https://doi.org/10.65091/icicset.v2i1.20

Analyzing Behavior of Agricultural Commodities in Kalimati Tarkari Market using Machine Learning Technique and Prediction Strategies

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***Abstract*—Seasonal price volatility of agricultural commodities poses significant challenges to farmers and market stakeholders in Nepal due to climate variability, supply disruptions, and limited access to predictive market information. This study analyzes long-term seasonal price behavior using daily wholesale price data from Kalimati Tarkari Bazaar spanning 2013–2023. Machine learning and time-series techniques including Facebook Prophet, logistic regression, STL decomposition, and K-means clustering are employed to examine seasonal patterns, price volatility, and future price trends across six Nepali seasons. The results reveal strong and consistent seasonal dependencies, with most vegetables exhibiting peak prices during winter (Hemanta) and lower prices during the monsoon (Barsha). Prophet-based forecasting demonstrates moderate predictive performance with an average MAE of 32.95 and an average R^2 of 0.42, effectively capturing trend and seasonal components for most commodities. Volatility analysis identifies high-risk commodities with substantial price dispersion, while clustering reveals distinct market segments based on price levels and variability. The findings highlight the importance of seasonal awareness and data-driven forecasting in improving production planning, market participation, and policy formulation in Nepal's agricultural sector.**

***Index Terms*—Agricultural commodity prices, Seasonal price variation, Kalimati Tarkari Bazaar, Machine learning, Time-series forecasting, Prophet model, Price prediction, Data visualization, Nepal agricultural market, Market trend analysis.**

I. INTRODUCTION

In Nepal, pricing of agricultural commodities is heavily affected by seasonal patterns, variability in climate and fluctuating market supply. These create substantial uncertainty for farmers, traders, and consumers, making it difficult to predict market behavior with accuracy. With the increasing availability of digital records and the emergence of ML techniques, it has led to long-term pricing trend analysis and we can extract meaningful insights from historical market data. This paper focuses soely on Kalimati Tarkari Bazaar dataset, one of the most comprehensive source of vegetable market information one can get in Nepal, to understand how seasonsal factors influence price movements.

A. Motivation

One of the core component of Nepal's economy is agriculture with almost eighty percent of households depending on directly. However, farmers usually expeience inconsistent income due to price fluctuations that vary across seasons, climate conditions, and market availability. Seasonal variability significantly impacts pricing, especially for perishable commodities such as vegetables and fruits. During certain seasons, supply shortages caused by weather disruptions, pest outbreaks, or logistical challenges result in sudden price hikes. Conversely, harvest seasons often cause price drops that can negatively affect farmers' earnings. The absence of predictive indicators leaves stakeholders unprepared for such fluctuations.

The main motivation is the need to bridge this gap of information through analytical and predictive tools.agricultural market ecosystem in Nepal.

B. Problem Statement

Seasonal variations in Nepal lead to fluctuations in agricultural commodity prices, affecting farmers' livelihoods and market stability. Farmers lack awareness of these patterns, which results in lower earnings and inefficient market participation. Without proper data analysis, price volatility and unpredictability increase, limiting stakeholders' ability to make informed decisions for sustainable farming. To summarize,

- **Lack of Awareness:** Farmers are not fully aware of seasonal price fluctuations, leading to suboptimal market participation.

- **Market Instability:** Price volatility and unpredictability affect the livelihoods of farmers and consumer affordability.
- **Limited Decision-Making:** The absence of data-driven insights restricts stakeholders from making informed decisions for future planning.

C. Objective

The major objectives of the study are listed below:

1) **Historical Pricing Trend Analysis:** Analysis of the historical data from Kalimati Tarkari Bazar to find patterns and variations in agricultural commodity across all seasons.
2) **Understand Seasonal Impacts:** Elaborate on the impact of seasonal factors in the establishment of price trends, and assess the fluctuations in the prices of the most important commodities.
3) **Actionable Insights:** Provide visualization techniques that offer clear representations of price trends for farmers and policymakers to act upon.
4) **Predict Future Prices:** Study predictive models to forecast pricing trends for the next year, which might help stakeholders anticipate market conditions and plan production and marketing strategies effectively.

II. LITERATURE REVIEW

Understanding the pricing behavior of agricultural commodities requires examining prior studies that explore seasonality, market fluctuations, and predictive modeling techniques. The need for data-driven approaches to support agricultural planning is highlighted by existing research, which shows how seasonal patterns and environmental factors drive significant price variability across different regions. Additionally, new possibilities for examining long-term market behavior and enhancing price prediction accuracy have been made possible by developments in machine learning and time-series forecasting. There are numerous stances of predictive analysis used in agricultural decision making [9].

A. Related Work

[1] Analyzes price flexibility regarding seasons and seasonality patterns in pricing of key vegetables. The findings may show that this seasonal trend, if noticed and adapted, would improve the livelihoods of small-scale farmers by informing better production and marketing strategies [2]. [3] Developed a vegetable stock and pricing optimization model using TCN-Attention and a genetic algorithm, focusing on short-term pricing and inventory decisions. Their approach optimizes retail-level stock management but does not analyze long-term seasonal trends, multi-year market behavior, or broader price volatility. In contrast, our study emphasizes seasonal patterns and annual price dynamics rather than operational stock optimization. The paper highlights behavioral and structural barriers that prevent consumers from purchasing healthier foods even when they have the means, and recommends policy actions to support healthier choices [4].

This [5] proposes a deep learning–based framework that integrates multiple neural architectures to accurately predict agricultural crop prices. By leveraging historical price patterns, temporal features, and market behavior, the model significantly improves forecasting performance over traditional machine-learning approaches. Here, [6] proposes data-driven pricing and replenishment strategies for vegetables using nonlinear programming, but it does not examine multi-year seasonal price behavior, long-term trend dynamics, or volatility patterns across different seasons. This work presents a hybrid deep learning framework combining PCA, polynomial regression, Seq2Seq, Adam optimization, and LSTM for power outage time-series prediction. However, it does not address agricultural commodity pricing, seasonal price behavior, or market-driven fluctuations [7]. This [8] develops mathematical methods for generating fractal functions based on Suzuki iterated function systems, focusing on functional analysis, fractal geometry, and iterative construction of complex function families. Its contributions lie entirely in theoretical mathematics and fractal function generation. The paper does not involve time-series forecasting, commodity markets, or any form of machine-learning-based price prediction. In contrast, our study focuses on agricultural price analysis, seasonal trend exploration, market behavior modeling, and predictive analytics.

Previous studies have repeatedly shown how production cycles, seasonality, and climate variability cause large price swings that impact farmer income and market stability. Numerous studies show how effective machine learning and time-series forecasting models are at predicting both short-term and long-term price behavior. These models include deep learning architectures, neural networks, and optimization frameworks. While some studies concentrate on pricing and inventory optimization, others use sophisticated modeling techniques to investigate forecasting accuracy. This study fills this gap by thoroughly examining long-term trends, seasonal dynamics, and predictive modeling using the Kalimati Tarkari Bazaar dataset. However, previous research frequently lacks a multi-year seasonal analysis using actual wholesale market data from Nepal.

III. METHODOLOGY

This section outlines the methodology used for analyzing the dataset from Kalimati Tarkari Bazaar. The steps detailed below guided the analysis from preprocessing the dataset to deriving meaningful insights into price trends and seasonal variations.

A. Description of the Dataset

The dataset used in this analysis has been collected from Kalimati Tarkari Bazaar, a major wholesale market for vegetables and fruits in Nepal. This dataset contains daily price details on various agricultural commodities from 2013 to 2023. The key attributes present in the dataset are:

1) **Commodity:** The name of the agricultural product; for example, *Tomato Big (Nepali)*, *Potato Red*, etc.

2) **Date:** The date when the pricing information was recorded.
3) **Unit:** The unit of measurement of the commodity, such as kg.
4) **Min:** The lowest price of the commodity on a given day.
5) **Max:** The highest price of the commodity on a given day.
6) **Average:** The mean price for the commodity, computed based on the minimum and maximum prices for that given day.

This dataset provided a comprehensive view of price dynamics and serves as an ideal foundation for seasonal trend analysis, variability identification, and forecasting future price movements. Its rich temporal scope and granularity made it a strong source for analyzing market behaviors and patterns.

B. Algorithm Description

1) Next Year's Price Forecast: **Algorithm: Facebook Prophet**

Prophet is designed for time-series forecasting, handling seasonal effects, holidays, and trend changes effectively. It is robust to missing data and outliers. Prophet decomposes the time series into components: trend, seasonality, and noise. And, fits a model to historical price data and predicts future prices based on observed patterns, providing confidence intervals (`yhat_lower` and `yhat_upper`) for uncertainty estimation.

The primary reason to choose Prophet was it's design which is highly compatible for daily time-series data with strong seasonal effects. It is also specially designed for missing observations and outliers, which closely match the characteristics of our dataset. The methods like ARIMA, LSTM and other hybrid approaches often require extensive tuning, are sensitive to missing data, or do not perform well with outliers. The Facebook Prophet model, offers a flexible approach capable of handling trend shifts, strong seasonality, missing values, and outliers. [11]. This makes it particularly suitable for agricultural commodity prices influenced by harvesting cycles, festivals, and irregular market shocks.

2) Price Fluctuation: **Algorithm: Logistic Regression**

Logistic Regression was used for modeling short-term price fluctuations by classifying movements into Decrease, Stable, and Increase categories. Logistic Regression treated price fluctuation as a categorical outcome and modeled the probability of each class using a logistic function. Also, incorporated engineered features (lagged returns, moving averages, and relevant exogenous variables) into a preprocessing pipeline followed by a one-vs-rest logistic classifier for multiclass predictions. The algorithm employed class-weighting and stratified train-test splitting to mitigate class imbalance and ensure reliable evaluation and evaluated classification performance using accuracy, precision, recall, F1-score, confusion matrices, and cross-validation to assess generalization.

Logistic Regression was selected as a baseline classifier due to its simplicity, computational efficiency, and interpretability for multiclass price movement prediction. The model demonstrated relatively modest predictive accuracy and weak performance in identifying the *Stable* class, primarily due to class imbalance and the limitations of linear decision boundaries. This limitation is explicitly acknowledged in this study. Logistic Regression is retained as a benchmark model, while future work will explore non-linear and ensemble-based classifiers to improve classification performance.

3) Seasonal Price Prediction: **Algorithm: Seasonal Decomposition of Time Series (STL Decomposition)**

STL decomposition is effective for identifying and isolating seasonal components from a time series. Decomposition methods are employed to divide a time series into its trend, seasonal, and residual components [10]. The algorithm separates the time series into trend, seasonality, and residual components and extracts seasonal patterns to analyze price behavior during specific periods, such as harvesting seasons. STL Decomposition also works effectively when combined with forecasting models such as Prophet or Logistic Regression.

STL decomposition was adopted to explicitly separate trend and seasonal components of the price time series, supporting clear visualization and interpretation of seasonal price behavior across the six Nepali seasons. When used alongside Prophet, STL decomposition helped revealing the underlying temporal structure of the data prior to forecasting.

4) Clustered Commodity Groups: **Algorithm: K-Means Clustering**

K-Means is effective for grouping similar items based on shared characteristics. Here, clusters commodities based on price patterns, unit measures, or other relevant attributes. This algorithm assigns commodities into groups with similar market behaviors or trends and helps identify categories with shared demand or pricing structures.

K-Means clustering was chosen to group commodities with similar price levels and volatility characteristics due to its computational efficiency and suitability for large datasets with continuous numerical features such as minimum, maximum, and average prices. The resulting clusters provided an intuitive segmentation of the market into low-price staples, moderately priced vegetables, and high-price or specialty commodities, facilitating interpretable analysis for policymakers and market participants.

C. Implementation Details

1) Data Preprocessing:

Loading the Dataset: The dataset was loaded into a Python environment using Pandas for data manipulation.

Date Parsing: The Date column was converted into a proper datetime format to enable the extraction of components such as Month and Year.

Missing Data Handling: Missing or null values in key columns, such as average prices, was identified and addressed through imputation/removal, depending on their impact on the analysis.

Outlier Detection: Outliers in price data was identified using statistical techniques such as the interquartile range (IQR) and visualized using boxplots. These outliers was addressed to minimize their influence on the results.

2) *Mapping Seasons:* Monthly data was mapped to six Nepali seasons: `Basanta Ritu (Spring: mid-March to mid-May), Grishma Ritu (Summer: mid-May to mid-July), Barsha Ritu (Monsoon: mid-July to mid-September), Sharad Ritu (Autumn: mid-September to mid-November), Hemanta Ritu (Pre-winter: mid-November to mid-January) and Shishir Ritu (Winter: mid-January to mid-March).` A predefined mapping dictionary was used to categorize each month into its respective season.

3) *Aggregating Seasonal Data:*

Seasonal Averages: Prices were grouped by Commodity and Season to calculate the average price for each commodity in each season.

Yearly Trends: Additional grouping by Commodity, Season, and Year allowed for an analysis of year-over-year changes in seasonal pricing.

4) *Visualization and Analysis:*

Boxplots: Boxplots were created for each commodity to illustrate the distribution of prices across seasons, highlighting variations and outliers.

Line Graphs: Line graphs were generated to represent average price trends for each commodity over the seasons.

Heatmaps: Heatmaps were created to visualize the interactions between season and year for each commodity, showcasing how prices vary over years within each season.

5) *Trend Analysis and Insights:* Seasonal price differences were analyzed to identify commodities with the highest price volatility. Prediction for the following year's pricing trends was based on historical data and observed patterns, offering actionable insights for farmers, traders, and policymakers.

6) *Validation:* The results were cross-validated using subsets of the data to ensure consistency and reliability. External factors such as market conditions and production cycles were considered when interpreting the findings.

IV. RESULT AND DISCUSSION

A system that predicted the minimum, maximum and average prices of different vegetable commodities for the next upcoming year was the one concrete outcome of this study. It provided in-depth visualizations regarding historical trends in prices, seasonal variations, and market dynamics along with actionable insights on factors affecting the fluctuatiion of prices for better decision-making by farmers, vendors, and policymakers.

A. Amla – Monthly Price Distribution

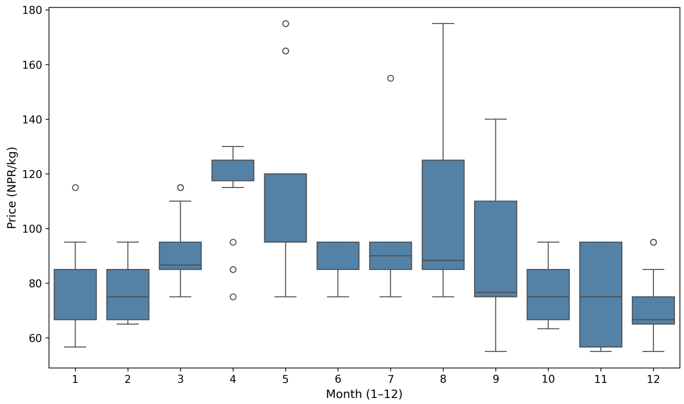

Fig. 1. Monthly distribution of Amla prices showing seasonal variations.

The monthly distribution of Amla prices (Fig. 1) shows clear seasonal behavior. Prices peak sharply in May, July, and August, indicating strong mid-year scarcity. The lowest prices typically occur in November and December, aligning with the harvest season. Significant outliers in months 5, 7, and 8 suggest periodic supply shocks or increased festival-driven demand. Additionally, the high variance observed in August reflects unstable supply conditions during the monsoon period. Overall, the pattern highlights Amla's strong sensitivity to monsoon dynamics and mid-year shortages.

B. Amla – Forecasted Price Trend

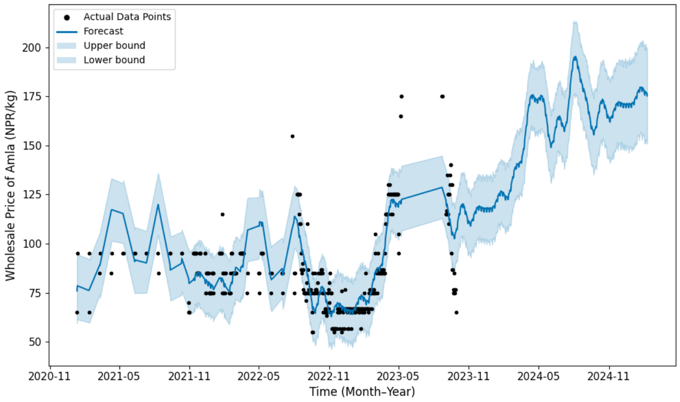

Fig. 2. Forecasted price trend for Amla with confidence intervals.

The forecasted price trend for Amla (Fig. 2) reveals a clear upward trajectory supported by strong seasonal patterns. The model captures recurring price spikes during mid-year months, consistent with historical fluctuations. The widening confidence interval toward the end of the forecast horizon reflects increasing uncertainty in long-term predictions. Despite short-term volatility, the overall trend suggests steady growth in Amla prices, driven by both seasonal influences and longer-term demand factors.

C. Tomato Big (Nepali) – Season-Year Heatmap

Fig. 4 illustrates the seasonal variation of Tomato Big prices across different years. Key observations include:

- **Winter spike:** Prices dramatically increase in Hemanta (winter), particularly in 2023, reaching over 110 NPR/kg.

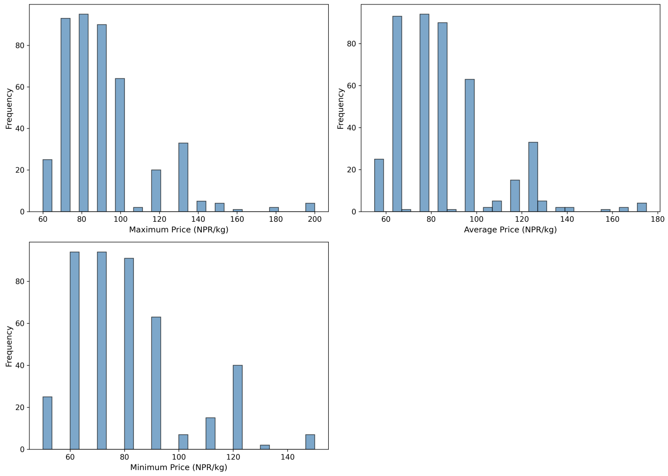

Fig. 3. Price frequency distribution of Amla across all observations.

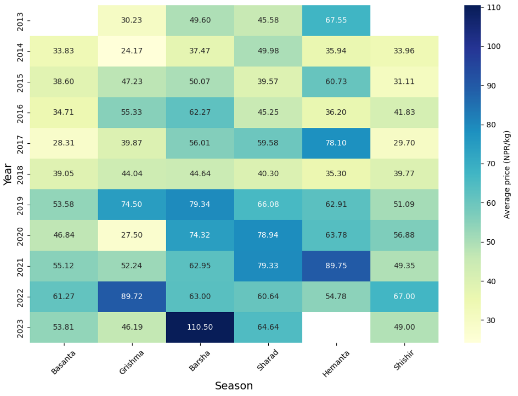

Fig. 4. Seasonal average prices of Tomato Big (Nepali) across years.

- **Monsoon rise:** Barsha (monsoon) also shows elevated prices due to reduced yields and disease-related losses.
- **Moderate seasons:** Basanta and Grishma generally exhibit moderate and relatively stable prices.
- **Inflation trend:** A clear upward price trend is observed after 2018.

Overall, the heatmap demonstrates strong seasonal dependency, with winter scarcity and monsoon production challenges driving the highest prices.

D. Price Volatility Analysis

Figure 5 presents the top 20 most volatile commodities based on their Coefficient of Variation (CV), a measure that captures the relative dispersion of prices over time. A higher CV indicates greater instability and unpredictability in market prices. Maize exhibits the highest volatility (CV $\approx$ 1.35), suggesting highly inconsistent price behavior influenced by seasonal harvest cycles, supply-chain disruptions, or import dependencies. Other commodities such as Lettuce, Mombin, Asparagus, and Coriander Green also show elevated volatility, indicating sensitivity to weather patterns, perishability, and short shelf-life.

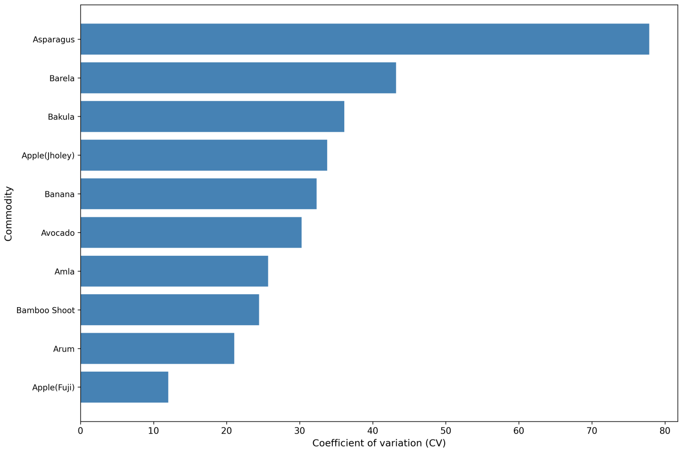

Fig. 5. Top 20 most volatile vegetable commodities based on the Coefficient of Variation (CV).

A second group of vegetables—including Mint, Broccoli, Parsley, Red Cabbage, and Lime—demonstrates moderate volatility, which may be linked to localized production and fluctuating market arrivals. The remaining commodities in the top twenty display relatively lower but still notable volatility, highlighting underlying instability in distribution or production.

Overall, the volatility analysis reveals that a significant portion of Nepal's vegetable market is characterized by moderate to high price fluctuations. These insights are crucial for stakeholders, as highly volatile commodities pose greater risk to farmers and traders and require improved storage, supply-chain planning, and targeted policy interventions.

E. Model Evaluation

This study evaluated two machine learning approaches applied to agricultural commodity price analysis, each serving a distinct predictive task. The Prophet model was employed for numerical price prediction using time-series forecasting, with directional price movement (Decrease, Stable, Increase) derived from predicted trends. In contrast, Logistic Regression was used exclusively for price fluctuation classification.

Model performance was assessed using appropriate evaluation metrics based on the nature of each task.

1) Prophet Model Evaluation (Price Prediction): The Prophet model was evaluated using regression metrics including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the R^2 score. These metrics assessed the accuracy of numerical price forecasting.

Across most commodities, Prophet demonstrated moderate to strong forecasting capability. Commodities such as Arum, Banana, Bamboo Shoot, and Amla recorded relatively low MAE and RMSE values, indicating accurate short-term price predictions. High R^2 values for Avocado and Apple (Fuji) indicated that the model effectively captured long-term trends and seasonal patterns.

However, for highly volatile commodities such as Asparagus, Prophet exhibited large error values and a negative R^2 score, indicating poor model fit. In some cases, MAPE values became infinite due to zero-valued actual prices, highlighting a limitation of percentage-based error metrics in agricultural datasets.

Overall, Prophet achieved an average MAE of 32.95 and an average R^2 score of 0.42, indicating moderate predictive performance.

2) Derived Price Movement Analysis from Prophet: Although Prophet was not designed as a classification model, price fluctuation labels were derived by comparing predicted prices across consecutive time steps. Using this approach, Prophet achieved high directional accuracy and F1-scores. However, the model showed bias toward predicting price increases, while performance for Stable and Decrease classes remained comparatively weaker due to class imbalance.

3) Logistic Regression Model Evaluation (Price Fluctuation Classification): Logistic Regression was applied exclusively to classify price fluctuations into Decrease, Stable, and Increase categories.

The model achieved an overall accuracy of 63.30% with a weighted F1-score of 60.35%. Cross-validation results confirmed stable performance across folds. While the model performed reasonably well for Decrease and Increase classes, it failed to classify the Stable category effectively due to dataset imbalance.

F. Model Performance Summary Tables

TABLE I
PRICE PREDICTION PERFORMANCE (PROPHET MODEL)

Commodity	MAE	RMSE	MAPE (%)	R^2
Amla	12.98	18.44	11.73	0.46
Apple (Fuji)	14.96	20.99	4.93	0.69
Apple (Jholey)	26.72	34.71	14.31	0.09
Arum	5.64	6.93	11.07	0.33
Asparagus	194.39	286.40	∞	-0.09
Avocado	30.22	39.15	7.26	0.92
Bakula	14.72	18.61	23.99	0.40
Bamboo Shoot	8.64	10.91	8.20	0.20
Banana	9.81	12.59	7.63	0.67
Barela	11.40	15.59	19.44	0.53
Average	**32.95**	**46.43**	∞	**0.42**

TABLE II
PRICE FLUCTUATION CLASSIFICATION PERFORMANCE

Model	Accuracy (%)	Precision	Recall	F1-Score
Prophet (Derived)	85.95	0.84	0.86	0.83
Logistic Regression	63.30	0.60	0.63	0.60

The experimental results indicated that Prophet was better suited for agricultural commodity price prediction due to its ability to model trend and seasonality. Logistic Regression, although efficient and interpretable, demonstrated limited performance in price fluctuation classification due to class imbalance and linear decision boundaries.

TABLE III
COMPARISON OF PROPHET AND LOGISTIC REGRESSION MODELS

Aspect	Prophet	Logistic Regression
Primary Task	Price Prediction	Price Fluctuation
Model Type	Time-Series	Linear Classifier
Seasonality	Yes	No
Regression Capability	Yes	No
Classification Capability	Derived	Direct
Average Accuracy	85.95%	63.30%
Volatility Robustness	Moderate	Low
Class Imbalance Sensitivity	High	High

G. Stationarity Tests (First 5 Commodities)

The table presents the stationarity test results for the first five commodities using the Augmented Dickey-Fuller (ADF) and KPSS tests. Each test's statistic, p-value, and resulting conclusion (Stationary / Non-Stationary) are shown. The overall summary highlights the total number of commodities tested and how many were stationary, non-stationary, or inconclusive based on the combination of both tests.

TABLE IV
STATIONARITY TEST RESULTS (ADF AND KPSS)

Commodity	ADF Statistic	ADF p-value	ADF Result	KPSS Statistic	KPSS p-value	KPSS Result
Banana	-2.8799	0.0477	Stationary	6.6489	0.0100	Non-Stationary
Apple (Jholey)	-2.8945	0.0460	Stationary	4.6598	0.0100	Non-Stationary
Bamboo Shoot	-3.6667	0.0046	Stationary	0.2412	0.1000	Stationary
Asparagus	-3.7729	0.0032	Stationary	1.1931	0.0100	Non-Stationary
Arum	-3.6422	0.0050	Stationary	4.7545	0.0100	Non-Stationary

TABLE V
OVERALL STATIONARITY SUMMARY

Metric	Count
Total commodities tested	10
Stationary (both tests)	1
Non-stationary (both tests)	1
Inconclusive (mixed results)	8

V. FINDINGS

The study identified strong seasonal behavior in vegetable prices across Nepal, with most commodities showing peak prices during winter and the lowest prices during the monsoon months. This consistent seasonality indicates that climate and production cycles significantly influence market pricing. Yearly trends showed a gradual rise in overall price levels, suggesting increasing demand or higher production and transportation costs over time. Some commodities also displayed noticeable fluctuations, highlighting periods of supply imbalance or market instability.

Clustering analysis grouped the vegetables into three meaningful categories based on their average, minimum, and maximum prices: low-price staples, moderately priced vegetables, and high-price or specialty items. These clusters reveal natural segmentation within the market and help identify which commodities are more volatile or consistently stable. Correlation analysis further showed that certain vegetables share similar price movement patterns, indicating shared seasonal cycles or supply-chain dependencies.

Forecasting results using the Prophet model captured both trend and seasonal components effectively. Most commodities showed upward projected trends with clear seasonal dips and peaks, while the prediction intervals highlighted differences in stability among commodities. Together, these findings show that Nepal's vegetable market is strongly seasonal, moderately inflationary, and segmented, with meaningful patterns that can support better planning for farmers, traders, and policymakers.

VI. CONCLUSION

This study investigated the seasonal price behavior of agricultural commodities in Nepal using a decade-long dataset from Kalimati Tarkari Bazaar and a combination of machine learning and time-series analysis techniques. The results confirm that vegetable prices in Nepal exhibit strong and persistent seasonal patterns, with pronounced price increases during winter months and relatively lower prices during the monsoon season. These patterns are largely driven by climate-sensitive production cycles, perishability, and supply-chain constraints.

Forecasting experiments using the Prophet model demonstrated its effectiveness in capturing both long-term trends and seasonal components for most commodities, achieving moderate predictive accuracy across the dataset. However, performance declined for highly volatile commodities, highlighting limitations in modeling abrupt market shocks using purely historical price data. Logistic regression, used for price movement classification, showed modest performance and was sensitive to class imbalance, underscoring the need for more advanced non-linear or ensemble-based classifiers.

Overall, the study contributes a comprehensive seasonal and volatility-focused analysis of Nepal's wholesale vegetable market using real market data. By quantifying seasonal dependencies, identifying volatile commodities, and evaluating forecasting performance, this research provides actionable insights for farmers, traders, and policymakers. These insights can support improved production scheduling, risk management, and evidence-based agricultural policy design, contributing to greater market stability and economic resilience.

VII. FUTURE ENHANCEMENTS

Although the current analysis provides meaningful insights, several improvements can enhance the accuracy, usability, and real-world applicability of the system:

- **Integration of External Factors:** Future models can incorporate weather data, rainfall, temperature, festival seasons, and supply-chain disruptions to improve prediction accuracy.
- **Real-Time Data Pipeline:** Implementing an automated system to fetch real-time price updates from Kalimati or other markets will enable dynamic forecasting and live dashboards for stakeholders.
- **Advanced Deep Learning Models:** Techniques such as LSTMs, GRUs, or Temporal Convolutional Networks (TCN) can be explored to capture long-range dependencies and non-linear price movements.
- **Improved Classification Techniques:** Ensemble models such as Random Forest, XGBoost, or LightGBM can address class imbalance and improve fluctuation classification.
- **Commodity Demand Forecasting:** Along with price prediction, forecasting consumer demand will provide a more holistic view of market conditions.

These enhancements can significantly strengthen the analytical framework and support the development of a robust, data-driven agricultural market intelligence system for Nepal.

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