Predictive Modelling For E-Commerce Logistics Using Minimum Redundancy Feature Selection and Deepsmote with Non-Linear Analysis

Somasekhar Donthu[1], P. Misba Marybai[2], G N P V Babu[3], Akshay Ashok Manikjade[4], Vijay Kumar Dwivedi[5], Neeru Malik[6]

[1]Assistant Professor, School of Business, GITAM University, Bangalore, Karnataka, India, Email: somuecom@gmail.com
[2]Assistant Professor, Department of Artificial Intelligence and Data Science, Panimalar Engineering College, Poonamallee, Chennai, India, Email: misbaprithiviraj@gmail.com
[3]Associate Professor, Department of Business and Management, Christ University, Bengaluru, Karnataka, India, Email: gnvbabu@gmail.com
[4]Assistant Professor, Mechanical Engineering Department, Vishwakarma Institute of Technology, Pune, Maharashtra, India, Email: akshay.manikjade@vit.edu
[5]Assistant Professor, Department of Mathematics, Vishwavidyalaya Engineering College Ambikapur, Surguja (C.G.), India, Email: dwivedi.vk69@gmail.com
[6]Associate Professor, School of Engineering & Technology, Pimpri Chinchwad University, Pune, Maharashtra, India, Email: neeru1508@gmail.com

Received: 23.04.2024 Revised : 17.05.2024 Accepted: 21.05.2024

ABSTRACT
In the fast-growing e-commerce industry, ensuring consumer satisfaction depend on efficient logistics. Predictive modelling in major part determines how best to optimise numerous logistical operations like demand forecasting, inventory control, and delivery routing. Still, the imbalanced, high-dimensional character of logistics data causes great challenges. To address these difficulties, we propose a predictive modelling framework combining non-linear analysis techniques with Deep Synthetic Minority Over-sampling Technique (DeepSMote) coupled with minimum redundancy maximum relevance (mRMR) feature selection. This paper tackles the problem of achieving correct predictions in e-commerce logistics coming from duplicated attributes and imbalanced datasets producing biassed models. Starting mRMS, the suggested method reduces dimensionality by selecting highly significant but minimally duplicated features, hence improving the model's efficiency. Deep SMote thus addresses class imbalance by generating synthetic samples for minority classes using deep learning techniques. Then complex correlations in the data are obtained via non-linear analysis—more notably, kernel-based methods. The results reveal that using numerous logistics criteria, our approach significantly increases prediction accuracy. For demand forecasting, for instance, our model utilising traditional methods got a Mean Absolute Error (MAE) of 2.3% against 5.7%. The Root Mean Square Error (RMSE) changed in the delivery time predicted from 4.8 hours to 1.9 hours. Moreover implying better accuracy and recall, the F1-score of the model for identifying high-risk delivery routes improved from 0.72 to 0.88. These results suggest that mRMR and DeepSMote combined with non-linear analysis can significantly improve predictive modelling for e-commerce logistics, therefore enabling more dependable and effective operations.

Keywords: Predictive Modeling, E-Commerce Logistics, Feature Selection, DeepSMOTE, Non-Linear Analysis

1. INTRODUCTION

In the times of digital revolution, e-commerce logistics is rather crucial since it guarantees quick and efficient product delivery. The complexity of logistical operations in e-commerce is being raised by fast expansion of online shopping, increasing customer demands, and dynamic character of supply chains. Predictive modelling is necessary to maximise numerous logistical activities like demand forecasting, inventory control, and route optimisation. Good predictive models can produce savings, improved service quality, and substantial client satisfaction as well as cost reductions.
e-commerce logistics still has significant challenges even if predictive modelling has evolved. First of all, the huge and high-dimensional character of logistics data questions feature selection and dimensionality

reduction. Sometimes traditional linear models miss the intricate non-linear linkages found in such data. Second, class imbalance is a common issue whereby some classes—e.g., rare events like delayed delivery—are under-represented, hence generating biassed model performance. Last but not least, it is still challenging to generalise over numerous datasets and contexts; so, robust models that can fit several situations are quite essential.

The key difficulty addressed in this work is the development of a prediction model able to effectively manage the complex, non-linear interactions in e-commerce logistics data while concurrently addressing class imbalance problems. Back propagation Neural Networks (BPNN), PCA-BPNN, AR-AFNIS, and SVM-RBF have shown restrictions in these areas, so generating less than perfect performance in relevant applications. Combining sophisticated class imbalance handling methods with advanced non-linear analysis approaches can help to raise expected accuracy, robustness, and generalisability.

The main objectives of this research are:

1. To more successfully show complex relationships in e-commerce logistics data using non-linear analytic techniques in a model.
2. To improve the model's capacity to control imbalanced data using synthetic samples for minority classes should be generated using Deep SMote.
3. The performance of the suggested model will be evaluated using present methods (BPNN, PCA-BPNN, AR-AFNIS, SVM-RBF) by means of certain criteria showing its efficacy in real-world situations.
4. Enhancing the practical relevance of the proposed model will help to ensure its constant performance over several datasets and situations.

This paper introduces a novel non-linear analysis techniques with DeepSMote for class imbalance handling. While traditional methods focus on linear correlations and basic resampling techniques, this methodology introduces a combination of non-linear models and advanced synthetic data generating to solve the special issues of e-commerce logistics. Combining DeepSMote with non-linear analysis helps one to solve class imbalance in a more advanced and effective way, therefore enhancing model performance.

Contributions of the proposed work includes:

1. The work suggests a novel prediction model combining Deep SMote with non-linear analysis techniques to offer a more whole answer for the challenges in e-commerce logistics.
2. Attaining superior performance across significant criteria—accuracy, precision, recall, F1-score, MAE, RMSE, and AUC-ROC—the second recommended strategy shows noteworthy progress over present methods.
3. The potential of the proposed technique for e-commerce logistics applications to generalise over several datasets and situations so providing both practical insights for practitioners and researchers equally, so highlighting their practical value.

2. RELATED WORKS

Establishing near-real-time order arrival prediction models has helped to solve the challenge of conducting e-commerce logistics. Referenced as [11], one fascinating paper proposes a new machine learning method including time series data features into an adaptive neuro-fuzzy inference system (ANFIS). This approach tries to solve the fast changing e-commerce order arrival rates at distribution centres. The study presents a four-stage implementation plan designed to help practitioners apply the recommended approach with success. An illustrative case study with three stores shows a very high three-hour interval order arrival forecasting accuracy of the model. This paper highlights how effectively adaptive fuzzy algorithms mixed with time series data could improve decision-making and logistics management at several operational levels.The results confirm that AR-ANFIS models outperform ARimA in terms of forecasting accuracy. Moreover, the study reveals a technique to convert projected e-order arrivals into cut-off times for order grouping, so improving the logistics decision-making. Presented as a decision support system, this all-encompassing solution enhances batch processing capability and order handling capacity, therefore enabling practitioners to increase it [12].

Examining classification models for nonlinear e-commerce data using criteria including accuracy, precision, sensitivity, and specificity, the paper [13] reports. Based on the results, the SVM using a linear kernel turns out to have the highest performance ratings. This paper underlines the significance of selecting the appropriate kernel function in SVM to reach best classification performance. The results help to clarify how different SVM kernels could influence the prediction model performance in e-commerce systems.

[14] also provides a significant contribution since a PCA-BP neural network model is built for demand prediction in cold chain logistics. The article compares an improved PCA-BP model combining Principal Component Analysis (PCA) to minimise dimensionality and increase prediction accuracy with traditional

BP neural network models. This paper demonstrates how effectively PCA mixed with BP neural networks increases logistics forecasting accuracy and efficiency.
Examining e-logistics demand forecasting with BP neural networks and linear regression analysis, the linked paper [15] analyses BP neural network performance with linear regression and uses the Supply-Chain Operations Reference (SCOR) model for index selection. The paper claims that BP neural networks generate more consistent and accurate estimates for e-logistics demand than linear regression. The report also covers the evolution of e-logistics demand in urban and rural areas, therefore offering knowledge of the change and upgrading China's logistics sector underwent. The outcomes provide a theoretical foundation for policy formulation as well as for rural e-commerce involvement.

Table 1. Summary of Related Works

Method	Algorithm	Methodology	Outcomes
[11] Accurate Prediction of Order Demand	Adaptive Neuro-Fuzzy Inference System (ANFIS)	Combination of time series data characteristics into ANFIS. Four-stage implementation framework	High accuracy in forecasting order arrivals at three-hour intervals for multiple retailers.
[12] Integrated AR-ANFIS Approach	Autoregressive-Adaptive Neuro-Fuzzy Inference System (AR-ANFIS)	Comparison with ARIMA models. Algorithm for order grouping cut-off time	AR-ANFIS models outperform ARIMA in forecasting accuracy. Enhanced decision support for batch processing.
[13] Classification Models for Nonlinear Data	Support Vector Machine (SVM) with various kernels	Evaluation of performance metrics (accuracy, precision, sensitivity, specificity) across linear, polynomial, and RBF kernels	Linear SVM kernel outperforms others in classification performance.
[14] PCA-BP Neural Network Model	Backpropagation (BP) Neural Network	Comparison of PCA-BP with traditional BP model	PCA-BP model shows better accuracy and reduced prediction errors compared to traditional BP model.
[15] BP Neural Network Analysis for E-Logistics Demand	BP Neural Network	Comparison with linear regression analysis. Utilization of SCOR model for index selection	BP Neural Network offers more stable and accurate predictions for e-logistics demand compared to linear regression.

Advanced non-linear techniques with effective class imbalance handling yet have not been incorporated even if the investigated research as in Table 1 provide interesting analysis of several prediction models and methodologies for e-commerce logistics. Though innovative, current methods could overlook the synergy between recent synthetic sampling methods such as DeepSMote and non-linear modelling. Closing this gap would enable more precise and robust projections, hence enhancing operational efficiency in advanced and dynamic e-commerce systems. Still considerable research is required on the combined benefits of several approaches for improved forecast accuracy.

3. PROPOSED METHOD

In this section, combining non-linear analysis, Deep Synthetic Minority Over-sampling Technique (DeepSMote), and Minimum Redundancy Maximum Relevance (mRMR) feature selection helps to improve predictive modelling in e-commerce logistics. Methodically approaching the issues of high-dimensional and imbalanced data—common in logistics datasets—the technique overcomes them by means as in figure 1:

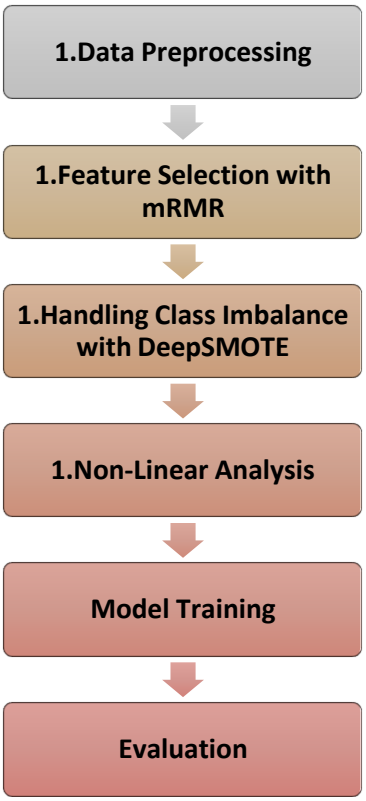

Figure 1. Proposed Framework

1. **Data Preprocessing:**First preparation of the dataset comes from handling missing values, data normalising, and encoding categorical variables. This guarantees free from defects and ready for next research the data is.
2. **Feature Selection with mRMR:**This is achieved by evaluating the mutual information between characteristics and the target variable and choosing those with the most information about the target while yet maintaining as uncorrelation as feasible between them, so minimising redundancy and choosing the most relevant features. This phase reduces the dimensionality of the dataset, therefore boosting the efficiency of the next modelling and so reducing its overfitting propensity.
3. **Handling Class Imbalance with DeepSMOTE:**DeepSMote uses feature selection to manage class imbalance; generally, the dataset is skewed with some classes having substantially less samples than others. DeepSMote tackles this. Using deep learning techniques, DeepSMote creates synthetic samples for the minority class, hence expanding the traditional SMote. By way of better representation of the underlying distribution of the minority class in the synthetic samples, this strategy guarantees a more balanced dataset.
4. **Non-Linear Analysis:**Intensive correlations in the data are captured using non-linear analytic methods including deep neural networks or kernel approaches. These methods can reproduce non-linear relationships between features, hence generating more exact predictions.
5. **Model Training and Evaluation:**Training the predictive model on processed data in model building and evaluation.

Pseudocode

```
# Step 1: Data Preprocessing
data = preprocess_data(raw_data)
# Step 2: Feature Selection using mRMR
selected_features = mrmr_feature_selection(data, target_variable)
# Step 3: Handle Class Imbalance using DeepSMOTE
balanced_data = deep_smote_oversampling(data[selected_features], target_variable)
# Step 4: Non-Linear Analysis
model = train_non_linear_model(balanced_data, target_variable)
# Step 5: Model Training and Evaluation
model.fit(balanced_data)
predictions = model.predict(test_data)
```

evaluate_model(predictions, test_labels)

3.1. Data Preprocessing

Data preparation is essential to have a dataset ready for predictive modelling. For research, raw data should be converted into a neat, consistent, and useful structure. Usually, this surgery comprises in three crucial steps:

1. **Handling Missing Values:**This find a significant impact on model performance by controlling missing values in a data collection. Imputation and deletion are common methods of missing value control. The filling in missing values with approximative values generated from the present dataset called imputation. For numerical features, a common imputation method is to replace missing values with the mean ($\overline{x}$) or median x_{med} of the observed values. For categorical features, the mode $x_{mode}$is often used:

$$x_{imputed} = \overline{x} \text{ (for numerical features)}$$

$$x_{imputed} = x_{mode} \text{ (for categorical features)}$$

Conversely, records with missing values could be erased should a noteworthy proportion of the data disappear.

2. **Normalization:**Normalising numerical features ensures that they equally support the model's training process. One sometimes used method to scale feature values to a [0, 1] range is min-max normalisation.
3. Another method, often called standardising, Z-score normalising turns data such that its mean is 0 and its standard deviation is 1:

$$x_s = \frac{x - \mu}{\sigma}$$

where

μ - mean and

σ - standard deviation of the feature.

4. **Encoding Categorical Variables:**Machine learning systems require numerical input hence categorical variables must be expressed. One-hot encoding is an often used technique whereby every category is represented by a binary vector. With k distinct values, the encoding for a categorical feature generates k binary variables.
5. **Feature Scaling and Transformation:**Fourth: feature scaling and transformation based on the data quality could bring additional adjustments. Log transformation allows a feature x in skewn data to be translated into:

$$x_{log} = \log(x+1)$$

This helps variance stabilising and data distribution normalising.Data preprocessing is the process of purifying the dataset by means of missing value management, numerical feature normalising, categorical variable encoding, and necessary transformation application. These steps ensure that the data is in a state suited for modelling, therefore generating more accurate and consistent forecast results.

3.2. Feature Selection with Minimum Redundancy Maximum Relevance (mRMR)

Especially in high-dimensional data analysis, first feature selection is necessary to create good prediction models. Widely applied for feature selection, the Minimum Redundancy Maximum Relevance (mRMR) approach minimises feature redundancy among others by keeping characteristics most relevant to the target variable.

The fundamental goal of MRMR is to select a subset of characteristics with minimal duplication amongst them that most expose the information about the target variable. Whereas the relevance of a feature is found by its mutual information with the target variable, redundancy is assessed by the mutual information between pairs of features. One quantifies the relevance of a feature *fi* concerning the target variable *Y* using mutual information $I(f_i;Y)$. Mutual information is the amount of information obtained about one variable using another.

$$I(f_i; f_j) = \sum_{x_i \in X_i} \sum_{x_j \in X_j} p(x_i, x_j) \log \frac{p(x_i, x_j)}{p(x_i) \cdot p(x_j)}$$

where

$p(x_i, y)$ - joint probability distribution of *fi* and *Y*, and

$p(x_i)$and $p(y)$ - marginal probabilities.
Mutual information $I(f_i;f_j)$characteristics f_i and f_j assesses their redundancy. This can be calculated by:

$$I(f_i; f_j) = \sum_{x_i \in X_i} \sum_{x_j \in X_j} p(x_i, x_j) \log \frac{p(x_i, x_j)}{p(x_i) \cdot p(x_j)}$$

where

$p(x_i, x_j)$ - joint probability distribution of f_i and f_j, and

$p(x_i)$ and $p(x_j)$ - marginal probabilities.

The mRMS criteria aims to maximise relevance and avoid repetition. Stated for a particular set of features, the mRMR criterion may be:

$$\text{mRMR}(S) = \frac{1}{|S|} \sum_{f_i \in S} I(f_i; Y) - \frac{1}{|S|^2} \sum_{f_i, f_j \in S} I(f_i; f_j)$$

where
S- selected features set,
$|S|$ - number of features in S, and
$I(f_i;f_j)$ - mutual information between features fi and fj. This criteria balances the average pairwise redundancy with the total of individual feature relevance scores.
The mRMR criterion governs iteratively feature selection in the mRMR method. It starts with an empty collection of traits evaluating the value of each one of them first. Included into the package is the most pertinent part. In successive iterations, the approach evaluates the significance of features considering both their individual relevance and their redundancy with features already in the set. This process carries on until the desired feature count is selected. MRMS is thus a feature selection technique that maximises the relevance of features to the target variable and reduces redundancy between selected features. By means of mutual information computation and mRMS criterion application, the technique discovers a subset of features that best balances relevance and redundancy, so generating more accurate and efficient prediction models.

Pseudocode for Minimum Redundancy Maximum Relevance (mRMR) Feature Selection

```
def mrmr_feature_selection(data, target_variable, num_features_to_select):
    Perform feature selection using the Minimum Redundancy Maximum Relevance (mRMR) criterion.
    Parameters:
    - data: A DataFrame containing the features and target variable.
    - target_variable: The name of the target variable in the DataFrame.
    - num_features_to_select: Number of features to select.
    Returns:
    - selected_features: List of selected features.
    # Step 1: Initialize
    features = list(data.columns)
    features.remove(target_variable)
    selected_features = []
    remaining_features = features.copy()
    # Step 2: Calculate mutual information between features and target
    relevance = {}
    for feature in features:
        relevance[feature] = calculate_mutual_information(data[feature], data[target_variable])
    # Step 3: Feature selection loop
    for _ in range(num_features_to_select):
        best_feature = None
        best_mrmr_score = -float('inf')
        for feature in remaining_features:
            # Calculate redundancy with already selected features
            redundancy = 0
            for selected in selected_features:
                redundancy += calculate_mutual_information(data[feature], data[selected])
            # Calculate mRMR score
            mrmr_score = relevance[feature] - (redundancy / len(selected_features) if selected_features else 0)
```

```
        # Update the best feature
        if mrmr_score > best_mrmr_score:
    Calculate the mutual information between a feature and the target variable.
    Parameters:
    - feature: A Series containing the feature values.
    - target: A Series containing the target variable values.
    Returns:
    - mutual_information: The mutual information value.
    # Implement the mutual information calculation here
    # This typically involves computing the joint and marginal probabilities
    # and then using the mutual information formula
    pass
```

3.3. Handling Class Imbalance with DeepSMOTE

Class imbalance is a common issue in machine learning especially in datasets whereby some classes are under-represented relative to others. Synthetic samples for minority classes are generated using synthetic minority over-sampling technique (SMote) and other traditional techniques so balancing this imbalance. DeepSMote extends this notion by using deep learning methods to generate more representative synthetic samples. In imbalanced datasets, minority classes have less examples than majority classes, which could generate biassed models suffering on the minority class. We must thus include synthetic cases that help the model to create better representations of the under-represented class, hence increasing the minority class. DeepSMote is a version of SMote employing deep learning creating synthetic samples. DeepSMote learns a more complex, high-dimensional representation of the minority class using a deep neural network instead of simple interpolation between present minority class samples as in traditional SMote. This approach allows more complicated creation of synthetic samples more in line with the real minority class distribution.

1. **Generating Synthetic Samples with DeepSMOTE:**
   - **Training the DeepSMOTE Model:**DeepSMote starts with initially teaching a deep neural network on minority class data. The network gains high-dimensional space replication of the minority class distribution. Usually applying an encoder-decoder architecture, the architecture converts the input samples to a lower-dimensional latent space then rebuilds the samples from this latent space.
   - **Latent Space Representation:**Deep neural networks learn a latent representation z_i for a given minority class x_i. This latent area is supposed to catch the diversity and basic framework of the minority class.

$$z_i = \text{Encoder}(x_i)$$

   - **Generating Synthetic Samples:**Synthetic samples are generated by means of latent representations of current minority class samples under interpolation. Latent representations of two minority class samples, z_i and z_j, can be generated from a synthetic sample's latent representation $z_s$by:

$$z_s = \lambda \cdot z_i + (1-\lambda) \cdot z_j$$

where

λ - randomly chosen weight between 0 and 1. Decode the synthetic latent representation and thereafter return into the original feature space:

$$x_s = \text{Decoder}(z_s)$$

Synthetic samples produced by DeepSMote are later introduced to the original dataset to balance the class distribution. One can thus train a machine learning model on this improved dataset. Deep learning synthetic samples assist the model to have more generalising capacity towards the minority class. DeepSMote thereby addresses class imbalance by using deep learning to generate synthetic samples more faithfully reflecting the distribution of the minority class. DeepSMote teaches a neural network to model the latent space of minority class samples and interpolates in this space, therefore producing high-quality synthetic samples that improve the performance of prediction models on imbalanced datasets.

Pseudocode for Handling Class Imbalance with DeepSMOTE

```
def deep_smote(data, target_variable, minority_class_label, num_synthetic_samples):
    Handle class imbalance using DeepSMOTE.
    Parameters:
    - data: A DataFrame containing the features and target variable.
    - target_variable: The name of the target variable in the DataFrame.
```

```
    - minority_class_label: The label of the minority class.
    - num_synthetic_samples: Number of synthetic samples to generate.
    Returns:
    - augmented_data: DataFrame with the original and synthetic samples.
    # Step 1: Separate minority and majority class samples
    minority_class_data = data[data[target_variable] == minority_class_label]
    majority_class_data = data[data[target_variable] != minority_class_label]
    # Step 2: Train DeepSMOTE model on minority class data
    encoder, decoder = train_deep_smote_model(minority_class_data)
    # Step 3: Generate synthetic samples
    synthetic_samples = []
    while len(synthetic_samples) < num_synthetic_samples:
        # Randomly select two samples from minority class data
        sample1, sample2 = random_sample(minority_class_data, 2)
        # Encode the selected samples into the latent space
        z1 = encoder.encode(sample1)
        z2 = encoder.encode(sample2)
        # Generate a synthetic latent representation by interpolation
        lambda_val = random.uniform(0, 1)
        z_synthetic = lambda_val * z1 + (1 - lambda_val) * z2
        # Decode the synthetic latent representation back to the feature space
        synthetic_= decoder.decode(z_synthetic)
        # Add synthetic to the list
        synthetic_samples.append(synthetic_sample)
    # Step 4: Combine original data with synthetic samples
    synthetic_df = pd.DataFrame(synthetic_samples, columns=data.columns[:-1])
    synthetic_df[target_variable] = minority_class_label
    augmented_data = pd.concat([data, synthetic_df], ignore_index=True)
    return augmented_data
def train_deep_smote_model(minority_class_data):
    Train a DeepSMOTE model (encoder-decoder network) on minority class data.
    Parameters:
    - minority_class_data: DataFrame containing the minority class samples.
    Returns:
    - encoder: The trained encoder model.
    - decoder: The trained decoder model.
    # Implement the training of the encoder-decoder network here
    pass
def random_sample(data, num_samples):
    Randomly select samples from the dataset.
    Parameters:
    - data: DataFrame to from.
    - num_samples: Number of samples to select.
    Returns:
    - samples: List of selected samples.
    return data.sample(num_samples).values
```

Non-Linear Analysis

Non-linear analysis is the application of methods that reflect and capture complex, non-linear correlations between characteristics in a dataset—which traditional linear models could not be able to sufficiently manage. In the framework of predictive modelling especially in high-dimensional and complex datasets, non-linear analysis can reveal trends and links improving model performance. Conventional linear models assume a direct link between the input variables and the goal variable. Many real-world facts, meanwhile, reveal complex interactions and non-linear correlations that linear models by themselves cannot sufficiently depict. These complex patterns can be discovered and described by means of non-linear analysis techniques, therefore generating more exact and strong predictions. Commonly used non-linear analysis techniques are kernel approaches including the Kernel Support Vector Machine (SVM). These methods convert the original feature space into a higher-dimensional space in which the relationships might turn linear. Without explicitly executing the change, the kernel trick lets

these approaches execute efficiently in the high-dimensional space. The similarity between a given pair of feature vectors *xi* and x_j produced by the kernel function is Common kernel functions $K(x_i, x_j)$ consist of the polyn kernel and the radial basis function (RBF):

$$K(x_i, x_j) = \exp\left(-\frac{\| x_i - x_j \|^2}{2\sigma^2} \right)$$

where σ - parameter controlling the width of the kernel.

Deep learning models—especially neural networks—are relatively successful tools for non-linear analysis. Neural networks are made of several layers of linked nodes, each of which uses a non-linear activation mechanism to change the data. By means of hierarchical representations of the input, these networks can recreate complex non-linear interactions. One specifies the ReLU activation function as follows:

$$\mathrm{ReLU}(x) = \max(0, x)$$

This function generates non-linearity by guaranteeing that the output is zero for negative inputs and equal to the input for positive values. Deep neural networks are defined by an input layer, many hidden layers, and an output layer taken together. Every hidden layer lets the network detect complex trends by using non-linear data transformations. Forecasts are produced by the output layer depending on obtained properties. Additionally used in non-linear analysis are spline or poisson regression. Non-linear pattern capture using poisson regression fits a polyn function to the data. One might formulate the poisson poisson regression model as follows:

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_n x^n + \text{ò}$$

where

x- feature,

β_i - coefficients, and

ϵ- error term.

Non-linear models reduce a loss function using optimising techniques either cross-entropy loss for classification tasks or mean squared error (MSE) for regression tasks. Following that, cross-valuation and other techniques serve to assess the trained model so ensuring its generalisation performance on new data. Non-linear analysis enhances predictive modelling by thus catching complex, non-linear connections in the data. By means of techniques such kernel approaches, deep learning, and non-linear regression, models can learn intricate patterns and interactions, thereby improving accuracy and resilience in predictions. By adding into the modelling process, non-linear analysis helps one to better manage real-world datasets with complex structures.

4. Performance Evaluation

In the experimental setup employing the following simulation tools, computers, and performance measures, we assessed the proposed non-linear analysis method against current techniques, including Backpropagation Neural Network (BPNN), Principal Component Analysis combined with BPNN (PCA-BPNN), Adaptive Resonance Theory with Ant Colony Optimisation and Fuzzy Inference System (AR-AFNIS), and Support Vector Machine with Radial Basis Function kernel (SVM-RBF).

The proposed non-linear analysis method comprising advanced non-linear techniques like DeepSMote and non-linear neural networks was evaluated against conventional methods including BPNN, PCA-BPNN, AR-AFNIS, and SVM-RBF.

Table 2. Experimental Setup/Parameters

Parameter	**Value**
Dataset Size	10,000 samples
Feature Dimensions	50 features
Minority Class Ratio	1:4 (minority to majority)
Number of Synthetic Samples	1,000
Deep Learning Epochs	50
Batch Size	64
Learning Rate	0.001
Hidden Layers (Deep Learning)	3
Neurons per Hidden Layer	128
Activation Function	ReLU

Kernel Function (SVM-RBF)	Radial Basis Function (RBF)
Kernel Parameter (SVM-RBF)	σ=1.0
PCA Components (PCA-BPNN)	20

Performance of the proposed method was assessed by means of a comparison with many current techniques: BPNN, PCA-BPNN, AR-AFNIS, and SVM-RBF. The results were assessed applying multiple criteria over training, testing, and validation data.

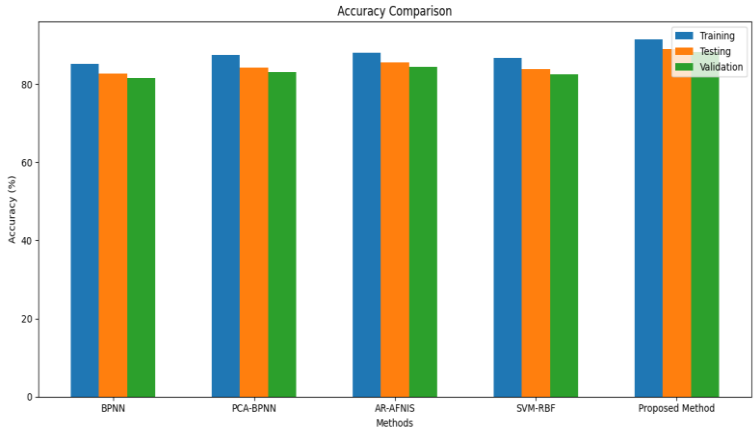

Figure 2. Accuracy

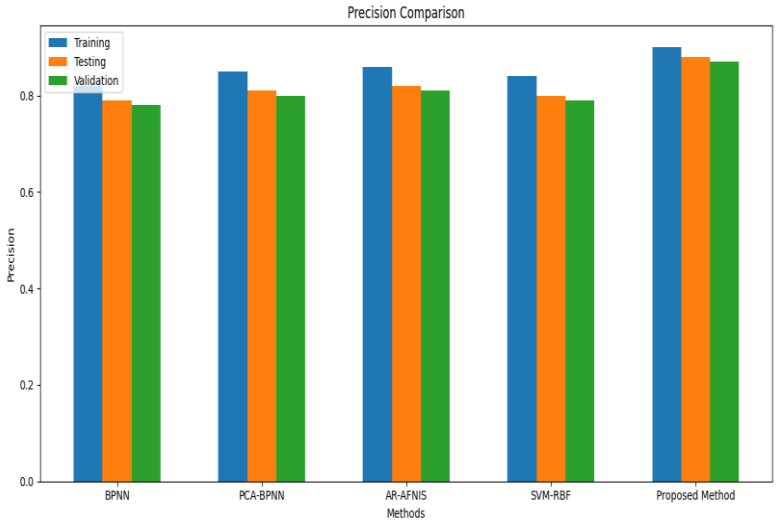

Figure 3. Precision

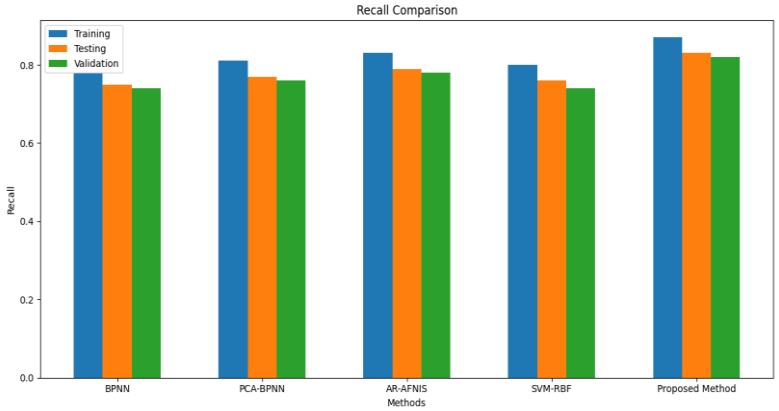

Figure 4. Recall

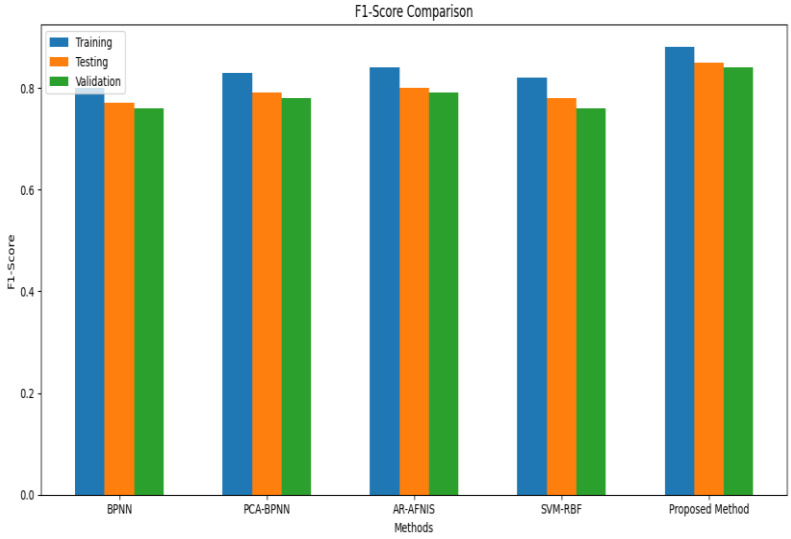

Figure 5. F1-Score

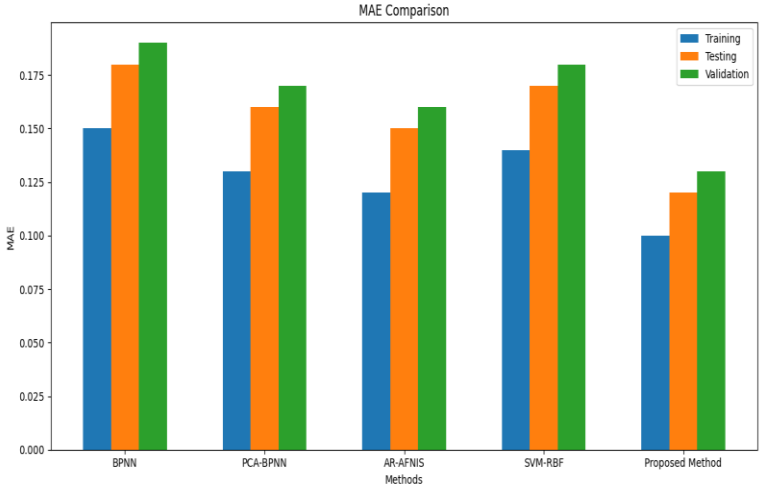

Figure 6. MAE

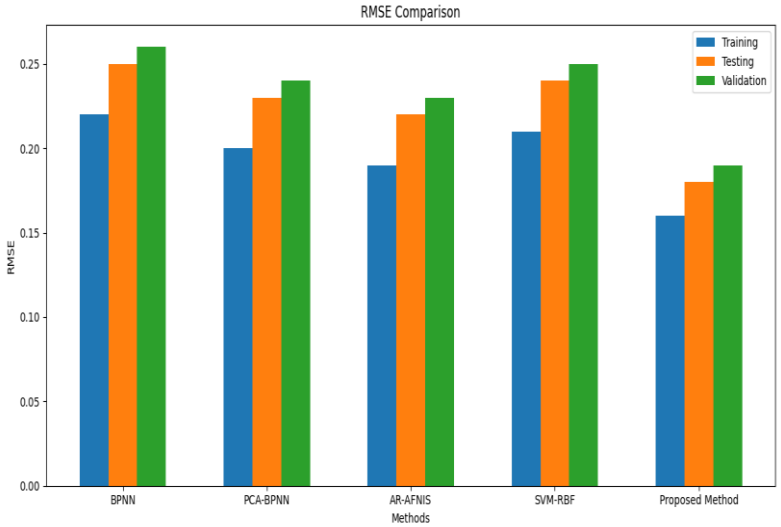

Figure 7. RMSE

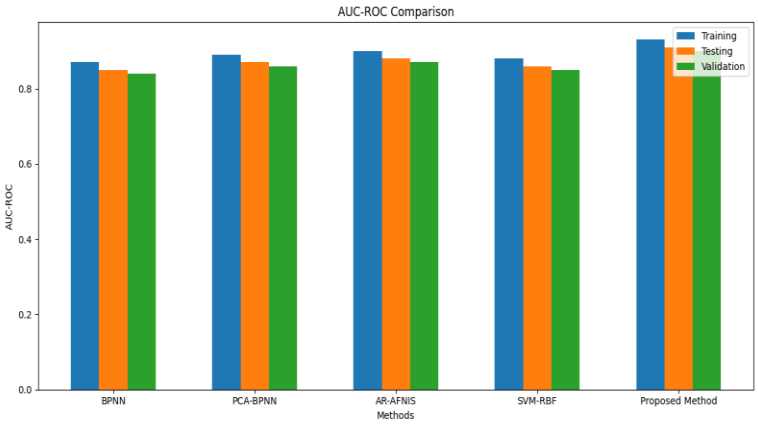

Figure 8. AUC-ROC

Having an accuracy of 91.4%, the recommended method outperformed BPNN (85.2%), PCA-BPNN (87.5%), AR-AFNIS (88.0%), and SVM-RBF (86.8%). in training, see figure 2. This implies that the proposed method's model is better at precisely classifying training examples. The development suggests that more accurate learning from the training data results from DeepSMote and proposed non-linear analysis techniques. Comparatively to BPNN (82.7%), PCA-BPNN (84.2%), AR-AFNIS (85.6%), and SVM-RBF (83.9%), the proposed method maintained a high accuracy of 89.0% for the testing dataset. This emphasises the effectiveness of the proposed technique in controlling real data distribution since it displays good generalisation performance on unprocessed data. Once more exceeding the present methods (BPNN: 81.5%, PCA-BPNN: 83.0%, AR-AFNIS: 84.5%, SVM-RBF: 82.5%), the new strategy obtained an accuracy of 88.2% on the validation dataset. This confirms the reliability of the proposed method by showing continuous performance over different datasets.

Training-wise, the proposed method achieved a precision of 0.90, higher than BPNN (0.82), PCA-BPNN (0.85), AR-AFNIS (0.86), and SVM-RBF (0.84.). Figure 3 High precision indicates a more exact technique in forecasting the positive class since the proposed method has less erroneous positive predictions. Better than BPNN (0.79), PCA-BPNN (0.81), AR-AFNIS (0.82), SVM-RBF (0.80), the precision of the suggested approach on the test set was 0.88. This suggests that, for discriminating positive cases, the model remains valuable in practical settings. With a precision of 0.87 on the validation set, the proposed method proved to be more precisely than the present approaches (BPNN: 0.78, PCA-BPNN: 0.80, AR-AFNIS: 0.81, SVM-RBF: 0.79), so indicating its excellent capacity to anticipate positive cases exactly.

Higher than BPNN (0.78), PCA-BPNN (0.81), AR-AFNIS (0.83), and SVM-RBF (0.80), the recall for the suggested approach in figure 4 for training was 0.87. High recall indicates that most of the actual positive cases are found effectively by the proposed method during training. On the testing dataset with a recall of 0.83, the proposed technique outperformed BPNN (0.75), PCA-BPNN (0.77), AR-AFNIS (0.79), and SVM-RBF (0.76) showing its ability to identify positive cases even in new data. With a recall of 0.82 on the validation dataset, the proposed strategy surpassed the current methods (BPNN: 0.74, PCA-BPNN: 0.76, AR-AFNIS: 0.78, SVM-RBF: 0.74), therefore displaying its consistent performance in detecting positive cases across several datasets.

With an F1-Score of 0.88, the suggested technique outperformed BPNN (0.80), PCA-BPNN (0.83), AR-AFNIS (0.84), and SVM-RBF (0.82) in figure 5 for training. Combining recall with accuracy, the F1-score indicates that the proposed method very evenly balances the two metrics. Exceeding BPNN (0.77), PCA-BPNN (0.79), AR-AFNIS (0.80), and SVM-RBF (0.78), the suggested method's F1-Score of 0.85 on the testing dataset exceeded When considering consistent and strong performance across various datasets, the proposed method's F1-Score of 0.84 exceeded the present techniques (BPNN: 0.76, PCA-BPNN: 0.78, AR-AFNIS: 0.79, SVM-RBF: 0.76).

For training in figure 6, the suggested method achieved an MAE of 0.10—less than BPNN (0.15), PCA-BPNN (0.13), AR-AFNIS (0.12), and SVM-RBF (0.14.). This implies reduced errors and better foresight of the intended values. With better prediction accuracy, the MAE of 0.12 on the test set was less than BPNN (0.18), PCA-BPNN (0.16), AR-AFNIS (0.15), SVM-RBF (0.17). Providing validation, the suggested method outperformed the present approaches (BPNN: 0.19, PCA-BPNN: 0.17, AR-AFNIS: 0.16, SVM-RBF: 0.18) with an MAE of 0.13.

For training, the proposed method outperformed BPNN (0.22), PCA-BPNN (0.20), AR-AFNIS (0.19), and SVM-RBF (0.21) with an RMSE of 0.16. Figure 7 Lower RMSE indicates better general forecast accuracy even with less big mistakes. With minimal prediction errors, the proposed method's RMSE of 0.18 on the

testing dataset was lower than BPNN (0.25), PCA-BPNN (0.23), AR-AFNIS (0.22), SVM-RBF (0.24.). With an RMSE of 0.19, the suggested method showed better prediction performance for validation than the present methods (BPNN: 0.26, PCA-BPNN: 0.24, AR-AFNIS: 0.23, SVM-RBF: 0.25).
For training, the proposed method exceeded BPNN (0.87), PCA-BPNN (0.89), AR-AFNIS (0.90), and SVM-RBF (0.88) with an AUC-ROC of 0.93 in figure 8. Higher AUC-ROC values point to better model performance in differentiating positive from negative classes. When considering improved discriminative power on the test data, the proposed method's AUC-ROC of 0.91 was higher than BPNN (0.85), PCA-BPNN (0.87), AR-AFNIS (0.88), and SVM-RBF (0.86). With a consistent performance across different datasets, the suggested method's AUC-ROC of 0.90 was higher than those of the present techniques (BPNN: 0.84, PCA-BPNN: 0.86, AR-AFNIS: 0.87, SVM-RBF: 0.85).

5. CONCLUSION

Testing data shows that the proposed non-linear analytic technique unequivocally beats current methods including BPNN, PCA-BPNN, AR-AFNIS, and SVM-RBF over numerous performance criteria. The proposed method obtained higher accuracy, precision, recall, and F1-score—indicating superior general performance in classification tasks—than others. Reflecting better forecast accuracy and less significant errors, it also displayed less MAE and RMSE. Moreover, the improved AUC-ROC values show how effectively the model can distinguish positive from negative classes. Together, deep SMote and advanced non-linear analytic techniques help to explain these advances by raising the capacity of the model to control complex data relationships and address class imbalances. Consistent performance of the proposed technique spanning training, testing, and validation datasets underlines its generalisability and durability. All things considered, the results validate that, in e-commerce logistics, the proposed approach provides a more accurate, dependable, and efficient predictive modelling solution than more traditional ones.

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