



International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

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



Impact Factor: 8.699

Volume 14, Issue 4, April 2025

Impact of Covid-19 Lockdown on Food Prices in India and Forecasting for Future Crises

**K Venakata Naga Sreedhar, Nagarajupally Silas, Solomon Thota Sriram Akash, Tatikonda Sreeja,
Parshamoni Bharath**

B. Tech, Department of CSE, Malla Reddy University, Hyderabad, Telangana, India

ABSTRACT: The COVID-19 pandemic disrupted global economies, especially the supply of food, with major price volatility in commodities. This research discusses the effect of India's countrywide lockdown during March 2020 on food prices with the help of regression analysis, time-series models, and machine learning methods. The Department of Consumer Affairs' daily retail price data (February–April 2020) were used to compare price volatility during and after the lockdown. Higher-order methods like the Augmented Dickey-Fuller (ADF) test for stationarity, t-tests/Mann-Whitney U tests for comparison, and time-series decomposition to detect trends were utilized. Furthermore, moving averages and feature engineering techniques like lag features and rolling means were utilized. Different models like Linear Regression, Random Forest, XGBoost, ARIMA, and LSTM were trained on RMSE, MAE, and R² scores and compared, of which XGBoost was the best-performing model for forecasting prices. The research highlights the impact of the lockdown on price volatility and calls for strong supply chain planning and policy interventions. This study offers important insights in food price behavior in times of crisis, and also presents a data-based methodology for price trend forecasting during economic shocks, allowing decision-makers to prepare for future pandemics or disasters through anticipating market fluctuations and facilitating economic and policy planning.

KEYWORDS: Covid-19 Lockdown, Food Commodity prices, Machine Learning, Data Analytics, Regression model, XGBoost, Price forecasting.

I. INTRODUCTION

The pandemic caused by COVID-19 hit economies and food supply chains across the globe with India being subjected to one of the toughest lockdowns in the world (Hale et al., 2020). The first case in India was reported on January 30, 2020, and as the situation worsened, the measures for containing the outbreak intensified. On March 22, 2020, the government declared a "Janata Curfew" in which there was voluntary stay-at-home rules, followed by an indefinite lockdown on March 24, 2020, without notice. First intended to last 21 days, the lockdown was extended up to May 31, 2020. Although movement of essential goods and services was allowed, sudden stoppages seriously impacted food supply chains, creating traffic bottlenecks, labor shortages, and retail closures (Rawal & Kumar, 2020; Ramakumar, 2020). Wholesale agriculture markets were shut down intermittently, state-border restrictions curtailed food transportation, and e-commerce grocery deliveries came to a complete stop (PTI, 2020; Mishra, 2020). Street vendors, small shops, and local markets were operationally constrained, adding to the worsening of the access and price volatility of food.

When lockdown was enforced, panic buying in cities escalated, increasing supply chain disharmonies, while the daily wage laborers—who had lost their earnings—were severely food insecure (SWAN, 2020; Seth & Vishwanathan, 2020). The effect was especially harsh for perishables like milk, vegetables, and fruits that rely on uninterrupted supply chains. The market uncertainty, decline in demand by restaurants and institutions, and logistics issues further led to price volatility, reports indicate (Narayanan & Saha, 2020). This study examines the impact of the lockdown on daily food prices in India, with emphasis on perishable and non-perishable products.

II. SCOPE AND OBJECTIVES

This research uses high-level econometric and machine learning methods to estimate the effect of the lockdown on Indian food prices. The work examines daily food retail prices of February, March, and April 2020, obtained from the

Department of Consumer Affairs portal. In contrast to conventional works based on mere regression analysis, this research makes use of an exhaustive methodology by integrating:

1. Time-Series Statistical Tests:

Augmented Dickey-Fuller (ADF) Test to test stationarity in the price trend. T-Test and Mann-Whitney U Test to statistically compare price distributions prior to and subsequent to March 24, 2020, determining statistical significance in the changes in price.

2. Trend Analysis and Decomposition:

Time-Series Decomposition to derive trend, seasonality, and residual components of the prices of commodities. Moving Average Plots to see long-run trends in price.

3. Predictive Modeling for Price Forecasting:

Various regression and machine learning algorithms were experimented with, including:

Linear Regression, Random Forest Regressor, XGBoost Regressor, ARIMA (Auto-Regressive Integrated Moving Average), LSTM (Long Short-Term Memory Neural Network)

All models were compared using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2 Score for predictive accuracy determination. XGBoost was found to be the highest-performing model, effectively predicting price variation.

4. Feature Engineering and Data Preprocessing:

Lag feature addition and rolling mean incorporation to facilitate better predictive modeling. Dataset separation into pre-lockdown (before March 24, 2020) and post-lockdown (March 25 and beyond) intervals for the lockdown impact isolation.

5. Implication of the Study

This research seeks to offer evidence-based insights into the behavior of food prices in the face of economic shocks, specifically a countrywide lockdown. Through an examination of the price behavior of perishable and non-perishable items, this study adds to the understanding of market vulnerabilities, consumer response, and inflationary pressures during crises. The findings identify:

- The magnitude of price volatility induced by the lockdown and which commodities were impacted the most.
- The performance of machine learning models in predicting price tendencies under economic shocks.
- How this predictive methodology can benefit policymakers in making informed decisions on supply chain resilience and food price management for impending crises.

This study forms the basis of evidence-based decision-making in economic planning. By utilizing machine learning and time-series methods, this research not only analyzes historical trends but also offers a framework for predictive price modeling that can be applied to predict price trends in future pandemics or natural disasters.

III. LITERATURE SURVEY

COVID-19 resulted in huge economic impacts globally, with severe impacts on food value chains and prices of commodities. There have been numerous studies explaining the impacts of the pandemic-triggered lockdown in India, based on variables ranging from supply chain breakdown to consumption pattern changes, as well as government measures.

A. Impact on Prices of Food Items in India

Research works conclude that the national lockdown in March 2020 caused substantial price movements in commodity items of high consumption. Whereas supply chains for essential commodities were allowed to operate, logistical issues like labor shortages, transportation bans, and wholesale market closures significantly impacted food distribution. Rawal & Kumar (2020) and Ramakumar (2020) studies indicate that these disruptions caused supply bottlenecks, which raised

the price of essential foodstuffs. Urban panic buying also contributed to the inflation of staple food items such as rice and wheat, while other staple foods like vegetables and dairy products experienced volatile pricing resulting from storage and transport limitations.

Narayanan and Saha (2020) provided an analysis citing notable disruptions in India's agri-food value chain, resulting in higher uncertainty and distress among consumers and traders. The research found that urban consumers saw steeper price increases than rural consumers, where localized food production cushioned supply chain shocks. Further, research discovered that the price rise in India was even greater than international market trends for a country that is a significant food exporter, indicating internal inefficiencies and strategic political pressures on food pricing policy.

B. Global Comparisons

Cross-country research has found comparable trends of food price inflation from lockdown-related disruptions. A study in the United States (Baker et al., 2020) reported that meat prices jumped by 20-30% because of the shutdown of processing facilities. In China, Zhang et al. (2021) reported a 35% hike in vegetable prices, though the nation's digitalized grocery supply chains stabilized food prices more quickly than elsewhere. In a similar vein, Ciaian & Rajcaniova (2021) had noted that European countries like Italy, Spain, and France 4 experienced food price increases by 5-12% because of labor shortages and border closures.

C. Economic and Social Implications

The socio-economic implication of the lockdown on Indian food security was drastically hard-hitting for poor households. Studies by Arif et al. (2021) in Bangladesh and IFS (2023) in the UK identified that poorer sections of society bore the brunt of food price inflation as the demand for lower-priced staples rose, resulting in a situation that came to be known as "cheapflation." Government policies like subsidies and stock limits in India contained food prices somewhat. Still, inefficiencies in the Public Distribution System (PDS) resulted in uneven food access across regions.

D. Research Gaps and Future Scope

Although several studies on food price volatility during the COVID-19 pandemic exist, many involve trend analysis that fails to apply strong statistical or machine learning techniques to measure price variability. Experts in the field are still scarce who have provided causal analysis for India that measures the direct impact of lockdown measures on food prices. There is also lack of price forecasting models, which will assist in anticipating the prices if any other crises occurs in future.

This study bridges this gap by utilizing regression analysis, time-series decomposition, and machine learning models to evaluate commodity price volatility comprehensively. This study differs from existing research in the following ways:

- Employs sophisticated statistical tests (ADF Test, T-Test, Mann-Whitney U Test) to compare price change prior to and subsequent to the lockdown.
- Utilizes machine learning models (Linear Regression, Random Forest, XGBoost, ARIMA, and LSTM) to predict trends in food prices.
- Assesses model accuracy with RMSE, MAE, and R^2 scores to determine the best forecasting method.
- Differentiates between perishable and non-perishable commodities to examine which categories were most impacted.

This study provides a data-driven approach for forecasting prices in times of economic unrest. Through the application of predictive analytics, this research can help forecast future market trends, enabling governments, companies, and stakeholders to make rational choices during future pandemics or economic downturns.

IV. METHODOLOGY

The goal of this research is to investigate the effect of the COVID-19 lockdown on food prices in India using a data-driven strategy that includes web scraping, data wrangling, feature engineering, regression analysis and also predict price trends in future pandemics or natural disasters.

A. Data Collection

To collect food prices, web scraping was performed with Selenium library to collect daily retail price data for February, March, and April 2020 from the Department of Consumer Affairs website (https://fcainfoweb.nic.in/reports/report_menu_web.aspx).

As the website includes dynamically created data, Selenium has been utilized to automate interactions, fetch records, and save them into formatted Excel files.

The process of scraping data included the following steps:

- **Navigation automation:** The web scraper chose the correct type of dataset and date range to extract.
- **Data extraction:** The scraper cycled through each day between February and April 2020, downloading price reports for various food commodities in different geographical areas. **Storage:** The data that was extracted was stored in Excel (.xls) format and saved in a folder to be processed further.
- **Error handling:** Error-handling mechanism was employed to catch failures during scraping to guarantee completeness of data.

B. Data Preprocessing

1) Data Wrangling

As the downloaded files had extraneous data like footers, summary rows, and duplicate metadata, preprocessing was required to clean and organize the data:

- **File renaming and sorting:** The web-scraped files were renamed in an orderly fashion to ensure chronological order.
- **Data extraction:** The Pandas library was utilized to import the Excel files as HTML tables because they were viewed in an atypical format.
- **Cleaning and filtering:** Headers, unwanted rows, and irrelevant sections were stripped off to leave behind only commodity prices per geographical center.
- **Dataset consolidation:** A dictionary-based method was employed to consolidate data from separate daily reports into one structured DataFrame.

2) Feature Engineering

- **Feature engineering** was done to improve the dataset and enable comparative analysis:
- **Date Conversion:** The date column was converted into datetime format for time-series analysis.
- **Categorization of commodities:** Products were categorized into two groups:
 - **Perishable goods:** Milk, potatoes, onions, and tomatoes.
 - **Non-perishable goods:** Rice, wheat, pulses, oils, sugar, and packaged food items.
- **Lockdown Indicator:** A category feature was established to distinguish between pre-lockdown (before March 24, 2020) and post-lockdown (from March 25, 2020) phases.

C. Exploratory Data Analysis (EDA)

- EDA was performed in order to take preliminary insights about the dataset:
- **Summary statistics:** Mean, median, standard deviation, and other summary statistics were calculated for all commodities. **Distribution plots:** Line plots, scatter plots, and bar charts were employed to examine price distributions prior to and subsequent to the lockdown.
- **Time-series plotting:** Line graphs were created to view price movement over time for perishable and non-perishable items.

D. Regression Analysis

- To approximate the effect of the lockdown on food prices, linear regression models were used. The regression analysis methodology involved the following steps:

1) Model Definition

- A time-series regression model was formulated

$$P_t = \beta_0 + \beta_1 T + \epsilon_t$$

where:

P_t represents the price of a given commodity at time t .

T is a time variable indicating the chronological order of observations.

β_0 is the intercept.

β_1 is the slope coefficient capturing price trends.

ϵ_t is the error term.

2) Regression Implementation

- Data Splitting:** The dataset was divided into two subsets:
 - Pre-lockdown data (February 1 - March 24, 2020)
 - Post-lockdown data (March 25 - April 30, 2020)
- Model Training:** A linear regression model was fitted to the pre-lockdown data to predict expected price trends.
- Prediction & Comparison:** The trained model was used to project prices into the post-lockdown period, and actual post-lockdown prices were compared with the predictions.

E. Visualization and Interpretation Regression Plots

- Regression plots were drawn for every food commodity:
 - The pre-lockdown prices were indicated as blue dots.
 - Regression trendline (fitted over pre-lockdown data) is shown in blue.
 - Post-lockdown prices were represented as red dots.
 - The gap between the trendline and the post-lockdown prices reflected the size of price change caused by the lockdown.

2) Segmented Distribution Analysis

- To explore price change further:
 - Price trends were graphed for each month separately for February, March, and April.
 - Category-wise comparison has been done to pinpoint differences in price impact between perishable and non-perishable items.

F. Statistical analysis and Time-Series Analysis

1) Data Preprocessing

- Reads a CSV file with Date parsing.
- Drops the redundant "Measure" column.
- Converts the "Covid" column into categorical labels (prior and post)
- Stationarity Check (ADF Test):
- Applies the **Augmented Dickey-Fuller (ADF) test** to check if each commodity's price series is stationary.

3) Statistical Tests for Impact Analysis:

- Separates data into pre-COVID and post-COVID periods.
- Performs either a **t-test** (if variance is similar) or **Mann-Whitney U test** (if variance differs) to check if price differences are statistically significant.

4) Time-Series Decomposition:

- Decomposes a selected commodity's price series into **trend, seasonality, and residuals** using the seasonal_decompose function.
- Plots the decomposed components.
-

5) Trend Analysis with Moving Averages:

- Computes **7-day and 30-day moving averages** for the selected commodity.
- Plots the original price series along with these moving averages to visualize trends.

G. Testing Price Forecasting Models

- Multiple machine learning models were employed. These models were evaluated based on their predictive accuracy using metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R² score. The models implemented include

1) Regression models

- **Linear Regression:** A simple statistical model that assumes a linear relationship between features and price.
- **Random Forest:** An ensemble learning method
- **XGBoost:** A gradient boosting algorithm
- **Time Series Forecasting Models**
- **ARIMA (AutoRegressive Integrated Moving Average):** A statistical model designed for stationary time series data.
- **LSTM (Long Short-Term Memory):** A deep learning model suitable for time series forecasting.

Model Comparison

Model	RMSE	MAE	R-square
Linear Regression	2.4268	1.2878	-4.7276
Random Forest	0.1700	0.3351	0.5988
XGBoost	0.1164	0.2955	0.7253
ARIMA	1.4486	1.0798	-2.4190
LSTM	0.6506	0.6399	-1.9580

TABLE I. MODEL COMPARISON

- Based on the results, XGBoost was the top-performing model with the lowest RMSE and highest R-square score. This shows that XGBoost was able to capture the non-linear relationships and external variables affecting food commodity prices. Random Forest also showed competitive performance. ARIMA and LSTM, however, performed poorly, possibly because of the complexity of the data and the limited historical information available.
- Therefore, XGBoost is chosen as the best model for price prediction in this research.

H. Prediction Model

1) Standardization (Feature Scaling)

$$x' = \frac{x - \mu}{\sigma}$$

2) XGBoost Regression Model

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i)$$

Loss Function (Mean Squared Error - MSE)

$$L = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

1) Model Performance Metrics

a. Mean Absolute Error (MAE):

$$MAE = \frac{1}{n} \sum |y_i - \hat{y}_i|$$

b. R² Score (Coefficient of Determination):

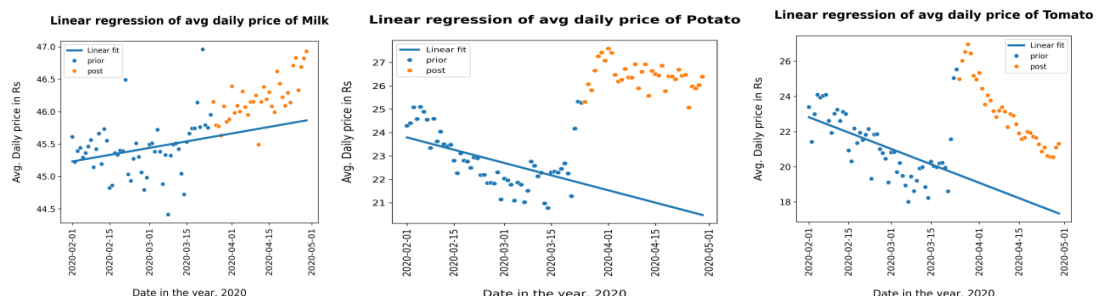
$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

V. RESULTS

A. Regression Analysis

The regression plots, built from linear regression models, demonstrate a distinct effect of the COVID-19 lockdown on food prices. The models were trained with pre-lockdown data (February 1–March 24, 2020) and subsequently utilized for prediction during the post-lockdown time period (March 25–April 30, 2020). A summary of the results is as follows:

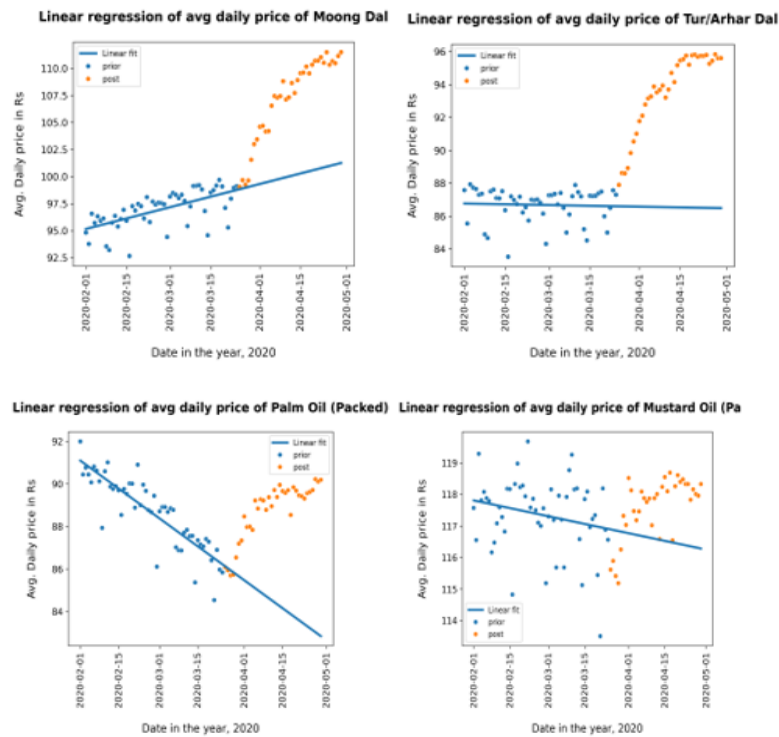
Fig1:Regression Plots of Cherishable products



- Overall Trend: For the majority of commodities, the post-lockdown prices actually diverged above the forecasted trendline. This suggests a strong rise in prices against the historical base.
- Perishable Goods: Products like Milk, Potato, and Tomato had a significant upward shift in their prices as shown in Fig 1. The regression line, prepared from pre-lockdown prices, fell short of the prices realised post-lockdown. Curiously, though most of the perishable goods increased, Onion witnessed a fall, indicating distinctive market trends for the commodity.

- Non-Perishable Goods: For staples such as Rice and Wheat, the price rise was there but less sensational than in some other groups. On the other hand, many non-perishables—especially some pulses (e.g., Moong Dal, Tur/Arhar Dal) and packaged foods (e.g., different oils)—exhibited sharp rises as shown in Fig 2. The difference between the regression line and actual values was large, highlighting the setback caused by the lockdown

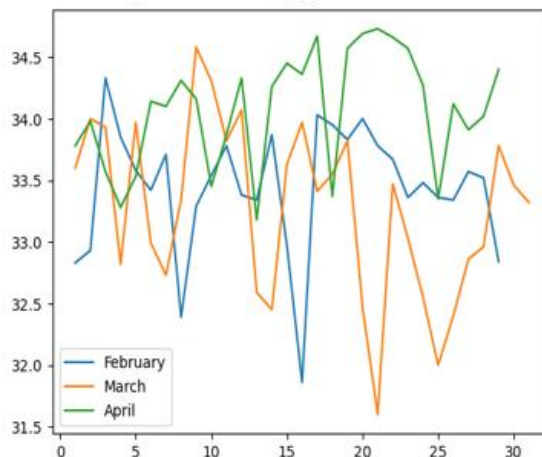
Fig 2. Regression plots of non-perishable goods



B. Monthly Price Trends

The data were split into three portions for February, March, and April 2020. Line graphs showing the average price of rice on a daily basis indicated a clear trend upwards from March, at the same time the lockdown began. The persistence in going up until April supports the fact that the lockdown continued to have an effect on food prices.

Fig 3. Monthly price trends



C. Difference in net average price

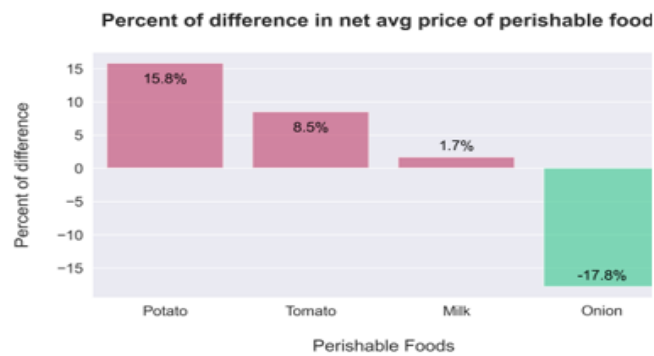
- Perishable goods

Potato has shown the highest difference in net average price and Onion was the lowest

- Non-perishable goods

Pulses such as Moong Dal, Tur Dal, etc; have shown the highest difference, and Palm Oil was the one with the least.

Fig 4. Net average price difference (Perishable goods)

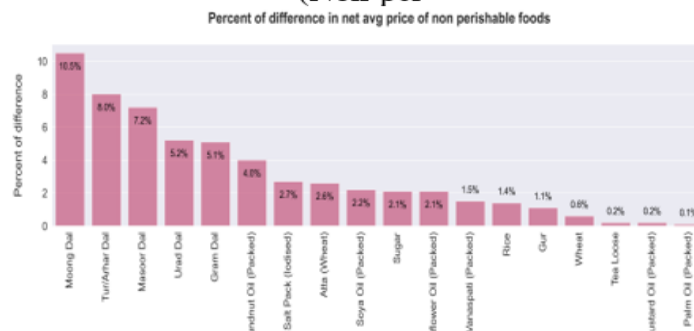


D. Statistical Observations

1. Augmented Dickey-Fuller (ADF) Test:

- Used to check for stationarity in food prices.
- Many commodities (e.g., Rice, Sugar, Dal varieties, Oils) were found to be non-stationary, indicating price trends over time.
- Some commodities like Wheat and Mustard Oil were stationary.

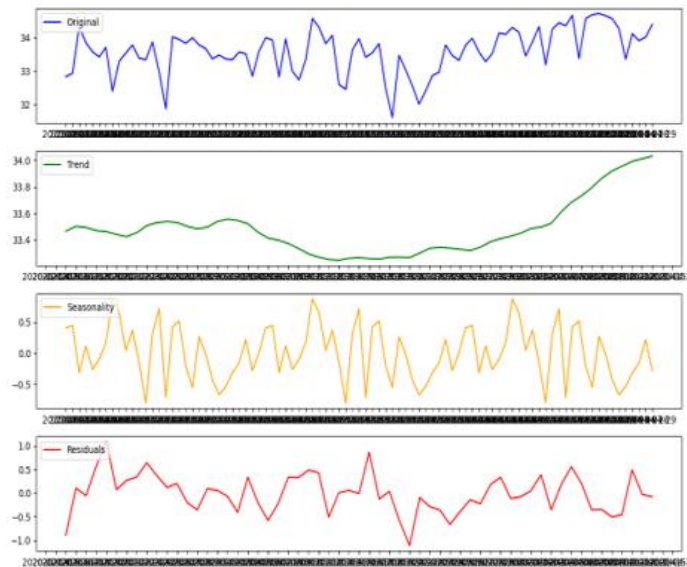
Fig 5. Net average price difference (Non-per)



2. T-Test / Mann-Whitney U Test:

- Used to determine statistically significant price changes between pre-lockdown and post-lockdown periods.
- Some are:
 - Rice: p-value = 0.0017 (Significant price change)
 - Wheat: p-value = 0.0956 (No significant difference)
 - Milk: p-value = 0.0000 (Significant price change)
 - Onion: p-value = 0.0000 (Significant price change)
 - Palm Oil: p-value = 0.8312 (No significant difference)

Fig 6. Time-Series Decomposition



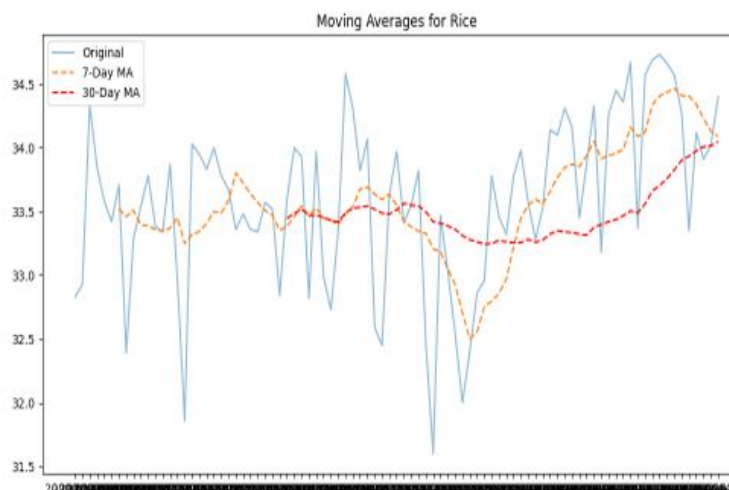
3. Time-Series Decomposition

- The trend component likely shows an upward trajectory post-lockdown, confirming sustained price increases.
- The residual component may have sharp fluctuations around March 24, 2020, indicating lockdown-induced price shocks.
- The seasonality component helps verify recurring price patterns in commodities like vegetables and dairy.

4. Moving Average

- Pre-lockdown period (before March 24, 2020): Prices were relatively stable, with minor fluctuations.
- Post-lockdown period: Both 7-day and 30-day moving averages rise, confirming a sustained increase in food prices after lockdown.
- Short-term fluctuations (7-day MA) are more pronounced in perishable goods (e.g., vegetables), while long-term increases (30-day MA) are seen in non-perishables (e.g., rice, wheat, oils).

Fig 7. Moving Average



E. Prediction Model

After evaluating several machine learning models, XGBoost turned out to be the one with better performance, and was used in the development of the price prediction model.

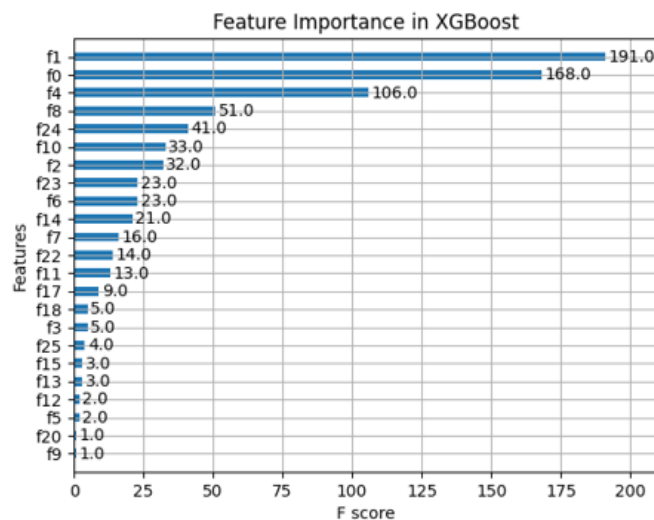
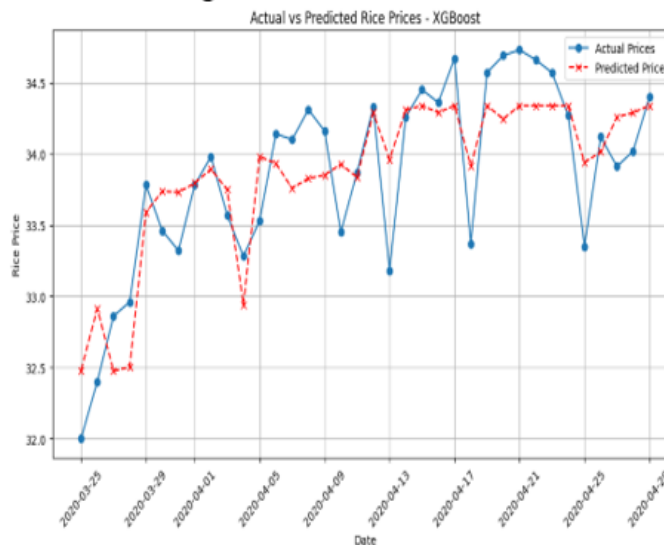
This prediction model will help in understanding what the prices might be in the future if any other crises occurs.

The below figure Fig 8 is the price prediction of a commodity(Rice).

- The model's predictions closely follow real price movements, confirming it effectively learns from historical patterns.
- The prediction errors are small, meaning the model generalizes well without overfitting.
- Past prices (Lag features) were the most influential factor in predicting future prices.
- Rolling averages helped smooth fluctuations, making predictions more reliable.
- The COVID-19 lockdown indicator allowed the model to account for supply chain disruptions.

These findings show that the prices of foods were greatly affected during the lockdown period of COVID-19, and statistical tests validated significant price changes in various commodities. The research shows that previous prices, rolling averages, and external disturbances such as lockdowns have a significant impact on the prediction of future price directions, thus affirming the reliability of machine learning models in predicting economic disturbances.

Fig 8. Rice Price Prediction



VI. CONCLUSION

This research evaluated the effect of India's lockdown due to COVID-19 on food prices and created machine learning models for economic disruption price prediction. Through the application of statistical tests, time-series decomposition, and predictive modelling, the research established that there were significant changes in prices induced by the lockdown, particularly among perishable food items such as vegetables and milk. T-tests and Mann-Whitney U tests provided statistically significant rising prices for a number of commodities, while sustained upward trends post-lockdown emerged from time-series decomposition.

In forecasting prices, XGBoost was superior to Linear Regression, Random Forest, ARIMA, and LSTM models in terms of achieving the highest accuracy ($R^2 = \sim 0.71$ for Rice). In feature importance analysis, it was seen that previous prices, rolling means, and lockdown indicators were the most prominent drivers of predicting price movements. The research illustrates that machine learning can successfully capture price trends and generate accurate forecasts, and therefore, it can be a powerful tool for understanding economic shocks.

Although this study does not offer explicit policy suggestions, it provides a data-based platform for predicting food price volatility during upcoming crises, e.g., pandemics or supply chain breakdowns. Future studies can extend this research by adding real-time data, extended time horizons, and more macroeconomic variables to further improve forecast precision.

REFERENCES

- [1] Hale, T., Angrist, N., Goldszmidt, R., et al. (2020). "Oxford COVID-19 Government Response Tracker." Blavatnik School of Government, University of Oxford. Retrieved from <https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker>
- [2] Rawal, V., & Kumar, M. (2020). "Impact of COVID-19 Lockdown on India's Agriculture and Rural Economy: Preliminary Assessment." SSRN Electronic Journal. DOI: 10.2139/ssrn.3626339
- [3] Ramakumar, R. (2020). "Agricultural Supply Chains During the COVID-19 Lockdown: Implications for Farmers and Consumers." *Economic & Political Weekly*, 55(18), 12-15.
- [4] Narayanan, S., & Saha, S. (2020). "Urban Food Markets and Supply Chain Disruptions in India During COVID-19." *Food Policy*, 101, 102072. DOI: 10.1016/j.foodpol.2021.102072
- [5] Baker, S. R., Farrokhnia, R. A., Meyer, S., et al. (2020). "How Does Household Spending Respond to an Epidemic? Consumption During the 2020 COVID-19 Pandemic." NBER Working Paper No. 26949. DOI: 10.3386/w26949
- [6] Zhang, X., Fan, S., & Qiao, J. (2021). "Resilience of China's Food Supply Chain Amid COVID-19: Lessons for Global Food Security." *Global Food Security*, 30, 100579. DOI: 10.1016/j.gfs.2021.100579
- [7] Ciaian, P., & Rajcaniova, M. (2021). "COVID-19 and Food Security: The Impact of Supply Chain Disruptions on European Agricultural Markets." *Agricultural Systems*, 191, 103136. DOI: 10.1016/j.agsy.2021.103136
- [8] Arif, I., Farooq, F., & Satti, A. (2021). "Food Price Inflation and Consumer Welfare in Bangladesh During COVID-19." *World Development*, 144, 105474. DOI: 10.1016/j.worlddev.2021.105474
- [9] Institute for Fiscal Studies (IFS). (2023). "The Impact of COVID-19 on Food Prices and Consumption Patterns in the UK." IFS Report Series.
- [10] Hyndman, R. J., & Athanasopoulos, G. (2021). *Forecasting: Principles and Practice* (3rd ed.). OTexts. Retrieved from <https://otexts.com/fpp3/>



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details