Economic Affairs, Vol. **69**(04), pp. 1671-1681, December 2024
DOI: 10.46852/0424-2513.5.2024.17

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RESEARCH PAPER

Intuitionistic Fuzzy Based Machine Learning Models for Prediction of the Oilseed Prices

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Received: 13-09-2024 **Revised:** 12-11-2024 **Accepted:** 29-11-2024

ABSTRACT

Oilseed prices are inherently volatile and uncertain, making accurate predictions is important for the stakeholders. In time series forecasting, fuzzy techniques have proven effective for managing complex and uncertain datasets. This study introduces an innovative approach to predicting oilseeds prices by developing intuitionistic fuzzy based machine learning models. The model integrates intuitionistic fuzzy logic with stochastic and advanced machine learning techniques to enhance predictive accuracy. The main objective is to assess how this integration improves prediction accuracy, focusing on monthly wholesale prices of Sunflower from various markets in Karnataka, covering the period from January 2010 to June 2024 from the AGMARKNET portal (https://agmarknet.gov.in/). Comparative analysis with traditional models demonstrated the superior performance of the intuitionistic fuzzy based models, particularly in reducing prediction errors and accurately capturing market trends. This research underscores the potential of integrating fuzzy logic into machine learning frameworks, offering a valuable tool for stakeholders in agricultural economics and commodity trading.

HIGHLIGHTS

- A study investigated the impact of using fuzzy logic to manage uncertainty.
- A new method for combining machine learning (ML) models with intuitionistic fuzzy logic is proposed.
- A comparison between fuzzy-based ML and traditional models is conducted.
- The prediction of monthly wholesale sunflower prices shows significant improvement.

Keywords: Artificial neural network, Autoregressive integrated moving average, Fuzzy C- means clustering, Support vector regression

The oilseeds sector has been one of the most important components of global agriculture over the past three decades, expanding at an annual rate of 4.1%, surpassing the growth of agriculture and livestock products. On the domestic front, the performance of oilseeds over the last two decades has been remarkable, enduring adverse weather conditions, global price fluctuations, and increasing domestic demand. The annual growth rates for oilseed crops from 1999 to 2009 have decreased compared to the period from 1986 to 1998. Specifically, the growth rates for area, production, and yield were 2.44%, 5.4%, and 2.96% respectively, whereas from 1986 to 1998, these rates

How to cite this article: Sarkar, A., Yeasin, Md., Paul, R.K., Mandal, B., Arti, Singh, A.K. and Paul, A.K. (2024). Intuitionistic Fuzzy Based Machine Learning Models for Prediction of the Oilseed Prices. *Econ. Aff.*, **69**(04): 1671-1681.

Source of Support: None; **Conflict of Interest:** None

were 3.05%, 6.36%, and 3.73%. India's vegetable oil economy is the fourth largest in world, following the USA, China, and Brazil. Oilseeds contributes for 13% of the gross cropped area, 3% of the Gross National Product (GNP), and 10% of the value of all agricultural commodities. The growth of oilseeds production in India is discussed in detail by Kaushik (1993). There are two major sources of oilseeds: primary and secondary. The main crop of oilseeds under edible group are Groundnut, Rapeseed (Toria, Mustard, and Sarson), Soybean, Sunflower, Sesame, Safflower, and Niger, and under the non-edible group are Castor and Linseed (Directorate of Oilseeds Development, Ministry of Agriculture and Farmers Welfare, Government of India (oilseeds.dac.gov.in/)). Oilseed crops are essential for achieving various Sustainable Development Goals (SDGs) by promoting economic growth, food security, and environmental sustainability. They offer vital nutrients and income to millions of smallholder farmers, thereby aiding in the reduction of poverty (SDG 1) and hunger (SDG 2). The cultivation of oilseed crops enhances health (SDG 3) by improving dietary quality and generating employment, thus boosting economic growth (SDG 8). Therefore, the current study aims to forecast oilseed prices, enabling stakeholders to make informed decisions, including government policy formulation and farmer planning, to stabilize markets and enhance production efficiency, as the accurate forecasts are crucial for effective risk management and optimizing resource allocation.

Precise prediction of events and phenomena is crucial in our daily lives, aiding in better decision-making under uncertain conditions. Modeling temporal price series enables the extraction of valuable features from the data and allows for the extrapolation of the series into the future based on this information (Paul and Bhardwaj, 2016). Numerous stochastic processes employ to model and forecast a specific series. Since the 1930s, the well-known Autoregressive Integrated Moving Average (ARIMA) model by Box and Jenkins (2007) methodology has been a dominant approach in time series analysis. In agricultural data, numerous applications of the linear and nonlinear time series model are well-documented in the literature (Bhardwaj *et al*. 2014; Paul, 2015; Jadhav *et al*. 2017; Noureen *et al*. 2019; Rakshit *et al*. 2021; Mapuwei *et al*. 2022). ARIMA and its component models have become particularly popular for modeling linear dynamics and providing linear forecasts. Various econometric and hybrid model are applied in this field to improve the price prediction (Mitra *et al.* 2017; Paul *et al.* 2015). However, oilseed price prediction is complex due to frequent fluctuations, instability, and cyclical patterns. Intelligent prediction methods, with their adaptive, self-learning, and self-organizing capabilities, are well suited to these market characteristics and increasingly used for price forecasting. These methods include artificial neural networks, chaos theory, extreme learning machines, radial basis functions, and support vector regression. Paul *et al.* (2022) proposed support vector regression (SVR) based machine learning (ML) for agricultural price forecasting. Jena *et al.* (2023) focused on constructing a low-complexity, adaptive Artificial Neural Network (ANN) based model for crop yield prediction. Several authors (Paul *et al*. 2023; Mohanty *et al*. 2023; Mantaw *et al*. 2023; Chelliah *et al*. 2024) in the literature have explored the performance of machine learning models for price forecasting in agriculture. Predicting precise future values is challenging due to the inherent uncertainty and nonlinearity of most real-world phenomena. However, accurately forecasting future linguistic terms related to a phenomenon is often enough for informed decision-making. For instance, in stock market investments, knowing the linguistic terms associated with future stock values, such as increase, decrease, significant increase, and significant decrease, is sufficient for making appropriate decisions. Consequently, over the past twenty-five years, fuzzy time series forecasting (FTSF) (Song and Chissom, 1993) methods have garnered consistent interest from researchers across various disciplines. FTSF techniques circumvent the fundamental assumptions inherent in traditional time series forecasting (TSF) methods. The FTSF approach is composed of four key stages: determining the effective length of intervals, fuzzifying the crisp time series data, modeling fuzzy logical relationships (FLRs), and defuzzifying. Each of these stages is crucial for enhancing the accuracy of forecasting. There have been only a few studies (Zhang and Na, 2018; Hegde *et al*. 2023; Dash *et al*. 2024) conducted on forecasting agricultural price systems using fuzzy time series models. Fatih (2022) provided a comprehensive review of fuzzy logic and fuzzy time series models, focusing on their practical application in estimating and forecasting monthly international coffee prices. Atanassov (1986) expanded the Zadeh's (1965) fuzzy sets theory by introducing the intuitionistic fuzzy set theory, which incorporates additional levels of uncertainty and hesitancy. This extension allows for the representation of not only membership degrees but also non-membership degrees and a degree of hesitation, thus effectively capturing the uncertainty and indecision commonly encountered in real-world situations. Dwivedi *et al.* (2023) proposed intuitionistic fuzzified time-series predicting approach employing deep fuzzy logical relationships.

The incorporation of fuzzy logic into time series forecasting introduces a new approach to model construction. This research combines fuzzy logic with ML models to address uncertainties in oilseed price forecasting. The primary objective of this paper is to evaluate and compare the predictive capabilities of efficient fuzzy based ML algorithms with traditional stochastic models. Therefore, fuzzy based ARIMA, SVR, and ANN models, referred to as FuzzyARIMA, FuzzySVR, and FuzzyANN, are developed for forecasting oilseed crop prices. To assess the performance of these proposed models, sunflower price data from various markets in Karnataka is used, employing statistical measures such as root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE).

The structure of this article is as follows: Section 2 provides model descriptions. Section 3 focuses on the development of proposed fuzzy-based models. In Section 4, an empirical analysis is presented, including the prediction of Sunflower price indexes and a performance comparison between the fuzzy-based model and existing models. Finally, Section 5 offers a summary of conclusions and suggests directions for future research.

Model descriptions

AutoRegressive Integrated Moving Average (ARIMA) model

The ARIMA model, widely used in time series forecasting and analysis, integrates autoregressive (AR) and moving average (MA) components with differencing to enhance predictability in non-stationary time series data. It is denoted as ARIMA (P, D, Q), where P is the autoregressive order, D represents the degree of differencing, and Q denotes the moving average order. Estimating model parameters involves using statistical techniques such as autocorrelation and partial autocorrelation analysis. The ARIMA model can be expressed as shown in equation (1).

$$y_t = a + a_1 y_{t-1} + a_2 y_{t-2} + \ldots + a_p y_{t-P} + \varepsilon_t - b_1 \varepsilon_{t-1} - b_2 \varepsilon_{t-2} - \ldots - b_q \varepsilon_{t-Q} \quad \ldots(1)$$

where, y_t is the D times differenced times series data at time $t(\in N)$; a is constant; ε_t is the residual term with zero mean and constant variance; $a_1\ y_{t-1} + a_2\ y_{t-2} + \ldots + a_p\ y_{t-P}$ is the AR part; and $\varepsilon_t - b_1\ \varepsilon_{t-1} - b_2\ \varepsilon_{t-2} - \ldots - b_q\ \varepsilon_{t-Q}$ is the MA part.

Support vector regression (SVR)

Given a training dataset $T = \{(y_1, x), (y_2, x_2), \ldots, (y_N, x_N)\}$, where y_t ($t = 1,2,\ldots,N$) represents a vector of real independent variables and x_t ($t = 1,2,\ldots,N$) denotes the corresponding scalar real dependent variable, the regression equation in the feature space can be expressed by,

$$S(y, w) = (w \cdot \emptyset(y) + \varepsilon) \quad \ldots(2)$$

where, w is the weight vector, ε is a constant, and $\emptyset(y)$ is the feature function. To obtain the weights minimize the following objective function:

$$q(\zeta) = \frac{1}{2}\|w\|^2 + \zeta \frac{1}{N} L_\varepsilon\big(x, S(y,w)\big) \quad \ldots(3)$$

where, the loss function L_ε (x, $S(y,w)$) is defined as;

$$L_\varepsilon\big(x, S(y,w)\big) = \begin{cases} 0, & if\ |x - S(y,w)| \le \varepsilon \\ |x - S(y,w)| - \varepsilon, & otherwise \end{cases} \quad \ldots(4)$$

The Equation (3) represents the empirical error, and ζ balances the trade-off between the empirical error and the model complexity indicated by the Equation (4) introduces the ε-insensitive loss function.

Artificial Neural Network (ANN) model

Neural network systems have been extensively used to address various forecasting challenges over the past few decades. The fundamental principle behind the use of ANNs is based on learning theory (Valiant, 1984). This learning process involves providing the system with input datasets and their corresponding target values, enabling it to identify underlying patterns and iteratively adjust internal parameters to generate accurate results. ANNs mimic the learning process of the human brain and can effectively handle non-linear data, which is often found in price datasets. Consequently, ANNs are particularly well-suited for accurately modeling such non-linear oilseeds price data. The numerical operation of a neuron can be represented by the formula given in equation (5).

$$y = \varphi(\sum_{t=1}^{N} \omega_t \, x_t + \eta) \qquad \ldots(5)$$

where y represents the neuron's output, x_t ($t = 1,2,\ldots, N$) are the input values, ω_t are the weights associated with each input, influencing their impact on the output, η is the bias term, which can be added to the weighted sum of inputs, and φ denote the activation function.

Intuitionistic Fuzzy Based Machine Learning Models

Intuitionistic fuzzy time series (IFTS)

Unlike FTS approaches that depend solely on membership functions, IFTS systems incorporate both membership and non-membership variables to establish fuzzy relationships. As a result, IFTS systems generally use more data compared to the FTS technique. Utilizing IFTS modeling enhances predictive capabilities for addressing real world time series problems. If A is the universal set and A_1, A_2, …, A_c are the IF sets defined on A and y_t; (t∈N), represents the time series with membership and non-membership values of A_1, A_2, …, A_c are $m_{A1}(t)$, m_{A2} (t),…, $m_{Ac}(t)$ and $n_{A1}(t)$, $n_A(t)$,…,nA_{c} $_{(t)}$ respectively. Then According to IFTS can be represent as (Egrioglu *et al*. 2019);

$$I_t = \{y_t, m_{A1}(t), m_{A2}(t), \ldots, m_{Ac}(t), n_{A1}(t), n_{A2}(t), \ldots, n_{Ac}(t)\} \qquad \ldots(6)$$

Intuitionistic fuzzy C-means (IFCM) algorithm

The study utilizes IFCM during the fuzzification phase of the proposed method. The IFCM process is outlined as;

Step 1: If is the value of time series in i^{th} cluster. The membership value for the t^{th} observation from the i^{th} cluster is formulated using the given equation (7).

$$\mathfrak{m}_{it} = \frac{u_{it}}{\sum_{i=1}^{c} u_{it}} \qquad \ldots(7)$$

where, u_{it} ($i = 1,2,\ldots,c$; $t = 1,2,\ldots ,N$) ~ $U(0,1)$..

Step 2: Using the membership values generated at step 1, intuitionistic fuzzy membership values (m_{ik}*) are obtained using equation (8) which are saved into a matrix;

$$\mathfrak{m}_{it}^{*} = \mathfrak{m}_{it} + h_{it} \qquad \ldots(8)$$

where, h_{it} is the hesitation degree and calculated as;

$$h_{it} = 1 - \mathfrak{m}_{it} - \left((1 - \mathfrak{m}_{it}^{\alpha})\right)^{1/\alpha} \qquad \ldots(9)$$

And non-membership values are obtained by equation (10);

$$\mathfrak{n}_{it} = 1 - \mathfrak{m}_{it}^{*} \qquad \ldots(10)$$

The hesitation degree refers to the level of uncertainty or ambiguity associated with assigning a data point to a specific cluster. It quantifies how unclear the clustering process is by indicating the extent to which a data point could potentially belong to multiple groups. A higher hesitation degree for a data point indicates greater uncertainty in its assignment to a cluster.

Step 3: Cluster centres are obtained by equation (11).

$$c_i^{*} = \frac{\sum_{t=1}^{N} (\mathfrak{m}_{it}^{*})^{\alpha} y_t}{\sum_{t=1}^{N} (\mathfrak{m}_{it}^{*})^{\alpha}} \; ; i = 1,2,\ldots,c \qquad \ldots(11)$$

where, α is the index of fuzziness.

Step 4: The membership values (m_{it}) generated from equation (7) are modified by equation (12) and are saved as m_{new}.

$$\mathfrak{m}_{it} = \frac{1}{\sum_{j=1}^{c} \left(\frac{l_{it}}{l_{jt}}\right)^{2/(\alpha-1)}} \qquad \ldots(12)$$

where, l_{it} is calculated by;

$$l_{it} = \sqrt{(y_t - c_i^*)^2} \quad \ldots(13)$$

Step 5: If $m_{new} = m_{old}$, proceed to step 3 and repeat the aforementioned process. If the difference between the new value of (m_{new}) and the old value of (m_{old}) is less than a small positive number *i.e.*, if $m_{new} - m_{old} < \varepsilon$ then the algorithm stops.

Step 6: Using the modified membership values, final intuitionistic fuzzy membership values, hesitation degree, and non- membership values are calculated using modified membership values by equation (8), (9), and (10).

The steps described above are illustrated in Fig. 1.

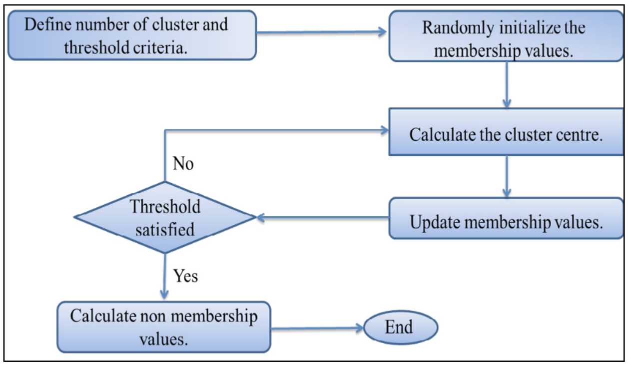


Fig. 1: The flow chart of IFCM algorithm

Fuzzy ARIMA Model

The Intuitionistic fuzzy based Autoregressive Integrated Moving Average (Fuzzy ARIMA) Model integrates fuzzy logic with the conventional ARIMA model to enhance time series forecasting. By employing fuzzy set theory, it addresses data uncertainty through fuzzy membership and non-membership functions. This fusion enhances the ARIMA model's ability to predict complex patterns in time series data, enabling more accurately forecasts in real-world scenarios. Equation (14) depicts the mathematical formulation of the Fuzzy ARIMA model.

$$y_t = a + a_1 y_{t-1} + ay_{t-2} + \ldots + a_P y_{t-P} + \varepsilon_t - b_1 \varepsilon_{t-1} - b_2 \varepsilon_{t-2} - \ldots - b_Q \varepsilon_{t-Q} + mm + nn \quad \ldots(14)$$

where, m and n are the membership and nonmembership vector respectively calculated by IFCM algorithm and m and n are the coefficient vectors respectively. In the Fuzzy ARIMA model, initial steps involve converting crisp input sequences into fuzzy sequences using Fuzzy IFCM. The lag values, along with their corresponding membership and non-membership values are then fitted using the proposed model to obtain predicted values. The initial order of the ARIMA model was determined based on the patterns observed in the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The best-fitting ARIMA model is selected using information criteria such as the Akaike Information Criterion (AIC), and Schwartz Bayesian Criterion (SBC). The structure of the proposed Fuzzy ARIMA model is illustrated in Fig. 2.

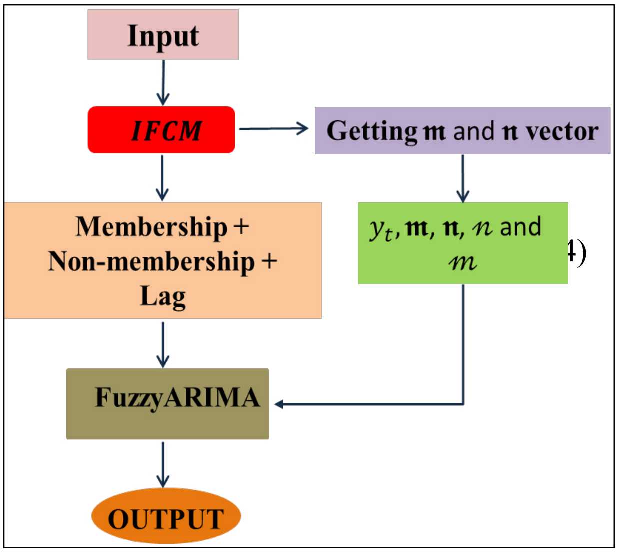


Fig. 2: The architecture of FuzzyARIMA model

Fuzzy ML model

The intuitionistic fuzzy based ML model integrates fuzzy logic with machine learning techniques for time series forecasting. This approach incorporates fuzzy set theory to handle data uncertainty through membership and non-membership functions. The study considers two popular ML models, SVR and ANN. This integration enhances the predictive capability of SVR and ANN models, enabling them to capture complex patterns in time series data and provide accurate forecasts in real-world scenarios characterized by significant uncertainty. The inputs for this model include lag values, membership, and non-membership values computed using the IFCM algorithm, alongside the time series data. The structure of the proposed Fuzzy ML model is illustrated in Fig. 3. The Fuzzy ANN and Fuzzy SVR models are trained by optimizing both parameters and hyper-parameters.

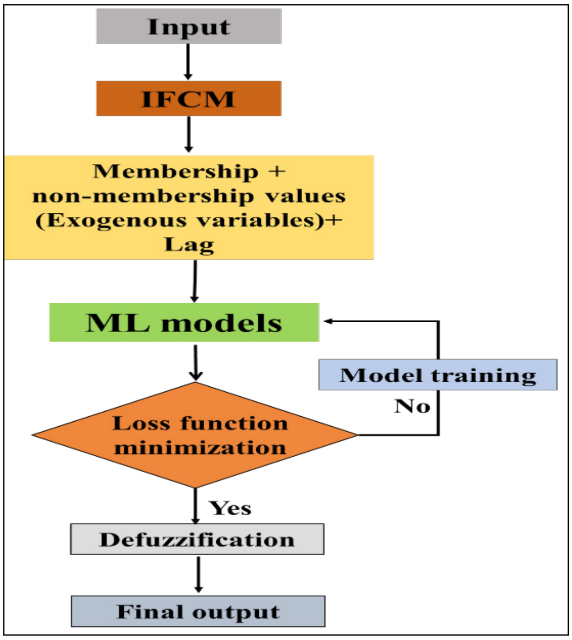


Fig. 3: Architecture of the Fuzzy ML model.

RESULTS AND DISCUSSION

Dataset

Monthly wholesale price data of Sunflower during the period January 2010 to June 2024 has been collected from six different markets (Mundragi, Bellary, Gadag, Rennebenur, Lingasugur, and Kushtagi) in Karnataka, India, from the AGMARKNET portal (https://agmarknet.gov.in/). This portal is managed by the Directorate of Marketing and Inspection, Government of India. Prior to analysis, missing observations in the dataset were imputed using appropriate statistical techniques.

Data description

Table 1 provides a summary of the overall statistics for the Sunflower price data from different markets in Karnataka. Analysing Table 1 shows that the average price is highest in the Lingasugur and Bellary market and lowest in the Gadag market over the study period. Kurtosis values indicate a platykurtic distribution across all markets, with generally lower kurtosis observed. The variability in the price series, as represented by the coefficient of variation (CV), ranges from a minimum of 28.12% in Gadag to a maximum of 32.01% in the Lingasugur market. Fig. 4 presents a graphical overview of Sunflower price data throughout the study period across various markets in Karnataka, offering insights into the supply and demand dynamics where dates are on the horizontal axis and prices on the vertical axis. The box plot and the density plot have been depicted in Fig. 4.

The monthly wholesale price dataset consisting of 174 data points, is divided into training and testing sets with 80:20 ratio. The training set includes the first 142 months of observations, used for model development, while the remaining 32 months has been used for evaluating the accuracy of the intuitionistic fuzzy based models. For implementing intuitionistic fuzzy logic, the number of clusters in the IFCM algorithm is set to 5 determined using

Table 1: Summary statistics of the monthly prices of Sunflower for the different markets in Karnataka

Descriptive Statistics	Mundragi	Bellary	Gadag	Rennebenur	Lingasugur	Kushtagi
Mean	3840.07	3904.39	3633.54	3719.29	3907.34	3887.52
Standard Error	82.96	84.23	77.45	84.90	94.81	85.69
Median	3525.75	3547.00	3378.95	3301.88	3306.38	3516.31
Mode	4538.00	3563.00	3200.00	3250.00	3300.00	3300.00
Standard Deviation	1094.33	1111.07	1021.58	1119.89	1250.61	1130.29
Kurtosis	1.03	1.00	1.22	1.99	0.18	0.35
Skewness	1.21	1.24	1.32	1.59	1.06	1.02
Range	5783.90	5228.60	4599.34	5406.67	5765.00	5140.00
Minimum	1666.33	2171.00	2024.76	2333.33	1925.00	1960.00
Maximum	7450.24	7399.60	6624.11	7740.00	7690.00	7100.00
Coefficient of Variation (CV %)	28.50	28.46	28.12	30.11	32.01	29.07

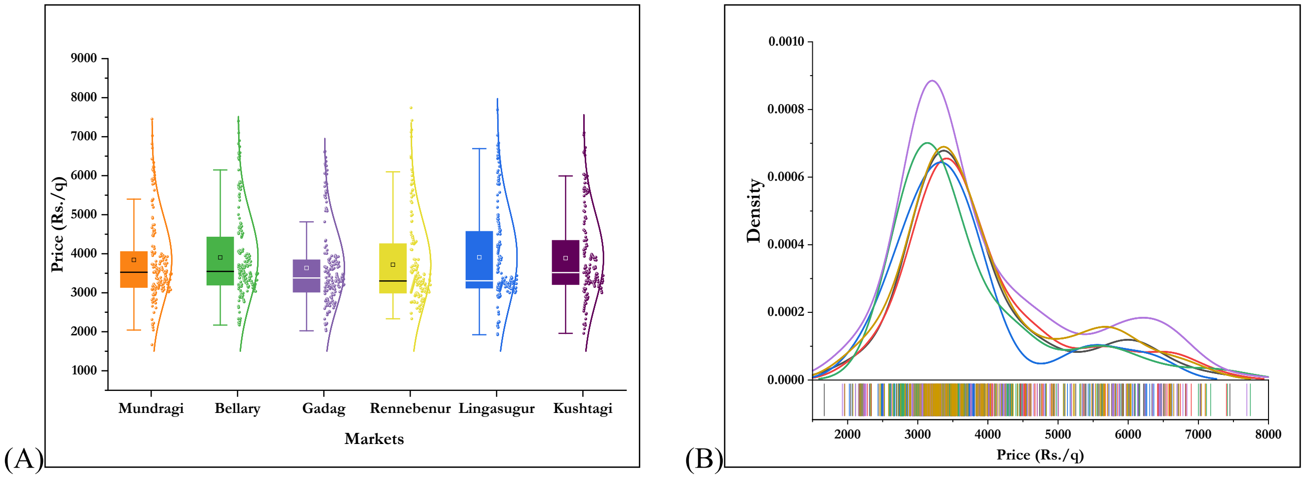


Fig. 4: Box and density plot of monthly wholesale price of Sunflower for different markets

the Elbow method. The dataset is subjected to stochastic models, specifically ARIMA, as well as machine learning techniques like SVR and ANN. The dependency of the current price has considered up to 12 lags for all markets. The accuracy of the proposed models has been compared using following accuracy measures:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(X(t) - \hat{X}(t)\right)^2} \qquad \ldots(15)$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{X(t)-\hat{X}(t)}{X(t)}\right| \qquad \ldots(16)$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|X(t) - \hat{X}(t)\right| \qquad \ldots(17)$$

Where, N is the number of observations, $X(t)$ is the observed value, and $\hat{X}(t)$ is the predicted value in the test data set. A model has considered effective when it produces lower values for RMSE, MAPE, and MAE.

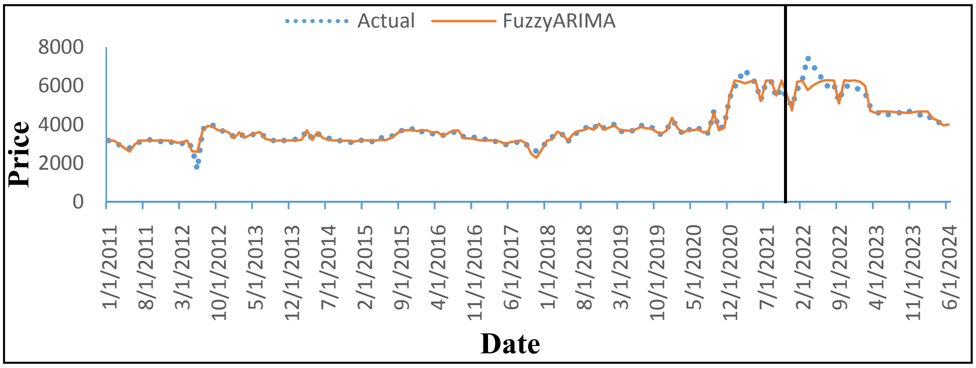
Table 2 shows that intuitionistic fuzzy based models significantly outperform conventional models across all markets. Specifically, FuzzyARIMA outperformed other stochastic, ML, and fuzzy based models in every market with RMSE values ranging between 131.94 (Gadag) to 237.84 (Lingasugur); MAPE values between 0.02 (Rennebenur) to 0.05 (Bellary); and MAE values between 104.71 (Rennebenur) to 218.36 (Bellary). A detailed analysis of Table 2 reveals that, based on RMSE values, Fuzzy ARIMA performed the best in the Mundragi and Gadag markets, having the lowest RMSE values, followed by FuzzyANN, FuzzySVR, SVR, ARIMA, and ANN, respectively. In other markets, FuzzyARIMA again performed the best, followed by FuzzySVR, FuzzyANN, SVR, ARIMA, and ANN, respectively. For MAPE values, FuzzyARIMA performed the best in the Mundragi, Gadag, Rennebenur, and Lingasugur markets, followed by FuzzyANN, FuzzySVR, SVR, ARIMA, and ANN. In the Bellary market, FuzzyARIMA, FuzzySVR, and FuzzyANN performed almost equally well, followed by SVR, ARIMA, and ANN. For the Kushtagi market, FuzzyARIMA performed best, followed by FuzzySVR, SVR, FuzzyANN, ARIMA, and ANN. Regarding MAE values, FuzzyARIMA performed the best in the Mundragi and Gadag markets, followed by FuzzyANN, FuzzySVR, SVR, ARIMA, and ANN. In the Bellary market, FuzzyANN performed the best, followed by FuzzySVR, FuzzyARIMA, SVR, ARIMA, and ANN. For the Rennebenur, Lingasugur, and Kushtagi markets, FuzzyARIMA again performed best, followed by FuzzySVR, FuzzyANN, SVR, ARIMA, and ANN. Therefore, it can be said that incorporating intuitionistic fuzzy logic into stochastic and machine learning techniques can improve the prediction accuracy of various forecasting models.

The line plots of actual and fitted values obtained from the best fitted model have been depicted in Fig. 5. In the figure, the vertical line denotes the division of training and testing sets.

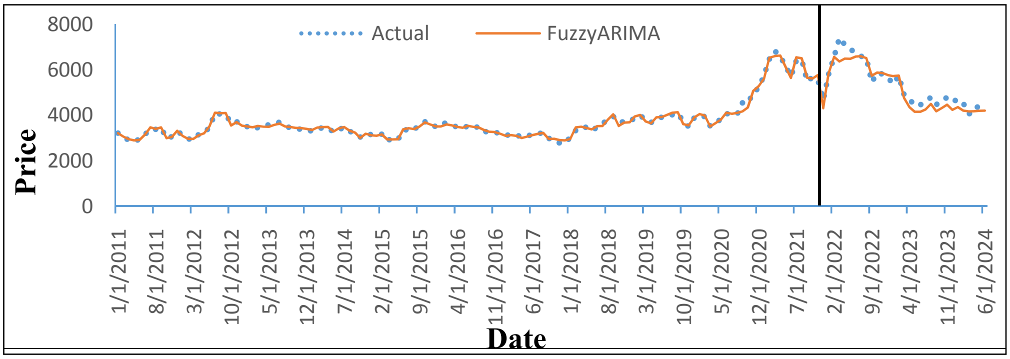
Table 2: Validation of different models for predicting Sunflower prices

Model	ARIMA	SVR	ANN	FuzzyARIMA	FuzzySVR	FuzzyANN
Metrices				**Mundragi**		
RMSE	1327.66	642.52	2058.69	162.5	292.609	233.282
MAPE	0.29	0.14	0.42	0.03	0.06	0.05
MAE	1300.00	628.27	1850.46	132.69	265.14	201.88
				Bellary		
RMSE	1193.57	723.416	2031.9	233.466	243.762	262.517
MAPE	0.26	0.15	0.41	0.05	0.05	0.04
MAE	1173.27	689.58	1873.10	218.36	206.56	205.15
				Gadag		
RMSE	821.39	616.79	1967.68	131.94	331.22	194.19
MAPE	0.20	0.14	0.45	0.03	0.08	0.04
MAE	771.99	524.7	1740.43	108.45	295.81	161.45
				Rennebenur		
RMSE	1206.79	671.42	2386.65	144.53	239.33	371.93
MAPE	0.27	0.15	0.48	0.02	0.05	0.08
MAE	1179.68	650.37	2113.35	104.71	208.58	363.38
				Lingasugur		
RMSE	1404.7	637.79	1752.55	237.85	357.23	1084.49
MAPE	0.28	0.13	0.33	0.04	0.07	0.20
MAE	1337.36	629.11	1568.72	200.43	325.87	971.96
				Kushtagi		
RMSE	1029.31	435.30	1988.32	214.58	383.96	517.62
MAPE	0.20	0.08	0.38	0.04	0.07	0.10
MAE	918.03	373.07	1756.60	203.33	332.60	481.84

Mundragi



Bellary



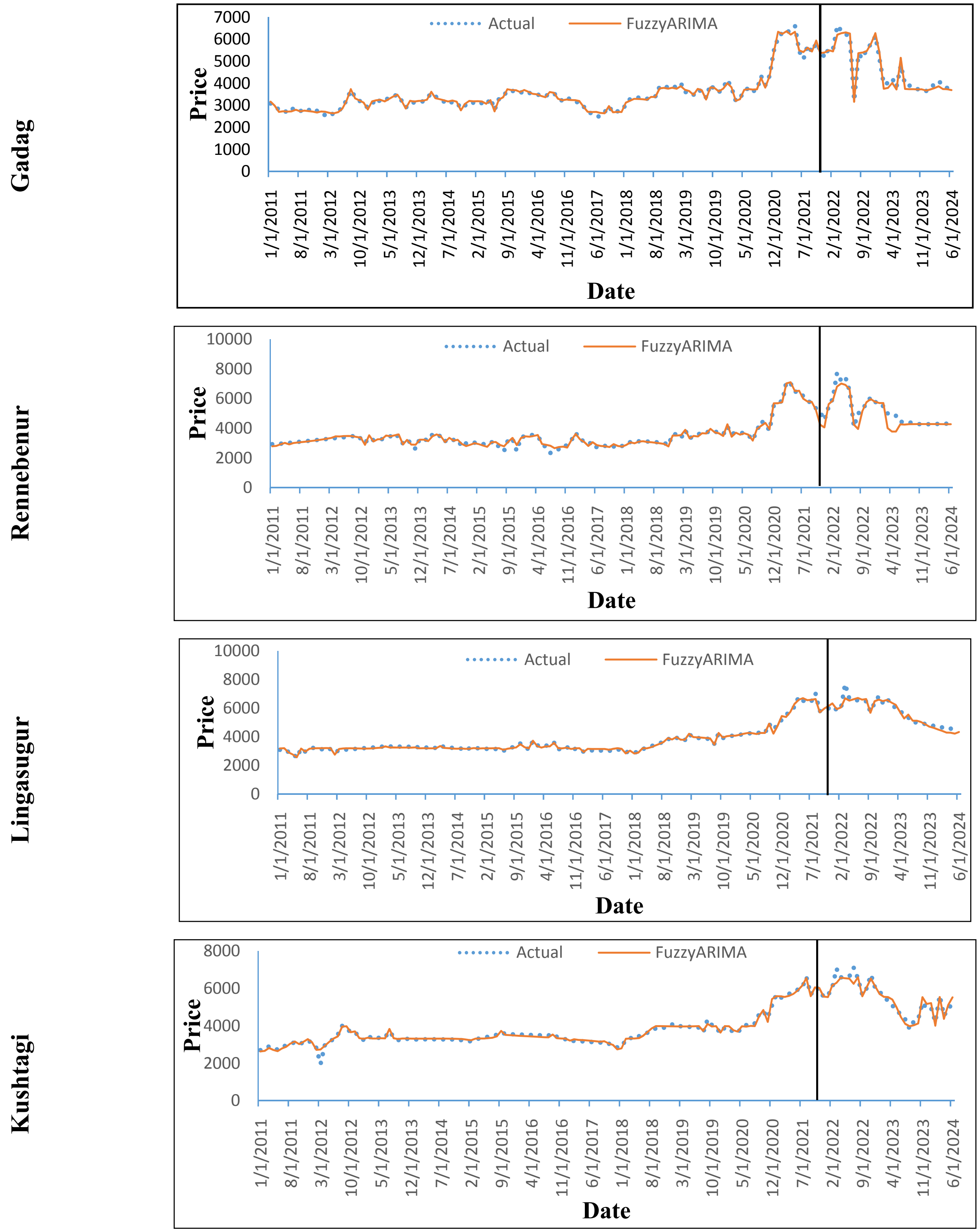


Fig. 5: Actual and predicted values of best fitted model for different markets in Karnataka

CONCLUSION

The volatile and unpredictable price fluctuations in oilseed markets present significant challenges for producers, consumers, researchers, and policymakers. In response to these challenges, the present study proposes an intuitionistic fuzzy based model designed to handle highly uncertain and volatile time series data. The research evaluates the performance of fuzzy based models across six different Sunflower markets in Karnataka. A comparison with traditional models using different accuracy measures such as RMSE, MAPE, and MAE reveals that the proposed fuzzy based models consistently outperform their non-fuzzy counterparts. This empirical study concludes that integrating intuitionistic fuzzy logic into machine learning models enhances their predictive accuracy. The future potential of intuitionistic fuzzy based machine learning models in agricultural time series forecasting includes improving predictions of crop yields and weather patterns, thereby helping farmers make better informed decisions. These models excel at handling the uncertainties present in agricultural data, leading to more accurate and reliable forecasts. Additionally, future advancements may involve integrating deep learning models with deep fuzzy logic to better manage data fuzziness.

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