COPRAS Neutrosophic Approach with Big Data Analytics for Enhancing Multi-Dimensional Customer Churn Prediction on Corporate Performance Assessment

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Abstract

A neutrosophic set (NS) is a new computing technology that accesses ambiguous data through three memberships. A soft expert set (SES) is based on the concept of a "soft set" with an expert system. Now, this technique has been applied in different domains namely measurement theory, intelligent systems, game theory, probability theory, cybernetics, etc. Customer Churn prediction implies identifying which consumers are expected to cancel a subscription to a service or leave a service. It is a crucial forecast for several businesses because obtaining new users frequently costs more than holding existing ones. The Churn prediction modeling methods try to understand the accurate customer attributes and behaviors that signal the risk and timing of customers leaving. This manuscript offers the design of an AI-based Multi-Dimensional Customer Churn Prediction for Corporate Performance Assessment (AIMD-CCPCPA) technique. The AIMD-CCPCPA technique mainly aims to detect the presence of customer churns and non-churns. It involves a two-stage process. At the initial stage, the AIMD-CCPCPA technique exploits the COPRAS Neutrosophic Method for prediction purposes. Secondly, the AIMD-CCPCPA technique involves parameter selection using a butterfly optimization algorithm (BOA). The experimental analysis of the AIMD-CCPCPA model is examined using a benchmark dataset. The acquired outcomes stated the supremacy of the AIMD-CCPCPA technique equated to other models

Keywords: Customer Churn Prediction; Neutrosophic Set; Butterfly Optimization Algorithm; Fuzzy Set; Intuitionistic Fundamental Sets; Corporate Performance Assessment.

1. Introduction

A range of new ideas that were accomplished with ambiguity and imprecision were offered in the fuzzy region since Zadeh recognized the Fuzzy Set (FS) [1]. Smarandache's Neutrosophic Sets (NSs) deliver the base for the addition of either Fundamentalist Sets or Intuitionistic Fundamental Sets (IFS) [2]. While the FS delivers the extent of the Truth value of a feature in a set group, the IFS delivers both a level of false and truth values, and the NS offers a level of Indeterminacy, truth, and false values [3]. In IFS, the function of false is not dependent on the true; but, in the event with FS, the function of false is dependent upon the true function [4]. The indeterminacy, truth, and falsity are distinct in NS [5]. Smarandache examined the differences between NS and the many alterations of FS that are accessible [6].

Customer churn, or attrition, is the rate at which customers choose to buy more of a business's services or products [7]. Customer churn analysis is a model for evaluating this rate [8]. At a higher level, churn analysis just tells you what ratio of your consumers don't return equated with the ratio who conduct repeat business [9]. By digging deeper into these statistics [10], you may be capable of classifying tendencies that can prevent failure or yield a previously effective service or product to the subsequent level [11]. Models to extend customer churn contain computing this KPI over numerous time-frames and trending those outcomes [12]; high-performing companies also extent the economic outcomes of consumers leaving and then standard those numbers beside key performance indicators (KPIs) which is vital to the business's success [13]. Customer churn forecast permits organizations to

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proactively technique at-risk customers and attempt to repair the relationship earlier the consumer leaves. In outcome, it is a pre-warning that allows you to perform [14]. It is commonly accepted that retaining a customer costs a lot less than obtaining a novel one. So being capable of forecasting a customer is going to churn and averting it, is better than losing them and discovering another to substitute them [15]. While knowing when a consumer has churned is significant, forecasting that a customer is almost to churn is much more significant. Customer churn forecast permits the company to recognize consumers at risk of leaving and yield action to avert them from ever occurring [16].

This manuscript offers the design of an AI-based Multi-Dimensional Customer Churn Prediction for Corporate Performance Assessment (AIMD-CCPCPA) technique. The AIMD-CCPCPA technique mainly aims to detect the presence of customer churns and non-churns. It involves a two-stage process. At the initial stage, the AIMD-CCPCPA technique exploits the COPRAS Neutrosophic Method for prediction purposes. Secondly, the AIMD-CCPCPA technique involves parameter selection using a butterfly optimization algorithm (BOA). The experimental analysis of the AIMD-CCPCPA method is examined utilizing a benchmark dataset.

2. Prior Works on Customer Churn Prediction

In [17], attribute selection analysis and DL were united to the consumer churn prediction method. The major features are nominated utilizing dual attribute selection methods namely chi-square and analysis of variance (ANOVA). The nominated features were served into an artificial neural networks (ANN) technique for prediction and analysis. Likewise, a learning rate scheduler was used, and executing it in this method can aid in averting over-fitting and improve the speed of convergence. Jajam et al. [18] proposed a SBi-LSTM and RNN system for the Arithmetic Optimiser Algorithm (AOA) in CCP. Firstly, the AOA system achieves pre-processing to alter the unique data into a valuable format. Furthermore, the SBLSTM-RNN system was employed to differentiate between non-churning and churning consumers. To enhance the CCP results of the SBLSTM-RNN method, an optimum Hyperparameters tuning procedure utilizing the Improved Gravitational Search Optimizer Algorithm (IGSA) is employed. In [19], initially, a CNN technique was used on an arithmetical database for employee churn forecasts in trading. Future, data loss is extremely ample in data transformation, a novel hybrid extended convolutional decision tree method (ECDT) has been projected by enhancing the CNN technique. Lastly, a new method (ECDT-GRID) was projected by relating a grid search optimizer to increase the identification precision of ECDT.

Bakhvalov et al. [20] presented an Intellectual System for CCP utilizing a Dipper Throat Optimizer with a DL (ISCCP-DTODL) approach. The ISCCP-DTODL method executes the normalization of Z-score data to pre-process the data. To decrease higher dimensional features, the ISCCP-DTODL model utilizes the DTO system. Also, the ISCCP-DTODL system utilizes of hybrid CNN-BiLSTM technique for churn forecast. Finally, the jellyfish optimizer (JFO) based hyperparameter tuning method is employed. Haridasan et al. [21] concentrated on designing an AOA with the SBLSTM technique for CCP. Originally, the AOA-SBLSTM method executed pre-processing to convert the novel data into a beneficial layout. Also, the SBLSTM approach was applied to classify data into non-churners and churners. To increase the CCP results of the SBLSTM technique, an optimum hyperparameter tuning procedure employing AOA was projected.

Sedighimanesh et al. [22] foremost aim is to enhance the precision of forecasting customer churn by using the Particle Swarm Optimizer (PSO) approach for enhancing the hyperparameter of a composite DL system. A composite DL technique was used, incorporating numerous neural network structures to influence their powers in exhibiting compound customer connections. The PSO system has been employed to enhance the model’s hyperparameter. Mengash et al. [23] presented the Archimedes optimizer algorithm-based FS with a hybrid DL-based churn prediction (AOAFS-HDLCP) approach for telecom businesses. The AOAFS-HDLCP method includes the AOAFS technique to select a set of features. Furthermore, the CNN-AE technique is also contained for the CP procedure. Lastly, the thermal equilibrium optimizer (TEO) method was employed for the hyperparameter range of the CNN-AE system.

3. Materials and Methods

In this manuscript, we offer the design of the AIMD-CCPCPA technique. The AIMD-CCPCPA technique mainly aims to detect the presence of customer churns and non-churns. It involves a two-stage process.

A. Design of COPRAS Neutrosophic Method

At the initial stage, the AIMD-CCPCPA technique exploits the COPRAS Neutrosophic Method for prediction purposes. It is appropriate to establish the neutrosophic set under analysis before analyzing the neutrosophic

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decision matrix [24]. The neutrosophic set can be determined as follows: true (ϑ), indeterminate (η), and false (δ) of x in Q, correspondingly, and the image constitutes a standard or non-standard subset [0,1]. The single-valued neutrosophic set Q over X was represented by $l = \{\langle x, \vartheta_A(x), \eta_A(x), \delta_A(x)\rangle : x\varepsilon X\}$.

Where $\vartheta_A(x), \vartheta_A, \eta_A(x)$ meets the condition $\eta_A(x), \delta_A(x)0 \leq,, \delta_A() \leq 3$ for all $x \in X$. Therefore, $h_t i_t j$ define the neutrosophic value to model the neutrosophic COPRAS technique. $h = \vartheta_A(x)$ for true membership function, where $\in \{0,1\}$.

$i = \eta_A(x)$ for indeterminate membership function, where $\in \{0,1\}$.

$j = \delta_A(x)$ for false membership function, where $\in \{0,1\}$.

Thus, the neutrosophic value determined by $= (h, i, j)$, where $h, i, j \in \{0,1\}$ and meet the condition $0 \leq h + i + j \leq 3$. Therefore, the score function B is defined.

COPRAS is a "Complex Proportional Assessment of Systems" and a mathematical method is used in decision-making, where weight is allocated to rank and classify another option. It evaluates and selects possibilities in complicated situations where criteria and various factors should be considered. To define the decision element within the neutrosophic set, the Neutrosophic COPRAS technique is selected to enable the selection and evaluation of alternatives in more complex and uncertain situations. As a result, it assesses which option is the best and visualizes the dependence and relationship with other options.

The modeling of Neutrosophic COPRAS techniques is as follows:

Describe the alternatives and criteria: Determine the relative alternatives and the criterion that is compared and evaluated.

Assign weights to the criteria: Identify the relevant weights of the criterion for reflecting the prominence in the decision-making.

Assessment of alternatives: The alternative is assessed for all the criteria and a score is allocated.

Normalization of scores: The score is normalized to ensure each alternative is comparable.

Computation of the association rule matrix: It combines the weights and the normalized scores of the criterion for calculating the last score for all the alternatives.

Rank the alternative: The alternative is ranked according to the final score for determining the better selection.

The Neutrosophic COPRAS technique chose the better decision alternative by taking the best and worst- solutions, in a step-wise evaluation and classification of the alternatives in terms of their indeterminacy, importance, degree of utility, and dependence. The steps of Neutrosophic COPRAS algorithm are given below:

Step 1: Computation of the normalized decision matrix l_{ij}^*, using Eq. (1).

$$l_{ij}^* = \frac{l_{ij}}{\sum_{i=1}^{m} \quad l_{ij}} \tag{1}$$

Step 2: Define the weighted neutrosophic normalized decision matrix D_{hij}:

$$D_{hij} = x_{hij}^* . w_{hj} = [w_{h1}l_{11} \; w_{h2}l_{12} \; \dots \; w_{h1}l_{1n} \; w_{h1}l_{21} \; w_{h2}l_{22} \; \dots \; w_{h2}l_{2n} \; \vdots \; \vdots \; \ddots \; \vdots \; w_{h1}l_{m1} \; w_{h2}l_{m2} \; \dots \; w_{hn}l_{mn} \;] \tag{2}$$

In Eq. (2), l_{ij}^* refers to the value of the normalized neutrosophic value of i_{th} alternative in j_{th} criterion and w_{hj} indicates the weight related to the j_{th} criterion.

Step 3: The S_{i+} and S_{i-} sums of the weighted normalized values are evaluated for beneficial (B) and non-beneficial (NB) criteria.

$$S_{i_{i+}} = \sum_{k=1}^{k} \quad D_{hij} \tag{3}$$

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$$S_{i_-} = \sum_{k=1}^{k} \quad D_{hij} \tag{4}$$

Step 4: Defined the relative importance of Q_i alternatives as.

$$Q_i = S_i + \frac{\Sigma_{j=1}^{m} S_i}{s_{i-}\Sigma_{j=1}^{m} \frac{-1}{s_{i-}}} \tag{5}$$

The Q_i of alternatives show the degree of satisfaction obtained.

Step 5: Evaluation of the performance index P_i:

$$P_i = \frac{Q_i}{Q_{max}} \cdot 100 \tag{6}$$

Here Q_{max} indicates the highest value of relative importance. P_{hi} obtains a complete rank of the candidate alternative. Briefly, the COPRAS Neutrosophic technique combines weights and criteria to select and evaluate alternatives in complex decision-making situations.

B. Model Tuning

Secondly, the AIMD-CCPCPA technique involves parameter selection using BOA. Naturally, every butterfly exits smell in the air at the time of mating and foraging, and butterflies in the population convey data to each other over the smell, where the BOA is stimulated by this [25]. Every butterfly was allowed to travel in any way or else near the finest butterfly which produces more smell, and the search object openly defines the incentive power in the population.

Initialization

In this stage, N butterflies were arbitrarily spread in the searching space in an assumed interval of $[lb, ub]$ by Eq. (7).

$$X_{i,j} = lb_j + rand * (ub_j - lb_j), i = 1,2,\cdots, N, j = 1,2,\cdots, D \tag{7}$$

The ith butterfly location in the tth iteration was stated as a vector $X_i^t = \{x_{i,1}, x_{i,'2}, \cdots, x_{i,D}\}$, Where, D denotes the dimension. The whole butterfly's population is kept in a matrix X which contains D columns and N rows, that is $X = \{X_1, X_2, \cdots, X_N\}^T$. The fitness value of X_i^t was intended by the fitness function $fitness(X_i^t)$.

Fragrance

The butterflies in the searching space exchange, their locations, and their equivalent fitness value are modified. So, the fragrance variant of butterflies enables data distribution within the population, where their smell is computed by Eq. (8).

$$f_i = c * I^a \tag{8}$$

Here, f_i denotes the observed scale of the smell of the ith butterfly, that is the strength of the smell observed by other butterflies, c refers to the sensor modality. I represents the incentive intensity defined by fitness. The parameter a signifies the power exponent reliant on modality, $a = 1$ specifies that no smell is occupied, which indicates that it released by every butterfly individual in the searching space will not decline in the proliferation procedure. This is equal to the spread of butterfly smell permitting other butterflies to obtain and observe a similar smell. a is enlarged from 0.1 to 0.3 over the sequence of iterations exposed in Eq. (9).

$$a = 0.1 + 0.2 * \frac{t}{T} \tag{9}$$

Here, t denotes the existing iteration, parameter a differs with iteration. T represents the highest iteration. a and c denote crucial to the rapidity of convergence. $a = 0$ indicates that any butterfly cannot able to sense the smell produced by any other butterflies, so there is no data sharing among entities.

Butterflies movement

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Mating and foraging butterflies will take place in both global and local searching spaces. However, the foraging is a major part. BOA changes the local and global searching by switch probability $p(p \in [0,1])$ which is definite as 0.8. The global search was signified as the measure of butterfly utilizing Eq. (10).

$$X_i^{t+1} = X_i^t + (r^2 * gbest - X_i^t) \times f_i \tag{10}$$

Here, X_i^{t+1} represents the location of the $(t+1)th$ iteration of the ith butterfly, X_i^t represents the location of the tth iteration of the ith butterfly. $gbest$ represents the best solution amongst all the solutions in the present iteration, r refers to the randomly generated value in [0 and 1], i.e. $r \in [0, 1]$. f_i denotes the smell of ith butterfly. Fig. 1 depicts the flowchart of BOA.

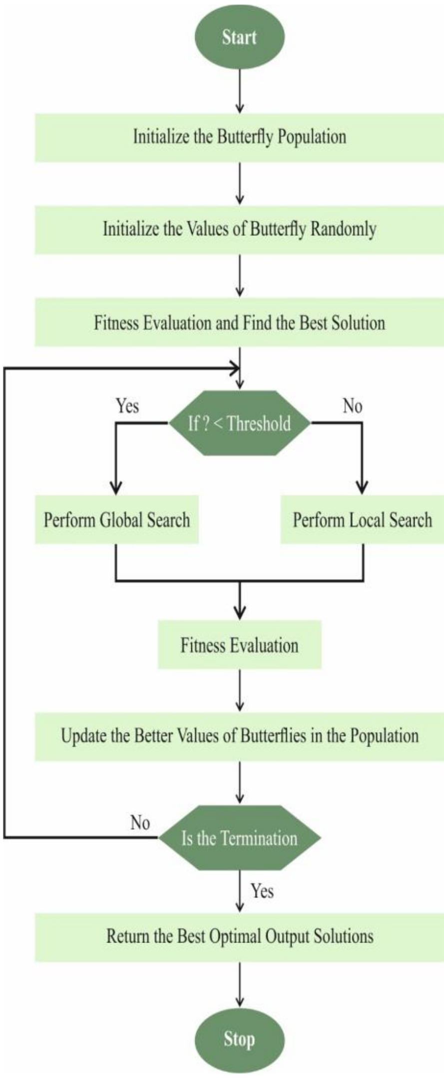

Figure 1: Flowchart of BOA

In the local searching stage, the individual's locations are upgraded over the solution in the population which is stated in Eq. (11).

$$X_i^{t+1} = X_i^t + (r^2 * X_k^t - X_l^t) \times f_i \tag{11}$$

Whereas, X_k^t and X_l^t denotes the kth and lth butterfly from the space of solution that are equally chosen individuals and arbitrarily nominated from the population, that is $k \in [1, N]$, $l \in [1, N]$ and $i \neq k \neq l$.

The BOA contains the abovementioned three stages, the pseudocode is defined in Algorithm1.

Algorithm 1: Explanation of the standard BOA

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Input: Dimension D, Maximum number of function, Population size N, Allowable boundary $[lb, nb]$, evaluations $maxFEs$, Sensory modality c, Switch probability p.
Output: Optimum solution.
% === Set population ===
Randomly set population utilizing Eq. (7);
Estimate the fitnesses of X and upgrade FEs; % FEs: function estimates
Get gbestualue (the finest fitness in the existing population) and gbest (the individual of gbestualue);
% === Iteration ===
$T = \lceil maxFEs/N \rceil$; % T: maximum amount of iterations
$t = 0$; % t: present iteration
while FEs <=maxFEs && t <= T do
$t = t + 1$;
Compute the power exponent utilizing Eq. (9);
for $i = 1$ to N do
Compute the fragrance employing Eq. (8);
if $rand$ < p then
Move near the finest butterfly (solution) utilizing Eq. (10);
else
Move randomly employing Eq. (11);
end
Check limitations and assess the fitness of X_i;
$FEs = FEs + 1$;
Upgrade $gbestvalue$, $gbest$, and FEs;
end
end
End: Return the global optimum solution best.

The fitness function (FF) is the significant factor inducing the performance of BOA. The hyperparameter range procedure includes the solution encoded method to assess the efficiency of the candidate solution. In this paper, the BOA reflects accuracy as main standard to project the FF that given below.

$$Fitness = max\,(P) \tag{12}$$

$$P = \frac{TP}{TP + FP} \tag{13}$$

Here, TP denotes the true positive and FP represents the false positive value.

4. Performance Evaluation

The experimental analysis of the AIMD-CCPCPA method is examined utilizing a benchmark dataset [26]. The dataset has 1000 samples with dual class labels are represented in Table 1.

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Table 1: Details on database

Classes	No. of Instances
Churn	500
Non-Churn	500
Total Instances	1000

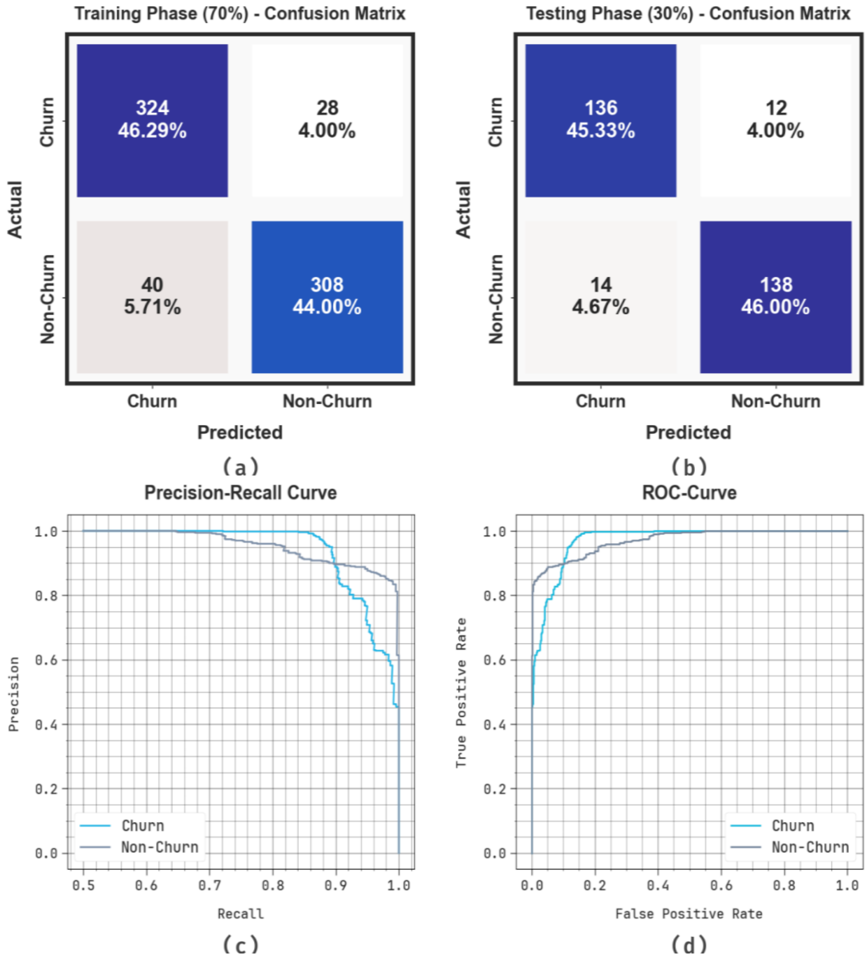

Figure 2: Classifier outcomes of (a-b) 70%TRAS and 30%TESS of confusion matrices and (c-d) PR and ROC curves

Fig. 2 determines the classifier outcomes of the AIMD-CCPCPA system under the test dataset. Figs. 2a-2b reveals the confusion matrices presented by the AIMD-CCPCPA method on 70%TRAS and 30%TESS. The figure shows that the AIMD-CCPCPA technique has recognized and classified all 2 classes exactly. Similarly, Fig. 2c exposes the PR study of the AIMD-CCPCPA system. The outcome stated that the AIMD-CCPCPA technique has got maximum performance of PR under all classes. Finally, Fig. 2d demonstrates the ROC investigation of the AIMD-CCPCPA model. The outcome portrayed that the AIMD-CCPCPA technique has resulted in proficient results with the maximum ROC values under different class labels.

In Table 2 and Fig. 3, the CCP output of the AIMD-CCPCPA system is demonstrated. The results ensured the ability of the AIMD-CCPCPA approach on churn and non-churn classes. With 70%TRAS, the AIMD-CCPCPA technique offers average $accu_y$, $prec_n$, $reca_l$, $F_{measure}$, and MCC of 90.28%, 90.34%, 90.28%, 90.28%, and 80.61%, respectively. In addition, with 30%TESS, the AIMD-CCPCPA system provides average $accu_y$, $prec_n$, $reca_l$, $F_{measure}$, and MCC of 91.34%, 91.33%, 91.34%, 91.33%, and 82.67%, respectively.

Table 2: CCP outcome of AIMD-CCPCPA model under 70%TRAS and 30%TESS

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Classes	$Accu_y$	$Prec_n$	$Reca_l$	$F_{Measure}$	MCC
TRAS (70%)					
Churn	92.05	89.01	92.05	90.50	80.61
Non-Churn	88.51	91.67	88.51	90.06	80.61
Average	90.28	90.34	90.28	90.28	80.61
TESS (30%)					
Churn	91.89	90.67	91.89	91.28	82.67
Non-Churn	90.79	92.00	90.79	91.39	82.67
Average	91.34	91.33	91.34	91.33	82.67

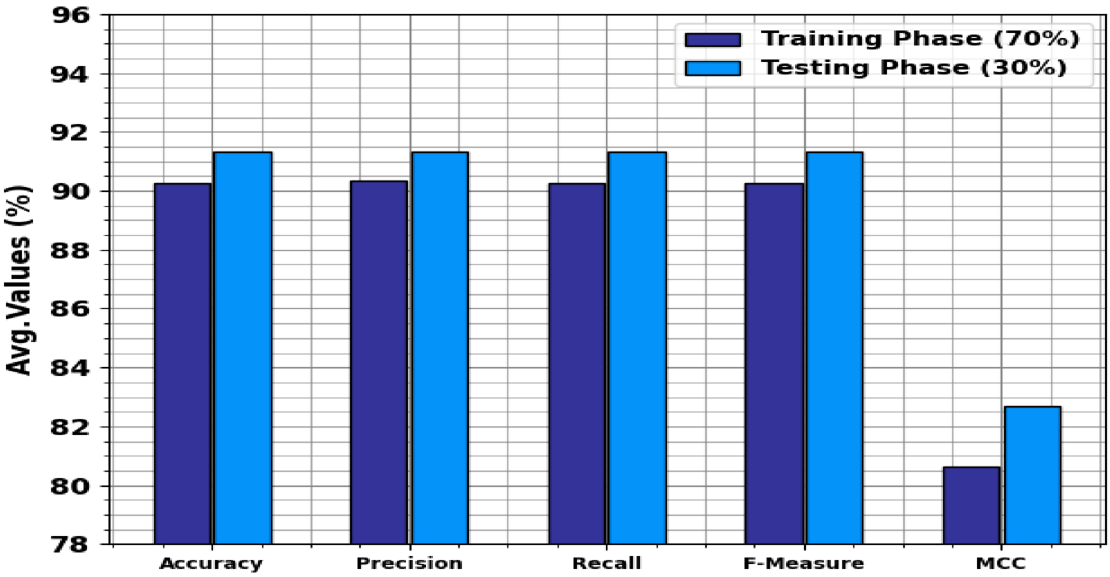

Figure 3: Average of AIMD-CCPCPA technique under 70%TRAS and 30%TESS

The performance of AIMD-CCPCPA system is graphically offered in Fig. 4 in the method of validation accuracy (VALAC) and training accuracy (TRAAC) curves. The figure shows a useful clarification of the behavior of the AIMD-CCPCPA technique over numerous epoch counts, establishing its learning procedure and generalized skills. Remarkably, the figure concludes a steady improvement in the VALAC and TRAAC with development in epochs. It certifies the adaptive nature of AIMD-CCPCPA technique in the design recognition procedure on both the data. The expanding tendency in VALAC summarizes the capability of the AIMD-CCPCPA approach to adapt to the TRA data and also excels in delivering precise identification of hidden data, pointing out strong general skills.

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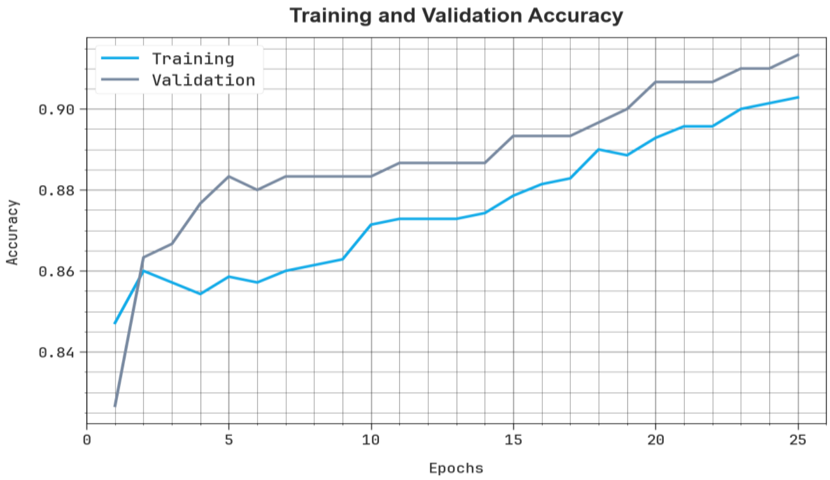

Figure 4: $Accu_y$ curve of the AIMD-CCPCPA technique

Fig. 5 establishes a complete representation of the validation loss (VALLS) and training loss (TRALS) outcomes of the AIMD-CCPCPA technique over dissimilar epochs. The progressive decline in TRALS underlines the AIMD-CCPCPA approach enhancing the weights and diminishing the classification error on the TRA and TES data. The figure specifies a clear understanding of the AIMD-CCPCPA model's suggestion with the TRA data, emphasizing its proficiency in taking patterns within both datasets. Remarkably, the AIMD-CCPCPA approach repeatedly increases its parameter in declining the changes between the prediction and actual TRA classes.

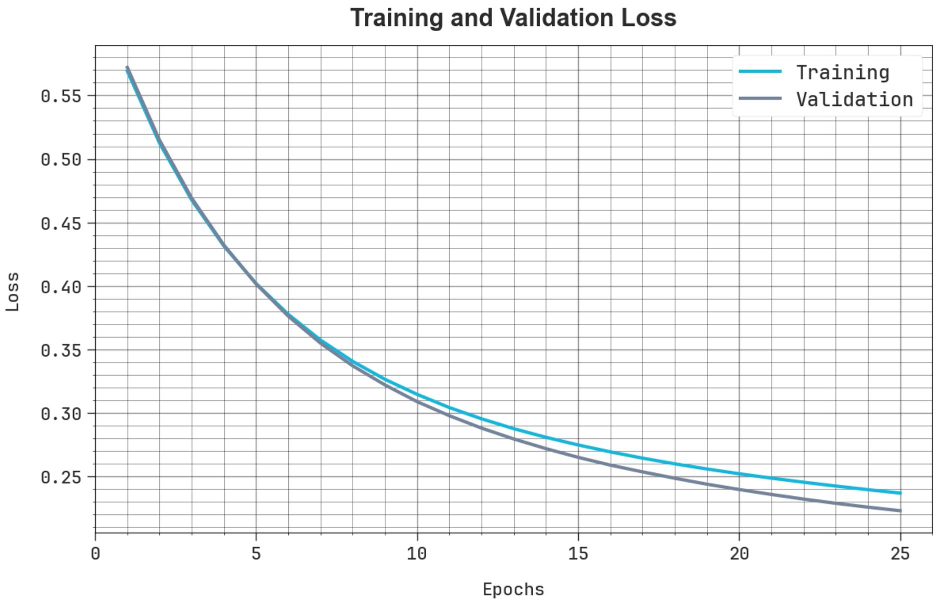

Figure 5: Loss curve of the AIMD-CCPCPA technique

In Table 3 and Fig. 6, the overall outcomes of the AIMD-CCPCPA approach undergo comparison with other models [27]. Based on $accu_y$, the AIMD-CCPCPA technique reaches increased $accu_y$ of 91.34% while the SVM, Bagging, Boosting (AdaBoost), DT, KNN, and BiLSTM-CNN techniques obtain decreased $accu_y$ of 82.32%, 80.37%, 75.47%, 81.03%, 74.09%, and 84.40%, correspondingly. Moreover, based on $prec_n$, the AIMD-CCPCPA technique reaches increased $prec_n$ of 91.33% while the SVM, Bagging, Boosting (AdaBoost), DT, KNN, and BiLSTM-CNN techniques obtain decreased $prec_n$ of 51.38%, 47.56%, 39.51%, 60.40%, 47.40%, and 69.51%, correspondingly. In addition, based on $reca_l$, the AIMD-CCPCPA model attains increased $reca_l$ of 91.34% whereas the SVM, Bagging, Boosting (AdaBoost), DT, KNN, and BiLSTM-CNN system gets reduced $reca_l$ of 72.17%, 66.51%, 53.34%, 65.23%, 52.27%, and 67.30%, respectively. Finally, based on $F_{measure}$, the AIMD-CCPCPA technique reaches increased $F_{measure}$ of 91.33% whereas the SVM, Bagging, Boosting (AdaBoost), DT, KNN, and BiLSTM-CNN methodologies obtain diminished $F_{measure}$ of 60.32%, 54.09%, 45.28%, 62.21%, 49.30%, and 68.43%, respectively.

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Table 3: Comparative analysis of AIMD-CCPCPA technique with other approaches

Models	$Accu_y$	$Prec_n$	$Reca_l$	$F_{Measure}$
SVM Model	82.32	51.38	72.17	60.32
Bagging	80.37	47.56	66.51	54.09
Boosting (AdaBoost)	75.47	39.51	53.34	45.28
Decision Tree	81.03	60.40	65.23	62.21
KNN Algorithm	74.09	47.40	52.27	49.30
BiLSTM-CNN	84.40	69.51	67.30	68.43
AIMD-CCPCPA	91.34	91.33	91.34	91.33

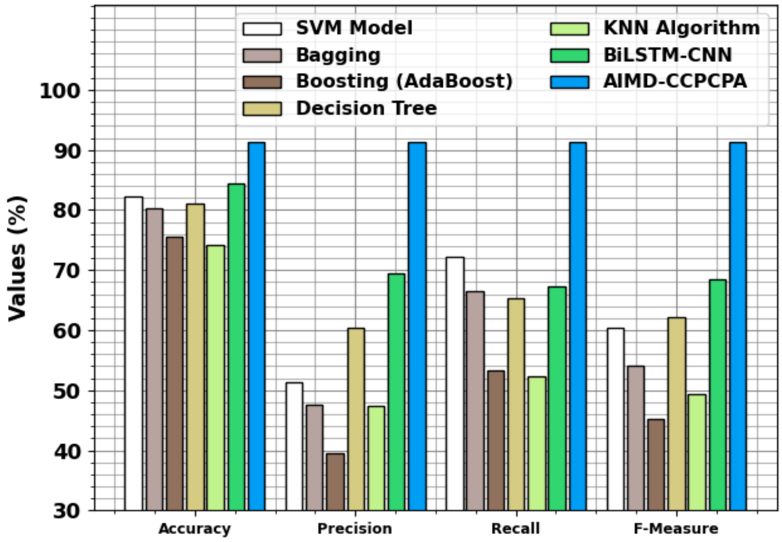

Figure 6: Comparative analysis of AIMD-CCPCPA technique with other approaches

5. Conclusion

In this manuscript, we offer the proposal of the AIMD-CCPCPA model. The AIMD-CCPCPA technique mainly aims to detect the presence of customer churns and non-churns. It involves a two-stage process. At the initial stage, the AIMD-CCPCPA technique exploits the COPRAS Neutrosophic Method for prediction purposes. Secondly, the AIMD-CCPCPA technique involves parameter selection using BOA. The experimental analysis of the AIMD-CCPCPA system is examined using a benchmark dataset. The obtained results stated the supremacy of the AIMD-CCPCPA technique compared to other models

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