Prediction and Assessment of Credit Risk using an Adaptive Binarized Spiking Marine Predators' Neural Network in Financial Sector

[*1]Vadipina Amarnadh · [2]Nageswara Rao Moparthi

Abstract The rapid advancement of technologies has pushed for additional enhancements to banking and other credit platforms. While assisting small and medium sized business in lowering financing costs, banks and credit platforms must take into account practical matters like, their own capital expenses and risk evaluation. Even though, there are several methods for credit risk assessment, no comprehensive literature reviews have provided sufficient accuracy and better results while implementing in banking sectors. To overcome these issues, this manuscript proposes credit risk assessment in the banking sector using an Adaptive Binarized Spiking Marine Predators Neural Network (ABSMPNN) for accurate identification of customer credit quality within a short period of time. The evaluation using the credit risk dataset from Kaggle leads to the decision to grant or reject the customer's loan application. The concentration phase of the Variable Color Harmony Algorithm (VCHA) effectively achieves the selection of the most relevant features from the noisy and irrelevant ones. The optimization of neural network parameters with Adaptive Marine Predators Algorithm (AMPA) has further improved the overall accuracy (98.9%) with minimization of loss function. The outcomes depict that the introduced model attains higher accuracy and lower computational period of credit risk evaluation when compared with state-of-the-art.

Keywords Credit Risk, Approve Loan, Reject Loan, Neural Network, Banking Sector, Loan Status

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[*1]Research Scholar,
Department of Computer Science and Engineering,
Koneru Lakshmaiah Education Foundation,
Vaddeswaram, Andhra Pradesh-522302, India.
E-mail: vadipina@gmail.com

[2]Supervisor,
Department of Computer Science and Engineering,
Koneru Lakshmaiah Education Foundation,
Vaddeswaram, Andhra Pradesh-522302, India.
E-mail: rao1974@gmail.com

1 Introduction

Prediction and assessment of credit risk refers to the process of evaluating the likelihood that a borrower defaults on their financial obligations, such as loan repayments or credit card payments. In the financial sector, prediction and assessment of credit risk are essential processes that involve evaluating the likelihood of borrowers defaulting on their debt obligations [1]. Financial institutions, such as banks, credit card companies, and lending agencies, use credit risk assessment to determine the creditworthiness of individuals, businesses, or entities applying for credit. These processes are crucial for banks, credit institutions, and other financial entities to make informed lending decisions and manage credit portfolios effectively [2]. By accurately predicting credit risk and continuously assessing borrowers' creditworthiness, financial institutions make informed decisions, safeguard their assets, and maintain a healthy and stable lending business. These processes are instrumental in ensuring the overall stability and soundness of the financial system. To check the credit merit of debtors, those methods mostly depends on untrue subjective assessment and were supplemented with contemporary quantitative models [3].

Despite the advancements in technology and risk management practices, there are still several challenges and problems faced in credit risk assessment in the banking sector. Accurate and comprehensive data is essential for credit risk assessment. However, sometimes banks may lack access to reliable historical data or encounter issues with data accuracy and completeness, making it challenging to assess credit risk accurately. Some credit risk assessment models may lack transparency, making it difficult for borrowers to understand the process of their creditworthiness evaluation [4]. This lack of transparency leads to mistrust and dissatisfaction among customers. Credit risk assessment typically relies on historical data, but human behavior is unpredictable. Borrower behavior may change over time, leading to deviations from historical patterns and making risk assessment more challenging. Borrower behavior may change over time, leading to deviations from historical patterns and making risk assessment more challenging. Obtaining accurate risk assessment information is challenging for certain borrowers, particularly small and medium-sized enterprises, as well as individuals with limited credit history [5].

Therefore, credit risk assessment and prediction are vital for banks to maintain a healthy and sustainable lending business. By accurately predicting credit risk and continuously assessing borrowers' creditworthiness, banks make informed decisions, protect their assets, and optimize their overall risk return profile. The realm of literature in credit risk assessment presents a vast array of Machine Learning (ML) [6] literatures. These studies suggest utilizing various techniques, including artificial neural networks, support vector machines, decision trees, k-nearest neighbors, and Naïve Bayes classifiers. Researchers have not only explored the application of individual classifiers but have also delved into complex credit scoring and evaluation models to better capture the variations of real-world data. Ensemble learning has been gaining popularity as one of the prominent methods for large-scale credit risk assessment. Notable algorithms such as extreme gradient boosting [7], Light Gradient Boosting Machine (Light GBM) [8], and Categorical Boosting (CatBoost) [9] exemplify the effectiveness and appeal of this approach. These techniques are favored due to their efficient training and low computational requirements. Additionally, researchers have experimented with combining ensemble methods with diverse base classifiers, forming heterogeneous ensembles. Such combinations enable more diversified predictions and enhance adaptability across various credit datasets. In contrast, other studies have focused on ensemble classification for credit risk, approaching the subject from different angles and utilizing distinct datasets. However, one noteworthy observation is that the literature suggests Deep Learning (DL) methods for credit risk estimation, comparing them to conventional techniques. Previous implementation results indicates that, in credit risk assessment applications, DL methods continue to outperform ML and ensemble algorithms.

The choice of DL technique is based on the specific characteristics of the credit risk dataset and the resources available for model development and deployment. Various DL approaches like Multi-Layer Perceptron's (MLPs) [10], Recurrent Neural Networks (RNNs) [11], Long Short-Term Memory (LSTMs) [12], Gated Recurrent Units (GRUs) [13], Convolutional Neural Networks (CNNs) [14] and autoencoders [15] has been implemented in previous researches. But they possess several drawbacks like requirements of training samples, vanishing gradient issue, less interpretable, computational complexity, inaccuracy, more processing time etc.

Binarized Spiking Neural Networks (BSNN) have gained attention in recent years due to their unique advantages over traditional deep neural networks. This is particularly advantageous for deploying models on resource-constrained devices. Applications requiring low-latency predictions or immediate responses benefit from the inherent speed of spiking neural networks. An effective optimization algorithm helps in training and tuning of the BSNN efficiently, allowing it to perform in real-time.

1.1 Motivation

The motivations behind this research work are given as follows.

The internal and external management systems, policies as well as employees influence the commercial banks in the course of daily operations, making their operating outcomes erratic. Credit risk in commercial banking pertains to the potential that the bank may face difficulty in recovering both the principal amount and interest on a loan from its customers within the designated time frame, subsequent to the loan being disbursed. If there is no credit risk, management utilize certain measures to infer that higher credit risk in a customer corresponds to a higher likelihood of causing future losses. Conversely, in the presence of credit risk, the extent of a customer's credit risk directly correlates with the magnitude of the potential losses they may cause. Unlike operational risk, credit risk is characterized by its irreversibility, i.e. once it occurs, its impact is not undone. Credit risk is heavily influenced by legal regulations and is primarily managed through credit contracts. Due to its unpredictable nature, losses resulting from credit risk is not easily foreseen. Moreover, credit risk has a direct and significant impact on commercial banks. Therefore, prevention of risk is the main and core content for commercial banks and institutions. Investment institutions in several countries faces unprecedented credit risks due to the fluctuations of global regional economy and financial globalization.

Therefore, a management theory or systems is required for minimizing the credit risk in commercial banks or financial institutions. The management strategies must collect all the data within the target range and then analyze and identify the data available for risk assessment.

By the above concerns, the key contributions of this research work are summarized below:

- This research introduces a novel solution, ABSMPNN, which addresses a major issue of inaccurate assessment in the banking sector. ABSMPNN offers a unique approach to credit risk assessment, significantly improving accuracy and quality.
- The computational efficiency of the introduced method is greatly enhanced through the application of VCHA's concentration phase, which optimizes feature selection, thereby reducing the overall computational duration.
- To achieve faster convergence during training, a groundbreaking update to the loss function of the BSNN is introduced. This linear approximation significantly reduces training time steps and accelerates the learning process.
- The utilization of AMPA provides a remarkable boost in assessment accuracy. By maximizing the weight and minimizing the loss function parameter using AMPA, the performance of the BSNN is greatly enhanced.
- The introduced ABSMPNN's statistical validity is rigorously demonstrated using Paired-t-test and Analysis of Variance (ANOVA) test. This quantitative analysis reinforces the credibility and robustness of the introduced credit risk assessment methodology.
- Comparative experiments against existing methods validate the effectiveness of the introduced credit risk assessment approach. The results showcase higher accuracy and lower computational periods, solidifying the novelty and superiority of the introduced method in credit risk identification.

The remaining of this manuscript is organized as follows: related works are reported in section 2. Preprocessing stage, feature selection, identification of credit risk quality and optimization processes are elaborated in section 3. Performance analysis and comparisons are discussed in section 4. Finally, section 5 provides conclusion.

2 Related Works

Among the frequent research works on credit risk assessment, some of the latest investigations were assessed in this section.

Recent advancements in machine learning and DL have sparked innovative approaches for credit risk assessment, aiming to improve the accuracy and efficiency of evaluating borrower creditworthiness. A credit risk assessment using ML with Genetic Algorithms (MLGA) was presented by Lappas PZ and Yannacopoulos AN (2021) [16], from the unbalanced distribution of data categories of Credit dataset. The parameters that assist most to the categorization of borrowers were analyzed using a wrapper-based feature selection technique. The Analytic Hierarchy Process (AHP) was applied for helping specialists to make partialities for cluster attributes. But, the overall implementation of this approach was time consuming. In the same year, Dahooie et al. [17] examines the credit quality of 21 clients at the Tehran, (Iran) Beekeeping Business Funding Association from 2014 to 2017. For assessing credit management, Data Envelopment Analysis

(DEA) was used with Multi-Attribute Decision Making (MADM). With the help of the dynamical DEA, criteria weights were computed. The cumulative score was finally calculated using Correlation Coefficient and Standard Deviation (CCSD). In practical applications, the suggested approach was not achieved maximum efficiency.

To evaluate credit risk in financial institutions, Self- learning Back Propogation Neural Network (BPNN) Assessment algorithm (SL-BPNN-A) based approach was presented by Liu L (2022) [18] that combines qualitative and quantitative approaches. The input data for this sample was taken from Banking dataset with 2234 monetary banking remarks from Romanian media platforms. However, performance of decision makers were not appropriately given. Also, another neural network called e-commerce credit risk assessment based on Fuzzy Neural Network (FNN) chooses 40 online retailers from the e-commerce infrastructure by Wang L and Song H (2022) [19]. Multilayer optimization engine techniques was used for parameter optimization based on a joint strategy to divide the FNN constraints into linear and non-linear factors for joint optimization. Accurate prediction results were not provided using this method. The Multifactor Analysis based on BPNN (MA-BPNN) model was developed by Zhang L and Fan J (2022) [20] for predicting farmer access to formal bank and credit requirements. The sample data was provided by conducting survey in November 2021 in Jiutai District, Changchun Town, Jilin territory. However, the regional restrictions of this technique was limited. Blockchain-based models like, Blockchain and Automated ML Classification Strategy (BACS) the one presented by Yang F et al. (2022) [21] have shown promise in providing secure credit scoring. The overall credit scoring scheme was ensured by the organization of credit data and blockchain storage. This method provides a traceable scoring system and the data was stored on the blockchain model in a quick, secure and tamper-proof manner. For performing feature extraction, selection, construction of credit model and evaluation, a pipeline model was designed using random forest approach. But, mutable and scalable characteristics of data makes the system inefficient. In the same year, Genetic Algorithm Neural Network (GANN) was utilized with cluster analysis for commercial bank cedit grading by Bai Y and Zha D (2022) [22]. The BPNN undergoes slow covergence speed and easy to fall into the local minimum problems. An effective optimization technology which perform global searches by its multipoint search was used thereby to improve the efficiency of the network evaluation. However, challenges related to time constraints and improved fitness function correlation analysis persists. Zeng H (2022) [23] have presented a credit risk evaluation technique under smart city construction by using CNNs in enterprise financial management. The credit risks of Small and Medium sized Enterprises (SMEs) was overcome using the self learning and adaptive CNN method. The convolutional kernal path and the influence of learning rate was explored by using indicator factor analysis. The setting up of initial learning rate reduces the accuracy of the model. Also, there was a need to improve the system to solve loan difficulties in SMEs. ML algorithm based supply chain management for supplier credit risk assessment was presented by Wei Y (2022) [24]. The effects of assorted variables of supply chain approaches was analyzed using the ML based Linear Regression Algorithm (ML-LRA). In Supply Chain Management (SCM) identifying the supplier system was done by ML. This method operated more smoothly with less energy consumption. But, there was a need to reduce the supplier risk. Credit risk evaluation on sports public service venue of Public Private Partnership (PPP) project was presented using Random Forest (RF) algorithm by Wang Y (2022) [25]. The audition indicator of credit risk evaluation was screened by using the integrated asset securitization credit risk evaluation system and the random forest algorithm. The development of sports public service venue was gaurenteed by asset securitization thereby reduced the financing costs. However, there was a need to verify its performance in extended datasets. To conduct risk simulation research and to build a model in financial management a machine learning algorithm based Support Vector Machine (SVM) model was used by Sun M and Li Y (2022) [26]. This method improved the bank credit activities and provides economic benefits. Lack of internal information, limited analysis of financial problems were considered as major problems.

In the present year, Rao C et al. (2023) [27] used a ML assessment of personal auto loan's credit risk. Balanced data set was obtained using an integrated Filter-Wrapper (FW) selection of features. Assessment was done by integrating eXtreme Gradient Boosting technique with Particle Swarm Optimization (PSO-XGBoost). This technique does not work well with unstructured data. Also, this technique was hardly scalable. A prediction of credit default risk using different Kaggle datasets with interpretable selective learning was implemented by Chen D et al. (2023) [28] for enhancing the interpretability by distinguishing whether the datasets were explained by linear models or not. This selective learning approach, builds the bridge between transparent logistic regression and a highly accurate black-box neural network for credit risk. Improved accuracy were one of the advantages of this technique but the real time implementation were difficult.

Yin W et al. (2023) [29] developed a Max-Relevance And Min-Redundancy (MRMR) for selecting the finest features and k-means clustering approach for removing the inappropriate features. Based on these features, the accurate predictions were made using ensemble stacking approach. However, this model possess increased complexity. Another Ensemble approach based on Logistic Model (ELM) was developed by Runchi Z et al. (2023) [30]. This work initially performs preprocessing, and forms sub models by spliting the datasets for training. Then, based on validation stage, each submodel's prediction weights were determined. The presented approach has superior generalization capability. Although an optimization algorithm was required to hybrid with the presented ensemble model for further enhancing the its capability. Baser F et al. (2023) [31] suggeseted a Clusturing Based Fuzzy Classification (CBFC) approach for credit scoring. This method also chosses the best features and predicts the risk with the help of membership function. The main drawback of this approach was considered as lack of accuracy rates. An Improved Fuzzy Neural Network (IFNN) was also utilised by Fan B and Qin J in the same year [32] for assessment of credit risk enterprise. A transimission of variable speed credit data is done with simulink using the suggested approach. Assessment of risk and response effects were achieved using the presented technique, but, this approach requires more computaional resources leads to time consuming. Roy PK and Shaw K (2023) [33] developed a Multi-Criterion Decision-Making (MCDM) strategy-based credit risk evaluation. This technique also uses a credit scoring approach with the help of AHP-Technique for Order of Preference by Similarity to Ideal Solution (AHP-TOPSIS). Several stages include choosing criteria, calculating weights for criteria and sub-criteria. Finally the credit scoring is determined by utilizing these weights. However, these works doesnot consideres healthy and defaulted firms data.

While these researches have paved the way for innovative credit risk assessment techniques, there remain significant gaps in achieving greater efficiency, accuracy, time, and applicability in real-world scenarios. These gaps signal opportunities for further research and development to enhance the capabilities of machine learning approaches in effectively managing credit risk and facilitating informed decision-making processes in the financial domain. From the above discussion, the major problems of the existing approaches has been highlighted in Table 1.

Table 1: Problems of existing approaches

Reference	Techniques used	Performance metrics used	Problems
[16]	MLGA AHP	Area Under Curve Computational time	Time consuming
[17]	MADM CCSD DEA	Sensitivity coefficient	Ineffective classification
[18]	SL-BPNN-A	Accuracy Error index Time fit index Model error index Mean square error index	Weak performance of decision makers
[19]	FNN	Accuracy	Inaccuracy
[20]	MA-BPNN	Accuracy Prediction time Mean square error	Regional restrictions were limited
[21]	BACS	Specificity Accuracy	Inefficient assessment
[22]	GANN	Mean absolute error Accuracy	Limited time and level constraints of algorithm
[23]	CNN	Accuracy	Need improvement in system performance
[24]	ML	Accuracy	Increased risk of network suppliers
[25]	RF	Accuracy Sensitivity Specificity Error rate	Poor performance on training
[26]	SVM	Mean absolute error Mean relative error Accuracy	Lack of internal data and analysis
[27]	PSO-XGBoost	Accuracy	Poor performance on sparse data

	FW	Computational time Recall Precision	
[28]	Interpretable Selective Learning	Accuracy	Implementation is complex
[29]	MRMR k-means clustering	Accuracy Precision Recall	Complexity is high
[30]	ELM	Area Under Curve (AUC) Sensitivity Specificity G-mean F1-score Matthews Correlation Coefficient	Weak performance of classifier in training
[31]	CBFC	Accuracy Brier score H measure AUC Sensitivity Specificity Average of each performance metrices (AvgR)	Inaccurate prediction
[32]	IFNN	Accuracy	Time consuming Need more computational resources
[33]	MCDM AHP-TOPSIS	Spearman's correlation coefficient	Not considers all data

2.1 Problem Statement

Several limitations of existing methods from the Table 1 made the existing network and system futile. Major drawbacks such as high computational time, poor training performance, inaccurate prediction rate in identifying credit risk quality and ineffective classification which makes the credit risk assessment process ineffective are considered. To overcome such problems, this manuscript proposes a novel credit risk assessment to accurately identify credit risk quality with lower computational time. The details of the introduced scheme of credit risk assessment are explained below.

3 Introduced Credit Risk Assessment

This section delves into a detailed explanation of the credit risk assessment process within the banking sector, employing an innovative approach known as the ABSMPNN. This sophisticated model aims to discern the quality of customer credit by effectively integrating two key components: the BSNN and the AMPA. The combination of these elements results in the development of the ABSMPNN, a cutting-edge framework designed to enhance the accuracy and efficiency of credit risk evaluation. The ABSMPNN model encompasses four pivotal stages, each contributing to the holistic process of credit assessment. Firstly, the process initiates with the utilization of Mean Curvature Flow (MCF) based preprocessing, a technique that facilitates the refinement and enhancement of the input data. Subsequently, the VCHA based feature selection stage comes into play. VCHA strategically identifies and selects the most relevant features from the dataset, thereby reducing the dimensionality and optimizing the subsequent analysis. Following the feature selection phase, the ABSMPNN employs the BSNN for classification purposes by determining the customer's loan application as approve or reject. The BSNN leverages the unique characteristics of spiking neurons to process information in a manner akin to biological neurons, enabling it to effectively categorize customers based on their credit quality. This neural network component forms a key building block in the ABSMPNN's architecture. Lastly, the AMPA is introduced to optimize the parameters of the BSNN. By capitalizing on the predator-prey dynamics observed in marine ecosystems, AMPA seeks to maximize the network's efficiency and minimize its loss function, thereby fine-tuning its predictive capabilities. This optimization phase plays a crucial role in enhancing the ABSMPNN's accuracy and performance in credit risk assessment.

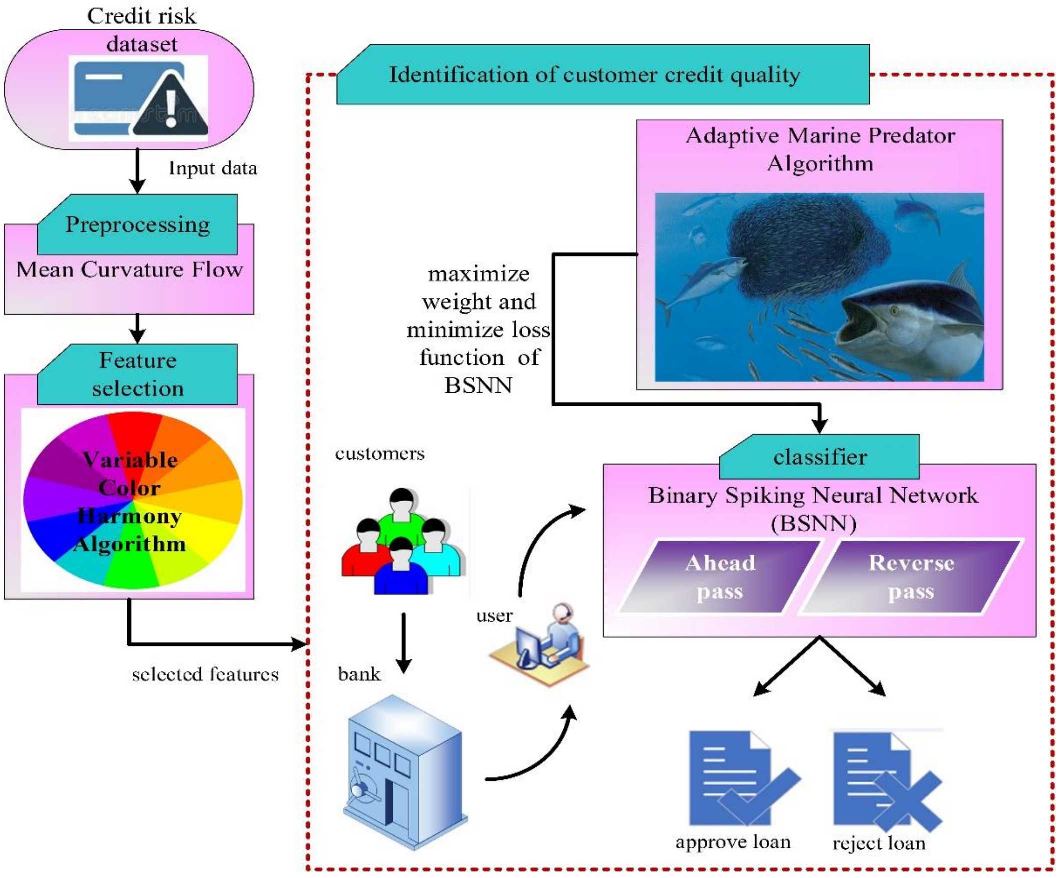


Fig. 1. Architecture of introduced credit risk assessment

As a result, the exact assessment of loan application has been attained proficiently. Fig. 1 depicts the general schematic diagram of credit risk assessment.

3.1 Input-Data gathering

The input data used in this analysis is derived from the credit risk dataset [34] specified in Kaggle, which includes 239 enterprises (91 high-risk cases and 148 low-risky cases) that received loans from the Commercial and Investment Bank of China. The implemented Kaggle dataset comprises the thorough economic records of financial businesses and the related evaluation outcomes. Detailed data description of the credit risk dataset is given in Table 2.

Table 2 Dataset features and description

Feature Name	Description
person_age	Age
person_income	Yearly Income
person_home_ownership	Homeownership
person_emp_length	Employ length (in years)
loan_intent	Loan purpose of loan
loan_grade	Loan rating of loan
loan_amnt	amount of loan
loan_int_rate	Interest degree
loan_status	Status of loan (0 is reject, 1 is the approve)
loan_percent_income	Percent revenue
cb_person_default-on_file	Ancient default
cb_preson_cred_hist_length	Credit ancient length

The Table 2 represents a dataset with various features related to loans and borrowers. Person_age represents the age of the person applying for the loan. Person_income represents the yearly income of the person applying for the loan. It indicates the amount of money they earn in a year. Person_home_ownership indicates whether the person applying for the loan owns a home or not. It has values like "Yes" or "No" to denote whether the person is a homeowner. Person_emp_length represents the length of time (in years) the person has been employed. It gives an idea of the applicant's work stability and employment history. Loan_intent represents the purpose for which the loan is being taken. It could include categories like "Debt Consolidation," "Home Improvement," "Medical Expenses," etc. Loan_grade indicates the rating or grade of the loan. Loan grades are used by lenders to assess the risk associated with a loan. Higher grades generally indicate lower risk. loan_amnt represents the amount of money being requested in the loan application. loan_int_rate represents the interest rate associated with the loan. It indicates the percentage of interest the borrower pays on top of the loan amount. Loan_status indicates the status of the loan application. A value of 0 typically means the loan was rejected, while a value of 1 means the loan was approved. Loan_percent_income represents the percentage of the person's income that the loan amount represents. It gives an indication of the borrower's income going towards repaying the loan. Cb_person_default-on_file indicates whether the person has a record of defaulting on a loan in the past. It could have values like "Yes" or "No." Cb_preson_cred_hist_length represents the length of the person's credit history. It shows the durability of the person using credit facilities and managing their credit accounts. This input data is initially given for preprocessing.

3.2 Preprocessing

In credit risk assessment, data preprocessing is a crucial step to clean and prepare the data before building predictive models. Credit data may contain noisy or inconsistent information due to various factors like human error or data collection issues. Preprocessing of data for removing noise and undesirable information [35] is done using MCF. It is a mathematical approach based on partial differential equations. Applying MCF could help in denoising the data and smoothening out small fluctuations or outliers, resulting in cleaner and more reliable credit data. MCF safeguards and illustrates the directionality of features, shapes, and texture data. This method eliminates noise and erratic peaks as expressed in eqn. (1) as,

$$i_{MCF} = \theta|\nabla i| \tag{1}$$

where i denotes the input, θ represents the isophotes curve [36, 37].

This step helps in building better predictive models. From the preprocessed output using eqn. (1), the dataset's top attributes are selected using the variable Color Harmony algorithm.

3.3 Variable Color Harmony Algorithm-based feature selection

VCHA is the modified form of the Color Harmony Algorithm (CHA) for presenting a feature selection strategy. This algorithm sustain a generation of solutions for the optimization issues. Each solutions and the design variables of the optimization approach are supposed to characterize as a color and its psychological and physical impacts. In the context of the CHA, two key phases, namely concentration and dispersion, play integral roles in the algorithm's operation. These phases delineate specific steps in the algorithm's decision-making process. However, a novel variation known as VCHA strategically leverages solely the concentration phase during the selection process. The primary rationale behind this modification is to optimize and streamline the computational efficiency of credit risk evaluation. By focusing exclusively on the concentration phase, the VCHA algorithm seeks to expedite the algorithmic calculations and decision-making steps, thereby reducing the overall time required for assessing credit risk. This approach showcases a deliberate effort to strike a balance between accuracy and computational efficiency, enabling more rapid and streamlined credit risk evaluations in practical applications. The step-by-step procedure for selecting the features are discussed below:

Step 1 - Initialization

Each solution candidate $x'(i, j)$is determined as a color with several decision factors (features). Colors are initially dispersed at random over the boundaries as seen in eqn. (2).

$$x'^{0}(i, j) = x'^{L'}(i) + r \cdot \left(x'^{U'}(i) - x'^{L'}(i)\right) \qquad \begin{array}{l} i = 1,2,\ldots,n'_v \\ j = 1,2,\ldots,n'_c \end{array} \tag{2}$$

$x'^{0}(i, j)$, $x'^{U'}(i)$, $x'^{L'}(i)$ are the starting values for the j^{th} color, highest and lowest bound of the i^{th} factor; r is a evenly allocated numeral in the interval [0,1]; n'_v and n'_c corresponds to the summation of factors and colors, respectively. Fig. 2 explains flowchart of variable color harmony algorithm.

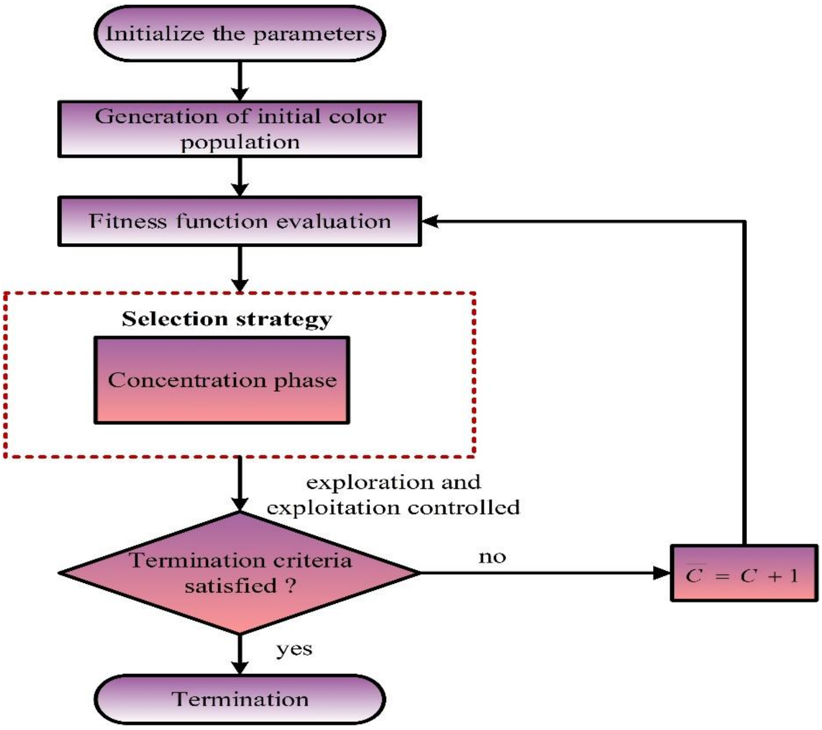


Fig. 2. Flowchart of VCHA

Step 2 - Random generation

Through endless random generation in the search area, the basic population is produced based on the count of Color's and its dimension of the problem.

Step 3 - Fitness function

The fitness function of the VCHA for selecting the dataset's best features is given in below eqn.(3),

$$fitness\ function = \alpha' Classification_{error} + \beta' \left(\frac{chosen\ features}{total\ features} \right) \tag{3}$$

where, α' and β' signifies the values of accuracy and loss function which are set in the range of $\alpha' \in [0,1]$ and $\beta' = 1 - \alpha'$.

Step 4 - Concentration phase

This phase manages the exploration and exploitation of the boundary and makes use of a selection technique, both of which are detailed in eqn.(4), in order to achieve a balance between global and regional searches.

$$x'(M',i) = r_1 \cdot x'(a_{M'},i) + r_2 \cdot x'(b_{M'},i) \qquad \begin{matrix} M' = 1,2,\ldots n'_{Cmb} \\ i = 1,2,\ldots,n'_v \end{matrix} \tag{4}$$

where x' denotes combination set; the random values in (0,1) are represented as r_1 and r_2; the total number of combinations is denoted as n'_{Cmb}; $x'(a_{M'},i)$ and $x'(b_{M'},i)$ are the components of M'^{th}; $a_{M'}$ and $b_{M'}$ are the number of sectors of each component.

The power of agent P_a parameter is defined by eqn. (5), which specifies the appearence of the agent as a component in the combinations, to control exploration and exploitation.

$$P_a = MIN\left(n'_{Cmb}, FLOOR\left(\frac{Iter_{CP}}{Step} \right) \right) \tag{5}$$

The $Step$ in (5) is described by eqn.(6) as follows,

$$\text{where } Step = \frac{n'_{Cmb} + 1}{n'_{comb} + n'_i} \tag{6}$$

The quantity of i^{th} iteration is calculated using eqn.(7).

$$n'_i = MIN\left(n'_{comb}, FLOOR\left(\frac{Iter_{DP}}{n'_{D^{th}} / n'_{Cmb}} \right) \right) \tag{7}$$

The quantity of time $n'_{D^{th}}$ is evaluated using eqn. (8) as follows.

$$n'_{D^{th}} = FLOOR\left(\frac{\log\left(\frac{D_f^{th}}{D_i^{th}} \right)}{\log(damp)} \right) \tag{8}$$

The n'_{Cmb}, $n'_{D^{th}}$, $Iter_{DP}$ and $Iter_{CP}$ characterizes the four parameters of P_a. n'_{comb} signifies the overall number of combinations, $n'_{D^{th}}$ is the number of times that D_i^{th} is increased by a constant, to be equivalent to the value of final diversity D_f^{th}.

Thus, using the concentration phase, both exploration and exploitation are controlled and the optimal features are selected with minimal computational time. Table 3 depicts the pseudocode of the VCHA's feature selection process.

Table 3 Feature selection pseudocode

Input: Preprocessed output
Output: Find the best features

```
Initialize the parameters of VCHA with random values within factor bounds
for each candidate color in basic population:
    Calculate accuracy and loss function using the candidate's features
    Calculate fitness using eqn. (3)
Update the VCHA's concentration phase
for each iteration from 1 to maximum iterations:
    Calculate the quantity of time using eqn. (8)
    Calculate the quantity of iteration using eqn. (7)
    for each combination in combination set:
        Calculate the power of agent using eqn. (5)
        for each component in combination:
            Update component values based on exploration and exploitation
        end for
        Calculate the fitness of the combination
        if fitness is better than current best fitness:
```

Update current best fitness and optimal combination
end if
end for
Update exploration and exploitation parameters based on eqn. (6)
end for
repeat until pausing conditions are fulfilled:
Go to Step 3
end repeat

Step 5 - Termination

If the optimal feature selection is achieved then iteratively repeat step 3 to 4 until the pausing conditions $\overline{C} = C + 1$ is fulfilled [38,39]. The finest features are chosen by variable color harmony algorithm and given to the introduced technique for identifying the customer credit quality, and these traits automatically speed up credit risk identification while slowing down computation.

3.4 Identification of credit risk quality by Binarized spiking neural network

For identifying whether to approve or reject the loan, the suggested neural network's input layer transforms the selected features into spikes. The dual Integrate and Fire (IF) neurons that are found in invisible and output layers are then prevented from firing more than once for each feature once such spikes have been relayed across the network. Each output neuron is allocated to a separate class, and the network's choice is made by the initial output neuron to fire. By contrasting the network's actual firing time with a targeted firing time, each output neuron's loss function is determined. The overall classification process is done by two stages as follows.

- Ahead pass
- Reverse pass

Ahead pass

Using the introduced technique, the input layer transforms the incoming features into a barrage of spikes. For spikes with pixel intensities between $[0, i'_{MAX}]$,the firing period of the i^{th} input neuron (t'_i), equivalent to the i^{th} pixel strength (i'_i), is expressed in eqn. (9) as,

$$t' = \left\lfloor \frac{i_{MAX} - i_i}{i_{MAX}} t'_{MAX} \right\rfloor \tag{9}$$

where, t'_{MAX} represents the maximum firing period. The i^{th} input neuron's spike pattern is defined in eqn. (10),

$$s_i'^{0}(t') = \begin{cases} 1 & if\ t' = t'_i \\ 0 & otherwise \end{cases} \tag{10}$$

There are non-leaky IF neurons in the invisible and output layers that follow. The dual synaptic weights in the range of -1 or +1 are used by the j^{th} IF neuron of the i^{th} layer to accept incoming spikes and change its membrane potential, $v_j'^{l}$ using eqn. (11),

$$v_j'^{l}(t) = v_j'^{l}(t'-1) + \beta^l \Sigma_i b_{ji}'^{l} s_i'^{l-1}(t') \tag{11}$$

where $b_{ji}'^{l}$ and $s_i'^{l-1}$ are the dual synaptic weight and the input spike sequence joining the i^{th} presynaptic neuron to the neuron j respectively. The scaling factor β^l is shared by all of the neurons in the i^{th} layer. The network is aided by these scaling parameters in preventing the generation of mute neurons (i.e., unable to respond to the threshold value) which is highly probable with dual weights. When its membrane potential initially reaches the threshold, the IF neuron fires only once.

$$s_j'^{l}(t) = \begin{Bmatrix} 1 & if\ v_j'^{l}(t') \geq \phi\ and\ s_j'^{l}(< t') \neq 1 \\ 0 & otherwise \end{Bmatrix} \tag{12}$$

where $s_j'^{l}(< t') \neq 1$ determines the neuron has fired on any preceding clock cycles. Simultaneously, by replacing ϕ with ϕ / β^l, scaling factor β^l is transferred from eqns. (11) to (12).

Backward pass

In eqn. (12), the term $s_j'^{l}(< t') \neq 1$ represents a neuron that hasn't been hit by any preceding equations. For categorizing tasks with C classes, the temporal deviation is defined using eqn.(13) as a function of the j^{th} output neuron's actual $(t_j'^{0})$ and target $(T_j'^{0})$ firing time.

$$e'_j = (T_j'^{0} - t_j'^{0}) / t'_{MAX} \tag{13}$$

where the target time is represented in eqn. (14).

$$T_j'^{0} = \begin{Bmatrix} \mu - \varphi & if\ j = 1 \\ \mu + \varphi & if\ j \neq i\ and\ t_j'^{0} < \mu + \varphi \\ t_j'^{0} & if\ j \neq i\ and\ t_j'^{0} \geq \mu + \varphi \end{Bmatrix} \tag{14}$$

where, φ is represented as a constant value that is positive and $\mu = \min\{t_j^0 | 1 \leq j \leq C\}$ indicates the smallest striking time on the output layer that falls under the i^{th} category. This encourages the right neuron to fire first while penalizing other neurons for firing later than $\mu + \varphi$.

A collection of real-valued weights is employed by eqn. (15) as a substitute to solve the issue during learning stage,

$$b_{ji}'^{l} = SIGN\left(w_{ji}'^{l}\right) \tag{15}$$

Modified real valued weights are in eqn. (16),

$$W_{ji}'^{l} = w_{ji}'^{l} = \mu \frac{\partial L'}{\partial b_{ji}'^{l}} \tag{16}$$

where μ is the learning rate factor, $\frac{\partial L'}{\partial b_{ji}'^{l}}$ is the loss function relative to the dual weights and L'

denotes mean squared loss function which is given by eqn. (17) [40,41].

$$L' = 0.5\,\Sigma_{j=1}^{c'} e_j^2 \tag{17}$$

The process involves a refinement of the loss function indicated by eqn. (16), which is achieved through the implementation of a linear approximation, as depicted in eqn. (18). This strategic adjustment is aimed at streamlining the training process by reducing the number of required time steps, while simultaneously accelerating the convergence rate. By adopting this approach, the training procedure becomes more efficient, enabling the model to learn and adapt more rapidly, thus enhancing its performance and responsiveness in various tasks.

$$\frac{\partial L'}{\partial b'^{l}_{ji}} = k \max\left(0, 1 - \left|b'^{l}_{ji} - v'^{l}_{j}(t)\right|\right) \tag{18}$$

where k represents a constant and $v'^{l}_{j}(t)$ is the membrane potential at time t.

From eqn. (16), the ideal constraints such as w'^{l}_{ji} and $\frac{\partial L'}{\partial b'^{l}_{ji}}$ of the BSNN classifier needed to be optimized for efficient and accurate classification. By integrating the AMPA, a significant and noteworthy enhancement in assessment accuracy is achieved. This improvement stems from the strategic approach of AMPA, which focuses on maximizing the weight parameter and simultaneously minimizing the loss function within the context of the BSNN. This optimization process leads to a substantial elevation in the overall performance of the BSNN model. By manipulating these crucial parameters, AMPA contributes to refining the network's capability to accurately classify and predict outcomes. The utilization of AMPA's innovative methodology, designed to effectively balance weight maximization and loss function minimization, emerges as a powerful tool for improving the predictive accuracy and reliability of the BSNN model, thereby advancing the quality of assessments and outcomes. Hence AMPA is used for optimizing the weight parameter and minimizing the loss function of neural network. ABSMPNN is algorithmically expressed in Table 4.

Table 4 Algorithmic presentation of introduced ABSMPNN

Algorithm for credit risk assessment using ABSMPNN
Step 1
Loading the datasets
Step 2
Defining training and testing sets
Step 3
Defining BSNN architecture
Step 4
Defining fitness function for AMPA which is maximizing the accuracy and minimizing the classification loss on the training set of BSNN
Step 5

Defining the optimization variables

Step 6

Optimizing the paramaters value using AMPA approach

Step 7

Assigning AMPA parameters mentioned before

Step 8

Initializing population of AMPA

Step 9

Creating new solutions to optimize the weight and loss function parameters to adjust the global learning rate obtained by AMPA in BSNN

Step 10

Sorting the solutions

Step 11

Updating the optimal solutions

3.5 Adaptive Marine Predators algorihthm for optimization

AMPA is a meta-heuristic technique that draws its motivation from nature and the intelligence of marine predators. It is the adapted version of Marine Predators Algorithm (MPA). With a spiral trajectory, MPA changes its speed in various phases of hunting. This algorithm is used to solve issues with global optimization. It reveals increased attention in travelling and searching for prey during the initial hunting phase and reveals increased attention in attacking during final hunting phase. The newly introduced AMPA employs the cruising and hunting behaviors observed in marine predators as a basis for its optimization strategy. This approach capitalizes on the inherent efficiency of marine predators in maximizing their weight parameter $(w_{ji}'^{l})$ while concurrently minimizing the loss function $\frac{\partial L'}{\partial b_{ji}'^{l}}$ of the BSNN. By drawing inspiration from these natural behaviors, AMPA seeks to enhance the performance of the BSNN by finding a balance between optimizing its weight parameter and reducing the loss function. This innovative utilization of marine predator actions offers a novel perspective for improving the optimization process, potentially leading to more effective and efficient neural network models. The flowchart of this algorithm is implicated in Fig. 3. The stepwise procedure for AMPA is explained below.

Step 1: Initialization

The population distribution of AMPA is initialized uniformly in the solution space based on below eqn. (19),

$$x_{i,i''} = x_i^L + rand\left(x_i^U - x_i^L\right) \tag{19}$$

where, x_i^U and x_i^L represents the upper and lower boundaries of i^{th} individuals of AMPA.

The group's most dominant predator is known as the top predator. They play a crucial role in constructing an $Elite$ matrix as in eqn. (20), which holds the current location information of the prey for each predator during the upcoming foraging phase.

$$Elite = \begin{bmatrix} x_{1,1}^i & x_{1,2}^i & \cdots & x_{1,d}^i \\ x_{2,1}^i & x_{2,2}^i & \cdots & x_{2,d}^i \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ x_{p,1}^i & x_{p,2}^i & \cdots & x_{p,d}^i \end{bmatrix}_{p \times d} \tag{20}$$

where, d and p denotes the variable dimension and size of population. The topmost predator vector is represented by x^i which is duplicated several times for elite matrix construction. This elite matrix is updated when the predator with superior predation capability appears.

The prey matrix as in eqn. (21) with the same size as elite matrix is used for updating the predator's position.

$$prey = \begin{bmatrix} x_{1,1} & x_{1,1} & \cdots & x_{1,d} \\ x_{2,1} & x_{2,1} & \cdots & x_{2,d} \\ x_{3,1} & x_{3,1} & \cdots & x_{3,d} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ x_{p,1} & x_{p,2} & \cdots & x_{p,d} \end{bmatrix}_{p \times d} \tag{21}$$

where $x_{i,j}$ signifies i^{th} prey's j^{th} dimension. The primary focus of AMPA optimization centers on these two matrices.

Step 2: Random Generation

Input parameters of AMPA are randomly generated after initialization. The greatest fitness values are occurred and then the best path is chosen with respect to the fitness function.

Step 3: Compute the Fitness function

Fitness function is related to weight parameter and loss function. Fitness function is calculated in eqn. (22).

$$Fitness_{function} = \left\{ \max\left(w_{ji}'^{l}\right), \min\left(\frac{\partial L'}{\partial b_{ji}'^{l}}\right) \right\} \tag{22}$$

Eqn. (22) depicts that, fitness solution of classification must be maximal for weight parameter and minimal for loss function. The pseudocode of AMPA is illustrated in Table 5.

Step 4: Optimization

Two stages of AMPA optimization process are used according to the predator's and prey's different speed ratios, namely high low velocity ratio.

- *high velocity ratio*

In this ratio, the predator is moving slower than prey A_0' at the exploration phase, and it occurs in first third of the total count of generations which is denoted by eqn. (23).

$$MAX_{velocity}\left(prey_i\right) = E'l_i + c \cdot \frac{\partial L'}{\partial b_{ji}'^{l}} \otimes \left[\left(\vec{S}_k \otimes E'l_i - S_k' \otimes prey_i\right)i\right] \quad i = 1,2 \ldots n \tag{23}$$

By using the above eqn. (23), the loss function $\frac{\partial L'}{\partial b'^{l}_{ji}}$ is minimized.

Table 5 Pseudocode of AMPA

Initialize populations of search agent $i = 1,..., p$

while $iteration < max\ iteration$

Determine the fitness function as in eqn. (22)

Construct elite matrix and prey matrix by equation respectively

if $iteration < \frac{1}{3} max\ iteration$

Updated solution according to eqn. (22)

else if $\frac{1}{3} max\, iteration \leq iteration \leq \frac{2}{3}\ max\ iteration$

for $i = 1 : \frac{p}{2}$

Updated ideal constraints by eqns. (23) and (24)

end for

for $i = \frac{p}{2} : p$

Updated ideal constraints by eqns. (23) and (24)

end for

else if $iteration > \frac{2}{3} max\ iteration$

Updated ideal constraints by eqns. (23) and (24)

end if

Update elite

end while

- *low velocity ratio*

The minimum velocity ratio is the final optimization process that is caused when the actions of predator is faster than the prey. Hence, it is known as exploitation phase and it is formulated using eqn. (24).

$$MIN_{velocity}(prey_i) = prey_i + q \cdot w'^{l}_{ji} \otimes \left[\left(\vec{S}_k \otimes E'l_i - S'_k \otimes prey_i\right)i\right] \quad i = 1,2...n \quad (24)$$

where $S' \in [0,1]$ represents the vector uniform random numbers, c and q represents constant numbers, S' specifies prey movement, $E'l_i$ represents the elite, that specifies Brownian motion and $\otimes$ represents the process of element wise multiplication. Using eqn. (24), the weight parameter w'^{l}_{ji} is optimized.

Step 5: Termination

The output of AMPA provides an optimal solution, which iteratively repeats the process (22) to (24) until halting criteria $\overline{It} = It + 1$ is met [42,43].

AMPA successfully maximizes the weight parameter and minimizes the loss function of the neural network for improving the classification accuracy. Finally, the data is used to classify whether or not to approve with the customers loan application. Thus, the credit risk quality of the customers is identified with higher accuracy within a short time using ABSMPNN.

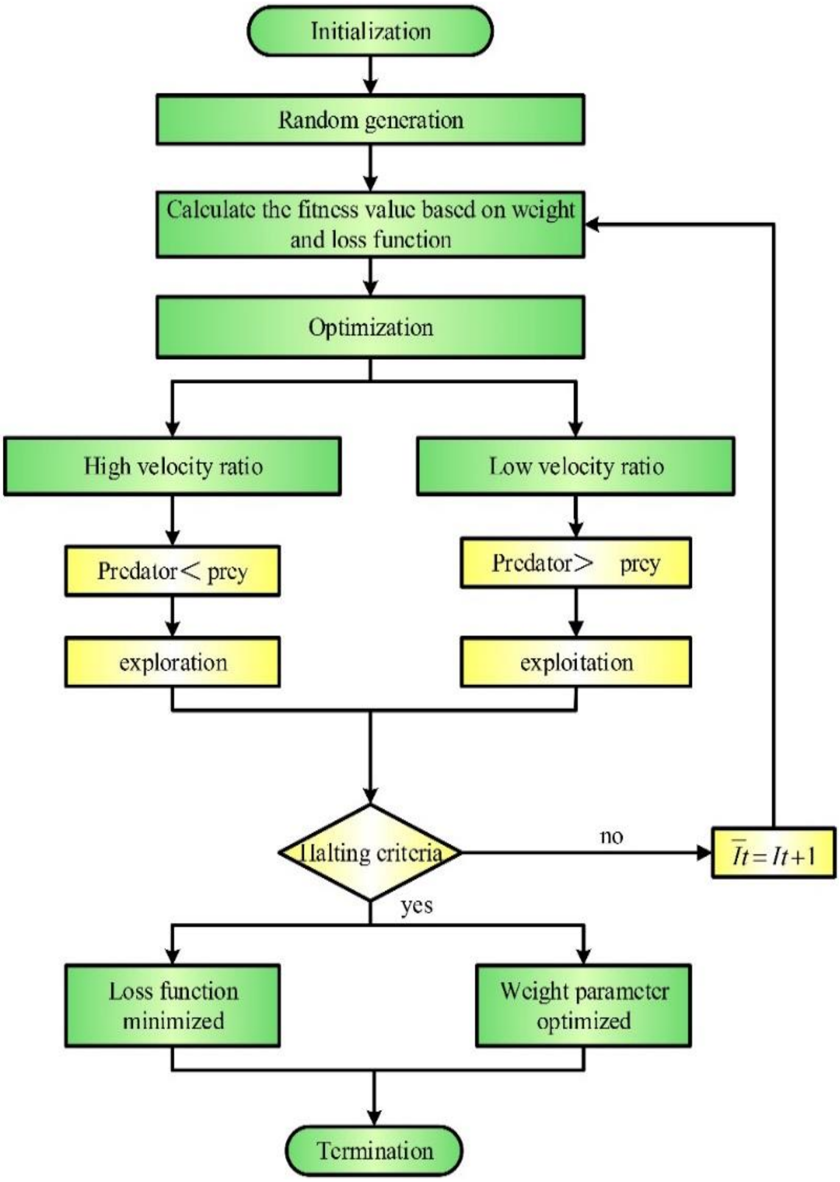


Fig. 3. Flowchart of AMPA

4 Results and Discussions

This research work explains the experimental outcomes for BSNN optimized with AMPA. The exact identification of loan has been attained proficiently by classifying as approve loan or reject loan. The introduced approach is implemented using PYTHON. The performance evaluation is done using the metrices like accuracy, precision, specificity, sensitivity, F1-score and computational time. The data for credit risk assessment is collected from the credit risk dataset.

4.1 Evaluation metrics

The performance of retrieval techniques is typically assessed using the measure of accuracy, precision, specificity, sensitivity, F1-score and computational time.

- *True positive rate* $(t'p'r')$: correctly classified as rejected loan
- *True negative rate* $(t'n'r')$: correctly classified as approved loan
- *False positive rate* $f'p'r'$: incorrectly classified as rejected loan
- *False negative rate* $f'n'r'$: incorrectly classified as approved loan

4.1.1 Accuracy

It measures the proportion of accurate classifications to the dataset's overall proceedings count. It is given by eqn. (25) [44].

$$accuracy(A') = \frac{t'p'r' + t'n'r'}{t'p'r' + t'n'r' + f'p'r' + f'n'r'} \tag{25}$$

4.1.2 Precision

Precision is calculated using eqn. (26).

$$precision(P') = \frac{t'p'r'}{t'p'r' + t'n'r'} \tag{26}$$

4.1.3 Sensitivity

Sensitivity is calculated using eqn. (27) [45].

$$sensitivity(S'en) = \frac{t'p'r'}{f'p'r' + t'n'r'} \tag{27}$$

4.1.4 Specificity

Specificity is calculated using eqn. (28) [46].

$$specificity(S'pe) = \frac{t'n'r'}{f'n'r' + t'p'r'} \tag{28}$$

4.1.5 F1-score

An F1-score is the harmonic mean of a system's precision and recall values which is calculated using eqn. (29) [47].

$$F1 - score = 2\left(\frac{P' \times S'en}{P' + S'en}\right) \tag{29}$$

4.1.6 Computational period

Computational period is the time taken to classify a loan as approved or rejected. It is expressed in eqn. (30).

$$Computational\ time(C_t) = \frac{L' * CPI}{R'} \tag{30}$$

where L' represents the count of loans, CPI is Cycles Per Instructions and R' denotes the computational period.

4.2 Statistical analysis

This research work also check the statistical stability of the ABSMPNN using Paired-t-test and ANOVA.

- By paired-t-test, ABSMPNN achieves a statistic value= 2.6, probability (p-value)= 0.029 and degree of freedom (df)= 9.
- By ANOVA, ABSMPNN achieves a statistic value=4.63, p-value= 0.016.

Thus, the p-values are lesser than 0.05, credit risk assessment using ABSMPNN is statistically significant.

4.3 Performance evaluation

The results of the dataset in this research work are categorized as the samples of class 0 (loan rejection) and class 1 (loan approval). Due to the low default rate, there is a substantial class imbalance in the credit registry, and the objective is to accurately anticipate the minority class.

The confusion matrix is used to evaluate the introduced ABSMPNN's performance. Rows and columns represent the predicted and actual label instances. As in Fig. 4, 0 and 1 represents the rejection and approval of loan respectively. Both the actual and predicted classes are predicted and the approval and rejection of the loan application is based on the confusion matrix's output.

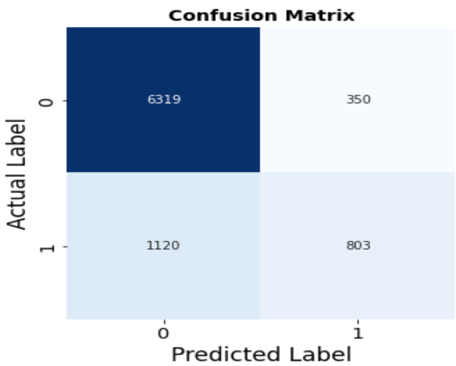


Fig. 4. Confusion matrix

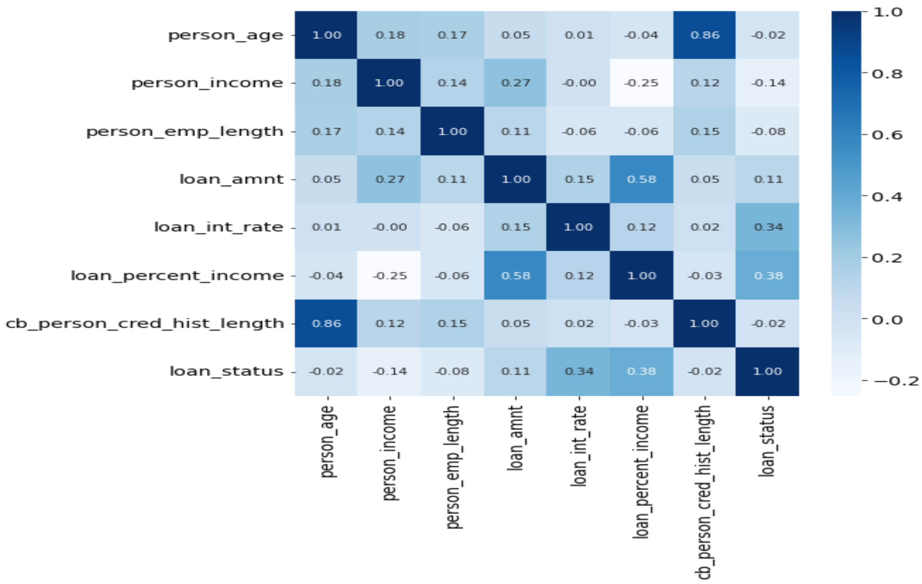


Fig. 5. Correlation study of features

To omit redundant or inappropriate features that interrupt the model's performances, the correlation matrix is used with appropriate coloring representing feature correlation. According to Fig. 5, the diagonal row represents the higher correlation. Positive correlations help for better predicting approval and rejection of loan.

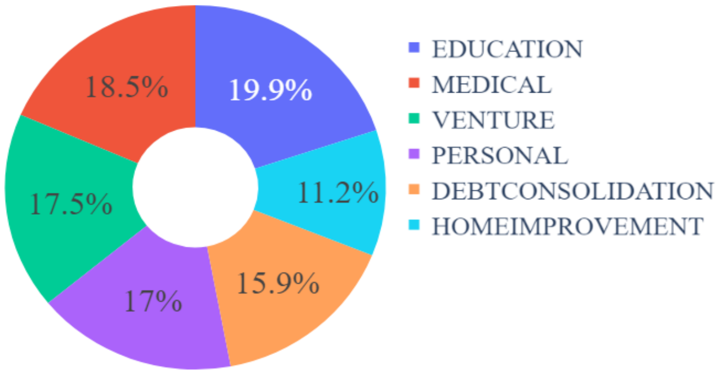


Fig. 6. Proportion of loan intent

Fig. 6 depicts the proportion of loan intent. The customers apply for various purpose of loan like education (19.9%), medical (18.5), venture (17.5%), personal loan (17%), debt consolidation (15.9%), and home improvement (11.2%). Fig. 6 shows that most of the customers apply for educational loans in the credit risk dataset.

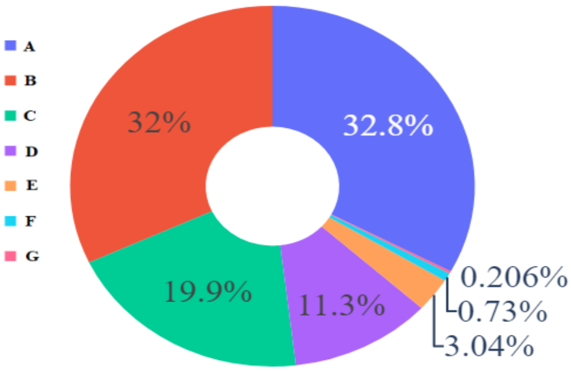


Fig. 7. Proportion of loan grades

Fig. 7 depicts the proportion of loan grades. Grading of loan is done for assigning a quality score to a loan application to identify a risk of default. The proportion of loans as grade A is 32.8%, grade B is 32%, grade C is 19.9%, grade D is 11.3%, grade E is 3.04%, grade F is 0.73% and grade G is 0.206%. The risky customers for the loan are identified more in grade A category.

The age categories of customers who apply for loans are portrayed in Fig. 8 The customer's age and the number of loan applications are represented in X-axis and Y-axis. Fig. 8 depicts that, as the customer's age increases, the application for a loan exponentially decreases. It shows more rejections (in blue line) and approval (in orange line) of loans are obtained to customers between the age of 22 to 26.

Fig. 9 depicts the credit history length of the customers. X-axis represents the customer's credit history length and Y-axis represents the number of loan applications. From Fig. 9, the customer's accounts have been reported open at credit history length 3 in case of loan rejection (blue) and credit history length 2 in case of loan approval (orange). Also, the number of approved and rejected loans gradually decreases with an increase in credit history length.

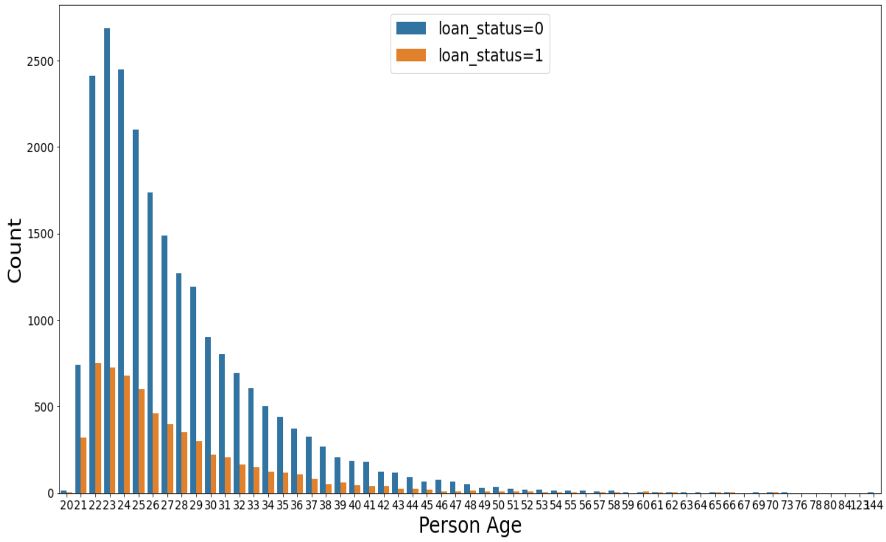


Fig. 8. Customers by age

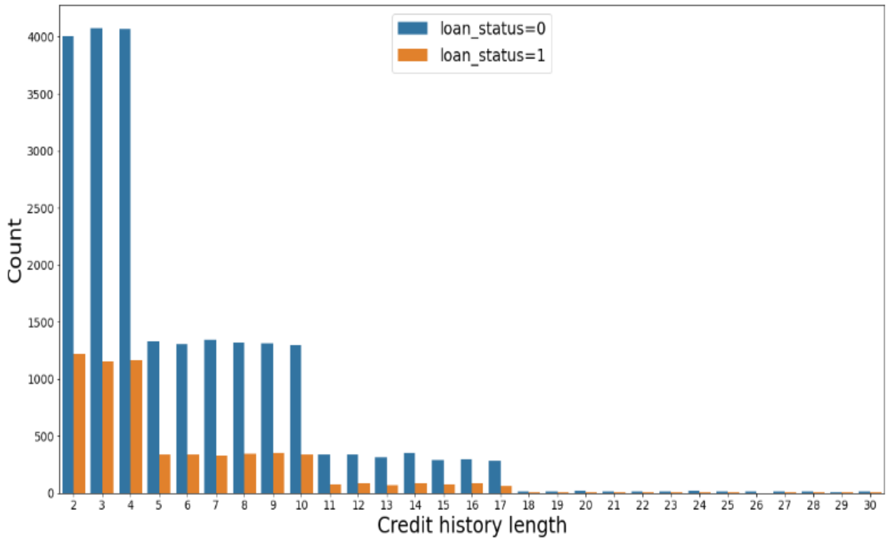


Fig. 9. Customers credit history length

Fig. 10 shows the loan grading of the customers (in X-axis) with total loan applications (in Y-axis). This grading allocates a superiority score based on customer's credit history in order to decide whether to approve or reject the loan application. The risk of default on the loan application of the customers is identified more at grade A loan (indicated in blue), and the approval of default is more at grade D loan (indicated in orange).

This work describes the status of the loans in Figs. 11 and 12. The total count of people with rejected loans is 22435, and the number of people with approved loans is 6203 as in Fig. 11. Fig. 12 represents the proportion of rejected and approved loans as 78.3% and 21.7%. From the above result, it is noted that ABSMPNN accurately identifies the risky customers and rejects the loan for them.

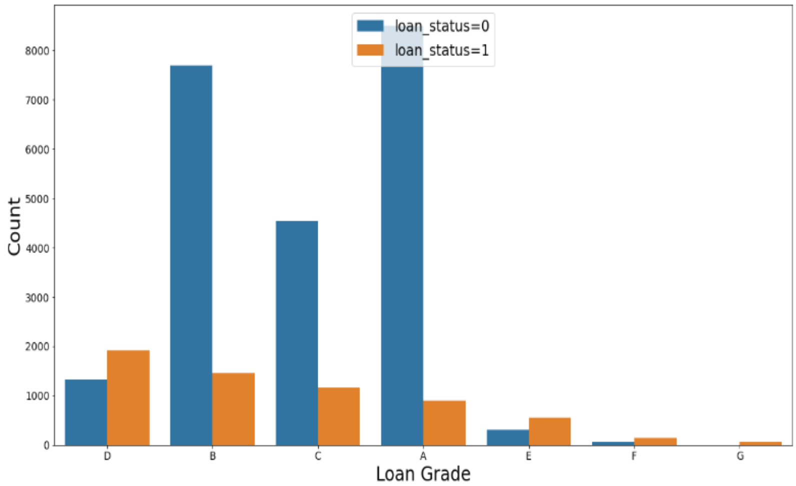


Fig.10. Customers by loan grade

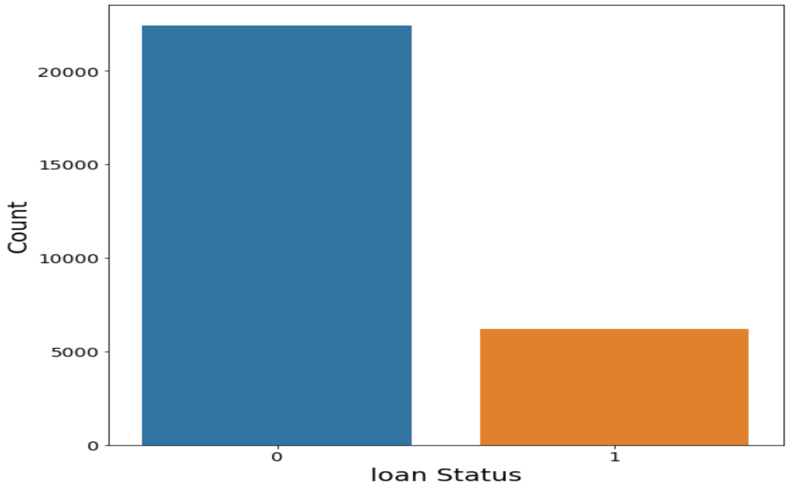


Fig. 11. Loan status

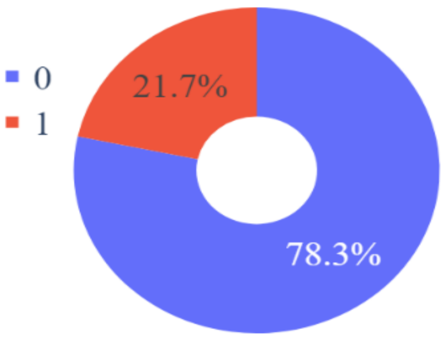
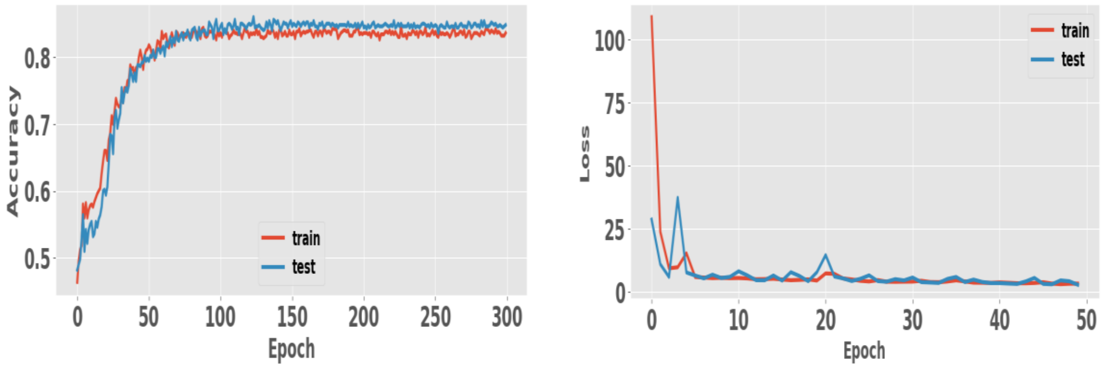


Fig. 12. Proportion of loan status

Figs. 13(a) and (b) displays the accuracy and loss curves of the positive and negative sample's classification scores of predicted by the ABSMPNN throughout the training stage. The total number of epochs is configured to be 300 and 50 for accuracy and loss curves. The accuracy curves increase dramatically until 70 epochs and remain constant over 300 epochs. The test and train accuracy are almost the same but at some epochs, test data is higher than the training accuracy. Similarly, the loss curve gradually decreases with increases in epochs and achieves a convergence in 5 epochs which shows the training stability of ABSMPNN.



(a) (b)

Fig. 13(a) Accuracy and (b) loss curves

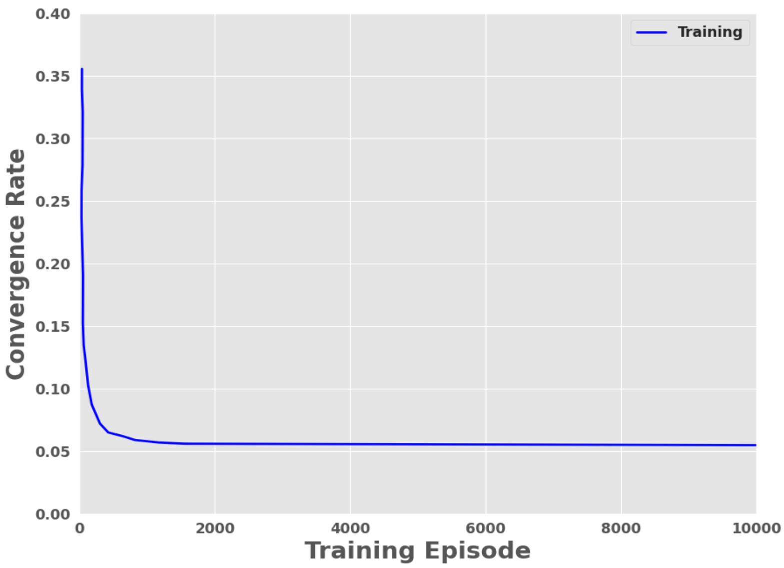


Fig. 14. Convergence rate

The convergence curve for the number of training episodes is depicted by Fig. 14. The convergence rate of ABSMPNN decreases dramatically at the starting and achieves a faster training convergence with increases in training episodes. It is observed that, 1000 training episodes is enough to guarantee the ABSMPNN's convergence with fewer time steps, because this research work uses a linear approximation procedure for loss function updation in order to achieve improved training stability.

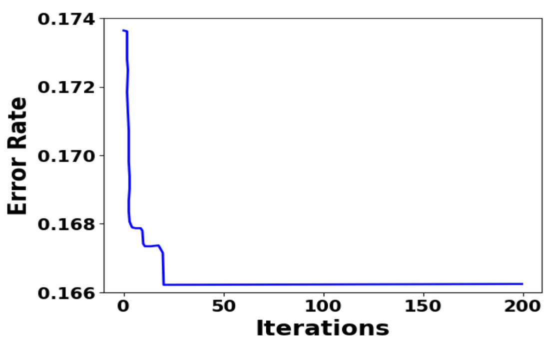


Fig. 15. Error rate

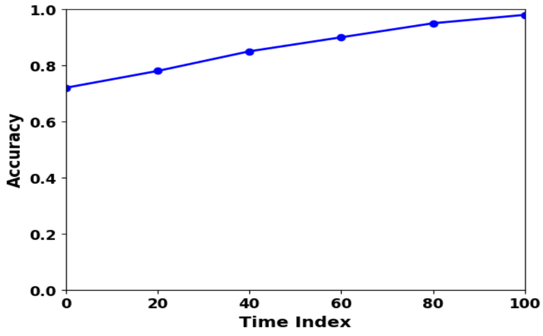


Fig. 16. Accuracy

The loss function of the ABSMPNN is set as the fitness function of the introduced approach to be minimized. The correlation of the overall iterations with respesct to the loss function is depicted in Fig. 15. As the number of iterations increases, the introduced approach effectively optimizes the fitness function with minimized loss function.The convergence value of the loss function is achieved within 25 iterations. Fig. 16 is a graphical representation illustrating the accuracy rate trend throughout the training process, relative to the time index. The chart clearly indicates a progressive rise in network accuracy as time advances. This observation validates both the introduced network convergence concept and the network's efficacy in SPP.

5 Discussion on Performance Evaluation

The performance of ABSMPNN is compared with several previous techniques such as MADM [17], BPNN [18], FNN [19], MLGA [16] and has been proved that ABSMPNN effectively identifies the customer credit quality in the banking sector. The overall performance of ABSMPNN is depicted in Figs. 17-22.

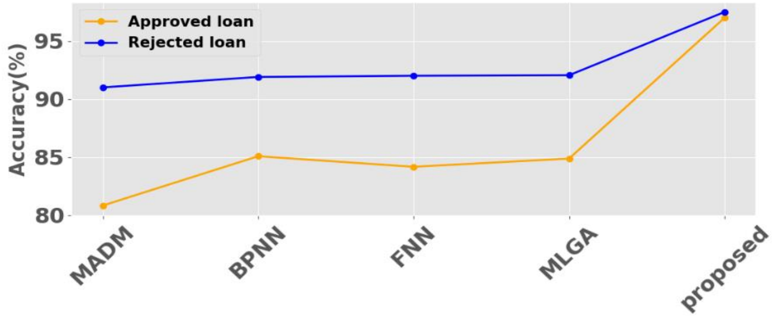


Fig. 17. Comparison of accuracy

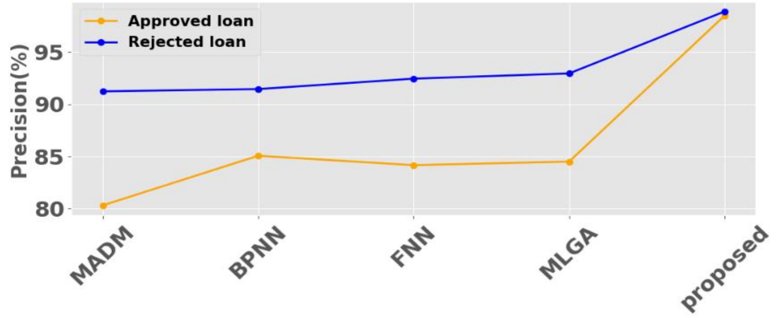


Fig. 18. Comparison of precision

Fig. 17 illustrates the accuracy of ABSMPNN to classify the loan application as approved loans or reject loans by identifying the credit risk quality. ABSMPNN is compared with four other techniques and it is proven that the overall accuracy of the ABSMPNN is 99% in rejected loans and 98.8% in approved loans. By optimizing the weight and loss function parameters of BSNN with the high and low velocity ratio of the AMPA's exploration and exploitation, the accuracy rate of the introduced model increases intensely than previous approaches.The precision rate of ABSMPNN in Fig. 18 is 99.1% in rejected loans and 98.9% in approved loans. This precision rate is comparatively higher than other techniques such as MADM (91.5% in case of rejected loans and 80.3% in case of approved loans, BPNN (92% in case of rejected loans and 85% in case of approved loans), FNN (93% in case of rejected loans and 84.5% in case of approved loans) and MLGA (93.2% in case of rejected loans and 84.9% in case of approved loans).

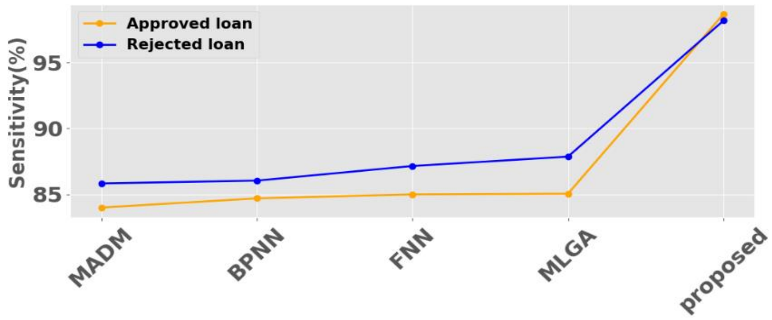


Fig. 19. Comparison of sensitivity

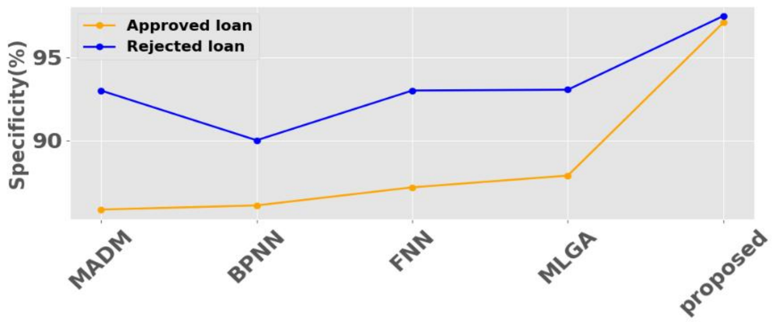


Fig. 20. Comparison of specificity

The sensitivity and specificity rate of the ABSMPNN is analyzed using Figs. 19 and 20. From Fig. 19 it is noted that the overall sensitivity rate of ABSMPNN is 99.2% in approved loans and 99% in case of rejected loans. But the precision of previous techniques such as MADM (83% in case of approved loans and 86% in case of rejected loans, BPNN (84.9% in case of approved loans and 86.1% in case of rejected loans), FNN (85% in case of approved loans and 87.3% in case of rejected loans) and MLGA (85.1% in case of approved loans and 88% in case of rejected loans) is comparitively lower than the introduced model. The overall performance comparison is depicted in the below Table 6.

The overall specificity rate of ABSMPNN in Fig. 20 is 97.3% in case of approved loans and 97.6% in case of rejected loans. This specificity rate is comparatively higher than other techniques such as MADM (85.9% in case of approved loans and 93% in case of rejected loans, BPNN (86.1% in case of approved loans and 90% in case of rejected loans), FNN (87.7% in case of approved loans and 93.1% in case of rejected loan) and MLGA (88% in case of approved loans and 93% in case of rejected loans).

Table 6 Performance metrices comparison

Metrices		MADM [17]	BPNN [18]	FNN [19]	MLGA [20]	**Introduced/ Proposed**
Accuracy (%)	Rejected	91	92.5	92.3	92.7	**99**
	Approved	81	85	84	85	**98.8**
Precision (%)	Rejected	91.5	92	93	93.2	**99.17**
	Approved	80.3	85	84.5	84.9	**98.9**
Sensitivity (%)	Rejected	86	86.1	97.3	88	**99**
	Approved	83	84.9	85	85.1	**99.2**
Specificity (%)	Rejected	93	90	93.1	93	**97.6**
	Approved	85.9	86.1	87.7	88	**97.3**
F1-score (%)	Rejected	93.2	93.8	93	93.1	**99**
	Approved	85.9	86	88	88	**98.3**
Computationl time (sec)	Rejected	0.65	0.45	0.42	0.32	**0.15**
	Approved	0.55	0.49	0.35	0.38	**0.2**

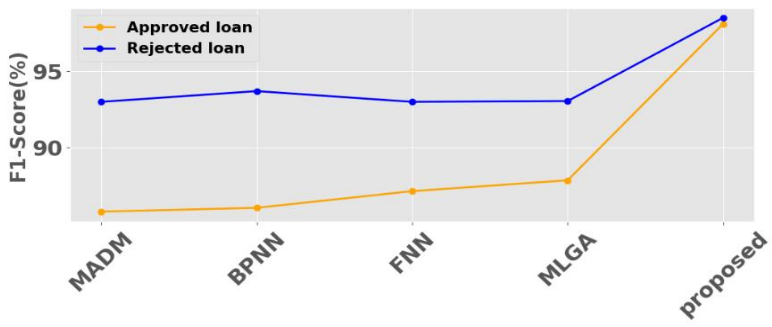


Fig. 21. Comparison of F1-score

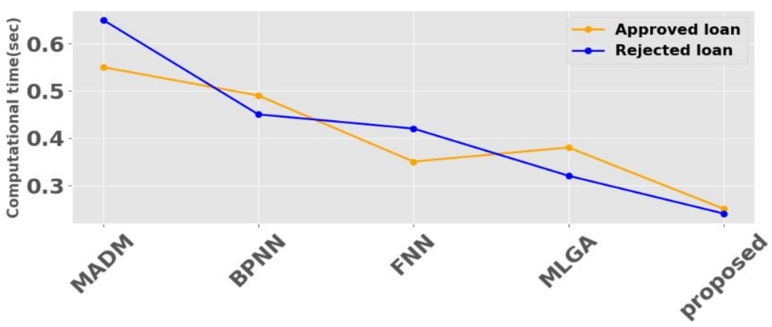


Fig. 22. Comparison of computational period

When both precision and sensitivity of ABSMPNN is higher, F1-score automatically increases (99% in case of rejected loans and 98.3% in case of approved loans) as depicted in Fig. 21. The ABSMPNN's computational period in Fig. 22 for classifying loan applicaiton as approved and rejected are 0.15s and 0.2s respectively which are reasonably lower thaan traditional methods because of the removal of irrelevant and noisy data by MCF-based preprocessing. Further, VCHA permits only the optimal features for classification by updating its concenration phase for reducing the computational duration.

Similarly, the effectiveness of ASBMPNN in accuracy, time complexity and training process is proven by comparing it with the recent state-of-the art like MRMR [29], PSO-XGBoost [27], ELM [30], MA-BPNN [20], ML [24] and GANN [22].

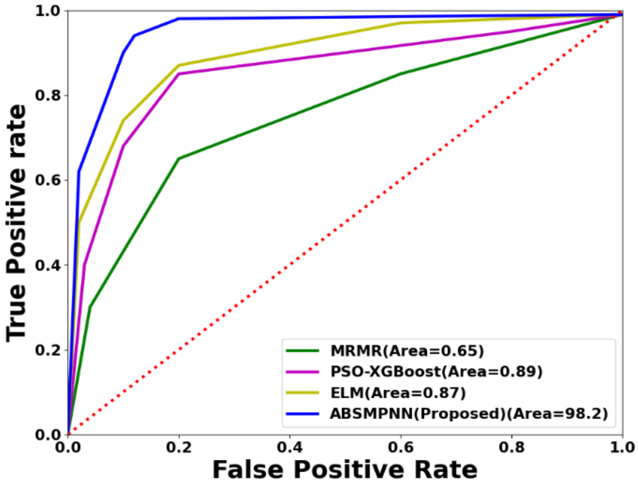


Fig. 23. ROC curve

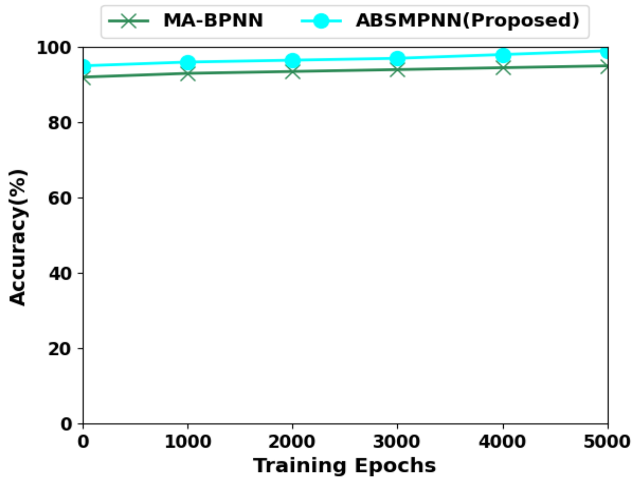


Fig. 24. Accuracy vs training time

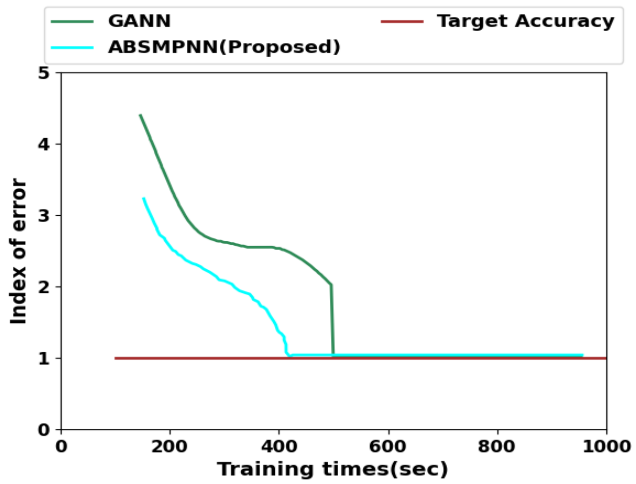


Fig. 25. Error index

The introduced SPP method's overall performance is evaluated using the ROC curve presented in Fig. 23. The area under the curve, which measures 0.98, attests to the introduced method's efficacy than other state-of-the-art like MRMR, PSO-XGBoost and ELM. Additionally, the margin curve offers support for the stability and comprehensibility of the ABSMPNN. As depicted in Fig. 24, the formal credit risk assessment model designed in this research demonstrates remarkable accuracy. When contrasted with the traditional MA-BPNN approach, the predictive accuracy surpasses 95% throughout the training period spanning from 0 to 5000 epochs. This superiority is attributed to adept feature selection in the research dataset and the optimization of neural network performance through the manipulation of weight and loss function parameters using AMPA. Fig. 25 depicts the training process various models. As evident in the Fig. 25, the conventional GANN model required 52 training steps to reach the desired level of accuracy. In contrast, the newly introduced ABSMPNN algorithm evaluation model accomplished the same accuracy goal in just 418 steps. This highlights the training efficiency achieved by integrating the linear approximation update into the BSNN framework.

Table 7 Performance metrices evaluation on Kaggle datasets

Kaggle datasets	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-score (%)	Computational period (s)
Give me some credit [28]	92.9	-	82	-	-	-
Personal auto loan dataset [27]	78.05	78.27	77.45	-	-	24
Credit card dataset [21]	78	-	-	81	-	-
Credit card fraud dataset [48]	97.16	95.98	97.82	-	-	-
Credit Risk Dataset (used in introduced work)	**98.9**	**99.035**	**99.1**	**97.45**	**98.65**	**0.175**

The introduced model is also evaluated with similar Kaggle datasets to prove the performance analysis as depicted in Table 7. When compared with similar Kaggle datasets, the introduced approach performs better credit risk assessment in banking sector.

Table 8 Overall accuracy and running time comparison

Techniques	Accuracy (%)	Overall Time (s)
PSO-XGBoost [27]	83.11	24
GANN [22]	94.17	6.154
ML [24]	93.7	32.9
Introduced/ Proposed	**98.9**	**4.3**

Table 8 provides a comparison of different techniques based on their accuracy and the time it takes for them to complete the overall process. The introduced technique stands out with the highest accuracy of 98.9%, indicating that it has the best predictive performance among the listed techniques. Additionally, it is efficient in terms of time, taking only 4.3 seconds to complete the task.

6 Conclusion and Future Scope

Thus, the credit risk assessment in the banking sector using an ABSMPNN is successfully implemented using PYTHON. Introduced ABSMPNN model accurately identified the credit risk quality and classifies the loan application as approved or rejected within a short period. An effective feature selection strategy is achieved by VCHA’s concentration phase which automatically limits the computational duration. This suggested credit risk assessment is an alternative source of useful data that aids banks in making wise choices about granting loans. The training steps in the classification process is reduced with faster convergence rate by the linear approximation of network’s loss function. The classification accuracy is improved quickly by using the AMPA by optimizing the weight parameter and minimizing the loss function of BSNN. The implementation results show that ABSMPNN performs better in accuracy, precision, sensitivity, specificity, F1-score, and computational period than other existing methods. Customers’ credit risk from the credit risk dataset is effectively predicted utilizing historical loan data across all banks. In future, the credit risk evaluation will be immensely guided by automation. Another direction of future research is to conduct an experimental evaluation on the other kernel functions using different types of datasets and validate the real time applicability of the introduced model. While DL shows great promise for credit risk assessment, it also raises challenges related to data privacy, potential biases in training data, and regulatory compliance. Addressing these concerns will be crucial for ensuring the responsible and effective deployment of DL models in credit risk assessment in the future.

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