An Adaptive Intelligent Decision Support Framework for Business-to-Business Sales Estimation Using Generalized Q-rung Neutrosophic Soft Set

Ilyos Abdullayev[1,*], Jamshid Pardaev[2], Mansur Eshov[3], Sanat Chuponov[4], Elena Klochko[5]

[1]Department of Business and Management, Urgench State University, Urgench, 220100, Uzbekistan

[2]Department of Finance and Tourism, Termez University of Economics and Service, Termez, 190111, Uzbekistan

[3]Department of Management and Marketing, Alfraganus University, Tashkent, 100000, Uzbekistan

[4]Department of Accounting and Business Management, Mamun University, Khiva, 220900, Uzbekistan

[5]Department of Management, Kuban State Agrarian University named after I.T. Trubilin, Krasnodar, 350044, Russia

Emails: ilyos.a@urdu.uz; jamshid_pardaev@tues.uz; m.eshov@afu.uz; chuponov_sanat@mamunedu.uz; klochko.e@edu.kubsau.ru

Abstract

The neutrosophic set (NS) is a powerful tool for representing uncertain information in decision-making, extending conventional, fuzzy sets (FS), and intuitionistic fuzzy sets (IFS) by incorporating three degrees: truth, falsity, and indeterminacy. Sales prediction analysis wishes for intellectual data mining systems with precise predictive methods and higher trustworthiness. In the majority of cases, business depends heavily on information in addition to demand prediction of sales performance. The B2B data can offer information on how a business has to manage its products, sales team, and budget flows. Clear prediction techniques were analysed and examined using the model of machine learning (ML) to improve future sales predictions. It is challenging to manage sales prediction precision and big data (BD) when the technique of classic prediction is applied. Thus, the ML method can also be used to analyze the B2B sales reliability. This study proposes an Intelligent Business to Business Sales Estimation Framework Using Neutrosophic Soft Set (IB2BSEF-NSSS) method. The primary purpose of IB2BSEF- NSSS method is to develop an effective system for B2B sales estimation using advanced techniques for greater predictive precision. Initially, the min-max method is adopted in the data pre-processing phase to normalize input data. Additionally, the IB2BSEF-NSSS model leverages the zebra optimization algorithm (ZOA) technique for feature selection. Additionally, the generalized q-rung neutrosophic soft set (GqRNSSS) methodology is exploited for the sales prediction operation. To further increase prediction performance, the Kepler Optimizer Algorithm (KOA) model is employed for model fine-tuning, assuring optimum hyperparameter selection for upgraded accuracy. To expose the better performance of the IB2BSEF- NSSS technique, a wide-ranging experimental analysis is conducted under the B2B sales and customer insight analysis dataset. The comparison study of the IB2BSEF-NSSS technique exposed greater predictive performance, accomplishing the lowest MSE of 0.00670, indicating its efficacy over each other evaluated techniques.

Keywords: Business to Business; Sales Estimation; Generalized Q-rung Neutrosophic Soft Set; Kepler Optimization Algorithm; Fuzzy Set; Neutrosophic Set

1. Introduction

Neutrosophic logic is an innovative area in which every proposition is allocated percentages of truth (T), indeterminacy (I), and falsity (F) [1]. NS is effectually utilized for indeterminate data processing and specifies

DOI: https://doi.org/10.54216/IJNS.270204

advantages for tackling indeterminacy in data. Ns also delivers a precise and effectual model to clategorize-unbalanced data depend on features [2]. Its application is also being actively promoted for classification and data analysis tasks. Business-to-Business (B2B) relates to companies targeting other business with their services or products, instead of than individual customers. In B2B commerce, firms compete to secure sales opportunities to increase their profit [3]. In this context, correctly predicting sales opportunity results are vital for sustained B2B business success. B2B sales typically requires significant resources and expenses, thus necessitating meticulous assessments in the initial phase. To calculate the probability of acquiring novel sales prospects is an essential foundation for optimal resource deployment, preventing resource depletion, and maintaining the company's financial goals [4].

Traditionally, estimating the sales opportunity outcome is performed based on a subjective human rating. Many customers' relationship management (CRM) systems enable sales professionals to manually input the estimated likelihood of securing new sales deals. These likelihoods are used in various sales process, for instance, computing a weighted revenue from each sales record [5]. Often, every salesperson relies on gut feeling (non-systematic intuition) to predict sales success, often without sound numerical justification, overlooking the intricacies of the business landscape [6]. Additionally, sales opportunities are often intentionally undervalued to reduce competition among salespeople or overvalued to ease pressure from management to maintain high performance [7]. In B2B environments, predicting future needs is essential because the whole production and supply processes are determined by these predictions. Numerous conventional prediction techniques typically rely on past sales [8]. With the progress in information technology, businesses increasingly acquire substantial volumes of information, offering prospects for insightful discovery and sophisticated analytical applications, for example, ML [9]. A large portion, approximately 80 to 90% of BD, is comprised of unstructured data, which is expanding at a quicker rate than any other data type. Moreover, NLP is powerful in automating data extraction from extensive unstructured text [10]. An ML model is employed to examine the crucial variables and patterns in this data, which enables precise estimation of sales. ML models have developed as an important tool in analysis. Its interpretability and ease make it an effective tool to model sales trends [11].

1.1. Motivation for the IB2BSEF-NSSS Model

The motivation for developing an adaptive intelligent decision support structure for B2B sales estimate utilizing the GQNS is driven by numerous critical requirements:

- Complexity and uncertainty in B2B surroundings demand advanced method and imprecise data common in real-world sales scenarios.
- GQNS provides a robust mathematical tool to model uncertainty by integrating degrees of truth, indeterminacy, and falsity, enabling more accurate and flexible decision-making.
- Accurate B2B sales estimation is crucial for strategic planning, resource allocation, and maximizing profitability, specifically in highly competitive markets.
- Imbalanced and inconsistent data often faced in B2B transactions need intelligent classification techniques, and GQNS outperforms at handling such data structures effectually.
- Existing decision support systems lack adaptability, making it significant to develop frameworks that can dynamically respond to growing data and market conditions.
- Neutrosophic logic introduces a novel paradigm for managing uncertainty in data-driven environments, presenting promising improvements in prediction and classification tasks.

1.2. Key Contributions and Novel Insights: Advancements in B2B Sales Estimation Using Neutrosophic Soft Sets

This study introduces a novel Intelligent Business to Business Sales Estimation Framework Using Neutrosophic Soft Set (IB2BSEF-NSSS). The main objective of proposed method is to effective model for B2B sales estimation using advanced methods. To perform that, the min-max standardization is applied to normalize input data. In addition, the IB2BSEF- NSSS technique utilizes the zebra optimizer algorithm (ZOA) for feature selection. Moreover, the generalized q-rung neutrosophic soft set (GqRNSSS) technique has been deployed for the sales prediction operation. To further improve prediction solution, the Kepler Optimizer Algorithm (KOA) is utilized for model fine-tuning, ensuring optimum parameter choice for enhance accuracy. To show the better outcome of the IB2BSEF- NSSS methodology, a wide-ranging stimulated study is shown under the B2B sales and customer insight analysis database. The major contribution of the IB2BSEF- NSSS is listed below.

- The min-max method to preprocess data, making sure all input features are normalized within a specific range, which enhances consistency and comparability across variables.
- The ZOA for performing optimal feature reduction that reduces dimensionality and eliminates irrelevant data.
- The GqRNSSS model for effectually dealing with uncertainty, indeterminacy, as well as inconsistency in sales data, enabling predictions that are more reliable.

DOI: https://doi.org/10.54216/IJNS.270204

- The proposed approach exploits the KOA technique for fine-tuning the hyperparameters.
- The comparison study of the IB2BSEF- NSSS technique exposed greater predictive performance, indicating its efficacy over each other evaluated techniques.

2. Review of Literature Works on B2B Sales Estimation

Zhang et al. [12] focused on designing and implementing a decision support system (DSS), employing BD. With a thorough assessment economic data, the main factors, namely cost of sales, current liabilities, sales revenue, shareholders' equity, current assets, net profit, and total assets, are chosen. Jiang et al. [13] introduced TimeSpeaks, a method that implements sequence modelling in NLP to the adaptive model selection problem in prediction. To exemplify the method, the authors utilize transformer-based (TimeXer) and sequential (BiLSTM) DL approaches for learning temporal relations among candidate algorithms. Time Speaks stands out as an appropriate prediction method because of its capability to adjust to emerging data trends and its minimum dependence on external inputs. Gupta and Agarwal [14] examined the ability to enhance sales forecasting precision using CRM and enterprise resource planning (ERP) systems integrated with AI methods. Businesses can obtain in-depth understandings of customer preferences, behavior, and market dynamics by utilizing AI models, like ML and predictive analytics, with data from CRM and ERP models.

Xu et al. [15] discovered the usage and benefits of widespread AI techniques in logistics and supply chains. Classical firms require assistance with the prompt recognition of anomalies in the supply chain. Simultaneously, AI systems can rapidly detect irregular patterns in data and send warnings, assisting enterprises in adjusting practical approaches to guarantee the steady process of the supply chain. AI also decreases financial losses and inventory expenses by forecasting fluctuations in market demand and enhancing inventory management. Li [16] constructed a business DSS depending on DL and optimized it. AI as well as DL technologies, are employed by intermediate-level systems for adaptively modelling and predicting commercial retail. A CNN framework depending on networking performance is presented that efficiently advances the CNN's dynamic performance and advances its prediction capability. The DL method that relies on the NN technique can efficiently process and analyse BD. Oskooei and Adak [17] implemented a new method by focusing on strengthening the client relationships through RESTful services. This study contains an inclusive approach that integrates broad investigation, complex software design, and meticulous data analysis. Eboigbe et al. [18] delved into the more effective role of AI as well as data analytics within the domain of business intelligence (BI). This study aims to meticulously examine the BI progress, highlighted by the incorporation of AI to forecast the upcoming technology in the commercial environment.

2.1. Limitations and research gaps in current AI-driven decision support and sales forecasting models: challenges in managing uncertainty, data imbalance, dynamic market conditions, and the need for integrated, adaptive, and optimized solutions for enhanced B2B sales prediction

Despite crucial improvements in AI-driven decision support systems and sales forecasting models, existing models mostly encounter threats in effectually handling uncertainty and indeterminate data inherent in intrinsic B2B environments. Various methods mostly dependent upon enormous volumes of structured data and may face difficulty with imbalanced, incomplete, or ambiguous databases. Besides, DL and transformer-based models illustrate robust solution, it is frequently require extensive computational resources and lack adaptability to quickly growing market conditions. Furthermore, the majority of frameworks lack robust optimization strategies for adjustment model parameters, which can restrict their predictive accuracy and practical applicability in dynamic business scenarios.

- Existing methods do not adequately address uncertainty, indeterminacy, and incomplete data in B2B sales prediction, restricting decision-making reliability.
- There is a lack of comprehensive structures that integrate several business factors namely financials, customer behaviour, and supply chain dynamics into a combined prediction method.
- Current AI models mostly need large, balanced datasets and are less effectual in managing unbalanced or sparse data common in real-world B2B contexts.
- Various DL and sequence modelling models encounter threats in adapting quickly to growing data patterns without relying heavily on external data.
- Either optimization techniques for hyperparameter fine-tuning are underutilized or inefficient, reducing model performance and generalizability.
- Few studies have explored the potential of neutrosophic logic integrated with metaheuristic optimization in handling uncertainty and improve predictive accuracy in business forecasting tasks.

DOI: https://doi.org/10.54216/IJNS.270204

3. System Design and Techniques

This article presents an IB2BSEF-NSSS approach. The main objective of proposed method is to develop a successful method for B2B sales estimation. It has four diverse stages such as data pre-processing, feature reduction, prediction, and parameter selection. Fig. 1 represents the workflow of proposed method.

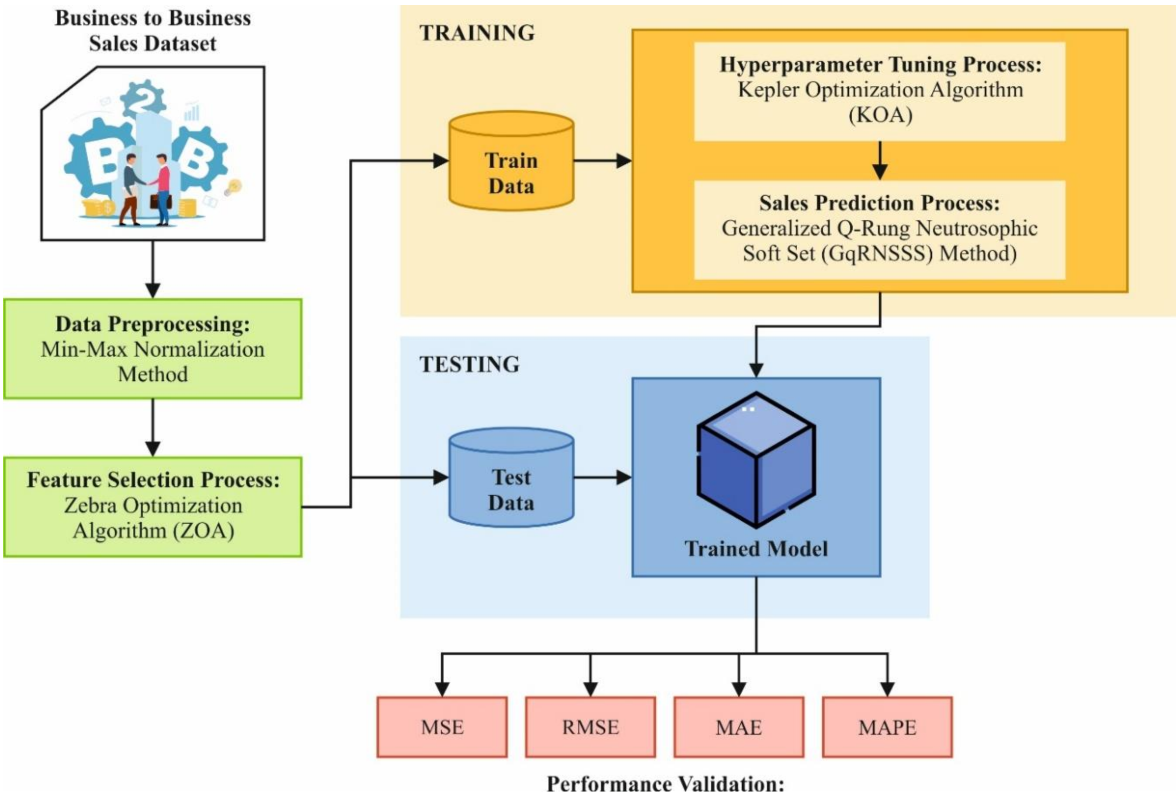

Figure 1. Entire workflow of IB2BSEF-NSSS method

A. Pre-processing using Min-max Method

At the primary stage, the min-max method is used in the data-pre-processing step for normalizing the input data [19]. This model is preferred for its effectiveness in scaling data to a fixed range [0-1], which preserves the original feature distribution. This technique does not assume a normal distribution and is less affected by outliers, making it appropriate for varied and complex B2B sales data. This model guarantees an equitable influence of all features during model training. Additionally, it accelerates the rate at which optimization algorithms converge and enriches the overall robustness of the model. Its computational efficiency and ease of implementation additionally justify its preference over more complex scaling methods.

A vital stage in data mining is data pre-processing. It is performed for preparing the data for examining the process, like converting, integrating, and cleansing. Let the initial data D as input for this stage. It is the method for implementing a linear adaptation in the primary range of data. This model ensures that the relations between new data points were maintained. An elementary model named min-max normalization precisely modifies the data inside particular ranges. It is specified in Eq. (1).

$$D_{no} = \frac{D - D_{min}}{D_{max} - D_{min}} \tag{1}$$

Now D signifies the original data. D_{no} depicts the normalized data value and D_{min} and D_{max} Refers to the minimal and maximal data values correspondingly.

B. ZOA-based Feature Selection Model

For the process of FS, the IB2BSEF- NSSS model implements ZOA [20]. This model is selected for its robust global searching ability and exploration as well as exploitation, crucial in detecting the most pertinent features.

DOI: https://doi.org/10.54216/IJNS.270204

Compared to approaches like recursive feature elimination (RFE) or filter-based methods, ZOA is more effective in navigating intrinsic, nonlinear feature spaces. Its bio-inspired mechanism allows it to avoid local optima and converge toward optimal or near-optimal feature subsets. This results in mitigated model complexity, faster training times, and enhanced prediction accuracy. Additionally, the adaptability of the model makes it appropriate for dynamic datasets mostly seen in business environments. Fig. 2 illustrate ZOA structure.

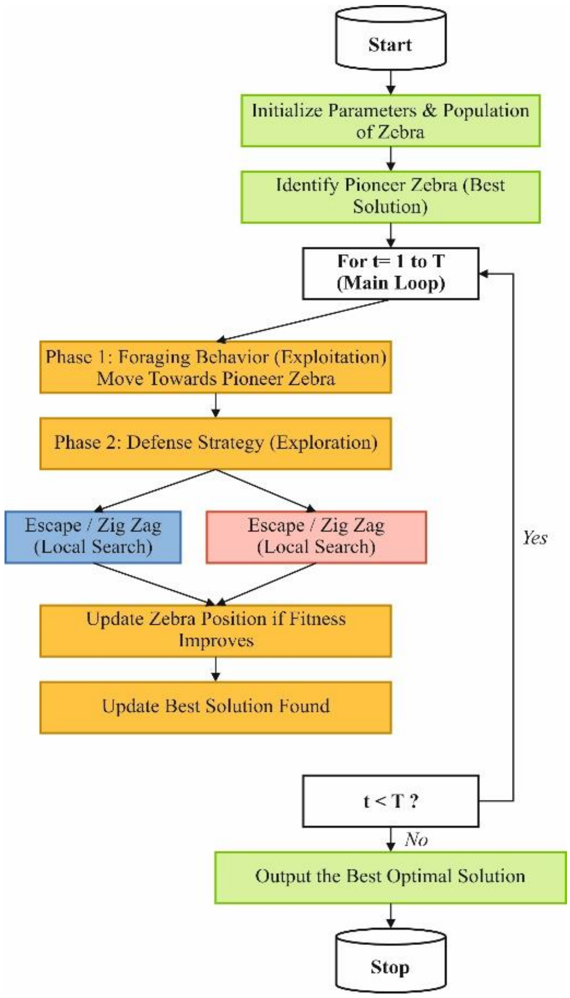

Figure 2. Architecture of ZOA model

The ZOA is an optimizer motivated by zebras' behaviour naturally. ZOA directs the searching procedure by emulating the defines and searching strategies of zebras for solving intricate optimization concerns. The location of all zebras in this area is equivalent to the decision variable's value, and the zebra's overall population is denoted in the form of a matrix.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,m} \end{bmatrix}_{N\times m} \tag{2}$$

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times m} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(F_i) \\ \vdots \\ F(F_n) \end{bmatrix}_{N\times m} \tag{3}$$

DOI: https://doi.org/10.54216/IJNS.270204

Now X_i indicates a single zebra, X is zebra counts, m represents the count of problem variables, and N signifies the populace size of zebras. The value $x_{i,j}$ depicts the j_{th} decision variable values for i_{th} zebra. The objective of zebra is to modify their location frequently, finding the optimum solution.

In every iteration, the ZOA models upgrade the position of population by pretending dual significant behaviours of zebras: defence and foraging tactics, depicting exploration and safety of searching area, correspondingly.

Foraging Phase: Zebras upgrade their locations depend upon the position of leader zebra that depicts the finest solution in existing population. This stage examines the searching area, directing the population towards probable global bests.

Defence Stage: While challenging a predator, they utilize a defence approach, mimicked as a local search. The dominant zebra strengthens the search for their location to evade being stuck in a local best. The fitness function (FF) balances classifier accuracy and the number of selected features by maximizing accuracy while minimizing feature set size. It is used to evaluate individual solutions as shown in Eq. (4).

$$Fitness = \alpha * \ ErrorRate + (1-\alpha) * \frac{\#SF}{\#All\_F} \tag{4}$$

Here, $ErrorRate$ signifies the classifier error rate and is computed as the ratio of incorrect classifications to the total classification, represented in [0-1], $\#SF$ denotes sum of preferred attributes, and $\#All\_F$ signifies complete feature counts in new datasets. α is applied to control the implication of subset length and classification quality.

C. Sales Prediction using GqRNSSS Technique

Moreover, the GqRNSSS model is applied for the sales prediction procedure [21]. This model is chosen for sales prediction for its superior capability in handling inconsistency in complex B2B data. Different conventional prediction models that assume clear, crisp input values, GqRNSSS provides a flexible mathematical structure for representing partial truth, falsity, and indeterminacy simultaneously. It enhances the decision-making process by enabling more accurate and robust predictions in uncertain environments, making it ideal for dynamic sales forecasting tasks.

The Generalized FSS and Pythagorean NSS, 2 famous literary concepts, are studied, and some new ideas are presented in this paper. Assume $\mathcal{X}$be the universal, Pythagorean NSIV (PyNSIV) set P in $\mathcal{X}$is$\vec{F} = c\zeta_F(\sigma = \varsigma), \vec{\eta}_F(\varsigma), \vec{\sigma}_F(\varsigma) | \varsigma \in \mathcal{X}\}$, while $\vec{\zeta}_F(\varsigma) = [\zeta_F^{\mathcal{L}}(\varsigma), \zeta_F^{\mathcal{J}}(\varsigma)]$ and $\vec{\eta}_F(\varsigma) = [\eta_F^{\mathcal{L}}(\varsigma), \eta_F^{\mathcal{J}}(\varsigma)]$and $\vec{\sigma}_F(\varsigma) = [\sigma_F^{\mathcal{L}}(\varsigma), \sigma_F^{\mathcal{J}}(\varsigma)]$ signifies the degree of falsity membership (DFM), indeterminacy membership (DIM), and truth membership (DTM) of F, correspondingly. $\vec{\zeta}_F: \mathcal{X} \to D[0,1], \vec{\eta}_F: \mathcal{X} \to D[0,1], \vec{\sigma}_F: \ \mathcal{X} \to D[0,1]$ and $0 \le (\vec{\zeta}_F(\varsigma))^2 \to +(\vec{\eta}_F(\varsigma))^2 + (\vec{\sigma}_F(\varsigma))^2 \le 2$indicates$0 \le (\zeta_F^{\mathcal{J}}(\sigma))^2 + (\eta_F^{\mathcal{J}}(\sigma))^2 + (\sigma_F^{\mathcal{J}}(\sigma))^2 \le 2.$ Therefore, $\vec{F} = \langle [\zeta_F^{\mathcal{L}}, \zeta_F^{\mathcal{J}}], [\eta_F^{\mathcal{L}}, \eta_F^{\mathcal{J}}], [\sigma_F^{\mathcal{L}}, \sigma_F^{\mathcal{J}}] \rangle$ is named PyNSIVN number.

Consider $\overrightarrow{\kappa_1} = \{\zeta_{\overrightarrow{\kappa_1}}, \eta_{\overrightarrow{\kappa_1}}, \sigma_{\overrightarrow{\kappa_1}}\rangle, \overrightarrow{\kappa_2} = \{\zeta_{\overrightarrow{\kappa_2}}, \eta_{\overrightarrow{\kappa_2}}, \sigma_{\overrightarrow{\kappa_2}}\rangle$ and $\overrightarrow{\kappa_3} = \{\zeta_{\overrightarrow{\kappa_3}}, \eta_{\overrightarrow{\kappa_3}}, \sigma_{\overrightarrow{\kappa_3}}\rangle$ means some 3 PyNSIVNs over $(\mathcal{X}, E)$. Demonstrate that

(i) $\overrightarrow{\kappa_1^c} = \langle \sigma_{\overrightarrow{\kappa_1}}, \eta_{\overrightarrow{\kappa_1}}, \zeta_{\overrightarrow{\kappa_1}} \rangle$

(ii) $\overrightarrow{\kappa_1} \sqcap \overrightarrow{\kappa_2} = \langle \min(\zeta_{\overrightarrow{\kappa_1}}, \zeta_{\overrightarrow{\kappa_2}}), \min(\eta_{\overrightarrow{\kappa_1}}, \eta_{\overrightarrow{\kappa_2}}), \max(\sigma_{\overrightarrow{\kappa_1}}, \sigma_{\overrightarrow{\kappa_2}}) \rangle$

(iii) $\overrightarrow{\kappa_1} \sqcup \overrightarrow{\kappa_2} = \langle \max(\zeta_{\overrightarrow{\kappa_1}}, \zeta_{\overrightarrow{\kappa_2}}), \min(\eta_{\overrightarrow{\kappa_1}}, \eta_{\overrightarrow{\kappa_2}}), \min(\sigma_{\overrightarrow{\kappa_1}}, \sigma_{\overrightarrow{\kappa_2}}) \rangle$

(iv) $\overrightarrow{\kappa_1} = \overrightarrow{\kappa_2}$ if and only if $\zeta_{\overrightarrow{\kappa_1}} = \zeta_{\overrightarrow{\kappa_2}}$ and $\eta_{\overrightarrow{\kappa_1}} = \eta_{\overrightarrow{\kappa_2}}$ and $\sigma_{\overrightarrow{\kappa_1}} = \sigma_{\overrightarrow{\kappa_2}}$

(v) $\overrightarrow{\kappa_1} \le \overrightarrow{\kappa_2}$ if and only if $\zeta_{\overrightarrow{\kappa_1}} \le \zeta_{\overrightarrow{\kappa_2}}$ and $\eta_{\overrightarrow{\kappa_1}} \le \eta_{\overrightarrow{\kappa_2}}$ and $\sigma_{\overrightarrow{\kappa_1}} \geqslant \sigma_{\overrightarrow{\kappa_2}}$

Consider $\mathcal{X} = \{\varsigma_1, \varsigma_2, \ldots, \varsigma_n\}$ and $E = \{\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_m\}$ be the universal and group of parameters correspondingly, and $(\mathcal{X}, \mathbb{E})$ means soft universe. The mapping $\vec{\mathcal{J}}: \mathbb{E} \to D(I)^{\mathcal{X}}$ and $\vec{\xi}$ be the IVF subset of $\mathbb{E}$, for example: $\vec{\xi}: \mathcal{J}: \mathbb{E} \to I = D[0,1]$. Assume $\vec{\mathcal{J}}: \mathbb{E} \to D(I)^{\mathcal{X}} \times D(I)$ is described as $\vec{\mathcal{J}}_{\xi}(\varepsilon) = [\vec{\mathcal{J}}(\varepsilon)(\varsigma), \to \vec{\xi}(\varepsilon)], \forall \sigma \in \mathcal{X}$. Next, $\vec{\mathcal{J}}_{\xi}$ is named generalized IVF softset (GIVFS) on $(\mathcal{X}, \mathbb{E})$. For all parameters $\varepsilon_i, \vec{\mathcal{J}}_{\xi}(\varepsilon_i) = [\vec{\mathcal{J}}(\varepsilon_i)(\varsigma), \vec{\mathcal{J}}(\varepsilon_i)(\varsigma)], \forall \sigma \in \mathcal{X}$, not only the degree to which the essential portions of $\mathcal{X}$ in $\vec{\mathcal{J}}(\varepsilon_i)$. Also, the IV likelihood of such belongingness that is specified in$\vec{\xi}(\varepsilon_i)$. Write $\vec{\mathcal{J}}_{\xi}(\varepsilon_i)$ as $\vec{\mathcal{J}}_{\xi}(\varepsilon_i) = [\left\{\frac{\varsigma_1}{\vec{\mathcal{J}}(\varepsilon_i)(\varsigma_1)}, \frac{\varsigma_2}{\vec{\mathcal{J}}(\varepsilon_i)(\varsigma_2)}, \ldots, \frac{\varsigma_n}{\vec{\mathcal{J}}(\varepsilon_i)(\varsigma_n)}\right\}$, whereas $\vec{\mathcal{J}}(\varepsilon_i)(\varsigma_1), \vec{\mathcal{J}}(\varepsilon_i)(\varsigma_2), \ldots, \vec{\mathcal{J}}(\varepsilon_i)(\varsigma_n)$ represent levels of belongingness and levels of such belongingness. IV possibility is $\vec{\xi}(\varepsilon_i)$.

Assume $\mathcal{X} = \{\varsigma_1, \varsigma_2, \ldots, \varsigma_n\}$ and $E = \{\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_m\}$ be the universe and a collection of parameters correspondingly. The mapping $\vec{\mathcal{J}}: \mathbb{E} \to \vec{\mathcal{J}}(\mathcal{X})$ and $\vec{\xi}$ be an IVF subset of $\mathbb{E}$, for example: $\vec{\xi}: \mathbb{E} \to \vec{\mathcal{J}}(\mathcal{X})$. Given that $\vec{\mathcal{J}}_{\xi}: \mathbb{E} \to \vec{\mathcal{J}}(\mathcal{X}) \times \vec{\mathcal{J}}(\mathcal{X})$ is described as $\vec{\mathcal{J}}_{\xi}(\varepsilon) = \left(\vec{\mathcal{J}}(\varepsilon)(\varsigma), \vec{\xi}(\varepsilon)(\varsigma)\right), \forall \sigma \in \mathcal{X}$. Next $\vec{\mathcal{J}}_{\xi}$ is named a possibility IVF soft (PIVFS) group. $(\mathcal{X}, \mathbb{E})$. For every parameter$\varepsilon_i, \vec{\mathcal{J}}_{\xi}(\varepsilon_i) = (\vec{\mathcal{J}}(\varepsilon_i)(\varsigma), \vec{\xi}(\varepsilon_i)(\varsigma))$ not only how much the elements

DOI: https://doi.org/10.54216/IJNS.270204

of $\mathcal{X}$ be together in $\vec{\mathcal{J}}(\varepsilon_i)$, the degree of IV possibility of this belongingness that is$\vec{\xi}(\varepsilon_i)$. Therefore, $\vec{\mathcal{J}}_{\xi}(\varepsilon_i) = \left\{\left[\frac{\varsigma_1}{\vec{\mathcal{J}}(\varepsilon_i)(\varsigma_1)}, \xi(\varepsilon_i)(\varsigma_1)\right], \left[\frac{\varsigma_1}{\vec{\mathcal{J}}(\varepsilon_i)(\varsigma_1)}, \xi(\varepsilon_i)(\varsigma_1)\right], \dots, \left[\frac{\varsigma_1}{\vec{\mathcal{J}}(\varepsilon_i)(\varsigma_1)}, \xi(\varepsilon_i)(\varsigma_1)\right]\right\}$.

Consider $\mathcal{X} = \{o_1, o_2, \dots, o_n\}$ be the universe and $E = \{\Omega 1, \Omega 2, \dots, \Omega m\}$ be the collection of parameters. Assume that $\overline{\mathcal{J}}: E \to \overline{S\mathcal{J}(\mathcal{X})}$ and f denote NS subset of $\mathbb{E}$. Namely: $\mathbb{E} \to \overline{[0,1]}$, while $\overline{S\mathcal{J}(\mathcal{X})}$ signifies the set of each NS subset of $\mathcal{X}$. When $\overline{\mathcal{J}_f} : \mathbb{E} \to \overline{S\mathcal{J}(\mathcal{X})} \times \overline{[0,1]}$ is described as $\overline{\mathcal{J}_f(\epsilon)} = [\overline{\mathcal{J}(\varepsilon)(x)}, \overline{f(\varepsilon)}], x \in \mathcal{X}$, then $\overline{\mathcal{J}_f}$ is a GqRNSSS on $(\mathcal{X}, \mathbb{E})$. For all parameters ε,

$$\overline{\mathcal{J}_f(\Omega i)} = \left[\left\{\frac{o_1}{(\Xi_{\mathcal{J}(\epsilon)}(o_1), \Lambda_{\mathcal{J}(\epsilon)}(o_1), \Omega_{\mathcal{J}(\epsilon)}(o_1))}, \dots, \frac{o_1}{(\Xi_{\mathcal{J}(\epsilon)}(o_1), \Lambda_{\mathcal{J}(\epsilon)}(o_1), \Omega_{\mathcal{J}(\epsilon)}(o_1))}\right\}, (f_1(\Omega i), f_2(\Omega i), f_3(\Omega i))\right]$$

To demonstrate Definition 3 given the following mathematical example is given:

Assume $\mathcal{X} = \{o_1, o_2, o_3\}$ be the universal, $E = \{\Omega 1, \Omega 2, \Omega 3\}$ is a collection of parameters. Presume that $\overline{\mathcal{J}_f}: \mathbb{E} \to \overline{S\mathcal{J}(\mathcal{X})} \times \overline{[0,1]}$ is provided by

$$\overline{\mathcal{J}_f(\Omega 1)} = \left[\left\{\begin{matrix}\frac{o_1}{(0.65,0.30,0.80)} \\ \frac{o_2}{(0.75,0.35,0.65)} \\ \frac{o_3}{(0.55,0.45,0.70)}\end{matrix}\right\}, (0.70,0.65,0.35)\right];$$

$$\overline{\mathcal{J}_f(\Omega 2)} = \left[\left\{\begin{matrix}\frac{o_1}{(0.55,0.35,0.80)} \\ \frac{o_2}{(0.65,0.50,0.70)} \\ \frac{o_3}{(0.60,0.40,0.80)}\end{matrix}\right\}, (0.50,0.40,0.60)\right];$$

$$\overline{\mathcal{J}_f(\Omega 1)} = \left[\left\{\begin{matrix}\frac{o_1}{(0.30,0.55,0.80)} \\ \frac{o_2}{(0.40,0.65,0.60)} \\ \frac{o_3}{(0.30,0.45,0.70)}\end{matrix}\right\}, (0.60,0.50,0.60)\right]$$

A similarity measure among GqRNSSSs is given in this work.

Given that $\mathcal{X} = \{0_1, 0_2, 0_m\}$ be the universal and $E = \{\Omega 1, \Omega 2, \dots, \Omega n\}$ be the collection of parameters. Assume that $\overline{\mathcal{J}_f}$ and $\overline{\mathcal{J}_g}$ represent dual GqRNSSSs on $(\mathcal{X}, \mathbb{E})$. The similarity measure among dual GqRNSSSs $\overline{\mathcal{J}_f}$ and $\overline{\mathcal{J}_g}$ is outlined as $Sim(\overline{\mathcal{J}_f}, \overline{\mathcal{J}_g}) = \Phi(\overline{\mathcal{J}}, \overline{\mathcal{J}}) \cdot \Psi(f, g)$ so that

$$\Phi(\overline{\mathcal{J}}, \overline{\mathcal{J}}) = \frac{1}{m}\sum_{z=1}^{m} \min\{T_1[\overline{\mathcal{J}(\varepsilon)(o_z)}, \overline{\mathcal{J}(\varepsilon)(o_z)}], T_2[\overline{\mathcal{J}(\varepsilon)(o_z)}, \overline{\mathcal{J}(\varepsilon)(o_z)}], S[\overline{\mathcal{J}(\varepsilon)(o_z)}, \overline{\mathcal{J}(\varepsilon)(o_z)}]\}$$

and $\Psi(f, g) = 1 - \frac{\sum_{y=1}^{n}|f(\Omega_y) - g(\Omega_y)|}{\sum_{y=1}^{n}|f(\Omega_y) - g(\Omega_y)|}$, whereas

$$T_1 = \left[\overline{\mathcal{J}(\varepsilon)(o_z)}. \overline{\mathcal{J}(\varepsilon)(o_z)}\right] = \frac{\sum_{y=1}^{n}(\Xi_{\mathcal{J}(\Omega_y)}(o_z) \cdot \Xi_{\mathcal{J}(\Omega_y)}(o_z))}{\sum_{y=1}^{n}\left(1 - \sqrt[q]{\left(1 - \Xi_{\mathcal{J}(\Omega_y)}(o_z)\right) \cdot \left(1 - \Xi_{\mathcal{J}(\Omega_y)}(o_z)\right)}\right)},$$

$$T_2 = \left[\overline{\mathcal{J}(\varepsilon)(o_z)}. \overline{\mathcal{J}(\varepsilon)(o_z)}\right] = \frac{\sum_{y=1}^{n}(\Lambda^q_{\mathcal{J}(\Omega_y)}(o_z) \cdot \Lambda^q_{\mathcal{J}(\Omega_y)}(o_z))}{\sum_{y=1}^{n}\left(1 - \sqrt[q]{\left(1 - \Lambda^{2q}_{\mathcal{J}(\Omega_y)}(o_z)\right) \cdot \left(1 - \Lambda^{2q}_{\mathcal{J}(\Omega_y)}(o_z)\right)}\right)},$$

$$S = \left[\overline{\mathcal{J}(\varepsilon)(o_z)}. \overline{\mathcal{J}(\varepsilon)(o_z)}\right] = \sqrt[q]{\frac{\sum_{y=1}^{n}\left|\Omega^q_{\mathcal{J}(\Omega_y)}(o_z) \cdot \Omega^q_{\mathcal{J}(\Omega_y)}(o_z)\right|}{\sum_{y=1}^{n} 1 + ((\Omega^q_{\mathcal{J}(\Omega_y)}(o_z)) \cdot (\Omega^q_{\mathcal{J}(\Omega_y)}(o_z)))}}, for\ z = 1,2, \dots, m.$$

Assume $\overline{\mathcal{J}_f}$, $\overline{\mathcal{J}_g}$ and $\overline{\mathcal{K}_h}$ be the same 3 GqRNSSSs over $(\mathcal{X}, \mathbb{E})$. Formerly, the following statements possessed:

DOI: https://doi.org/10.54216/IJNS.270204

(a) $Sim(\overline{\mathcal{J}_f}, \overline{\mathcal{J}_g}) = Sim(\overline{\mathcal{J}_g}, \overline{\mathcal{J}_f})$,

(b) $0 \leq Sim(\overline{\mathcal{J}_f}, \overline{\mathcal{J}_g}) \leq 1$,

(c) $\overline{\mathcal{J}_f} = \overline{\mathcal{J}_g} \Rightarrow Sim(\overline{\mathcal{J}_f}, \overline{\mathcal{J}_g}) = 1$,

(d) $\overline{\mathcal{J}_f} = \overline{\mathcal{J}_g} \Longrightarrow \overline{\mathcal{K}_h} \Rightarrow Sim(\overline{\mathcal{J}_f}, \overline{\mathcal{K}_h}) \leq Sim(\overline{\mathcal{J}_g}, \overline{\mathcal{K}_h})$,

(e) $\overline{\mathcal{J}_f} \sqcap \overline{\mathcal{J}_g} = \{\phi\} \Leftrightarrow Sim(\overline{\mathcal{J}_f}, \overline{\mathcal{J}_g}) = 0$.

D. Hyperparameter Tuning using KOA Approach

To further improve the prediction performance, the KOA is used for model refinement to assurance that the optimal hyperparameters are chosen for enhanced precision. This approach is chosen for its efficiency in convergence and optimization inspired by planetary motion dynamics. Unlike conventional grid or random search methods, KOA explores the hyperparameter space more intelligently, mitigating computational cost while enhancing the chances of finding optimal configurations. Its capability in balancing exploration and exploitation allows it to avoid local optima, which is a common drawback in various metaheuristic algorithms. The adaptive behaviour of the model makes it suitable for tuning intrinsic models where performance is sensitive to parameter settings. This results in an improved prediction accuracy, faster convergence, and improved generalization of the model. Fig. 3 illustrates the flowchart of KOA approach.

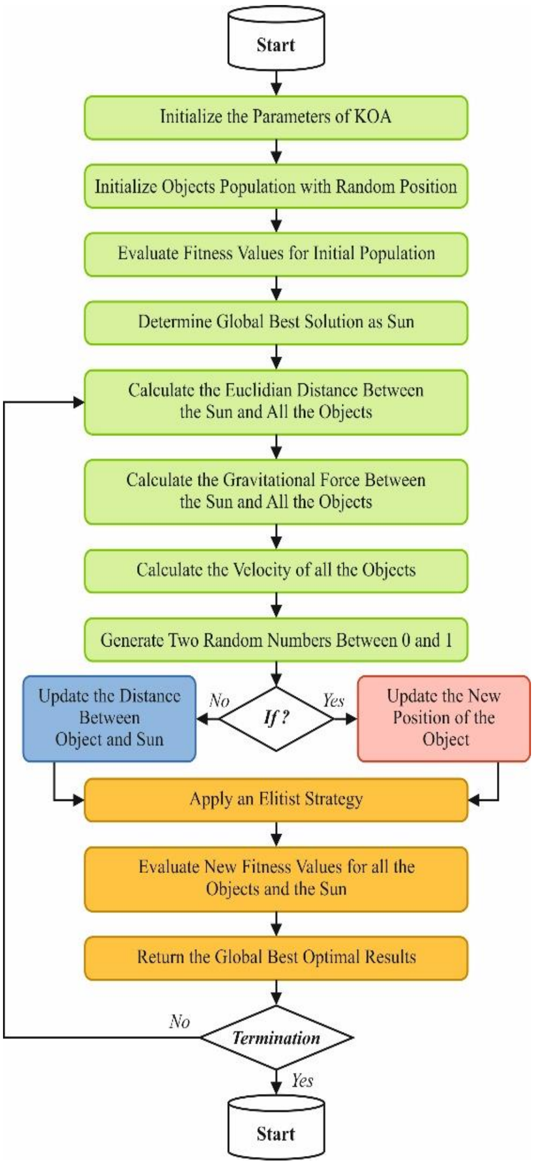

Figure 3: Flowchart of KOA model

DOI: https://doi.org/10.54216/IJNS.270204

KOA is a heuristic optimizer driven by the celestial bodies' motion law, utilizing planetary motions as a similarity to discover optimum applications for intricate optimization concerns [22]. Within this similarity, the "planets" depict the solution of a candidate, whereas the "star" indicates global optimum solutions, directing the procedure of searching.

The model functions on sources equivalent to orbital mechanics and celestial gravity; here, every planet's motion is impacted through the gravitational pull of a "star". These reasons cause the planet to move quicker and enhance its location. This procedure aids the model to evade local optima, which makes it suitable to resolve multi-objective and intricate optimization concerns.

KOA is an effective domain-like optimization. In this context, the model is to enhance arrangement and control approaches for increasing efficacy. The velocity of every planet is impacted through gravitational forces that is controlled by the distance between the optimum solution and the planet. The intensity of gravity diminishes as the planet revolves beyond the optimum solution. After a while, this gravitational method guides the planets, reaching the optimum region of solution. As the method develops, the planets enhance their velocities and positions, finally achieving the global optimal. This creates KOA, an efficient searching approach for optimization concerns. In every iteration of KOA, the location upgrade of planets is specified by the succeeding equation:

$$r_i(t+1) = r_i(t) + \alpha \cdot v_i(t) + G(t) \cdot \left(r_{best} - r_i(t)\right) \quad (5)$$

Here $r_i(t)$ depicts the location of i_{th} planet at time t, $v(t)$ signifies its velocity, $G(t)$ represents the control factor $G(t)$ indicates the gravitational coefficient, and r_{best} depicts location of existing optimum solutions. To modify the location of planet, KOA is exploring the optimum solution in the search area. KOA is able to discover global optimum solutions within a multi-objective optimizer concerned with representing the gravitational impacts of celestial motion.

Algorithm 1: KOA model

Input: initial location of planet $r_i(t)$, initial velocity $v_i(t)$, control factor $G(t)$, gravitational co-efficient, location of existing optimum solution r_{best}, number of iterations t, maximal iteration number T
Output: Optimized location of planet $r_i(t+1)$
for $r = 1$ to T do
for $i = 1$ to n (n is the number of planets) do
Upgrade the location of planet $r_i(t+1)$ based on the equation $r_i(t+1) = r_i(t) + \alpha \cdot v_i(t) + G(t) \cdot \left(r_{best} - r_i(t)\right)$
Upgrade the velocity $v_i(t)$ based on the location upgrade of planet (the velocity upgrade rule is controlled by the gravitational mechanism of technique)
end for
Upgrade the location of the existing optimum solution r_{best} (established by comparing the values of the objective function equivalent to the existing locations of every planet)
end for

The KOA has been adapted to define the hyperparameter dealing with the GqRNSSS methodology. The MSE measures the objective function as exhibited below.

$$MSE = \frac{1}{T}\sum_{j=1}^{L}\sum_{i=1}^{M}\left(y_j^i - d_j^i\right)^2 \quad (6)$$

Here, L and M denote the data as well as layer's resulting value. d_j^i and y_j^i implies the suitable and achieved sizes for j^{th} unit from the network's resulting layer in time t, individually.

4. Model Assessment and Results

The result analysis of IB2BSEF-NSSS model is examined under B2B sales and customer Insight Analysis dataset [23]. This dataset has 23 features, but only 17 features are chosen.

Fig. 4 shows the correlation matrices formed by the IB2BSEF-NSSS model. The outcomes denote that the IB2BSEF-NSSS model efficaciously detects and identifies each class.

DOI: https://doi.org/10.54216/IJNS.270204

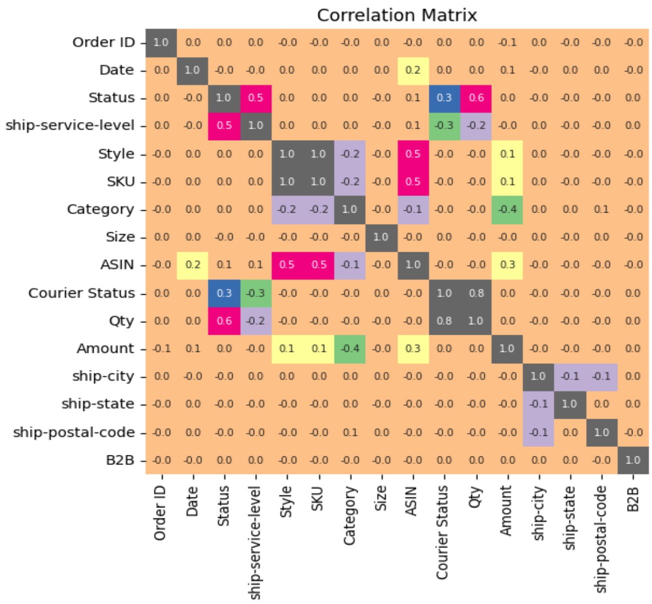

Figure 4. Correlation matrix of IB2BSEF-NSSS model

Table 1 and Fig. 5 illustrate the training set (TRAST) and testing set (TESST) of IB2BSEF-NSSS model with distinct metrics. On TRAST, the IB2BSEF-NSSS approach got MSE of 0.00670, RMSE of 0.08183, MAE of 0.01284, and MAPE of 0.27680. Likewise, at TESST, the IB2BSEF-NSSS approach got MSE of 0.00676, RMSE of 0.08219, MAE of 0.01289, and MAPE of 0.27626.

Table 1: TRAST and TESST output of IB2BSEF-NSSS technique under diverse metrics

Matrices	**Training Set**	**Testing Set**
MSE	0.00670	0.00676
RMSE	0.08183	0.08219
MAE	0.01284	0.01289
MAPE	0.27680	0.27626

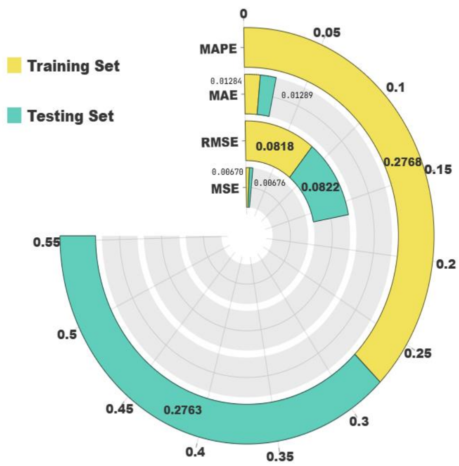

Figure 5. TRAST and TESST output of IB2BSEF-NSSS technique under diverse metrics

DOI: https://doi.org/10.54216/IJNS.270204

Fig. 6 illustrates the result analysis outcome for the actual vs predicted IB2BSEF-NSSS model at various epochs. The figure specifies that the IB2BSEF-NSSS model accurately predicted the outcome. Likewise, it is seen that the predicted values using the IB2BSEF-NSSS model are close to the real ones.

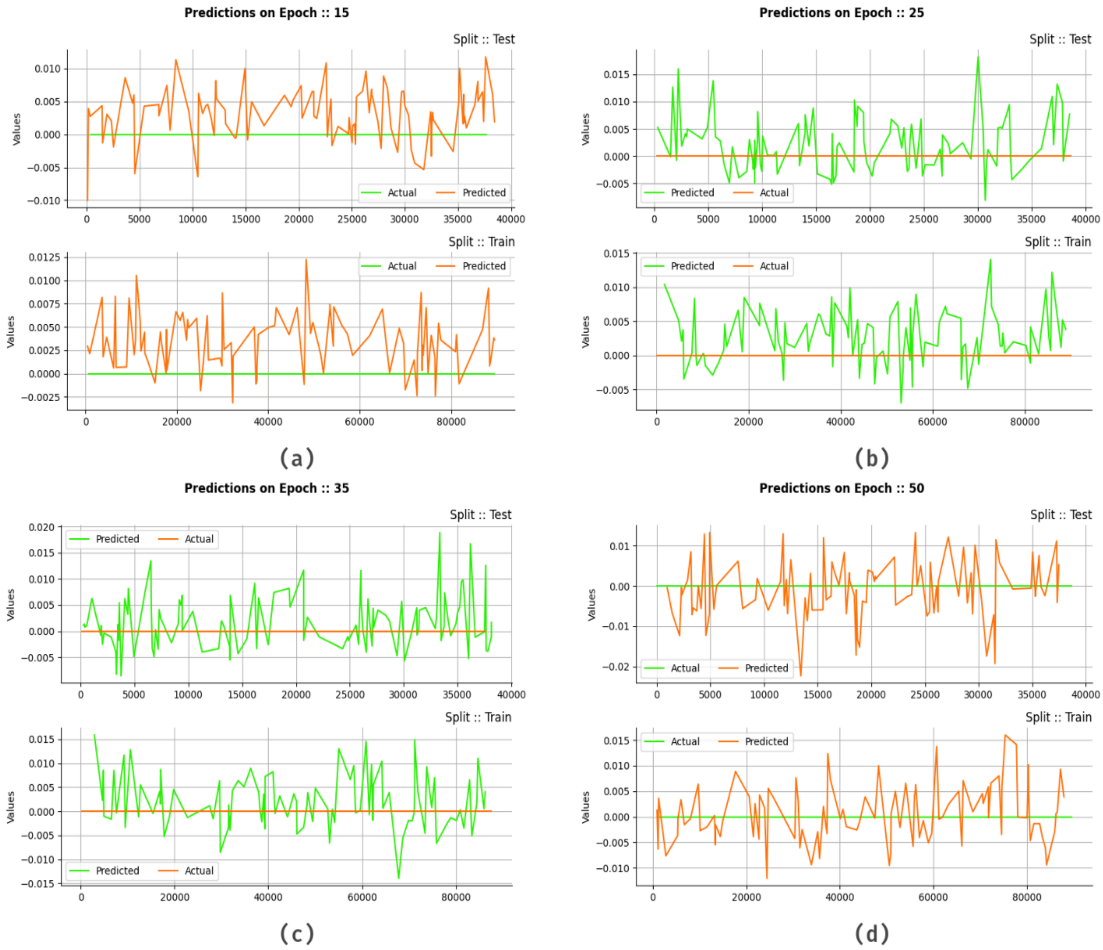

Figure 6. Result analysis for actual vs predicted of IB2BSEF-NSSS (a-d) Epochs 15-50

Fig. 7 exemplifies the train and test losses of IB2BSEF-NSSS method over various metrics. Initially, train and test losses are high, showing restricted data understanding. As training progresses, both losses steadily decrease, illustrating effective learning. Their close alignment suggests no overfitting and robust generalization to new data.

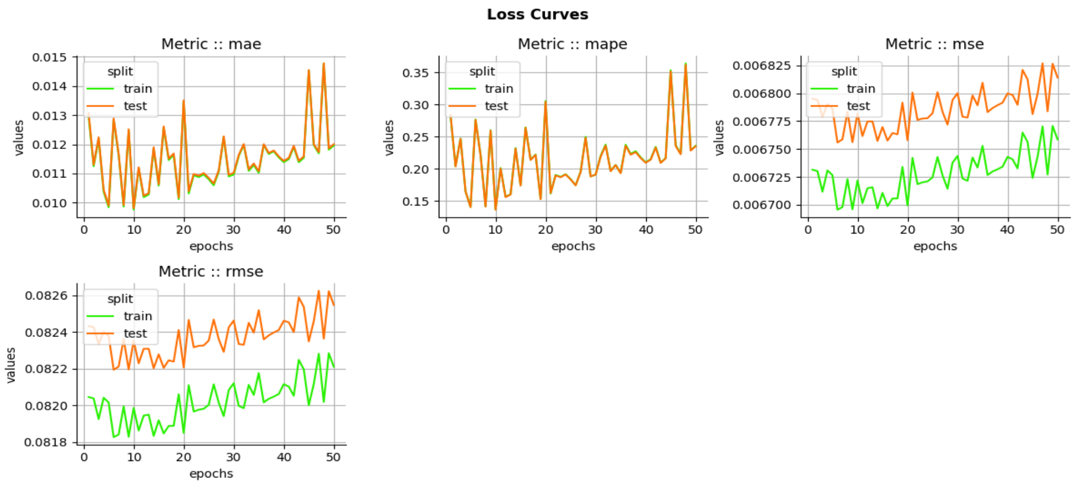

Figure 7. Loss curve of IB2BSEF-NSSS model

DOI: https://doi.org/10.54216/IJNS.270204

To reveal the effectiveness of the IB2BSEF-NSSS model, a comprehensive comparison study is displayed in Table 2 [24-26]. Fig. 8 presents experimental values that indicate the IB2BSEF-NSSS model has improved performances regarding MSE and RMSE. On MSE, the IB2BSEF-NSSS model has attained a lower MSE of 0.00670, while the SES, DES, ARMA, SVR, RNN, GRU, and TabNet methodologies have obtained the highest MSE of 0.01109, 0.01047, 0.00969, 0.00912, 0.00847, 0.00797, and 0.00733, respectively. Similarly, on RMSE, the IB2BSEF-NSSS approach got a minimum RMSE of 0.08183, whereas the SES, DES, ARMA, SVR, RNN, GRU, and TabNet methodologies got a maximum RMSE of 0.12643, 0.12113, 0.11493, 0.10723, 0.10153, 0.09603, and 0.08863, respectively.

Table 2: Comparative analysis of IB2BSEF-NSSS model with existing approaches

Models	**MSE**	**RMSE**	**MAE**	**MAPE**
SES	0.01109	0.12643	0.05764	0.32000
DES	0.01047	0.12113	0.05124	0.31480
ARMA	0.00969	0.11493	0.04614	0.30970
SVR	0.00912	0.10723	0.03854	0.30200
RNN	0.00847	0.10153	0.03144	0.29460
GRU	0.00797	0.09603	0.02414	0.28770
TabNet	0.00733	0.08863	0.01834	0.28200
IB2BSEF-NSSS	0.00670	0.08183	0.01284	0.27680

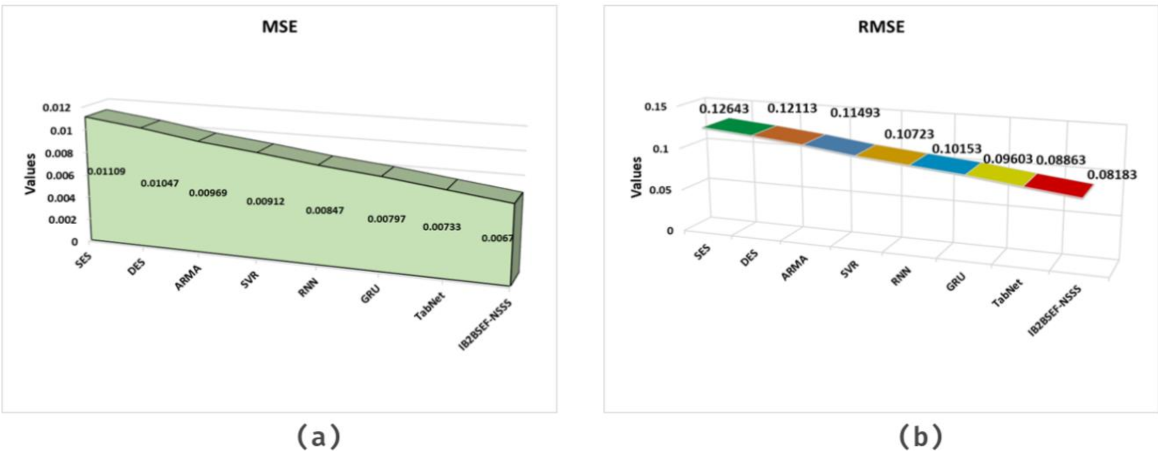

Figure 8. Comparative analysis of IB2BSEF-NSSS model (a) MSE and (b) RMSE

The MAE and MAPE outcome of IB2BSEF-NSSS approach with current methods are depicted in Fig. 9. Under MAE, the IB2BSEF-NSSS model got a lesser MAE of 0.01284, whereas the SES, DES, ARMA, SVR, RNN, GRU, and TabNet techniques have obtained higher MAE of 0.32000, 0.31480, 0.30970, 0.30200, 0.29460, 0.28770, and 0.28200, respectively. Finally, at MAPE, the IB2BSEF-NSSS model got a lower MAPE of 0.27680, while the SES, DES, ARMA, SVR, RNN, GRU, and TabNet methodologies attained higher MAPE of 0.32000, 0.31480, 0.30970, 0.30200, 0.29460, 0.28770, and 0.28200, correspondingly.

DOI: https://doi.org/10.54216/IJNS.270204

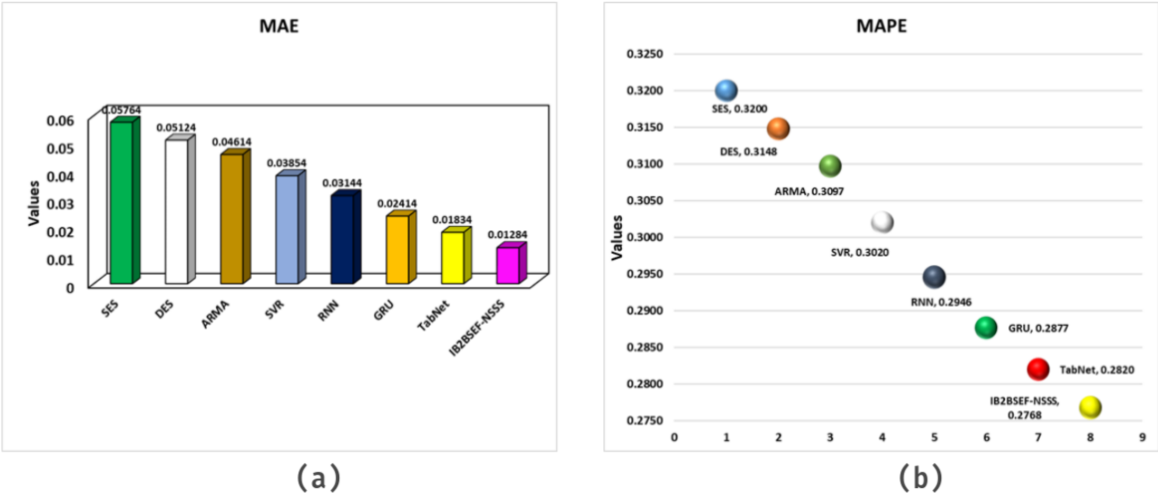

Figure 9. Comparative analysis of IB2BSEF-NSSS model (a) MAE and (b) MAPE

Table 3 and Fig. 10 specifies the computational time (CT) analysis of the IB2BSEF-NSSS method with present techniques. The IB2BSEF-NSSS methodology recorded the lowest CT at 5.77 seconds, making it significantly faster than all other methodologies. For instance, it is approximately 72% faster than SVR at 21.32 seconds, 71% faster than SES at 20.59 seconds, and 70% faster than TabNet at 19.03 seconds. Compared to GRU at 9.86 seconds and RNN at 12.39 seconds, the IB2BSEF-NSSS model still shows a considerable improvement in speed. This substantial reduction in computation time demonstrates the IB2BSEF-NSSS model's suitability for real-time applications where rapid decision-making is critical.

Table 3: CT evaluation of IB2BSEF-NSSS methodology with existing techniques

Methodologies	**CT (sec)**
SES	20.59
DES	19.05
ARMA	11.57
SVR	21.32
RNN	12.39
GRU	9.86
TabNet	19.03
IB2BSEF-NSSS	5.77

DOI: https://doi.org/10.54216/IJNS.270204

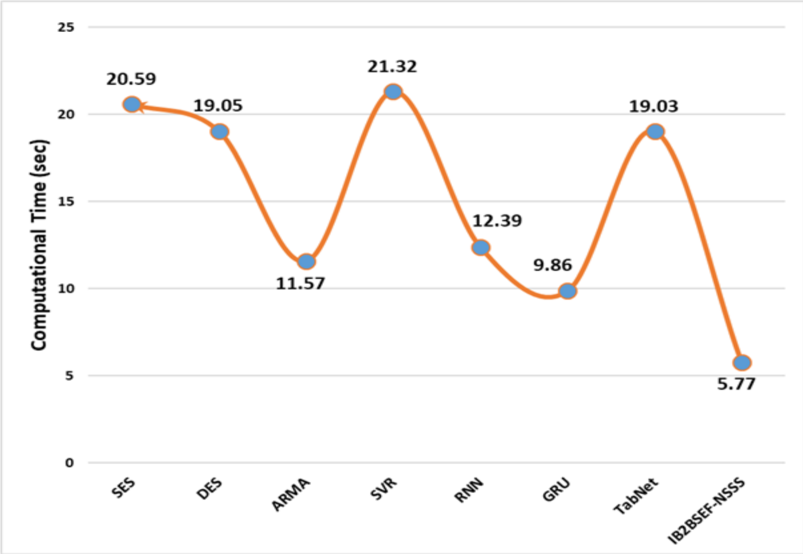

Figure 10. CT evaluation of IB2BSEF-NSSS methodology with existing techniques

5. Conclusion

In this paper, the IB2BSEF-NSSS method is proposed. The key motive of IB2BSEF- NSSS method is to develop an efficient model for B2B sales estimation. At the primary stage, the min-max method is used in the data-pre-processing phase for normalizing the input data. For the process of FS, the IB2BSEF- NSSS model implements the ZOA method. Furthermore, the GqRNSSS method is utilized for the sales prediction process. To further improve the prediction performance, the KOA is used for model refinement to assurance that the optimal hyperparameters are selected for enhanced precision. To show the better outcome of the IB2BSEF- NSSS methodology, a wide-ranging stimulated study is conducted under the B2B sales and customer insight analysis dataset. The comparison study of the IB2BSEF- NSSS methodology depicted superior predictive performance, achieving the lowest MSE of 0.00670, indicating its effectiveness over all other evaluated models.

Funding: “This research received no external funding”

Conflicts of Interest: “The authors declare no conflict of interest.”

References

[1] J. Smith and A. Johnson, "Modeling uncertainty in decision-making using fuzzy logic," *Journal of Uncertainty Analysis and Applications*, vol. 12, no. 3, pp. 45–60, 2023.

[2] R. Kumar, P. Singh, and M. Verma, "A novel approach to fuzzy decision-making in supply chain management," *International Journal of Decision Support Systems*, vol. 14, no. 2, pp. 75–89, 2022.

[3] T. Chen and Y. Zhao, "Fuzzy optimization techniques for resource allocation in project management," *Journal of Operations Research*, vol. 18, no. 1, pp. 101–115, 2024.

[4] L. Wang, H. Li, and X. Zhang, "An integrated fuzzy multi-criteria decision-making model for green supplier selection," *Sustainability*, vol. 15, no. 2, p. 789, 2023.

[5] A. Patel and S. Gupta, "Fuzzy logic-based risk assessment framework for construction projects," *International Journal of Project Management*, vol. 42, no. 4, pp. 512–525, 2021.

[6] M. R. A. Rahman, I. F. Ahmed, and K. S. Rahman, "A fuzzy-based approach for evaluating the performance of renewable energy sources," *Renewable Energy*, vol. 175, pp. 1102–1113, 2022.

[7] I. A. R. Noaman, A. H. Hasan, and S. M. Ahmed, "Optimizing Weibull distribution parameters for improved earthquake modeling in Japan: A comparative approach," *International Journal of Neutrosophic Science*, vol. 24, no. 1, pp. 65–75, 2024.

[8] D. N. Tomma and 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, pp. 87–93, 2024.

[9] P. Mathews, L. Sebastian, and B. Thankachan, "Neutrosophic fuzzy score matrices: A robust framework for advancing medical diagnostics," *International Journal of Neutrosophic Science*, vol. 23, no. 3, pp. 8–18, 2024.

DOI: https://doi.org/10.54216/IJNS.270204

[10] R. Saarumathi and W. Ritha, "A legitimate productive repertoire replica betwixt envirotech outlay towards fragile commodities using trapezoidal neutrosophic fuzzy number," *International Journal of Neutrosophic Science*, vol. 24, no. 1, pp. 104–118, 2024.

[11] G. Shanmugam, M. Palanikumar, K. Arulmozhi, A. Iampan, and S. Broumi, "Agriculture production decision making using generalized q-rung neutrosophic soft set method," *International Journal of Neutrosophic Science*, vol. 19, no. 1, pp. 166–176, 2022.

[12] O. Wisesa, A. Adriansyah, and O. I. Khalaf, "Prediction analysis for business to business (B2B) sales of telecommunication services using machine learning techniques," *Majlesi Journal of Electrical Engineering*, vol. 14, no. 4, 2020.

[13] S. Mortensen, M. Christison, B. Li, A. Zhu, and R. Venkatesan, "Predicting and defining B2B sales success with machine learning," in *Proc. 2019 Systems and Information Engineering Design Symposium (SIEDS)*, Apr. 2019, pp. 1–5.

[14] D. Rohaan, E. Topan, and C. G. Groothuis-Oudshoorn, "Using supervised machine learning for B2B sales forecasting: A case study of spare parts sales forecasting at an after-sales service provider," *Expert Systems with Applications*, vol. 188, p. 115925, 2022.

[15] M. Sarisa, V. N. Boddapati, G. K. Patra, C. Kuraku, S. Konkimalla, and S. K. Rajaram, "An effective predicting e-commerce sales & management system based on machine learning methods," *Journal of Artificial Intelligence and Big Data*, vol. 1, no. 1, pp. 75–85, 2020.

[16] M. Mattila, M. Yrjölä, and P. Hautamäki, "Digital transformation of business-to-business sales: What needs to be unlearned?," *Journal of Personal Selling and Sales Management*, vol. 41, no. 2, pp. 113–129, 2021.

[17] R. Han, H. K. Lam, Y. Zhan, Y. Wang, Y. K. Dwivedi, and K. H. Tan, "Artificial intelligence in business-to-business marketing: A bibliometric analysis of current research status, development and future directions," *Industrial Management and Data Systems*, vol. 121, no. 12, pp. 2467–2497, 2021.

[18] S. Zhang, "A big data-driven approach to financial analysis and decision support system design," *Informatica*, vol. 49, no. 11, 2025.

[19] J. Jiang, K. K. Bandeli, and K. Srinivasan, "Dynamic model selection in enterprise forecasting systems using sequence modeling," *Decision Support Systems*, vol. 193, p. 114439, 2025.

[20] A. Gupta and P. Agarwal, "Enhancing sales forecasting accuracy through integrated enterprise resource planning and customer relationship management using artificial intelligence," in *Proc. 2024 3rd International Conference on Artificial Intelligence and Internet of Things (AIIoT),* May 2024, pp. 1–6.

[21] Z. Xu, L. Guo, S. Zhou, R. Song, and K. Niu, "Enterprise supply chain risk management and decision support driven by large language models," *Academy Nexus Journal*, vol. 3, no. 2, 2024.

[22] Y. Li, "Design and optimization of business decision support system based on deep learning," in *Proc. International Conference on Artificial Intelligence and Communication Technology*, Singapore: Springer, Jun. 2023, pp. 239–248.

[23] A. R. Oskooei and T. E. Adak, "B2B customer engagement customer behaviour forecast application," *Orclever Proceedings in Research and Development*, vol. 3, no. 1, pp. 188–196, 2023.

[24] E. O. Eboigbe, O. A. Farayola, F. O. Olatoye, O. C. Nnabugwu, and C. Daraojimba, "Business intelligence transformation through AI and data analytics," *Engineering Science and Technology Journal*, vol. 4, no. 5, pp. 285–307, 2023.

[25] B. Bojarajulua, S. Tanwar, and T. P. Singh, "Enhanced SqueezeNet model for detecting IoT-bot attacks: A comprehensive approach," *MethodsX*, p. 103499, 2025.

[26] Q. Liu et al., "Classification prediction of jujube variety based on hyperspectral imaging: A comparative study of intelligent optimization algorithms," *Foods*, vol. 14, no. 14, p. 2527, 2025.

DOI: https://doi.org/10.54216/IJNS.270204