



(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 4, April 2025

⊕ www.ijirset.com ⊠ ijirset@gmail.com 🖄 +91-9940572462 🕓 +91 63819 07438





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 4, April 2025

|DOI: 10.15680/IJIRSET.2025.1404700|

Future of Monthly Vegetable Price Predicting

M Sathiya

Assistant Professor, PG & Research Department of Computer Science and Applications,

Vivekanandha College of Arts and Sciences Women (Autonomous), Tiruchengode, Tamil Nadu, India

J Janani

II-MCA, PG & Research Department of Computer Science and Applications,

Vivekanandha College of Arts and Sciences Women (Autonomous), Tiruchengode, Tamil Nadu, India

ABSTRACT: Predicting vegetable prices accurately is essential for improving the agricultural supply chain and reducing financial losses caused by unpredictable price changes. This project introduces a machine learning system that uses advanced techniques like Random Forest, Gradient Boosting, and Long Short-Term Memory (LSTM) networks to predict prices. By combining traditional methods such as STL decomposition with machine learning, the system can understand both simple and complex patterns, including seasonal changes and external factors like weather and soil erosion. The system collects data from various sources, including weather updates, market conditions, and local demand, to create accurate forecasts. It continuously updates its predictions with real-time data, making it more reliable. This helps farmers, sellers, and decision-makers make better choices based on the latest information. Additionally, the system offers a simple, interactive interface with visual tools to help users easily understand the predictions. Compared to older models, this approach is more accurate and responsive, providing a strong solution for predicting vegetable prices in ever-changing markets.

KEYWORDS: Vegetable price prediction, Machine learning, Weather impact, Real time data, Forecasting, Agricultural supply chain, User friendly interface.

I. INTRODUCTION

OVERVIEW

Agriculture has been the backbone of human civilization for centuries, providing food, raw materials, and employment to billions of people worldwide. Within the agricultural sector, vegetable farming holds a vital position due to its contribution to nutritional security and economic stability. However, the unpredictable nature of vegetable prices often poses challenges to farmers, traders, policymakers, and consumers. Price fluctuations in the vegetable market can be attributed to several factors, including: **Seasonal Variations**: Some vegetables have specific growing seasons, leading to predictable periods of oversupply or shortage. **Weather Conditions**: Extreme weather events, such as droughts or floods, can severely impact crop yields. **Market Demand and Supply**: Shifts in consumer demand, coupled with logistical inefficiencies, can cause price instability. **External Events**: Global events such as pandemics, trade restrictions, or geopolitical tensions can disrupt supply chains. For farmers, uncertain vegetable prices can lead to significant financial risks. They may face reduced incomes during periods of low prices or incur losses due to unsold stock. Similarly, traders and retailers struggle to manage inventory efficiently, while consumers experience price hikes for essential commodities.





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|



Figure 1: (STL Decomposition)

STL Decomposition: We use the STL class from the statsmodels library to decompose the sales data. The seasonal parameter specifies the periodicity of the seasonality (12 for monthly data).

II. LITERATURE REVIEW

[1]MACHINE LEARNING IN AGRICULTURAL PRICE PREDICTION

Amin et al. (2021) used machine learning techniques, particularly Random Forest and Support Vector Machine (SVM), to forecast agricultural commodity prices, including vegetables. Their study emphasized the importance of feature selection and the impact of external variables like weather patterns and crop yield on prediction accuracy. They found that ensemble learning techniques like Random Forest performed significantly better in predicting agricultural prices over simpler linear models.

[2] DEEP LEARNING FOR AGRICULTURAL PRICE FORECASTING

Li et al. (2022) proposed using Long Short-Term Memory (LSTM) networks for predicting vegetable prices, focusing on capturing time-series data with seasonal variations. They concluded that LSTM models could predict prices more accurately than traditional methods such as ARIMA by better capturing the long-term dependencies and seasonality inherent in vegetable pricing patterns. The study demonstrated that LSTM networks could effectively forecast prices for both short and long-term horizons.

[3] INTEGRATION OF WEATHER AND MARKET DATA

Chaudhary et al. (2021) integrated weather data, soil conditions, and market demand into machine learning models (e.g., Gradient Boosting and XGBoost) to predict vegetable prices. Their study showed that external factors such as temperature, precipitation, and soil moisture had significant predictive power when combined with historical price data. The results suggested that such hybrid models could improve forecasting accuracy by integrating multi-dimensional data sources.

[4]HYBRID MODELS COMBINING TIME-SERIES DECOMPOSITION AND MACHINE LEARNING

Jia et al. (2023) presented a hybrid approach for price forecasting, combining Seasonal-Trend decomposition using LOESS (STL) with machine learning models like Random Forest. Their study emphasized that STL decomposition could help extract seasonality and trend components from time-series data, which could then be used to train machine learning models more effectively. This approach significantly outperformed traditional time-series models in terms of accuracy.

[5] REAL-TIME DATA INTEGRATION VIA IOT FOR DYNAMIC PRICE PREDICTION

Zhou et al. (2020) explored the potential of using Internet of Things (IoT) sensors to collect real-time data (e.g., temperature, humidity, and soil conditions) for more dynamic and timely predictions of vegetable prices. Their study demonstrated that integrating IoT data with machine learning models like XGBoost could provide more accurate





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 4, April 2025

|DOI: 10.15680/IJIRSET.2025.1404700|

and responsive price forecasts, especially for perishable goods like vegetables, which are sensitive to environmental changes.

[6]SENTIMENT ANALYSIS AND SOCIAL MEDIA FOR PRICE FORECASTING

Singh et al. (2022) incorporated **sentiment analysis** from social media platforms like Twitter to predict shortterm price fluctuations in agricultural markets. Using Natural Language Processing (NLP) techniques combined with machine learning models like Random Forest, they demonstrated that public sentiment and news trends could help predict price shifts more effectively in volatile markets. This approach showed potential for short-term forecasting and decision-making in dynamic environments.

[7]ADVANCED ENSEMBLE LEARNING FOR PRICE FORECASTING

Kumar and Verma (2023) explored the use of ensemble learning methods, including XGBoost and CatBoost, for predicting agricultural prices. Their research indicated that ensemble models, when tuned properly, outperformed traditional machine learning algorithms in terms of prediction accuracy.

[8] TRADITIONAL APPROACHES TO PRICE FORECASTING

Earlier studies relied on econometric models such as ARIMA (AutoRegressive Integrated Moving Average) and its seasonal variant SARIMA. For example, Ghosh (2010) utilized SARIMA models to forecast onion prices in India, finding them useful for capturing seasonal trends but limited in handling nonlinearities and external shocks.

[9] BIG DATA AND REAL-TIME FORECASTING

With the rise of IoT and satellite data, researchers are exploring real-time prediction models. Dashboards and mobile apps are being developed to provide farmers and consumers with timely price forecasts. Projects such as AgMarkNet in India have served as a foundation for open agricultural data access.

[10] CHALLENGES AND FUTURE DIRECTIONS

Major challenges include data sparsity in rural markets, price manipulation, and sudden supply chain disruptions. Future research aims to enhance prediction accuracy through transfer learning, federated learning (for privacy-preserving predictions), and integration of social media sentiment analysis to gauge Smarket trends.

III. METHODOLOGY

The research methodology for the Future Of Monthly Vegetable Price Predicting project is designed to ensure the development of a agricultural supply chain and reducing financial lose. **Data Collection** The system gathers data from multiple sources **Market Prices:** Historical and current vegetable prices from wholesale and retail markets. **Weather Data** Temperature, rainfall, humidity, and other meteorological factors.Soil and Environmental Conditions Soil moisture, erosion levels, and other agricultural factors.**Economic Indicators** Demand-supply trends, inflation rates, and fuel costs.

IV. PROPOSED SYSTEM

The trend component represents the underlying direction in the data over a long period. To extract the trend, STL applies a smoothing process Loess Smoothing Locally Estimated Scatter plot Smoothing (Loess) is used to fit a smooth curve to the data points. This non-parametric regression technique helps to capture the overall direction by averaging out short-term fluctuations. Iterative Refinement STL iteratively applies Loess smoothing to refine the trend component. By using a large smoothing window, the process filters out high-frequency variations, leaving a smooth representation of the long-term progression. Seasonality captures periodic patterns that repeat over a fixed period, such as daily, monthly, or yearly cycles. To isolate seasonality, STL uses the following steps Detrending First, the trend component is subtracted from the original time series, leaving a detrended series that mainly contains seasonal and noise components. Seasonal Subseries the detrended series is then split into seasonal subseries. For example, for monthly data, each subseries would contain data points corresponding to the same month across different years. Loess Smoothing on Subseries Loess smoothing is applied to each subseries separately to capture the repeating pattern within each season. This step ensures that the seasonal component accurately reflects periodic variations. Noise, or the remainder component,





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 4, April 2025

|DOI: 10.15680/IJIRSET.2025.1404700|

represents the random fluctuations or irregularities in the data that are not explained by the trend or seasonal components. The noise is calculated by Residual Calculation After the trend and seasonality are extracted, the noise component is simply the residual left from the original series. This is computed by subtracting both the trend and seasonal components from the original data. R = Y - T - S Mathematically, the noise (R) is the difference between the original time series (Y) and the sum of the trend (T) and seasonal (S) components.

LSTM Model

An LSTM (Long Short-Term Memory) network is a type of RNN recurrent neural network that is capable of handling and processing sequential data. The structure of an LSTM network consists of a series of LSTM cells, each of which has a set of gates (input, output, and forget gates) that control the flow of information into and out of the cell. The gates are used to selectively forget or retain information from the previous time steps, allowing the LSTM to maintain long-term dependencies in the input data.



Figure 2: (LSTM MODEL)

An LSTM (Long Short-Term Memory) network is a type of RNN recurrent neural network that is capable of handling and processing sequential data. The structure of an LSTM network consists of a series of LSTM cells, each of which has a set of gates (input, output, and forget gates) that control the flow of information into and out of the cell.

Advantages

Improved Prediction Accuracy: By using advanced machine learning models like Random Forest, SVM, LSTM, and Gradient Boosting, the system captures complex, non-linear relationships in the data, leading to more accurate forecasts. Real-Time Data Adaptability Unlike traditional systems, this model integrates real-time data, including weather and market conditions, ensuring predictions stay relevant and timely. User-Friendly Dashboard: The interactive dashboard developed with HTML, CSS, JavaScript, and Python frameworks allows users to easily visualize trends and explore different forecasting scenarios. Informed Decision-Making: Farmers, retailers, and policymakers can make better decisions regarding crop planning, pricing strategies, and policy formation based on dynamic and data-driven insights. Comprehensive Data Integration Incorporates external factors like weather, demand, and economic indicators, offering a more holistic view of price fluctuations. Visualization Tools: Provides intuitive visualizations (line charts, bar graphs, heatmaps) that help users understand and analyze price trends effectively. Support for Agricultural





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 4, April 2025

|DOI: 10.15680/IJIRSET.2025.1404700|

Sustainability Helps reduce waste and inefficiencies in the supply chain by anticipating price changes and planning accordingly.



Figure 1: Analysis Of Vegetables Price Prediction

The image is a heatmap titled "Heatmap of Predicted Prices for Vegetables (All Months of 2025)", which displays the predicted prices of various vegetables for each month of the year 2025. The horizontal axis represents the months from January to December, while the vertical axis lists different vegetables including Broccoli, Cabbage, Cauliflower, Carrot, Onion, Potato, Spinach, and Tomato. Each cell in the heatmap contains a numerical value representing the predicted price of a specific vegetable in a particular month. The color gradient ranges from light yellow to dark blue, where lighter shades indicate lower prices and darker shades represent higher prices.





The image is a pie chart titled "Predicted Price Proportions by Vegetable for 2025", which visually represents the share of each vegetable in the total predicted price distribution for the year 2025. Each slice of the pie corresponds to a specific vegetable, with its size indicating the percentage contribution to the overall predicted vegetable prices. The vegetables included are Broccoli, Tomato, Spinach, Pumpkin, Potato, Peas, Onion, Cauliflower, Carrot, and Cabbage.

IJIRSET©2025





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 4, April 2025

|DOI: 10.15680/IJIRSET.2025.1404700|

Among them, Peas have the largest proportion at 10.9%, followed closely by Cabbage (10.7%), Carrot and Spinach (each 10.5%), and Pumpkin (10.3%). The smallest proportions are contributed by Onion (8.7%) and Cauliflower (9.0%). Tomato accounts for 9.3% of the total. The use of varying shades of color helps distinguish each vegetable clearly, making it easy to compare their respective price proportions.

V. CONCLUSION

This project successfully develops an advanced vegetable price prediction system using machine learning and deep learning techniques. By integrating models such as Random Forest, Gradient Boosting, and Long Short-Term Memory (LSTM), the system effectively captures seasonal trends, market fluctuations, and external factors like weather conditions and soil quality. The system's ability to incorporate real-time data makes it highly adaptable, ensuring that farmers, retailers, and policymakers receive accurate and dynamic forecasts. The interactive dashboard, built with HTML, CSS, JavaScript, and Python frameworks, provides a user-friendly interface for visualizing trends and adjusting input parameters. In conclusion, this data-driven forecasting system provides a powerful tool for mitigating risks in the agricultural market, improving supply chain decisions, and ensuring financial stability for all stakeholders in the farming ecosystem.

REFERENCES

- 1. Basu, S., &Sankar, P. (2020). Predicting Agricultural Price Trends Using Machine Learning Techniques. Journal of Agricultural Economics, 48(3), 267-283.
- 2. Chen, T., &Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 785-794.
- 3. Chaudhary, R., Verma, S., &Kumawat, R. (2021). Impact of Weather and Market Data on Agricultural Price Forecasting Using Machine Learning. Agricultural Economics Review, 34(2), 98-112.
- 4. Dash, S., &Biswal, S. (2020). Machine Learning Models for Price Prediction in Agricultural Markets: A Comprehensive Review. International Journal of Computational Intelligence and Data Science, 3(4), 209-220.
- 5. Ganaie, M. A., &Ganaie, S. (2021). Machine Learning in Agriculture: Applications, Challenges, and Future Prospects. International Journal of Computer Science and Applications, 18(2), 65-78.
- 6. Hernandez, M., &Petrovic, J. (2021). Economic Factors Influencing Agricultural Price Trends: A Machine Learning Approach. Agricultural Economics, 52(4), 421-430.
- 7. Jain, P., & Sharma, A. (2018). Price Prediction of Agricultural Products Using Machine Learning Algorithms. International Journal of Data Science and Analytics, 4(3), 32-45.
- Jia, W., Liu, Y., & Zhang, Y. (2023). Hybrid Seasonal-Time Series Decomposition with Machine Learning for Agricultural Price Forecasting. Computational Economics, 62(3), 1007-1022.
- 9. Kumar, A., &Verma, S. (2023). Ensemble Machine Learning Models for Predicting Agricultural Prices. Applied Artificial Intelligence, 37(1), 24-36.
- Kumar, V., & Meena, S. (2019). Big Data and Machine Learning for Price Prediction in Agricultural Sector. Springer Advances in Science and Technology, 10(2), 29-36.
- 11. Kotu, V., & Deshpande, B. (2019). Predictive Analytics and Data Mining: Concepts and Practice with RapidMiner Springer.
- 12. Li, S., Wang, Z., & Li, J. (2022). Forecasting Agricultural Price using LSTM Neural Networks. Journal of Agricultural Informatics, 14(1), 15-28.
- 13. Sattar, R., &Gohar, M. (2022). Improving Agricultural Price Forecasting with Machine Learning. International Journal of Machine Learning and Data Mining, 7(1), 48-61.
- 14. Singh, V., Sharma, P., &Rathi, A. (2022). Sentiment Analysis for Predicting Agricultural Price Movements. Data Science for Agriculture, 4(1), 55-64.
- 15. Yadav, A., & Gupta, M. (2020). Time Series Forecasting Using LSTM Networks for Agricultural Price Prediction. Proceedings of the International Conference on AI and Machine Learning, 112-120.
- 16. Zhou, P., Wang, Y., & Yang, S. (2020). IoT-Based Real-Time Agricultural Price Prediction Using Machine Learning. Sensors, 20(8), 2261.
- 17. Kour, H., & Arora, A. (2020). Agricultural Crop Price Prediction Using Machine Learning Algorithms. International Journal of Computer Applications, 176(13), 19-23.





www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 4, April 2025

|DOI: 10.15680/IJIRSET.2025.1404700|

- 18. Wang, Y., Yu, C., & Wang, D. (2019). Application of LSTM Neural Networks in Predicting Agricultural Product Prices. Procedia Computer Science, 147, 400-406.
- 19. Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep Learning in Agriculture: A Survey. Computers and Electronics in Agriculture, 147, 70-90.
- 20. Dey, A., Samanta, D., & Mukherjee, A. (2021). Predicting Agricultural Commodity Prices Using Social Media Sentiment and Machine Learning. Information Processing in Agriculture.









INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY





www.ijirset.com