Trademark Empowerment using Optimal Neutrosophic Topological Vector Space for Maximizing Customer Attraction

Alsadig Ahmed*[1]

[1]Applied Management Program, Applied College at Muhyle, King Khalid University, Saudi Arabia
Emails: amamoustafa@kku.edu.sa

Abstract

Neutrosophic set is introduced as a generalization of intuitionistic fuzzy set, where any elements $x \in X$ we have membership (T), non-membership (F), and indeterminacy (I)degrees. Neurosophic vague topological spaces are presented in various notations like neurosophic vague compactness and continuity. Trademarks are the essential components of intellectual property that allow owner to earn profit based on their name. In this industry, retailers typically use feedback channels like customer care service, website review complaints and suggestions boxes to gain user reviews on service satisfaction. But, there is a gap between these techniques. Customers are not fulfilled with them due to lack of trust in management, a lack of flexibility and slow responsiveness. This has prompted examination of the effect of customer feedback channels (CFCs) on client satisfaction and the necessity to develop a new CFC using artificial intelligence (AI). Thus, this study designs a Trademark Empowerment using Optimal Neutrosophic Topological Vector Space (TE-ONTVS) technique for Maximizing Customer Attraction. The intention of the TE-ONTVS technique lies in the prediction of customer behaviour and attraction. To accomplish this, the TE-ONTVS technique undergoes data scaling using Z-score normalization. In addition, the TE-ONTVS technique uses NTVS approach for the identification of customer behaviour and attraction. Lastly, whale optimization algorithm (WOA) is applied for optimal parameter tuning of the NTVS algorithm. A series of experiments were involved to demonstrate the enhanced outcomes of the TE-ONTVS algorithm. The obtained results stated that the TE-ONTVS technique reaches optimal performance over other models

Keywords: Customer Feedback; Whale Optimization Algorithm; Neutrosophic Set; Artificial Intelligence; Consumer Behaviour; Trade Mark Empowerment.

1. Introduction

Consumer behaviour and prospects differ across geography as numerous factors assume the purchase, re-purchase or profit of a product, fluctuating from the product features, logistics, inventory, and customer support [1]. The e-commerce market is very difficult owing to customer uncertainty in the safety of payments, success of distributions, and high cross-border taxes, each delivering the benefit to the local retailers [2]. So, the application of machine learning (ML) will permit retailers to overwhelm the tasks by learning more about the users, listening to what client has to say, enhancing product suggestions, price and demand estimating, and improving customer services [3]. The dynamic scenery of customer-centric companies needs sympathetic and enhancing client satisfaction. Traditional survey analysis infrequently produces real-time illegal insights [4]. However, ML predictive analysis permits organizations to utilize innovative techniques to change client satisfaction surveys [5]. ML predictive analysis varies depending on how companies evaluate and increase satisfaction of customers [6]. Customer feedback analysis is where unused client opinions can turn your corporate everywhere. Today's cutthroat competition and huge language methods make understanding client opinions vital [7]. Customer feedback analysis is an art and a science that removes illegal visions from surveys, social media, reviews, and support interactions [8]. Customers deliver more feedback than ever in the digital age, so companies struggle to beat into this wealth. Artificial intelligence (AI) and customer feedback collection tools analysis are united in this paper to disclose actionable visions utilizing NLP and ML [9].

Doi: https://doi.org/10.54216/IJNS.240312
Received: March 29, 2024 Revised: April 28, 2024 Accepted: May 19, 2024

With the fast growth that our world is perceiving in all regions of our everyday life, we face numerous practical issues that contain inconsistent, uncertain, and incomplete data, and this needs a novel and effectual mathematical devices in order to deal with issues [10]. Smarandache achieved to overwhelm the faults that were performed by forming an idea of a neutrosophic set (NS) [11]. An NS is measured as a more complete mathematical device for human thinking, as it shields the features of wrong and right and the indeterminacy among them over its mathematical structure, which holds 3 functions such as T(u) true function, I(u) indeterminacy function, and F(u) falsity function, such that imagery of all of them fit $]-0, +1[$. AI is such a usage of technology that permits machines to perform with greater levels of intellect and contain human skills like decision making etc [12]. In the period of digital transformation, the usage of AI in the direction of IP is always increasing. AI tools mechanize decision-making utilizing encoding rubrics and, training datasets [13]. For instance, AI tools can originate credit score dimensions from dissimilar datasets, and identify objects from imagery data. The latent for human error is one danger that can be addressed and diminished by use of AI [14]. The core of AI is to mimic human intelligence [15]. It is extremely utilized in numerous areas of the economy to make simpler complex and tiresome tasks so that human intelligence can be strayed to discover further measurements [16].

Paper Contributions

This study designs a Trademark Empowerment using Optimal Neutrosophic Topological Vector Space (TE-ONTVS) technique for Maximizing Customer Attraction. The intention of the TE-ONTVS technique lies in the prediction of customer behaviour and attraction. To accomplish this, the TE-ONTVS technique undergoes data scaling using Z-score normalization. In addition, the TE-ONTVS technique uses NTVS approach for the identification of customer behaviour and attraction. Lastly, whale optimization algorithm (WOA) is applied for optimal parameter tuning of the NTVS algorithm. The obtained results stated that the TE-ONTVS technique reaches optimal performance over other models.

2. Brief Review on Customer Behavior Prediction Models

In [17], a novel classifier for client consumption behavior forecasts was developed. The projected models namely a (i) feature selection (FS) model depend upon smallest absolute shrinkage and selection operator (Lasso) and PCA, to attain effectual FS and remove associations among variables. (ii) An enhanced genetic-XGBoost for client consumption behavior forecast. Also, the global search capability of the genetic device are employed in order to enhance XGBoost parameter. The mutation probabilities and adaptive crossover are intended. Furthermore, the grape-customer consumption behavior database is utilized. Alfian et al. [18] proposed utilizing RFID on shelves of stores and ML methods. This paper utilizes RFID tags to follow product drive and gathers information on user behavior utilizing RSS. The features of time-domain were removed from RSS dataset and ML techniques were employed in order to categorize dissimilar client shopping actions. The system also developed addition of iForest Outlier Detection, and MLP techniques. Lalwani et al. [19] projected method, that contains 6 stages. In the first dual stages, feature analysis and data pre-processing are executed. In the 3rd stage, FS is taken into account utilizing gravitational searching system. Then, the information was divided into dual parts training and testing datasets. Furthermore, K-fold cross-validation was employed.

Yang et al. [20] proposed 3 cost-sensitive anticipatory shipping methods, containing cost-sensitive LightGBM (CS-LightGBM), CS logistic regression (CSLR), and CS CatBoost (CS-CatBoost). Also, dual novel evaluation criteria are projected to evaluate the efficiency of the anticipatory shipping method. Lee et al. [21] projected a hybrid technique to forecast client churn by uniting ML and statistic approaches. Unlike traditional models, where churn is definite by a stable period of time, the projected method utilizes the possibility of consumer life resultant from the statistical technique to vigorously define the churn line. Afterward detecting customer churn over clustering over time, the developed model divided consumers into 4 behaviors such as novel, short-term, higher value, and churn, and nominated ML methods in order to forecast the churned consumers.

In [22], a hybrid framework of supervised/unsupervised ML techniques is developed. In this respect, client journeys are foremost coordinated with the log format directing to execute a Density-Based Spatial Clustering of Applications with Noise (DBSCAN). The multi-class decision tree (DT) model was used, and the smoothness of client satisfaction was forecast. Owing to the excessive nature of data, the over-sampling for excessive identification was developed. In [23], an ML workflow for higher identification precision and enhanced forecast confidence utilizing a dual classification technique on a publicly accessible database is proposed. This technique contains data analysis, training, transformation, and testing ML classifiers like NB, DT, RF, SVM, LR, ANN, AdaBoost, and Gradient Descent.

Doi: https://doi.org/10.54216/IJNS.240312
Received: March 29, 2024 Revised: April 28, 2024 Accepted: May 19, 2024

3. Modeling of TE-ONTVS Approach

In this study, we design a TE-ONTVS technique for maximizing customer attraction. The intention of the TE-ONTVS technique lies in the prediction of customer behaviour and attraction. To accomplish this, the TE-ONTVS technique contains three different phases Z-score scaling, NTVS-based predictive modelling, and WOA-based parameter selection phases. Fig. 1 represents the entire flow of TE-ONTVS technique.

A. Z-score Normalization

At initial phase, the TE-ONTVS technique undergoes data scaling using Z-score normalization. Z-score normalization, a basic statistical algorithm, is transforming customer behavior prediction via trademark empowerment [24]. This technique allows businesses to exploit the strength of their brand to anticipate and understand consumer activities. Brand could compare and standardize various data through Z-score that measures how farther the data point is from the mean under standard deviation. This technique ensures that variables with different scales equally contribute to the prediction method, improving its reliability and accuracy. With Z-score normalization at its core, this technique facilitates accurate prediction, which enables organizations to proactively tailor the strategy to meet consumer requirements.

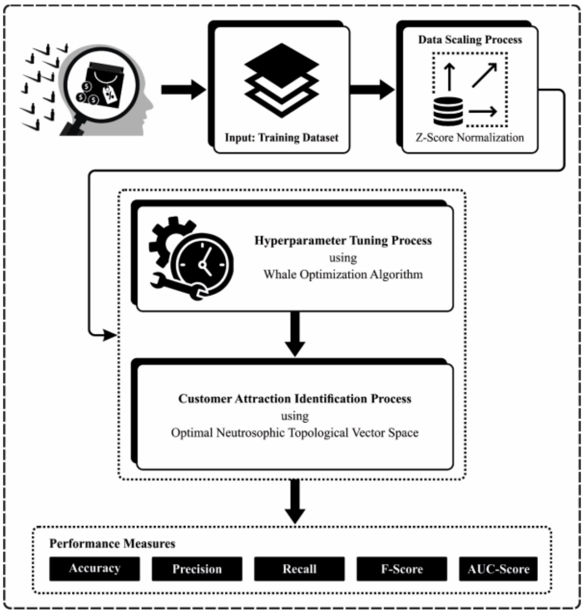

Figure 1: Overall flow of TE-ONTVS technique

B. Model Architecture Selection

Next, the TE-ONTVS technique uses NTVS approach for the identification of customer behaviour and attraction. NTVS is an addition of classical topological vector space for accommodating neutrosophic sets, which capture unknown information, indeterminacy, and ambiguity [25]. This study examines the connection between topological vector spaces and neutrosophic set theory, providing a thorough understanding of their applications and properties. The incorporation of neutrosophic logic offers an effective method to handle imprecise and uncertain information, which makes NTVS an essential basis for many real-time applications.

Assume N, M as the neutrosophic sets and X and Y as two non-empty sets. A neutrosophic set F of $X \times Y$ denotes the neutrosophic function from the neutrosophic set N to M if

$F(x,y) \leq N(x) \cap M(y)$ for $(x,y) \in X \times Y$.

For $x \in X$, there is a unique $y_0 \in Y$ such that $F(x,y_0) = N(x)$ and $F(x,y) = (0,1)$ if $y \neq y_0$.

Thus $F: N \to M$ denotes F is neutrosophic function from $N \in N^X$ into $M \in N^Y$, where N^X and N^Y represents the group of neutrosophic subsets of X and Y correspondingly.

$N = (\mu_N, I_N, \vartheta_N)$ of vector space X over K is Neutrosophic vector space (NTVS) over X when

$$N + N + N \subseteq N$$

Doi: https://doi.org/10.54216/IJNS.240312
Received: March 29, 2024 Revised: April 28, 2024 Accepted: May 19, 2024

$\alpha N \subseteq N$, for the scalar α.

Assume $N(X)$ as a NTVS over K and a τ topology is determined.

(i) $N^{\oplus}$:(V×V,τ×τ)→ (V, τ)

(ii) $N^{\odot}: (V \times V, \tau \times \tau) \rightarrow (V, \tau)$

are Neutrosophic continuous. $(N(X), \tau)$ is represented by the NTVS. Furthermore, the element of τ is known as Neutrosophic open set.

Neutrosophic Proper Function: Assume X as a NTVS over K with θ as a null vector. Consider V as an NTVS over X, $a \in X$ and $k \in$ is constant.

$N^{\oplus}: V \times V \times V \rightarrow V$ by $N^{\oplus}\big((x, y, z), t\big) = \{(V \times V \times V)(x, y, z)\ if x + y + z = t\ (0,1)\ if x + y + z \neq T\ \}$

$N^{\odot}: K \times V \rightarrow V$ by$N^{\odot}((k, x), t) = \{K \times (V)(k, x)\ if kx = y, k \neq 0\ sup_{x \in X} V(x)\ if kx = y, k = 0\ (0,1)\ if kx \neq y\ \}$

$N^{a}: V \rightarrow V$ by $N^{a}\big((k, x), t\big) = \{V(x)\ if\ y = k_{o}x, k \neq 0\ (0,1)\ if\ kx \neq y\ \}$

$N^{k_0}: V \rightarrow V$ by $N^{k_0}\big((x, y)\big) = \{K \times V(k, x)\ if\ y = k_0 x, k_0 \neq 0\ sup_{x \in X} V(x)\ if\ k_0 x = y, k_0 = 0\ (0,1)\ if\ k_0 x \neq y\ \}$

Assume strong (weak) NTVS is a vector topological space.

Assume that V(I) is a strong NTVS over $K(I)$. Apparently, $(V(l), +, .)$ is an abelian group.

Where $u = a + bl, v = c + dl \in V(l)$, and $\alpha = k + ml, \beta = p + nl \in K(l)$ where $a, b, c, d \in V$ and $k, m, n, p \in K$, then

1). $a(u + v) = (k + ml)(a + bl + c + dl)$

$$= ka + kc + [kb + kd + ma + mb + mc + md]l$$

$$= (k + ml)(a + bl) + (k + ml)(c + dl)$$

$$= au + av.$$

2. $(a + b)u = (k + ml + p + nl)(a + bl)$

$$= ka + pa + [kb + pb + ma + na + mb + nb]l$$

$$= (k + ml)(a + bl) + (p + nl)(a + bl)$$

$$= au + bu$$

3. $(ab)u = \big((k + ml)(p + nl)\big)(a + bl)$

$$= kpa + [kpb + kna + mpa + mna + knb + mpb + mnb]l$$

$$=\ (k + ml\ p + nl)(a + bl))$$

$$= a(bu)$$

4. For $1 + 1 + 0I\hat{I}K(l)$, we have

$$1u = (1 + 0l)(a + bl)$$

$$= a(b + 0 + 0)l$$

$$= a + bl.$$

Thus, $V(I)$ refers to a vector space. τ denotes a topology on V over the field, $(, \tau)$ indicates the vector topological space.

Doi: https://doi.org/10.54216/IJNS.240312
Received: March 29, 2024 Revised: April 28, 2024 Accepted: May 19, 2024

The Neutrosophic topology τ on V is an NTVS if and only if the Neutrosophic function $(V \times V \times V, \tau \times \tau \times \tau) \to (V, \tau)$ is Neutrosophic continuous.

$N_V^{L_{k,m,n}}: (V \times V \times V, \tau \times \tau \times \tau) \to (V, \tau)$ represented as

$N((x, y, z), t) = \{V(x, y, z)\ if\ x + y + z = r\ (0,1)\ if\ x + y + z \neq r\ \}$ is Neutrosophic continuous function.

$N^{\odot}: (k \times V, v \times \tau) \to (V, \tau)$ refers to Neutrosophic continuous function.

$N^{\odot} \circ N_k : (V, \tau) \to (V, \tau)$ is represented as

$N^{\odot} \circ N_k(x, y) = \{V(x)\ ify = kx, k \neq 0\ sup_{s \in X} V(s)\ ify = kx, k = 0\ (0,1)\ otherwise\ \}$ is Neutrosophic continuous function.

Likewise, $N^{\odot} \circ N_m : (V, \tau) \to (V, \tau)$ defined by

$N^{\odot} \circ N_m(z, t) = \{V(zx)\ ify = mx, m \neq 0\ sup_{s \in X} V(s)\ ify = mz, m = 0\ (0,1)\ otherwise\ \}$ is Neutrosophic continuous function.

Thus,

$\left(N^{\odot} \circ N_k\right) \times \left(N^{\odot} \circ N_m\right): (V \times V \times V, \tau \times \tau \times \tau) \to (V \times V \times V, \tau \times \tau \times \tau)$ represented as

$$\left(N^{\odot} \circ N_k\right) \times \left(N^{\odot} \circ N_m\right)\left((x, z), (y, T)\right) = \{V(V \times V)(x, z)\ if\ (x, z) = (y, t)\ (0,1)\ if\ (x, z) \neq (y, t)\ \}$$

is Neutrosophic continuous. Thus $N^{\oplus} \circ \left[\left(N^{\odot} \circ N_k\right) \times \left(N^{\odot} \circ N_m\right)\right] = N_V^{L_{k,m,n}}$ denotes the Neutrosophic continuous function. On the other hand, $N_V^{L_{k,m,n}}$ refers to the Neutrosophic continuous function for $k, m, n \in K$.

$p_I((k, x), z) = \{(K \times V)(k, x)\ if\ z = x\ (0,1)\ otherwise\ \}$ and θ is standard of V with regard to V, then $N_\theta: (V, \tau) \to (V \times V \times V, \tau \times \tau \times \tau)$ represented as

$N_\theta(x, (x_1, y_1)) = \{(K \times V)(k, x)\ if\ (x_1, y_1) = (x, \theta)\ (0,1)\ if\ (x_1, y_1) \neq (x, \theta)\ \}$ are Neutrosophic continuous function.

$N_\theta.\circ p_I : (K \times V, v \times \tau) \to (V, \tau)$ represented as

$N_\theta.\circ p_I\left((k, x), (x_1, y_1)\right) = \{(K \times V)(k, x)\ if\ (x_1, y_1) = (x, \theta)\ (0,1)\ if\ (x_1, y_1) \neq (x, \theta)\ \}$ is Neutrosophic continuous function.

Thus $N^{\odot} = \left(N_V^{L_{k,m,n}} \circ N_\theta \circ p_I\right) : (K \times V, v \times \tau) \to (V, \tau)$ where

$\left(N_V^{L_{k,m,n}} \circ N_\theta \circ p_I\right)\left((k, x), z\right) = \{(K \times V)(k, x)\ ifz = kx, k \neq 0\ sup_{s \in X} V(s)\ ifz = kx, k = 0\ (0_t 1)\ ifz \neq kx\ \}$ is Neutrosophic continuous function. $N_V^{L_{k,m,n}}$ indicates the Neutrosophic continuous for $k, m \in K$, take $k = 1, m = 1$. Thus

$N^{\oplus}: (V \times V \times V \to V, \tau \times \tau \times \tau) \to (V, \tau)$ refers to Neutrosophic continuous.

The Neutrosophic proper function $N: V \to W$ is a neutrosophic linear conversion if

If $N(\theta, \theta', \theta" = sup_{(x,y,z) \in (X \times Y \times Z)} N(x, y, z)$,

$$N(kx, ky, kz) = \left\{N(x, y, z)\ ifk \neq 0\ sup_{(x,y,z) \in (X \times Y \times Z)} N(x, y, z)\ ifk = 0\ \right\}$$

If $N(kx, ky, kz) = V(kx)$ and $N(ma, mb, mc) = V(ma)$ imply

$N(kx, ky, kz) + N(ma, mb, mc) = V(kx + mz)$ for $a, x \in X, b, y \in Y, c, z \in Z$ and $k, m \in K$.

Consider $N(X)$ as a NTVS over X. We have:

1. $N(X)$ refers to a NTVS over X.

2. For scalars α, β then $\alpha x + \beta x subseteq N(X) \forall x \in N(X)$

Doi: https://doi.org/10.54216/IJNS.240312
Received: March 29, 2024 Revised: April 28, 2024 Accepted: May 19, 2024

3. For scalars α, β and for, $y \in N(X)$, then $\mu_N(\alpha x + \beta y) \geq \mu_N(x) \wedge \mu_N(y), v_N(\alpha x + \beta y) \leq v_N(x) V v_N(y)$ and $\sigma(\alpha x + \beta y) \leq \sigma_N(x) + \sigma_N$

Noticeably (1) ⇒ (2) and (2) ⇒ (3) by NTVS.

To prove (2) ⇒ (1) : $N(X) + N(X) = 1.N(X) + 1.N(X) \subseteq N$

$\alpha N(X) = \alpha N(X) + ON(X) \subseteq N(X)$ Hence proved.

C. Model Optimization

Lastly, the WOA is applied for optimal parameter tuning of the NTVS algorithm. WOA is nothing but a sophisticated optimizer technique that is based on behavior of whale hunting [26]. It can be trained by using a unique tactic. This method has 3 phases namely bubble-net attack, circling, and hunting the prey. In the stage of circling, the whales fix the trap by surrounding the victim. Since the optimum location in the searching space is unknown at the start, the WOA model presumes that the objective prey or nearby to it is the existing finest solution candidate. The residual searching agents will try to alter their locations to equal the best searching agent once the top searching agent originates. This can be signified exactly in Eq. (1). Then, the whales use the spiral everywhere and update methods to contribute to the bubble-net attack approach. Depending upon the searching agent, the whales spiral near their target. Eq. (2) is employed in order to discover the existing location of the residual searching agents.

$$\vec{D} = \left|\vec{C}.\vec{X} * (t) - \vec{X}(t)\right| \quad (1)$$

$$\vec{X}(t+1) = \vec{X} * (t) - \vec{A}.\vec{D} \quad (2)$$

Where, $\vec{X}*$ represents the local optimum location; t signifies the existing iteration. $\vec{X}$ denotes the existing location. It is highly notifiable that $\vec{X}*$ should be upgraded in each iteration if a more appropriate choice occurs.

$$\vec{C} = 2 * \vec{r} \quad (3)$$

$$\vec{A} = 2.\vec{a}.\vec{r} - \vec{a} \quad (4)$$

Whereas $\vec{r}$ denotes the randomly generated vector among 0 and 1; $\vec{a}$ is condensed functionally from 2 to 0 during iteration.

To enhance the search, a solution that is randomly nominated is used to upgrade the location by top solution place recognized so far, rather than compelling the solution to hunt randomly liable on that location. Therefore, to drive a solution to differ considerably from the famous searching agent, the vector A with random value greater than one or smaller than -1 is used, and then the random searching agent's location has been calculated by Eqs. (5) and (6).

$$\vec{D} = \left|\vec{C}.\vec{X}_{rand} - \vec{X}\right| \quad (5)$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A}.\vec{D} \quad (6)$$

where $\vec{X}_{rand}$ denotes the random location vector from the existing population, and $\{\vec{A}, \vec{C}\}$ are said to be coefficient vectors.

Whales will pick either the spiral or the shrink enclosing method to upgrade the location for approaching the victim. The possibility of picking the track was signified by Eqs. (7).

$$\vec{X}(t+1) = \{\vec{X} * (t) - \vec{A}.\vec{D} \qquad p < 0.5\ \vec{D}.e^{b1}.cos\ cos\ (2\pi 1)\ + \vec{X} * (t)\ p \geq 0.5 \quad (7)$$

Here, $\vec{D}$ states to the distance of the ith whale; $\vec{X}$(t + 1) denotes the upgraded location of the whales; $\vec{X}*$ represents the local optimum location; b refers to the constant that signifies the outline of the logarithmic spiral; $\vec{A}$ denotes the coefficient vector as explained in Eq. (4); l signifies the randomly generated integer among −1 and +1; and p is an integer that is selected among 0 and 1 at random.

The WOA is used to derive an FF to attain better classifier outcome. It describes the positive integer for representing the best outcomes of the candidate solution. Here, the reduction of the classifier error rate is regarded as the FF.

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

Doi: https://doi.org/10.54216/IJNS.240312
Received: March 29, 2024 Revised: April 28, 2024 Accepted: May 19, 2024

$$= \frac{No.of\ misclassified\ samples}{Total\ No.of\ samples} * 100 \qquad (8)$$

4. Experimental Assessment

The experimental analysis of the TE-ONTVS technique takes place using dataset of 100 samples. It holds two classes purchase high and low as given in Table 1.

Table 1: Details of dataset

Classes	No. of Instances
Purchase-High	50
Purchase-Low	50
Total Instances	100

Fig. 2 illustrates the confusion matrices generated by the TE-ONTVS algorithm at 70:30 of TRAS/TESS. The outcomes represent that the TE-ONTVS approach has effective detection of the purchase-high and low samples under all class labels.

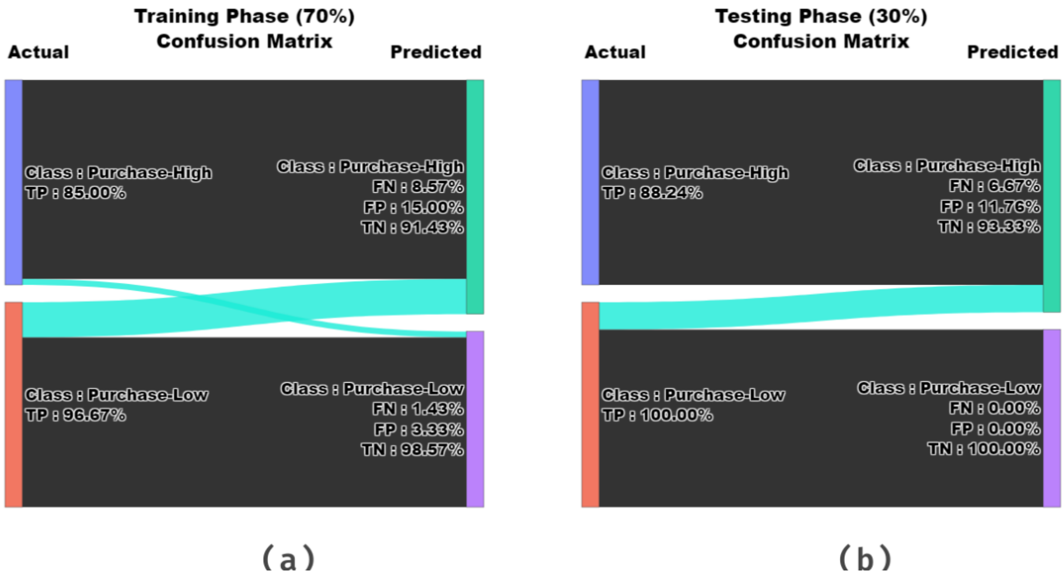

Figure 2: Confusion matrices of (a) 70%TRAS and (b) 30%TESS

Table 2 exhibits the entire results of the TE-ONTVS technique on the classification of samples. Fig. 3 highlights the performance of the TE-ONTVS technique on the applied 70%TRAS. The figure shows that the TE-ONTVS technique properly categorized the two classes. It is also noticed that the TE-ONTVS technique gains average $accu_y$, $prec_n$, $reca_l$, F_{score}, and AUC_{score} of 90.00%, 90.83%, 90.00%, 89.95%, and 90.00%, correspondingly.

Fig. 4 validates the performance of TE-ONTVS method on the applied 30%TESS. The figure portrayed that the TE-ONTVS method properly classified the two classes. Note that the TE-ONTVS approach obtains average $accu_y$, $prec_n$, $reca_l$, F_{score}, and AUC_{score} of 93.33%, 94.12%, 93.33%, 93.30%, and 93.33%, correspondingly.

Table 2: Classifier result of TE-ONTVS technique on 70%TRAS and 30%TESS

Classes	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	AUC_{Score}
TRAS (70%)					
Purchase-High	97.14	85.00	97.14	90.67	90.00
Purchase-Low	82.86	96.67	82.86	89.23	90.00

Doi: https://doi.org/10.54216/IJNS.240312
Received: March 29, 2024 Revised: April 28, 2024 Accepted: May 19, 2024

Average	90.00	90.83	90.00	89.95	90.00
TESS (30%)					
Purchase-High	100.00	88.24	100.00	93.75	93.33
Purchase-Low	86.67	100.00	86.67	92.86	93.33
Average	93.33	94.12	93.33	93.30	93.33

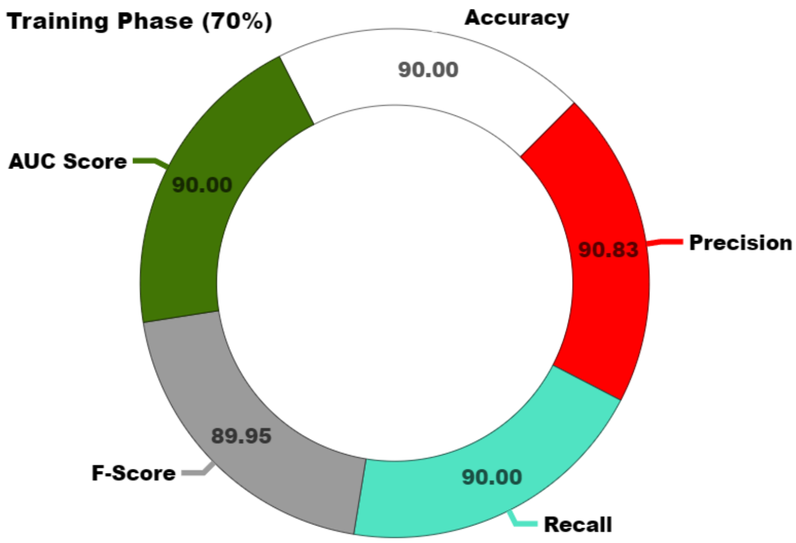

Figure 3: Average of TE-ONTVS technique on 70%TRAS

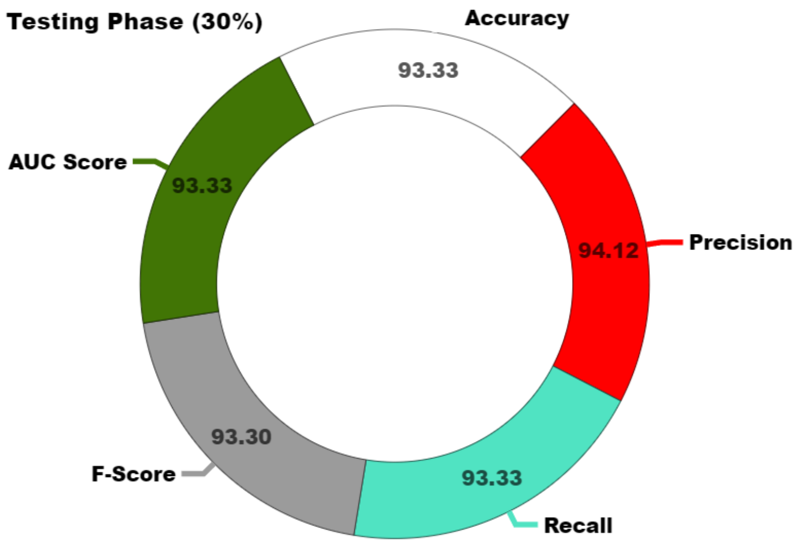

Figure 4: Average of TE-ONTVS technique on 30%TESS

The classifier outcomes of the TE-ONTVS method are graphically shown in Fig. 5 for training accuracy (TRAAC) and validation accuracy (VALAC). The outcome displays valuable analysis of the behavior of the TE-ONTVS model over different epochs, indicating its generalization capabilities and learning process. Notably, the figure indicates a constant development in the TRAAC and VALAC with increasing epoch count. It ensures the adaptable

Doi: https://doi.org/10.54216/IJNS.240312
Received: March 29, 2024 Revised: April 28, 2024 Accepted: May 19, 2024

nature of the TE-ONTVS model in the pattern detection model on both datasets. The increasing tendency in VALAC describes the capability of the TE-ONTVS model to adapt to the TRA dataset and excel in offering correct classifier of hidden dataset, showing strong generalisability.

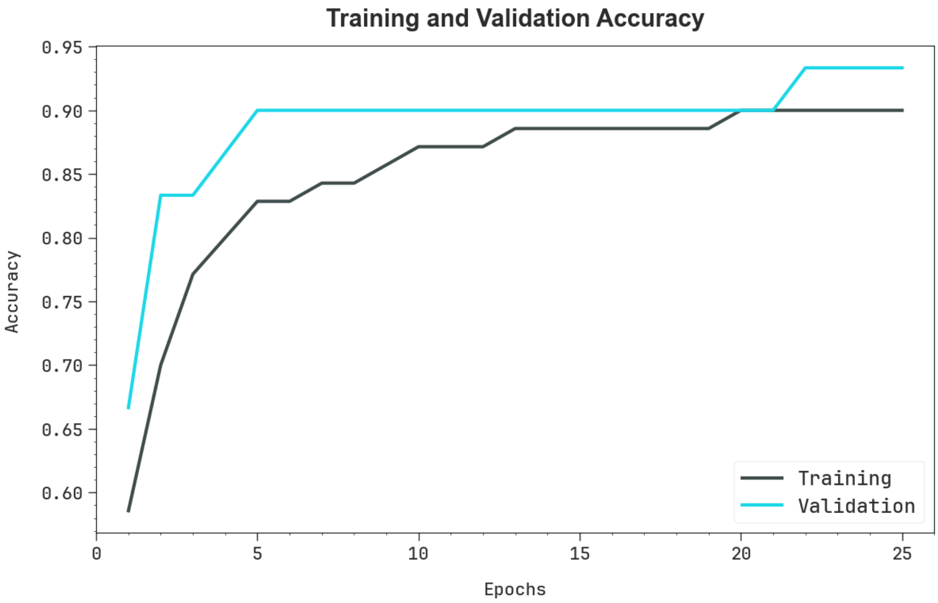

Figure 5: $Accu_y$ curve of the TE-ONTVS technique

Fig. 6 exhibits a comprehensive review of the training loss (TRALS) and validation loss (VALLS) results of the TE-ONTVS technique over dissimilar epoch counts. The progressive decline in TRALS highlights the TE-ONTVS method enhancing the weights and decreasing the classification error on both datasets. The figure demonstrates a clear insight into the TE-ONTVS model's relationship with the TRA dataset, which highlights its ability to capture patterns within both datasets. Notably, the TE-ONTVS method recurrently increases its parameters in diminishing the variances amongst the prediction and real TRA classes.

Inspecting the PR curve, as demonstrated in Fig. 7, the outcomes ensured that the TE-ONTVS technique increasingly achieves superior PR performance throughout all the classes. It confirms the better capabilities of the TE-ONTVS approach in the detection of various classes, showing proficiency in the detection of classes.

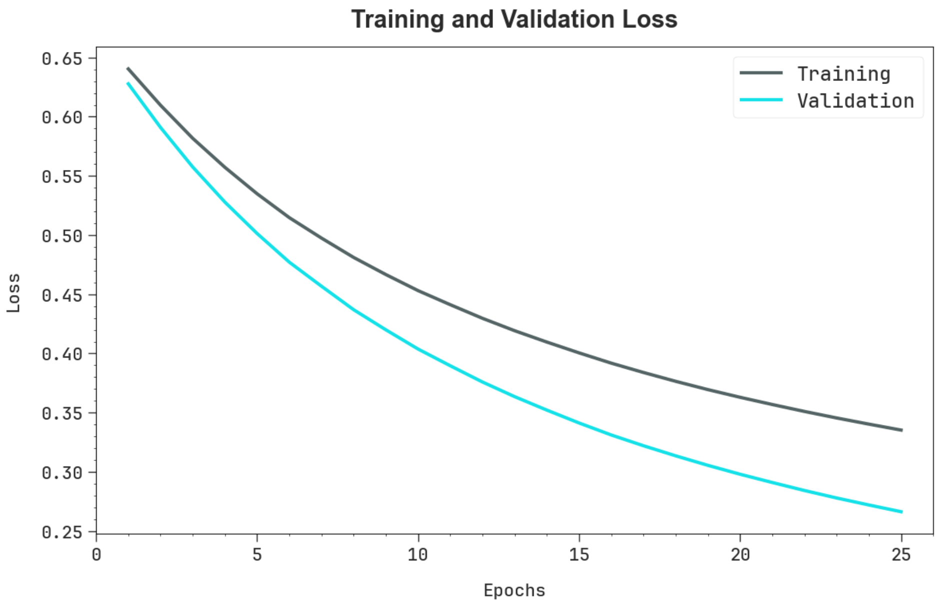

Figure 6: Loss curve of the TE-ONTVS method

Doi: https://doi.org/10.54216/IJNS.240312
Received: March 29, 2024 Revised: April 28, 2024 Accepted: May 19, 2024

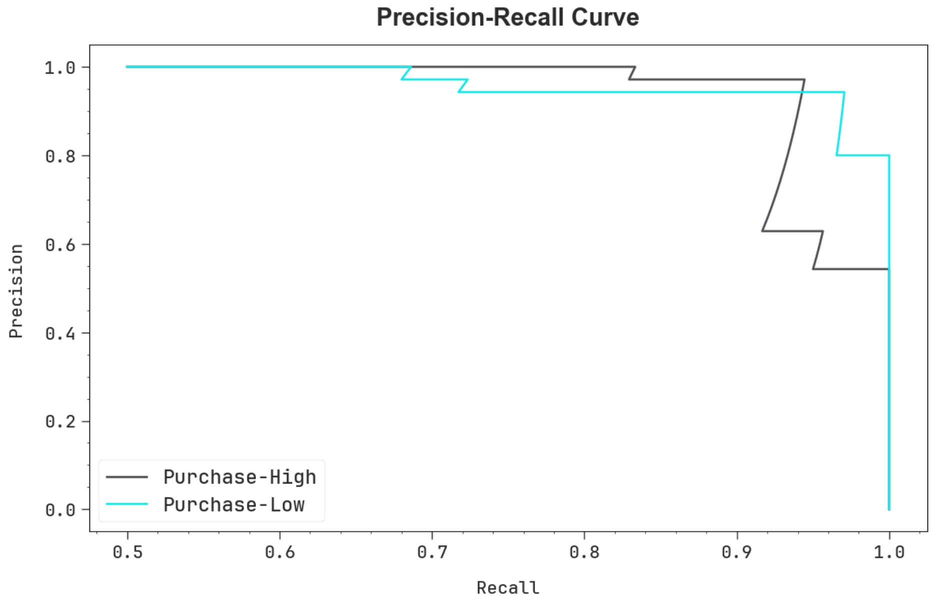

Figure 7: PR curve of the TE-ONTVS method

Furthermore, in Fig. 8, ROC curves generated by the TE-ONTVS technique outperformed the classifier of distinct labels. It provides comprehensive understanding of the tradeoff between TPR and FRP over various recognition threshold values and epoch counts. The figure indicated the superior classifier outcomes of the TE-ONTVS method under all classes, outlining the efficiency in addressing various classifier problems.

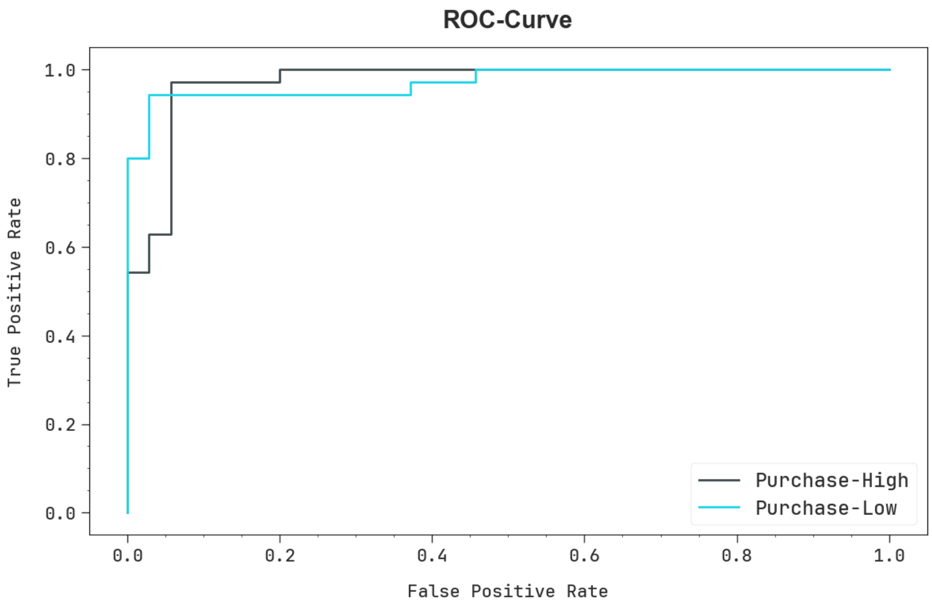

Figure 8: ROC curve of the TE-ONTVS technique

Table 3 and Fig. 9 represent the comparative outcomes of the TE-ONTVS technique [27]. The results imply that the LR, DT, NB, SV, and ANN models have shown least performance. Followed by, the KNN and RF models have obtained closer results than earlier models. Nevertheless, the TE-ONTVS technique demonstrates superior results with increased $accu_y$, $prec_n$, $reca_l$, and F_{score} of 93.33%, 94.12%, 93.33%, and 93.30%, correspondingly. Therefore, the TE-ONTVS technique is found to be effective over other models.

Table 3: Comparative analysis of TE-ONTVS technique with recent models

Algorithms	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}

Doi: https://doi.org/10.54216/IJNS.240312
Received: March 29, 2024 Revised: April 28, 2024 Accepted: May 19, 2024

TE-ONTVS	93.33	94.12	93.33	93.30
Logistic regression	89.39	88.15	90.37	90.97
Decision tree	86.36	89.67	88.85	88.34
KNN Algorithm	91.67	88.82	89.97	88.79
Naïve Bayes	88.64	89.41	89.06	90.42
Support vector	89.39	90.75	88.22	89.10
Random forest	90.15	88.97	90.92	90.07
Artificial Neural Network	68.45	89.47	88.92	90.29

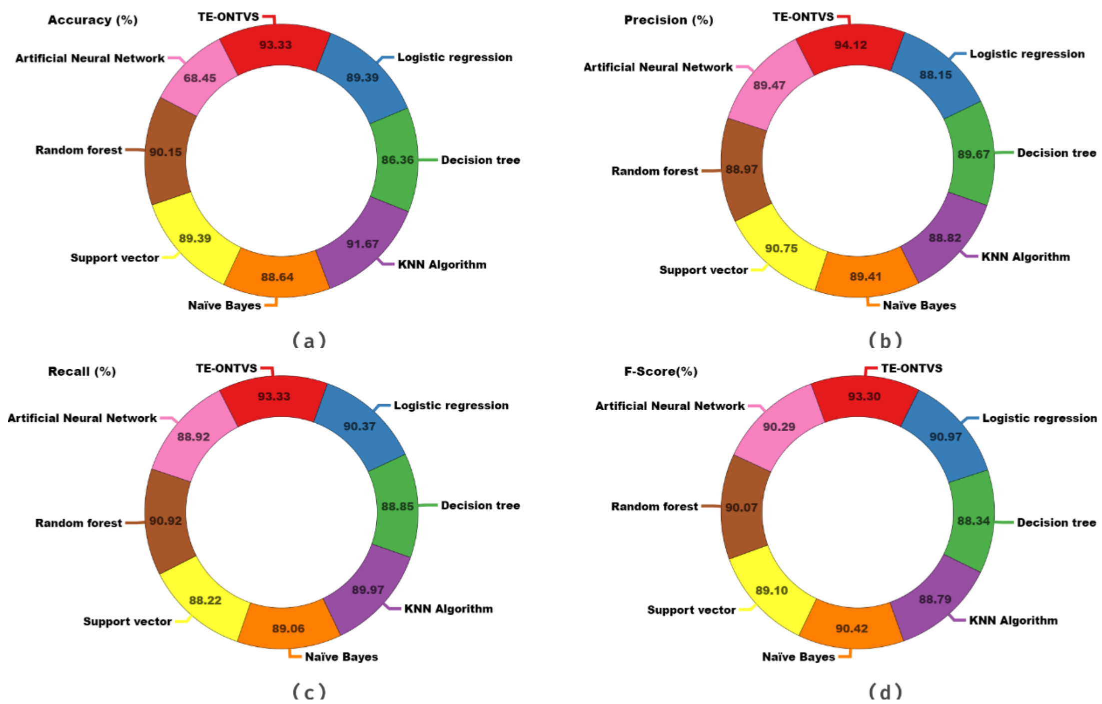

Figure 9: Comparative analysis of TE-ONTVS technique (a) $Accu_y$, (b) $prec_n$, (c) $reca_l$, and (d) F_{score}

5. Conclusion

In this study, we design a TE-ONTVS technique for maximizing customer attraction. The intention of the TE-ONTVS technique lies in the prediction of customer behaviour and attraction. To accomplish this, the TE-ONTVS technique contains three different phases Z-score scaling, NTVS-based predictive modelling, and WOA-based parameter selection phases. At initial phase, the TE-ONTVS technique undergoes data scaling using Z-score normalization. In addition, the TE-ONTVS technique uses NTVS approach for the identification of customer behaviour and attraction. Lastly, the WOA is applied for optimal parameter tuning of the NTVS algorithm. A series of experiments were involved to elucidate the superior outcomes of the TE-ONTVS algorithm. The obtained results stated that the TE-ONTVS technique reaches optimal performance over other models

Funding: "The authors extend their appreciation to the Deanship of Scientific Research at King Khalid University for funding this work through a Small-group Research Project under grant number (RGP.1/309/44)"

Conflicts of Interest: "The authors declare no conflict of interest."

Doi: https://doi.org/10.54216/IJNS.240312
Received: March 29, 2024 Revised: April 28, 2024 Accepted: May 19, 2024

References

[1] Do QH, Trang TV (2020) An approach based on machine learning techniques for forecasting vietnamese consumers' purchase behaviour. Decis Sci Lett, pp 313–322.

[2] Dawood EAE, Elfakhrany E, Maghraby FA (2019) Improve profling bank customer's behavior using machine learning. IEEE Access 7:109320–109327.

[3] Alhamido, R., and Abobala, M., "AH-Substructures in Neutrosophic Modules", International Journal of Neutrosophic Science, Vol. 7, pp. 79-86 , 2020.

[4] Hatip, A., and Olgun, N., " On Refined Neutrosophic R-Module", International Journal of Neutrosophic Science, Vol. 7, pp.87-96, 2020.

[5] Ibrahim, M.A., Agboola, A.A.A, Badmus, B.S., and Akinleye, S.A., "On Refined Neutrosophic Vector Spaces I", International Journal of Neutrosophic Science, Vol. 7, pp. 97-109, 2020.

[6] Smarandache F., and Abobala, M., " n-Refined Neutrosophic Vector Spaces", International Journal of Neutrosophic Science, Vol. 7, pp. 47-54, 2020.

[7] Tuqa A. H. Al-Tamimi, Luay A. A. Al-Swidi , Ali H. M. Al-Obaidi. "Partner Sets for Generalizations of MultiNeutrosophic Sets." International Journal of Neutrosophic Science, Vol. 24, No. 1, 2024 ,PP. 08-13

[8] Parimala, M., Karthika, M. and Smarandache, F., 2020. A review of fuzzy soft topological spaces, intuitionistic fuzzy soft topological spaces and neutrosophic soft topological spaces. International Journal of Neutrosophic Science, Vol. 10, No. 2, 2020 ,PP. 96-104.

[9] Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. Journal of Marketing, 80(6), 69–96

[10] Borg, A., & Boldt, M. (2020). Using VADER sentiment and SVM for predicting customer response sentiment. Expert Systems with Applications, 162, 113746.

[11] Fitri, F. S., Nasrun, M. & Setianingsih, C. (2018). November. Sentiment analysis on the level of customer satisfaction to data cellular services using the naive bayes classifer algorithm. In 2018 IEEE International Conference on Internet of Things and Intelligence System (IOTAIS) (pp. 201–206). IEEE

[12] Noaman, I.A.R., Hasan, A.H. and Ahmed, S.M., 2024. Optimizing Weibull Distribution Parameters for Improved Earthquake Modeling in Japan: A Comparative Approach. International Journal of Neutrosophic Science, 24(1), pp.65-5

[13] Doaa Nihad Tomma, L. A. A. Al-Swidi. "Necessary and Sufficient Conditions for a Stability of the Concepts of Stable Interior and Stable Exterior via Neutrosophic Crisp Sets." International Journal of Neutrosophic Science, Vol. 24, No. 1, 2024 ,PP. 87-93.

[14] Mathews, P., Sebastian, L. and Thankachan, B., 2024. Neutrosophic Fuzzy Score Matrices: A Robust Framework for Advancing Medical Diagnostics. International Journal of Neutrosophic Science, 23(3), pp.08-8

[15] Tarnowska, K., & Ras, Z. (2021). NLP-based customer loyalty improvement recommender system (CLIRS2). Big Data and Cognitive Computing, 5, 4.

[16] R. Saarumathi, W. Ritha. (2024). A Legitimate Productive Repertoire Replica Betwixt Envirotech Outlay Towards Fragile Commodities Using Trapezoidal Neutrosophic Fuzzy Number. International Journal of Neutrosophic Science, 24 (1), 104-118

[17] Li, Y., Qi, J., Jin, H., Tian, D., Mu, W. and Feng, J., 2024. An improved genetic-XGBoost classifier for customer consumption behavior prediction. The Computer Journal, 67(3), pp.1041-1059.

[18] Alfian, G., Octava, M.Q.H., Hilmy, F.M., Nurhaliza, R.A., Saputra, Y.M., Putri, D.G.P., Syahrian, F., Fitriyani, N.L., Atmaji, F.T.D., Farooq, U. and Nguyen, D.T., 2023. Customer Shopping Behavior Analysis Using RFID and Machine Learning Models. Information, 14(10), p.551.

[19] Lalwani, P., Mishra, M.K., Chadha, J.S. and Sethi, P., 2022. Customer churn prediction system: a machine learning approach. Computing, 104(2), pp.271-294.

[20] Yang, B., Xu, X., Cao, J., Zeng, K. and Yu, Z., 2024. An anticipatory shipping system for online retailers via mining customer behavior in large e-commerce promotion. Electronic Commerce Research and Applications, p.101403.

[21] Lee, N.T., Lee, H.C., Hsin, J. and Fang, S.H., 2023. Prediction of Customer Behavior Changing via a Hybrid Approach. IEEE Open Journal of the Computer Society.

[22] Akhavan, F. and Hassannayebi, E., 2024. A hybrid machine learning with process analytics for predicting customer experience in online insurance services industry. Decision Analytics Journal, 11, p.100452.

[23] Aldelemy, A. and Abd-Alhameed, R.A., 2023. Binary Classification of Customer's Online Purchasing Behavior Using Machine Learning. Journal of Techniques, 5(2).

Doi: https://doi.org/10.54216/IJNS.240312
Received: March 29, 2024 Revised: April 28, 2024 Accepted: May 19, 2024

[24] Prihanditya, H.A., 2020. The implementation of z-score normalization and boosting techniques to increase accuracy of c4. 5 algorithm in diagnosing chronic kidney disease. Journal of Soft Computing Exploration, 1(1), pp.63-69.
[25] Kungumaraj, E., Lathanayagam, E., Saikia, U., Anand, M.C.J., Khanna, S.T., Martin, N., Tiwari, M. and Edalatpanah, S.A., 2023. Neutrosophic Topological Vector Spaces and its Properties. International Journal of Neutrosophic Science, 23(2), pp.63-3.
[26] Rashed, B.M. and Popescu, N., 2024. Medical Image-Based Diagnosis Using a Hybrid Adaptive Neuro-Fuzzy Inferences System (ANFIS) Optimized by GA with a Deep Network Model for Features Extraction. Mathematics, 12(5), p.633.
[27] Chaubey, G., Gavhane, P.R., Bisen, D. and Arjaria, S.K., 2023. Customer purchasing behavior prediction using machine learning classification techniques. Journal of Ambient Intelligence and Humanized Computing, 14(12), pp.16133-16157

Doi: https://doi.org/10.54216/IJNS.240312
Received: March 29, 2024 Revised: April 28, 2024 Accepted: May 19, 2024