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Onion Price Forecasting: A Comparative Analysis of SARIMA, Holt-Winters and LSTM Models in the Bengaluru Market

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Abstract

Onion prices in India, particularly in major markets such as Bengaluru, are highly volatile due to seasonal factors, supply disruptions and unpredictable climatic conditions. Accurate price forecasting is crucial for stabilising markets and aiding informed decision-making by policymakers and stakeholders. Onions significantly influence the food inflation index, accounting for 10.66 per cent of the 6.04 per cent weight assigned to vegetables in the Consumer Price Index (CPI), emphasizing the need for reliable price forecasts to manage inflationary pressures. This study compares three forecasting models, Seasonal Auto-Regressive Integrated Moving Average (SARIMA), Holt-Winters Exponential Smoothing (H-WES) and Long Short-Term Memory (LSTM) to predict onion prices in Bengaluru. While SARIMA and Holt-Winters effectively capture seasonal patterns, they struggle with non-linear relationships and unexpected shocks inherent in agricultural markets. In contrast, the LSTM model excels in identifying complex temporal dependencies and non-linearities. Using historical price data, the study evaluated model performance based on accuracy metrics, including Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). The results showed that the LSTM model significantly outperforms compared to traditional models. For the Local variety, LSTM achieved RMSE of 429.58, lower than SARIMA (958.66) and Holt-Winters (749.25). For the Puna variety, LSTM showed RMSE of 513.14, compared to SARIMA (1399.16) and Holt-Winters (669.35). These findings confirmed that, LSTM's superiority in capturing intricate price patterns, particularly during volatility made it a reliable tool for onion price forecasting. This study suggests that LSTM provides actionable insights to mitigate the effects of price fluctuations on producers and consumers alike, informing policy interventions and market strategies.

Keywords : Price volatility, Forecasting, SARIMA, H-WES, Deep Learning, LSTM, Temporal Dependencies, Non-linearities

Onion is one of the closely monitored vegetables produced in India, along with tomato and potato and is often referred to as a *kitchen staple*. The prices of onions have a direct impact on consumers' consumption baskets, making this commodity a constant focus for the government. Price volatility in onion is a significant concern, where onions accounted for 14.21 per cent of the country's total vegetable production during 2022-23. For the 2023-24 season, production is expected to decline to 242.44 lakh tonnes, down from 302.08 lakh tonnes in the previous year. This represents a sharp reduction of approximately 59.64 lakh tonnes, mainly attributed to unfavourable climatic conditions and reduced output in key onion-producing states like Maharashtra, Karnataka and Andhra Pradesh (Anonymous, 2024). Such fluctuations in production and supply significantly impact on both consumer prices and the income stability of farmers, making onion price forecasting an important area of research to support economic and policy decision-making. In addition to its importance as a staple food, onions play a substantial role in shaping India's food inflation index. According to the Ministry of Statistics and Programme Implementation, vegetables are assigned a weight of 6.04 per cent in the Consumer Price Index (CPI), with onions account for 10.66 per cent of that total, alongside potato at 16.29 per cent and tomato at 9.52 per cent (Anonymous, 2015).

The volatility in onion prices, driven by seasonal supply disruptions, climatic variability and logistical challenges has a direct bearing on overall food inflation and the broader economy. As such, accurate price forecasts are critical for managing inflationary pressures and ensuring market stability. However, a large part of the variation in commodity prices is also attributable to variations of the trend itself (Bourdon, 2011). This study undertakes a comparative analysis of three prominent forecasting models Seasonal Auto-Regressive Integrated Moving Average (SARIMA), Holt-Winters Exponential Smoothing and Long Short-Term Memory (LSTM) to determine the efficacy in forecasting of onion prices in the Bengaluru market. Bengaluru, as a major trading hub for onions, frequently experiences significant price fluctuations that affect both local and national markets. Previous research has demonstrated that machine learning models, such as LSTM, tend to outperform traditional statistical models in handling complex, non-linear datasets (Zhang *et al.,* 2024). By evaluating the performance of these models in the context of onion price forecasting, this study aims to provide valuable insights that could enlighten policy interventions and market strategies for mitigating price volatility.

METHODOLOGY

Data Collection

The time series data on daily onion prices were obtained from the Krishi Marata Vahini portal, which provides comprehensive agricultural commodity prices from various markets across Karnataka. The onion commodity was selected for the analysis due to its significant economic impact, high market demand and regional importance within Karnataka. The Bengaluru market was chosen for its substantial volume of arrivals and the availability of a continuous and extensive dataset, establishing it as a pivotal regional trading hub for onions. Data on onion prices and arrivals were collected from July 2009 to August 2024. This study focuses on two specific onion varieties: Onion Local and Onion Puna. To effectively capture seasonal variations and facilitate modelling, the daily price data were averaged and resampled to a weekly frequency. Additionally, data retrieval was automated through the use of a Python package named *kmvahini* (Patil, 2024), which streamlines the extraction of relevant price data from the afore mentioned portal.

Analytical Techniques

Holt-Winters Model : Also known as the Triple Exponential Smoothing model, for time series forecasting. This approach extends simple exponential smoothing to capture trends and seasonality, making it suitable for datasets exhibiting both characteristics (Holt, 1957; Winters, 1960). The Holt-Winters model consists of three main components: the level, the trend, and the seasonality. The model can be expressed in two variations: additive and multiplicative, depending on whether the seasonal component is constant or proportional to the level of the series.

The model equations are given by:

$$Z_t = (\beta_0 + \beta_1 t) + SN_t + IR_t \rightarrow \text{ Additive}$$
$$Z_t = (\beta_0 + \beta_1 t) \times SN_t \times IR_t \rightarrow \text{ Multiplicative}$$

With three smoothing equations:

$$l_t = \alpha(y_t/sn_{t-l}) + (1-\alpha)(l_{t-1} + b_{t-1}) \rightarrow \text{ Level}$$
$$b_t = \gamma(l_t - l_{t-1}) + (1-\gamma)b_{t-1} \rightarrow \text{ Trend}$$
$$sn_t = \delta(y_t/l_t) + (1-\delta)sn_{t-l} \rightarrow \text{ Seasonal}$$

Where,

γ and δ: Smoothing constants

I: Number of seasons in a year

SN_t: Seasonal pattern

IR_t: Irregular components

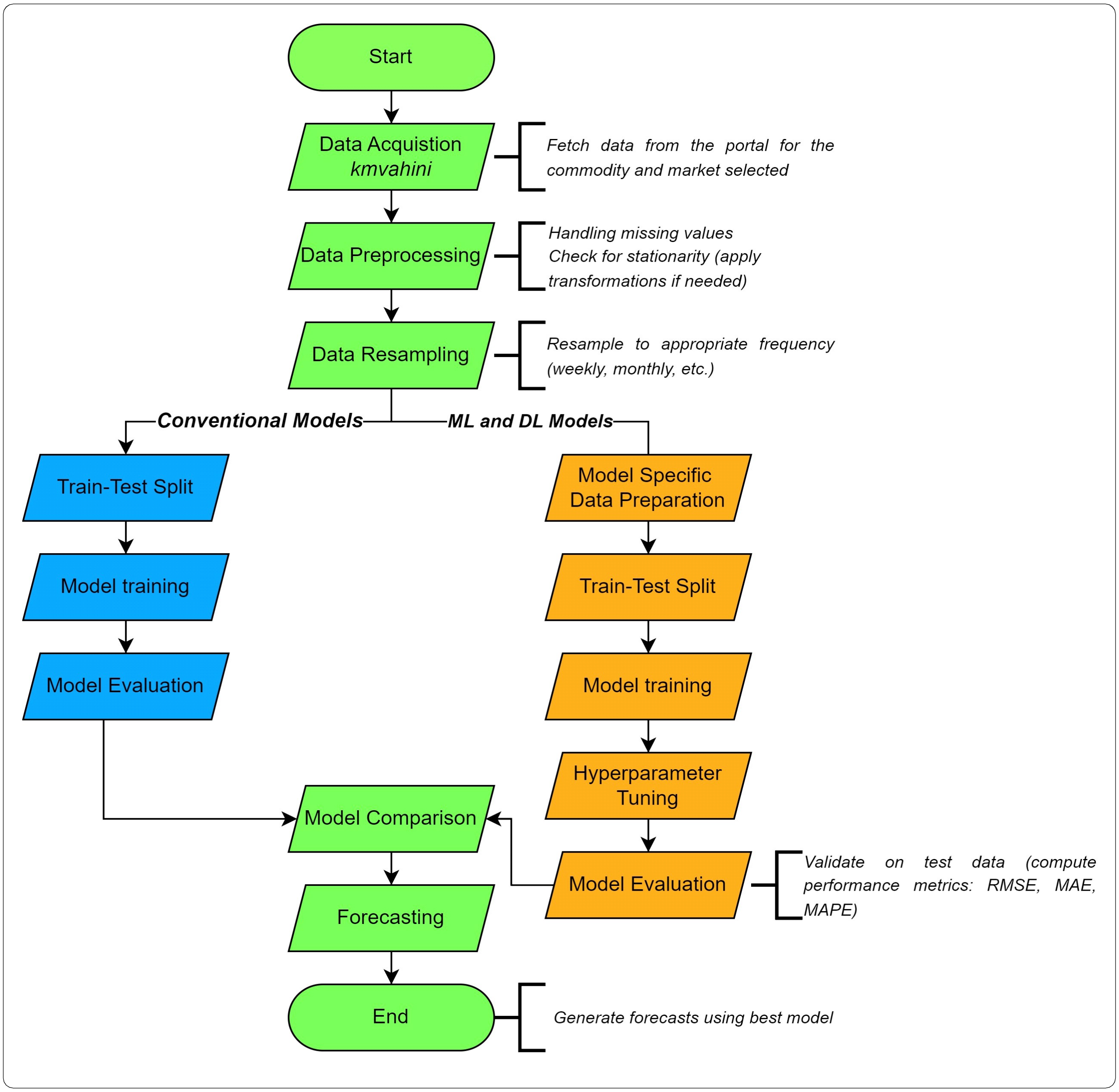


Fig. 1 : Proposed model framework for forecasting

***Seasonal ARIMA (SARIMA)*:** This model is an extension of the ARIMA framework, is specifically designed to account for seasonality (Box and Jenkins, 1976). By capturing both seasonal and non-seasonal components, it is well-suited for data with repeating patterns, such as monthly or quarterly observations, where trends recur over time.

The general form of the SARIMA (p,d,q)(P,D,Q)[s] model is:

$$\Phi_P(L^s)\phi_p(L)(1-L)^d(1-L^s)^D y_t = \Theta_Q(L^s)\theta_q(L)\varepsilon_t$$

Where,

L: Lag operator

$\Phi_P(L^s)\&\Theta_Q(L^s)$: Seasonal auto regressive and moving average polynomials of orders $P\&Q$, respectively

$\phi_p(L) \& \theta_q(L)$: Non-seasonal autoregressive and moving average polynomials of orders $p \& q$

$d \& D$: Degrees of differencing for non-seasonal and seasonal components

s: Length of the seasonal cycle

y_t: Observed time series

ε_t: Error term (Kendall and Ord, 1990)

The general forecasting equation for SARIMA, which incorporates both seasonal and non-seasonal components, is:

$$\hat{y}_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{P} \Phi_j y_{t-j\cdot s} - \sum_{k=1}^{q} \beta_k \varepsilon_{t-k} - \sum_{l=1}^{Q} \Theta_l \varepsilon_{t-l\cdot s} + \varepsilon_t$$

Where,

$\acute{y}_t$: Forecasted value

μ: Constant term

$\phi_i \& \Phi_j$: Non-seasonal and seasonal autoregressive parameters

$\beta_k \& \Theta_l$: Non-seasonal and seasonal moving average parameters

$y_{t-i} \& y_{t-j\cdot s}$: Past observations (non-seasonal and seasonal lags)

$\varepsilon_{t-k} \& \varepsilon_{t-l\cdot s}$: Past errors (non-seasonal and seasonal lags) (Box and Jenkins, 1976; Hyndman and Athanasopoulos, 2018)

To automate the process of selecting the best-fitting SARIMA model, the 'auto_arima' function from the Python 'pmdarima' package, was used based on the implementation originally developed in R by Hyndman and Khandakar (2008). This function evaluates different combinations of model parameters p, d, q, P, D, Q, and s using information criteria such as the Akaike Information Criterion (AIC) to identify the optimal model for the time series data. The 'pmdarima' package automates key steps like model identification, parameter estimation and diagnostic checking, thus improving efficiency in the forecasting process.

***Long Short-Term Memory (LSTM)*:** This model is a type of recurrent neural network (RNN) designed to capture temporal dependencies in sequential data. It is particularly effective for time series forecasting due to its ability to retain information over long periods, effectively mitigating the vanishing gradient problem that commonly affects traditional RNNs (Hochreiter and Schmidhuber, 1997). LSTM network consists of memory cells that maintain information through three primary gates: the input gate, the forget gate and the output gate. These gates regulate the flow of information, allowing the model to learn which data to remember or forget;

i. Input Gate: Controls the extent to which new information flows into the memory cell.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

ii. Forget Gate: Determines which information is discarded from the memory cell.

$$f_t = \sigma(W_f, [h_{t-1}, x_t] + b_f)$$

iii. Output Gate: Decides what information is sent to the next layer or output.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

Where,

$i_t, f_t, \& o_t$: Input, forget, and output gates, respectively.

h_t-1: Previous hidden state

x_t: Input at time t

$W_i, W_f, \& W_o$: Weight matrices for the respective gates

$b_i, b_f, \& b_o$: Bias terms

σ: Sigmoid activation function

The memory cell state C_t is updated as follows;

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

Where $\tilde{C}_t$ is the candidate cell state, computed as;

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

Finally, the hidden state h_t is produced using;

$$h_t = o_t \cdot \tanh(C_t)$$

In this study, LSTM model used the Keras library in Python, which simplifies the construction and training of neural network models. The LSTM architecture will be optimized through hyperparameter tuning,

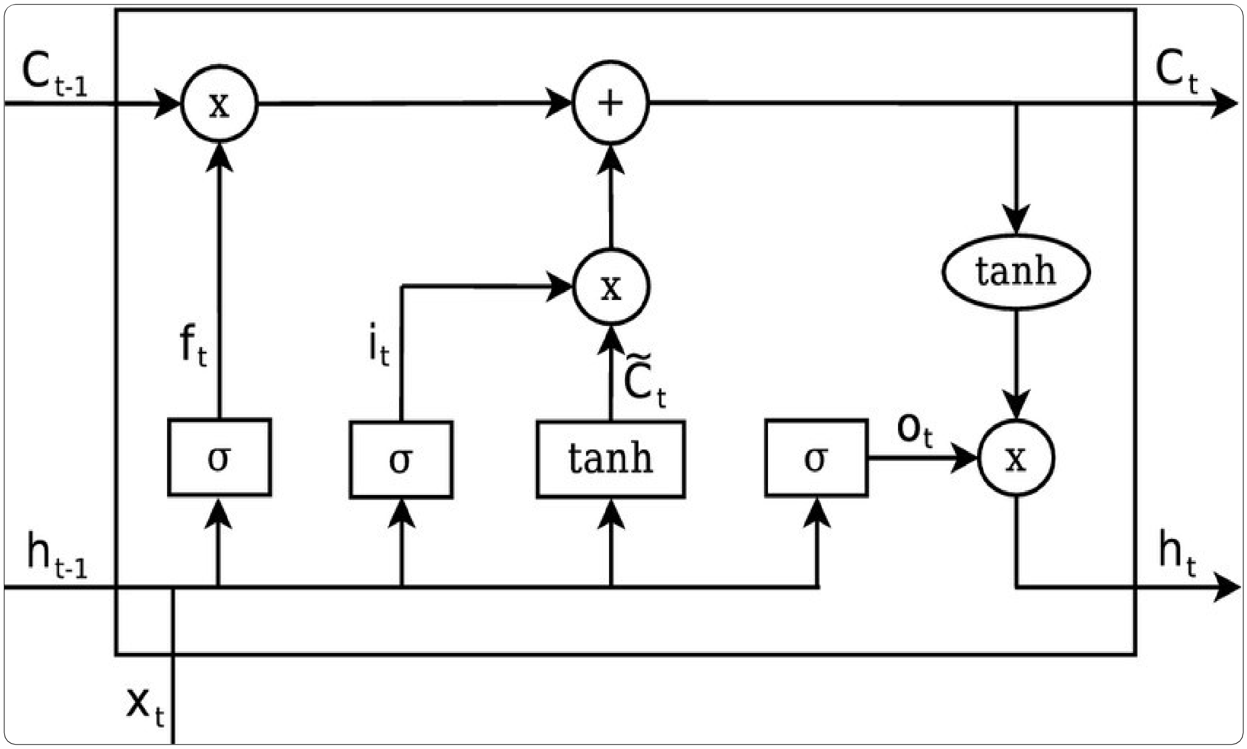


Fig. 2 : LSTM (Long Short-Term Memory) Neural Network

including the number of layers, number of units per layer, learning rate, and batch size.

Results and Discussion

The descriptive statistics of onion prices for the two varieties (Local and Puna) in the Bengaluru market is presented in Table 1. Over the past 15 years, 788 records were collected for both varieties. The Local onion variety had an average price of Rs.1367.08 per quintal, with a standard deviation of Rs.963.21, showed significant price variation from Rs.350 to Rs.9,800 per quintal. Similarly, the Puna variety had a higher average price of Rs.1,746.36 per quintal and greater volatility, with a standard deviation of Rs.1,177.06 and prices ranged from Rs.598.33 to Rs.12,100 per quintal. The larger price range suggested that the Puna variety was more susceptible to price spikes, potentially due to market preferences, storage differences, or supply chain factors. The higher average and greater standard deviation for Puna onions indicated that the variety fetched a premium price in the market and experienced larger fluctuations over time compared to the Local variety. These statistics provided a foundational understanding of the price behaviour of onion varieties in the Bengaluru market, setting the stage for further analysis using time-series forecasting models.

Table 1

Descriptive statistics of onion prices

Variety	Time period	Market	No. of records	Mean	SD	Min.	Max.
Local	05.07.2009 -04.08.2024	Bengaluru	788	1367.08	963.21	350.00	9800.00
Puna	05.07.20094 -04.08.202	Bengaluru	788	1746.36	1177.06	598.33	12100.00

The Augmented Dickey-Fuller (ADF) test results for the price series of the Local and Puna onion varieties are presented in Table 2. For the Local variety, the t-statistic was -5.722 with a p-value less than 0.001, providing strong evidence against the null hypothesis of non-stationarity. Similarly, the Puna variety had a t-statistic of -6.014 and a p-value below 0.001. These results indicated that both varieties exhibited stationarity, suggesting that the price data did not demonstrate trends over time, making them suitable for further time series analysis.

Table 2

Augmented-Dickey-Fuller (ADF) test results of onion price series

Variety	ADF Test		Conclusion
	t-statistics	p-value	
Local	-5.722	< 0.001	Stationary
Puna	-6.014	< 0.001	

Fig. 3 presented the monthly average prices of the Local and Puna onion varieties, highlighting fluctuations in price trends over time. The data showed that both varieties experienced price variations, with the Puna variety consistently exhibiting higher prices than the Local variety across all the observed months. This persistent price differential underscored the premium market value of the Puna variety compared to its Local counterpart.

The time-series decomposition plots of the onion price series into trend, seasonal, and residual components for the Local variety and the Puna variety in the Bengaluru market are presented in Fig. 4(a) and Fig. 4(b), respectively. Both varieties exhibited similar fluctuating trends in their prices, indicating closely aligned movements over time. Additionally, seasonality was clearly observed in both price series, reflecting recurring patterns influenced by seasonal factors that affected onion prices. This analysis highlighted how both varieties were subject to comparable market dynamics and seasonal effects.)

The parameter estimates for the Holt-Winters Exponential Smoothing (HWES) model, as shown in Table 3, provided insights into the pricing dynamics of Local and Puna onion varieties. For the Local variety, the level parameter (α) was estimated at 0.8889, indicating a strong emphasis on recent observations, while the Puna variety had an even higher-level parameter of 0.9950, reflecting a greater reliance on recent data. Both varieties exhibited minimal trend effects, with a trend parameter (β) of 0.0001, suggesting little significant upward or downward movement in prices. Additionally, the seasonal parameter (γ) for the Local variety was

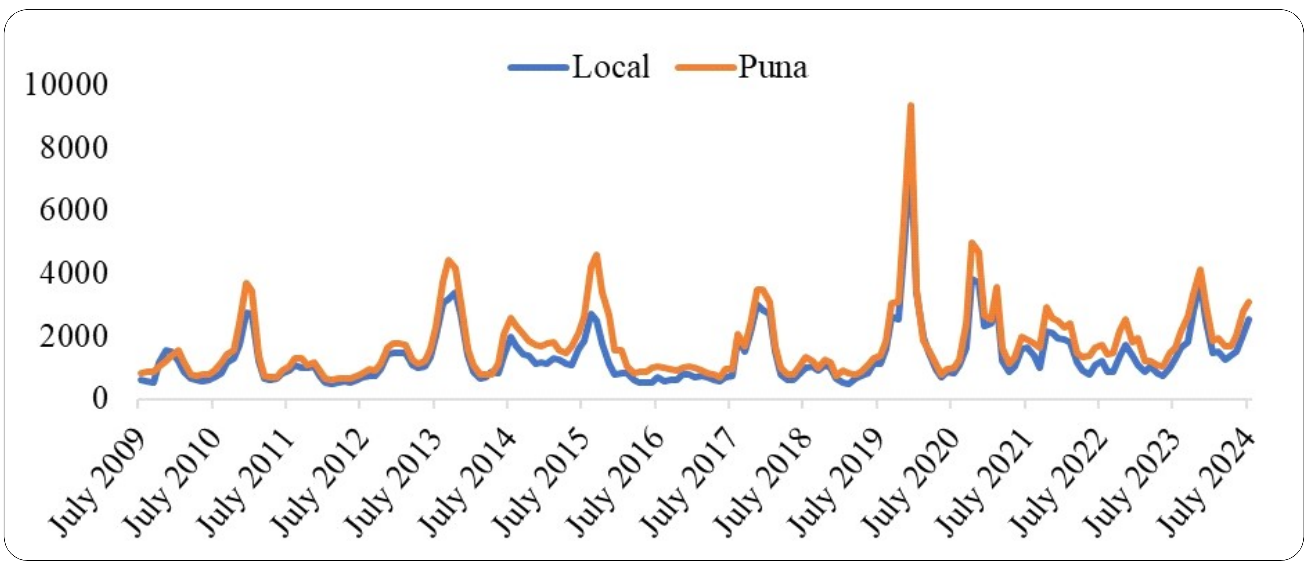
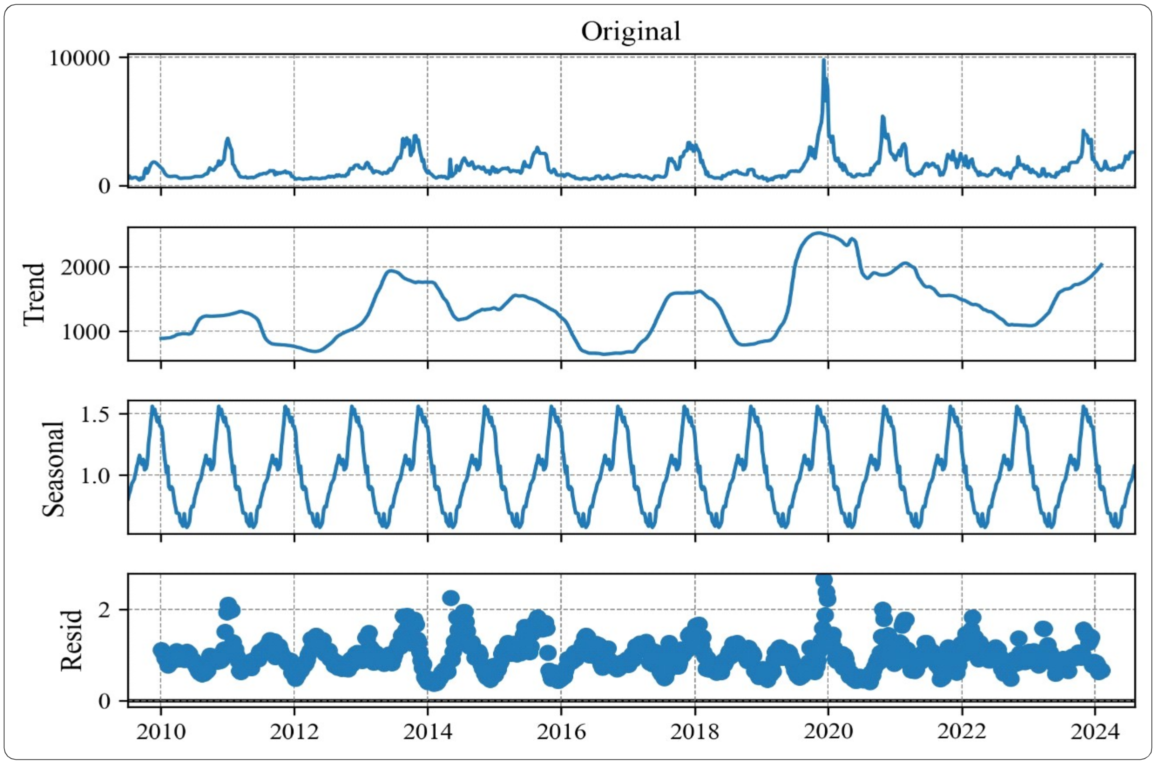
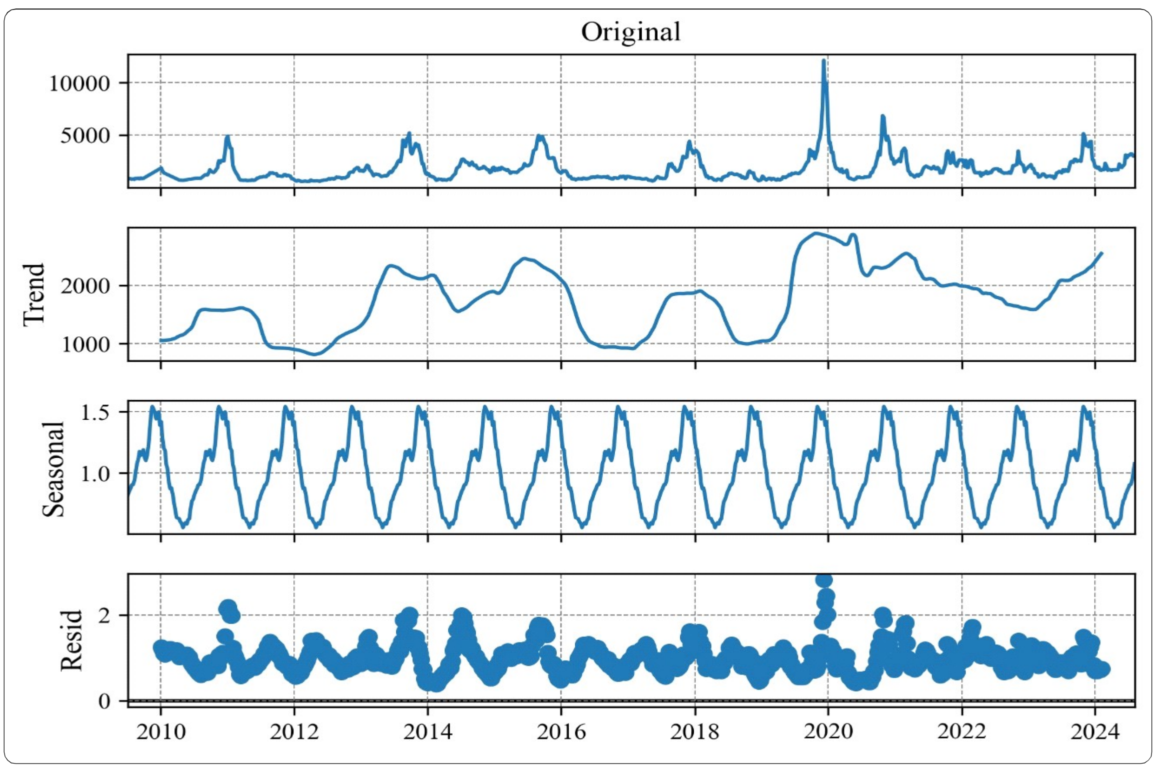


Fig. 3 : Time plot of weekly onion prices (Rs/quintal) for Local and Puna varieties in the Bengaluru market



(a) Local variety of onion price



(b) Puna variety in the Bengaluru market

Fig. 4 : Time-series decomposition plots of onion price series for (a) Local variety and (b) Puna variety in the Bengaluru market

Table 3

H-WES model parameter estimates

Model parameters	Estimates	
	Local variety	Puna variety
α (Level)	0.8889	0.9950
β (Trend)	0.0001	0.0001
γ (season)	0.0370	0.0050

0.0370, indicating a moderate seasonal influence, while the Puna variety showed a weaker seasonal effect with a γ value of 0.0050. These estimates provided valuable information about price behaviour.

The parameter estimates for the SARIMA model to Local variety of onion, detailed in Table 4, highlighted that the model's ability to capture patterns within the time series data. The autoregressive (AR) term estimated at 0.7883 was statistically significant indicating the relevance of past values in predicting future prices. The moving average (MA) term had a coefficient of -0.6639 with significant indicating the importance of past errors in the prediction process.

As presented in Table 5, the parameter estimates for the SARIMA model applied to onion Puna variety provided insights into the seasonal and autoregressive patterns within the data. The autoregressive term (AR) was estimated at -0.0835, while the seasonal autoregressive components for lag 52 and 104 were estimated at 0.0660 and 0.1289, respectively. These seasonal parameters highlighted the importance of yearly cycles in the price dynamics of Puna onion.

Table 4

Parameters estimate of the SARIMA models for Local variety of onion

Parameter	Co-efficient	Std. Error	z-statistic
AR (1)	0.7883	0.087	9.108 ***
MA (1)	-0.6639	0.103	-6.418 ***
σ^2	0.000014	0.000001	25.711 ***

Note: ***Significant at 1% ($p < 0.01$); *Significant at 10% ($p < 0.10$)

The comparison of forecast accuracy metrics-RMSE, MAE and MAPE-across the SARIMA, Holt-Winters, and LSTM models is provided in Table 6. The LSTM model significantly outperformed the conventional models in forecasting both Local and Puna onion prices. For Onion Local, the LSTM model had an RMSE of 429.58, which was substantially lower than SARIMA (958.66) and Holt-Winters (749.25). Similarly, for Onion Puna, the LSTM model exhibited the best performance with an RMSE of 513.14, compared to SARIMA (1399.16) and Holt-Winters (669.35). These results clearly demonstrate the LSTM model's superior forecasting accuracy, confirming it as the most effective approach for predicting onion prices in the study. A similar conclusion was reached by Zhang *et al*. (2024), who found that the LSTM model achieved higher accuracy compared to several machine learning methods, including CNN-based time series forecasting approaches. In contrast, Mohan Kumar *et al*. (2011a) identified the optimal ARIMA model for potato price forecasting, while in a separate analysis, they found that ARIMA outperformed Holt-Winters for onion prices (Mohan Kumar *et al*., 2011b). However, in this study, while Holt-Winters showed better performance than SARIMA, the LSTM model clearly surpassed both, indicating its potential as a more effective forecasting method in this context.

The forecasting performance of the LSTM model for onion prices was illustrated in Fig. 5 and 6 for the Local and Puna varieties, respectively. Fig. 5 showed the actual historical prices for the Local variety in blue, spanning from 2008 to 2022, with the orange line representing the model's training predictions. The close alignment of these lines indicated the model's

Table 5

Parameters estimate of the SARIMA model for Puna variety of onion

Parameter	Co-efficient	Std. Error	z-statistic
AR (1)	-0.0835	0.021	-4.002 ***
AR (Seasonal L52)	0.0660	0.040	1.667 *
AR (Seasonal L104)	0.1289	0.047	2.732 ***
σ2	0.000035	0.000001	36.072 ***

Note: ***Significant at 1% ($p < 0.01$); *Significant at 10% ($p < 0.10$)

Table 6
Forecast accuracy estimates for SARIMA, Holt-Winters and LSTM

Variety	SARIMA			Holt-Winters			LSTM		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
Local	958.66	956.78	468.83	749.25	647.477	0.55	429.58	303.93	0.20
Puna	1399.16	1399.16	687.61	669.35	525.28	0.27	513.14	343.99	0.16

Note: RMSE: Root Mean Square Error, MAE: Mean Absolute Error, MAPE: Mean Absolute Percentage Error

effectiveness in capturing key trends during the training period. Similarly, Fig. 6 displayed the historical prices for the Puna variety, with the same colour coding. Predictions on the test data, shown in green for both figures, closely matched the actual prices, further validating the model's performance. The similar result was observed by Ge and Wu (2020) in maize price as the dependent variable and the LSTM model showed much close to actual values and forecasted prices were more accurate. The red dashed lines represented future predictions beyond 2024, demonstrating the model's capability to provide reliable forecasts for upcoming price movements. Overall, these findings emphasized the LSTM model's effectiveness in forecasting the complex price behaviour of onions, offering valuable insights for stakeholders in the agricultural sector. Similar results were found in the study conducted by Sabu & Kumar (2020), Kamdem *et al.* (2020) and Ameur *et al.* (2024) demonstrated the effectiveness of the LSTM model as a forecasting tool for price prediction to support decision-making in the agricultural supply chain and minimize the risk of price fluctuations.

The vegetables play significant role in the average Indian household's diet, their price fluctuations directly impact the cost of living for a large portion of the population. The observed volatility in these onion prices contributes not only to short-term fluctuations in inflation but also have the potential to influence overall food inflation rates. With this background the study developed and compared

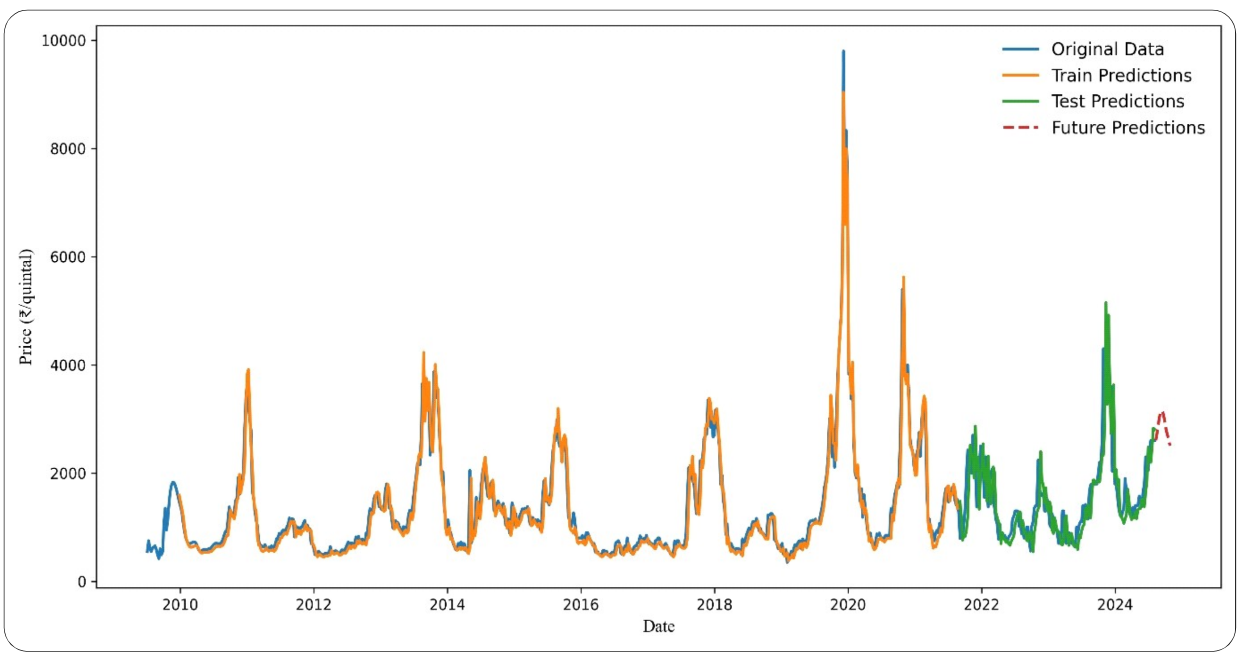


Fig. 5: Ex-Post and Ex-Ante forecasted prices (Rs/quintal) for Local onion variety in the Bengaluru market using the LSTM model

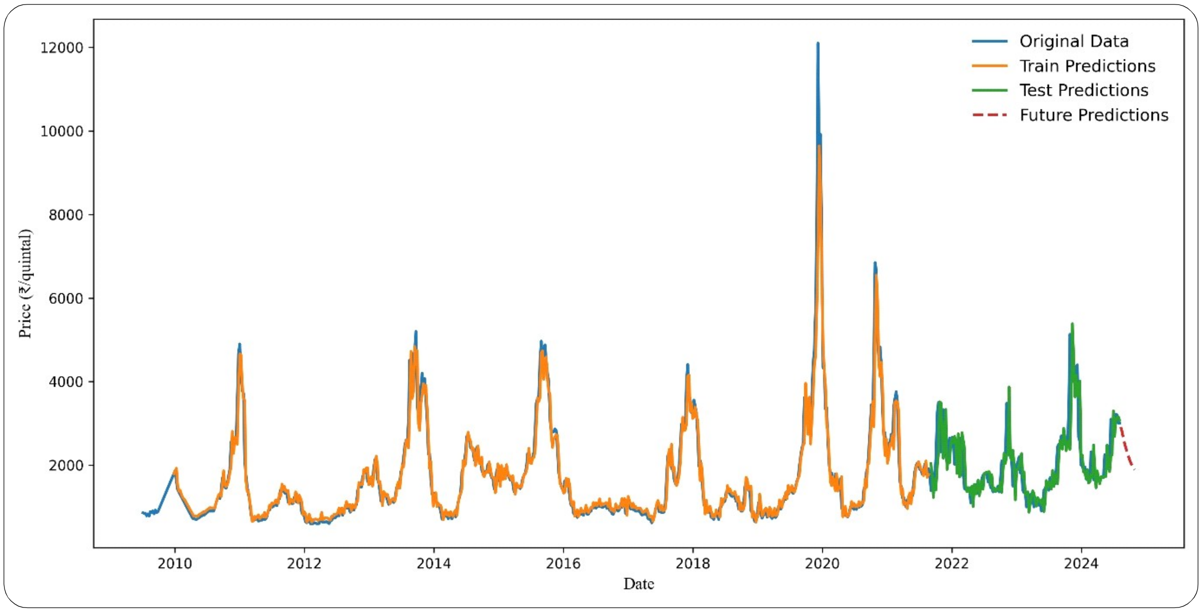


Fig. 6: Ex-Post and Ex-Ante forecasted prices (Rs/quintal) for Puna onion variety in the Bengaluru market

SARIMA, Holt-Winters and LSTM models for forecasting onion prices, focusing on two varieties-Local and Puna in the Bengaluru market. The results demonstrated that while traditional models such as SARIMA and Holt-Winters provides useful parameter estimates, fall short in forecasting accuracy compared to the LSTM model. The LSTM model outperformed, offered significantly better predictions with lower RMSE, MAE and MAPE values. Its ability to closely align forecasts with historical price trends highlighted its effectiveness in capturing the complex dynamics of onion prices. Additionally, forecasts for the upcoming weeks suggests the LSTM model's reliability in providing consistent and accurate predictions. These findings suggested that LSTM is a powerful tool for price forecasting, offering valuable insights to farmers, traders, economists and policymakers for formulating effective measures to mitigate the impact of such fluctuations on inflation and ensure food security for the population also informed decision-making and better market planning. To conclude, managing and predicting the volatility of these key vegetables is crucial for maintaining economic stability and the well-being of the Indian populace. Understanding and forecasting the price movements of these vegetables is crucial for stakeholders in the agricultural and food industries to make informed decisions and develop effective risk management strategies.

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