Intelligent Bankruptcy Prediction using Cutting-Edge N-Valued Interval Neutrosophic Sets for Classification

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Abstract

As a generalization of fuzzy set (FS) and intuitionistic FS (IFS), neutrosophic sets (NS) were proposed to signify imprecise, uncertain, inconsistent and imperfect data present in real-time. Moreover, the interval NS (INSs) were developed just to find out the problems with an array of statistics in the actual unit interval. Then, there are least consistent processes for INSs, along with the decision-making process and INS aggregation operator. The vital operations are presented on n-valued interval NSs like intersection, union, multiplication, addition, scalar division, scalar multiplication, false-favorite and truth favorite. Bankruptcy prediction was a major concern in the areas of finance and management science that appealed to the attention of practitioners and researchers. With the great progress of up-to-date information technology, it has been developed to utilize machine learning (ML) or deep learning (DL) techniques to perform the prediction, from the primary analysis of financial statements. If ML methods have adequate interpretability, they might be employed as effectual analytical methods in bankruptcy calculation. This manuscript presents a Bankruptcy Prediction using Cutting-Edge N-Valued Interval Neutrosophic Sets (BP-CENVINS) mechanism. The projected BP-CENVINS method is a complicated approach to bankruptcy forecast that affects radical data preprocessing, classification, and hyper parameter optimization approaches. Initially, the Z-score normalization regularizes the fiscal details to increase the comparability and stability throughout the information. Next, it employs the CENVINS for the classification, skillfully detecting the subtle communication amongst variables to differentiate between creditworthy and bankrupt organizations. Finally, the Grasshopper Optimization Algorithm (GOA) is applied for parameter tuning to improve the predictive outcomes of the CENVINS classifiers, systematically purifying design parameters to achieve finest efficiency. An extensive experiments is made to illustrate the betterment of the BP-CENVINS technique. The simulation outcomes of the BP-CENVINS method have exhibited better performances than other existing methodologies

Keywords: Bankruptcy Prediction; Interval Neutrosophic Sets; N-Valued Neutrosophic Sets; Grasshopper Optimization Algorithm; Fuzzy Set

1. Introduction

Fuzzy sets (FS) and fuzzy logic (FL) are extensively utilized in numerous requests which contain uncertainty [1]. FS theory is very popular for processing uncertainties arising from partial belongingness or vagueness of an element in a set, it can't display all kinds of uncertainties presented in various physical difficulties such as

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difficulties containing partial data [2]. Additional generalization of the FS that is termed as intuitionistic fuzzy sets (IFS). In IFS, every element is linked to a non-membership grade in addition to a single membership grade [3]. Additionally, there is a limitation that the total of two grades is equal or less to unity. Neutrosophic sets (NSs) are presented by the generality of FS and IFS, and it is a great tool to resolve indeterminate, inconsistent, and incomplete data that are present in the actual world [4]. NS are categorized by truth (T), false (F), and Indeterminacy (I) degrees.

In recent times, bankruptcy prediction has been one of the significant problems tackled by decision-makers in the finance area [5]. Bankruptcy causes several crashes that affect stockholders, consumers, management, and finances. A bankruptcy prediction aims to determine whether a business or organization will go bankrupt. The financial concern or bankruptcy is a point that proceeds when a financial business validates its economic obligations [6]. The improvement of technology aids in acquiring data on the dangerous condition of a business in several methods, namely professional agencies and mass media. The reasons for bankruptcy and business loss are economic, disaster, fraud, and finance [7]. In bankruptcy, the economic aspects include the weakness of industry, poor location, and financial factors consisting of huge obligations.

In the area of Machine learning (ML), recent developments have resulted from the acceptance of ML systems for the prediction of bankruptcy [8]. ML techniques are progressively applied for bankruptcy prediction through financial ratios. A research by Altman and Barboza, Kimura discovered ML methods that can outperform standard statistical methods such as multiple discriminant analysis (MDA) by an important margin in bankruptcy prediction [9]. In recent times, deep learning (DL) has appeared and progressively advanced into an effective method for a wide variety of applications [10]. It has reached great achievement in, computer vision, auto-driving, natural language processing(NLP), voice recognition, and categorizing difficulties into management and business such as credit scoring and bankruptcy prediction.

This manuscript presents a Bankruptcy Prediction using Cutting-Edge N-Valued Interval Neutrosophic Sets (BP-CENVINS) mechanism. Initially, the Z-score normalization regularizes the fiscal details to increase the comparability and stability throughout the information. Next, it employs the CENVINS for the classification, skillfully detecting the subtle communication amongst variables to differentiate between creditworthy and bankrupt organizations. Finally, the Grasshopper Optimization Algorithm (GOA) is realistic for parameter tuning to improve the predictive outcomes of the CENVINS classifiers, systematically purifying design parameters to achieve finest efficiency. An extensive experiments is made to illustrate the betterment of the BP-CENVINS technique.

2. Literature Works

Khashei et al. [11] introduced a novel discrete direction-based LR classifier technique. It can show overall outcomes of the introduced discrete direction-based classifier cannot be lesser than its endless counterpart, an estimation of the recommended classifier is performed to determine its superiority. In [12], several machine learning (ML) algorithms have been researched for the business's bankruptcy prediction tasks based on financial parameters. While developing the dataset methods different approaches and models are compared and trained, especially, in data balancing techniques. Smith et al. [13] suggest to construct an interpretable and accurate classification method. Tri-XGBoost, is a recommended semi-supervised method. These suggested techniques associate Borderline-Smote (BLSmote) based on ENN sampling methods.

In [14], the Category Boosting (CatBoost) algorithm is suggested after utilizing OpenRefine to update and clean the data. The advanced research method is described for utilizing the Shapash library, including domain knowledge. Economic experts in banks or depositors can use the specified outcomes presented by the method to improve their decision-making methods, without extensive knowledge of AI. Singla et al. [15] examine the usage of the SMOTE associated with the CatBoost classification algorithm. The SMOTE method aims to resolve the difficulty of class imbalance by producing synthetic samples for the minority class. The CatBoost algorithm accesses the categorical feature handling skills with an effective boosting method, it is employed to analyze the expanded dataset and improve a robust prediction method for the bankruptcy recognition task. Adisa et al. [16] introduce a new method of bankruptcy prediction in this paper. The new technique contains a developed PSO method for determining important features and optimizing the LSTM method for bankruptcy prediction. This paper uses multi-learning and self-learning plans to improve social learning parts and cognitive of the PSO algorithm. The last bankruptcy prediction method associates optimal feature selection (FS) with the LSTM method.

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3. Methodology

In this manuscript, we have presented a new BP-CENVINS algorithm. The projected BP-CENVINS method is a complicated approach to bankruptcy forecast that affects radical data preprocessing, classification, and hyperparameter optimization processes. Fig. 1 establishes the entire flow of BP-CENVINS algorithm.

A. Z-score Normalization

Initially, the Z-score normalization regularizes the fiscal details to increase the comparability and stability throughout the information. Z-score normalization is paramount in regulating economic indicators during varying scales [17]. By changing variables into distinctive scales as stated by the mean and variance, it guarantees that the variable is similarly subsidized to the predictive approach. This method optimizes the results of bankruptcy prediction by modifying the disparities impact and outliers in raw information, hence augmenting the consistency of financial risk calculations.

B. Bankruptcy Prediction using CENVINS Classifier

Next, it employs the CENVINS for the classification process. After the n-valued NS and range NS determined and Wang et al. in, correspondingly [18].

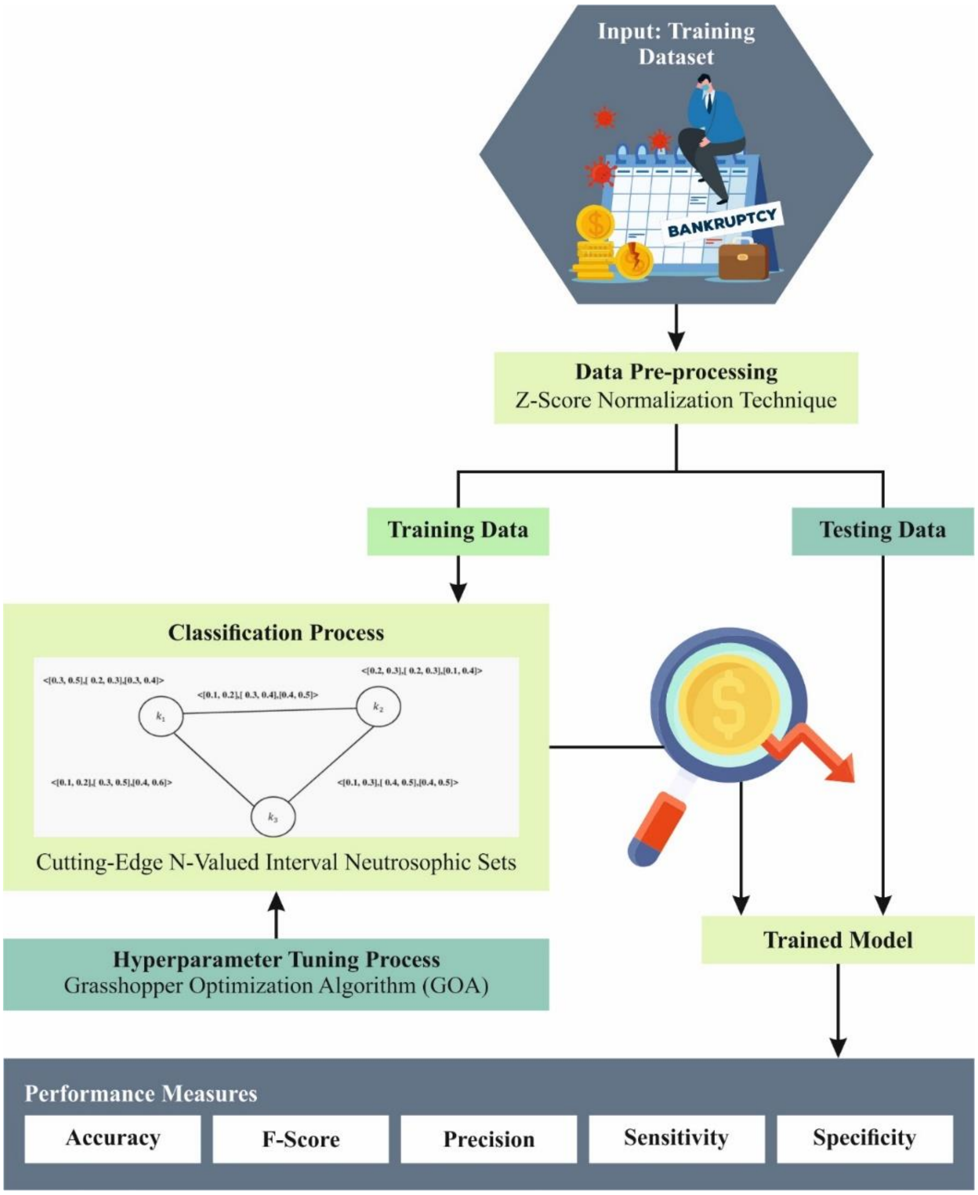

Figure 1. Overall flow of BP-CENVINS algorithm

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Assume X as a universal discourse, an NVINS on X is:

$$A = \{x, \begin{pmatrix} [\inf T_A^1(x), \sup T_A^1(x)], [\inf T_A^2(x), \sup T_A^2(x)], \dots, \\ [inf T_A^p(x), \sup T_A^p(x)] \end{pmatrix},$$

$$\begin{pmatrix} [\inf I_A^1(x), \sup I_A^1(x)], [\inf I_A^2(x), \sup I_A^2(x)], \dots, \\ [inf F_A^1(x), \sup I_A^q(x)] \end{pmatrix},$$

$$([inf F_A^1(x), \sup I_A^q(x)], ([inf F_A^2(x), \sup F_A^2(x)], \dots,$$

$$([inf\ F_A^p \sup F_A^r(x)]) : x \in X\}$$

Where

$$inf T_A^1(x), \inf T_A^2(x), \dots, inf T_A^p(x), \inf I_A^1(x), inf I_A^2(x), \dots / \inf I_A^p(x), \inf$$

$F_A^1(x), inf F_A^2(x), \dots, \inf F_A^q(x), \sup T_A^1(x), \sup T_A^2(x), \dots, \sup T_A^p(x)$,

$\sup I_A^1(x), \sup I_A^2(x), \dots, \sup I_A^q(x)$,

$$\sup F_A^1(x), \sup F_A^2(x), \dots, \sup F_A^r(x) \in [O, 1]$$

thus $0 \le sup T_A^i(x) + sup I_A^i(x) + sup F_A^i(x) \le 3, \forall i = 1,2, \dots, p.$

If $p = q = r$ is the truth- and false degrees of the x, correspondingly. p refers to the NVINS dimension. Clearly, once the lower and upper conclusions of the range $T_A^i(x), I_A^i(x), F_A^i(x)$ in an NVINS are equivalent, then NVINS decreases to NVINS.

Assume $X = \{X_1, X_2\}$ as the universal discourse and A is an NVINS

$$A = \{< x_1, \{[.1, .2], [.2, .3]\}, \{[.3, .4], [.1, .5]\}, \{[.3, .4], [.2, .5]\} >, \\ < x_2, \{[.3, .4], [.2, .4]\}, \{[.3, .5], [.2, .4]\}, \{[.1, .2], [.3, .4]\} >\}$$

$A^c = \{x, ([inf F_A^1\ (\mathrm{x}),\ \sup F_A^1\ (\mathrm{x}), ([inf F_A^2\ (\mathrm{x}), \sup F_A^2(x)], /$

$([inf\ F_A^p(x), \sup F_A^p(x)]),$

$$\begin{pmatrix} [1 - \sup I_A^1(x), 1 - \inf I_A^1(x)], [1 - \sup I_A^2(x), 1 - \inf I_A^2(x)], \dots, \\ [1 - \sup I_A^p(x), 1 - \inf I_A^p(x)] \end{pmatrix}$$

$([inf\ T_A^1(x), \sup T_A^1\ [inf\ T_A^2(x), \sup T_A^2(x)], \dots, [inf T_A^p(x), \sup T_A^p\ (x) : x \in X\}$.

For $\forall i = 1,2, \dots, P$ if $inf T_A^i(x) = \sup T_A^i(x) = 0$ and $inf I_A^i(x) = \sup I_A^i(x) = inf F_A^i(x) = \sup F_A^i(x) = 1$, then A is known as null NVINS as Φ, for $x \in X$.

Assume $X = \{x_1, x_2\}$ as the universal discourse and A is an NVINS

For $\forall i = 1,2, \dots, P$ if $inf T_A^i(x) = \sup T_A^i(x) = 1$ and $inf I_A^i(x) = \sup I_A^i(x) = \inf F_A^i(x) = \sup F_A^i(x) = 0$, then A is known as universal NVINS as E, for $x \in X$.

Assume $X = \{x_1, x_2\}$ as the universal discourse and A denotes an NVINS

$inf T_A^1(x) \le inf T_B^1(x), inf T_A^2(x) \le inf T_B^2(x), \dots, inf T_A^p(x) \le inf T_B^p(x),$

$\sup T_A^1(x) \le \sup T_B^1(x),\ \sup T_A^2(x) \le \sup T_B^2\ (x), \dots, \sup T_A^p(x) \le \sup T_B^p(x),$

$inf I_A^1(x) \ge inf I_B^1(x), inf I_A^2(x) \ge inf I_B^2\ (x), \dots, inf I_A^p(x) \ge inf I_B^p(x),$

$\sup I_A^1(x) \ge \sup I_B^1\ (x), \sup I_A^2(x) \ge \sup I_B^2\ (x), \dots, \sup I_A^p(x) \ge \sup I_B^p(x),$

$inf F_A^1(x) \ge inf F_B^1(x), inf F_A^2(x) \ge inf F_B^2(x), \dots, inf F_A^p(x) \ge inf F_B^p(x)$,

$$\sup F_A^1(x) \ge \sup F_B^1\ (x), \sup F_A^2(x) \ge \sup F_B^2(x), \dots, \sup F_A^p(x), \ge \sup F_B^p(x)$$

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for $x \in X$.

Assume $X = \{X_1, X_2\}$ As the universal discourse and A and B are two NVINS

Thus $A \subseteq B$.

Assume A and B as two NVINS. Next, A and B are equivalent, as $A = B$ when A subset B and $B \subseteq A$.

C. Hyper parameter Tuning

Finally, the GOA is employed for parameter tuning to improve the predictive outcomes of the CENVINS classifiers. GOA is a bioinspired model that imitates the foraging behaviour of grasshoppers [19]. Generally, grasshoppers are tarnished for their probable to lay on severe harm to yields and experience a lifecycle including different phases: egg, nymph, and adult. In general, the nymphs that arise from eggs are tiny, wingless, slow and short distance measures that are considered by a step size. These nymphs steadily transform into adult grasshoppers which are capable of navigating longer distances. These dual actions are exploitation and exploration which are equivalent to the nymph and adult stages, correspondingly. The mathematical method of the GOA is conveyed as below:

$$X_i = S_i + G_i + W_i \tag{1}$$

Where X_i indicates the position of the i^{th} individuals, S_i shows the social communication, G_i denotes the force of gravity on the i^{th} individuals, and W_i refers to the wind advection. The social interaction is assumed as below:

$$S_i = \sum_{\substack{j=1 \\ j \neq i}}^{M} s(e_{ij})\widehat{e_{ij}} \tag{2}$$

From the above equation, M designates the number of grasshoppers, s signifies the social force, whereas e_{ij} Denotes the Euclidean distance amongst $i\text{-}th$ and $j\text{-}th$ grasshoppers. Whereas, $e_{ij} = |X_j - X_i|$ and $\widehat{e_{ij}} = \frac{x_j - x_i}{e_{ij}}$. The function G_i Is defined as follows:

$$G_i = -g\widehat{e_g} \tag{3}$$

Where g refers to the gravity constant and $\widehat{e_g}$ Denotes the unity vector near the earth midpoint. The W_i is provided as:

$$W_i = d\widehat{u_w} \tag{4}$$

In the above-mentioned formula, d signifies the drift constant, and $\widehat{u_w}$ is the vector of unity fixed near the wind. The grasshoppers' location is determined as below:

$$X_i = \sum_{\substack{j=1 \\ j \neq i}}^{M} s(|X_j - X_i|)\frac{X_j - X_i}{e_{ij}} - g\widehat{e_g} + d\widehat{u_w} \tag{5}$$

The equation is altered to find out the optimization issue as explained in Eq. 8 as follows:

$$X_i^d = c\left(\sum_{\substack{j=1 \\ j \neq i}}^{M} c\frac{ud - l_d}{2} s(|X_j^d - X_i^d|)\frac{X_j - X_i}{e_{ij}}\right) + \widehat{O_d} \tag{6}$$

Where ud denotes the upper bound, l_d refers to the lower bound of the $d\text{-}th$ dimension, $\widehat{O_d}$ signifies the best solution. The variable c represents the weight of inertia and attraction area. The c value is defined as:

$$c = c_{\max} - t\frac{c_{\max} - c_{min}}{T} \tag{7}$$

While $c_{\min}$ and $c_{\max}$ and represents the minimum and maximum value, correspondingly; t indicates the present iteration, and T symbolizes the highest iteration count. Fig. 2 depicts the steps involved in GOA

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Figure 2. Steps involved in GOA

The GOA method derives an FF to accomplish developed organization presentation. It regulates a positive integer to symbolize the amended presentation of the applicant's solutions.

$$fitness(x_i) = ClassifierErrorRate(x_i)$$
$$= \frac{No.of\ misclassified\ samples}{Total\ No.of\ samples} * 100 \quad (8)$$

4. Performance Validation

The performance outcome of the BP-CENVINS algorithm is tested using qualitative bankruptcy dataset [20], which comprises 250 instances with two classes represented in Table 1.

Table 1: Details of dataset

Classes	No. of Instances
Bankruptcy	107
Non-Bankruptcy	143
Total Instances	250

Fig. 3 validates the classifier fallouts of the BP-CENVINS method in test dataset. Figs. 3a-3b illustrates the confusion matrices accessible by the BP-CENVINS method on 70%TRAS and 30%TESS. The outcome represented that the BP-CENVINS method has known and considered different classes correctly. Likewise, Fig. 3c establishes the PR examination of the BP-CENVINS method. The outcome described that the BP-CENVINS method has gained extreme PR presentation in different classes. Lastly, Fig. 3d proves the ROC examination of the BP-CENVINS method. The outcome characterized that the BP-CENVINS method has resulted in skilled outcomes with supreme ROC values in different classes.

Table 2 and Fig. 4 indicate the overall prediction outcomes of BP-CENVINS technique under 70%TRAS and 30%TESS. The results exemplify that the BP-CENVINS method appropriately documented both classes. With 70%TRAS, the BP-CENVINS technique presents average $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{score} of 96.37%, 95.64%, 96.37%, 96.37%, and 95.92%, correspondingly. Followed by, with 30%TESS, the BP-CENVINS method offers average $accu_y$, $prec_n$, $sens_y$, $spec_y$, and F_{score} of 95.12%, 94.74%, 95.12%, 95.12%, and 94.66%, correspondingly.

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Table 2: Prediction outcome of BP-CENVINS method in 70%TRAS and 30%TESS

Class	$Accu_y$	$Prec_n$	$Sens_y$	$Spec_y$	F_{Score}
TRAS (70%)					
Bankruptcy	98.63	92.31	98.63	94.12	95.36
Non-Bankruptcy	94.12	98.97	94.12	98.63	96.48
Average	96.37	95.64	96.37	96.37	95.92
TESS (30%)					
Bankruptcy	100.00	89.47	100.00	90.24	94.44
Non-Bankruptcy	90.24	100.00	90.24	100.00	94.87
Average	95.12	94.74	95.12	95.12	94.66

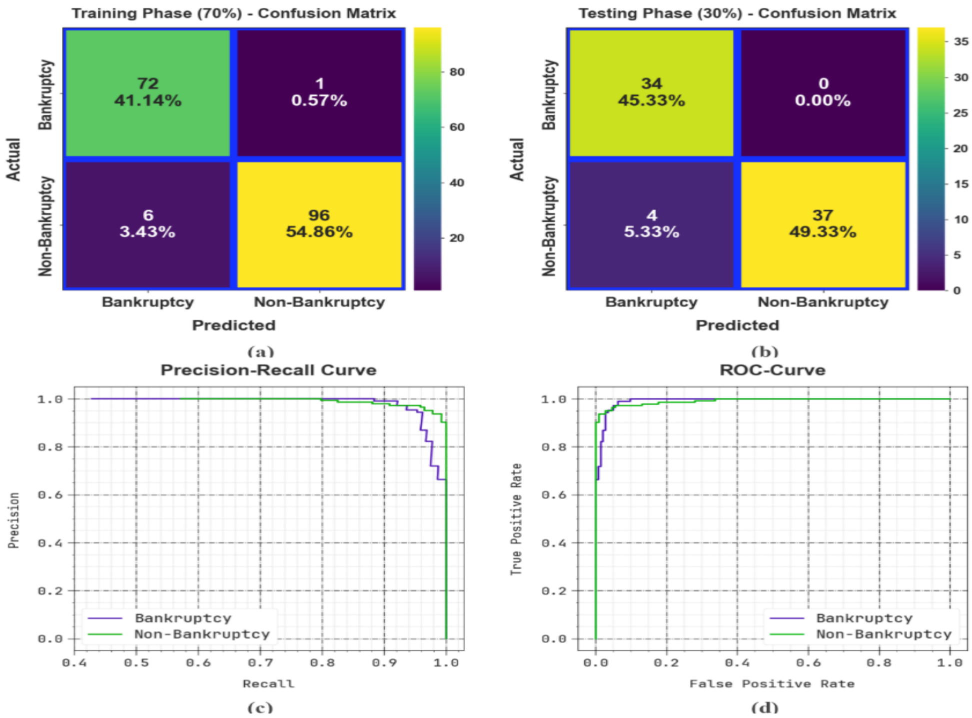

Figure 3. Classifier outcomes of (a-b) 70% and 30% confusion matrices (c-d) PR and ROC curves

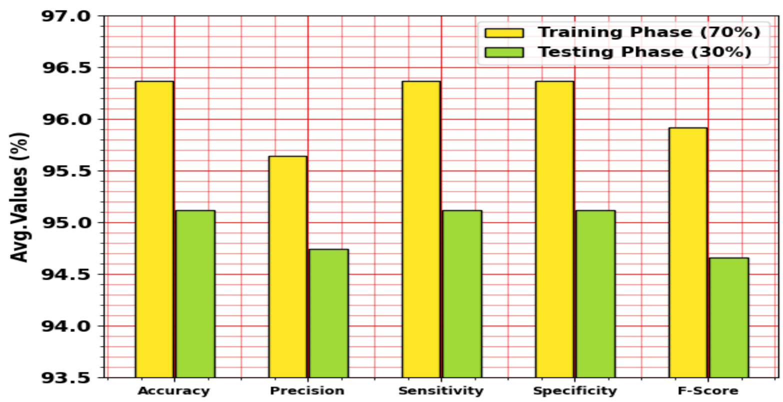

Figure 4. Average outcome of BP-CENVINS method in 70%TRAS and 30%TESS

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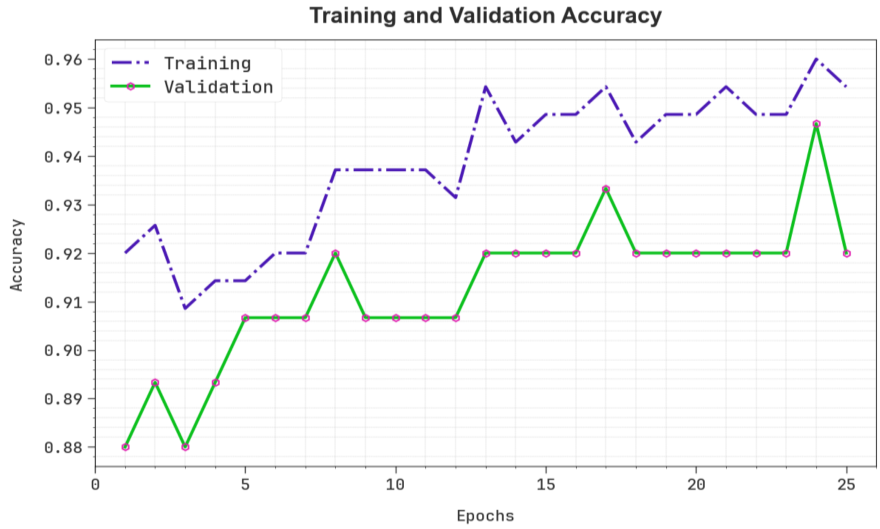

Figure 5. $Accu_y$ curve of the BP-CENVINS technique

In Fig. 5, the training and validation accuracy outcomes of the BP-CENVINS method are established. The accuracy values are calculated within the range of 0-25 epochs. The figure emphasized that the training and validation accuracy values display a growing tendency which notified the capability of the BP-CENVINS method with amended presentation over numerous iterations. Furthermore, the training accuracy and validation accuracy remain closer over the epochs, which exhibits improved performance and indicates low nominal overfitting of the BP-CENVINS method, ensuring reliable prediction on hidden samples.

In Fig. 6, the training and validation loss graph of the BP-CENVINS method is shown. The loss values are calculated within the range of 0-25 epochs. It is characterized that the training and validation accuracy values demonstrate a declining tendency, which notified the capability of the BP-CENVINS method in balancing a tradeoff between data fitting and generalization. The recurrent reduction in loss values further guarantees the enhanced outcomes of the BP-CENVINS technique and tunes the predictive outcomes over time.

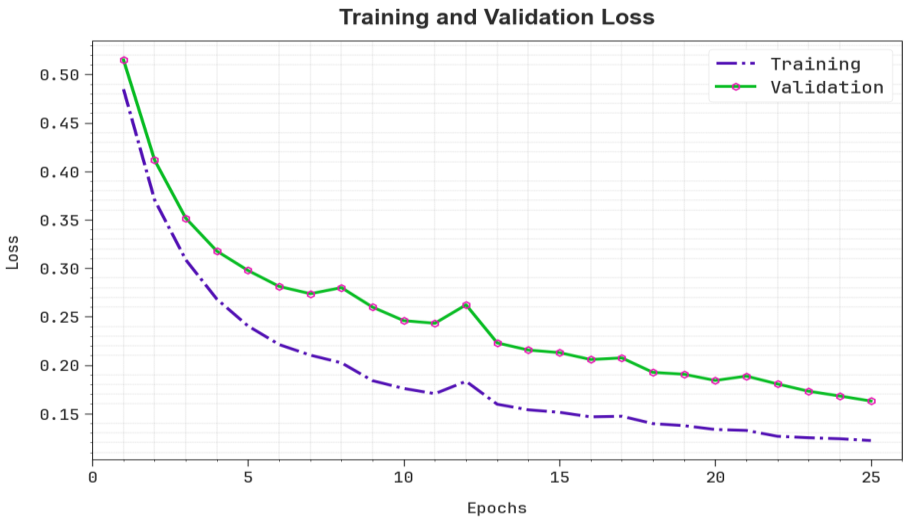

Figure 6. Loss curve of the BP-CENVINS technique

In Table 3 and Fig. 7, a comparison examination of the BP-CENVINS approach is described [21]. The outcomes established that the RF, NB, RBF, MLP, and LR models have revealed weak detection outcomes with least $accu_y$ of 90.67%, 91.03%, 92.37%, 92.56%, and 93.18%, correspondingly. Now, the KNN method has displayed significant presentation with $accu_y$ of 93.25%, $sens_y$ of 93.58%, $spec_y$ of 92.54%, and F_{score} Of 94.21%. Moreover, the Ant-Miner method has skilful reasonable outcomes with $accu_y$ of 95.73%, $sens_y$ of 95.03%, $spec_y$ of 92.20%, and F_{score} of 95.00%. Finally, the BP-CENVINS method determines greater presentation with augmented $accu_y$ of 96.37%, $sens_y$ of 96.37%, $spec_y$ of 96.37%, and F_{score} of 95.92%.

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Table 3: Comparative analysis of BP-CENVINS method with existing approaches

Algorithm	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}
BP-CENVINS	96.37	96.37	96.37	95.92
Ant-Miner Model	95.73	95.03	92.20	95.00
Logistic Regression	93.18	93.13	91.60	94.82
MLP Algorithm	92.56	90.75	90.03	90.29
Random Forest	90.67	91.20	90.37	92.93
RBF Model	92.37	93.50	92.30	92.63
Naïve Bayes	91.03	92.77	92.27	91.81
KNN Classifier	93.25	93.58	92.54	94.21

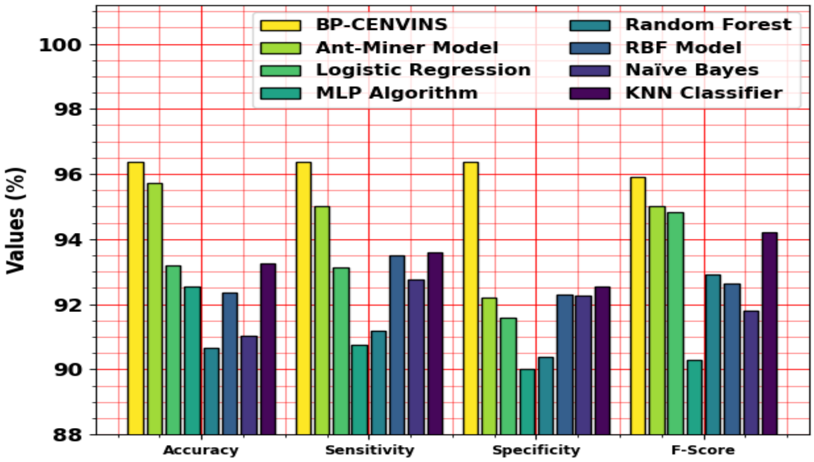

Figure 7. Comparative analysis of BP-CENVINS method with existing approaches

5. Conclusion

In this manuscript, we have presented a new BP-CENVINS algorithm. The projected BP-CENVINS method is a complicated approach to bankruptcy forecast that affects radical data pre-processing, classification, and hyper parameter optimization approaches. Initially, the Z-score normalization regularizes the fiscal details to increase the comparability and stability throughout the information. Next, it employs the CENVINS for the classification, skilfully detecting the subtle communication amongst variables to differentiate between creditworthy and bankrupt organizations. Finally, the GOA is exploited for hyper parameter fine-tuning to improve the predictive outcomes of the CENVINS classifiers, systematically purifying design parameters to achieve finest efficiency. An extensive experiment is made to illustrate the betterment of the BP-CENVINS technique. The simulation outcomes of the BP-CENVINS method have exhibited better performances than other existing methodologies.

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