Neutrosophic Prediction of Consumer Decisions Using the RBF Neural Network Method

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Abstract

The utilization of neutrosophic concept to forecast patron purchase conduct has been thoroughly tested in preceding research using various fashions. This study examines the number one elements affecting clients' selections to shop for mobile phones, dividing them into 4 separate ranges consistent with their purchasing behaviours. The tiers, from the first to the fourth layer, characterize exclusive ranges of customer hobby and participation. The main intention is to create an efficient neutrosophic predictive version that examines purchaser conduct thru pertinent traits that signify their opportunity of buying. We utilize the Neutrosophic Radial Basis Function (NRBF) model for neutrosophic class to do that. The results indicate a minimal blunders fee and improved neutrosophic category accuracy, mainly in contrast to the BIC version, which exhibited lower accuracy. NRBF exhibited a sturdy location below the curve (AUC) rating, underscoring the model's efficacy. These findings provide big insights into consumer preferences and decision-making methods, enhancing procedures for market analysis and cantered advertising initiatives.

Keywords: Neutrosophic Predict; Consumer's Decision; Determining Basis Functions (DBF); Sensitivity Analysis; Mobile phones

1. Introduction

Discrimination is an important thing of choice making in everyday lifestyles, requiring people to prioritize sure elements while making picks [1]. In the context of this research, we analyse consumer opinions concerning their decision to buy a mobile device based totally on numerous influencing variables [2]. Consumer conduct is especially dynamic, making it hard to be expecting purchasing decisions as it should be. With the upward push of machine gaining knowledge of, computational techniques have turn out to be instrumental in addressing these complexities [3]. Among these techniques, Neutrosophic Radial Basis Function (NRBF) Neural Networks have verified effectiveness in neutrosophic classification obligations, making them a suitable approach for modelling purchaser-shopping conduct. This study leverages NRBF Neural Networks to develop a neutrosophic predictive version that classifies clients' shopping selections primarily based on key influencing elements.

Understanding client conduct is important for agencies to refine their marketing strategies and optimize product offerings [4]. However, the complexity of client selection making gives challenges in figuring out the maximum critical elements influencing shopping selections [5]. Variables consisting of Random Access Memory (RAM) capability, display screen decision, battery life, and price considerably effect client options. Traditional neutrosophic type strategies frequently warfare with the non-linear patterns inherent in client facts, leading to faulty neutrosophic predictions [6-8]. Furthermore, companies require actual-time decision help to modify marketing techniques quick, a need that conventional strategies fail to meet effectively. To cope with those troubles, this study proposes the use of Neutrosophic Radial Basis Function (NRBF) to beautify the accuracy of customer purchasing neutrosophic predictions [9].

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The proposed method contains characteristic selection and sensitivity analysis to become aware of the most influential factors affecting purchasing behavior. It additionally optimizes the neural community model with the aid of nice-tuning its neutrosophic parameters to lessen neutrosophic class errors. The dataset is divided into education and check units, wherein model overall performance is evaluated the use of accuracy, blunders charge, and Receiver Operating Characteristic (ROC) curves [11, 12]. This method targets to expand an optimized neutrosophic classification version that provides agencies with treasured records-pushed insights, enabling them to refine advertising techniques and product services efficaciously.

The studies employs NRBF Neural Networks to assess patron critiques on cellular tool purchases, helping groups tailor their advertising and product development strategies to align with customer preferences. The study includes two levels: a theoretical phase, which discusses computational techniques for acquiring mathematical consequences, and a practical section, which information the neutrosophic type of consumer opinions on shopping selections. The dataset is split into two subsets: a schooling sample comprising 70% of the statistics and a check pattern masking the final 30%. An established neutrosophic class manner utilising 4 hidden layers was carried out, with consequences offered in tables and graphs illustrating the envisioned neutrosophic parameters, neutrosophic category accuracy, and misclassified information.

Findings suggest that customer-purchasing decisions are most importantly stimulated by 3 key factors: RAM capacity (measured in Megabytes), pixel decision peak, and general battery capability (measured in mAh). The neutrosophic category effects revealed wonderful consumer corporations, with one class efficaciously classified at the same time as others exhibited varying degrees of misneutrosophic classification. These insights provide companies with a deeper understanding of patron priorities, allowing them to beautify marketing efforts and optimize product functions to meet consumer expectations. The contributions of this paper can be summarized as follows:

- We propose a customer shopping neutrosophic prediction model based totally on NRBF Neural Networks, improving neutrosophic type accuracy and choice-making performance.
- A feature selection and sensitivity analysis approach is implemented to determine the maximum influential elements affecting mobile telephone shopping conduct.
- The proposed model is evaluated using key performance metrics, which include accuracy, mistakes price, and ROC curves, demonstrating its superiority over traditional neutrosophic category methods.

2. Neutrosophic Radial Basis Function (NRBF) Network

A NRBF community is a feed-forward, supervised getting to know neural network that consists of an unmarried hidden layer, known as the radial basis feature layer [13]. The NRBF network fashions the connection between one or extra neutrosophic predictor variables (also called inputs or unbiased variables) and one or greater target variables (outputs) via minimizing neutrosophic prediction mistakes [14]. These neutrosophic predictors and goals can encompass each categorical and numerical (scale) variables. The NRBF network is based into three (3) primary layers:

$$input\ layer\ J_0 = P\ Units\ a_{0:1}, \dots, a_{0:J_0}\,; with\ \ a_{0:J} = x_{j.} \tag{1}$$

NRBF layer J_1 units $a_{1:1}, \dots, a_{1:J_1}$ with $a_{1:J} = \emptyset_{j.}(X)$ and $\emptyset_{j.}(X)$ described below:

$$output\ layer\ J_2 = R\ Units\ a_{I:1}, \dots, a_{I:J_2}\,; with\ \ a_{I:r} = w_{r0} + \sum_{j=1}^{J_1} w_{rJ}\,\emptyset_j(X) \tag{2}$$

There are numerous types of radial foundation features, with two number one types of Gaussian NRBF architectures. The first is the Ordinary Radial Basis Function (ORBF), which makes use of the exponential (exp) activation feature. In this method, the activation of the NRBF unit follows a Gaussian "bump" shape in reaction to the enter values [5]. The Gaussian basis characteristic for ORBF is described in Equation (3).

$$\emptyset_j(X) = \exp\left(-\sum_{p=1}^{P} \frac{1}{2\sigma_{jp}^2}\left(x_p - \mu_{jp}\right)^2\right) \tag{3}$$

This variant employs Softmax activation function that normalizes the activations of NRBF units so that they add up to one. This form stabilizes the neutrophil categorization and makes the model more pliable. The NRBF network is demonstrated in (4).

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$$\emptyset_j(X) = \exp\left(-\sum_{p=1}^{P}\frac{1}{2\sigma_{jp}^2}\left(x_p-\mu_{jp}\right)^2\right) / \sum_{j=1}^{J_1} exp\left(-\sum_{p=1}^{P}\frac{1}{2\sigma_{jp}^2}\left(x_p-\mu_{jp}\right)^2\right) \quad (4)$$

Sum-of-squares error is used in Equation (5)

$$E_T(w) = \sum_{m=1}^{M} E_m(w) \quad (5)$$

Where

$$E_m(w) = \frac{1}{2}\sum_{r=1}^{R}(y_r^{(m)} - a_{I:r}^{m})^2 \quad (6)$$

Both scale and categorical targets can use the sum-of-squares error function with the identity activation function of the output layer. In the case of scale targets, $a_{I:r}^{m}$ is an approximation of the conditional expected value of the target $E\left(y_r \backslash X^{(m)}\right)$. In the categorical case, $a_{I:r}^{m}$ is an approximation to the posterior probability of class$k$: $P\left(y_r = 1 \backslash X^{(m)}\right)$. The model utilizes four (4) hidden layers with the softmax activation function. The dependent variable, representing mobile phone prices, is categorized into different levels. Eight (8) key neutrosophic predictor variables, as illustrated in Figure 1, were used in the model. These variables pass through the four hidden layers, where they are processed to classify data into the appropriate groups. The neutrosophic classification process within the network ensures accurate categorization of consumer purchasing decisions.

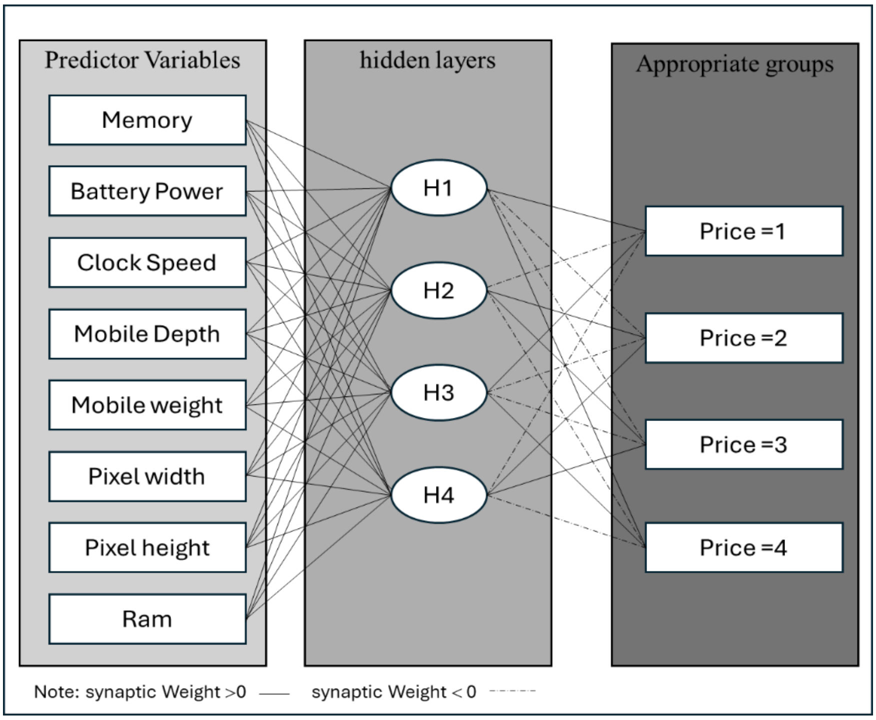

Figure 1. Neural networks for NRBF layers

The network training process consists of two (2) stages. First, the fundamental basis functions are determined using clustering methods. Second, the corresponding weights are computed based on these basis functions. To achieve this, the model employs ordinary least-squares regression to estimate the weights, enabling fast and efficient training of the NRBF network.

The centers of the NRBF are found with the help of a two-step clustering algorithm, and the widths are calculated. The scale variables are averaged and their standard deviation and the proportion of categorical variables are estimated in each cluster. According to the result of clustering, the center of j-th NRBF can be defined as in (7).

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$$\mu_{jp} = \begin{cases} \bar{x}_{jp} & if\ pth\ variables\ is\ scale \\ \bar{x}_{jp} & if\ pth\ variable\ is\ dummy\ varibles\ of\ a\ categoorical\ varibale \end{cases} \quad (7)$$

In this case, w_{jp} is the proportion of a categorical variable category to which the p-th input variable belongs and c_{jp} is the *j-th* cluster mean of the p-th input variable in the case that it is a scale variable. The *j-th* NRBF gets its width according to these neutrosophic parameters and is formally defined in Equation (8).

$$\sigma_{jp} = h^{1/2} \begin{cases} s_{jp} & if\ pth\ \ variables\ is\ scale \\ \sqrt{p_{jp}(1-p_{jp})} & if\ pth\ variable\ is\ dummy\ varibles\ of\ a\ categoorical\ varibale \end{cases} \quad (8)$$

With s_{jp} being the jth cluster standard deviation of the p-th variable and h>0 the RBF overlapping factor which regulates the degree of overlap between the NRBFs. As some of these can be zeros we take spherical shaped Gaussian bumps; i.e. a usual width.

In this case, $s_{jp}$is the *j-th* standard deviation of cluster *p-th* variable and h>0 is RBF overlapping factor, which controls the degree of overlapping between the NRBFs. As some values can be zero a spherical-shaped Gaussian bump is employed, such that there is a usual width of all basis functions to keep uniformity in the model.

$$\sigma_j = \sqrt{\frac{1}{p}\sum_{p=1}^{P} \sigma_{jp}^2} \quad (9)$$

The NBF algorithm attempts a sensible set of values of the number of hidden units and selects the "best". The reasonable range $[K1, K2]$ is calculated by default as follows: the number of clusters, K, is automatically found by applying the two-step clustering method, and then the reasonable range $[K1, K2]$ is calculated according to it. Then take $K1 = min(K, R)$ in case of ORBF and $K1 = max\{2, min(K, R)\}$ in case of NRBF and $K2 = max(10, 2K, R)$. In the event that test data set is specified then the best model is that which has the smaller error on the test data. In case test data is absent, the NBIC (Neutrosophic Bayesian information criterion) is applied to determine the "best" model. Equation (10) is the definition of the BIC [12].

$$BIC = MRln(MSE) + kLn(M) \quad (10)$$

$$MSE = \frac{1}{MR}\sum_{m=1}^{M}\sum_{r=1}^{R}(y_r^{(m)} - a_{I:r}^{m})^2 \quad (11)$$

The relative error for each scale target r as seen in Equation (12):

$$\frac{\sum_{m=1}^{M}(y_r^{(m)} - \hat{y}_r^{(m)})^2}{\sum_{m=1}^{M}(y_r^{(m)} - \bar{y}_r^{(m)})^2} \quad (12)$$

For each categorical target r, report, the percentage of incorrect neutrosophic predictions. The equation of relative error can be seen in Equation (13).

$$\frac{\sum_{m=1}^{M}\sum_{r=1}^{R}(y_r^{(m)} - \hat{y}_r^{(m)})^2}{\sum_{m=1}^{M}\sum_{r=1}^{R}(y_r^{(m)} - \bar{y}_r^{(m)})^2} \quad (13)$$

Where $\bar{y}_r$ and $y_r^{(m)}$ are the mean and over patterns respectivaly. If all targets are categorical, report the average percent of incorrect neutrosophic predictions:

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$$\frac{1}{C}\sum_{r=1}^{C} Pr \tag{14}$$

where C denotes the quantity of categorical variables. For each neutrosophic predictor *p* and each input pattern *m*, compute using the Equation (15):

$$d_{pm} = max_{x_{p1}}, x_{p2} \in S_p \left\| \hat{Y}_{p1}^{(m)} - \hat{Y}_{p2}^{(m)} \right\| \tag{15}$$

Where $\hat{Y}_{pk}^{(m)}$ is the neutrosophic predicted output vector (standardized if standardization of output variable is used in training) using $(x_1^{(m)}, \dots, x_{p-1}^{(m)}, x_{pk}^{(m)}, x_{p+1}^{(m)}, \dots x_p^{(m)})$ as its input, and for scale neutrosophic predictors and $S_p = (x_p^{min}, x_p^{(2)}, x_p^{(3)}, x_p^{(4)}, x_p^{(max)})\{(1,0,\dots,0),(0,1,0,\dots,0),\dots,(0,0,\dots,1)\}$ for categorical neutrosophic predictors. Then compute:

$$d_p = \frac{1}{M}\sum_{m=1}^{M} d_{pm} \tag{16}$$

Afterward, the sensitivity values are normalized to sum to 1, ensuring a standardized measure across all neutrosophic predictors. These normalized values represent the sensitivity of each neutrosophic predictor, indicating the extent to which changes in the *p-th* neutrosophic predictor influence the model's output. A higher sensitivity value suggests a greater expected impact on the output when the corresponding neutrosophic predictor variable changes, highlighting its significance in the neutrosophic classification process.

3. Results and Discussions

Research Data the empirical data utilized for this investigation were procured from the following online platform: https://www.kaggle.com/, in this research, nine (9) variables were selected for the study, consisting of one dependent variable and eight independent variables. The dependent variable, price, represents different price levels of mobile phones, while the independent variables capture key features influencing purchasing decisions. Table 1 provides an overview of these variables.

Table 1: Research data

Variable	Index
Price	Price range
Battery Power	The total energy a battery can store at one time is measured in mAh
Clock Speed	The speed at which the microprocessor executes instructions
Memory	Internal Memory in Gigabytes
Mobile Depth	Mobile Depth in cm
Mobile weight	Weight of mobile phone
Pixel height	Pixel Resolution Height
Pixel width	Pixel Resolution Width
ram	Random Access Memory in Megabytes

For model evaluation, the dataset was divided into two parts:

- Training set: 1,412 observations (70.6% of the total data) were used for model training.
- Test set: 588 observations (29.4% of the total data) were used for validation.

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Table 2 presents the model performance metrics. The sum of squared errors (SSE) for the training set was 264.144, with an error rate of 20.3%. For the test set, the SSE was 113.420, with an error rate of 22.8%. These results indicate the effectiveness of the model in classifying mobile phone price categories while maintaining a reasonable error margin.

Table 2: Model summary

Training	The sum of Squares Error	264.144
	Percent Incorrect Neutrosophic Predictions	20.3%
	Training Time	0:00:00.34
Testing	The sum of Squares Error	113.420a
	Percent Incorrect Neutrosophic Predictions	22.8%

The Neutrosophic Radial Basis Function (NRBF) Neural Network model is established with four (4) hidden layers, as targeted in Table 3. The expected neutrosophic parameters for the hidden nodes (H1 to H4) decide the neutrosophic classification results. Analysis of the neutrosophic parameter values reveals that RAM (Random Access Memory) has the highest have an impact on the neutrosophic class manner, gambling a dominant function in both H1 and H2. Clock velocity is the most tremendous factor for H3, at the same time as cellular depth has the very best impact on H4. The closing variables show off nice and terrible neutrosophic parameter values, indicating various ranges of impact throughout one-of-a-kind nodes.

Table 3: Neutrosophic parameter estimates (Input layer)

Input Layer	**H1**	**H2**	**H3**	**H4**
Battery power	0.302	-0.01	-0.29	-0
Clock speed	-0.02	0.039	0.025	-0.05
Mobile depth	-0.04	-0.01	-0.04	0.089
Mobile weight	-0.12	0.122	0.019	-0.01
Memory	0.076	-0.03	-0.04	0.001
Pixel height	0.241	-0.02	-0.23	0.017
Pixel width	0.288	-0.06	-0.23	-0
Ram	1.231	0.424	-1.22	-0.4
Hidden Unit Width	1.271	1.256	1.235	1.275

Each hidden layer plays a vital function inside the neutrosophic classification method, with four (4) output nodes representing the one of a kind cellular phone price classes. These hidden layers system the enter capabilities, remodeling them into meaningful representations that enhance the model's potential to as it should be differentiate among price tiers. Table 4 offers the estimated output neutrosophic parameters of the neural network model, demonstrating how each hidden node contributes to the final neutrosophic class decision.

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Table 4: Neutrosophic parameter estimates (Output layer)

Hidden Layer	Output Layer			
	Price (0)	Price (1)	Price (2)	Price (3)
H1	0.594	-1.039	-0.978	2.424
H2	-0.923	0.208	1.971	-0.256
H3	3.034	-1.52	-1.381	0.867
H4	-0.839	2.509	0.707	-1.377

Table 5 offers the neutrosophic type results for each the training and test datasets. Out of 1,977 observations, the model effectively classified 1,568 cases, attaining a standard accuracy of 79.7%. The neutrosophic category accuracy for each price organization in the training set changed into 94.2% for the primary group, 65.2% for the second group, 65.2% for the 1/3 institution, and 93.3% for the fourth organization.

For the test dataset, the model correctly classified 454 out of 588 observations, resulting in an overall accuracy of 77.2%. The neutrosophic classification accuracy for individual groups in the test set was 93.5% for the first group, 62.5% for the second group, 63.4% for the third group, and 91.7% for the fourth group. These results indicate that the model performs well, particularly in distinguishing between the first and fourth price categories, while the second and third groups exhibit slightly lower neutrosophic classification accuracy.

Table 5: Neutrosophic classification phase

Sample	Observed	Neutrosophic Predicted				
		0	1	2	3	Results
Training	0	340	21	0	0	94.2%
	1	54	232	70	0	65.2%
	2	0	71	221	47	65.2%
	3	0	0	24	332	93.3%
	Overall Percent	27.9%	22.9%	22.3%	26.8%	79.7%
Testing	0	130	9	0	0	93.5%
	1	22	90	32	0	62.5%
	2	0	29	102	30	63.4%
	3	0	0	12	132	91.7%
	Overall Percent	25.9%	21.8%	24.8%	27.6%	77.2%

Figure 2 illustrates the neutrosophic classification errors detected by the model. Correctly, classified observations are represented in blue, while neutrosophic classification errors for the second group are shown in green. Errors in other groups are depicted in red and orange, with red indicating higher misneutrosophic classification rates than orange. The neutrosophic classification errors for the second group are closely aligned with those of the first group, suggesting a significant overlap in their feature values.

This indicates that some observations in the second group share characteristics with those in the first group, leading to misneutrosophic classification. For the third group, neutrosophic classification errors are more prevalent

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compared to the first and second groups. However, the correctly classified values in this group are closer to the fourth group, implying that these two groups share similar feature distributions. In the fourth group, the neutrosophic classification error rate is lowest when distinguishing it from the first group.

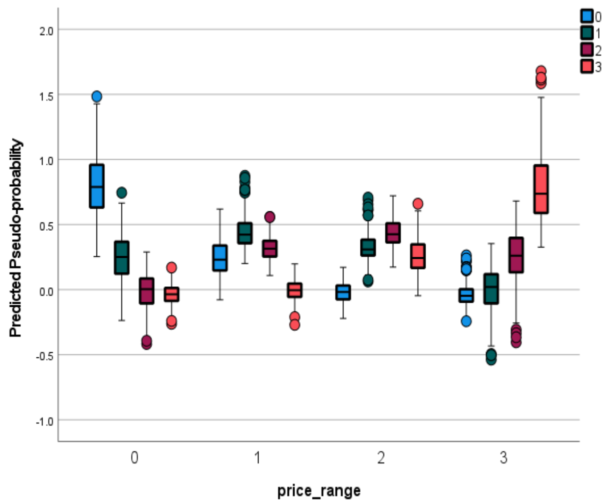

Figure 2. Neutrosophic predicted probability within the price

However, misneutrosophic classifications are more frequent between the third and fourth groups, as they exhibit some overlapping characteristics. The highest misneutrosophic classification percentage occurs when observations from the third group are incorrectly classified into other categories. Overall, the figure demonstrates that neutrosophic classification errors are more likely to occur between neighboring price categories, with greater distinction between the lowest (first) and highest (fourth) price groups. Figure 3 contains two key visualizations used to assess the model's performance. The Left Chart (ROC Curves), represents the ROC curves for the different price categories (0, 1, 2, and 3) of the dependent variable "price" The ROC curve illustrates the trade-off between the true positive rate (Sensitivity) and the false positive rate (1 - Specificity) for each class. A curve that is closer to the top-left corner indicates a better-performing model. In this case, the curves for each class are tightly grouped, suggesting that the model exhibits consistent performance across all categories with no significant performance bias toward any specific group. Right Chart (Cumulative Gain Chart), shows the cumulative percentage of correctly classified instances as a function of the percentage of the dataset considered. A steep initial slope suggests that the model is highly effective at correctly identifying instances with the highest probabilities. This indicates that the model successfully prioritizes more confident neutrosophic predictions early in the neutrosophic classification process, making it useful for targeted decision-making and business applications.

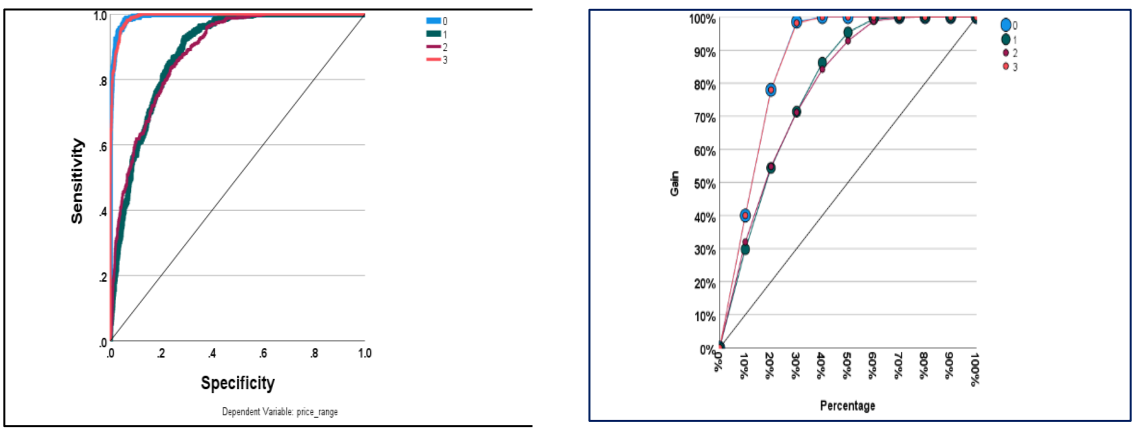

Figure 3. ROC Curves

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Based on Table 6, the weights of the variables inside the neutrosophic class feature may be diagnosed, highlighting their relative significance in figuring out cellular smartphone charge categories. The maximum influential variables within the neutrosophic type process are people with the best weights, as they have the best effect at the version's choice-making technique.

Table 6: Independent variable importance

variables	Importance	Normalized Importance
ram	0.417	42%
Pixel height	0.154	57%
Battery power	0.134	71%
Pixel width	0.12	83%
Mobile depth	0.062	89%
Mobile weight	0.061	95%
Memory	0.033	98%
Clock speed	0.019	100%

The pinnacle-ranked variable is Random Access Memory (RAM), observed via Pixel Resolution Height, Battery Power, and Pixel Resolution Width. These functions play a critical position in distinguishing between distinct fee classes, as they directly have an effect on patron buying decisions. The closing variables, along with Mobile Depth, Mobile Weight, Internal Memory, and Clock Speed, make contributions to the neutrosophic class procedure however with relatively decrease have an impact on.

The evaluation of variable importance within the neutrosophic classification feature highlights Random Access Memory because the most influential aspect, accounting for 42% of the total weight. This shows that RAM capability performs an important function in customer choice making whilst purchasing a mobile device. Following this, Pixel Resolution Height contributes 15.4%, representing the vertical resolution of the tool's show, which appreciably affects screen clarity and person enjoy.

Battery strength, measured in mAh, ranks 1/3 with a 13.4% contribution, emphasizing its importance in determining battery existence and typical usability. Pixel Resolution Width, contributing 12%, additionally plays a key function in neutrosophic category, further reinforcing the importance of display nice in mobile cellphone choice. Other factors contributing to the neutrosophic class process consist of Mobile Depth (6.2%), which affects device layout and portability, and Mobile Weight (6.1%), influencing user comfort. Internal Memory, responsible for 3.3% of the model's weight, determines the storage ability available for programs and information, whilst Clock Speed, at 1.9%, defines the processing energy of the tool.

Collectively, those factors sum to 100%, making sure an accurate representation of their have an effect on inside the neutrosophic category model. The ranking underscores the importance of RAM, display decision, and battery existence as the number one factors affecting client preferences whilst choosing a cell telephone.

Based on Table 7, compute the Goodness of Fit of BIC model, And compare it to see which shows the standard deviation criteria, that measure the extent to which the model differs from the full model. The deviation value is 204.340, which is very small compared to the dimension of freedom, which is 1991. This suggests a high fit, which translates to a percentage of 0.103, implying that the model describes the data satisfactorily. A number of 0.103 signifies a favorable match, as it is below the true value.

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Table 7: Goodness of Fit

Goodness of Fit	Value	Df	Value/ df
Deviancea	204.340	1991	.103
Pearson Chi-Squarea	204.340	1991	.103
Log Likelihoodb	-556.760		
Akaike's Information Criterion (AIC)a	1133.520		
Finite Sample Corrected AIC (AICC)a	1133.631		
Bayesian Information Criterion (BIC)a	1189.529		
Consistent AIC (CAIC)a	1199.529		

Form table 8 we can see the significant of the model parameter that indicate that 8 of 10 parameter are significate, parameter are not are (clock_speed and m_dep) , the data can provide opining of the customer to select his mobile according to the 8 variables.

Table 8: Parameter test

Parameter	B	Hypothesis Test		
		Wald Chi-Square	df	Sig.
(Intercept)	-1.553	1025.695	1	.000
battery_power	.001	985.661	1	.000
clock_speed	-.013	2.090	1	.148
int_memory	.001	4.775	1	.029
m_dep	-.009	.125	1	.724
mobile_wt	-.001	18.839	1	.000
px_height	.000	215.184	1	.000
px_width	.000	211.022	1	.000
ram	.001	20600.854	1	.000

Figure 4 indicates that the initial group was entirely identical, as per the model. The second, third, and fourth groups exhibit a significantly reduced proportion of similarity compared to the first group, as illustrated in the image.

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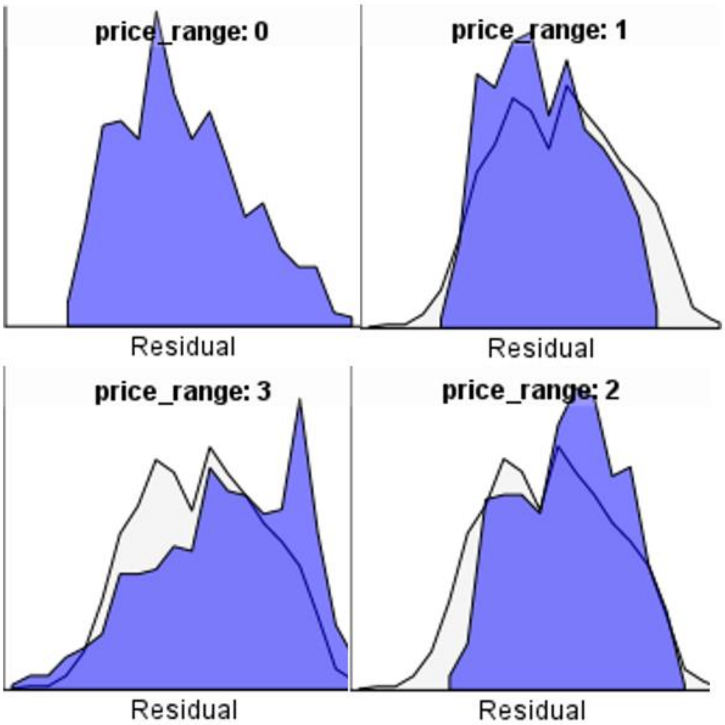

Figure 4. Subgroup plots

4. Conclusion

The NRBF network demonstrated significant flexibility in classifying data based on the studied variables, necessitating pre-processing before input to ensure optimal performance. The model's ease of use facilitated efficient neutrosophic classification, particularly when dealing with large datasets, The NRBF network exhibited considerable adaptability in categorizing data according to the analyzed factors, requiring preprocessing prior to input to guarantee optimal performance. The model's user-friendliness enhanced efficient neutrosophic classification, especially with extensive datasets, resulting in superior and more precise outcomes. Its efficacy was apparent in the precise matching and categorization of data, with ongoing assessment and refining further improving its performance. The straightforwardness of the NRBF network significantly enhanced neutrosophic classification accuracy, highlighting the significance of critical influencing factors in consumer decision-making regarding the acquisition of smart gadgets. In the subsequent section of this study, we will develop a model utilizing the Bayesian Information Criterion. Subsequently, we will juxtapose the outcomes of NRBF and BIC, revealing that NRBF outperforms BIC. Furthermore, we intend to analyze specific variables according to their weights. Ultimately, the findings indicate that smart device producers should prioritize the major characteristics highlighted, as they substantially influence user preferences. Utilizing insights from the model, developers can enhance their comprehension of market trends and optimize their tactics to meet consumer demands, hence advancing product development and market competitiveness.

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