Robust Financial Market Share Prediction using Intuitionistic Possibility Fermatean Neutrosophic Soft Set

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Abstract

An addition of soft set theory, Neutrosophic soft set theory offers a versatile framework for handling indeterminacy and uncertainty in data. Using this theory for the prediction of market share includes representing market data in a neutrosophic soft-set format, where elements pose truth, indeterminacy, and false degrees. The predictive model is constructed to estimate future market shares with consideration for ambiguity and uncertainty by analyzing previous market factors and trends affecting market dynamics within these frameworks. The stock market prediction pattern is interpreted as a significant action and it is more beneficial. Therefore, stock prices will result in substantial profits from sound taking choices. Thus, stock market forecasting is a main task for investors to spend their money to create maximum profit due to the noisy and stagnant data. Stock market prediction uses learning tools and mathematical strategies. Therefore, this manuscript offers the design of Financial Market Share Prediction using the Intuitionistic Possibility Fermatean Neutrosophic Soft Set (FMSP-IPFNS) technique. In the FMSP-IPFNS technique, a three-stage approach is followed. Firstly, the data normalization process is executed using a min-max scalar approach. Secondly, the prediction process can be carried out using the IPFNS approach. Thirdly, the parameter adjustment of the IPFNS approach takes place using the grasshopper optimization algorithm (GOA). To validate the performance of the FMSP-IPFNS system, a sequence of experimentations were tested. The obtained values demonstrate the promising results of the FMSP-IPFNS system compared to other models

Keywords: Stock Market Prediction; Neutrosophic Soft Set; Grasshopper Optimization Algorithm; Machine Learning; Data Normalization

1. Introduction

The finance market is one of the most fascinating inventions in the current time. This finance market has a considerable impact on several sectors like employment technology, and business [1]. Investing money and earning maximum profits with a low level of risk are the two major strategies that investors use for making decisions on the stock market. Over the last few decades, advances in information technology have revolutionized the path of businesses. Financial markets have a significant impact on the nation's economy as the most captivating invention [2]. Recently, stock trading has become a cornerstone, which can be mainly responsible for advances in technology [3]. Investors look for techniques and tools that might reduce the risk and increase profit. However, due to its dynamic, non-linear, unreliable, and stochastic nature, the Stock Market Prediction (SMP) is not an easy task. SMP is an instance of time-series prediction that estimates preceding and future data promptly [4]. Financial market prediction is a major concern for analysts in several domains, such as computer science, economics, mathematics, and material science [5]. Driving profits from the trading of stock is a major aspect of the stock market prediction. The stock market is based on several parameters, namely the natural calamities, the market value of shares, government policies, the company's performance, the inflation rate, the country's Gross Domestic Product (GDP), etc [6].

Popular theories recommend that the stock market is a random walk that is accompanied by certain rules of the exact price of the preceding day [7]. The classical time series prediction method is dependent on stationary trends; therefore the stock price prediction handles intrinsic uncertainty. Moreover, stock price prediction is a challenge

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in itself due to the several parameters [8]. In the longer term, it behaves similarly to a weighing machine, but in the short term, the market acts similarly to a voting machine and therefore it is still possible to predict the market movement for the long time. Machine learning (ML) is a robust mechanism that involves various techniques to optimize performance [9]. It is a common concept that ML has great promise to detect patterns and valid information from the data. A neutrosophic set (NS) is an intuitionistic fuzzy set and generalization of fuzzy sets, an effective method to handle indeterminate, inconsistent, and incomplete data in real time [10]. NSs are classified into truth membership function (T), indeterminacy membership function (I), and false membership function (F).

This manuscript offers the design of Financial Market Share Prediction using the Intuitionistic Possibility Fermatean Neutrosophic Soft Set (FMSP-IPFNS) technique. In the FMSP-IPFNS technique, a three-stage approach is followed. Firstly, the data normalization process is executed using a min-max scalar approach. Secondly, the prediction process can be carried out using the IPFNS approach. Thirdly, the parameter adjustment of the IPFNS approach takes place using the grasshopper optimization algorithm (GOA). The obtained values demonstrate the promising results of the FMSP-IPFNS technique compared to other models.

2. Related Works

Castilho et al. [11] projected a method that estimates market correlation framework from node- and link-based economic system feature utilizing ML. The structure of the market is demonstrated as a dynamic asset system by measuring time-dependent co-movement. This method also delivers experiential signs utilizing 3 dissimilar network filtering techniques to evaluate the structure of the market such as Dynamic Minimal Spanning Tree, Dynamic Asset Graph, and Dynamic Threshold Networks. Sharma et al. [12] concentrated on forecasting stock market news sentiments depending on their textual and polarity data utilizing the theory of ontological knowledge-based CNNs as an ML technique. So, the swarm-based ABC technique is employed with the Lexicon feature extraction model utilizing a new FFF. Sivri and Ustundag [13] presented a state-of-the-art forecast structure that unites ensemble learning techniques to efficiently capture everyday stock actions. The research concentrates on forecasting the alteration among the closing and opening prices of the successive day and uses an everyday descending window cross-validation approach. The structure includes 14 variable groups including a sort of economic and operational indicators.

Shilbayeh and Grassa [14] utilize the decision tree (DT) ML system as a base learner directing an in-depth contrast with the collective DT and RF. To evaluate the earlier explained methods, a 10 cross-validation system was employed. This algorithm contains segmenting the datasets into 10 folds, with 9 for training and 1 for testing. Venkateswararao and Reddy [15] proposed a hybrid ML system for long-term stock market price trend prediction (LT-SMF). This method used an enhanced butterfly optimizer (IBO) to eliminate objects from input data. Next, a brown Planthopper optimizer (BPO) method decreases data dimensionality for optimum FS. To estimate stock market price variants, a hybrid FEL-DNN was employed.

Deng et al. [16] projected an innovative price tendency forecast and trading simulation method for the Shenzhen Component index and Shanghai Stock Exchange index. Furthermore, the SHAP system was used as a model analysis system to examine the significance of the sentiment variables and measure their influences on the forecasts from both global and local viewpoints. The authors [17] developed a forecasting technique that unites unsupervised learning with reinforcement learning (RL). Initially, the model takes the stock tendency from past stock and builds the trading atmosphere condition by growing a neural gas (GNG) system in unsupervised learning. Next, the reward function was modernized to deliver on-time feedback on the data of trading. Lastly, Triple Q-learning method was intended.

3. The Proposed Method

In this manuscript, we offer the design of the FMSP-IPFNS technique. In the FMSP-IPFNS model, a 3-stage approach is followed data normalization, prediction procedure, and hyperparameter tuning procedure. Fig. 1 establishes the entire procedure of the FMSP-IPFNS technique.

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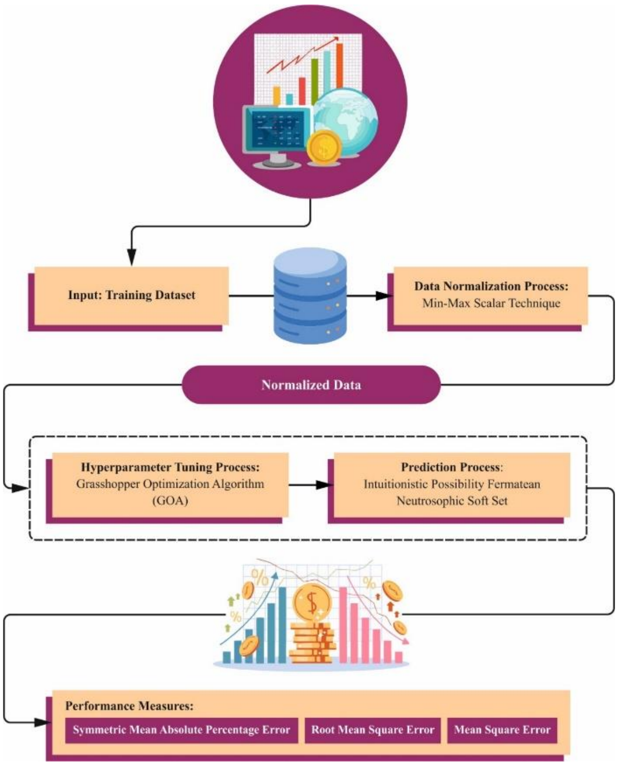

Figure 1: Overall process of FMSP-IPFNS technique

A. D Normalization

Firstly, the data normalization process gets executed using the min-max scalar approach. Min-max scaling (min-max normalization), is a widespread data pre-processing method in data analytics and ML to normalize features within certain intervals $(0,1)$ [18]. The process includes rescaling all the features by subtracting the lowest value and separating by the variance among the highest and lowest values. This ensures that the feature value lies within the uniform range, thus preventing features with large scale from controlling the analysis. Min-max scaling is very effective while working with approaches sensitive to the normalization of features, like support vector machines and neural networks, as it enhances performance and convergence.

B. Prediction using the IPFNS Model

Secondly, the prediction process can be carried out using the IPFNS approach. Dliouah et al. present the Intuitionistic Possibility of Fermatean fuzzy soft set (IPFFSS) which is discussed in this section [19].

Definition 11: Intuitionistic Possibility Fermatean Neutrosophic Soft Set

Consider $U = \{c_1, c_2, \dots, c_n\}$ as a set of universes and $E = \{e_1, e_2, \dots, e_m\}$ as a collection of parameters. Determine $F: E \to FE(U)$ where $FE(U)$ refers to the group of Fermatean fuzzy subsets of U. Consider μ as an intuitionistic fuzzy subset of U, viz., $\mu: E \to IN(U)$ where IN (U) represents the set of intuitionistic fuzzy subsets of U and F_μ : $E \to FE(U) \times IN(U)$ as a function:

$F_\mu(e) = (F(e)(x), \mu(e)(x))$, where $F(e)(x) = (\alpha(x), \beta(x))$ and $\mu(e)(x) = (\lambda(x), v(x)) \forall x \in U$. Include the conditions: $0 \le (\alpha(x))^3 + (\beta(x))^3 \le 1$ and $0 \le (\lambda(x)) + (v(x)) \le 2$.

F_μ is known as an IPFFSS through the soft universe (U, E). For $e \in E$, $F_\mu(e) = (F(e)(x), \mu(e)(x))$ specifies the belongingness degree of the rudiments of U in $F(e_i)$, and the possibility degree of belongingness of the components U of in $F(e_i)$ that is characterized as $\mu(e_i)$.

$$F_\mu(e_i)(x) = \left\{\left(\frac{x}{F(e_i)(x)}, \mu(e_i)(x)\right), \forall x \in U\right\}$$

Assume $U = \{c_1, c_2, c_3\}$ as a universe set. $E = \{e_1, e_2, e_3\}$ as a collection of parameters, and: $E \to IN(U)$. Determined F_μ : $E \to FE(U) \times IN(U)$ as given below:

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$$F_\mu(e_1) = \left\{\left(\frac{c_1}{(0.5,0.3)},(0.7,0.1)\right),\left(\frac{c_2}{(0.8,0.1)},(0.5,0.2)\right),\left(\frac{c_3}{(0.6,0.2)},(0.6,0.3)\right)\right\},$$

$$F_\mu(e_2) = \left\{\left(\frac{c_1}{(0.7,0.2)},(0.5,0.3)\right),\left(\frac{c_2}{(0.6,0.2)},(0.6,0)\right),\left(\frac{c_3}{(0.5,0.1)},(0.8,0.1)\right)\right\},$$

$$F_\mu(e_3) = \left\{\left(\frac{c_1}{(0.9,0)},(0.6,0.2)\right),\left(\frac{c_2}{(0.8,0.1)},(0.7,0.1)\right),\left(\frac{c_3}{(0.7,0.2)},(0.5,0.1)\right)\right\},$$

F_μ refers to IPFFSS over (U,E).

$$F_\mu = \begin{pmatrix} (0.5,0.3),(0.7,0.1) & (0.8,0.1),(0.5,0.2) & (0.6,0.2),(0.6,0.3) \\ (0.7,0.2),(0.5,0.3) & (0.6,0.2),(0.6,0) & (0.5,0.1),(0.8,0.1) \\ (0.9,0),(0.6,0.2) & (0.8,0.1),(0.7,0.1) & (0.7,0.2),(0.5,0.1) \end{pmatrix}$$

Consider F_μ and G_ρ as two IPFFSSs over (U,E). F_μ as an IPFFS subset of G_ρ and $F_\mu \subseteq G_\rho$ if:

for $e \in E, \mu(e)$ is an intuitionistic fuzzy subset of $\rho(e)$,

for $e \in E, F(e)$ is a Fermatean fuzzy soft subset of $G(e)$.

Consider $U = \{x_1, x_2, x_3\}$ as a universe set and $E = \{e_1, e_2, e_3\}$ as a collection of parameters. F_δ and G_ρ are functions as given below:

$$F_\delta(e_1) = \left\{\left(\frac{x_1}{(0.5,0.3)},(0.7,0.1)\right),\left(\frac{x_2}{(0.8,0.1)},(0.5,0.2)\right),\left(\frac{x_3}{(0.6,0.2)},(0.6,0.3)\right)\right\},$$

$$F_\delta(e_2) = \left\{\left(\frac{x_1}{(0.7,0.2)},(0.5,0.3)\right),\left(\frac{x_2}{(0.6,0.2)},(0.6,0.1)\right),\left(\frac{x_3}{(0.5,0.1)},(0.8,0.2)\right)\right\},$$

$$F_\delta(e_3) = \left\{\left(\frac{x_1}{(0.6,0.2)},(0.4,0.2)\right),\left(\frac{x_2}{(0.4,0.3)},(0.7,0.1)\right),\left(\frac{x_3}{(0.7,0.2)},(0.5,0.3)\right)\right\}.$$

$$G_\rho(e_1) = \left\{\left(\frac{x_1}{(0.6,0.2)},(0.8,0)\right),\left(\frac{x_2}{(0.9,0)},(0.6,0.1)\right),\left(\frac{x_3}{(0.7,0.1)},(0.7,0.2)\right)\right\},$$

$$G_\rho(e_2) = \left\{\left(\frac{x_1}{(0.8,0.1)},(0.6,0.2)\right),\left(\frac{x_2}{(0.7,0.1)},(0.7,0)\right),\left(\frac{x_3}{(0.6,0)},(0.9,0.1)\right)\right\}$$

$$G_\rho(e_3) = \left\{\left(\frac{x_1}{(0.7,0.1)},(0.5,0.1)\right),\left(\frac{x_2}{(0.5,0.2)},(0.8,0)\right),\left(\frac{x_3}{(0.8,0.1)},(0.6,0.2)\right)\right\}.$$

F_δ refers to an IPFFS subset $of\, G_\rho$

Assume F_μ and G_ρ as two IPFFSSs over (U,E). F_μ is equivalent and $F_\mu = G_\rho$ if:

for all $e \in E, \mu(e)$ is equivalent to $p(e)$,

for all $e \in E,\ F(e)$ is equivalent to $G(e)$.

The IPFFSS is a null IPFFSS, represented as N, if $N: E \to FE(U) \times IN(U)$ thus: $N(e) = (F(e)(x), \mu(e)(x))$, $\forall e \in E$, Where $F(e) = (0,1)$, and

$\mu(e) = (0,1), \forall e \in E.$

Consider $U = \{c_1, c_2, c_3\}$ as a universe set. $E = \{e_1, e_2, e_3\}$ as a collection of parameters. F_μ is given below:

$$F_\mu(e_1) = \left\{\left(\frac{c_1}{(0,1)},(0,1)\right),\left(\frac{c_2}{(0,1)},(0,1)\right),\left(\frac{c_3}{(0,1)},(0,1)\right)\right\}$$

$$F_\mu(e_2) = \left\{\left(\frac{c_1}{(0,1)},(0,1)\right),\left(\frac{c_2}{(0,1)},(0,1)\right),\left(\frac{c_3}{(0,1)},(0,1)\right)\right\}$$

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$$F_\mu(e_3) = \left\{\left(\frac{c_1}{(0,1)},(0,1)\right),\left(\frac{c_2}{(0,1)},(0,1)\right),\left(\frac{c_3}{(0,1)},(0,1)\right)\right\}$$

Then F_μ denotes the null IPFFSS.

An IPFFSS is an absolute IPFFSS, represented as A, if $A: E \to FE(U) \times IN(U)$ thus: $A(e) = (F(e)(x), \mu(e)(x))$, $\forall e \in E$, Where $F(e) = (1,0)$, and $\mu(e) = (1,0)$, $\forall e \in E$.

Assume an absolute IPFFSS, we have F_μ:

$$F_\mu(e_1) = \left\{\left(\frac{c_1}{(1,0)},(1,0)\right),\left(\frac{c_2}{(1,0)},(1,0)\right),\left(\frac{c_3}{(1,0)},(1,0)\right)\right\}$$

$$F_\mu(e_2) = \left\{\left(\frac{c_1}{(1,0)},(1,0)\right),\left(\frac{c_2}{(1,0)},(1,0)\right),\left(\frac{c_3}{(1,0)},(1,0)\right)\right\}$$

$$F_\mu(e_3) = \left\{\left(\frac{c_1}{(1,0)},(1,0)\right),\left(\frac{c_2}{(1,0)},(1,0)\right),\left(\frac{c_3}{(1,0)},(1,0)\right)\right\}$$

Consider F_δ as an IPFFSS over (U, E). The complement of F_δ, represented as $F_\delta^c = G_\rho$ thus $\rho(e) = (\delta(e))^c$ and $G(e) = (F(e))^c$, $\forall e \in E$, where C is an intuitionistic fuzzy complement and $G(e)$ is the Fermatean fuzzy soft complement.

Assume the basic intuitionistic and Fermatean fuzzy soft complements, such that $F_\mu^c = G_\rho$

$$G_\rho = \begin{pmatrix} (0.3,0.5),(0.1,0.7) & (0.1,0.8),(0.2,0.5) & (0.2,0.6),(0.3,0.6) \\ (0.2,0.7),(0.3,0.5) & (0.2,0.6),(0,0.6) & (0.1,0.5),(0.1,0.8) \\ (0,0.9),(0.2,0.6) & (0.1,0.8),(0.1,0.7) & (0.2,0.7),(0.1,0.5) \end{pmatrix}$$

C. Hyperparameter Tuning Process

Thirdly, the parameter adjustment of the IPFNS approach takes place using GOA. GOA is stimulated by swarming behaviors of grasshoppers naturally and these behaviors can be mathematically expressed by [20]:

$$P_i = SO_i + GRE_i + W_i \tag{1}$$

In Eq. (1), P_i refers to the position, GRE_i shows the gravity force, SO_i indicates the power of social interaction, and W_i denotes the wind advection of i^{th} grasshoppers. Note that the metaheuristic algorithm is based on the randomly distributed search agent. Eq. (1) is rewritten to deliver the random behaviors of GOA:

$$P_i = r_1 SO_i + r_2 GRE_i + r_3 W_i \tag{2}$$

In Eq. (2), r_1, r_2, and r_3 are the random integers between $[0,1]$. The force of social interaction in the GOA is the key element of search that can be computed by using Eq. (3):

$$SO_i = \sum_{j=1; j\neq i}^{N} s\left(d_{ij}\right)\widehat{d_{ij}} \tag{3}$$

Now, N refers to the grasshopper count and d_{ij} indicates the Euclidean distance between i^{th} and j^{th} grasshoppers.

$$d_{ij} = \left|P_j - P_i\right| \tag{4}$$

Furthermore, $\widehat{d_{ij}}$ indicates the single vector from i^{th} to j^{th} grasshoppers:

$$\widehat{d_{ij}} = \frac{\left(P_j - P_i\right)}{\left|P_j - P_i\right|} \tag{5}$$

s represents the social force as follows:

$$s = fexp\left(-\frac{r}{l}\right) - \exp(-r) \tag{6}$$

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In Eq. (6), l denotes the intensity of attractive and f represents the attraction length scales. The social interaction among grasshoppers has dual different types of forces viz., attraction and repulsion. The attraction increases within [2.079, 4], along with decreases regularly, while the repulsion rises within [0, 2.079]. The space is considered within [0,15]. When the distance is 2.079, then the area is in the comfort region without force. The f and l values are 0.5, and 1.5, correspondingly.

The gravity force (GRE_i) of i^{th} grasshoppers are described as follows:

$$GRE_i = -g\widehat{e_g} \tag{7}$$

Where the gravitational constant is denoted by g and the unity vector is represented by $\widehat{e_g}$, respectively. The wind advection of i^{th} grasshoppers, W_i, is calculated by:

$$W_i = u\widehat{e_g} \tag{8}$$

In Eq. (8), u denotes the drift constant and $\widehat{e_w}$ represents the unity vector towards the wind. By substituting the value of the aforementioned components ($viz., SO_i, GRE_i$, $\mathrm{W_i}$), Eq. (1) is formulated by:

$$P_i = \sum_{j=1, j\neq i}^{N} s\left(\left|P_j - P_i\right|\right)\frac{\left(P_j - P_i\right)}{\left|P_j - P_i\right|} - g\widehat{e_g} + u\widehat{e_w} \tag{9}$$

Figure 2: Steps involved as GOA

Eq. (8) cannot resolve the optimization problem since the swarming of grasshoppers doesn't converge towards a certain point. Therefore, an enhanced version is considered to attain the optimum solution to problems.

$$P_i^d = c\left(\sum_{j=1, j\neq i}^{N} c\frac{ub_d - lb_d}{2} s\left(\left|P_j^d - P_i^d\right|\right)\frac{\left(P_j - P_i\right)}{\left|P_j - P_i\right|}\right) + \widehat{T_d} \tag{10}$$

In Eq. (10), ub_d and lb_d are the upper and lower boundaries within d^{th} dimension. T_d refers to the d^{th} dimension target. The c parameter converges swarm to the target.

$$c = c_{max} - r\frac{c_{max} - c_{min}}{r_{max}} \tag{11}$$

In Eq. (11), r and r_{mox} are the existing and the maximal iterations correspondingly. c_{max} and c_{min} are the maximum and minimum coefficient value of c correspondingly. The value of c_{max} and c_{min} is 1 and 10^{-5} correspondingly. Fig. 2 depicts the steps involved as GOA.

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The GOA derives a fitness function (FF) to get enhanced classifier performance. It describes a positive integer to suggest the enhanced performance of the candidate solution. In this work, the minimizing of the classification rate of error is measured as FF as set in Eq. (12).

$$fitness(x_i) = ClassifierErrorRate(x_i)$$
$$= \frac{No.\ number\ of\ misclassified\ samples}{Total\ no. of\ samples} * 100 \quad (12)$$

4. Experimental Validation

In this section, the predictive performance of the FMSP-IPFNS technique is examined utilizing 8 company shares.

In Table 1 and Fig. 3, the comparative study of the FMSP-IPFNS system in terms of SMAPE is given [21]. The results indicate that the KNN and LR models have reached poor performance with maximum SMAPE values. At the same time, the SVR and DTR models have shown moderately reduced SMAPE values. Although the LSTM model reaches considerable SMAPE values, the FMSP-IPFNS technique outperforms others with the least SMAPE values. On the axis bank, the FMSP-IPFNS technique demonstrates least SMAPE of 1.18 while the KNN, LR, SVR, DT, and LSTM models have attained increased SMAPE of 16.97, 10.37, 5.64, 8.48, and 1.88, respectively.

Table 1: SMAPE analysis of FMSP-IPFNS technique with existing models under various parameter

Parameters	SMAPE (Symmetric Mean Absolute Percentage Error)					
Classifiers	KNN	LR	SVM	DTR	LSTM	FMSP-IPFNS
Axis	16.67	10.37	5.64	8.48	1.88	1.18
HDFC	20.46	11.00	6.22	12.56	2.19	1.50
ICICI	14.45	8.92	7.02	7.37	2.31	1.52
Kotak	12.44	10.51	5.81	10.26	1.43	0.67
Maruti	15.92	11.13	3.09	13.92	1.32	0.67
Tata Steel	16.08	13.10	5.75	8.06	1.75	1.01
TCS	15.84	9.95	4.41	10.05	1.40	0.90
Titan	12.90	3.50	3.33	11.39	1.06	0.40
Average	15.60	9.81	5.16	10.26	1.67	0.98

In Fig. 4 the average SMAPE results of the FMSP-IPFNS technique with compared approaches are given. The figure illustrates that the FMSP-IPFNS system gains improved performance with the least average SMAPE of 0.98 while the KNN, LR, SVR, DT, and LSTM models have shown higher average SMAPE of 15.60, 9.81, 5.16, 10.26, and 1.67, correspondingly.

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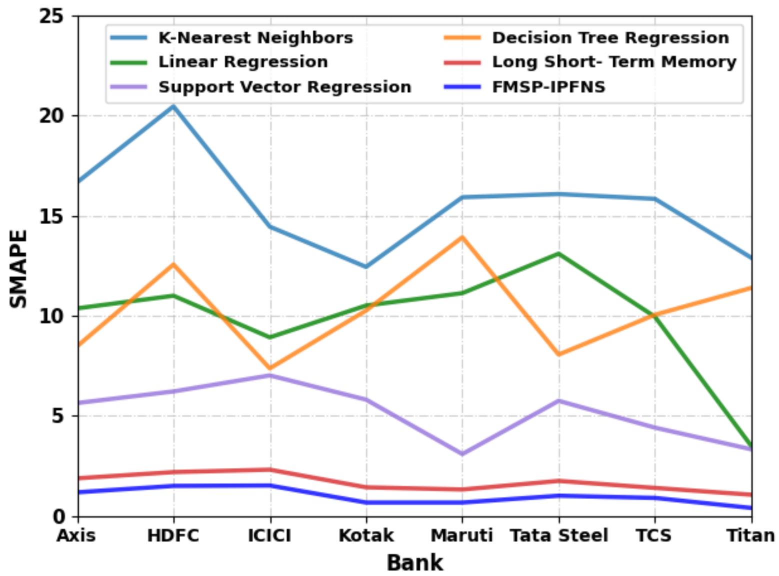

Figure 3. SMAPE analysis of FMSP-IPFNS technique under various parameter

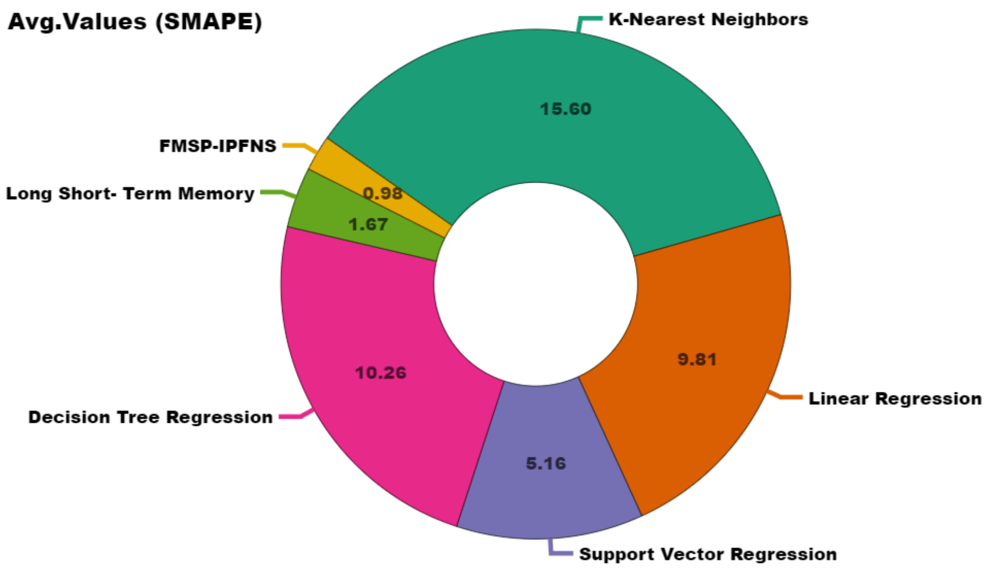

Figure 4: Average SMAPE of FMSP-IPFNS technique with existing models

In Table 2 and Fig. 5, the comparative study of the FMSP-IPFNS system in terms of MSE is given. The outcomes show that the KNN and LR techniques have poor performance with the highest MSE values. Simultaneously, the SVR and DTR systems have revealed moderately reduced MSE values. While the LSTM method gets considerable MSE values, the FMSP-IPFNS system outperforms others with the smallest MSE values. On the axis bank, the FMSP-IPFNS technique shows a minimum MSE of 202.21 while the KNN, LR, SVR, DT, and LSTM techniques have achieved bigger MSE of 2247.71, 3603.60, 4386.41, 2366.82, and 248.69, respectively.

Table 2: MSE analysis of FMSP-IPFNS technique with existing models under various parameter

Parameters	MSE (Mean Square Error)				
Classifiers	KNN	LR	SVM	DTR	LSTM	FMSP-IPFNS
Axis	2247.71	3603.60	4386.41	2366.82	248.69	202.21

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HDFC	4377.15	4015.76	2918.16	3479.82	1275.20	1168.96
ICICI	2520.04	2434.44	1513.21	2470.09	258.89	207.07
Kotak	2491.01	2501.00	1726.40	2799.47	1212.43	1100.25
Maruti	7177.48	5422.85	470.89	3996.77	167.44	125.89
Tata Steel	4923.83	2526.07	2935.47	5050.94	519.84	444.37
TCS	4506.44	3100.26	3450.39	1948.34	933.91	839.84
Titan	3176.45	3646.95	2549.24	598.29	433.89	373.26
Average	3927.51	3406.37	2493.77	2838.82	631.29	557.73

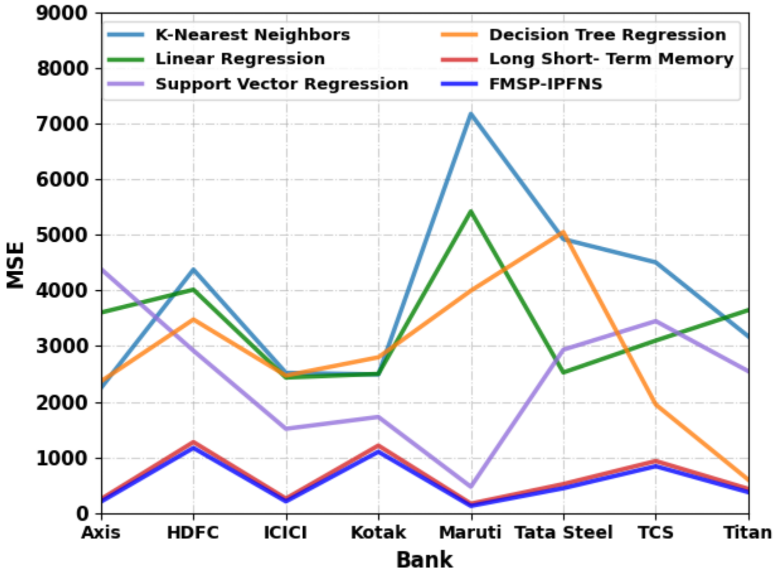

Figure 5: MSE analysis of FMSP-IPFNS technique under various parameter

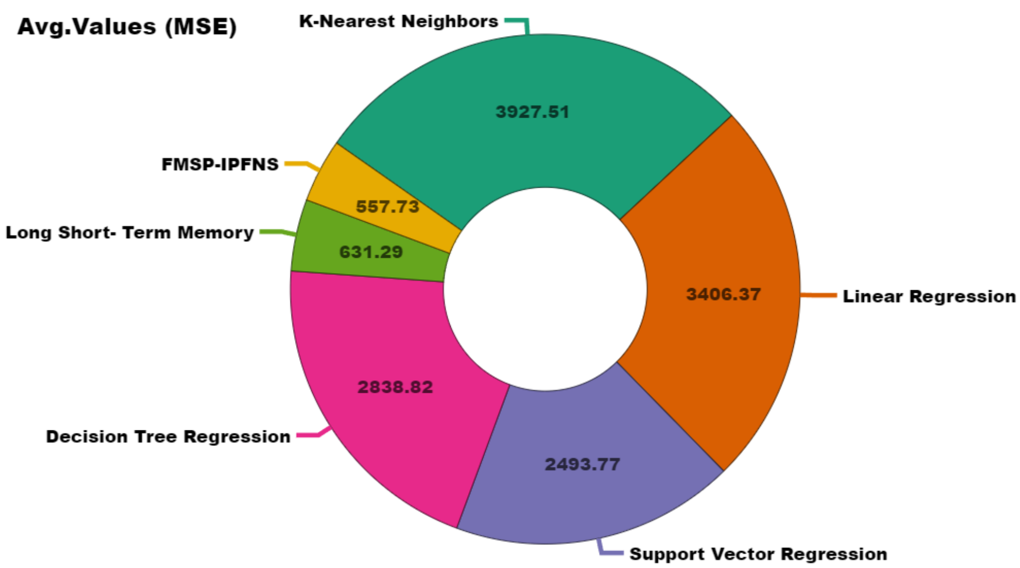

Figure 6: Average MSE of FMSP-IPFNS technique with existing models

In Fig. 6 the average MSE outcomes of the FMSP-IPFNS system with equated techniques are given. The figure shows that the FMSP-IPFNS system attains better performance with the smallest average MSE of 557.73 whereas

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the KNN, LR, SVR, DT, and LSTM approaches have shown greater average MSE of 3927.51, 3406.37, 2493.77, 2838.82, and 631.29, respectively.

In Table 3 and Fig. 7, the comparative study of the FMSP-IPFNS system in terms of RMSE is given. The outcomes specify that the KNN and LR methods have poor performance with the highest RMSE values. While, the SVR and DTR approaches have shown moderately decreased RMSE values. Although the LSTM model reaches considerable RMSE values, the FMSP-IPFNS technique outperforms others with minimum RMSE values. On the axis bank, the FMSP-IPFNS system establishes the smallest RMSE of 14.22 whereas the KNN, LR, SVR, DT, and LSTM approaches have achieved increased RMSE of 47.41, 60.03, 66.23, 48.65, and 15.77, correspondingly.

Table 3: RMSE analysis of FMSP-IPFNS model with existing models under various parameter

Parameters	RMSE (Root Mean Square Error)					
Classifiers	KNN	LR	SVM	DTR	LSTM	FMSP-IPFNS
Axis	47.41	60.03	66.23	48.65	15.77	14.22
HDFC	66.16	63.37	54.02	58.99	35.71	34.19
ICICI	50.20	49.34	38.90	49.70	16.09	14.39
Kotak	49.91	50.01	41.55	52.91	34.82	33.17
Maruti	84.72	73.64	21.70	63.22	12.94	11.22
Tata Steel	70.17	50.26	54.18	71.07	22.80	21.08
TCS	67.13	55.68	58.74	44.14	30.56	28.98
Titan	56.36	60.39	50.49	24.46	20.83	19.32
Average	61.51	57.84	48.23	51.64	23.69	22.07

In Fig. 8 the average RMSE results of the FMSP-IPFNS approach with compared models are given. The figure demonstrates that the FMSP-IPFNS system attains better performance with the smallest average RMSE of 22.01 whereas the KNN, LR, SVR, DT, and LSTM techniques have shown greater average RMSE of 61.51, 57.84, 48.23, 51.64, and 23.07, correspondingly.

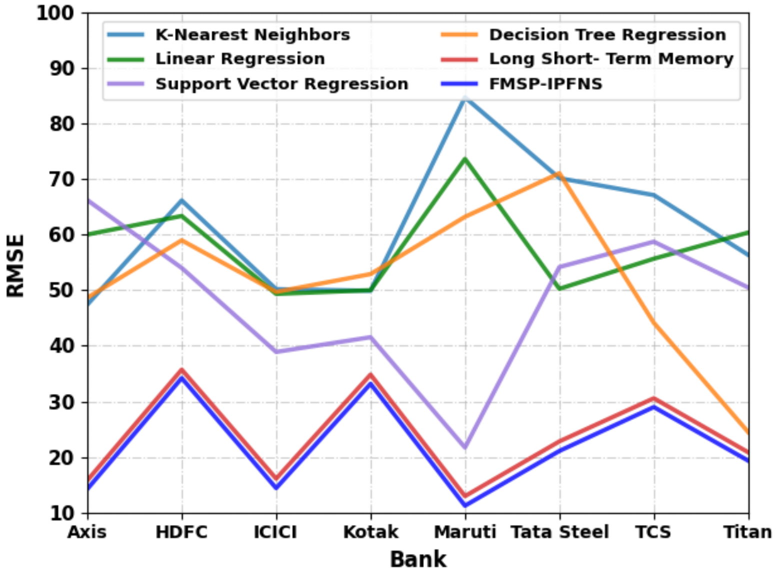

Figure 7: RMSE analysis of FMSP-IPFNS technique under various parameter

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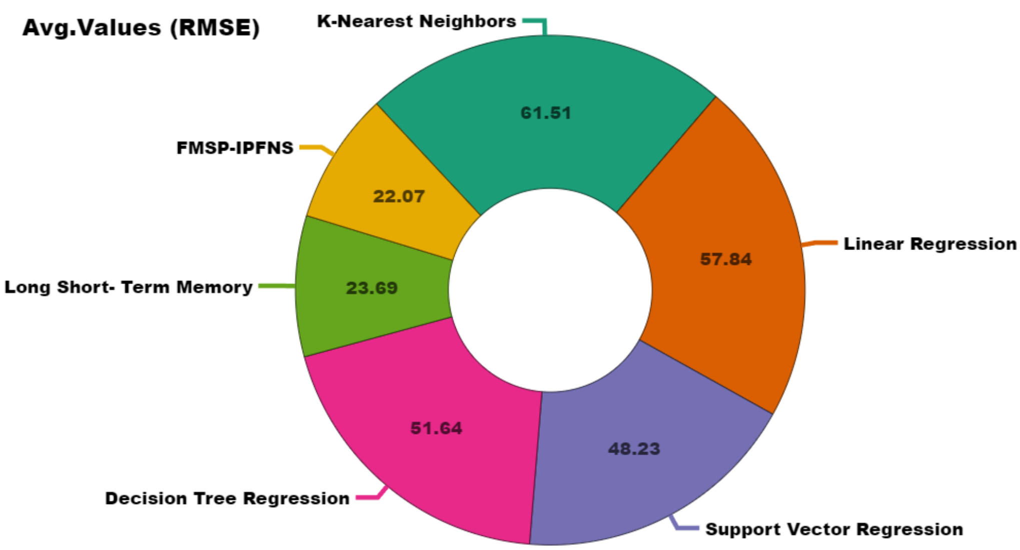

Figure 8: Average RMSE of FMSP-IPFNS technique with existing models

Therefore, the FMSP-IPFNS technique can be employed for enhanced prediction processes in the financial market shares.

5. Conclusion

In this manuscript, we offer the design of the FMSP-IPFNS technique. In the FMSP-IPFNS model, a 3-stage approach is followed data normalization, prediction process, and hyperparameter tuning process. Firstly, the data normalization process gets executed using the min-max scalar approach. Secondly, the prediction process can be carried out using the IPFNS approach. Thirdly, the parameter adjustment of the IPFNS approach takes place using GOA. To validate the performance of the FMSP-IPFNS technique, a sequence of experimentations were tested. The obtained values demonstrate the promising results of the FMSP-IPFNS system compared to other models.

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