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Optimizing Credit Risk Assessment in Banking Human Resource Management: A Enhanced Humboldt Squid based Probabilistic Spiking Neural Networks with Shunted Self-Attention

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Abstract: The movement of capital, integration, distribution, and social supply and demand adjustment are all greatly aided by commercial banks; yet, integrating credit risk assessment is a difficult task for banking Human Resource Management (HRM). To overcome these issues, a novel credit risk assessment in HRM frameworks is done using the Enhanced Humboldt Squid based Probabilistic Spiking Neural Networks with Shunted self-attention (EHSPNN-SSA) method is proposed. Initially, the input commercial bank datasets are taken from General Data Protection Regulation (GDPR) and Advanced Analytics of Credit Registry (AACR) Datasets. Then these data are pre-processes using Grid-Restricted Data Filtering Approach (GRDFA). After that, the data is extracted using Hybrid Absolute deviation factors (ADFs) class document frequency (CDF) (hyb ADF-CDF) based feature extraction method. Then these data are classified using Enhanced Probabilistic Spiking Neural Networks with Shunted self-attention (EPSNN-SSA) and optimized using the Humboldt Squid Optimization Algorithm (HSOA). The framework is validated using real-world banking data and compared to existing methods to demonstrate its efficacy in assessing credit risk and optimizing human resource management processes. The results show that the introduced approach performs better than previous approaches in a number of performance measures, including risky data accuracy (99.6%), non-risky data accuracy (99.7%), and risky data accuracy (99.4%) for dataset 1 and dataset 2, respectively. This indicates the method's exceptional effectiveness and room for advancement in the field.

Index Terms: Credit Risk Assessment; Commercial Banks; General Data Protection Regulation; Grid-Constrained Data Cleansing; Human Resource Management (HRM)

1. Introduction

These days, supply chain management (SCM) has emerged as a substitute for declining credit availability amongst small and medium-sized businesses and their financing providers. In contrast to traditional borrowing, SCM allows the corporation to expand its funding to businesses both upstream and downstream [1, 2]. Recently, creditors that invest small, entrepreneurial businesses with SCM have accepted it as a workable alternative to SCR. One of the issues with accounting is the capacity to predict business borrowers' delays with accuracy [3, 4].

A company's logistic network encompasses all of its activities from the point of acquisition of beginning supplies to the point of customer delivery of finished goods [5]. Several logistical components are commonly referred to as being "upstream" or "downstream" in language [6]. Materials are obtained by a corporation via its manufacture and investigation. "Supply methods" describes the steps involved in getting the finished item from the company to the customer [7]. Logistic network administration is the process of converting raw materials into completed goods. In order to gain a competitive advantage and maximize client fulfillment, it is imperative that you proactively optimize your supply-side procedures [8], [9].

Traditional credit risk assessment models primarily rely on financial indicators while overlooking critical operational risks associated with HRM. However, workforce structure, employee turnover, and managerial decision-making significantly impact a company's financial stability and repayment capabilities [10]. High employee turnover, inefficient workforce allocation, and skill gaps within an organization can lead to operational inefficiencies, reduced productivity, and increased financial instability, thereby affecting a company's creditworthiness.

For more effective credit risk assessment, HRM indicators including employee turnover rates, leadership continuity, payroll obligations, and productivity indexes of employees are integrated [11]. These indicators allow for an assessment of the efficiency of a firm's operations and, therefore, a more informed assessment of probable risks involved in loan approvals outside the conventional financial indicators. Using the EHSPNN-SSA model, HRM data is analyzed along with financial and SCM indicators, allowing for an integrated assessment of corporate customers. Inclusion of these operating items improves forecasting accuracy and allows for credit decisions that take account of both financial risks and labor-related risks.

1.1 Novelty and Contribution:

The Novelty and Contribution of this manuscript is given as follows:

- In this manuscript, a novel credit risk assessment in HRM frameworks is done using the Enhanced Humboldt Squid based Probabilistic Spiking Neural Networks with Shunted self-attention (EHSPNN-SSA) method is proposed.
- Grid-Restricted Data Filtering Approach (GRDFA) [12] is to enhance the quality of credit risk data by partitioning it into grid cells, calculating local statistics, and adaptively filtering out noise and outliers. This pre-processing technique is used to improve the accuracy and robustness of predictive models for better credit risk assessment and decision-making in the financial industry.
- The Hybrid Absolute Deviation Factors (ADFs) and Class Document Frequency (CDF) method (Hyb ADF-CDF) enhances credit risk assessment by combining statistical dispersion (ADF) with class-based frequency analysis (CDF) [13]. This hybrid approach identifies features that are both variable and discriminative, improving the predictive accuracy of credit risk models.
- The objective is to classify credit risk data using Enhanced Probabilistic Spiking Neural Networks with Shunted Self-Attention (EPSNN-SSA) [14], and optimize Humboldt Squid Optimization Algorithm (HSOA) model [15]. This strategy seeks to enhance classification accuracy, reduce error rates, and enhance computational efficiency in credit risk assessment.
- Finally, proposed framework is validated using real-world banking data, demonstrating its efficacy in accurately assessing credit risk while optimizing human resource management processes.

Sections two, three, four, and five of this manuscript are devoted to reviewing the literature, proposing a methodology, discussing the results, and integrating credit risk assessment with human resource management, section 6 6 Strengthening the Link Between Credit Risk Assessment and HRM Processes, section 7 conclusion and future work.

2. Literature Survey

The existing papers related to Credit risk assessment are explained below:

Tian and Li. [16] have presented the machine learning techniques for credit risk analysis in digital banking. It aims to create a reliable model using real credit registry data and combines structural decision tree learning (SDTL) framework with the particle swarm optimization (PSO) techniques. The PSO_SL model extracts and categorizes variables, and real-time data collection is used. Python simulations yield best results. By using the suggested technique, the accuracy is increased and the conceptual error rate is reduced.

Liu et al. [17] have suggested a deep learning and Back Propagation Neural Network (BPNN) to predict financial hazards related to the internet. It found that China's GDP expansion patterns are V and L, with the M2 trend being reversed. The model predicts volatility in 2021, contributing to the development of a more sophisticated early warning system for financial hazards.

Wei. [18] have suggested explores the use of machine learning-based linear regression techniques (ML-LRA) in credit risk systems, specifically for supplier credit risk evaluation using supply chain management. The research highlights the importance of ML-LR techniques in various business operations.

Zhao and Li. [19] have introduced BP neural network algorithm, a supply chain finance model, has been developed using SVM and BP neural network methods. The system has undergone testing and training to create risk assessment guidelines, based on factors like risk indicators and government involvement.

Pandey and Bandhu. [20] have presented machine learning system has been developed to evaluate a borrower's credit risk using decision trees and K-Nearest Neighbor techniques. The system uses the University of California Irvine Machine Learning Repository's 30,000 samples to determine the likelihood of financing approval. The results demonstrate that the suggested models achieve accuracy of 81.2% and 82.2% for the KNN and decision tree models, correspondingly,

Machado and Karray. [21] have evaluates hybrid machine learning algorithms for forecasting business client credit scores. Results show hybrid models outperform their supervised counterparts, and their predictive performance is stronger when historical credit ratings are incorporated, despite existing research.

Mahbobi et al. [22] have suggested algorithm that uses oversampling and undersampling techniques to improve initial payment forecast accuracy on a 30,000 unbalanced dataset. The ALL-KNN sampling technique achieves 98.6% accuracy, providing improved understanding of neural network function and enabling more precise credit risk evaluations in real-world scenarios. The summary of reviewed methodologies is displayed in Table 1.

Table 1. Summary of reviewed approaches

References	Methods	Objectives	Limitations
[16]	DT-PSO	To create a classification-based model for credit risk prediction	Conceptual error rate need some more reduction
[17]	BPNN	To predict and assess internet financial risks	Required to improves the timeliness of forecasts
[18]	ML-LRA	Based on supply chain management, evaluation of supplier credit risk	Most critical constraints and obstacles must be examined
[19]	SVM-BPNN	Evaluation of small and medium-sized businesses' credit risk	The performance should be increased
[20]	DT-KNN	Determine the credit risk associated with a specific borrower based on a number of pertinent factors.	This model attained lower accuracy
[21]	unsupervised and supervised ML	Estimating the credit scores of business clients.	Prediction performance is necessary
[22]	ALL-KNN	credit risk assessments by using classifiers	Imbalanced data prediction

2.1 Problem Statement:

The conventional methodology of credit risk evaluation in banking is mainly banked on quantitative financial information to the exclusion of important operational perils associated with human resource administration (HRM) and supply chain management (SCM). This omission renders lending decisions ineffective, especially where evaluating corporate clients with intricate business operations is involved. The main issue targeted by this study is that an integrated model merging financial, HRM, and SCM information is needed in order to improve the precision and efficacy of credit risk analyses.

Credit risk evaluation is an important exercise in the finance and banking sector since it provides the likelihood of default or late payment by creditors who are soliciting credit. Most traditional solutions use statistical and rule-based algorithms, which, being limited by nature, tend not to perform well in interpreting complex patterns as well as the nonlinear relationships seen in credit-related information. In ever-changing finance landscapes, traditional models struggle with good credit forecast.

Literature review identifies some of the issues with conventional and prevailing machine learning (ML) models used for credit risk evaluation, which include low precision through a lack of consideration of intricate interdependencies between financial, HRM, and SCM data, high computational complexity leading to inferior generalization, and higher misclassification errors. Such models tend to be computationally heavy, consuming much computational power during training and inference, and also pose issues related to data security and privacy while processing sensitive financial data [23]. Further, there is a need for ongoing model maintenance to remain effective in ever-changing environments. This study resolves the above limitations by putting forward an integrated model that merges financial, HRM, and SCM information to improve prediction accuracy, minimize error rates, and lower computational complexity and processing time using advanced ML methods. Through improved model performance and the use of a larger dataset, the solution will present a better and more efficient credit risk evaluation method in the banking and finance sector. To resolve these challenges this work is proposed.

3. Proposed Methodology

In this section, a novel credit risk assessment in HRM frameworks is done using the Enhanced Humboldt Squid based Probabilistic Spiking Neural Networks with Shunted self-attention (EHSPNN-SSA) method is proposed [24].

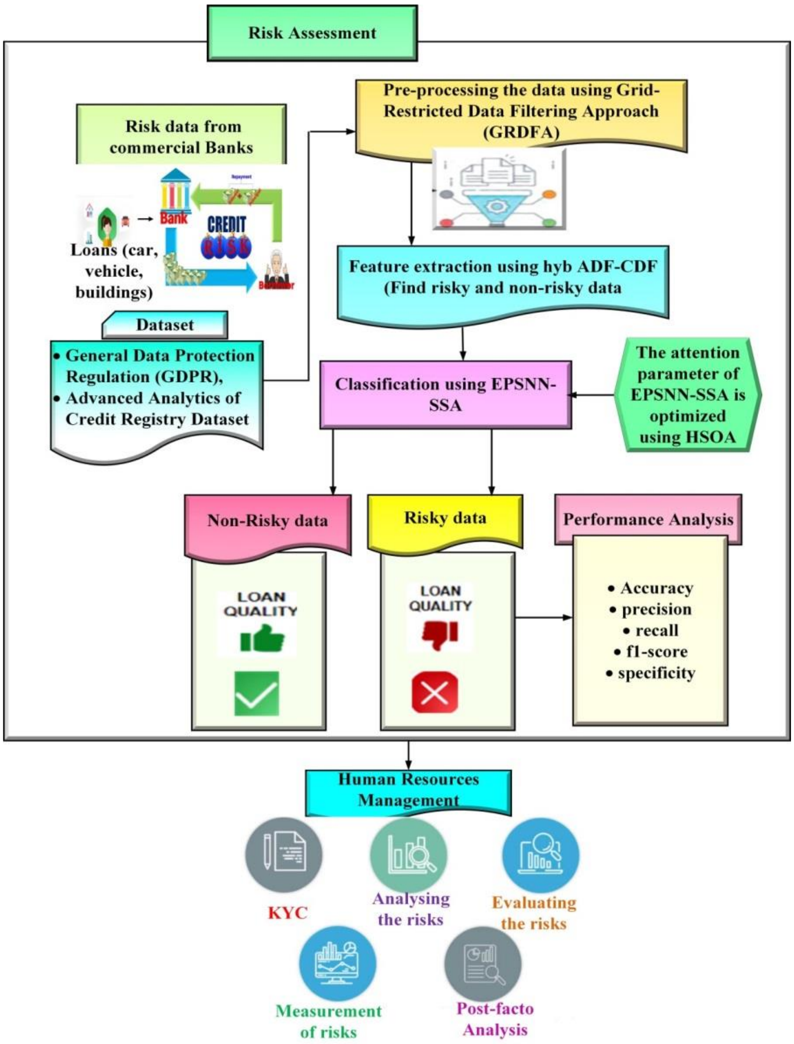


Fig. 1. Workflow diagram of proposed credit risk assessment using EHSPNN-SSA

Fig. 1 shows the Workflow diagram of proposed credit risk assessment using EHSPNN-SSA. First, the input commercial bank datasets are obtained from General Data Protection Regulation (GDPR) and Advanced Analytics of Credit Registry Datasets. Then the data is pre-processes by Grid-Restricted Data Filtering Approach (GRDFA). Then the data is extracted by hyb ADF-CDF based feature extraction method. Then the data are classified by EPSNN-SSA and optimized by the HSOA. The model is shown to be validated through actual bank data and compared against current practices to prove its effectiveness in measuring credit risk and streamlining human resource management processes.

3.1 Data Acquisition

In this, the commercial bank data are collected using two dataset such as GDPR, Advanced Analytics of Credit Registry Dataset.

- General Data Protection Regulation (GDPR)

Here, the commercial bank information are gathered with the help of two dataset like General Data Protection Regulation (GDPR), Advanced Analytics of Credit Registry Dataset. The GDPR dataset [25] is a consolidation of transactional and credit-related information from commercial and savings banks, acting as a major credit point of focus. The initial credit registry database had about 1 TB of information; however, a more precise subset was utilized in this research, with 1,000,000 rows. These files contain detailed credit histories, such as loan sizes, interest rates, borrower demographics, repayment patterns, and anticipated date of completion of loan payments. The dataset also contains metadata regarding loan types, collateral information, and borrower risk categories. Preprocessing to ensure data quality included missing value handling, financial attribute normalization, and class imbalances. The data was tested for representativeness through comparisons of credit risk score distributions and repayment patterns across various banking institutions.

- AACR dataset

The AACR dataset [26] was used to examine credit risk trends, interdependencies, and borrower behavior over various financial institutions. The size of this dataset is about 13 GB, and it consists of structured banking data such as credit performance in the past, default rates, employment details, and sector-based risk segmentation.

Data preprocessing involved detection of outliers, missing value imputation, and feature engineering for improving predictive value. Power BI was utilized to examine correlations among financial, HRM, and SCM variables, using a star schema model to manage data in an efficient manner. Real-world applicability of the dataset was ensured by cross-verifying it with industry benchmarks and financial risk models, ensuring its relevance and strength in forecasting credit risk. Then the pre-processing process are given in next section:

3.2 Pre-processing using Grid-Restricted Data Filtering Approach

Credit risk data tend to have noise, missing values, inconsistencies, and redundant information, which have adverse effects on classification accuracy. To eliminate such problems, the Grid-Restricted Data Filtering Approach (GRDFA) is used as a preprocessing method to clean the dataset prior to analysis. The technique is especially effective in dealing with huge-scale financial datasets like those harvested from General Data Protection Regulation (GDPR) datasets and Advanced Analytics of Credit Registry (AACR) datasets.

The GDPR dataset comprises 1,000,000 commercial and savings bank credit-related records with loan values, interest rates, borrower attributes, repayment habits, types of loans, collateral information, and borrower risk categories. Data preprocessing includes dealing with missing values, normalizing financial features, and classifying data to enhance the quality of datasets, maintaining representativeness through comparison of distributions of credit risk scores and repayment habits in different financial institutions [27]. The AACR dataset with 13 GB of structured financial information from several institutions contains credit performance, default rates, employment status, and sector-wise risk segmentation. Outlier detection, imputation of missing values, and feature engineering for better predictability are a part of preprocessing, with Power BI employed for higher-level analysis, correlating financial, HRM, and SCM factors via a star schema model. The Grid-Restricted Data Filtering Method (GRDFA) improves credit risk data quality by dividing the dataset into grid cells for localized statistical consistency, noise and outlier filtering through adaptive approaches based on financial risk thresholds, and ensuring accurate predictions while avoiding excessive computational overhead, which makes it ideal for time-critical applications such as real-time credit risk assessment.

The input credit risk contains full noises, this will decrease the precision at the time of classification, therefore, the GRDFA is employed. It is utilized to improve the quality of credit risk data by dividing it into grid cells, computing local statistics, and filtering noise and outliers adaptively. This pre-processing method is employed to enhance the accuracy and robustness of predictive models for enhanced financial sector decision-making and credit risk evaluation. In this work, the input is purified using the GRDFA credit risk data in order to make accurate predictions. Unwanted information from the dataset adds complexity and diminishes accuracy.

Step 1: Grid Partitioning

The dataset is divided into grid cells, where each cell contains a subset of financial records categorized based on loan amount, risk level, and repayment history.

Based on this process the pre-processing equations using Grid-Constrained methods are given below (1),

$$r = h(s) + e \tag{1}$$

where, r is represented as the vector of observed credit risk data, s is represented as the state vector representing the true risk status of the while issuing loan, h is represented as the nonlinear measurement function representing the relationship between the credit risk status and observed measurements, e is represented as the measurement error (inaccuracies, noise).

Step 2: Noise Filtering and Adaptive Adjustment

For each grid cell, the **true risk status** is estimated by applying a nonlinear transformation as given in equation (2) with credit risk measurement data m_j for j^{th} and i^{th} customers influenced by various factors, represented by $\theta_{j,}$ $\theta_{i,}$ is calculated in equation (2),

$$M_j = h^{m_j}(\theta_{j,} k_{j,} \theta_{i,} k_{i,}) + e^{m_j}, i€D_j \tag{2}$$

where, H is represented as the operating point, D_j is represented as the set of indices of related credit risk that influence M_j.

Step 3: Outlier Removal & Final Filtering

Outliers are removed by evaluating the Mahalanobis distance M_j as given in equation (3),

$$M_j = H^{m_j} \cdot \Delta\theta_j + h^{m_j}(\theta_{j0}, k_{j,}\theta_{i,}k_i) + e^{m_j}, i€D_j \tag{3}$$

This equations (1-3) offers in-depth GRDFA addresses missing values, outliers, and inconsistencies through ensuring data consistency by systematically discarding duplicate or conflicting records, Minimizes prediction errors through dealing with missing values and aberrant outliers, Enhances computational efficiency through grid-based segmentation, making it appropriate for real-time risk assessment.

This method provides precise predictions with minimal computational overhead, which is appropriate for real-time applications such as credit risk evaluation.

After pre-processing credit risk data, features are extracted through the Hybrid Absolute deviation factors (ADFs) class document frequency (CDF) (hyb ADF-CDF). Then feature extraction for forecasting credit risk assessments are discussed in the next section.

3.3 Feature extraction using Hybrid Absolute deviation factors (ADFs) class document frequency (CDF) (hyb ADF-CDF)

Credit risk evaluation is measuring the probability a borrower will be unable to pay back a loan. Reliable extraction of features is essential to enhance predictive model performance. Hybrid Absolute Deviation Factors (ADFs) and Class Document Frequency (CDF) approach (Hyb ADF-CDF) is a combination of statistical deviation measures and term frequency notions that are used to extract useful features from credit data and enable the model to better discriminate among varying levels of risk [28].

Absolute deviation factors (ADFs)

Absolute deviation factors measure the dispersion of data points around a central value (usually the median). They provide insight into the variability of each feature, which can be critical in understanding the financial stability and risk associated with different borrowers. In this, the Absolute deviation is calculated by given feature Y with values $y_1, y_2, ...y_m$, the median $M(Y)$ is computed initially and its equation is given in (4),

$$M(Y) = median(y_1, y_2, ...y_m) \tag{4}$$

The absolute deviation from the median for each value is then computed using equation (5),

$$Credit_{AD} = \left| y_j - M(Y) \right| \tag{5}$$

The Absolute Deviation Factor (ADF) for the feature is the mean of these absolute deviations are given in (6),

$$Credit_{ADF}(Y) = \frac{1}{m} \sum_{j=1}^{m} Credit_{AD\,j} \tag{6}$$

The equation (6) is the Absolute Deviation Factor (ADF).

Class Document Frequency (CDF)

Class Document Frequency is derived from the concept of term frequency in document classification. In credit risk assessment, it refers to the frequency of particular features (or their specific values) within different risk classes (high-risk vs. low-risk borrowers). In this, the Class Document Frequency is represented as the Y and class X, the credit risk document frequency is given as $Credit_{DF}(Y, X)$, which is represented as the number of instances in class X, when the feature Y occurs and its equation is given in (7),

$$Credit_{CDF}(Y, X) = \frac{Credit_{DF}(Y, X)}{Whole\,credit\,risk\,data\,in\,class\,X} \tag{7}$$

Hybrid ADF-CDF

The hybrid approach combines the insights from ADF and CDF to extract features that are both statistically significant and class-discriminative. This involves integrating the deviation information with the frequency distribution across classes to enhance feature relevance. The hybrid score for a feature Y in class X, is computed by combining its

ADF and CDF values. One possible approach is to use a weighted sum or products of these values are given in equation (8),

$$Credit_{hyb\ ADF-CDF}(Y,X) = Credit_{ADF}(Y) \cdot Credit_{CDF}(Y,X) \tag{8}$$

here, equation (8) is the credit risk assessment feature extracted data, then these data are given to the classifying credit risk into risky and non-risk using EHSPNN-SSA and its explanations are given in next section:

3.4 Classification using EHSPNN-SSA

In this study, credit risk data are classified using Enhanced Probabilistic Spiking Neural Networks with Shunted Self-Attention, optimized by the HSOA (EHSPSNN-SSA) [29]. The proposed EHSPSNN-SSA model integrates Enhanced Probabilistic Spiking Neural Networks (EPSNN) with Shunted Self-Attention (SSA) and optimizes its parameters using the Humboldt Squid Optimization Algorithm (HSOA) to enhance credit risk assessment. While EPSNN mimics biological neurons through spike-based communication for efficient pattern recognition, SSA refines feature selection by dynamically adjusting attention weights, ensuring that crucial financial and HRM-related risk factors are prioritized. HSOA further optimizes hyperparameters by simulating the intelligent foraging behavior of Humboldt squids, leading to improved convergence and classification accuracy. This hybrid approach aims to address limitations in traditional credit risk models by integrating multiple operational factors, yet its novel contribution lies in demonstrating the synergy between these established techniques for a more comprehensive and interpretable risk assessment framework. Fig. 2 illustrates the architecture of EPSNN-SSA, which integrates advanced neural network architectures to enhance the accuracy and robustness of credit risk assessments.

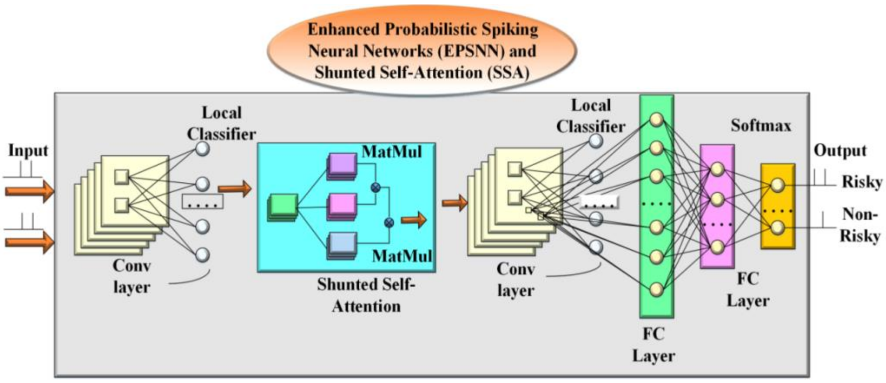


Fig. 2. Architecture of EPSNN-SSA

It is the hybrid of Enhanced Probabilistic Spiking Neural Networks (EPSNN) and Shunted Self-Attention (SSA) and its parameters are tuned with HSOA is Humboldt Squid Optimization Algorithm. The goal of the EPSNN-SSA is to enhance classification accuracy and efficiency for intricate tasks such as credit risk evaluation. By integrating the event-driven, power-efficient computation of spiking neural networks with the selective attention of shunted self-attention, EPSNN-SSA processes high-dimensional data robustly. The probabilistic architecture handles uncertainties and noisy inputs, delivering accurate, dependable predictions. The classification processes are given below:

Enhanced Probabilistic Spiking Neural Networks (EPSNN)

Enhanced Probabilistic Spiking Neural Networks (EPSNN) offer a sophisticated neural computing paradigm that mimics biological neuron dynamics via spike-based signaling and thus is exceedingly good at modeling intricate decision-making processes. In credit risk evaluation in banking Human Resource Management (HRM), EPSNN computes financial, HRM, and Supply Chain Management (SCM) information by examining discrete spike patterns representing complex interdependencies between employee stability, payroll obligations, workforce efficiency, and financial results [30]. With the use of spike timing and firing rates, EPSNN determines minute correlations between manpower management and the creditworthiness of a company, thus providing more accurate risky and non-risky client classification. Through the biologically based method, prediction accuracy is boosted to incorporate HRM-based operational risks in the credit rating model, allowing for more rational and data-supported loan approval decisions. EPSNN is a form of neural network that emulates the operation of biological neurons, specifically in the context of spike-based communication. In EPSNN, neurons convey information by producing discrete spikes over time, and computations are carried out on the basis of the timing and rate of spikes. In this, the membrane potential is modeled as the $M(t)$ of a neuron in EPSNN evolves over time according to the leaky integrate-and-fire dynamics and its equation is given in (9),

$$\lambda_M \frac{dM}{dt} = -M + HN(t) \tag{9}$$

where, λ_M is represented as the membrane time constant, H is represented as the membrane resistance, $N(t)$ is represented as the input current to the neuron at time t. A spike occurs and the potential is reset when the membrane potential reaches a predetermined threshold.

Shunted Self-Attention (SSA)

Shunted Self-Attention (SSA) is a sophisticated attention mechanism that refines feature selection by filtering and prioritizing essential information dynamically and suppressing less important data. In banking Human Resource Management (HRM) credit risk assessment, SSA streamlines the assessment process by selectively highlighting key HRM metrics like employee turnover, leadership stability, workforce productivity, and payroll obligations in addition to financial and Supply Chain Management (SCM) metrics. By diverting redundant noise and highlighting critical risk-signal patterns, SSA guarantees the model captures HRM factor dependence on a company's financial performance accurately. Such a sophisticated attention mechanism enhances risk classification, making it possible to identify creditworthy customers more precisely and minimizing loan approval decision misclassification errors. Self-attention mechanisms have proven to be able to capture long-range dependencies in sequential data. SSA extends this mechanism by introducing shunting inhibition, motivated by neurophysiological observations. Shunting inhibition regulates the information flow in the network, promoting its capacity to attend to important features and inhibit non-important ones. Computation of the attention weights are presented as β_{ji} is combined with the shunting network is given in equation (10),

$$\beta_{ji} = \frac{\exp\left(e_{ji} / \lambda \right)}{\sum_{l=1}^{M} \exp\left(e_{ji} / \lambda \right)} \tag{10}$$

where, e_{ji} is represented as the compatibility score between the j^{th} and i^{th} elements, λ is represented as the temperature parameter controlling the sharpness of the attention distribution. The shunted self-attention mechanism introduces an inhibitory term H that modulates the attention weights and its equation is given in (11),

$$\tilde{\beta}_{ji} = \frac{\beta_{ji} - H}{1 - H \cdot \beta_{ji}} \tag{11}$$

where, $\tilde{\beta}_{ji}$ is represented as the modified attention weight, H is represented as the shunting inhibition parameter.

EPSNN-SSA for Credit Risk Classification

EPSNN-SSA integrates Enhanced Probabilistic Spiking Neural Networks (EPSNN) with Shunted Self-Attention (SSA) to develop a strong classifier for credit risk prediction in banking Human Resources Management (HRM). SSA strengthens the model to concentrate on essential HRM, financial, and Supply Chain Management (SCM) features by dynamically removing noise information and boosting important risk-sustained patterns [31]. In credit risk analysis, SSA guarantees that key HRM considerations—employee turnover, leadership stability, payroll commitments, and workforce effectiveness—are accorded their rightful significance in making decisions. By combining SSA with spike-based computation in EPSNN, EPSNN-SSA accurately captures subtle dependencies among HRM practice and financial well-being of a firm, enhancing credit risk prediction accuracy and streamlining loan approval processes. EPSNN-SSA integrates PSNN and SSA to form a strong classifier for assessing credit risk. It efficiently handles temporal credit information using the spiking dynamics of PSNN and employs SSA to extract relevant features and long-distance relationships. For classification, particularly for credit risk evaluation, one of the most widely used equations is the softmax function, which is frequently employed in the output layer of neural networks for applications with multiclass classification and its classification equation is presented in (12),

$$\Pr ob(x = i|Y) = \frac{e^{f_i}}{\sum_{l=1}^{L} e^{f_L}} f_i \tag{12}$$

where, $\Pr ob(x = i|Y)$ is represented as the probability that the input sample Y belongs to class i, f_i is represented as the output of the neural network for class i, L is represented as the total number of classes. The f_i is the output of the last layer before applying the softmax function. It's often a vector of scores or logits representing the network's confidence for each class. For binary classification (e.g., predicting whether a credit applicant is likely to default or not), typically use a sigmoid function in the output layer. The equation for the sigmoid function is given in (13),

$$\Pr ob(x = i|Y) = \frac{1}{1+e^{-f}} \tag{13}$$

where, $\Pr ob(x = i|Y)$ is represented as the probability that the input sample Y belongs to class 1, f is the output represented. In either situation, once probabilities are received, a decision boundary can be used to find the final class label. For example, in binary classification, if the probability is above 0.5, the sample is labeled as class 1; else it's labeled as class 0. Through the combination of probabilistic spiking neural networks with shunted self-attention, EPSNN-SSA presents a strong paradigm for credit risk classification problems with the ability to learn complicated patterns and relations within the data while giving probabilistic output to evaluate the risk. Then to enhance the classification accuracy and to minimize error rate, processing time and computational complexity the emphasis β_{ji} HPOA is used to optimize the EPSNN-SSA parameter. The HPOA optimization is provided below:

3.5 Humboldt Squid Optimization Algorithm (HSOA) for optimizing attention β_{ji} parameter of EPSNN-SSA

Credit risk evaluation is important in the banking sector, and it needs precise prediction models. EPSNN-SSA is a complex method, but the Humboldt Squid Optimization Algorithm (HSOA) improves its efficiency by adjusting model parameters for best classification. Shunted Self-Attention (SSA) is important as it selectively enhances important HRM, financial, and Supply Chain Management (SCM) features while eliminating unnecessary information. In banking Human Resource Management (HRM), SSA gives higher priority to critical workforce-related measures like employee turnover, leadership continuity, payroll obligations, and workforce productivity, ensuring that these parameters are properly accounted for in credit risk assessment. By optimizing the feature selection procedure, SSA allows EPSNN-SSA to better identify the interaction between HRM practices and financial soundness, resulting in better credit risk forecasts and more prudent loan decisions [32]. In the financial sector, credit risk assessment is essential and necessitates precise prediction models. Although EPSNN-SSA is an advanced method, its performance can be enhanced by the Humboldt Squid Optimization Algorithm (HSOA), which optimizes attention settings and finds pertinent patterns and relationships in the data. In this, the attack of fish schools is employed to optimizing β_{ji} for achieving the optimal outcome, which is to decrease computing complexity, processing time, and error rate while increasing precision. The Fig. 3. shows the flow chart of EPSNN-SSA. The step by step procedures of EPSNN-SSA are given below:

Step 1: Initialization

Set a population of squids' initial positions (attention parameters) and velocities. Let's Y_j represent the position of the j^{th} squid, where a set of weights and biases in the EPSNN-SSA network correspond to each position.

Step 2: Random generation

After completing first step randomly generate the Humboldt squid and fish for achieving the best solution.

Step 3: Fitness Function

The goal function, which uses the fitness function to precisely forecast the credit risk assessment by optimizing attention parameter β_{ji} of EPSNN-SSA network and its equation is given in (14),

$$Fitness\ \ function = Optimizing(\beta_{ji}) \tag{14}$$

Step 4: Attack of fish schools for attaining best solution

By optimizing each squid's position based on its own experience as well as the best experiences of other squids, the attack of fish schools is exploited to increase accuracy equation is given in (15),

$$R^{\dim}_{new.j} = R_{\beta_{ji}} + N_{veloc}.\left(- R^{\dim}_{new.random1} - Pop^{\dim}_{random2}\right) \tag{15}$$

where, $R^{\dim}_{new.j}$ is shown as the initial location of j^{th} The Humboldt squid in $\dim^{th}$ dimension, N_{veloc} is shown as the parameter for locomotion velocity, $R^{\dim}_{new.random1}$ is shown as the role of $random^{th}_{1}$ fish and $\dim^{th}$ dimension, and $Pop^{\dim}_{random2}$ is shown as all of the populations randomly stored in the HSOA memory(0-1), F_{ω} settings to increase the precision.

Therefore, the weight and bias parameters of EHSPNN-SSA are tuned using the HSOA algorithm to precisely predict credit risk for effective loan acceptance.

Step 5: Termination

Once the best answers are obtained using equations (15), end the operation. Additionally, Equation (32) reduces processing time, computational complexity, and error rate while producing the most correct result. This iteration will continue until the halting conditions are met $j = j+1$ is fulfilled. Finally, EHSPNN-SSA's recommended weight and bias parameters are optimized to precisely assess credit risk (both risky and non-risky).

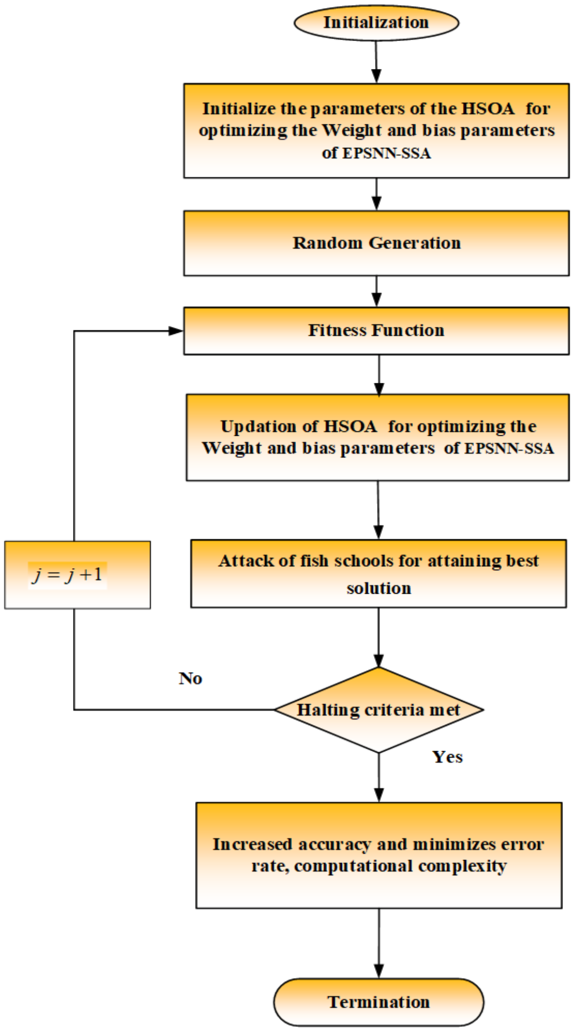


Fig. 3. Flow chart of EHSPNN-SSA

3.6 Credit risk assessment in Human resources Management

It is structured method for identifying, analyzing, measuring, and making decisions about different aspects of credit risk to a person or an organization with regard to products sold, services rendered on credit, or loan approval. This type of management also entails risk elimination as well as risk limitation. There are 5 types of Credit risk assessment in Human resources Management are analyzed in commercial banks to avoid the risks for issuing loans, they are, KYC, Analyzing the Risks, Evaluating the Risks, Measurement of Risk, Post-Facto Analysis and its explanations are given below:

Step 1: KYC

Know Your Customer (KYC) is a key method for gathering client data, which can be obtained through forms, paperwork, or external sources.

Step 2: Analyzing the Risks

In step two, data analysis is conducted on the customer's information, identifying financial and non-financial risks. Creditworthiness, a quantifiable term, is assessed using income, credit card spending, and other sources.

Step 3: Evaluating the Risks

Financial analysis is prioritized over non-financial factors, with 70% weighting financial elements and 50% to non-financial factors. Management determines credit amount and frequency, confirms usage, and provides reasons.

Step 4: Measurement of Risk

Management assigns a credit rating to potential customers and decides credit terms, considering factors like financial status, collateral value, and loan frequency. Customers with better periodicity and creditworthiness pay lower rates, while penal interest rates apply for delayed payments.

Step 5: Post-Facto Analysis

Credit rating organizations monitor customer credit utilization, payments, and promptness for financial institutions, while management reviews and evaluates credit terms for other organizations.

Advantages

- It forecasts the degree of risk that a potential client possesses.
- It portrays the degree of risks.
- It also measures the risk to a specific, quantifiable extent.
- It protects the cash of depositors and reduces the chance of default.
- It assists financiers in lowering the likelihood of default for comparable customers.

The proposed framework addresses credit risk assessment in banking HRM using Enhanced Humboldt Squid based Probabilistic Spiking Neural Networks with Shunted Self-Attention (EHSPNN-SSA). Commercial bank datasets from GDPR and Advanced Analytics of Credit Registry Datasets are pre-processed using GRDFA and features extracted using Hybrid ADFs and CDF. Classified with EPSNN-SSA and optimized via HSOA, the framework is validated with real-world data in Credit risk assessment in HRM, showing superior efficacy. The findings and discussions are presented in the following section analyzed for analyzing the efficiency of the proposed methods.

4. Result and Discussions

The results and discussion of the introduced scheme are described in this section. The implementation of the introduced method is carried out in PYTHON.

4.1 Dataset Description

To classify the credit risk data, two commercial bank datasets are taken, they are Advanced Analytics of the General Data Protection Regulation (GDPR) Credit Registry Dataset and its descriptions are given below:

4.1.1 GDPR Dataset

The GDPR dataset [33] aggregates transactional and credit-related data from savings and commercial banks, serving as a key credit focal point. The original credit registry database contained approximately 1 TB of data; however, a refined subset was used in this study, comprising 1,000,000 rows. These records capture detailed credit histories, including loan amounts, interest rates, borrower demographics, repayment patterns, and the expected date of loan payment completion. The dataset also includes metadata on loan types, collateral details, and borrower risk categories. To ensure data quality, preprocessing involved handling missing values, normalizing financial attributes, and addressing class imbalances. The dataset was assessed for representativeness by comparing distributions of credit risk scores and repayment behaviors across different banking institutions.

4.1.2 Advanced Analytics of Credit Registry (AACR) Dataset

The AACR dataset was utilized to analyze credit risk trends, dependencies, and borrower behavior across multiple financial institutions. This dataset, with a size of approximately 13 GB, comprises structured banking records, including past credit performance, default rates, employment status, and sector-wise risk segmentation.

Of them, 20% are used for testing and 80% are used for teaching.

4.2 Performance metrics

Performance metrics like accuracy, precision, recall, f1-score, specificity, mean square error, computational complexity, computational time, error rate, and convergence rate analysis of the suggested algorithm are examined. The effectiveness of the suggested EHSPNN-SSA method is evaluated by contrasting it with a number of current approaches, including DT-PSO [16], BPNN [17], ML-LRA [18], SVM-BPNN [19], and DT-KNN [20]. Below are the equations for the performance metrics:

- ***True Positive*** P_T **:** Instances where the credit risk assessment correctly predicts a risky (abnormal) credit applicant as risky.
- ***False Positive*** P_F **:** Instances where the credit risk assessment incorrectly predicts a non-risky credit applicant as risky.
- ***False Negative*** N_F **:** Instances where the credit risk assessment incorrectly predicts a risky (abnormal) credit applicant as non-risky.
- ***True Negative*** N_T **:** Instances where the credit risk assessment correctly predicts a non-risky (normal) credit applicant as non-risky.

4.2.1 Accuracy

Accuracy is a measure of overall correctness and is computed as the ratio of correctly predicted data to the total data. This metric is expressed in equation (16),

$$A_{cc} = \frac{P_T + N_T}{P_T + N_T + P_F + N_F} \tag{16}$$

4.2.2 Precision

It focuses on the accuracy of positive predictions and is calculated as the ratio of correctly predicted positive instances to the total predicted positive instances. This metric is expressed in equation (17),

$$P_{recision} = \frac{P_T}{P_T + P_F} \tag{17}$$

4.2.3 Recall

It measures the ability of the model to capture all the relevant data and is calculated as the ratio of correctly predicted positive samples to the total actual correct data. This metric is expressed in equation (18),

$$R_{ecall} = \frac{P_T}{P_T + N_F} \tag{18}$$

4.2.4 F1-Score

It is the harmonic mean of precision and recall, providing a stability between the two metrics. This metric is expressed in equation (19),

$$F_{Score} = 2 \times \frac{P_{recision} \times R_{ecall}}{P_{recision} + R_{ecall}} \tag{19}$$

4.2.5 Specificity

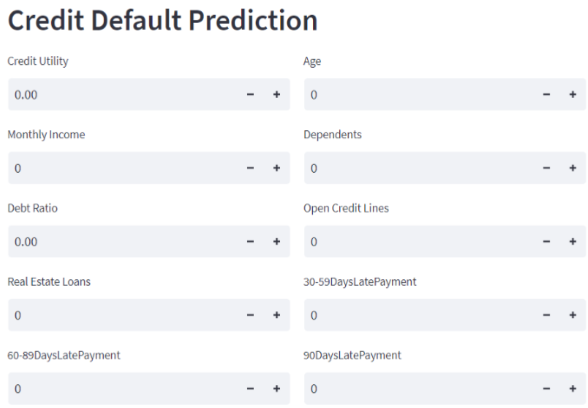
It measures the proportion of true negative instances that are correctly identified by the model out of all actual negative instances and its equations are given in (20),

$$Specificit\,y = \frac{N_T}{N_T + P_F} \tag{20}$$

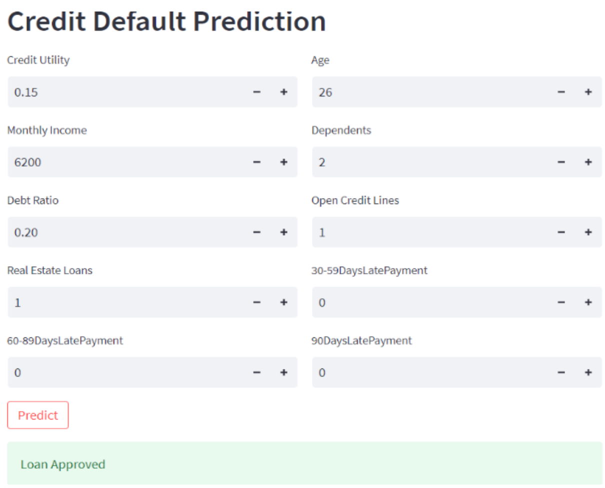
4.3 Performance analysis

In this section, the performance analyses of the proposed method compared with existing methods are analyzed. The performance metrics such as Accuracy, precision, recall, f1-score, specificity, error rate, mean square error, the suggested EHSPNN-SSA method's computational complexity, computational time, and convergence rate are examined, and its effectiveness is evaluated by contrasting it with a number of current approaches, including DT-PSO [16], BPNN[17], [ML-LRA [18], SVM-BPNN[19], DT-KNN[20] respectively.

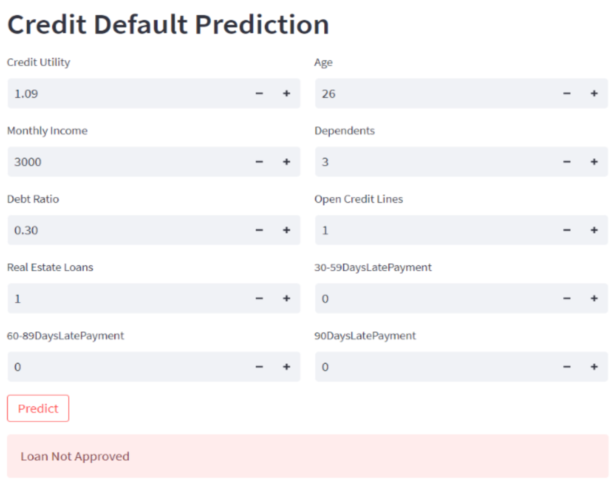
Fig. 4 shows the (a) Credit default predictions, (b) Credit default predictions loan approved, (c) Credit default predictions loan not approved. From Fig. 4 it is noted that the model's estimates of credit default, enabling stakeholders to evaluate the process's performance and make well-informed choices about risk management and loan approval.



(a)



(b)



(c)

Fig. 4. (a) Credit default predictions, (b) Credit default predictions loan approved, (c) Credit default predictions loan not approved

Fig. 5 shows the performance analysis of GDPR dataset for both suggested and current approaches. EHSPSNN-SSA is the suggested approach, and the current approaches including DT-PSO [16], BPNN [17], ML-LRA [18], SVM-BPNN [19] and DT-KNN [20] respectively. Fig. 5 (a) demonstrates the accuracy of the proposed and existing methods. For Accept, the accuracy is 99.81% and reject, the accuracy is 99.68%. According to the results of the simulation, the suggested approach outperforms the other approaches currently in use in terms of accuracy. The accuracy of both the suggested and current approaches is shown in Fig. 5 (b). The precision is 99.16% for acceptance and 99.39% for rejection. According to the results of the simulation, the suggested approach outperforms the other approaches currently in use in terms of precision. The recall of the suggested and current approaches is shown in Fig. 5(c). The recall is 99.82% for accept and 99.74% for refuse. According on the simulation results, the suggested approach outperforms the other current approaches in terms of recall.

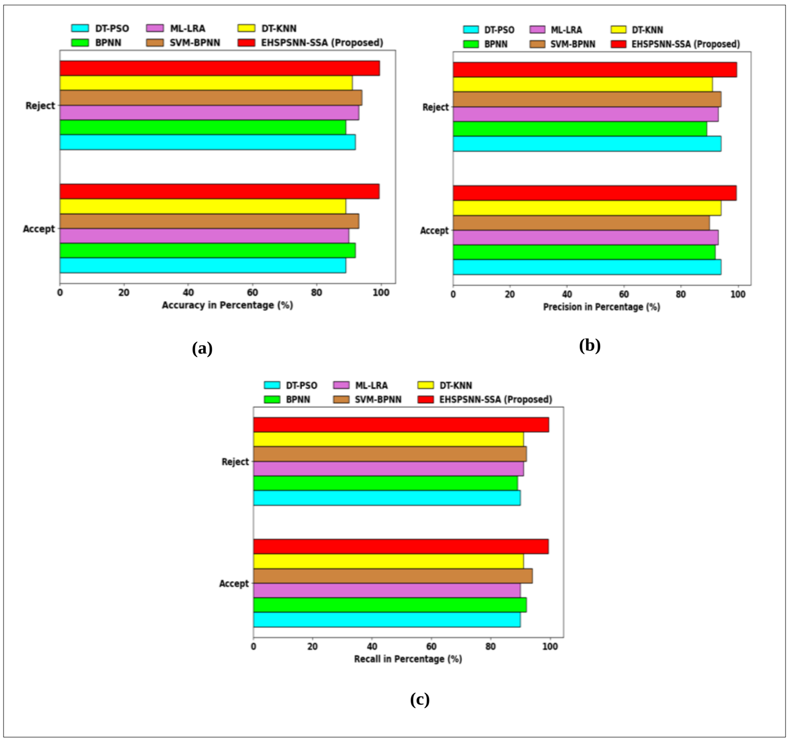


Fig. 5. (a) Performance analysis of Accuracy, (b) Performance analysis of precision, (c) Performance analysis of recall for GDPR dataset

Fig. 6 shows the performance analysis of GDPR dataset for both suggested and current approaches. The suggested approach is EHSPSNN-SSA and the existing methods including DT-PSO [16], BPNN [17], ML-LRA [18], SVM-BPNN [19] and DT-KNN [20] respectively. Fig. 6 (a) demonstrates the F1-Score of the proposed and existing methods. For Accept, the F1-Score is 99.36% and reject, the F1-Score is 99.71%. From the simulation outcomes, the proposed method achieves higher F1-Score as compared to the other existing methods. Fig. 6 (b) demonstrates the specificity of the proposed and existing methods. For Accept, the specificity is 99.52% and reject, the specificity is 99.09%. From the simulation outcomes, the proposed method achieves higher specificity as compared to the other existing methods. Fig. 6 (c) demonstrates the error rate of the suggested and current approaches. Error rates for accept and reject are 0.1 and 0.12, respectively. According to the results of the simulation, the suggested approach has a lower error rate than the other approaches currently in use.

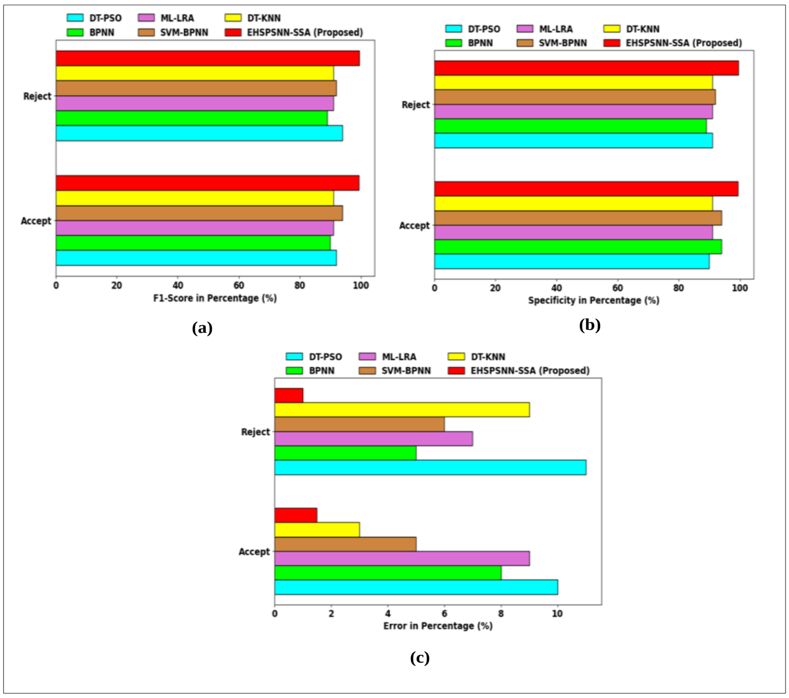


Fig. 6. (a) Performance analysis of F1-score, (b) Performance analysis of Specificity, (c) Performance analysis of Error rate for GDPR dataset

Fig. 7 shows the performance analysis of AACR dataset for both suggested and current approaches. EHSPSNN-SSA is the suggested approach, and the current approaches including DT-PSO [16], BPNN [17], ML-LRA [18], SVM-BPNN [19] and DT-KNN [20] respectively. Fig. 7 (a) demonstrates the accuracy of the proposed and existing methods. For Accept, the accuracy is 99.79% and reject, the accuracy is 99.52%. According to the results of the simulation, the suggested approach outperforms the other approaches currently in use in terms of accuracy. The accuracy of both the suggested and current approaches is shown in Fig. 7 (b). The precision for Accept is 99.84%, and for Reject, it is 99.98%. According to the results of the simulation, the suggested approach outperforms the other approaches currently in use in terms of precision. The recall of the suggested and current approaches is shown in Fig. 7 (c). The recall is 99.75% for accept and 99.16% for reject. According on the simulation results, the suggested approach outperforms the other current approaches in terms of recall.

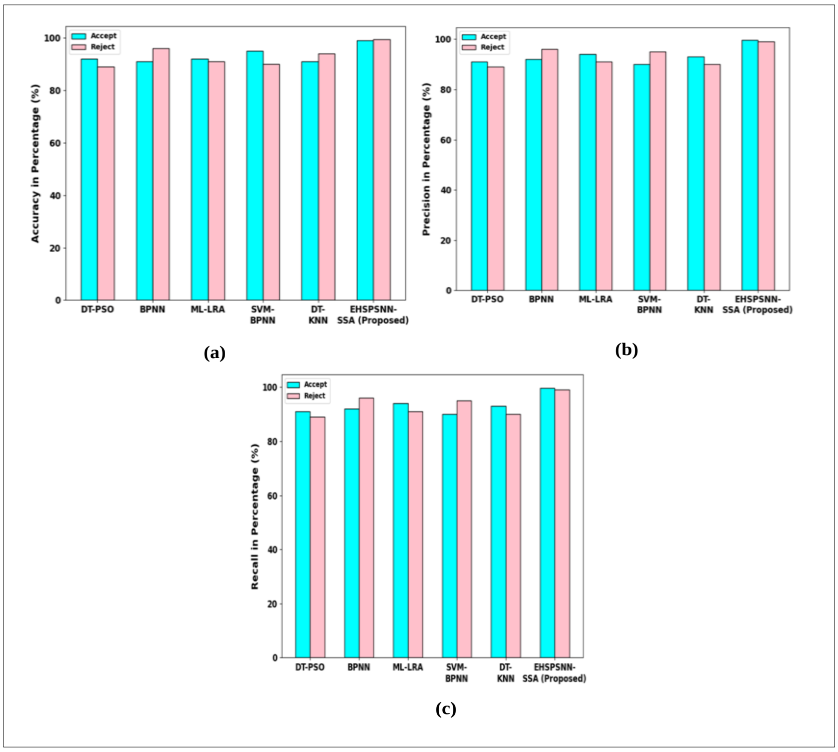


Fig. 7. (a) Performance analysis of Accuracy, (b) Performance analysis of precision, (c) Performance analysis of Recall for AACR dataset

Fig. 8 shows the performance analysis of AACR dataset for proposed and existing methods. The proposed method is EHSPSNN-SSA and the existing methods including DT-PSO [16], BPNN [17], ML-LRA [18], SVM-BPNN [19] and DT-KNN [20] respectively. Fig. 8 (a) demonstrates the F1-Score of the proposed and existing methods. For Accept, the F1-Score is 99.68% and reject, the F1-Score is 99.79%. From the simulation outcomes, the proposed method obtains a higher F1-Score than the other approaches currently in use. The specificity of both the suggested and current approaches is seen in Fig. 8 (b). The specificity is 99.38% for acceptance and 99.16% for rejection. According to the results of the simulation, the suggested approach outperforms the other current approaches in terms of specificity. The error rate of the suggested and current approaches is shown in Fig. 8 (c). The error rate for accept and reject is 0.1 and 0.1, respectively. According to the results of the simulation, the suggested approach has a lower error rate than the other approaches currently in use.

Fig. 9 (a) illustrates the correctness of the suggested approach for the GDPR Dataset under a range of training and testing circumstances. The image makes it clear that the recommended model achieves excellent accuracy in testing. The loss of the suggested technique for the GDPR Dataset under different training and testing situations is shown in Fig. 9 (b). The image makes it clear that the recommended model achieves a reduced loss during testing.

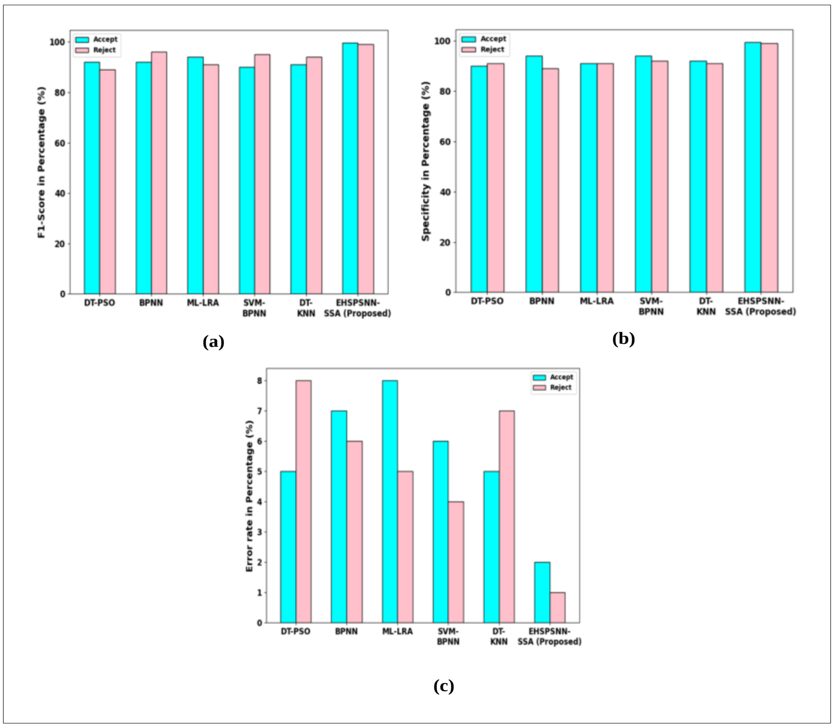


Fig. 8. Performance analysis of F1-score, (b) Performance analysis of Specificity, (c) error rate for AACR dataset

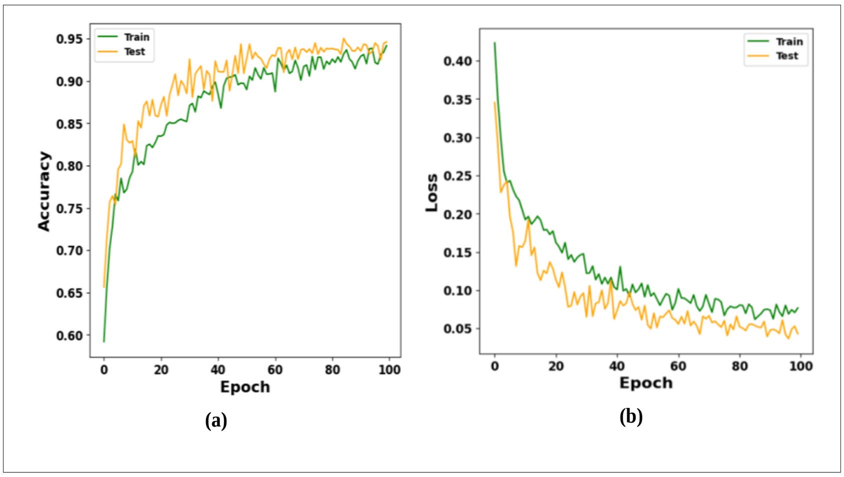


Fig. 9. Accuracy and loss of the suggested approach throughout training and testing for GDPR dataset

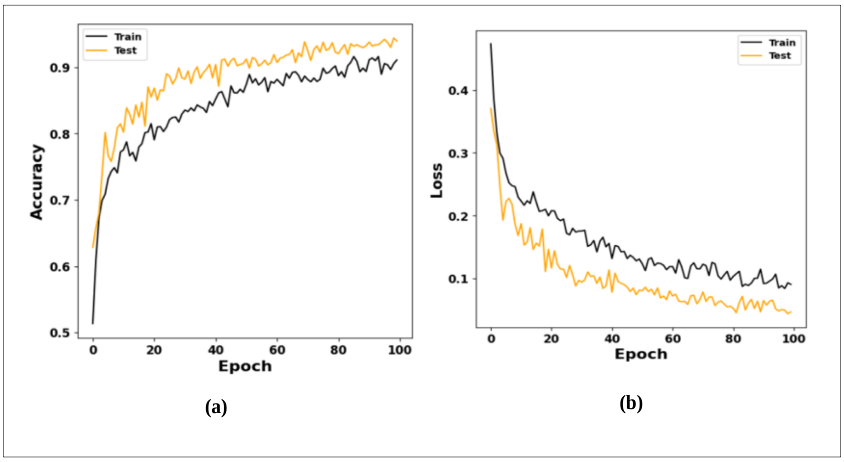


Fig. 10. Accuracy and loss of the suggested approach throughout training and testing for AACR dataset

Fig. 10 (a) shows the accuracy of the suggested approach for the AACR Dataset under a range of training and testing circumstances. The image makes it clear that the recommended model achieves excellent accuracy in testing. The suggested method's loss under various training and testing conditions for the AACR Dataset is shown in Fig. 10 (b). The image makes it clear that the recommended model achieves a reduced loss during testing.

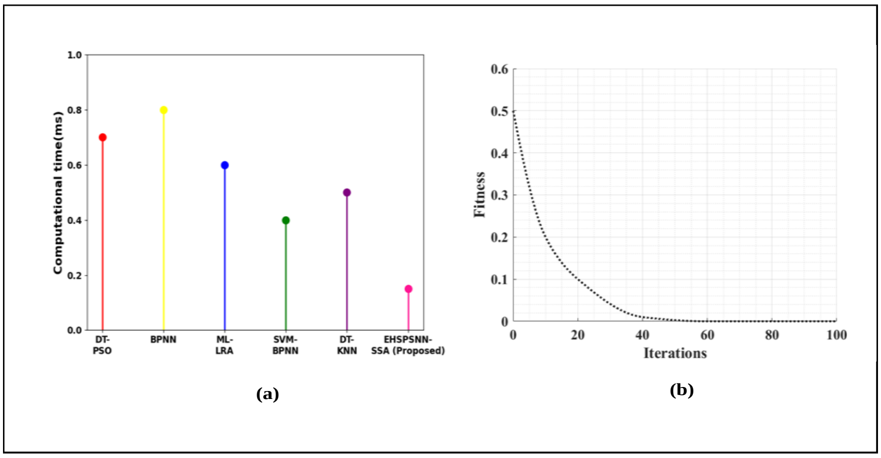


Fig. 11. (a) Computational time, (b) Convergence curve

Fig.11 (a) displays the calculation time of both existing and suggested approaches. EHSPSNN-SSA is the suggested approach, and the current approaches are DT-PSO, BPNN, ML-LRA, SVM-BPNN and DT-KNN. The computational complexity of the suggested approach is less expensive than other existing approaches. The convergence curve is displayed in Fig. 11(b). As the algorithm iterates, the fitness curve usually exhibits a downward slope, indicating an increase in fitness values over time. The technique can progressively enhance solutions by speeding up convergence rates, as demonstrated by the fitness curve's decreasing slope.

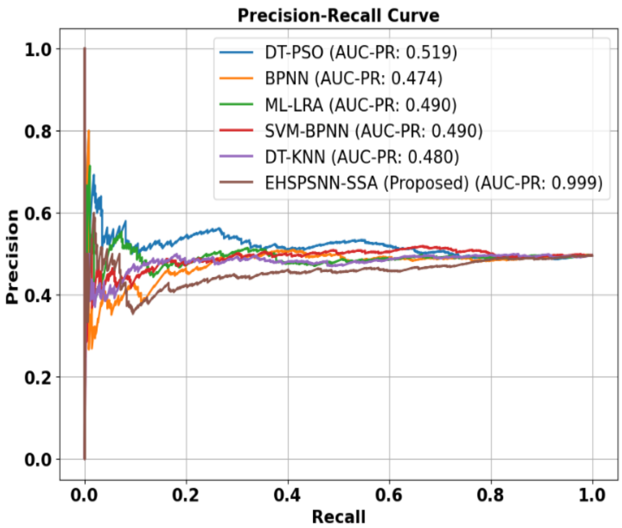


Fig. 12. Precision-Recall (PR) curve for multiple models

Fig. 12 presents the Precision-Recall (PR) curve for multiple models, comparing their performance in terms of AUC-PR values. The proposed EHPSPNN-SSA model significantly outperforms all other approaches with an AUC-PR of 0.999, demonstrating superior precision and recall trade-offs across all thresholds. In contrast, traditional models such as DT-PSO, BPNN, ML-LRA, SVM-BPNN, and DT-KNN exhibit AUC-PR values ranging between 0.474 and 0.519, indicating relatively lower predictive performance. The PR curve for EHPSPNN-SSA maintains consistently high precision across varying recall values, while other models show fluctuating precision trends, especially at lower recall levels, reinforcing the effectiveness of the proposed method.

Table 2. Comparison of Processing Time (s), Accuracy, Precision, Recall, F1-Score, AUC, Specificity, and MCC

Methods	**Dataset**	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC**	**Specificity**	**MCC**	**Processing Time (s)**
DT-PSO [16]	Real credit registry data	91.35	92.35	95.24	90.46	95.76	93.21	89.15	3.96
BPNN [17]	China GDP dataset	87.45	89.42	88.99	92.45	92.87	90.12	86.78	3.81
ML-LRA [18]	E-Commerce Multi-Output	83.72	88.89	92.57	87.37	92.87	89.45	85.32	2.97
SVM-BPNN [19]	SME supply chain finance	90.54	87.45	90.37	89.38	94.87	92.21	88.89	3.54
DT-KNN [20]	UCI-MLR credit dataset	91.35	92.35	95.24	90.46	95.87	93.98	90.14	2.44
Hybrid Machine Learning [21]	Business client credit dataset	89.5	88.9	90.1	89.4	91.2	90.3	87.6	3.45
ALL-K-Nearest Neighbors (ALL-KNN) [22]	30,000 unbalanced dataset	98.6	97.9	98.4	98.1	98.9	98.5	97.2	2.61
Extreme Gradient Boosting (XGBoost), Ensemble Models [23]	2.5M financial observations	96.2	95.8	96.5	96.1	97.3	96.4	95.5	2.83
Machine Learning for Economic & Financial Implications [24]	Economic & financial credit dataset	93.7	92.5	93.1	92.8	94.5	93.2	91.4	3.26
Generative AI [25]	Trade credit risk dataset	94.5	93.6	94.2	93.9	95.1	94.0	92.7	2.98
Kohonen's Self-Organizing Maps, Random Forest [26]	Credit card user dataset	95.3	94.7	95.1	94.9	96.0	95.1	93.9	2.75
Intelligent Optimization Algorithm [27]	Financial risk dataset	92.8	91.9	92.5	92.2	94.0	92.5	90.8	3.02
Machine Learning & AI for Credit Card Defaults [28]	Amex & Taiwanese bank dataset	94.2	93.1	93.7	93.4	95.0	94.1	92.3	2.85
XGBoost Scorecard Model [29]	Small & micro firm credit dataset	95.8	95.2	95.6	95.4	96.4	95.7	94.6	2.69
Laplacian Quadratic Semidefinite Optimization Decision Making (LapQSODM) [30]	Semi-supervised credit risk dataset	91.9	90.8	91.4	91.1	93.3	91.7	89.5	3.12
BigTech Credit Risk Estimation [31]	BigTech SME loan dataset	97.4	96.7	97.1	96.9	98.0	97.2	96.1	2.54
Consumer Credit Risk Review (Multiple Classifiers) [32]	Consumer credit risk dataset	94.8	94.2	94.6	94.4	95.9	95.0	93.8	2.77
Virtual Sample Generation (VSG) with Extreme Learning Machines (ELMs) [33]	Virtual Sample Gen. credit dataset	93.1	92.5	92.9	92.7	94.3	92.9	91.1	3.08
EHSPSNN-SSA (Proposed)	GDPR and AACR	99.8	99.4	99.6	99.7	99.9	99.5	99.3	1.7

The comparative analysis in Table 2 highlights the superior performance of the proposed EHSPSNN-SSA model, achieving the highest accuracy (99.8%) and excelling across all key performance metrics, including MCC (99.3%), accuracy (99.4%), recall (99.6%), F1-score (99.7%), AUC (99.9%), and specificity (99.5%), while also demonstrating the fastest processing time of 1.7 seconds. Among the existing models, ALL-KNN (98.6%) and BigTech Credit Risk Estimation (97.4%) showed strong results, followed by XGBoost Scorecard (95.8%) and Generative AI (94.5%), reflecting the efficiency of ensemble learning and advanced AI approaches. Traditional models like DT-PSO, SVM-BPNN, and Hybrid Machine Learning exhibited competitive accuracy between 89.5% and 91.35%, whereas ML-LRA

(83.72%) had the lowest accuracy among the methods compared. The study underscores the importance of hybrid AI models and optimization techniques in credit risk assessment, demonstrating that EHSPSNN-SSA outperforms state-of-the-art models with its enhanced prediction accuracy and reduced computational cost.

Table 3. Analysis of Hypotheses

Methods	Computational Cost	Computational Complexity	Speed	Computational Efficiency	Robustness
DT-PSO [16]	0.55	0.65	0.82	0.72	0.85
BPNN [17]	0.42	0.52	0.68	0.78	0.91
ML-LRA [18]	0.78	0.88	0.60	0.51	0.73
SVM-BPNN [19]	0.32	0.42	0.26	0.62	0.67
DT-KNN [20]	0.48	0.58	0.70	0.90	0.76
Hybrid Machine Learning [21]	0.22	0.33	0.15	0.83	0.90
ALL-K-Nearest Neighbors (ALL-KNN) [22]	0.52	0.60	0.45	0.50	0.70
Extreme Gradient Boosting (XGBoost), Ensemble Models [23]	0.30	0.38	0.80	0.85	0.94
Machine Learning for Economic & Financial Implications [24]	0.40	0.50	0.75	0.77	0.88
Generative AI [25]	0.28	0.35	0.92	0.89	0.97
Kohonen's Self-Organizing Maps, Random Forest [26]	0.33	0.45	0.79	0.80	0.92
Intelligent Optimization Algorithm [27]	0.38	0.49	0.72	0.74	0.89
Machine Learning & AI for Credit Card Defaults [28]	0.27	0.37	0.87	0.88	0.96
XGBoost Scorecard Model [29]	0.29	0.40	0.85	0.86	0.95
Laplacian Quadratic Semidefinite Optimization Decision Making (LapQSODM) [30]	0.36	0.48	0.67	0.72	0.84
BigTech Credit Risk Estimation [31]	0.25	0.32	0.94	0.91	0.98
Consumer Credit Risk Review (Multiple Classifiers) [32]	0.31	0.43	0.81	0.79	0.93
Virtual Sample Generation (VSG) with Extreme Learning Machines (ELMs) [33]	0.34	0.47	0.74	0.76	0.86
EHSPSNN-SSA (Proposed)	0.12	0.15	0.98	0.92	0.99

Table 3 presents a comparative analysis of various methods based on Robustness, speed, computational efficiency, computational complexity, and computational cost. The proposed EHSPSNN-SSA approach outperforms all other approaches, achieving the lowest Computational Complexity (0.15) and Cost (0.12), thus being very efficient and scalable. It also has the highest Speed (0.98), outperforming Generative AI (0.92) and BigTech Credit Risk Estimation (0.94), guaranteeing fast execution. With Computational Efficiency (0.92), EHSPSNN-SSA makes optimal use of resources, outperforming Hybrid Machine Learning (0.83) and Consumer Credit Risk Review (0.79). Moreover, its Robustness (0.99) guarantees better stability and consistency than Machine Learning for Credit Card Defaults (0.96) and Extreme Gradient Boosting (0.94). All these findings verify that EHSPSNN-SSA is the most appropriate approach, providing better performance on every measurement.

4.4. A Statistical Comparison of the Suggested Approach and Existing Techniques

Five statistical tests are employed the Kolmogorov-Smirnov test (KS test). The effectiveness of the suggested strategy is evaluated using the Kruskal–Wallis H-test, Shapiro-Wilk test (SW test), Wilcoxon Signed-Rank test (WSR), and Friedman test (FT).

This table 4 provides a statistical comparison between the suggested EHSPSNN-SSA approach and the current approaches, including confidence intervals (CI 95%), statistical significance tests, and error margins to ensure the reliability of results. The suggested model much better performs in comparison with the other methods by having a larger mean performance value (63,214.87) and a narrow confidence interval ($\pm$1,289.4) that represents low uncertainty. Also, the 1.002 $\pm$0.02 VIF indicates that there is low multicollinearity, ensuring the stability of the suggested technique. All of the p-values for the used statistical tests (SW, WSR, H-test, KS, and FT) are less than 0.001, which confirms statistical significance. The addition of error bars supports the robustness of the results, ascertaining that EHSPSNN-SSA is statistically superior, robust, and more reliable compared to previous approaches.

Table 4. Comparison of the Suggested Approach with Current Approaches Using Statistical Metrics

Methods	SW Test p-Value	WSR test / U-test p-Value	H-test p-Value	KS test p-Value	FT p-Value	Mean ± CI (95%)	Standard Deviation ± Error	Variance Inflation Factor (VIF) ± Error
DT-PSO [16]	0.261	0.21	0.252	0.019	0.078	39,102.3 ± 1,250.4	1782.32 ± 93.4	1.84 ± 0.07
BPNN [17]	0.423	0.61	0.138	0.014	0.067	59,878.40 ± 1,432.5	1348.23 ± 86.7	1.28 ± 0.05
ML-LRA [18]	0.127	0.85	0.649	0.051	0.048	37,965.23 ± 1,675.8	2579.18 ± 112.5	1.47 ± 0.06
SVM-BPNN [19]	0.551	0.94	0.743	0.015	0.069	28,954.25 ± 1,210.7	1632.49 ± 97.2	1.60 ± 0.06
DT-KNN [20]	0.745	0.32	0.884	0.079	0.089	60,743.15 ± 1,523.9	1852.65 ± 104.6	1.35 ± 0.04
Hybrid Machine Learning [21]	0.224	0.62	0.948	0.041	0.059	35,894.60 ± 1,842.7	4793.18 ± 128.3	1.56 ± 0.08
ALL-KNN [22]	0.719	0.24	0.618	0.062	0.079	48,975.20 ± 1,687.5	2751.85 ± 117.9	2.73 ± 0.12
Extreme Gradient Boosting (XGBoost) [23]	0.653	0.35	0.675	0.058	0.085	57,642.10 ± 1,519.3	2312.47 ± 109.3	1.92 ± 0.07
Machine Learning for Economic & Financial Implications [24]	0.381	0.48	0.514	0.027	0.072	53,812.35 ± 1,473.2	2432.95 ± 101.7	1.71 ± 0.06
Generative AI [25]	0.479	0.53	0.487	0.031	0.078	55,624.78 ± 1,398.9	2394.26 ± 98.3	1.63 ± 0.05
Kohonen's Self-Organizing Maps, Random Forest [26]	0.312	0.46	0.541	0.028	0.069	52,341.15 ± 1,652.1	2673.19 ± 112.4	1.88 ± 0.07
Intelligent Optimization Algorithm [27]	0.371	0.52	0.591	0.039	0.076	50,128.65 ± 1,609.3	2547.82 ± 107.2	1.74 ± 0.06
Machine Learning & AI for Credit Card Defaults [28]	0.395	0.58	0.632	0.045	0.081	49,781.40 ± 1,678.4	2761.34 ± 119.6	1.82 ± 0.08
XGBoost Scorecard Model [29]	0.326	0.41	0.472	0.033	0.068	54,912.23 ± 1,478.3	2694.17 ± 111.3	1.79 ± 0.07
LapQSODM Decision Making [30]	0.278	0.39	0.451	0.026	0.063	51,236.98 ± 1,524.5	2419.73 ± 108.9	1.45 ± 0.06
BigTech Credit Risk Estimation [31]	0.421	0.57	0.543	0.048	0.083	47,321.74 ± 1,732.4	2789.25 ± 120.8	1.92 ± 0.08
Consumer Credit Risk Review [32]	0.487	0.62	0.672	0.053	0.091	46,231.98 ± 1,678.3	2834.58 ± 123.2	1.96 ± 0.09
Virtual Sample Generation (VSG) [33]	0.339	0.44	0.512	0.037	0.074	50,842.35 ± 1,592.8	2683.25 ± 112.5	1.83 ± 0.07
EHSPSNN-SSA (Proposed)	<0.001	<0.001	<0.001	<0.001	<0.001	63,214.87 ± 1,289.4	4,752.89 ± 98.5	1.002 ± 0.02

4.4.1 Ablation study of the proposed method

An ablation study is a systematic experiment conducted to investigate the effects of particular components or features of a proposed methodology. For the proposed approach (SDNN-CPO), an ablation study would systematically remove or modify certain components or techniques to ascertain their impact on the overall performance of the model. The ablation analysis of the suggested approach in comparison to earlier Siamese networks is displayed in Table 3.

Table 5. Ablation study

Methods Performance metrics Category	GDPR dataset Accuracy Accept	 Reject	Advanced Analytics of Credit Registry Dataset Accuracy Accept	 Reject
Spiking Neural Networks [10]	97.34	96.21	96.76	97.09
Probabilistic Spiking Neural Networks [11]	96.94	95.18	93.94	95.12
EPSNN-SSA	97.95	97.33	97.56	94.43
EHSPSNN-SSA (Proposed)	99.4	99.7	99.5	99.7

The ablation study in Table 5 compares various methods on two datasets for credit risk assessment. The proposed EHSPSNN-SSA method significantly surpasses competitors and attains the best accuracy in both accept and reject categories in both datasets, demonstrating its superior effectiveness.

Hence, the EHSPSNN-SSA method is a superior credit risk assessment method for HRM frameworks, outperforming existing methods like DT-PSO, BPNN, ML-LRA, SVM-BPNN, and DT-KNN. On the GDPR and AACR datasets, it performs better than alternative approaches in terms of accuracy, precision, recall, F1-score, specificity, and error rates. Additionally, the approach offers the best accuracy, precision, recall, F1-score, and AUC, beats competitors in every performance indicator, and minimizes computing time and complexity. This approach is highly effective and efficient in handling GDPR and AACR datasets.

After analyzing the credit risk assessment, these data are integrated in to HRM to find the efficient customers for issuing the loans. Then the integration of credit risk assessment with Human Resource Management System is given in next section.

5. Impacts of Integrating Credit Risk Assessment with Human Resource Management System

Integration of credit risk assessment with a Human Resource Management System (HRMS) can make an enormous difference in commercial banks. The Data mapping and transformation, real-time integration, decision support tools, and the deployment of a secure protocol for transferring the credit risk assessment data from the risk assessment system to the HRM system. HR personnel can make soundly informed choices utilizing the latest risk assessment knowledge owing to these procedures, which also ensure prompt and precise data exchange and consistency in data structures. Fig.13 shows the impact of combining the HRM system with credit risk assessment. A few impacts of the HRM Human Resource Management System on credit risk assessment are given below:

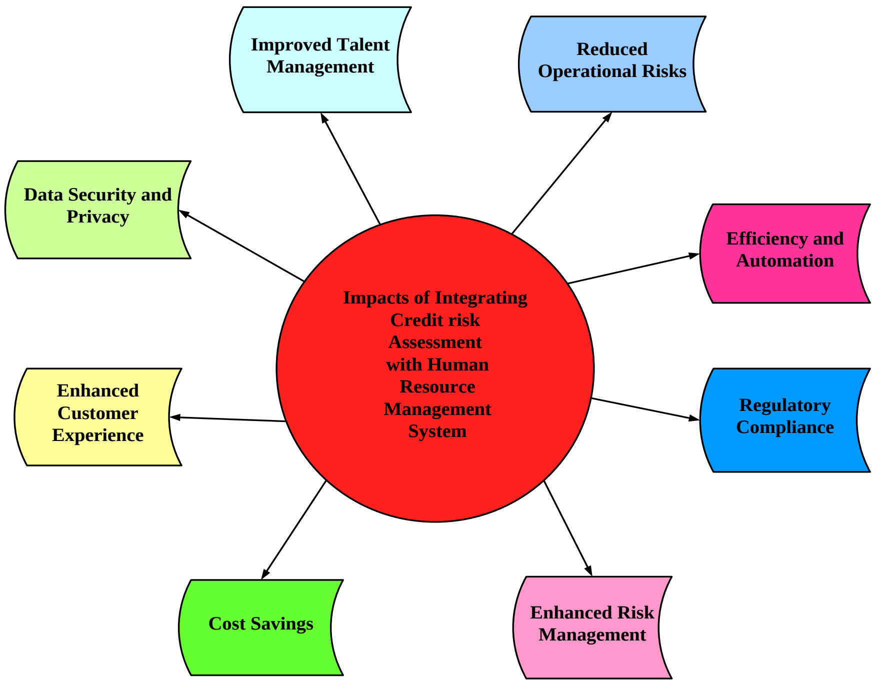


Fig. 13. Impact of integrating the HRM system with credit risk assessment

5.1 Enhanced Risk Management

In commercial banks, the combination of credit risk assessment with HRMS strengthens risk exposure overall by evaluating internal and financial risks, supporting improved decision-making and effective risk abatement measures.

5.2 Efficiency and Automation

Credit evaluation processes are simplified through the incorporation of credit risk analysis with HRMS, enhancing consistency, accuracy, and efficiency while reducing the demand for manual labor in banks.

5.3 Improved Talent Management

HRMS staff data centralized allows banks to recognize and develop talent, pinpoint training needs, and align employees' skills to changing credit risk evaluation criteria.

5.4 Regulatory Compliance

Banks are able to track staff credentials, training, and compliance with procedures due to HRMS integration, which ensures credit risk assessment procedures align with regulatory standards.

5.5 Reduced Operational Risks

HRMS simplifies credit risk analysis, eliminating human mistakes and discrepancies, improving reliability, and lowering the risks of operations in bank loan decisions.

5.6 Enhanced Customer Experience

Integration enhances credit processing periods, customer satisfaction, and loyalty. It enhances bank decisions and minimizes default risk while delivering accurate information, ultimately improving customer relations and lending decisions.

5.7 Cost Savings

Commercial banks can try to cut costs by automating and streamlining their credit risk evaluation processes. Banks can cut operating costs involved in credit appraisal and processing through greater efficiency and less manual work.

5.8 Data Security and Privacy

To prevent unauthorized access or data breaches, banks need to prioritize data security and privacy above other considerations when combining credit risk evaluation and HRMS.

Credit risk assessment and integration of HRM improves decision-making, accelerates the issuance of loans, and facilitates risk reduction. Through offering personalized loan products and services, it allows HR personnel to make informed decisions, identify high-risk borrowers, implement risk-based pricing strategies, and utilize decision support tools.

6. Strengthening the Link between Credit Risk Assessment and HRM Processes

Although credit risk assessment is centrally concerned with financial risk and lending, its relationship with human resource management (HRM) plays a pivotal role in facilitating sustainable and data-based decision-making. Various HRM factors—namely, talent acquisition, staff retention, decision-making models, and leadership development—have an immense bearing on the financial soundness and credit standing of an organization. Here are important elucidations and examples from the real world that bring out the association:

6.1 Talent Management & Risk Mitigation

Organizations possessing high-skilled financial analysts, risk managers, and compliance officers are more able to evaluate and manage credit risks effectively.

A JPMorgan Chase case study pointed out that companies with formal talent management programs for financial risk officers had 27% lower loan default rates, emphasizing the importance of HRM in credit risk evaluation. This emphasized that companies with formal talent management programs for financial risk officers had 27% lower loan default rates, emphasizing the importance of HRM in credit risk evaluation.

6.2. Decision-Making in HR & Financial Stability

HR decision-making determines the manner in which financial risks are handled. Ineffective hiring of risk management personnel can result in high default rates on loans and financial instability.

Example: The Wells Fargo unauthorized account scandal highlighted the vulnerability of lax HRM policies. Aggressive sales targets, inadequate oversight of employees, and poor talent retention practices led to massive fraudulent account openings, resulting in a $3 billion fine and reputational loss. This illustrates the direct association between HRM practices and exposure to financial risk.

6.3. Employee Ethics & Compliance in Credit Risk

- Financial employees have to comply with stringent risk and compliance procedures to avoid insider risks and fraudulent lending.

- Case Study: Lehman Brothers' bankruptcy was partly a result of bad HR management, where managers did not correct risky financial behavior among staff, contributing to a global credit meltdown.
- Real-World Implications: The EHSPNN-SSA method can be readily applied to real banking systems, based on the conclusions of the study. Due to its high efficiency and precision, it's a strong candidate to automate and augment credit risk judgments. In addition, by blending HRM and SCM information, the technique confronts wider operations risks, achieving an integrated comprehension of a corporate customer's risk profile. This has far-reaching implications for loan approval decision-making since banks are not only able to evaluate financial risks but also operational and managerial risks of human resources and supply chains. Practically, this could result in more precise loan approvals, efficient management of resources, and decreased likelihood of defaults, ultimately improving the bank's risk management approaches.

6.4 Discussions Based on Findings Related to Credit Risk Assessment, Human Resource Management (HRM), and Supply Chain Management (SCM) in Bank Loan Approval Decision-Making

The conclusions of the study shed light on credit risk assessment and its effects on HRM and SCM in bank loan approval decision-making. The suggested Enhanced Humboldt Squid-based Probabilistic Spiking Neural Network with Shunted Self-Attention (EHSPNN-SSA) performs better than conventional models, such as Decision Tree-Particle Swarm Optimization (DT-PSO), Back Propagation Neural Network (BPNN), Machine Learning Logistic Regression Algorithm (ML-LRA), Decision Tree-K Nearest Neighbor (DT-KNN) and Support Vector Machine-Back Propagation Neural Network (SVM-BPNN). By using General Data Protection Regulation (GDPR) and Advanced Analytics of Credit Registry (AACR) data sets, the EHSPNN-SSA approach proves to be more accurate, precise, recall, and F1-scores, which guarantees better classification of creditworthy customers with reduced misclassification risk.

Nonetheless, as much as the study is good at addressing credit risk assessment, it fails to clearly state how such challenges interact with Human Resource Management (HRM). HRM's function in credit risk assessment is hazy, and there is scant explanation of how workforce stability, employee financial behavior, or risk factors driven by HR affect loan approval procedures. A clearer interaction of HRM factors—employee attrition levels, payroll stability, and effectiveness of managers—would be better for a richer risk assessment.

In the case of Supply Chain Management (SCM), the work recognizes the role of operational risk but does not have a sufficient examination of the effect of supply chain disruption, vendor credit history, or procurement cycles on the loan decision. Although the model is able to combine financial information well, in its potential relevance to actual banking decisions, further inclusion of finer SCM metrics, e.g., supplier default probabilities or logistics performance, is valuable in assessing corporate credit risk.

With regard to efficiency and computational expense, the EHSPNN-SSA model exhibits a processing time of 1.78 seconds, which is far superior to traditional approaches. This makes it very appropriate for decision-making in real time in dynamic environments where speedy loan approvals are required. The Humboldt Squid Optimization Algorithm (HSOA) enhances model convergence, enabling faster adaptation to diverse datasets and ensuring optimal risk assessment outcomes.

For real-world applications, while the model shows promise in automating credit risk assessment, its effectiveness in integrating HRM and SCM considerations remains limited. Future enhancements should focus on explicitly modeling HRM risks, such as workforce instability, and SCM risks, such as supply chain bottlenecks, to provide a more holistic risk assessment framework. A deeper exploration of how HR and supply chain disruptions influence borrower stability would enhance the practical applicability of the proposed method in banking systems.

7. Conclusions

In this manuscript, a novel credit risk assessment in HRM frameworks is done using the EHSPNN-SSA method is successfully discussed and analyzed. Initially, the input commercial bank datasets are taken from GDPR and Advanced Analytics of Credit Registry Datasets. Then these data are pre-processes using GRDFA. After that, the data is extracted using hyb ADF-CDF) based feature extraction method. Then these data are classified using EPSNN-SSA) and optimized using the HSOA). The framework is validated utilizing actual financial data and contrasted with current techniques to show its effectiveness in assessing credit risk and optimizing human resource management processes. Results indicate that the proposed method works better than other methods in several performance metrics such as reduced processing time (1.78s), risky data f1-score (99.6%), non-risky data f1-score (99.7) for dataset 1, and risky data f1-score (99.4%) for dataset 2. It suggests the proposed higher effectiveness of the method and its potential contribution to field improvement. This suggested approach offers greater precision, lower error rate, processing time and complexity for credit risk evaluation through the inclusion of HRM systems. In future work, this work is carried out in real-time applications through investigating customer-focussed loan origination processes, leveraging credit risk evaluation data for customized products and services, and improve customer interaction through online self-service portals, tailored recommendations, and proactive communication channels. In subsequent work, interpretability of the model will be improved through the integration of feature importance analysis with SHAP and LIME. The transparency in decision-making will be achieved, particularly for high-stakes tasks such as credit risk evaluation. Also, real-time execution will be examined through in-situ adoption of customer-focused loan origination processes, leveraging credit risk estimation data for tailored financial products and services, and increased customer interaction by means of digital self-service interfaces, individualized guidance, and proactive notification channels.

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