



# Neutrosophic Fusion Based Rough Set Theory for Intelligent Decision Support System on Business-to-Business (B2B) Sales Estimation

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## Abstract

One of the most effective devices to model uncertainty in decision-making difficulties is the Neutrosophic set (NS) and its extensions, like interval NS (INS), interval complex NS (ICNS), and complex NS (CNS). Predicting the result of sales benefits is the essential element of effective business management. Traditionally, undertaking this prediction has depended generally on individual human analyses in the sales decision-making process. A model of business-to-business (B2B) sales predicting is a difficult decision-making procedure. There are several methods for supporting this procedure; however, generally it is even established on the individual judgments of the decision-maker. The B2B sales predicting problem is represented as the prediction problem. Presently, intelligible predictive methods were analyzed and studied utilizing the technique of machine learning (ML) to increase the upcoming sales prediction. This paper presents an Adaptive Intelligent Business to Business Sales Estimation using Neutrosophic Fusion of Rough Set Theory (AIB2BSE-NFRST) model. The main intention of AIB2BSE-NFRST technique is to enhance prediction analysis for B2B sales estimation using advanced techniques. Initially, the data pre-processing performs min-max normalization to prepare raw input data for analysis by transforming it into a structured format. Furthermore, the proposed AIB2BSE-NFRST technique utilizes NFRST method for the prediction process. To further optimize model performance, the seagull optimization algorithm (SOA) is utilized for hyperparameter tuning to ensure that the best hyperparameter is selected. To exhibit the enhanced performance of the presented AIB2BSE-NFRST model, a comprehensive experimental analysis is made under the E-commerce sales dataset. The AIB2BSE-NFRST model outperforms existing techniques with a superior MSE of 0.0033, highlighting its exceptional accuracy in B2B sales estimation.

**Keywords:** Business-to-Business; Sales Estimation; Neutrosophic Logic; Neutrosophic Fusion of Rough Set Theory; Neutrosophic Set; Seagull Optimization Algorithm

## 1. Introduction

Neutrosophic Logic (NL) is a new research field where every proposal is projected to have the proportion of falseness in a subset  $F$ , the proportion of indeterminacy in a subset  $I$ , and the proportion of truth in a subset  $T$  [1]. NS was used successfully for indeterminate processing of data and exhibits benefits for dealing with indeterminacy

information of data and it is yet a method to promote application classification and data analysis [2]. NS delivers an effectual and precise method for defining information unevenness regarding the features of the data. In B2B, enterprises contend to earn higher value sales opportunities for maximizing their profit [3]. From this perspective, a main aspect is to maintain an effective B2B firm. It can be the task of predicting the result in opportunities for sales. The B2B sales procedure normally demands major costs and resources [4]. Therefore, it needs cautious calculations in the initial stage. Computing the possibilities to win fresh sales opportunities is a significant base for proper allocation of resources to prevent misuse of resources and maintain enterprise's financial goals [5]. Traditionally, predicting the sales opportunity outcome typically depends upon the ratings of the human [6].

Many customer relationship management (CRM) methods permit salespeople to manually allocate a winning possibility of new sales opportunities. These possibilities are then utilized at several phases of the sales pipeline [7]. For example, to calculate the weighted income of the sales histories. Frequently every salesperson progresses a non-structural instinct for predicting the probabilities to win opportunities of sales with less or no quantitative rationale, ignoring the complications of the dynamics of the business [8]. Additionally, sales opportunities are purposely undervalued to prevent some internal rivalry with other salespeople or overvalued to avoid the stress from the management for sustaining great performance. However, with crucial growth in predicting techniques as the result of deep learning (DL) and ML developments, sales predicting techniques experience less progression, particularly in the B2B sales area [9]. The most common DL and ML methodologies to estimate sales are time series, which primarily uses black box, approaches in higher-level. Therefore, to provide a smaller vision within the main drivers affects the closing of the exact sale. In contrast with time series, studies on propensity scoring of sales opportunities utilizing ML procedures are not present, although it is an important procedure for sales business and its prediction [10].

### 1.1 Study Contribution and Novelty

This paper presents an Adaptive Intelligent Business to Business Sales Estimation using Neutrosophic Fusion of Rough Set Theory (AIB2BSE-NFRST) technique. The main intention of AIB2BSE-NFRST technique is to enhance prediction analysis for B2B sales estimation using advanced techniques. Initially, the data pre-processing performs min-max normalization to prepare raw input data for analysis by transforming it into a structured format. Furthermore, the proposed AIB2BSE-NFRST technique utilizes NFRST method for the prediction process. To further optimize model performance, the seagull optimization algorithm (SOA) is utilized for hyperparameter tuning to ensure that the best hyperparameter is selected. To exhibit the enhanced performance of the presented AIB2BSE-NFRST model, a comprehensive experimental analysis is made under the E-commerce sales dataset. The key contribution of the AIB2BSE-NFRST model is listed below.

- The AIB2BSE-NFRST approach utilizes min-max normalization to improve data preprocessing, ensuring that all input features are scaled within a consistent range. This step plays a significant role in improving the accuracy and stability of the model. By standardizing the data, the model is better equipped to handle discrepancies across diverse features, resulting in predictions that are more reliable.
- The AIB2BSE-NFRST model employs NFRST technique to effectually handle uncertain and incomplete data in B2B sales estimation. This integration improves the capability of the method to process imprecise information, enhancing the robustness of predictions. By addressing uncertainty, the model delivers more reliable and accurate sales forecasts.
- The AIB2BSE-NFRST technique implements the SOA methodology for effectual parameter tuning, improving the overall optimization process. By exploring the solution space more effectively, SOA significantly improves the performance of the model. This results in improved accuracy and faster convergence, ensuring optimal parameter settings for B2B sales estimation.
- The integration of NFRST with SOA-based tuning introduces a novel approach to B2B sales estimation. This unique incorporation handles uncertainty in the data while simultaneously optimizing model parameters, which significantly improves prediction accuracy. The method outperforms conventional approaches by giving a more reliable and effectual solution to complex sales forecasting problems. Its novelty is in the simultaneous management of uncertainty and optimization for improved performance.

## 2. Review of Literature

In [11], this model utilized an ensemble model involving XGBoost and a modified version of Poisson Gamma technique for forecasting customer order patterns with accuracy. It offers an in-depth inspection of the strategical fusion of ML and an empirical Bayesian model, bolstered by the judicious choice of pertinent aspects. Oskooei and Adak [12] introduce the Casper Customer Behaviour Forecast Application an innovative analysis concentrated on the development of progressive decision support software system. The experimental analysis applies a novel technique by aiming at the improvement of client interactions over the employment of RESTful service. Shan [13] presented an innovative method those implements Fuzzy TOPSIS MCDM and Fuzzy association rule mining (FARM) models. Subsequently, during 6-month trial period, there is significant progress in the efficacy of

selecting prices for every product. Meng et al. [14] advanced an innovative suggestion engine intended situations like managing the lesser frequency and lengthy cycle nature of B2B transactions. This model contains algorithmic improvements to enhanced procedure and translates the confined data accessible, and data pre-processing models intended to improve the sparse database. This study also presented a procedural invention that incorporates multi-dimensional data, integrating product specifics, user E-commerce activity, and vital non-tendering data.

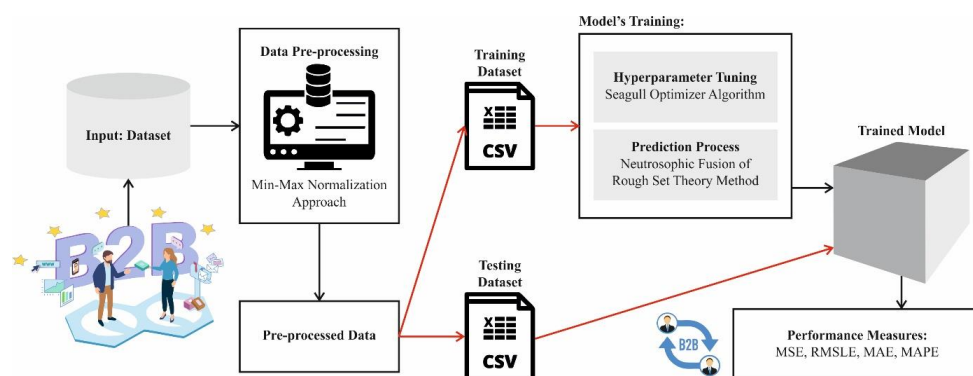
The projected engine leverages a progressive ML methodology to offer more relevant and precise suggestions. Curiskis et al. [15] develops an adaptable structure of ML methodology to forecast customer lifetime value (CLV) in the B2B SaaS environment. The modelling and substantive challenges that surface in this context involve more nuanced customer relations, temporal data constraints, heterogeneous populations and numerous product offerings. Lump sum prediction allows the employment of large variety of supervised ML models that offer added flexibility and richer aspects and shows the enlargement through more standard predicting approaches. Schubert et al. [16] inspects either business or technical model features are involved to handle data with the setting of Industry 4.0 use cases and their consequences to B2B incorporation structure. Kalusivalingam et al. [17] develop a hybrid approach that utilizes the ability of ensemble learning integrating various ML models to enhance predictive performance and anomaly detection techniques, which is proficient in recognizing unusual patterns indicative of fraudulent behaviour. This study assesses the efficacy of this hybrid model employing a database comprising various B2B transaction reports, implementing several ensemble approaches like XGBoost, RF, and voting classifier techniques combined with anomaly detection models namely Local Outlier Factor, One-Class SVM and Isolation Forest.

## 2.1. Limitations and Research Gaps

Despite the promising improvements in B2B sales estimation and customer behaviour prediction, various limitations still exist. First, many models, such as the XGBoost and Poisson Gamma ensemble, still face difficulty with handling high-dimensional data and real-time adaptation to dynamic market changes. Moreover, the focus on specific domains, like the Casper customer behaviour forecast application [12], restricts generalizability to other industries. While hybrid methodologies improve anomaly detection, they often lack scalability and efficiency when applied to large, heterogeneous datasets. Furthermore, approaches incorporating ML and Bayesian methods tend to overlook the complexity of non-linear relationships between multiple variables. A crucial research gap exists in developing more adaptive, scalable, and generalized models that effectually handle complex, multi-dimensional B2B data across diverse sectors.

## 3. Methodology

In this paper, an AIB2BSE-NFRST technique is presented. The main intention of AIB2BSE-NFRST technique is to enhance prediction analysis for B2B sales estimation using advanced techniques. Fig. 1 illustrates the workflow of AIB2BSE-NFRST approach.



**Figure 1.** Overall process of AIB2BSE-NFRST approach

### A. Min-Max Normalization

Initially, the data pre-processing stage applies min-max normalization to prepare raw input data for analysis by transforming it into a structured format [18]. Min-max normalization is a data pre-processing approach applied for scaling numeric values inside a predefined range, normally [0, 1]. In B2B sales prediction, its assistances normalizing sales data, like transaction frequency, customer interactions, and revenue, guaranteeing that no particular feature directs the study. This model converts every value utilizing the equation:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Whereas  $X'$  denote normalized value,  $X$  refers to original value, and  $X_{max}$  and  $X_{min}$  represents maximum and minimum values. By using this method, DL techniques are capable of processing sales data more effectively, resulting in enhanced precision in predicting tendencies, sales and customer behavior.

## B. B2B Sales Prediction using NFRST Model

Furthermore, the proposed AIB2BSE-NFRST technique designs NFRST method for the prediction process [19]. After that, the NFRST was applied for stronger classification, efficiently handling roughness and vagueness in economic data points. The researcher presented the NS idea according to the philosophic theory view, which splits each of the ideas from the particular falsity, truth, and indeterminacy degrees simultaneously. Next, NS determined stronger fundamentals for the sequence of novel science philosophies along with NSs, NS, NSL statistical information, NS probability, and many more. Mostly like the enhanced variation of conventional FL which concentrates on understanding major idea of NS, NL is the logic whereas each of the proposals is assessed to individual truth membership function (MF) in the sub-section  $\mu$ , the indeterminate quantity in a sub-section  $v$ , and the false amount in the sub-set  $w$ . In addition, NL presents the structure of NS links such as negation conjunction, and disjunction namely dominant in NL incorporation of RST. The mathematical equation of NS link is provided under.

During NL, the researcher determined NSs over non-regular studies. Let  $\varepsilon$  represent a small value, and the hyperactive actual value denotes prevalence of the real value that keeps class of infinite and infinitesimal numbers. Let  $U$  like random universal discourse. For the complete basic  $x$  in  $U$ , an NS  $A$  in  $U$  is in mathematical terms provided further down:

$$A = \{(x, \mu_A(x), v_A(x), \omega_A(x)) | x \in U\} \quad (2)$$

Here,  $\mu_A(x), v_A(x)$  and  $\omega_A(x)$  signifies the actual non- or normal sets of non-normal ranges  $[0^-, 1^+]$ , namely  $\mu, v, \omega: U \rightarrow ]0^-, 1[$  [symbolizes the false, the truth and the indeterminate units subsequently on each of the modules  $x \in U$  to  $A$ . As a result, an NS is made from philosophic perspective that makes it difficult to overwhelm real-world conditions. Moreover, there are no constraints for  $\mu_A(x) v_A(x) \omega_A(x)$ .

During these NSs, it is difficult to straight use NSs in real-time applications due to the duration of  $\mu_A(x), v_A(x)$  and  $\omega_A(x)$  is restricted to  $[0^-, 1^+]$ . Instead of  $[0^-, 1^+]$ , it is important for upgrading to  $[0, 1]$ . Consequently  $0 \leq \mu_H(x) + v_H(x) + \omega_H(x) \leq 3$ . Additionally, value of range outshines crisp value while processing damaged data systems, therefore it's normal to propose the concept of INS.

Concerning certain applications of NS, it is significant for proposing the mathematic equation of NS link.

Let  $U$  denote randomly formed universal discourse,  $A$  and  $A^f$  refers to dual NSs as demonstrated:

Accompaniment: the accompaniments of  $A$  is

$$A^c = \{(x, \omega_A(x), 1 - v_A(x), \mu_A(x)) | x \in U\} \quad (3)$$

Connection: the connections of  $A$  and  $A'$  is

$$A \cap A' = \{(x, \min(\mu_A(x), \mu'_A(x)), \max(v_A(x), v'_A(x)), \max(\omega_A(x), \omega'_A(x))) | x \in U\}: \quad (4)$$

Unification: the unifications of  $A$  and  $A'$  is

$$A \cup A' = \{(x, \max(\mu_A(x), \mu'_A(x)), \min(v_A(x), v'_A(x)), \min(\omega_A(x), \omega'_A(x))) | x \in U\}: \quad (5)$$

Addition: for  $x$  in  $U, A \subseteq A^f$  contains

$$\mu_A(x) \leq \mu'_A(x), v_A(x) \geq v'_A(x) \text{ and } \omega_A(x) \geq \omega'_A(x):$$

Equality: for  $x$  in  $U, A = A'$  contains

$$\mu_A(x) = \mu'_A(x), v_A(x) = v'_A(x) \text{ and } \omega_A(x) = \omega'_A(x):$$

Following the general rule of new RSs, data system given an adaptable framework to label many objects concerning the equal features, data system sets a stronger foundation for building RSs.

During the typical data system, for the object representations, considering  $U = \{x_1, x_2, \dots, x_n\}$  like randomly formed universal discourse; because feature demonstration, considering  $A = \{a_1, a_2, \dots, a_m\}$  like random feature set. Formerly, the couple  $(U, A)$  is named data systems. Besides,  $a: U \rightarrow Va$  for each  $a \in \mathcal{A}$  and characterizing  $a(x) \in V_a$ .

Concerning a data system, each of the feature sub-sets  $B \subseteq A$  encourages the relationship of indiscernibility.  $RB = \{a(x) = a(y) | \forall a \in B, (x, y) \in U \times U\}$  that various  $U$  into one complementary module as  $U/RB = \{[x]B | x \in U\}$ , whereas  $[x]B$  represents corresponding class stimulated by  $x$  under  $B$ , i.e.,  $[x]B = \{(x, y) \in RA | y \in U\}$ .

Let  $U$  as a randomly formed universal discourse, and a corresponding relationships across  $U$  is  $R$ . For the NS  $A$ , the dual estimations of  $A$  are provided below:

$$\underline{Q}(A) = \{(x, \mu_{\underline{Q}(A)}(x), v_{\underline{Q}(A)}(x), w_{\underline{Q}(A)}(x)) | y \in [x]_R, x \in U\} \tag{6}$$

$$\overline{Q}(A) = \{(x, \mu_{\overline{Q}(A)}(x), v_{\overline{Q}(A)}(x), w_{\overline{Q}(A)}(x)) | y \in [x]_R, x \in U\} \tag{7}$$

Whereas,

$$\mu_{\underline{Q}(A)}(x) = \wedge_{y \in [x]_R} \mu_A(y), v_{\underline{Q}(A)}(x) = \vee_{y \in [x]_R} v_A(y), \omega_{\underline{Q}(A)}(x) = \vee_{y \in [x]_R} \omega_A(y), \mu_{\overline{Q}(A)}(x) = \vee_{y \in [x]_R} \mu_A(y), v_{\overline{Q}(A)}(x) = \wedge_{y \in [x]_R} v_A(y), \omega_{\overline{Q}(A)}(x) = \wedge_{y \in [x]_R} \omega_A(y).$$

Unlike RNS that utilizes the indiscernibility relationships for estimation of an NS idea, NRS targets developing an estimation of NS below an NS area of estimation. Formerly, the mathematical equation of NRS is provided as.

Let  $U$  refer to randomly formed universal discourse,  $R$  denote an NS relationship on  $U$ . Then, for the arbitrary relationships of NS, the pair  $(U, R)$  is identified as an area of estimation related to NS.

$$\underline{R}(A) = \{(x, \mu_{\underline{R}(A)}(x), v_{\underline{R}(A)}(x), w_{\underline{R}(A)}(x)) | x \in U\} \tag{8}$$

$$\overline{R}(A) = \{(x, \mu_{\overline{R}(A)}(x), v_{\overline{R}(A)}(x), w_{\overline{R}(A)}(x)) | x \in U\}, \tag{9}$$

According to the NRS and RNS ideas, it was easier to understand the important contribution that exists by opening a novel study course for RST and NS.

### C. Parameter Tuning using SOA

To further optimize model performance, the SOA is utilized for hyperparameter tuning to ensure that the best hyperparameter is selected [20]. This is an effective technique for improves the performance of the model due to its capability to explore complex solution spaces with high efficiency. SOA, inspired by the foraging behaviour of seagulls, outperforms at balancing exploration and exploitation, allowing it to find optimal solutions more effectively than conventional methods such as grid or random search. Compared to other optimization techniques, SOA presents superior convergence speed and robustness, specifically in high-dimensional and non-linear parameter spaces. Furthermore, SOA's population-based nature allows it to avoid local optima and gives improved global search capabilities. This makes it specifically appropriate for optimizing models in massive, complex datasets where conventional methods may face difficulty. The ability to dynamically adjust to diverse problem landscapes makes SOA a more adaptable and reliable choice for parameter tuning, resulting in an enhanced model accuracy and efficiency. Fig. 2 depicts the flowchart of SOA.

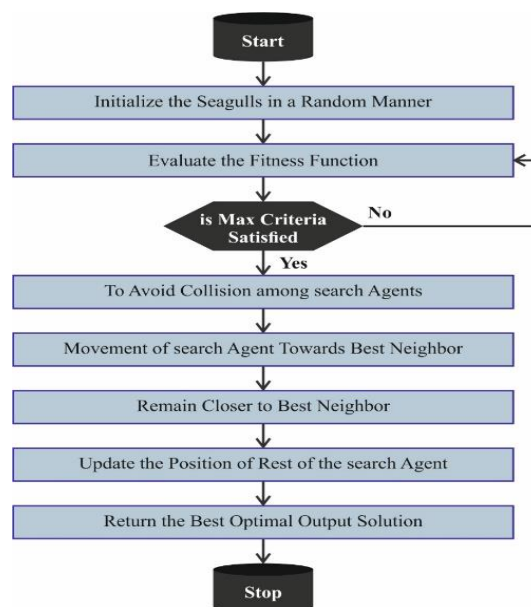


Figure 2. Flowchart of SOA

The SOA effectually integrates local searching and global exploration ability by imitating the migration and attack behaviour of seagulls, providing a powerful tool to solve intricate optimizer concerns. This model functions following stages:

**Population initialization:** The population is arbitrarily initialized to generate a different set of solutions for candidate.

**Fitness evaluation:** The fitness value of every individual is assessed, and the population is graded to recognize highly-performed individuals.

**Migration simulation:** The migration behaviour of seagulls is pretend, allowing exploration through a wide-searching region.

**Attack simulation:** This model transitions to the phase of attack, now the predation behaviour of seagulls is mimicked over location upgrades, enhancing the quality of solution.

During iterative optimization of these stages, the SOA increasingly converges to the optimum solution. The concept of seagull methodology exists in its capability to balance exploitation and exploration, guaranteeing effective and efficient optimizations.

#### Migration Behaviour of Seagulls

The process of seagull migration imitates the behaviour of seagull populations from one to another place.

There are 3 conditions met in this global searching stage.

**Condition 1: Avoid a collision.** The upgraded position of seagull must be evaded similarly to another seagull, and collisions among seagulls are evaded by recognizing the novel parameter  $A$ .

$$P_N(x) = A \times P_S(x) \quad (10)$$

$$A = f_c - \left( x \times \frac{f_c}{\text{Max}(x)} \right) \quad (11)$$

Here  $P_N(x)$  denoted the upgraded location of seagull whereas avoiding a collision and  $x$  represents existing iteration counts,  $\text{Max}(x)$  is the set maximal iteration counts limits the total algorithm running counts,  $P_S(x)$  is the existing location of seagull in the  $x$ th iteration, and  $f_c$  denotes a control constant employed to fine-tune the parameter change  $A$  by fine-tuning  $f_c$ . The value of  $f_c$  can distress the speed and the method seagull discovers the searching region and iteration count rises, the parameter  $A$  reduces linearly from the initial value to 0.

**Condition 2: Establish the finest location orientation.** The background of avoiding collision requires computing the direction of non-optimum location to optimum seagull.

$$M_S = B \times (P_B(x) - P_S(x)) \quad (12)$$

$$B = 2 \times A \times R \quad (13)$$

Here  $x$  is existing iteration counts,  $M_S$  for the existing direction to the optimum position of seagull,  $B$  specifies the arbitrary value of global and local searching capability of balanced algorithm,  $P_B$  is the location of optimum seagull at the  $x$ th iteration, and  $R$  specifies an arbitrary number among  $[0,1]$ .

**Condition 3: Moving to the optimum position.** Non-optimal gulls upgrade their location based on equation.

$$D_S = |P_N + M_S| \quad (14)$$

Now  $D_S$  is novel location for seagulls when the migration behavior ends.

#### Aggressive Behavior of Seagulls

Seagull assaults at its core by adjusting the angle of flight attitude and wings, in  $x, y, z$  3D space in the spiral trajectory approaches the prey. The spiral motion of seagull can keep incessant track of prey; it produces visual illusion for the prey decreasing the likelihood of its escape. The position of seagull attack behavior is upgraded:

$$\begin{cases} r = u \times e^{\beta v} \\ x = r \times \cos(\beta) \\ y = r \times \sin(\beta) \\ z = r \times \beta \end{cases} \quad (15)$$

$$P'_S(x) = x \times y \times z \times D_S(x) + P_B(x) \quad (16)$$

Here  $r$  represents the radius of every circle of the spiral trajectory curve,  $P'_s(x)$  specifies location of the seagull whereas ending the behavior of attack,  $v$  and  $u$  are constants, jointly describing the shape of spiral line, and  $\beta$  is the arbitrary number with  $[0, 2\pi]$ .

In this paper, the SOA is applied to control the hyperparameter included in the NFRST method. The MSE is measured as the objective function and is described as shown.

$$MSE = \frac{1}{T} \sum_{j=1}^L \sum_{i=1}^M (y_j^i - d_j^i)^2 \quad (17)$$

Here,  $L$  and  $M$  characterize the resulting value of data and layer individually,  $d_j^i$  and  $y_j^i$  shows the appropriate and attained sizes for  $j^{th}$  unit from the resulting layer of network in time  $t$  respectively. Algorithm 1 illustrates the SOA method.

#### Algorithm 1: SOA method

##### Initialize Population:

Create a population of seagulls  $P = \{S_1, S_2, \dots, S_n\}$ , where each  $S_i$  represents a potential solution in the search space.

Initialize random positions for all seagulls in the search space.

##### Evaluate Fitness:

Calculate the fitness of each seagull based on the problem objective function  $f(S_i)$ .

##### Search for Prey (Exploration Phase):

A seagull searches for prey by exploring the space. Each seagull updates its position by following the equation:

$$S_i^{new} = S_i + \gamma \cdot (P_{best} - S_i)$$

where:

$S_j$  is the current position of the  $i^{th}$  seagull.

$P_{best}$  is the position of the best seagull (best solution so far).

$\gamma$  is a random coefficient controlling the exploration rate.

##### Attack Phase (Exploitation Phase):

When a seagull locates prey, it attacks and adjusts its position to find a better solution. The position update is done as:

$$S_i^{new} = S_i + \beta \cdot (S_{best} - S_i)$$

where:

$S_{best}$  is the position of the best solution  $S_{best}$  found by the population so far.

$\beta$  is a random coefficient controlling the exploitation rate.

##### Update Best Solution:

Update the global best position  $S_{best}$  based on the fitness evaluations of all the seagulls.

If the fitness of a seagull is better than the global best, update the global best solution.

##### Termination Condition:

Repeat steps 3 to 5 until a stopping criterion is met (e.g., a maximum number of iterations or convergence criteria).

##### Return Best Solution:

The solution corresponding to the best position  $S_{best}$  is returned as the optimal solution.

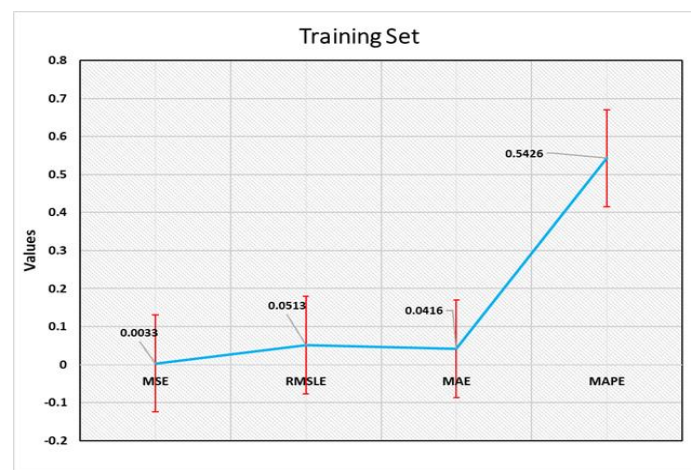
## 4. Result Analysis and Discussion

The experimental analysis of AIB2BSE-NFRST method is inspected under E-commerce Sales dataset [21].

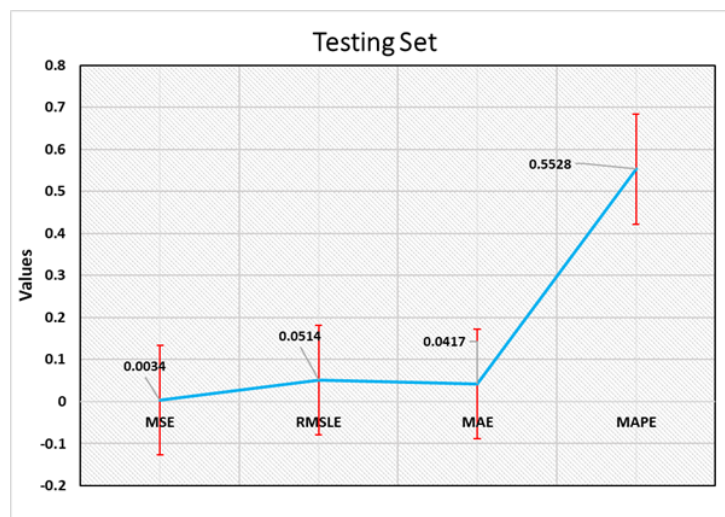
Table 1 and Fig. 3-4 presents the training set (TRAST) and testing set (TESST) result of AIB2BSE-NFRST approach under multiple metrics. Under TRAST, the AIB2BSE-NFRSTX technique accomplishes MSE, RMSLE, MAE, and MAPE of 0.0033, 0.0513, 0.0416, and 0.5426, respectively. In addition, with TESST, the AIB2BSE-NFRST methodology gains MSE, RMSLE, MAE, and MAPE of 0.0034, 0.0514, 0.0417, and 0.5528, correspondingly.

**Table 1:** TRAST and TESST outcome of AIB2BSE-NFRST model

Metrics	TRAST	TESST
MSE	0.0033	0.0034
RMSLE	0.0513	0.0514
MAE	0.0416	0.0417
MAPE	0.5426	0.5528



**Figure 3.** TRAST outcome of AIB2BSE-NFRST approach



**Figure 4.** TESST outcome of AIB2BSE-NFRST approach

Fig. 5 depicts the Actual vs prediction outcome of AIB2BSE-NFRST approach under epochs 10-100. The figure indicates that the AIB2BSE-NFRST approach correctly predicted the result. It is also noticed that the predicted values by the AIB2BSE-NFRST method is closer to the actual values.

Fig. 6 established loss curves of AIB2BSE-NFRST approach under several metrics. The values of loss are computed across a time of 0-50 epochs. It is denoted that the training values demonstrate a diminishing trend, informing the capacity to balance a trade-off between generalization and data fitting. The constant decreasing in values of loss values besides guarantees the superior performance and tune the prediction outcomes over time.

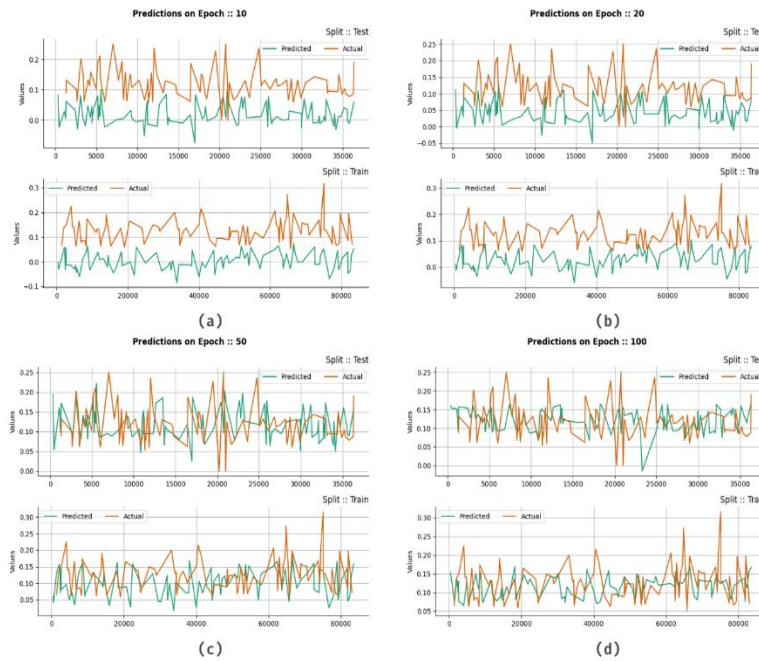


Figure 5. Actual vs Prediction outcome of AIB2BSE-NFRST technique on (a-d) Epochs 10-100

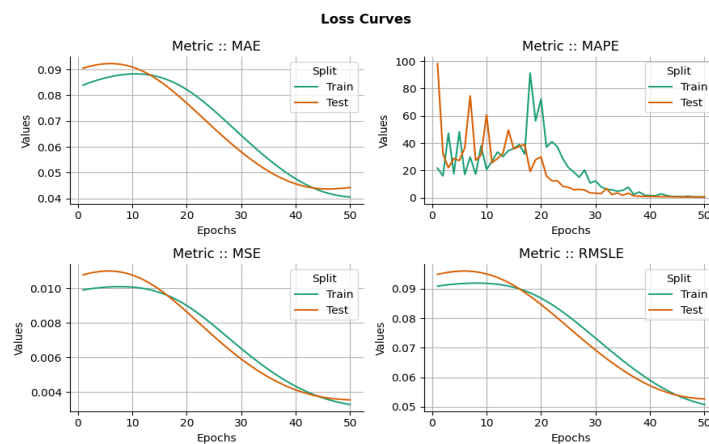


Figure 6. Loss curves of AIB2BSE-NFRST technique under various metrics

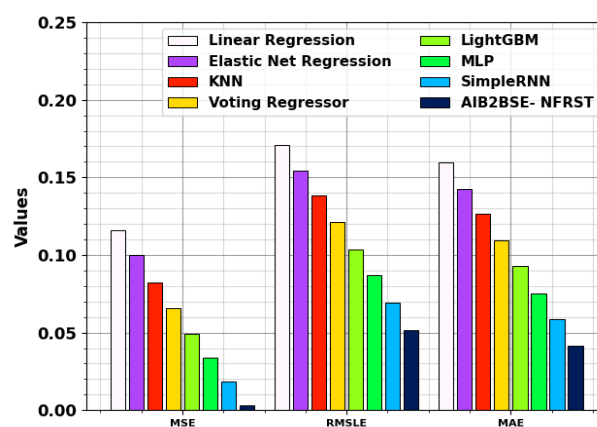
#### 4.1. Comparison Evaluation of the AIB2BSE-NFRST Model with Existing Approaches

To establish the proficiency of the AIB2BSE-NFRST technique, a thorough comparison outcome is through in Table 2 with existing approach under several metrics [22-24].

Fig. 7 depicts the MSE, RMSLE, and MAE result of AIB2BSE-NFRST approach with existing methods. Under MSE, the proposed AIB2BSE-NFRST approach attains lesser MSE of 0.0033, whereas the existing methodology such as Linear Regression (LR), Elastic Net Regression (ENR), k-nearest neighbour (KNN), Voting Regressor (VR), LightGBM, multilayer perceptron (MLP), and simple recurrent neural network (RNN) methods have achieved greater MSE of 0.1161, 0.1001, 0.0825, 0.0658, 0.0494, 0.0338, and 0.0183, respectively. Moreover, under RMSLE, the proposed AIB2BSE-NFRST technique obtains lesser RMSLE of 0.0513, whereas the existing approaches such as LR, ENR, KNN, VR, LightGBM, MLP, and simple RNN methods have gained optimal RMSLE of 0.1706, 0.1544, 0.1381, 0.1213, 0.1038, 0.0870, and 0.0691, correspondingly. Finally, under MAE, the proposed AIB2BSE-NFRST technique accomplishes lower MAE of 0.0416, whereas the existing techniques such as LR, ENR, KNN, VR, LightGBM, MLP, and simple RNN methods have obtained greater MAE of 0.6576, 0.6408, 0.6245, 0.6084, 0.5934, 0.5774, and 0.5598, respectively.

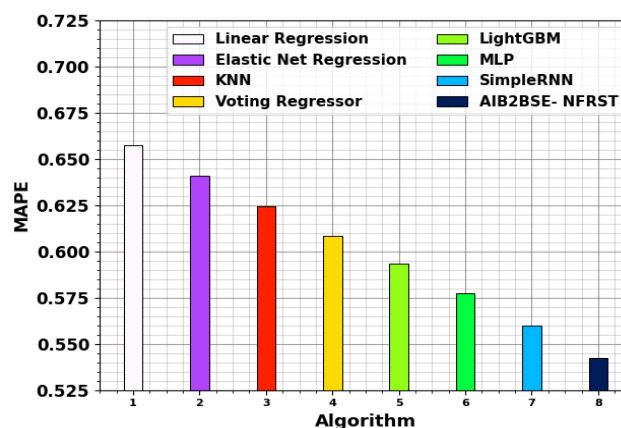
**Table 2:** Comparative analysis of AIB2BSE-NFRST technique with existing models

Technique	MSE	RMSLE	MAE	MAPE
LR	0.1161	0.1706	0.1596	0.6576
ENR	0.1001	0.1544	0.1423	0.6408
KNN	0.0825	0.1381	0.1267	0.6245
VR	0.0658	0.1213	0.1093	0.6084
LightGBM	0.0494	0.1038	0.0927	0.5934
MLP	0.0338	0.0870	0.0754	0.5774
Simple RNN	0.0183	0.0691	0.0588	0.5598
AIB2BSE-NFRST	0.0033	0.0513	0.0416	0.5426



**Figure 7.** MSE, RMSLE, and MAE outcome of AIB2BSE-NFRST technique with existing models

Fig. 8 portrays the MAPE result of AIB2BSE-NFRST methodology with existing techniques. Under MAPE, the proposed AIB2BSE-NFRST methodology accomplishes greater MAPE of 0.5426, whereas the existing techniques such as LR, ENR, KNN, VR, LightGBM, MLP, and Simple RNN have obtained minimal MAPE of 0.6576, 0.6408, 0.6245, 0.6084, 0.5934, 0.5774, and 0.5598 respectively.



**Figure 8.** MAPE outcome of AIB2BSE-NFRST technique with existing models

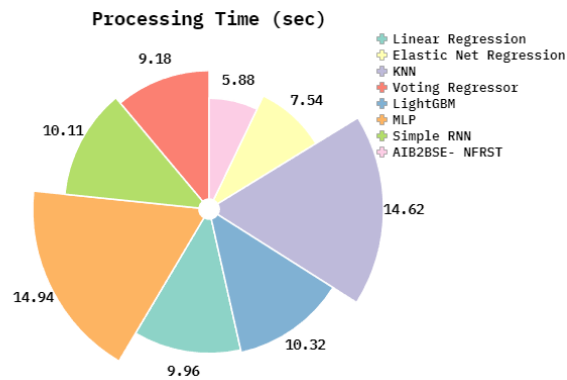
#### 4.2. Processing Time Analysis of the AIB2BSE-NFRST Technique with Existing Models

Table 3 and Fig. 9 illustrates the processing time (PT) evaluation of the AIB2BSE-NFRST technique with existing methods. Among the models, LR has a PT of 9.96 seconds, while ENR performs slightly faster at 7.54 seconds. KNN exhibits a higher PT of 14.62 seconds, showing its computational intensity. VR performs with a PT of 9.18 seconds, while LightGBM, a gradient boosting framework, takes 10.32 seconds. The MLP and Simple RNN have

PTs of 14.94 and 10.11 seconds, respectively, emphasizing their complexity. The proposed AIB2BSE-NFRST model, with a PT of 5.88 seconds, outperforms all other models, illustrating its superior efficiency in terms of PT without sacrificing prediction accuracy.

**Table 3:** PT evaluation of AIB2BSE-NFRST approach with existing methods

Approach	PT (sec)
LR	9.96
ENR	7.54
KNN	14.62
VR	9.18
LightGBM	10.32
MLP	14.94
Simple RNN	10.11
AIB2BSE-NFRST	5.88



**Figure 9.** PT evaluation of AIB2BSE-NFRST approach with existing methods

## 5. Conclusion and Potential for Future Enhancement

In this paper, an AIB2BSE-NFRST technique is presented. The main intention of AIB2BSE-NFRST technique is to enhance prediction analysis for B2B sales estimation using advanced techniques. Initially, the data pre-processing stage applies min-max normalization to prepare raw input data for analysis by transforming it into a structured format. Furthermore, the proposed AIB2BSE-NFRST technique designs NFRST method for the prediction process. To further optimize model performance, the SOA is utilized for hyperparameter tuning to ensure that the best hyperparameter is selected. To exhibit the enhanced performance of the presented AIB2BSE-NFRST model, a comprehensive experimental analysis is made under the E-commerce sales dataset. The AIB2BSE-NFRST model outperforms existing techniques with a superior MSE of 0.0033, highlighting its exceptional accuracy in B2B sales estimation.

### 5.1. Limitations and Future Works

The limitations of the AIB2BSE-NFRST model are in its reliance on specific assumptions made during the model formulation, which may not apply universally across all types of data or industries. While the model illustrates robust performance in certain use cases, it may not fully generalize to highly dynamic or volatile environments. Additionally, the capability of the technique to handle large-scale datasets with diverse, intrinsic variables remains limited, which could affect its applicability in real world, large-scale systems. Furthermore, the computational complexity of the proposed technique might affect its real-time deployment in resource-constrained environments. Lastly, the interpretability of the model, particularly in explaining its decisions to end users, remains a challenge, which could restrict its acceptance in sectors requiring transparency.

Future works in this domain could concentrate on addressing these limitations by exploring alternative normalization techniques such as robust scaling or adaptive normalization methods that are more resilient to

outliers. Moreover, improvements to the NFRST model can be considered to improve its capability for handling real-time data and adapt to rapidly changing business environments. Integrating hybrid optimization techniques, namely incorporating SOA with other metaheuristics like GAs or PSO, could assist in improving performance on more complex, high-dimensional problems. Additionally, extending the model to integrate DL-based methods for more accurate and scalable predictions could offer promising avenues for future research.

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