Based on the quality of solution, bats change the frequencies they encounter.

$$f_i = f_{\min} + (f_{\max} - f_{\min}) \cdot rand(0,1) \tag{13}$$

In Eq. (13), $f_{\min}$ and f_{max} are the minimal and maximal frequencies, f_i refers to the frequency of bat i, and $rand(0,1)$ shows the random value within [0,1].

Movement: Bats explore new locations based on the frequency and the echolocation of discharge or move to the optimum solution they have encountered:

$$x_i(t+1) = x_i(t) + \epsilon \cdot \left(x_{best} - x_j(t)\right) + \alpha \cdot A_i \tag{14}$$

In Eq. (14), $x_i(t+1)$ and $x_i(t)$ are the newest locations of i^{th} bat at $t+1$ and t time, α is a constant, x_{best} denotes the optimum location obtained, ϵ is a random vector, and A_i refers to the random amplitude.

Pulse Rate: during the search process, the pulse rate of bat is modified. Bats with best solution emit pulses at high rate:

$$r_i(t+1) = r_i(0) \cdot \left(1 - \exp(-\gamma \cdot t)\right) \tag{15}$$

In Eq. (15), t characterizes the existing iteration, and γ is a constant.

Updating Solution: Bat engages in location update and persists in the search until terminating condition is met. It maintains the record of optimum solution obtained at the search process.

The BOA shows versatility, making it more relevant to large range of optimization issues. It successfully balances exploitation and exploration by changing the movement and pulse rate of bats. The optimization technique shows great potential in resolving complex optimization tasks and becomes a powerful technique in the domain of computational intelligence.

The BOA derives an FF to obtain superior classifier accuracy. It shows a positive integer to characterize the high efficiency of the solution candidate. Here, the decline of classifier error rate is regarded as the FF.

$$fitness(x_i) = ClassifierErrorRate(x_i)$$
$$= \frac{No.of\ misclassified\ samples}{Total\ No.of\ samples} * 100 \tag{16}$$

4. Result Analysis

The experimental validation of AOA-ANFIS technique has examined two databases German credit [21] and Australian credit [22].

The best cost (BC) outcomes of the AOA-ANFIS technique with other FS approaches are described in Fig. 3. The outcome demonstrates that the AOA-ANFIS method provides better outcomes with optimum BC value on both databases. Based on the German Credit database (GCD), the AOA-ANFIS method offers an average BC of 0.082 whereas the HHPODL-FCP, QABO-FS, ACO-FS, and GWO-FS models offers a maximum BC of 0.156, 0.179, 0.188, and 0.200 correspondingly. In addition, based, on the Australian Credit database (ACD), the AOA-ANFIS model provides an average BC of 0.035 whereas the HHPODL-FCP, QABO-FS, ACO-FS, and GWO-FS approaches provide a maximum BC of 0.081, 0.092, 0.120, and 0.129 correspondingly.

Doi: https://doi.org/10.54216/IJNS.230435
Received: August 15, 2023 Revised: January 21, 2024 Accepted: March 21, 2024

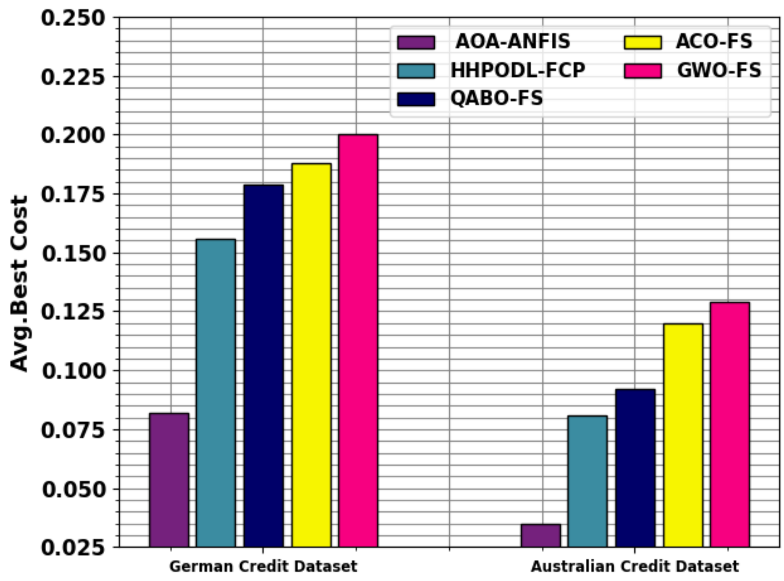

Figure 3. BC analysis of AOA-ANFIS method under two databases

The classifier results of the AOA-ANFIS method are graphically represented in Fig. 4 in the form of training accuracy (TRAAC) and validation accuracy (VALAC) curves on GCD. The outcome shows meaningful insight into the behavior of AOA-ANFIS technique over various epochs, illustrating its generalization capabilities and learning process. Notably, the outcome indicates the consistent development from TRAAC and VALAC with maximum epoch. It confirms the adaptive landscape of the AOA-ANFIS technique in the pattern detection model on both databases. The rising trend in VALAC describes the ability of the AOA-ANFIS method to adapt to the TRA database and excels in providing precise classifier on hidden database, illustrating the strong generalisabilities.

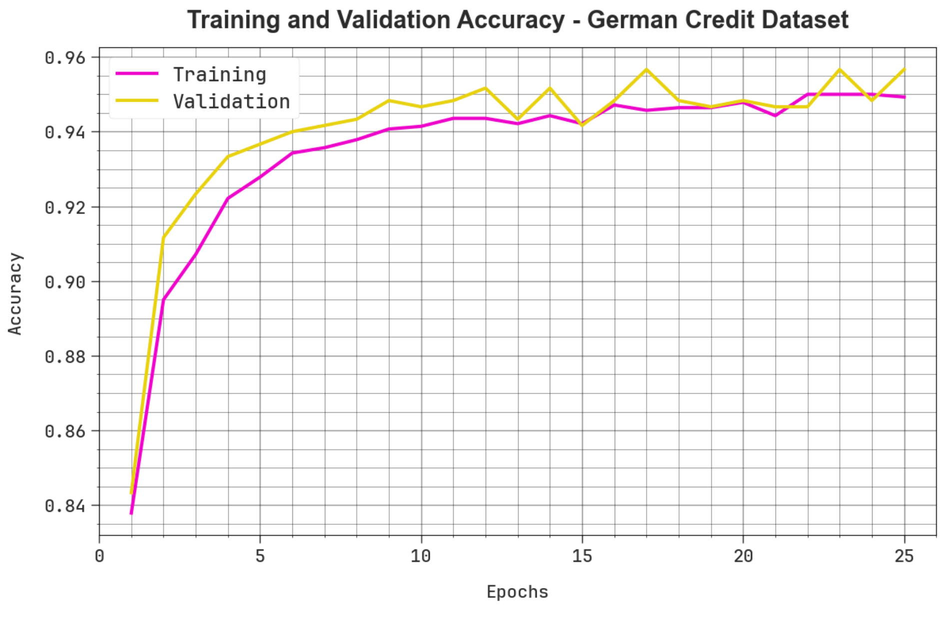

Figure 4: $Accu_y$ curve of AOA-ANFIS method on GCD

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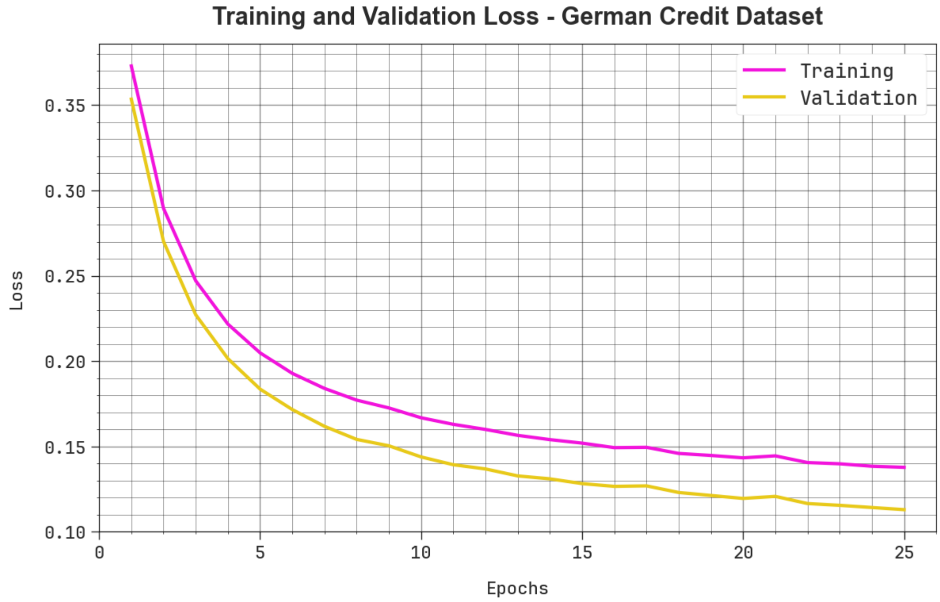

Figure 5: Loss curve of AOA-ANFIS method on GCD

Fig. 5 illustrates a wide-ranging review of the training loss (TRALS) and validation loss (VALLS) outcomes of the AOA-ANFIS method over various epoch counts on GCD. The gradual decline in TRALS underlines the AOA-ANFIS model minimizing the classifier error and enhancing the weights on both databases. The outcome shows a clear understanding of the AOA-ANFIS model's relationship with the TRA database, which highlights its ability to capture patterns within both databases. Notably, the AOA-ANFIS technique continuously optimizes its parameters in decreasing the variances amongst the prediction and real TRA classes.

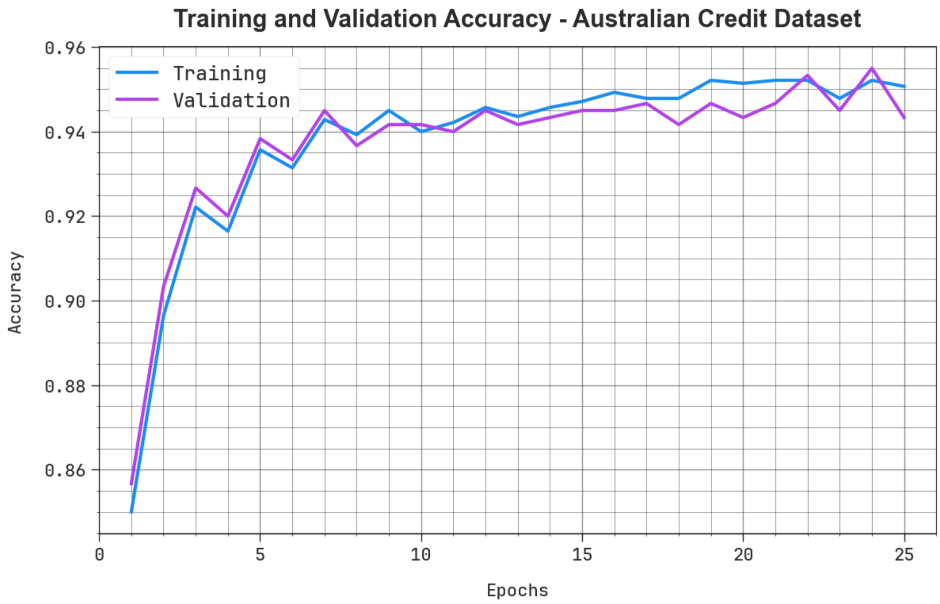

Figure 6: $Accu_y$ curve of AOA-ANFIS algorithm on ACD

The classifier outcomes of the AOA-ANFIS method are graphically represented in Fig. 4 in the form of TRAAC and VALAC curves on ACD. The outcome shows meaningful insight into the behavior of AOA-ANFIS technique over various epochs, illustrating its generalization capabilities and learning process. Notably, the outcome indicates the consistent development in the TRAAC and VALAC with maximum epoch. It confirms the adaptive landscape of the AOA-ANFIS system in the design recognition algorithm on TRA and TES databases. The rising trend in VALAC describes the proficiency of the AOA-ANFIS model to adapt to the TRA database and also excels in providing correct classifier on hidden data, illustrating the strong generalisabilities.

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Figure 7: Loss curve of AOA-ANFIS algorithm on ACD

The comparative FCP outcomes of the AOA-ANFIS method on the GCD are represented in Table 1 and Fig. 8 [12]. The experimental values reported that the QABO-LSTM-RNN, LSTM-RNN, ACO, MLP, SVM, and AdaBoost approaches had demonstrated worse FCP outcomes over other techniques. Moreover, the HHPODL-FCP technique attained reasonable FCP performance with $sens_y$, $spec_y$, $accu_y$, and F_{score} of 93.68%, 94.19%, 95.05%, and 93.89%, correspondingly. Nonetheless, the AOA-ANFIS method shows potential outcomes with maximum $sens_y$, $spec_y$, $accu_y$, and F_{score} of 94.19%, 94.69%, 95.83%, and 94.57%, correspondingly.

Table 1: Comparative analysis of AOA-ANFIS method with recent models on GCD

GCD				
Classifiers	$\boldsymbol{Sens_y}$	$\boldsymbol{Spec_y}$	$\boldsymbol{Accu_y}$	$\boldsymbol{F_{score}}$
AOA-ANFIS	94.19	94.69	95.83	94.57
HHPODL-FCP	93.68	94.19	95.05	93.89
QABO-LSTM-RNN	87.39	93.73	92.12	90.26
LSTM-RNN	82.36	88.70	84.74	88.91
ACO	78.48	69.45	75.93	85.53
MLP	74.03	67.01	71.06	75.29

Doi: https://doi.org/10.54216/IJNS.230435
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SVM	72.84	66.54	71.33	71.92
AdaBoost	71.51	61.47	67.68	71.42

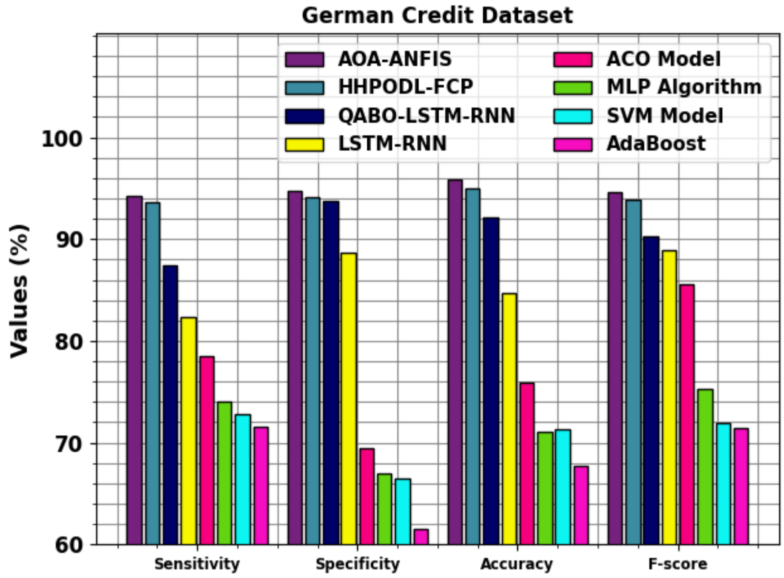

Figure 8: Comparative analysis of AOA-ANFIS algorithm on GCD

The comparative FCP results of the AOA-ANFIS method on the ACD are represented in Table 2 and Fig. 9. The simulation outcome indicated that the QABO-LSTM-RNN, LSTM-RNN, ACO, MLP, SVM, and AdaBoost techniques had proved worse FCP outcomes over other techniques. Furthermore, the HHPODL-FCP algorithm attained moderate FCP performance with $sens_y$, $spec_y$, $accu_y$, and F_{score} of 94.42%, 94.71%, 95.19%, and 94.74%, correspondingly. Nevertheless, the AOA-ANFIS method reports promising outcomes with high $sens_y$, $spec_y$, $accu_y$, and F_{score} of 95.16%, 95.41%, 95.99%, and 95.24%, correspondingly.

Table 2: Comparative analysis of AOA-ANFIS algorithm with existing models on ACD

ACD				
Classifiers	$\boldsymbol{Sens_y}$	$\boldsymbol{Spec_y}$	$\boldsymbol{Accu_y}$	$\boldsymbol{F_{score}}$
AOA-ANFIS	95.16	95.41	95.99	95.25
HHPODL-FCP	94.42	94.71	95.19	94.74
QABO-LSTM-RNN	91.04	93.31	93.44	94.75
LSTM-RNN	86.10	93.16	93.14	91.74
ACO	79.86	89.44	89.76	82.04
MLP	76.63	84.54	84.52	78.78
SVM	71.21	75.80	76.24	77.51
AdaBoost	69.19	67.45	67.80	68.57

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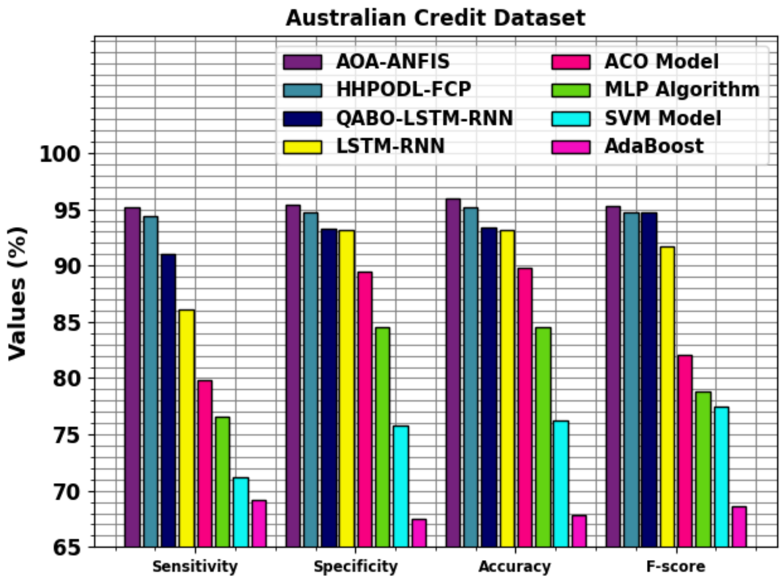

Figure 9: Comparative analysis of AOA-ANFIS method on ACD

The computation time (CT) investigation of the AOA-ANFIS method on both databases is shown in Fig. 10. The outcome safeguarded that the AOA-ANFIS algorithm needed the minimum CT values on both databases. For example, on the GCD, the AOA-ANFIS method presented the least CT of 0.78s whereas the HHPODL-FCP, QABO-LSTM-RNN, LSTM-RNN, ACO, MLP, SVM, and AdaBoost techniques provided the highest CT of 1.01s, 2.01s, 2.96s, 1.85s, 3.80s, 1.94s, and 3.00s, correspondingly. Furthermore, on the ACD, the AOA-ANFIS model presented a least CT of 0.99s while the HHPODL-FCP, QABO-LSTM-RNN, LSTM-RNN, ACO, MLP, SVM, and AdaBoost methods provided a high CT of 1.20s, 2.10s, 4.00s, 2.11s, 3.14s, 4.92s, and 4.01s, correspondingly.

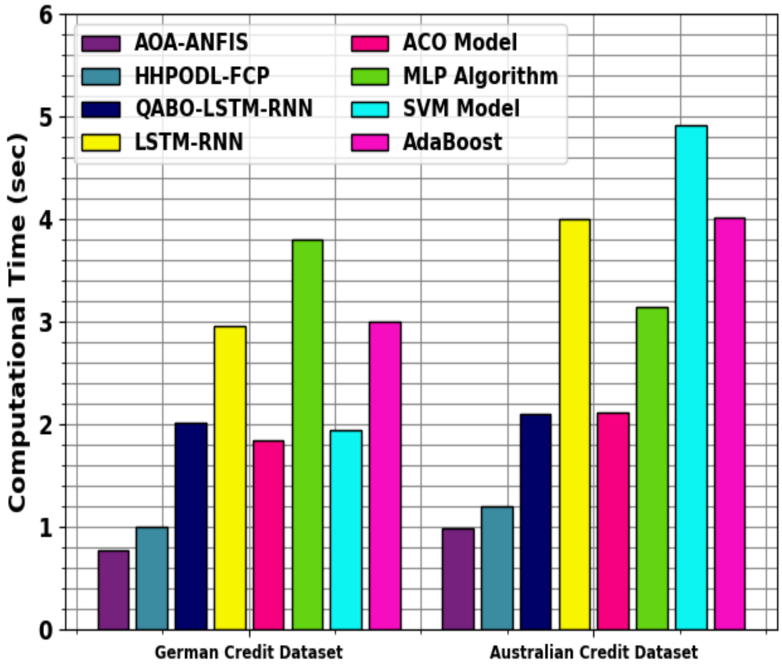

Figure 10: CT analysis of AOA-ANFIS technique on two databases

5. Conclusion

In this article, we have established a new AOA-ANFIS model for predicting financial crises. The presented AOA-ANFIS technique aims to predict the presence of financial crises or not. The model incorporates three major

Doi: https://doi.org/10.54216/IJNS.230435
Received: August 15, 2023 Revised: January 21, 2024 Accepted: March 21, 2024

elements AOA for feature selection, ANFIS as the classification algorithm, and BOA for parameter tuning. The AOA-FS model effectively detects the important attributes from large proportion of financial indicators, augmenting the model's prediction capability while decreasing computational difficulty. Subsequently, the ANFIS classifier exploits the features selected for capturing the intricate non-linear relations intrinsic in financial data, permitting accurate crisis calculation. Additionally, the BOA parameter tuning model augments the ANFIS model's parameters, ensuring robustness and optimum performance. Experimental outcomes on varied financial databases validate the higher efficiency of the AOA-ANFIS technique over underlying processes, demonstrating its effectiveness in forecasting financial crises with great reliability and precision.

Funding: “The authors extend their appreciation to the Deanship of Scientific Research at King Khalid University for funding this work through large group Research Project under grant number (RGP2/48/44)”

Conflicts of Interest: “The authors declare no conflict of interest.”

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