An Efficient Approach for Customer Attrition Prediction Using Regression-Based Feature Reduction and Neutrosophic Soft Set in Big Data Ecosystems

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ABSTRACT

The Neutrosophic Set (NS) concept is an overview of the theory of fuzzy sets and Indeterminant Fuzzy Sets (IFSs). NS is depicted by a truth Membership Function (MF), a false MF, and an indeterminant MF, and every membership level is a subset of the unit interval [−0, 1+]. Customers are the most significant strength of any organization and are reflected as the major source of income. Customer churn or attrition is a widespread phenomenon in several industries. Predicting customer attrition has great promise in improving customer retention. Recently, studies for customer churn prediction tend to employ Deep Learning (DL) approaches to handle huge amounts of data. This paper presents a Customer Attrition Prediction Using Regression-Based Feature Reduction and Neutrosophic Soft Sets (CAP-RFRNSS) model for big data ecosystems. The key objective was to explore the prediction of customer attrition to improve accuracy and scalability using an advanced neutrosophic model. In the data preprocessing stage, the standard scaler technique was employed to standardize the input. In addition, the Least Absolute Shrinkage and Selection Operator (LASSO) regression technique was deployed to select a feature subset to improve model generalization and reduce overfitting. Finally, for the customer attrition prediction process, the Possibility Interval-Valued Neutrosophic Soft Set (PIVNSS) method is implemented. A wide-ranging experimental analysis was conducted to determine the performance of the proposed CAP-RFRNSS system, demonstrating its supremacy with a maximum accuracy of 99.05%.

Keywords-Neutrosophic Soft Sets (NSS); customer attrition prediction; fuzzy set; standard scaler; interval-valued NSS; big data ecosystems

I. INTRODUCTION

Dealing with inconsistency and uncertainty is a crucial concern in mathematical modeling research. Several approximations have been introduced for mathematical models to solve uncertain and inconsistent data problems, such as the theory of Fuzzy Sets (FS) and Indeterminant Fuzzy Sets (IFS). Neutrosophic Set (NS) theory offers a more robust and generalized approach [1]. This theory, rooted in Neutrosophy (a philosophical concept), allows for handling truth, indeterminacy, and falsity as independent components [2]. In today's service-oriented landscape, especially within the telecommunications sector, achieving expanded market presence is becoming increasingly difficult due to heightened competition and a market nearing saturation. Customer attrition, also known as customer churn, signifies the phenomenon in which existing customers discontinue their relationship with a company and move to a competitor [3]. Industrial practice has demonstrated that customer churn can result in massive financial losses and even damage the business's public image.

Currently, Big Data Analytics (BDA) has developed as a ground-breaking method to shift several businesses. The use of advanced models and Machine Learning (ML) approaches to analyze data has fundamentally changed how retailers forecast customer behavior and make decisions [4]. Retailers have consistently strived to decipher customer preferences, behaviors, and buying habits to improve their marketing tactics. With the arrival of BDA, retailers can now use various data sources, such as social media interactions. Currently, companies apply analytical and predictive models to monitor and understand customer patterns.

This paper presents a Customer Attrition Prediction Using Regression-Based Feature Reduction and Neutrosophic Soft Sets (CAP-RFRNSS) model for big data ecosystems. Initially, the data preprocessing phase involves using a standard scaler model to standardize the input. Then, the Least Absolute Shrinkage and Selection Operator (LASSO) regression technique is utilized to select a feature subset. Finally, the Possibility Interval-Valued Neutrosophic Soft Set (PIVNSS) model is employed to predict customer attrition.

II. RELEVANT LITERATURE FOR CUSTOMER ATTRITION PREDICTION

CostLearnGAN [5] is a tabular Generative Adversarial Network (GAN)-hybrid sampling technique for cost-sensitive learning. Conventional ML models demonstrate small execution times, which makes them appropriate for forecasting churn in massive customer bases. In [6], an ML-based approach was proposed to dynamically enhance customer experience, utilizing multidimensional behavioral data such as clickstream patterns, transactional records, biometric indicators, Sentiment Analysis (SA), and contextual variables. By merging supervised and unsupervised ML methods, this approach adaptively recognized customer intent, predicted satisfaction levels, and started customized interventions among digital touchpoints. In [7], a big data-based hybrid method integrated a DNN alongside ML to effectively predict customer churn. This method utilized Long Short-Term Memory (LSTM) with GRU for identifying trends in subscribers' usage patterns. In [8], a Bi-LSTM neural network was employed to forecast customer churn in e-commerce industries, capturing sequential patterns from user purchase history, interactions, and other relevant time-series data. The study in [9] explored the role of ML in customer retention, aimed at predictive analytics for churn deterrence. These methods examine broad data, such as behavioral patterns, customer transaction history, SA, and external factors, to detect churn risk promptly.

In [10], an enhanced ensemble learning approach was introduced for classification. In contrast to other ensemble models, this method utilized an advanced weighted soft voting ensemble, integrating a sequence of weights to prioritize the predictions of individual base learners, acknowledging that certain models within the ensemble are inherently more accurate than others. In [11], ML and sophisticated Feature Selection (FS) methods were examined to predict customer churn. The investigation leveraged an inclusive dataset encompassing customer traits, churn labels, and historical behavior. Utilizing advanced ML models, such as DT, RF, and SVM, a predictive model was developed to recognize possible churners precisely. The AI-based Multi-Dimensional Customer Churn Prediction for Corporate Performance Assessment (AIMD-CCPCPA) technique [12] aimed to detect the presence of customer churn and non-churn. The study in [13] introduced a new method for these problems using neutrosophic sets to deal with more flexible and nuanced data analysis. In [14], the aim was to align the decisions of the subsidiaries with the strategic intentions of the parent companies, which undoubtedly involves numerous criteria/dimensions.

III. ALGORITHM AND SYSTEM DESIGN

The proposed CAP-RFRNSS model aims to perform customer attrition prediction with enhanced scalability and precision using a cutting-edge neutrosophic model. It contains three main processes, namely preprocessing, feature subset selection, and customer attrition prediction. Figure 1 describes the overall procedure of the CAP-RFRNSS system. A customer churn dataset in CSV format was divided into a training and a test dataset. The data underwent preprocessing using a standard scaler to normalize feature values and produce a clean, pre-processed dataset. LASSO regression was used for FS. The selected features were then converted into PIVNSS-based neutrosophic values, transformed into truth, indeterminacy, and falsity to form the PIVNSS representation. The final churn decision is made by aggregating these values and assigning each instance to the class with the highest score.

A. Data Collection

The dataset contains a total of 100,000 instances, evenly distributed between two classes: "Churn", denoting customers who have discontinued a service, and "Non-Churn", indicating customers who have remained. The dataset was split into 70% for training and 30% for testing.

B. Data Preprocessing Using Standard Scaler

The preprocessing step involves the standard scaler model to normalize the input data. Normalization ensures that each feature is equally weighted, despite of its original units or scale. The normalized data has unit variance and zero mean. This model operates by subtracting the mean from all features and then scaling them to unit variance.

$$Z = \frac{x-u}{s} \tag{1}$$

where s indicates the feature standard deviation, u signifies the feature mean, x denotes the original value of the feature, and z refers to the standardized value.

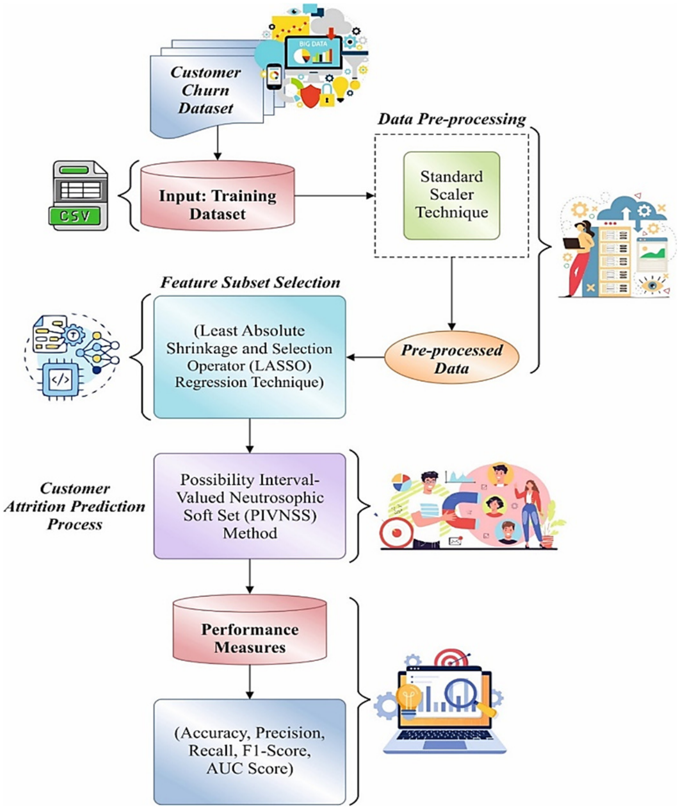

Fig. 1. Overall procedure of the CAP-RFRNSS technique.

C. LASSO-Based Feature Subset Selection Model

Additionally, the LASSO regression method is employed for the feature subset selection to reduce overfitting and enhance model generalization. It is significant to decrease the feature set to improve training and model performance [15]. To accomplish this, dimensionality reduction is evaluated utilizing LASSO regression. L1 or LASSO regularization utilizes a linear model

$$Y_i = \beta_0 + x_{i1}\beta_1 + x_{i2}\beta_2 \dots + x_{ik}\beta_k + e \tag{2}$$

where $i = 1, 2 \dots n$ signifies the sample counts, $\beta_0, \beta_1, \beta_2, \dots, \beta_k$ refers to the coefficients of the linear regression technique, k is the explanatory variable count, and e indicates an error with zero mean, normal distribution, and unit variance. A vector form is:

$$Y = X\beta + e \tag{3}$$

$$\left(\frac{||Y-X\beta||^2}{n}\right) \tag{4}$$

$$\sum_{j=1}^{k} ||\beta|| < t \tag{5}$$

where t denotes the upper bound for the addition of coefficients.

$$\beta(\lambda) = \underset{\beta}{\operatorname{argmin}} \left(\frac{||Y-X\beta||^2}{n} + \lambda\left||\beta|\right|\right) \tag{6}$$

This equation is extended to:

$$\beta(\lambda) = \\ \operatorname{argmin}\left\{\frac{1}{2}\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j\right)^2 + \lambda\sum_{j=1}^{k}|\beta|\right\} \tag{7}$$

The parameter $\lambda \geq 0$ directs a penalty of regularization, with greater values and parameter reduction. Based on λ value, $\beta(\lambda) = 0$. Either LASSO or ridge regression models discover the point in the constraint area. LASSO is a diamond-shaped constraint area that depends on $|\beta_1| + |\beta_2| \leq t$, while ridge regression contains a circle which depends upon $\beta_1^2 + \beta_2^2 \leq t$. The ellipses depict the border of the least-squares error function.

D. Customer Attrition Prediction for PIVNSS Method

The PIVNSS model is used for customer attrition prediction. Some of the concepts, like NS, FS, SS, IVNS, and IVNSS, that prove helpful, are summarized in this section [16].

- Definition 1: Let $\hat{\mathbb{T}} = \{\tau_1, \tau_2, \tau_3, \dots, \tau_n\}$ be a reference set. Next, FS is performed using the following framework:

  $$\mathcal{Q} = \left\{\left(\tau, \langle\ddot{\wp}_Q^t(\tau_i)\rangle\right)\middle|\tau \in \hat{\mathbb{T}}\right\}$$

  where $\ddot{\wp}_Q^t(\tau_i)$ denotes true membership of the object τ_i in $\hat{\mathbb{T}}$ and constant as a mapping: $\ddot{\wp}_Q^t : \hat{\mathbb{T}} \to [0,1]$.

- Definition 2: Assume that $\mathcal{Q}_1 = \left\{\left(\tau, \langle\ddot{\wp}_{Q_1}^t(\tau_i)\rangle\right)\middle|\tau \in \hat{\mathbb{T}}\right\}$ and $\mathcal{Q}_2 = \{(\tau, \langle\ddot{\wp}_{Q_2}^t(\tau_i)\rangle)|\tau \in \hat{\mathbb{T}}\}$ denote dual FS on the reference set $\hat{\mathbb{T}}$. Next, the basic process on FS is described as:

  1. Union $Q_3 = \{(\tau, \langle\max(\ddot{\wp}_{Q_1}^t(\tau_i), \ddot{\wp}_{Q_2}^t(\tau_i))\rangle)|\tau \in \hat{\mathbb{T}}\}$.
  2. Intersection: $Q_3 = \left\{\left(\tau, \langle\min\left(\ddot{\wp}_{Q_1}^t(\tau_i), \ddot{\wp}_{Q_2}^t(\tau_i)\right)\rangle\right)\middle|\tau \in \hat{\mathbb{T}}\right\}$.
  3. Complement $Q_1^c = \{(\tau, \langle(1 - \ddot{\wp}_{Q_1}^t(\tau_i))\rangle)|\tau \in \hat{\mathbb{T}}\}$.
  4. Subset $\mathcal{Q}_1 \subseteq \mathcal{Q}_2$ if $\ddot{\wp}_{Q_1}^t(\tau_i) \leq \ddot{\wp}_{Q_2}^t(\tau_i)$.

- Definition 3: Suppose $\hat{\mathbb{T}} = \{\tau_1, \tau_2, \tau_3, \dots, \tau_n\}$ be a reference set. Formerly, the NS is generated as follows:

  $$\hat{A}_{NS} = \left\{\left(\tau, \langle\ddot{\wp}^t{}_{\hat{A}}(\tau_i), \ddot{\wp}^i{}_{\hat{A}}(\tau_i), \ddot{\wp}^f{}_{\hat{A}}(\tau_i)\rangle\right)\middle|\tau \in \hat{\mathbb{T}}\right\}$$

  where $\ddot{\wp}^t{}_{\hat{A}}(\tau_i)$, $\ddot{\wp}^i{}_{\hat{A}}(\tau_i)$, $\ddot{\wp}^f{}_{\hat{A}}(\tau_i)$ represent true, indeterminacy, and falsehood memberships of an object τ_i in $\hat{\mathbb{T}}$, consistent as a mapping:

  $$\ddot{\wp}^t{}_{\hat{A}}(\tau_i),\ \ddot{\wp}^i{}_{\hat{A}}(\tau_i),\ \ddot{\wp}^f{}_{\hat{A}}(\tau_i) : \hat{\mathbb{T}} \to [0,1].$$

- Definition 4: Presume $T = \{\tau_1, \tau_2, \tau_3, \ldots, \tau_n\}$ be a reference set. Afterward, the IVNS is established as a succeeding infrastructure:

  $$\hat{A}_{IVNS} = \{(\ddot{\wp}^{t}{}_{\hat{A}}(\tau_i),\ \ddot{\wp}^{i}{}_{\hat{A}}(\tau_i),\ \ddot{\wp}^{f}{}_{\hat{A}}(\tau_i)\rangle)|\tau \in \widehat{\mathbb{T}}\}$$

  Now, the three IVNS memberships are characterized by an interval real number as follows:

  $$\ddot{\wp}^{t}{}_{\mathcal{P}}(\tau_i) = \left[\ddot{\wp}^{t,l}{}_{\mathcal{P}}(\tau_i),\ \ddot{\wp}^{t,u}{}_{\mathcal{P}}(\tau_i)\right]$$

  $$\ddot{\wp}^{i}{}_{\mathcal{P}}(\tau_i) = \left[\ddot{\wp}^{i,l}{}_{\mathcal{P}}(\tau_i),\ \ddot{\wp}^{i,u}{}_{\mathcal{P}}(\tau_i)\right]$$

  $$\ddot{\wp}^{f}{}_{\mathcal{P}}(\tau_i) = \left[\ddot{\wp}^{f,l}{}_{\mathcal{P}}(\tau_i),\ \ddot{\wp}^{f,u}{}_{\mathcal{P}}(\tau_i)\right]$$

  which indicate true, indeterminacy, and falsehood interval memberships of the object τ_i in $\widehat{\mathbb{T}}$, determined as a mapping: $\ddot{\wp}^{t}{}_{\hat{A}}(\tau_i),\ \ddot{\wp}^{i}{}_{\hat{A}}(\tau_i),\ \ddot{\wp}^{f}{}_{\hat{A}}(\tau_i) : \widehat{\mathbb{T}} \rightarrow [0,1]$.

IV. MODEL PERFORMANCE ANALYSIS

The proposed model was simulated using Python 3.6.5 on a PC with an i5-8600k, GeForce 1050Ti 4 GB, 16 GB RAM, 250 GB SSD, and 1 TB HDD. The total number of features was 11, but only 8 were selected, namely Tenure, Usage Frequency, Support Calls, Payment Delay, Age, Gender, Subscription Type, and Monthly Charges. These features were retained as the most relevant predictors of customer churn. The experimental analysis of the CAP-RFRNSS technique was conducted on the Customer Churn database [17]. The records in the dataset indicate customers with certain features, such as age, gender, tenure, usage frequency, support calls, payment delay, subscription type, contract length, total spend, and last interaction.

Figure 2 illustrates the confusion matrices generated by the CAP-RFRNSS model for 70:30 splits of TRAP/TESP. The results indicate that the CAP-RFRNSS technique accurately recognizes and classifies all classes.

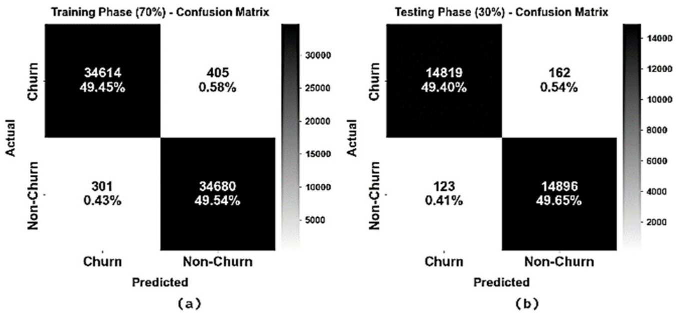

Fig. 2. Confusion matrix of the proposed CAP-RFRNSS model.

Table I displays the customer churn predictions of the CAP-RFRNSS system at the training (TRPHE) and testing phases. In the 70% TRPHE, the proposed CAP-RFRNSS model achieved average $accu_y$, $prec_n$, $reca_l$, $F1_{Score}$ and AUC_{score} of 98.99%, 98.99%, 98.99%, 98.99%, and 98.99%, respectively. In 30% TSPHE, the proposed CAP-RFRNSS model achieved average $accu_y$, $prec_n$, $reca_l$, $F1_{Score}$ and AUC_{score} of 99.05%, 99.05%, 99.05%, 99.05%, and 99.05%, respectively.

TABLE I. CUSTOMER CHURN PREDICTION OF THE CAP-RFRNSS MODEL

Classes	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{Score}$	AUC_{score}
TRPHE (70%)					
Churn	98.84	99.14	98.84	98.99	98.99
Non-Churn	99.14	98.85	99.14	98.99	98.99
Average	98.99	98.99	98.99	98.99	98.99
TSPHE (30%)					
Churn	98.92	99.18	98.92	99.05	99.05
Non-Churn	99.18	98.92	99.18	99.05	99.05
Average	99.05	99.05	99.05	99.05	99.05

Table II depicts a comparison of the CAP-RFRNSS approach with previous techniques [18-21]. The results show that the LightGBM, Ensemble Model, Gradient Boosting, and XAI-Churn TriBoost methods reported lower performance, with $accu_y$ of 80.33%, 84.73%, 82.49%, and 83.87%, respectively. RBF SVM, XGBoost, and Ridge Classifier methods obtained closer values with $accu_y$ of 97.49%, 98.15%, and 94.05%, respectively. The proposed CAP-RFRNSS model achieved superior performance with the highest $accu_y$, $prec_n$, $reca_l$, and $F1_{score}$ of 99.05%, 99.05%, 99.05%, and 99.05% respectively. The highest and constant performance values are due to the efficient integration of LASSO-based feature selection that eliminates redundant and irrelevant attributes, and the PIVNSS framework, which robustly handles uncertainty and enhances classification discrimination. Additionally, the dataset used exhibits well-separated classes. In addition, the inclusion of pre-processing contributes to stable results across evaluations.

TABLE II. COMPARATIVE STUDY OF CAP-RFRNSS MODEL WITH RECENT SYSTEMS [18-21]

Method	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{Score}$
RBF SVM [18]	97.49	89.24	79.27	94.16
LightGBM [19]	80.33	92.47	83.54	98.88
Ensemble Model [19]	84.73	86.86	87.39	93.66
Gradient Boosting [20]	82.49	97.58	87.00	85.67
XGBoost [20]	98.15	81.56	89.03	98.85
XAI-Churn TriBoost [21]	83.87	94.00	92.83	82.16
Ridge Classifier [21]	94.05	83.23	95.57	88.30
CAP-RFRNSS	99.05	99.05	99.05	99.05

Table III presents the K-fold cross-validation results of the proposed model across 10 folds. The consistent performance in terms of accuracy, precision, recall, and F1-score demonstrates the robustness and reliability of the model.

TABLE III. K-FOLD CROSS VALIDATION FOR CAP-RFRNSS

K-fold	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{Score}$
CV-1	89.70	96.12	90.16	90.76
CV-2	92.68	95.05	97.83	91.32
CV-3	97.09	91.23	94.67	89.91
CV-4	96.15	92.94	89.23	94.68
CV-5	89.48	91.43	93.54	91.55
CV-6	90.94	93.10	93.76	97.30
CV-7	97.26	91.14	91.27	93.92
CV-8	97.81	89.67	89.32	96.83
CV-9	89.92	97.87	93.99	91.56
CV-10	91.42	94.48	95.46	94.92

V. CONCLUSION

This study presented a novel CAP-RFRNSS model for big data ecosystems, with the main objective of predicting customer attrition for enhanced precision and scalability, utilizing an advanced neutrosophic technique. The data preprocessing step involved using the standard scaler to normalize the input. Additionally, the LASSO regression model was used to select a feature subset to reduce overfitting and enhance model generalization. The PIVNSS model was used to predict customer attrition. A comprehensive performance assessment was conducted, which showed that the CAP-RFRNSS method outperformed existing models with an improved accuracy of 99.05%. Therefore, the proposed model can be employed for automated and accurate customer attrition prediction.

Future work in customer attrition prediction can focus on incorporating real-time behavioral and transactional data to enhance early churn recognition and proactive retention strategies. Advanced DL and ensemble approaches can also be developed to further boost accuracy. Incorporating explainable AI can increase the transparency of the model and support executive decision-making. In addition, future work can extend sentiment analysis from customer reviews and social media data to better understand hidden dissatisfaction factors.

DECLARATION OF COMPETING INTERESTS

The authors declare that they have no competing interests.

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DATA AVAILABILITY

The data that support the findings of this study are available at [17].

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