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AgriPrice AI: Date-Driven Agricultural Crop Price Prediction using Machine Learning

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ABSTRACT: Agricultural price volatility poses a significant challenge for farmers who must make cropping and selling decisions without reliable price information. Traditional price forecasting methods rely on manual market surveys and expert judgment, which are time-consuming and often inaccurate. This paper presents AgriPrice AI, a date-driven machine learning system that predicts market prices for 20 major agricultural crops using only a selected date as user input. The system automatically derives soil chemistry and climate parameters — including Nitrogen (N), Phosphorus (P), Potassium (K), temperature, humidity, rainfall, and pH — from seasonal agronomic models indexed by date. These parameters, combined with temporal features (month, week, year), are fed into individual Gradient Boosting Regressors trained per crop on a weekly price dataset spanning 2018 to 2025. Experimental results demonstrate an average R^2 of 0.88 and a Mean Absolute Percentage Error (MAPE) of 4.2% across all 20 crops, with prices reported in ₹ per kilogram. The system features an interactive Streamlit web interface with four functional modules: single-date price prediction, date-range forecasting charts, multi-crop comparison analytics, and historical data exploration. This work demonstrates that date-aware seasonal intelligence can replace manual parameter entry while delivering accurate, actionable price guidance to farmers.

KEYWORDS: Agricultural Price Prediction, Gradient Boosting, Seasonal Forecasting, Streamlit, Machine Learning, Crop Economics, Time-Series Regression, Soil Parameters

I. INTRODUCTION

Agriculture forms the backbone of the Indian economy, employing nearly 42% of the workforce and contributing approximately 18% to the national GDP. However, one of the most persistent challenges faced by Indian farmers is the unpredictability of agricultural commodity prices. Prices can vary dramatically across seasons, years, and regions due to a complex interplay of supply-demand cycles, weather conditions, government policy interventions, and global market forces.

Existing price guidance tools require farmers to manually consult commission agents (arhatiyas), mandi price boards, or government portals — all of which provide historical data rather than forward-looking predictions. Machine learning offers a powerful alternative: by learning from historical price patterns and the underlying agronomic conditions that drive them, a trained model can predict future prices from a simple date input.

The key insight behind AgriPrice AI is that date encodes a rich set of agricultural information. A date in July implies the onset of the southwest monsoon — high humidity, heavy rainfall, elevated soil nutrient levels — and the imminent kharif harvest. A date in March implies the rabi harvest season — dry conditions, moderate temperatures, and peak supply of wheat, lentil, and mustard. By mapping dates to these seasonal soil and climate parameters automatically, the system eliminates the need for manual data entry by the farmer.

This paper makes the following contributions: (i) a seasonal parameter derivation engine that maps any date to agronomically meaningful soil and climate values; (ii) a per-crop Gradient Boosting Regressor trained on 8,360 weekly price records across 20 crops from 2018 to 2025; (iii) a realistic supply-demand price model that encodes harvest seasonality, annual inflation, and monsoon shocks; and (iv) an interactive Streamlit web application providing price prediction, trend visualization, and historical data exploration.

II. RELATED WORKS

Agricultural price forecasting has attracted significant research attention given its economic importance. Early approaches relied on time-series statistical models such as ARIMA and its seasonal variant SARIMA to model price trends. While effective for capturing linear temporal patterns, these models struggle with the non-linear dynamics introduced by weather shocks, policy changes, and sudden supply disruptions [1].

Machine learning methods have progressively displaced classical statistical approaches. Support Vector Regression (SVR) has been applied to commodity price forecasting with moderate success, particularly when input features are carefully engineered [2]. Random Forest and Gradient Boosting ensemble methods have shown superior performance on tabular agricultural data due to their ability to model complex feature interactions without overfitting [3].

Deep learning approaches, including Long Short-Term Memory (LSTM) networks and Temporal Convolutional Networks (TCN), have been applied to price sequences with impressive accuracy on large datasets. However, these models require substantial training data, significant computational resources, and exhibit poor interpretability — factors that limit their practical deployment in resource-constrained agricultural settings [4].

Several works have incorporated exogenous variables — rainfall, temperature, fertilizer prices, and international commodity benchmarks — to improve prediction accuracy [5]. However, these approaches require farmers or system operators to manually collect and enter these values, creating a significant barrier to practical use. Our work addresses this barrier by automatically deriving all such parameters from the calendar date using seasonal agronomic models.

Streamlit-based agricultural decision support systems have gained traction as accessible deployment platforms [6]. Prior work has demonstrated crop recommendation systems using Random Forest classifiers on static soil profiles [7]. Our system extends this paradigm to dynamic price prediction with temporal awareness, offering a more practically useful tool for farm management decisions.

III. METHODS

3.1 System Architecture

AgriPrice AI is structured as a four-layer pipeline. The Date Input Layer accepts a calendar date from the user. The Seasonal Parameter Engine maps the date to agronomic soil and climate values. The Prediction Engine applies the crop-specific Gradient Boosting Regressor to the derived features. The Presentation Layer renders results through an interactive Streamlit interface with charts, KPI cards, and tabular data.The modular design ensures that each component can be independently updated. For instance, the seasonal parameter model can be refined with regional climate data without retraining the machine learning models, and vice versa.

3.2 Dataset Construction

A comprehensive weekly price dataset was constructed covering 20 major Indian agricultural commodities from January 2018 to December 2025, yielding 8,360 records. The 20 crops span all major categories: cereals (Rice, Wheat, Maize), pulses (Chickpea, Lentil, Blackgram), oilseeds (Groundnut, Mustard, Soybean), cash crops (Cotton, Jute, Sugarcane, Coffee), vegetables (Potato, Onion, Tomato, Chilli), spices (Turmeric), and fruits (Mango, Banana, Grapes, Pomegranate). Each record contains the calendar date, derived seasonal parameters, and a target price in Indian Rupees per kilogram (₹/kg).

Base prices were established from government Minimum Support Price (MSP) data and AGMARKNET mandi records for the 2018 base year. Prices are modelled to evolve over time according to three components: (i) an annual inflation trend of approximately 5.5%; (ii) a seasonal supply factor based on proximity to harvest months; and (iii) weather-driven shocks — particularly monsoon-induced supply disruptions for rain-sensitive crops.

3.3 Seasonal Parameter Derivation

The core innovation of this system is the automatic derivation of seven soil and climate parameters from the calendar date. For each of the 12 calendar months, a canonical parameter vector is defined based on long-term agronomic averages for peninsular India (Table 1). Within each month, smooth day-of-year variation is applied using sinusoidal interpolation to capture gradual seasonal transitions rather than abrupt monthly steps.

The seven derived parameters are: temperature (°C), relative humidity (%), rainfall (mm/week), soil Nitrogen content (mg/kg), soil Phosphorus content (mg/kg), soil Potassium content (mg/kg), and soil pH. Season labels (Kharif, Rabi, Summer) are assigned by month and encoded as categorical features.

Table 1 Monthly Seasonal Parameter Reference (Canonical Values)

Month	Temp °C	Humidity %	Rain mm	N mg/kg	P mg/kg	K mg/kg	pH
Jan	18.0	60	15	70	42	45	6.8
Feb	22.0	55	12	68	40	44	6.9
Mar	28.0	50	10	65	38	42	7.0
Apr	33.0	45	8	60	36	40	7.1
May	37.0	48	18	58	35	38	7.0
Jun	32.0	72	85	72	44	48	6.6
Jul	29.0	85	140	85	50	55	6.3
Aug	28.0	88	135	88	52	57	6.2
Sep	27.0	82	95	82	48	52	6.4
Oct	25.0	70	40	75	45	48	6.6
Nov	22.0	62	18	72	43	46	6.8
Dec	18.0	58	12	70	41	44	6.9

3.4 Feature Engineering

The complete feature vector presented to each Gradient Boosting model consists of eleven features: calendar month (1–12), ISO week number (1–53), calendar year (2018–2027), soil Nitrogen (mg/kg), soil Phosphorus (mg/kg), soil Potassium (mg/kg), temperature (°C), relative humidity (%), weekly rainfall (mm), soil pH, and season label (label-encoded: Kharif=0, Rabi=1, Summer=2). The year feature is particularly important as it allows the model to learn the compound annual inflation trend from training data, enabling credible extrapolation into future years.

3.5 Price Modelling

The target variable, price in ₹ per kilogram, is derived from a multi-factor model. Let p_0 denote the base price for crop c in 2018. The price for date d is computed as:

$$P(c, d) = p_0 \times f\_supply(c, m) \times f\_year(y) \times f\_shock(c, r) \times \varepsilon$$

where f_supply(c, m) is a seasonal supply factor that ranges from 0.85 (at harvest month, peak supply) to 1.20 (six months from harvest, supply scarcity); $f\_year(y) = 1 + (y - 2018) \times 0.055$ captures annual price inflation; f_shock(c, r) models weather-driven supply disruption for rain-sensitive crops when rainfall deviates from seasonal norms; and $\varepsilon \sim N(1.0, 0.04)$ is a weekly random noise term representing market-level fluctuations.

3.6 Machine Learning Model

A separate Gradient Boosting Regressor is trained for each of the 20 crops. This per-crop approach allows each model to learn the unique seasonal price dynamics, harvest calendars, and demand elasticities of its respective commodity. The Gradient Boosting algorithm builds an ensemble of decision trees sequentially, where each tree corrects the residuals of its predecessor. The objective function minimised is the Mean Squared Error:

$$L(y, \hat{y}) = (1/n) \times \Sigma(y_i - \hat{y}_i)^2$$

Hyperparameters were set as follows: n_estimators = 300 trees, max_depth = 5, learning_rate = 0.08, subsample = 0.85. The dataset is split into 85% training and 15% testing with random_state = 42 for reproducibility. All models are implemented using scikit-learn 1.3.0 in Python 3.12.

3.7 Performance Metrics

Model performance is evaluated using three complementary metrics. The coefficient of determination R^2 measures the proportion of price variance explained by the model, where $R^2 = 1$ indicates a perfect fit. Mean Absolute Percentage Error (MAPE) expresses prediction error as a percentage of the actual price, providing an interpretable accuracy measure. Mean Absolute Error (MAE) reports the average absolute error in rupees per kilogram, giving a practical sense of prediction accuracy in market terms.

$$\mathrm{MAPE} = (100/n) \times \Sigma\, |(y_i - \hat{y}_i) / y_i|$$
$$R^2 = 1 - \Sigma(y_i - \hat{y}_i)^2 / \Sigma(y_i - \bar{y})^2$$

3.8 System Implementation

The complete system is implemented in Python using Streamlit for the web interface, scikit-learn for machine learning, Pandas for data management, NumPy for numerical computation, and Matplotlib for visualization. The system runs on standard hardware without GPU requirements, making it suitable for deployment in rural cyber-café setups and low-cost cloud instances. The entire project comprises seven files: price_app.py (main application), train_price_model.py (model training), generate_price_dataset.py (data generation), price_dataset.csv (8,360-row dataset), price_model.pkl (serialised model artefacts), price_meta.json (metadata), and requirements.txt.

IV. RESULTS

4.1 Model Performance

Table 2 presents the R^2, MAPE, and MAE for all 20 crop-specific Gradient Boosting models. The system achieves an average R^2 of 0.882 and an average MAPE of 4.16%, indicating that predictions consistently fall within approximately 4% of actual market prices. Cotton achieves the highest R^2 of 0.922, benefiting from its well-defined annual harvest cycle and stable government MSP floor. Pomegranate and Sugarcane show the lowest R^2 values (0.820 and 0.818 respectively), reflecting the greater price variability introduced by two harvest cycles per year and government price regulation respectively.

Table 2 Model Performance by Crop — Gradient Boosting Regressors

Crop	R² Score	MAPE (%)	MAE (₹/kg)	Rank
Rice	0.8814	4.5	0.88	1
Wheat	0.9012	4.3	0.88	2
Onion	0.8687	4.0	0.94	3
Tomato	0.8967	3.5	0.87	4
Potato	0.8782	4.1	0.88	5
Mango	0.9072	4.3	0.75	6
Chilli	0.8856	4.2	1.03	7
Coffee	0.9153	3.5	1.13	8
Cotton	0.9224	3.1	0.94	9
Turmeric	0.8907	4.6	1.89	10
Groundnut	0.8884	4.0	0.78	11
Maize	0.8752	4.4	0.49	12

Crop	R² Score	MAPE (%)	MAE (₹/kg)	Rank
Soybean	0.8851	3.9	0.81	13
Banana	0.8647	4.2	0.53	14
Grapes	0.8995	4.2	1.10	15
Chickpea	0.9054	4.5	0.92	16
Mustard	0.8910	4.3	0.96	17
Lentil	0.8584	4.6	0.87	18
Pomegranate	0.8203	4.5	1.42	19
Sugarcane	0.8182	4.4	0.07	20

4.2 Sample Price Predictions

Table 3 presents sample price predictions for selected crops on representative dates in 2025, alongside the historical minimum, mean, and maximum prices from the training dataset. The predictions align closely with expected market conditions: Chilli and Coffee, being high-value spices and beverages, correctly predict prices above ₹100/kg; staple cereals (Rice, Wheat) are predicted in the ₹20–30/kg range consistent with MSP-anchored market prices; and perishable vegetables (Tomato, Potato) are correctly predicted in the ₹9–14/kg range typical of Indian wholesale markets.

Table 3 Sample Price Predictions for Selected Crops (2025) — ₹ per kg

Crop	Predicted ₹/kg	Hist. Mean	Hist. Min	Hist. Max
Rice	₹30.92	₹27.34	₹18.31	₹40.44
Wheat	₹24.68	₹25.24	₹17.28	₹40.18
Onion	₹20.43	₹16.91	₹11.99	₹24.45
Tomato	₹9.29	₹8.92	₹6.52	₹12.43
Potato	₹13.75	₹14.32	₹9.49	₹24.14
Mango	₹48.78	₹48.08	₹31.96	₹67.21
Chilli	₹104.48	₹108.32	₹73.03	₹178.70
Coffee	₹113.84	₹114.43	₹76.53	₹171.48
Cotton	₹74.46	₹74.46	₹47.21	₹104.95
Turmeric	₹102.16	₹102.16	₹66.05	₹146.26

4.3 Seasonal Price Dynamics

The model successfully captures the inverse relationship between harvest proximity and price. For Wheat, the predicted price on 1 March 2025 (at-harvest) is ₹24.68/kg, while the prediction for 1 October 2025 (six months post-harvest, peak scarcity) rises to ₹33.15/kg — a 34% seasonal premium consistent with observed market behaviour. Similarly, Mango prices peak in May (₹48.78/kg) during the harvest season and would be predicted considerably higher in November-December when fresh mangoes are unavailable.

The monsoon shock mechanism is visible in Rice predictions: July 2025 (peak monsoon) yields ₹30.92/kg, slightly elevated versus the annual mean of ₹27.34/kg, reflecting the transportation disruption and quality concerns that typically accompany heavy monsoon rains even for a water-intensive crop.

4.4 Comparison with Baseline Models

To benchmark performance, the Gradient Boosting model is compared against three baseline approaches on the Rice price series: a naïve seasonal baseline (mean price for that calendar month), Linear Regression on temporal features, and a single-shared Random Forest trained on all crops combined. The per-crop Gradient Boosting achieves MAPE of 4.5% versus 12.3% for the naïve baseline, 8.7% for Linear Regression, and 6.1% for the shared Random Forest, confirming that per-crop specialisation and the non-linear Gradient Boosting approach are both beneficial.

V. DISCUSSION AND CONCLUSIONS

This paper presented AgriPrice AI, a date-driven agricultural price prediction system that removes the burden of manual parameter entry from the user by automatically deriving soil and climate features from the selected date. The system covers 20 major Indian crops, outputs predictions in ₹ per kilogram, and achieves an average MAPE of 4.16% with an average R^2 of 0.882 across all crop-specific Gradient Boosting models.

The date-to-parameter mapping mechanism is the central contribution of this work. By encoding seasonal agronomic knowledge into a deterministic lookup table with smooth interpolation, the system bridges the gap between data availability and model usability. A farmer with no knowledge of soil science can obtain a meaningful price forecast simply by selecting a date on a calendar widget.

The supply-demand price model, incorporating harvest calendar effects, annual inflation, and monsoon shocks, produces realistic price trajectories that the machine learning models can learn from effectively. The seasonal price swing of 15–35% observed across crops aligns with published AGMARKNET price spread data for the 2018–2023 period.The Streamlit interface lowers the barrier to adoption further by providing an intuitive four-tab layout: Price Forecast (single-date prediction with auto-derived parameters and 30-day trend comparison), Seasonal Parameters (visual explanation of the date-to-parameter mapping), Crop Analytics (multi-crop price cycle comparison and model performance metrics), and Historical Data (filterable dataset exploration with per-crop price charts).This project has several limitations that suggest directions for future work. First, the seasonal parameter model uses national averages for peninsular India; regional calibration using district-level IMD and soil survey data would improve prediction accuracy for specific geographies. Second, the price model does not currently incorporate government policy variables such as export bans, import duty changes, or procurement price revisions — factors that have historically caused sudden price discontinuities. Third, incorporating real-time mandi price feeds from AGMARKNET through API integration would allow the model to be continuously recalibrated against actual market prices.In future work, we plan to extend the system with a crop recommendation module that jointly optimises crop selection and expected selling price, providing integrated planting-and-pricing guidance in a single user session. We also plan to explore LSTM-based models for capturing longer-range price autocorrelation patterns that the current tree-based approach does not leverage.In conclusion, AgriPrice AI demonstrates that thoughtful feature engineering — specifically, the date-to-parameter seasonal mapping — can substantially improve both the usability and accuracy of agricultural price prediction systems. The system is computationally lightweight, practically deployable on standard hardware, and designed with the end user — the Indian farmer — at the centre.

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