Advancement in Customer Attrition Prediction: Design of Optimal Triple Refined Indeterminate Neutrosophic Sets in Large-Scale Financial Sectors

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Abstract

Background: Neutrosophy is the subject area of philosophy that researches all associated with neutralities, owing to the contradictory information, lack of information, imprecise and paradoxical information, among them. The scale's design is organized to take the subjective quality of opinion, being responsible for either uncertainty or the indeterminacy of the respondents' opinions. It relies on the triple refined indeterminate neutrosophic sets (NS) for improved accuracy in understanding the agreement or disagreement level on particular items, like the competence of activities cost and financial management inside the legal services. Currently, customer abrasion is more and more serious in commercial banks, mainly, high-valued customers in retail banking. Therefore, it is stimulated to advance a prediction mechanism and recognize this customer may be at attrition risk. Thus, recognizing and lowering customer churn has become important for financial institutions trying to maintain customers. Currently, several researchers concentrate on customer attrition rate studies utilizing sophisticated machine learning (ML) and deep learning (DL) methods. Methodology: This study develops a Customer Attrition Prediction Using Triple Refined Indeterminate Neutrosophic Sets with an Optimization Algorithm (CAP-TRINSOA) technique. The main aim of the CAP-TRINSOA technique is to improve the attrition prediction of a customer in large-scale financial sectors using state-of-the-art techniques. In the initial stage, the data normalization employs mean normalization to transfer input data into an even format. Furthermore, the classification process is performed by implementing the triple refined indeterminate neutrosophic sets (TRINS). Finally, the honey badger algorithm (HBA) alters the parameter tuning value of the TRINS method optimally and results in greater performance of classification. Results: An extensive set of simulations is accomplished to exhibit the promising results of the CAP-TRINSOA method under the bank customer churn prediction dataset. The experimental validation of the CAP-TRINSOA technique portrayed a superior accuracy value of 97.65% over exisitng model in the customer attrition prediction process.

Keywords: Neutrosophy; Neutrosophic Sets; Triple Refined Indeterminate Neutrosophic Sets; Customer Attrition Prediction; Financial Sectors; Honey Badger Algorithm

1. Introduction

Managing inconsistency and uncertainty is a very significant problem for investigators who explore mathematical modeling [1]. Investigators projected numerous approximate values for developing mathematical techniques with

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few concerns including inconsistency and uncertainty data [2]. One of the well-known approximations is fuzzy set (FS) and intuitionistic FS (IFS) theories were proposed [3]. FS is known for its membership function and AN IF is well known for non- and membership function. However, FS and IFS keep out of the unpredictable and undefined data [4]. Thus, NS theory is considered a generalization of IFS and FS depends on Neutrosophy, which is the subject area of philosophy [5]. Currently, domestic commercial banks are experiencing complex and massive changes, and dealing with several challenges. Information technologies depicted by cloud computing, and mobile Internet are rising, financial regulation proficient in capital regulation, and the process of interest rate marketization and financial disintermediation are slowly speeding up, inducing the sharply narrowed attention margin for banks [6].

Simultaneously, financial consumption needs for consumers rising slowly. The industry has made substantial investments for improving the value of consumers. Thus, forecasting customer churn has turned imperative at the right time [7]. Timely and accurate churn prediction strengthens the relationship- of the bank with perceptions to effectively make involving customer initiatives. Forecasting customer attrition with higher precision is crucial for customer retention [8]. Furthermore, dependable prediction of changes in the customer population will enhance resource allocation and business planning efficacy. To forecast customer attrition for commercial banks, multiple experts implemented data mining models [9]. Many specialists utilized a classification model for forecasting customer churn. Several data mining models were employed for predicting customer churn by recognizing the critical contributing factors. ML methodologies have become vital devices for forecasting customer behavior, to provide the capability for recognizing tendencies that can be challenging to identify employing conventional models [10]. The telecommunication industries are a more widely investigated field for churn prediction.

A. Existing Works on Customer Attrition Prediction

Yu et al. [11] projected an effective method by combining multi-scale feature learning with backpropagation (BP) neural networks. The BP model fine-tunes weights to reduce prediction errors. Primarily, weather data and electricity usage from the UMass Smart Datasets are pre-processed; comprising levels namely standardization, normalization, and data cleaning. Afterward, features are removed through three-time scales. Then, these aspects are input to the BP method employing the multi-scale feature learning technique. Văduva et al. [12] introduce a progressive ML model, utilizing a synthetic database derived from the Kaggle platform. The database endures a pre-processing stage to choose variables instantly affecting behavior of customer churn. SMOTETomek is a hybrid model that integrates the oversampling of the minority class with SMOTE, and the reduction of borderline or noisy samples across. Dual advanced ML methodologies were implemented like LGBM and RF techniques. Panimalar et al. [13] developed a new model called Multipath BP with Weighted MLP (MBP-WMLP). This method employs a specific multi-layer perceptron (MLP) framework with weights. Furthermore, an enhanced multi-path BP model was introduced. The proposed methodology integrates weighted MLP and improved multi-path BP. In addition, this methodology will be implemented for authentic Telco customer churn databases including churn labels indicating subscription cancellations and sanitized customer activity for generating predictive methods.

In [14], a structure for the privacy-preserving customer churn prediction (PPCCP) technique is proposed in a cloud setting. The model projects an innovative methodology that integrates adaptive Weight-of-Evidence (aWOE) and Generative Adversarial Networks (GANs). These experimentations are applied by utilizing 8 diverse ML techniques on 3 openly available databases from the telecommunication sector. Saxena et al. [15] introduce proactive models for online marketplaces. Classification is done by utilizing ML methodologies. This study modernizes the churn prediction by utilizing a unique ensemble of ML techniques. The distinct aspects are systematic model comparison, in-depth exploratory data analysis (EDA), and the innovative application of XGBoost as a unifying force. Arshad et al. [16] developed Q-Ensemble Learning, a new method incorporating Quantum Computing (QC) with ensemble models for enhancing predictive performance. This structure combines quantum models and others into an ensemble, utilizing their higher computational competencies.

B. Limitations and Research Gap

While the methods proposed in existing studies exhibit significant improvements in churn prediction and multi-scale feature learning, various limitations persist. Many models depend heavily on pre-processing techniques such as standardization and normalization, which may not always generalize well to unseen data. Furthermore, while hybrid models and ensemble methods show promise, they may still face difficulty with imbalanced datasets and noisy data. The use of advanced techniques like GANs and QC in some approaches introduces high computational complexity, which can limit their scalability. Furthermore, the datasets utilized in these studies, such as those from telecommunication and online marketplaces, may not be representative of other industries, affecting the broad applicability of these models. Lastly, privacy concerns remain crucial, as models focused on privacy preservation only partially address data protection in real-world settings. These gaps suggest a requirement for further optimization of models and consideration of more diverse, privacy-preserving strategies.

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C. Paper Contribution

This study develops a Customer Attrition Prediction Using Triple Refined Indeterminate Neutrosophic Sets with an Optimization Algorithm (CAP-TRINSOA) technique. The main aim of the CAP-TRINSOA technique is to improve the attrition prediction of a customer in large-scale financial sectors using state-of-the-art techniques. In the initial stage, the data normalization employs mean normalization to transfer input data into an even format. Furthermore, the classification process is performed by implementing the triple refined indeterminate neutrosophic sets (TRINS). Finally, the honey badger algorithm (HBA) alters the parameter tuning value of the TRINS method optimally and results in greater performance of classification. Results: An extensive set of simulations is accomplished to exhibit the promising results of the CAP-TRINSOA method under the bank customer churn prediction dataset.

D. Paper Organization

The rest of the paper is organized as follows. Section 2 explains the detailed proposed methodology and Section 3 discusses the result analysis. Lastly, section 4 concludes the paper.

2. Materials and Methods

This study develops a CAP-TRINSOA technique. The main aim of the CAP-TRINSOA technique is to improve attrition prediction of a customer in large-scale financial sectors using state-of-the-art techniques. To accomplish that, the CAP-TRINSOA model contains various levels such as data normalization, classification process, and hyperparameter tuning model. Fig. 1 depicts the overall working process of the CAP-TRINSOA model.

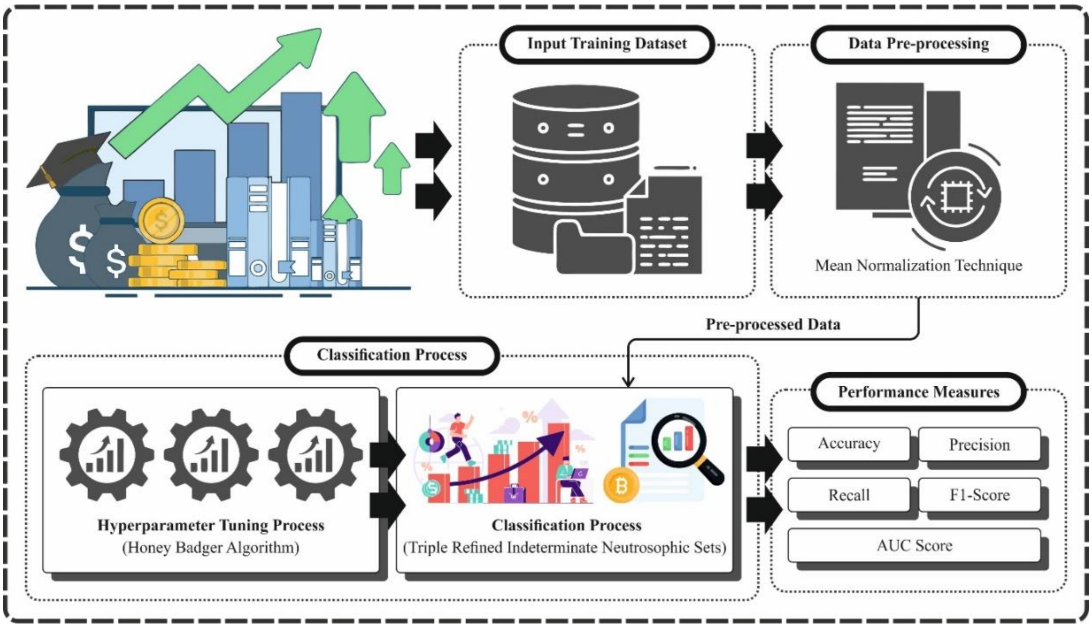

Figure 1. Overall working process of CAP-TRINSOA model

A. Data Normalization

In the initial stage, the data normalization employs mean normalization to transfer input data into an even format. Mean normalization is a feature scaling approach applied in customer attrition prediction to normalize numeric data [17]. It converts features by dividing the range and subtracting the mean, guaranteeing values focused on zero. This aids ML methods to converge quicker and increases precision by stopping the dominance of large-scale characteristics. Mean normalization is mainly beneficial after features have varying sizes or dissimilar units. It improves the stability of the model, making it simpler to identify patterns in the behaviour of customers. This model is generally used before training methods such as neural networks or logistic regression.

B. TRINS-based Classification Process

Furthermore, the classification process has been implemented by the TRINS. Primarily, this classification model presents the basic ideas to the Indeterminate Likert Scale [18]. Subsequently, the following subsection reconsiders the basic principles of Neutrosophic Similarities.

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Definition1: The Single-Valued NS (SVNS) N across U is $A = \{> x; T_A(x), I_A(x), F_A(x) >: x \in U\}$, while $T_A: U \to [0,1]$, $I_A: U \to [0,1]$, and $F_A: U \to [0,1]$, $0 \le T_A(x) + I_A(x) + F_A(x) \le 3$.

Definition2: The advanced Neutrosophic logic was described so as: a truth T is separated into various kinds of truths: $T_1, T_2, \dots, T_p$, I into several indeterminacies: $I_1, I_2, \dots, I_r$ and F into numerous falsities: $F_1, F_2, \dots, F_s$, while every $p, r, s \ge 1$ are numbers and $p + r + s = n$.

Definition3: The TRINS A in X is described by positive $P_A(x)$, negative $N_A(x)$, positive indeterminacy (IDY) $I_{P_A}(x)$, negative IDY $I_{N_A}(x)$, and IDY $I_A(x)$ membership functions (MF). All of them contain a weight $w_m \in [0,1]$ related to it. Under $x \in X$, there is a $P_A(x), I_{P_A}(x), I_A(x), I_{N_A}(x), N_A(x) \in [0,1]$, $w_P^m(P_A(x)), w_{Ip}^m\left(I_{P_A}(x)\right), w_I^m(I_A(x)), w_{IN}^m\left(I_{N_A}(x)\right), w_N^m(N_A(x)) \in [0_t 1]and0 \le P_A(x) + I_{P_A}(x) + I_A(x) + I_{N_A}(x)(x) + N_A(x) \le 5$. Then, a TRINS, A is denoted by $A = \{\langle x; P_A(x), I_{P_A}(x), I_A(x), I_{N_A}(x), N_A(x)\rangle | x \in X\}$.

Assume A and B are dual TRINS in a limited discourse universe, $= \{x_1, x_2, \dots, x_n\}$, which is signified by:

$A = \{\langle x; P_A(x), I_{P_A}(x), I_A(x), I_{N_A}(x), N_A(x)\rangle | x \in X\}$ and $= \{\langle x; P_B(x), I_{P_B}(x), I_B(x), I_{N_B}(x), N_B(x)\rangle | x \in X\}$,

Whereas,$P_A(x_i), I_{P_A}(x_i), I_A(x_i), I_{N_A}(x_i), N_A(x_i), P_B(x_i), I_{P_B}(x_i), I_B(x_i), I_{N_B}(x_i), N_B(x_i) \in [0,1]$, in accordance with $x_i \in X$. Assume $w_i (i = 1,2, \dots, n)$ remain weighting of the component $x_i (i = 1,2, \dots, n)$, with $w_i \ge 0 (i = 1,2, \dots, n)$ and $\sum_{i=1}^{n} w_i = 1$. The TRINS is:

$$d_\lambda(A, B) = \{\frac{1}{5}\sum_{i=1}^{n} w_i \, [|P_A(x_i) - P_B(x_i)|^\lambda + |I_{P_A}(x_i) - I_{P_B}(x_i)|^\lambda + |I_A(x_i) - I_B(x_i)|^\lambda + |I_{N_A}(x_i) - I_{N_B}(x_i)|^\lambda + |N_A(x_i) - N_B(x_i)|^\lambda]\}^{1/\lambda} \quad (1)$$

Here, $\lambda > 0$.

Definition4: The similarity degree among dual SVNS,A and B denote mapping $S: N(X) \times N(X) \to [0,1]^3$, whereas $N(X)$ represent collection of each SVNS in $X = \{x_1, x_2, \dots, x_n\}$, thereby $S(A, B) = \left(S_T(A, B), S_I(A, B), S_F(A, B)\right)$.

Definition5: Assume $A, B \in N(X)$ in $= \{x_1, x_2, \dots, x_n\}$, formerly the similarity measures among A and B are computed by $S(A, B) = (S_T(A, B), S_I(A, B), S_F(A, B)$ while $S_T(A, B)$ denote a degree of truthfulness similarity (DoTS), $S_I(A, B)$ represents a degree of IDY similarity (DoIS), and $S_F(A, B)$ signifies a degree of falsity similarity (DoFS).

$$S_T(A, B) = \left(\sum_{i=1}^{n} \left[\frac{\min(T_A(x_i), T_B(x_i))}{\max(T(x_i), T_B(x_i))}\right]\right) / n \quad (2)$$

$$S_I(A, B) = 1 - \left(\sum_{i=1}^{n} \left[\frac{\min(T_A(x_i), T_B(x_i))}{\max(T(x_i), T_B(x_i))}\right]\right) / n \quad (3)$$

$$S_F(A, B) = 1 - \left(\sum_{i=1}^{n} \left[\frac{\min(F_A(x_i), F_B(x_i))}{\max(F_A(x_i), F_B(x_i))}\right]\right) / n \quad (4)$$

$$\forall x_i \in X.$$

Definition6: Assume that for all $x_i \in X = \{x_1, x_2, \dots, x_n\}$ a weight $w_i \in [0,1]$ is related so as $\sum_{i=1}^{n} w_i = 1$. Assume $A, B \in N(X)$, formerly the weighted measures of similarity amongst A and B is computed by $S_w(A, B) = (S_w^T(A, B), S_w^I(A, B), S_w^F(A, B)$ while $S_w^T(A, B)$ denote the DoTS, $S_w^I(A, B)$ symbolize DoIS, and $S_w^F(A, B)$represents a degree of falsehood similarity.

$$S_w^T(A_t B) = \sum_{i=1}^{n} w_i \left[\frac{\min(T_A(x_i), T_B(x_i))}{\max(T(x_i), T_B(x_i))}\right] \quad (5)$$

$$S_w^I(A_t B) = 1 - \sum_{i=1}^{n} w_i \left[\frac{\min(T_A(x_i), T_B(x_i))}{\max(T(x_i), T_B(x_i))}\right] \quad (6)$$

$$S_w^F(A_t B) = 1 - \sum_{i=1}^{n} w_i \left[\frac{\min(F_A(x_i), F_B(x_i))}{\max(F_A(x_i), F_B(x_i))}\right] \quad (7)$$

$$\forall x_i \in X.$$

Definition7: Assume $A, B \in N(X)$ in $= \{x_1, x_2, \dots, x_n\}$, then similarity measures among A and B are measured by $L(A, B) = (L_T(A, B), L_I(A, B), L_F(A, B)$, while $L_T(A, B)$ denote the DoTS, $L_I(A, B)$ represent DoIS, and $L_F(A, B)$ refers to DoFS.

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$$L_T(A,B) = 1 - \frac{\Sigma_{i=1}^{n}|T_A(x_i) - T_B(x_i)|}{\Sigma_{i=1}^{n}|T_A(x_i) + T_B(x_i)|} \quad (8)$$

$$L_I(A,B) = \frac{\Sigma_{i=1}^{n}|I_A(x_i) - I_B(x_i)|}{\Sigma_{i=1}^{n}|I_A(x_i) + I_B(x_i)|} \quad (9)$$

$$L_F(A,B) = \frac{\Sigma_{i=1}^{n}|F_A(x_i) - F_B(x_i)|}{\Sigma_{i=1}^{n}|F_A(x_i) + F_B(x_i)|} \quad (10)$$

$$\forall x_i \in X.$$

Definition8: Assume $A, B \in N(X)$ in $= \{x_1, x_2, \dots, x_n\}$, formerly similarity measures among A and B are measured by $M(A,B) = (M_T(A,B), M_I(A,B), M_F(A,B)$, whereas $M_T(A,B)$ stands for DoTS, $M_I(A,B)$ means DoIS, and $M_F(A,B)$ symbolize the DoFS.

$$M_T(A_t B) = \frac{1}{n}\sum_{i=1}^{n}(1 - \frac{|T_A(x_i) - T_B(x_i)|}{2}) \quad (11)$$

$$M_I(A_t B) = \frac{1}{n}\sum_{i=1}^{n}(\frac{|I_A(x_i) - I_B(x_i)|}{2}) \quad (12)$$

$$M_F(A_t B) = \frac{1}{n}\sum_{i=1}^{n}(\frac{|F_A(x_i) - F_B(x_i)|}{2}) \quad (13)$$

$$\forall x_i \in X.$$

Definition9: Assume $A, B \in N(X)$ whereas $= \{x_1, x_2, \dots, x_n\}$, formerly similarity measures according to the distance among A and B is computed by:

$$S^1(A,B) = \frac{1}{1 + d(A,B)} \quad (14)$$

So that $d(A,B)$ refers to the distance function among the dual SVNS.

C. HBA-based Parameter Tuning

At last, the HBA adjusts the parameter tuning values of TRINS model optimally and outcomes in greater performance of classification. The HBA model imitates how honey badger's forage. The primary state is referred to as excavating mode, and the second state is honey mode [19]. During the initial phase, it digs into the prey through its knowledge of smell. After it has found its prey, it moves all over the place to pick the optimal location for digging and capturing it. During the second model, the honey badger emulates the head to capture hives.

Stage1: Initialization

Initialization input features such as temperature, PV irradiance, battery voltage and current, population, and maximum iteration.

Stage2: Random Generation

This part offers a computational expression of the presented HBA process. As HBA comprises steps in every exploitation and exploration, it is promising to remember it as a global optimizer technique. Now, the applicant solution's population in HBA is indicated as presented in Eq. (15).

$$population\ of\ candidate\ solutions = \begin{bmatrix} q_{11} & q_{12} & q_{13} & \cdots & q_{1M} & \\ q_{21} & q_{22} & q_{23} & \cdots & q_{2M} & \\ \vdots & \vdots & \iddots & \vdots & \ddots & \vdots \\ q_{N1} & q_{N2} & q_{N3} & \cdots & q_{NM} & \end{bmatrix} \quad (15)$$

The honey badger position,

$$q_I = [q_I^1, q_I^2, \dots, q_I^M] \quad (16)$$

Main the number of HBs (size of the population N) and their specific positions rely on Eq. (16).

$$q_I = lb_I + r_1 \times (ub_I - lb_I) \quad (17)$$

Here, $r1$ denote a randomly generated number between (0, 1). Whereas, q_I specifies I honey badger position in the population of N, over lb_I and ub_I is similarly lower and upper bounds of the exploration region in Eq. (17).

Stage3: Fitness Function (FF)

To compute the fitness value, apply Eq. (18).

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$$F = \min(THD) \tag{18}$$

Stage4: Describing Intensity (I)

Intensity is related to the prey's capability to focus and the place among it and the honey badger. It was described by Eq. (19).

$$P_I = r_2 \times \frac{S}{4\pi d_I^2}, \tag{19}$$

Whereas, r_2 is a randomly generated number between $(0,1)$

$$S = [q_I - q_{I+1}]^2 \tag{20}$$

$$d_I = q_{prey} - q_I \tag{21}$$

Here, S signifies concentration asset or source intensity pointed out in Eq. (20). In Eq. (21), di specifies the area between prey and I badger.

Stage5: Update Density Factor

To promise a constant development from exploration to exploitation, time-changing randomization is expanded by thickness variable (α). The lower randomness by upgrading a decreasing factor α that decreases with either iteration, utilizing Eq. (22).

$$\alpha = J \times \exp\left(\frac{-T}{T_{MAX}}\right), \tag{22}$$

Where, T_{MAX} denote a maximum number of iterations and C signifies constant ≥ 1 (default = 2).

Stage6: Upgrading the Agents Positions

As before said, the HBA location updated process (q_{new}) is separated into dual portions namely the "honey stage" and "digging stage". During the digging stage, a honey badger attains action equivalent to a Cardioid shape. It is simulated by utilizing Eq. (23)

$$q_{new} = q_{prey} + G \times P \times q_{prey} + G \times r_3 \times \alpha \times d_I \times |\cos(2\pi r_4) \times [1 - \cos(2\pi r_5)]| \tag{23}$$

Where q_{prey} states position of the prey is the optimal place discovered to now global optimal position. $\beta \geq 1$ (default=6) is the ability of honey badger to attain food. d_I Is the area between prey and I honey badger, r_3, r_4, and r_5 represent 3 different casual quantities between $(0,1)$. G operates as fag that variations searching direction; it is delineated by Eq. (23). During dig out phase, honey badger extremely relies on odor intensity P of $prey$ q_{prey}, space between the prey and badger, and time-varying searching effect variable α. Additionally, badgers might participate in problems while digging, which permits them to discover prey further successfully. A honey phase once honey badger trajectories honey leader bird to spread hive is simulated as Eq. (24).

$$q_{new} = q_{prey} + G \times r_7 \times \alpha \times d_I \times r_7 \tag{24}$$

Here, r_7 denote random number between $(0,1)$, q_{new} reference to the location of honey badger, whereas q_{prey} signifies location of the victim, prey $position q_{prey}$ discovered thus far, relies on space dating. In this stage, the search is biased by exploration behavior varying by time α. Moreover, honey badger can determine disturbance G.

Step 7: Termination Criteria

Checking end conditions are encountered; if so, the model is completed; if not, travel to stage 3.

The HBA creates a FF to achieve enhanced classification performance. It delineates a progressive number to exemplify the best result of the candidate solution. In this study, the reduction of the classification error rate was exhibited as FF. Its mathematical representation is symbolized in Eq. (25).

$$fitness(x_i) = ClassifierErrorRate(x_i)$$

$$= \frac{number\ of\ misclassified\ samples}{Total\ number\ of\ samples} \times 100 \tag{25}$$

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3. Experimental Analysis

A. Implementation Data

The simulation validation of CAP-TRINSOA model is inspected under the bank customer churn prediction dataset [20]. It holds 10002 sample counts, which holds dual class labels such as churned and non-churned. The complete details of this dataset are depicted in Table 1.

Table 1: Details of dataset

Class Labels	Sample Count
Churned	2038
Non-Churned	7964
Total Count	10002

B. Results Analysis

Fig. 2 signifies the customer attrition prediction of CAP-TRINSOA technique below 80:20 of TRAPHA/TESPHA. The performance reported that the CAP-TRINSOA technique has properly categorized all the distinct classes. With 80% TRAPHA, the proposed CAP-TRINSOA method reaches typical $accu_y$ of 96.39%, $prec_n$ of 95.57%, $reca_l$ of 93.12%, $F1_{score}$ of 94.28%, and AUC_{score} of 93.12%. Also, with 20% TESPHA, the proposed CAP-TRINSOA method attains typical $accu_y$ of 97.65%, $prec_n$ of 97.64%, $reca_l$ of 95.07%, $F1_{score}$ of 96.29%, and AUC_{score} of 95.07%.

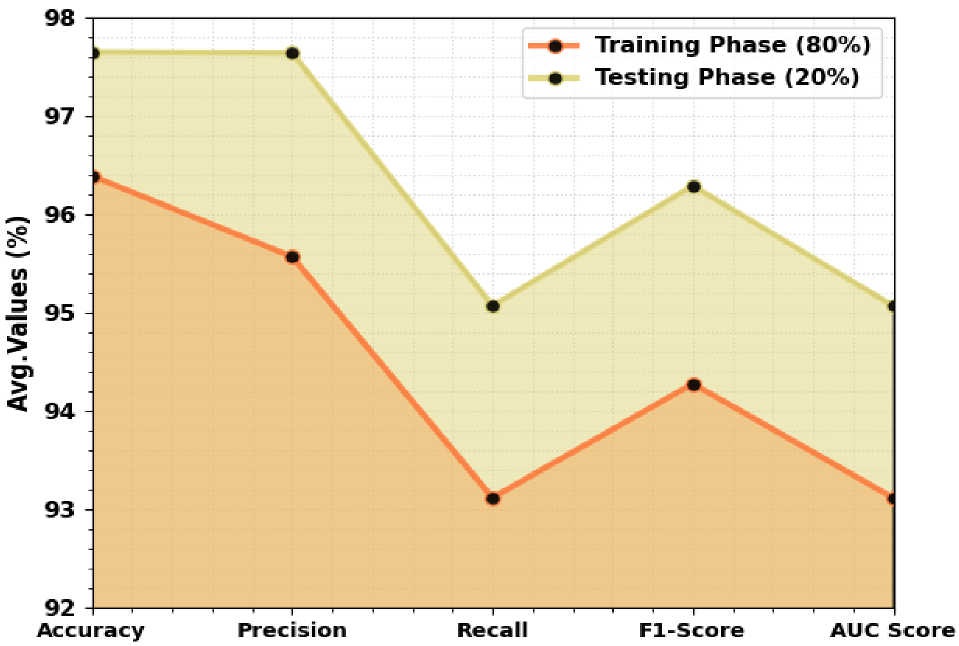

Figure 2. Average of CAP-TRINSOA model under 80:20 of TRAPHA/TESPHA

In Fig. 3, the training (TRAN) $accu_y$ and validation (VALN) $accu_y$ performances of the CAP-TRINSOA approach below 80:20 is depicted. The values of $accu_y$ are computed through period of 0-25 epochs. The figure underscored that the TRAN and VALN$accu_y$ values express a growing propensity, indicating the proficiency of the CAP-TRINSOA technique with superior outcome through various iterations. Additionally, the values of TRAN and VALN $accu_y$ ruins nearer through the epochs, notifying diminished overfitting and showing superior outcomes of the CAP-TRINSOA technique, assuring steady calculation on unseen samples.

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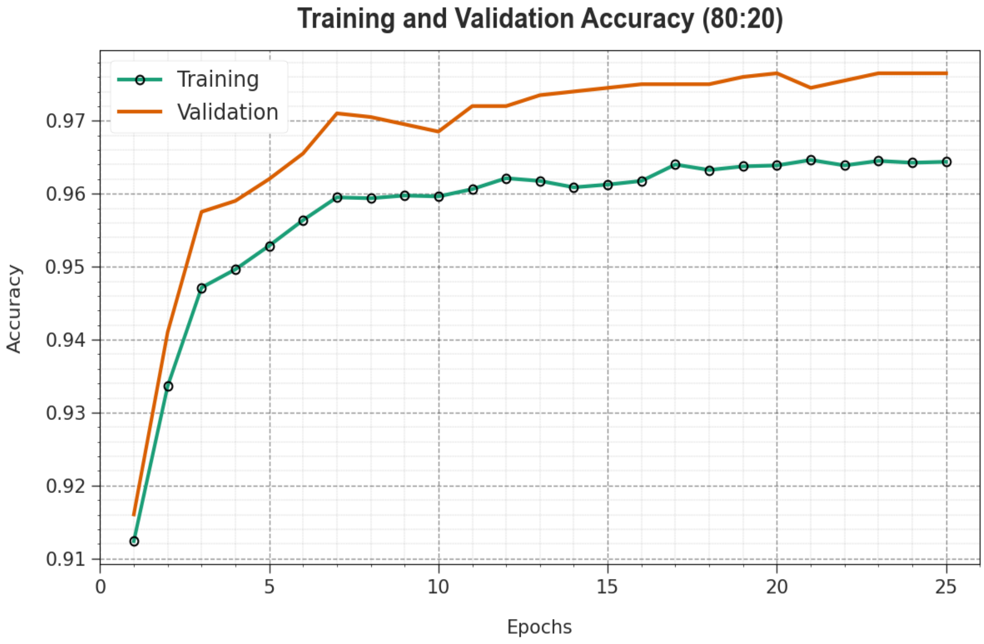

Figure 3. $Accu_y$ Curve of CAP-TRINSOA model under 80:20

In Fig. 4, the training loss (TRANLOS) and validation loss (VALNLOS) graph of the CAP-TRINSOA technique below 80:20 is showcased. The values of loss are computed through a period of 0-25 epochs. It is demonstrated that the values of TRANLOS and V VALNLOS represent a diminishing tendency, indicating the competency of the CAP-TRINSOA technique in equalizing an equilibrium between generalization and data fitting. The subsequent decrease in values of loss as well as securities is the maximum outcome of the CAP-TRINSOA method and tunes the calculation solutions gradually.

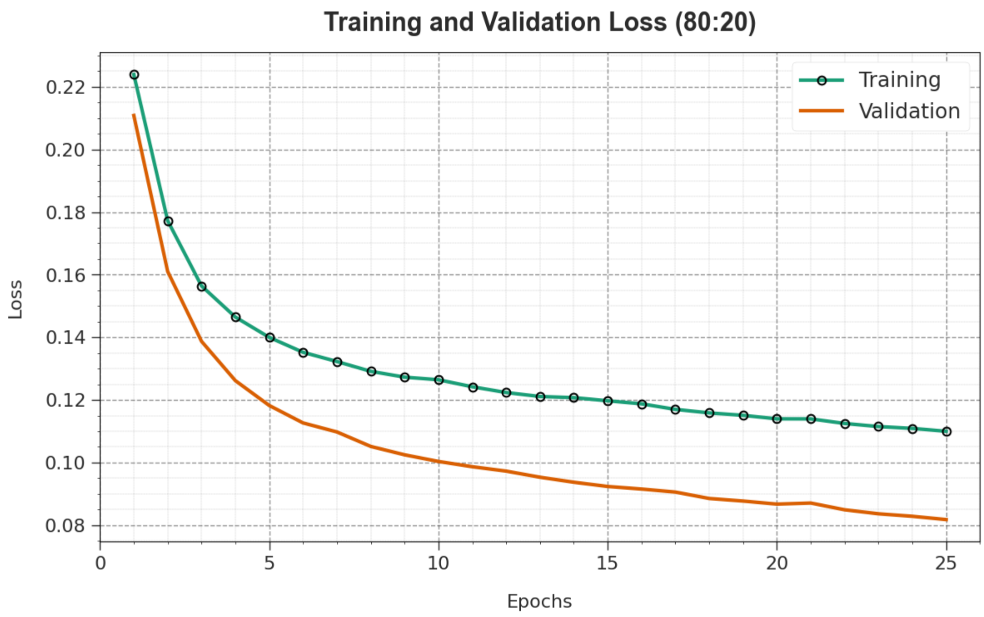

Figure 4. Loss curve of CAP-TRINSOA model under 80:20

Fig. 5 depicts the customer attrition prediction of the CAP-TRINSOA technique below 70:30 of TRAPHA/TESPHA. According to 70% TRAPHA, the proposed CAP-TRINSOA model attains typical $accu_y$ of 95.86%, $prec_n$ of 95.59%, $reca_l$ of 91.33%, $F1_{score}$ of 93.27%, and AUC_{score} of 91.33%. Moreover, on 30% TESPHA, the proposed OFND-EDLEDBO model obtains typical $accu_y$ of 96.60%, $prec_n$ of 96.54%, $reca_l$ of 93.01%, $F1_{score}$ of 94.64%, and AUC_{score} of 93.01%.

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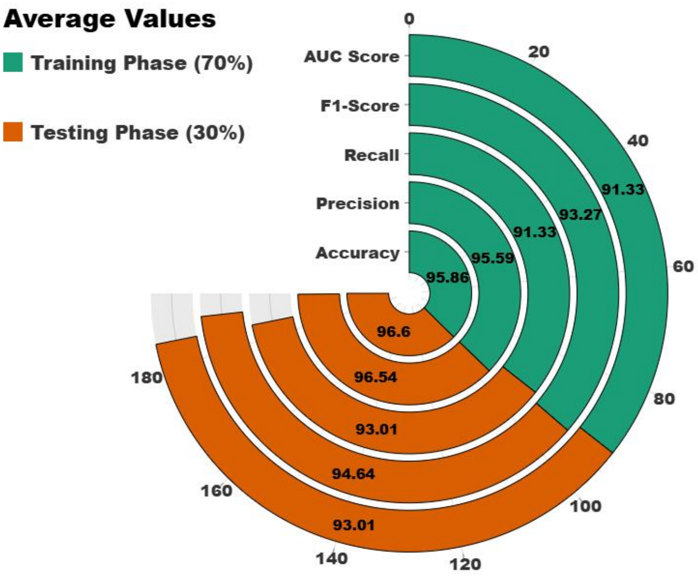

Figure 5. Average of CAP-TRINSOA model under 70:30 of TRAPHA/TESPHA

In Fig. 6, the TRAN $accu_y$ and VALN $accu_y$ performances of the CAP-TRINSOA technique below 70:30 is exemplified. The values of $accu_y$ are computed across a time of 0-25 epochs. The figure underscored that the TRAN and VALN$accu_y$ values display a cumulative propensity, which indicates the proficiency of the CAP-TRINSOA method with increased outcomes through various iterations. In addition, the values of TRAN and VALN $accu_y$ ruins nearer through the epochs, notifying decreased overfitting and expressing the higher outcome of the CAP-TRINSOA method, securing balanced calculation on hidden samples.

In Fig. 7, the TRANLOS and VALNLOS graph of the CAP-TRINSOA method below 70:30 is showcased. The values of loss are computed through a period of 0-25 epochs. It is depicted that the values of TRANLOS and V VALNLOS show a declining propensity, indicating the competency of the CAP-TRINSOA technique in corresponding to an equilibrium between generalization and data fitting. The subsequent dilution in values of loss as well assurances of the improved outcome of the CAP-TRINSOA technique and tuning the calculation solutions after a while.

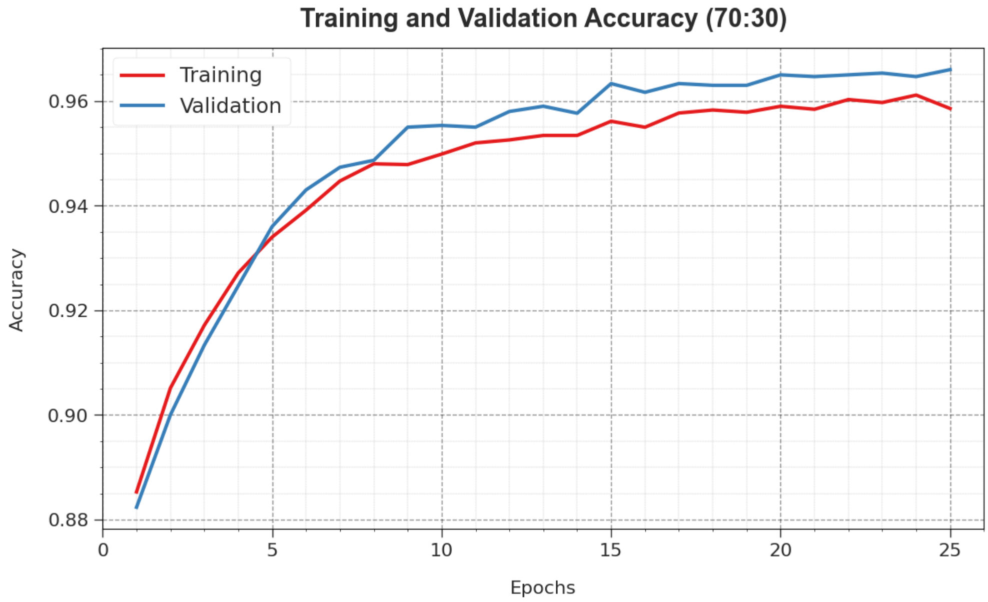

Figure 6. $Accu_y$ Curve of CAP-TRINSOA model under 70:30

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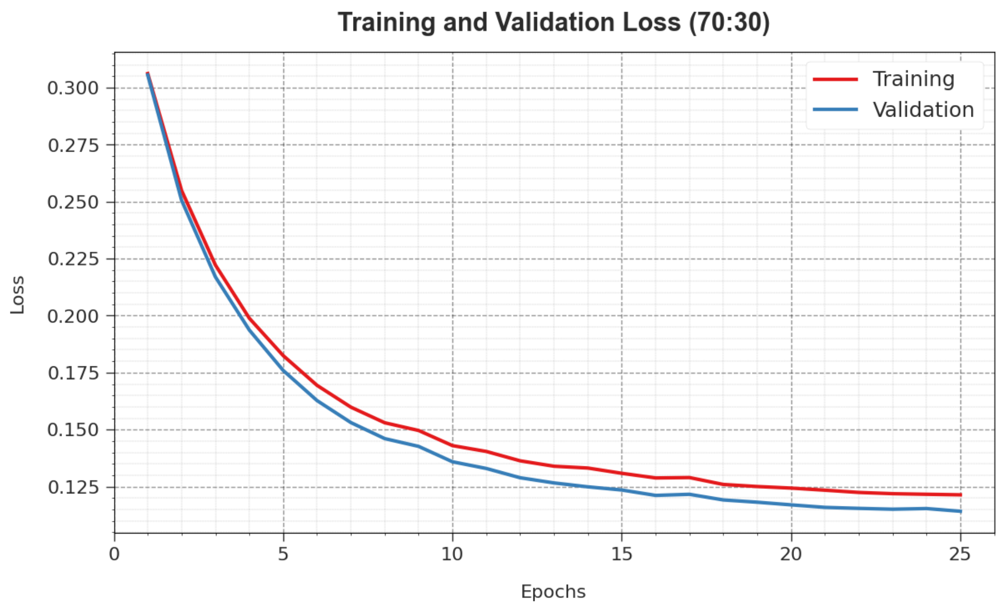

Figure 7. Loss curve of CAP-TRINSOA model under 70:30

C. Discussions

Fig. 8 examine the comparison outcome of CAP-TRINSOA approach with existing methodologies [12 and 21]. The performances underscored that the RF Baseline, LGBM Calibrated, Extra Trees, SVC, Bagging, and Bernoulli NB models have stated poorer performance. In the meantime, the Gaussian NB approach has attained slightly nearer solutions through $accu_y, prec_n, reca_l$ and $F1_{score}$ of 96.25%, 96.40%, 89.70%, and 86.52%, respectively. While the proposed CAP-TRINSOA method indicated maximum performance with higher $accu_y, prec_n$, $reca_l$ and $F1_{score}$ of 97.65%, 97.64%, 95.07%, and 96.29%, respectively.

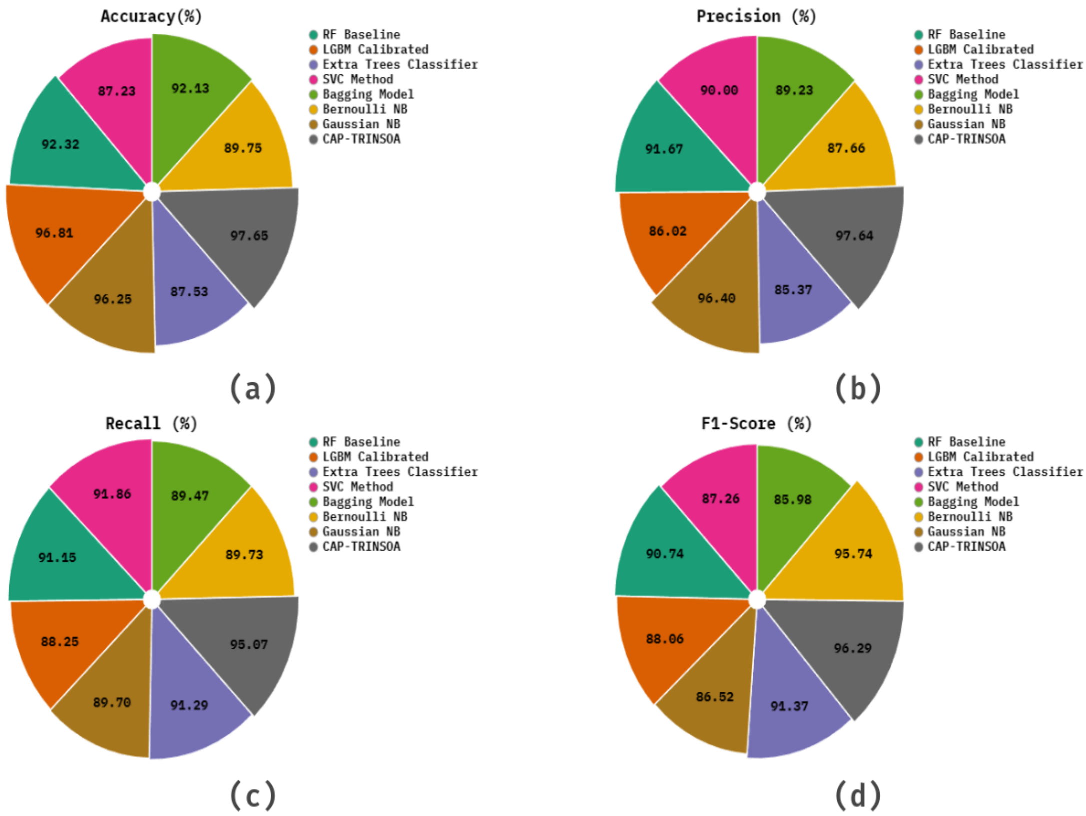

Figure 8. Comparative analysis of CAP-TRINSOA technique with existing models

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4. Conclusion

This study develops a CAP-TRINSOA model. The main aim of CAP-TRINSOA technique is to improve attrition prediction of a customer in a large-scale financial sector using state-of-the-art techniques. In the initial stage, the data normalization employs mean normalization to transfer input data into an even format. Furthermore, the classification process has been implemented by the TRINS. At last, the HBA adjusts the hyperparameter values of the TRINS method optimally and outcomes in greater classification performance. An extensive set of simulations is accomplished to exhibit the promising results of the CAP-TRINSOA method under the bank customer churn prediction dataset. The experimental validation of the CAP-TRINSOA technique portrayed a superior accuracy value of 97.65% over exisitng model in the customer attrition prediction process.

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