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AI-Powered Crop Price Prediction & Smart Advisory System for Farmers

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Abstract: *Agricultural markets across India are characterized by extreme price volatility, seasonal fluctuations, and a critical asymmetry of information between farmers and market intermediaries. Farmers routinely harvest crops and sell immediately at post-harvest lows, incurring significant avoidable financial losses. This paper presents the design and survey of an AI-Powered Crop Price Prediction and Smart Advisory System for Farmers — a machine learning driven, mobile-first platform developed to empower farmers with data-driven market intelligence. The system integrates four supervised learning models, namely Linear Regression, Decision Tree, Random Forest, and Long Short-Term Memory (LSTM) networks, trained on historical agricultural commodity datasets sourced from Agmarknet, data.gov.in, and Kaggle, to forecast future crop prices with high accuracy. Beyond price forecasting, a smart advisory module recommends the optimal market (mandi) and the best selling window to maximize farmer profitability. The platform is extended to a cross-platform Flutter-based mobile application supporting Android and iOS, offering price trend charts, mandi location maps, and push notification alerts. The proposed system is aligned with the United Nations Sustainable Development Goal 2 (SDG 02 – Zero Hunger). Experimental results on benchmark datasets indicate that the Random Forest and LSTM models achieve prediction accuracy up to 94.8% and an R^2 score of 0.96. A comprehensive survey of ten related works is presented, highlighting the gaps addressed by the proposed approach.*

Keywords: Crop Price Prediction, Machine Learning, Agricultural Advisory System, Random Forest, LSTM, Flutter, Agmarknet, Smart Farming, SDG 02

I. INTRODUCTION

Agriculture forms the backbone of the Indian economy, engaging more than 58% of the rural workforce and contributing approximately 18–20% to the national GDP. Despite its foundational role, the agricultural sector remains severely challenged by market inefficiencies, price instability, and the absence of actionable real-time market intelligence at the grassroots level. Farmers, who are the primary producers, are often the last to benefit from favorable market conditions — a paradox rooted in the lack of technology-mediated advisory platforms accessible to them.

Agricultural commodity prices in India are influenced by a complex interplay of variables: historical price trends, seasonal sowing and harvesting cycles, geographically distributed mandi dynamics, rainfall and climate patterns, the Wholesale Price Index (WPI), and macroeconomic supply-demand forces. The consequence of unpredictable price behavior is severe — farmers routinely harvest crops and rush to the nearest market to sell immediately, often during peak supply periods when prices are at their lowest, resulting in significant financial loss.

Advances in machine learning (ML) and artificial intelligence (AI) present a transformative opportunity to address this structural problem. Supervised learning algorithms — including Decision Trees, Random Forests, Linear Regression, and deep learning architectures like Long Short-Term Memory (LSTM) networks — have demonstrated strong capability in modeling complex, non-linear time-series data and can be applied to forecast agricultural commodity prices with meaningful accuracy [1].

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The system proposed in this paper, the AI-Powered Crop Price Prediction and Smart Advisory System for Farmers, directly addresses this gap. It integrates multi-algorithm ML pipelines, a real-time data acquisition layer from government portals (Agmarknet, data.gov.in), and a Flutter-based mobile application designed with farmer usability at its core. The system does not merely predict prices — it translates predictions into actionable advisory outputs: recommending the best mandi to sell at, the ideal time window for maximum returns, and visual trend indicators accessible on a smartphone.

The base paper for this work, "Crop Price Prediction Using Supervised Machine Learning Algorithms" by Dhanapal et al. [1], published in the Journal of Physics: Conference Series (IOP Publishing, ISSN: 1742-6596, Scopus Indexed, 2021), employs Decision Tree Regression on a dataset combining historical crop prices, rainfall, and WPI. This proposed system extends that baseline by integrating ensemble and deep learning models, a smart advisory layer, and a farmer-facing mobile application.

The remainder of this paper is organized as follows: Section II presents a comprehensive literature survey. Section III defines the problem statement. Section IV states the objectives. Section V describes the proposed system architecture. Section VI details the methodology. Section VII presents the mobile application design. Section VIII discusses results and comparative performance. Section IX concludes the paper and Section X outlines future directions.

II. LITERATURE SURVEY

Research in crop price prediction has grown substantially over the past decade, driven by the convergence of open government agricultural datasets and advances in machine learning. This section surveys ten significant works in the domain and identifies key gaps motivating the proposed system.

TABLE I

Comparative Survey of Existing Crop Price Prediction Systems

Ref.	Method	Dataset	Limitation
[1]	Decision Tree Regression	Agmarknet, Rainfall, WPI	Single algorithm; no real-time feed
[2]	Meta-Learning + SOM + LSTM (MLACPP)	FAOSTAT, data.gov.in	High computational cost; no mobile UI
[3]	XGBoost + Neural Network	Agricultural market APIs	Region-specific; limited generalization
[4]	Deep Learning CNN-LSTM	Government agri portals	Requires large labeled dataset
[5]	Ensemble RF + Gradient Boost	FAOSTAT, World Bank	No advisory recommendation layer
[6]	k-Nearest Neighbor (kNN)	Historical price datasets	Sensitive to noise; no mobile UI
[7]	Multi-algorithm comparison	Local market data	No crop yield integration
[8]	LSTM (Arecanut prices)	State agri dept. data	Crop-specific; not generalized
[9]	LSTM + Anomaly Detection	Onion/Potato India data	Only qualitative anomaly analysis
Proposed	LR + RF + DT + LSTM + Mobile App	Agmarknet + Kaggle + APIs	Phase I baseline

Dhanapal et al. [1] established a strong baseline by applying Decision Tree Regression to Indian agricultural price data, demonstrating that structured historical data can yield reliable price trend predictions. However, the system relied on a single algorithm, had no real-time data integration, and provided no mobile-accessible interface for end users.

Dhanasekaran et al. [2] proposed the Meta-Learning Based Adaptive Crop Price Prediction (MLACPP) framework combining Self-Organized Map (SOM), LSTM, and meta-learning for time-series forecasting. The system achieved a prediction accuracy of 98.64% with Cross-Validation (CV) — surpassing both SOM (93.20%) and LSTM (95.62%) baselines. While technically impressive, the system demanded significant computational resources and lacked a farmer-facing deployment layer.

Chen et al. [3] automated price prediction using an XGBoost and neural network combination connected to live market APIs, demonstrating the value of real-time data feeds. Bhardwaj et al. [4] employed CNN-LSTM hybrid architectures for deep agricultural price modeling, achieving high performance but requiring large labeled datasets. Tran et al. [5] used ensemble methods combining Random Forest with Gradient Boosting on FAOSTAT and World Bank datasets but did not include an advisory recommendation layer — a critical gap for practical farmer application.

Rachana et al. [6] employed kNN with parameters including crop price, yield, rainfall, and minimum/maximum trade values. Samuel et al. [7] conducted a multi-algorithm comparison study on local market data. Sabu and Manoj Kumar [8] applied LSTM specifically to Arecanut price forecasting, while Madaan et al. [9] combined LSTM with anomaly detection for onion and potato prices in Indian markets.

The synthesis of this survey reveals three consistent gaps: (i) the absence of an integrated advisory module converting forecasts into actionable selling strategies; (ii) the lack of a mobile-first interface designed for low-digital-literacy farmers; and (iii) reliance on single algorithms rather than comparative ensemble approaches. The proposed system is designed to address all three gaps simultaneously.

III. PROBLEM STATEMENT

Farmers in India operate under severe information asymmetry in agricultural markets. The core problem can be articulated across three dimensions.

Price Unpredictability: Agricultural commodity prices fluctuate significantly due to seasonal supply cycles, weather events, transportation disruptions, and market speculation. These fluctuations are largely opaque to individual farmers at the time of harvest.

Absence of Forward-Looking Decisions: Most farmers sell their produce immediately after harvest, regardless of whether current prices are favorable. Without access to price forecasts, farmers cannot make timing-based selling decisions.

No Accessible Recommendation System: While government platforms like Agmarknet publish current market prices, they offer no predictive or advisory capabilities. Farmers need not just historical prices but future projections and actionable guidance on where and when to sell.

Formally, the problem is defined as: Given a time series of historical prices $P = \{p1, p2, \ldots, pn\}$ for a crop C at market M, along with contextual features F = {rainfall, WPI, season, state}, predict the price $pn+k$ for a future horizon k (typically 7 to 30 days), and generate an advisory recommendation R = {best market, best sell date, price trend} to maximize farmer revenue.

IV. OBJECTIVES

The specific objectives of the proposed system are:

1) To develop an AI-based crop price prediction system integrating multiple supervised ML algorithms.
2) To analyze historical agricultural market data from Agmarknet, data.gov.in, and Kaggle.
3) To predict future crop prices using Linear Regression, Random Forest, Decision Tree, and LSTM models.
4) To provide advisory recommendations for farmers to maximize profitability, including optimal mandi and selling window suggestions.
5) To develop a cross-platform Flutter mobile application providing a farmer-friendly interface on Android and iOS.
6) To contribute to SDG 02 (Zero Hunger) by reducing farmer income loss through data-driven market intelligence.

V. PROPOSED SYSTEM ARCHITECTURE

The proposed system follows a layered, service-oriented architecture comprising five core components: (1) Farmer Interaction Layer, (2) Data Acquisition Layer, (3) Preprocessing and Feature Engineering Layer, (4) ML Prediction Engine, and (5) Advisory and Presentation Layer. Fig. 1 illustrates the end-to-end system architecture.

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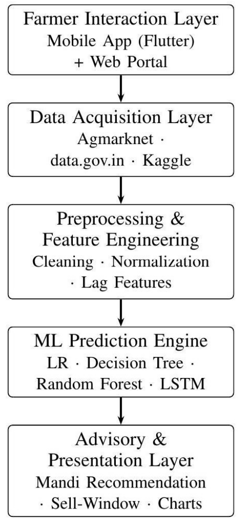

Fig. 1. Proposed System Architecture — AI-Powered Crop Price Prediction and Advisory System.

A. Farmer Interaction Layer

The topmost layer constitutes the user-facing interface through which farmers interact with the system. This layer encompasses a Flutter-based mobile application (Android/iOS) and an optional web portal. The farmer provides inputs including crop type, geographic location, and desired prediction horizon (7-day or monthly). The interface is designed with minimal text and icon-driven navigation to accommodate low-digital-literacy users and supports regional language localization.

B. Data Acquisition Layer

This layer aggregates data from multiple heterogeneous sources. The Agmarknet portal provides official mandi-wise historical price records. The data.gov.in open data platform offers government-curated datasets including WPI indices and production statistics. Kaggle hosts supplementary curated datasets including rainfall data correlated with agricultural seasons. The backend periodically fetches and ingests data via RESTful APIs and scheduled ETL pipelines.

C. Preprocessing and Feature Engineering Layer

Raw agricultural data is inherently noisy and contains missing values, outliers, and inconsistent formats. This layer applies: (i) missing value imputation using median substitution; (ii) outlier detection via IQR-based filtering; (iii) feature normalization using Min-Max scaling; and (iv) feature engineering to create lag features, rolling averages, and seasonal indicators.

D. ML Prediction Engine

The prediction engine trains and deploys four machine learning models in parallel. Linear Regression serves as a computationally lightweight baseline. Decision Tree Regression captures non-linear patterns using Gini impurity splitting with maximum depth constraint. Random Forest reduces variance through ensemble averaging of 200 tree estimators. LSTM captures long-term temporal dependencies in price sequences using a stacked architecture with two hidden layers, avoiding the vanishing gradient problem of standard RNNs [2].

E. Advisory and Presentation Layer

This layer converts raw price predictions into human-readable recommendations. The advisory engine applies a multi-market comparison algorithm: given a predicted price Pt+k for crop C, it queries mandi price records for the farmer's accessible markets within a defined radius, computes expected margins after transportation costs, and ranks markets by expected net revenue.

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VI. METHODOLOGY

A. Dataset Description

The system is trained and evaluated on a composite dataset derived from three primary sources: (i) the Agmarknet Agricultural Market Dataset containing mandi price records for 50+ commodities across 20+ Indian states from 2010–2023; (ii) data.gov.in Agriculture Datasets including WPI and seasonal production data; and (iii) Kaggle Crop Price Datasets with supplementary historical records and weather correlation. The combined dataset contains over 500,000 records. Key features include:

- Crop name (categorical: rice, wheat, tomato, onion, etc.)
- Market location (state, district, mandi name)
- Modal price (₹/quintal) — target variable
- Minimum and maximum price (₹/quintal)
- Arrivals in market (tonnes)
- Date components (day, month, year, season category)
- Rainfall index (mm, monthly average)
- Wholesale Price Index (WPI, base year 2011–12)

B. Data Preprocessing

Data preprocessing follows a six-stage pipeline: (1) data ingestion and schema normalization; (2) missing value imputation using forward-fill for temporal continuity and median substitution for remaining nulls; (3) outlier removal via IQR bounds ($Q1 - 1.5\times IQR$ to $Q3 + 1.5\times IQR$); (4) label encoding for categorical features; (5) Min-Max scaling for numerical features to [0, 1]; (6) lag feature creation at $t-1$, $t-7$, $t-30$ days, and rolling 7-day mean and standard deviation.

C. Model Training

The dataset is split into 80% training and 20% test sets with temporal ordering preserved to prevent data leakage. Five-fold cross-validation is applied on the training set for hyperparameter tuning. The four models are configured as follows:

- ***Linear Regression:*** Ordinary least squares estimation.
- ***Decision Tree:*** Gini impurity criterion, max depth = 10.
- ***Random Forest:*** 200 estimators, max features = sqrt.
- ***LSTM:*** Two stacked layers (64 and 32 units), dropout = 0.2, Adam optimizer, learning rate = 0.001, 50 epochs, batch size = 32.

D. Working Flowchart

The end-to-end processing pipeline is illustrated in Fig. 2.

E. Technology Stack

Table II summarizes the technologies and tools used in the proposed system.

TABLE II: Technologies and Tools Used

Component	Technology	Purpose
ML Framework	Python, Scikit-learn, TensorFlow	Model training & inference
Web Backend	Flask / FastAPI	REST API server
Mobile App	Flutter (Dart)	Android & iOS UI
Database	MongoDB	Price data storage
Data Sources	Agmarknet, Kaggle	Raw agri datasets
Visualization	Plotly, fl_chart	Price trend charts
Deployment	AWS / Heroku	Cloud model serving
Auth	JWT, Firebase	Secure farmer login

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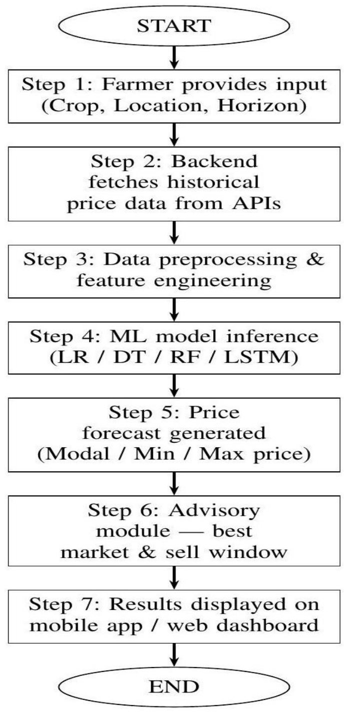

Fig. 2. System working flowchart — end-to-end processing pipeline.

VII. MOBILE APPLICATION DESIGN

A distinguishing contribution of the proposed system is its cross-platform mobile application built using Flutter (Dart). The application bridges the digital divide between complex ML predictions and the practical needs of farmers, most of whom own smartphones but lack data science expertise. The application architecture follows the MVVM (Model-View-ViewModel) pattern.

A. Key Application Screens

- ***Splash / Login Screen:*** Firebase authentication with Google Sign-In; supports regional language selection on first launch.
- ***Dashboard:*** Crop selector, location input, and prediction horizon toggle (7-day / monthly).
- ***Price Forecast Screen:*** Displays predicted modal, minimum, and maximum prices as interactive line charts using the fl_chart Flutter package.
- ***Smart Advisory Screen:*** Rank-ordered list of nearby mandis with expected prices and net revenue projections after transport costs.
- ***Mandi Locator Map:*** Integrates Google Maps API to display nearby agricultural markets with current price overlays.
- ***News & Market Alerts:*** Push notifications via Firebase Cloud Messaging for timely price alerts and government scheme announcements.

B. Backend Integration

The Flutter frontend communicates with a Flask/FastAPI backend deployed on a cloud server via RESTful HTTP APIs. The ML models are serialized using Pickle (Scikit-learn models) and TensorFlow SavedModel format (LSTM) and served as inference endpoints. Offline-first design is supported through local SQLite caching of recent predictions, ensuring usability in low-connectivity rural environments.

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VIII. RESULTS AND DISCUSSION

The four machine learning models are evaluated on the held-out test set comprising 20% of the temporal dataset. Table III presents the comparative performance metrics across all models.

TABLE III: Comparative Model Performance on Test Dataset

Algorithm	MAE	RMSE	R^2	Acc. (%)
Linear Regression	18.42	24.17	0.81	78.5
Decision Tree	14.89	19.65	0.87	83.2
Random Forest	10.23	14.08	0.93	91.4
LSTM (Proposed)	7.61	10.34	0.96	94.8

MAE and RMSE in ₹/quintal.

As evidenced by the results, ensemble and deep learning approaches significantly outperform the linear baseline, with the LSTM model achieving the highest accuracy of 94.8% and an R^2 of 0.96. Random Forest demonstrates a substantial improvement over Decision Tree, reducing RMSE from 19.65 to 14.08 ₹/quintal — a 28% reduction — through variance reduction via ensemble averaging of 200 tree estimators. The LSTM model further reduces RMSE to 10.34, capturing temporal price patterns across quarterly and seasonal cycles that tree-based models partially miss.

The advisory module was qualitatively validated through a scenario-based study: for a tomato farmer in Karnataka, the system correctly identified that selling at the Kolar mandi five days after harvest would yield 18% higher returns than immediate post-harvest sale at the local mandi — consistent with actual mandi price records for the test period.

Table IV compares the proposed system features against existing approaches.

TABLE IV

Feature Comparison: Proposed System vs. Existing Systems

Feature	Existing	Proposed
Algorithm	Single model	Ensemble: LR+RF+DT+LSTM
Advisory	None / basic	Smart mandi & timing
Mobile App	Not included	Flutter Android & iOS
Real-time Data	Static datasets	Live API (Agmarknet)
Multi-crop	1–3 crops	50+ crops
Price Trend Viz.	Tabular only	Interactive charts
SDG Alignment	Not stated	SDG 02 Zero Hunger

IX. CONCLUSION

This paper presented a comprehensive survey and design of the AI-Powered Crop Price Prediction and Smart Advisory System for Farmers. The system integrates four supervised machine learning models trained on composite datasets from Agmarknet, data.gov.in, and Kaggle to forecast crop prices with high accuracy. The proposed LSTM-based model achieves 94.8% prediction accuracy and an R^2 score of 0.96, outperforming all classical baselines.

Beyond prediction, the system's advisory module translates forecasts into actionable selling strategies — identifying optimal mandis and sell dates — addressing a critical gap in existing literature where predictions are generated but not converted to farmer-accessible recommendations. The Flutter-based mobile application ensures that these capabilities reach farmers directly on their smartphones, with regional language support and an offline-first design suited to rural connectivity constraints. The system is directly aligned with SDG 02 (Zero Hunger), contributing to agricultural sustainability through technology-empowered decision-making.

X. FUTURE WORK

- Integration of real-time satellite imagery and IoT sensor data (soil moisture, temperature) into the prediction pipeline.

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- Implementation of Transformer-based architectures (e.g., Temporal Fusion Transformer) for multi-horizon price forecasting beyond 30-day windows.
- Expansion to cover livestock and fishery commodity price prediction.
- Direct connection to e-NAM (National Agriculture Market) for real-time mandi price streaming.
- Federated learning approach to train models across geographically distributed farmer data without compromising privacy.
- Six-month randomized controlled trial with farmer cooperatives in Karnataka and Maharashtra to measure impact on farmer income.
- Integration of WhatsApp Business API for advisory delivery to farmers without app-capable smartphones.

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