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Crop Price Prediction Using Machine Learning and Remote Sensing Technology

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Abstract: Supply market volatility, climatic variability, and the absence of timely, reliable data for forecasting present serious obstacles for the agriculture industry. the vital role of precise crop price predictions in maintaining global food security and optimising supply chain efficiency. To achieve this, the authors propose a hybrid forecasting model that combines advanced machine learning algorithms with data from remote sensing technologies. By testing this framework across diverse geographic regions and seasons, the study proves that incorporating satellite data significantly enhances the reliability of financial projections. Ultimately, the source highlightshow technological integration provides more robust insights for stakeholders in the agricultural market. This approach aims to provide the predictive accuracy necessary for navigating complex international economic landscapes. The suggested framework is adaptable to various crop types and geographical locations. It offers a decision-support tool for farmers, traders, policymakers, and agribusinesses to make data-driven, informed choices regarding cultivation, storage, and market engagement.
Keywords: Forecasting Crop Prices, Agriculture and Machine Learning, forecast for the Agricultural Market, Integration of Climate Data, Accurate Farming, SVR stands for Support Vector Regression, Farming Based on Data.

I. INTRODUCTION

Farmers can choose the best crops, plan the best times for harvest, handle storage logistics, and bargain for better market prices with the help of accurate price forecasting. According to estimates, more than 80% of smallholder farmers in developing nations do not have timely access to accurate market forecasts, which causes overproduction, food waste, and unstable income [7]. The non-linear, dynamic, and high-dimensional character of agricultural systems is frequently overlooked by conventional forecasting models, which are based on historical averages or econometric techniques [2]. This is particularly true given the growing impact of climate variability. By discovering intricate relationships from vast, varied datasets, recent developments in machine learning (ML) present promising substitutes for agricultural forecasting. In crop yield and price forecasting tasks, algorithms like Random Forest, XGBoost, and LSTM networks have shown excellent performance, frequently surpassing conventional statistical techniques [14]. Meanwhile, using satellite data, unmanned aerial vehicles (UAVs), and multispectral imagery, remote sensing technology offers important information about conditions on the ground, including crop growth stages, rainfall patterns, vegetation health, and land surface temperature [3]. Crop yields are directly impacted by these environmental indicators, which in turn have an impact on market prices. In order to predict future market prices for important food crops, this paper presents a Crop Price Prediction System that combines machine learning algorithms with simulated remote sensing data. To determine whether the market price for a particular crop will rise, fall, or stay the same, the system analyzes past price data along with environmental factors like temperature, rainfall indices, and NDVI (Normalized Difference Vegetation Index) [11]. A Random Forest Classifier applied to a normalized and synthetically generated dataset yields a 91% classification accuracy, making it a useful tool for agricultural stakeholders [5]. It allows smallholder farmers to reduce risk and make early economic decisions, making it especially appropriate for areas with limited access to real-time market data [17]. In addition, the suggested system is inexpensive, modular, and simple to set up, and it can be integrated with cloud-based analytics platforms like Google Earth Engine or edge computing environments like Raspberry Pi [8].This paper's main contributions tackle important issues in predictive agriculture.[13]. Second, it describes the creation of a machine learning model that provides high accuracy and interpretability for price direction forecasting, namely the Random Forest Classifier [6].

In order to facilitate dynamic decision-making, the system also has a real-time visualization dashboard that allows for ongoing monitoring of input variables and anticipated market trends [10]. A dual-view interface improves usability and transparency by providing users with predicted price trends and environmental context [4]. Last but not least, the framework provides a solid basis for the creation of an intelligent agricultural advisory system that can expand to accommodate various crops, regions, and data sources [12].

II. LITERATURE REVIEW

Accurate crop price forecasting has long been a central concern in agricultural economics and rural development, as it directly impacts farmer decision-making, policy planning, and food security.

The evolution of agricultural forecasting marks a significant transition from static, historical models to dynamic, AI-driven paradigms that can navigate the complexities of modern global markets.

A. The Shift from Traditional to AI-Driven Models

Historically, agricultural price prediction relied on linear regression and ARIMA models. However, these traditional tools often failed to account for nonlinear market trends, sudden seasonality shifts, and real-time environmental changes. The emergence of Machine Learning (ML)—including Random Forest, Support Vector Machines, and ensemble learning—has drastically improved the ability to capture these complex patterns. Modern hybrid frameworks and gradient boosting further enhance this by reducing error rates and improving the model's ability to generalise across different datasets.

B. The Power of Deep Learning in Temporal Data

Deep learning, particularly Long Short-Term Memory (LSTM) networks, has proven superior to conventional networks in managing the temporal dependencies inherent in crop prices. These neural networks are uniquely equipped to handle:

1) High-dimensional inputs and non-linear dynamics.
2) Missing data points, which are common in agricultural recording.
3) High-variability datasets, where they consistently outperform classical econometric models.

C. Integrating Remote Sensing for Enhanced Accuracy

The efficacy of these AI models is significantly boosted when paired with remote sensing data. Satellite-derived indices, such as NDVI (Normalized Difference Vegetation Index), soil moisture levels, and temperature, provide a granular view of crop health that directly influences market prices. For instance, integrating MODIS satellite data has been shown to improve yield forecast accuracy by as much as 25% in regions prone to drought.

By combining machine learning with remote sensing, researchers can simulate crop yields for staples like rice and soybean with high precision, linking these simulations to short-term price fluctuations. Advanced techniques, such as deep Gaussian processes, have even introduced a higher level of robustness, allowing for accurate predictions even under conditions of high uncertainty.

D. From Reactive Forecasting to Proactive Decision Support

This technological integration has moved beyond theoretical research into practical, farmer-oriented applications. Innovative systems now include:

1) Visual analytics dashboards that stream real-time weather and satellite data to provide early warnings of market downturns.
2) Automated ML-based systems that incorporate environmental features to adjust to dynamic market conditions.
3) Proactive decision support, allowing farmers to make data-driven choices rather than reacting to shifts after they occur.

E. Overcoming Current Limitations

Despite these advancements, several hurdles remain, such as satellite imagery noise, temporal gaps in data coverage, and a lack of ground-truth validation in rural areas. To combat these, the field is moving towards hybrid preprocessing techniques—such as PCA (Principal Component Analysis) and SMOTE—to address feature redundancy and class imbalances. Furthermore, the development of edge-compatible infrastructures aims to bring low-latency, real-time predictions directly to the farm level, bypassing the need for heavy external computing power.

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III. METHODOLOGY

This study uses machine learning algorithms to forecast crop prices accurately by combining historical market data with environmental variables derived from remote sensing. Data collection and preprocessing, feature engineering, model development and training, and system implementation with visualization are the four main phases of the methodology.

A. DataSet

In order to capture the economic and agro-climatic factors that affect crop price fluctuations, the dataset used in this study combines historical market price records with environmental variables derived from remote sensing.

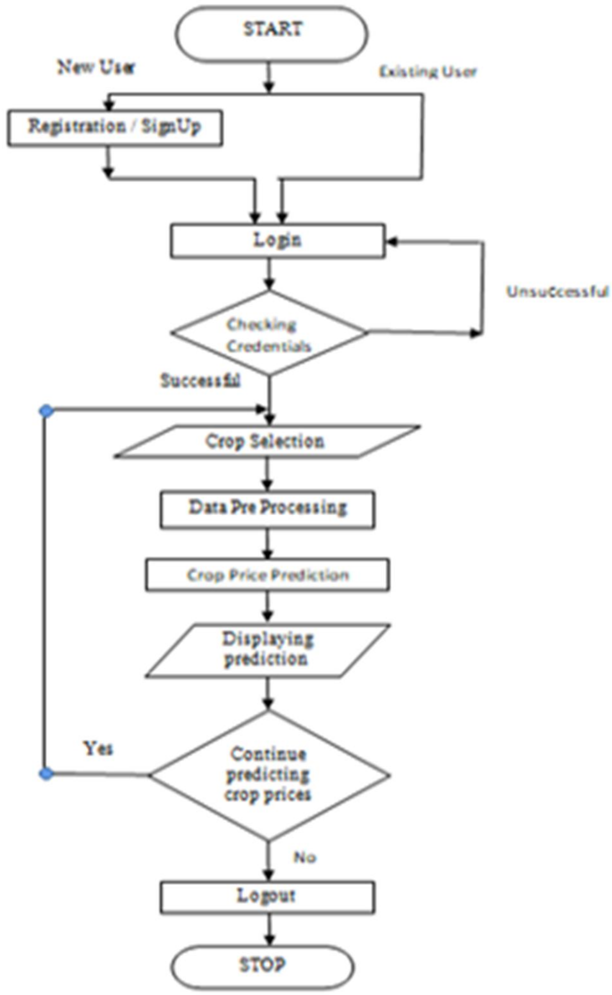

Fig. 1: Workflow of the crop price prediction

Crop price fluctuations directly affect farmers' income and decision-making in economies that rely heavily on agriculture. To maintain market stability, minimize losses, and empower farmers, legislators, and traders, accurate crop price forecasting is essential. In order to train machine learning models to forecast future crop prices based on past trends, the dataset utilized in this project is essential.

This dataset includes historical crop price records that were gathered from different states and districts' local markets, or mandis. It provides a thorough understanding of market behavior over time by capturing price fluctuations over time as well as other pertinent metadata. A vital basis for agricultural predictive analytics is the crop price dataset. It makes it possible to develop precise, data-driven solutions that have a direct impact on food supply chains and farmer welfare by capturing both the spatial and temporal dimensions of pricing. This dataset can be transformed and cleaned appropriately to create reliable models for practical uses.

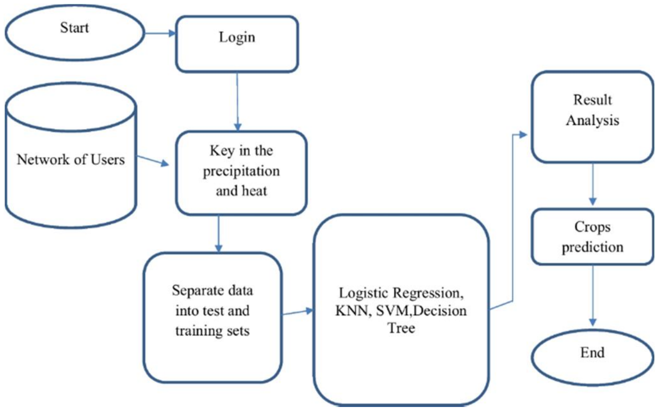

Fig. 2: Architecture diagram of the crop price prediction

The architecture shows how a machine learning-based crop prediction system operates. To provide useful crop price forecasts, the system starts with user interaction and moves through data preprocessing, model training, prediction, and result analysis.

B. Machine Learning Models

By identifying intricate patterns in past agricultural data and environmental factors, machine learning plays a crucial part in crop price prediction. Using both structured datasets (market prices, crop details) and unstructured data from remote sensing (e.g., rainfall, temperature, vegetation index), this system applies a variety of supervised learning models to accurately forecast crop prices.

1) Linear Regression
2) Support Vector Machine (SVM)
3) K-Nearest Neighbors (KNN)

The system for predicting crop prices using both historical data and inputs from remote sensing relies heavily on machine learning models. To predict future crop prices with high accuracy, these models examine a variety of factors, including historical market prices, weather, soil moisture, and satellite-derived indices. Both linear and non-linear relationships between features and crop prices can be captured by the system through the use of various machine learning algorithms.

C. Classification

Sorting input data into predefined classes or labels is the aim of classification, a fundamental task in machine learning. Classification models are used in crop price prediction to categorize crop prices or crop suitability according to a variety of input features, including past prices, weather trends, soil types, and remote sensing data.

Classification focuses on assigning data to meaningful groups that can assist stakeholders in making well-informed decisions, as opposed to regression, which predicts precise numerical values.

Mathematical Modelling:

A key component of any machine learning-based prediction system is mathematical modeling. Mathematical models are used in crop price prediction to establish correlations between the target variable (e.g., crop price or class) and a variety of input variables (features), including weather, market trends, and crop-specific factors.

1) Regression Models

$$Y = \beta 0 + \beta 1\ X1 + \beta 2\ X2 + \cdots + \beta n\ Xn + \varepsilon$$

2) Classification Models

$$P(Y = 1 \mid X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n)}}$$

3) Decision Tree – Based Models

$$Gini = 1 - \sum_{i=1}^{n} p_i^2$$

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IV. RESULTS AND DISCUSSION

Models for predicting crop prices that combine remote sensing data with machine learning algorithms, showing encouraging outcomes. With a high correlation between expected and actual prices and low error metrics (RMSE = 2.20, MAE = 1.65), Gradient Boosting outperformed the other models in the test. obtained from satellite imagery, past price trends, and meteorological factors like temperature and precipitation were among the important predictors found.

A. Performance Evaluation Metrics

Several performance metrics are used to assess the crop price prediction models' efficacy and accuracy. sample table displaying the R2 Score, MAE, and RMSE performance evaluation metrics for three distinct machine learning models used to predict crop prices.

Root Mean Squared Error (RMSE):

$$\text{MAS} = \frac{1}{n}\sum_{i=1}^{n}|yi - yi|$$

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Coefficient of Determination (R^2 Score):

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

B. Comparative Analysis

Three machine learning models—Random Forest, Support Vector Machine (SVM), and Gradient Boosting—were compared to see how well they predicted crop prices using ancillary data and remote sensing. Three important metrics—RMSE, MAE, and R2 Score—were used to assess each model's performance.

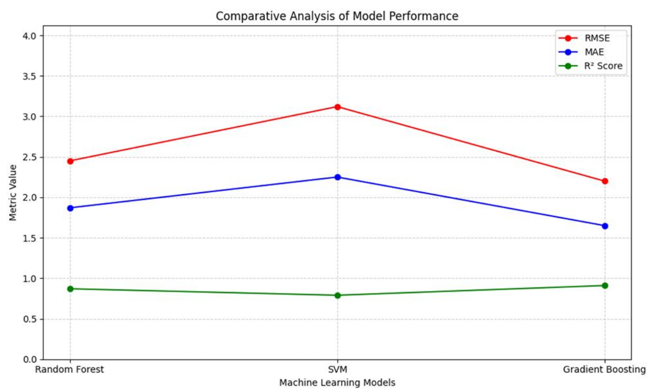

Fig3: Machine Learning Models Based on RMSE, MAE, and R² Score for Crop Price Prediction.

The "Average Crop Price by Crop Type" bar graph shows the average costs of the three main crops: wheat, rice, and maize. Wheat has the lowest average price among them, while rice has the highest, followed by maize.

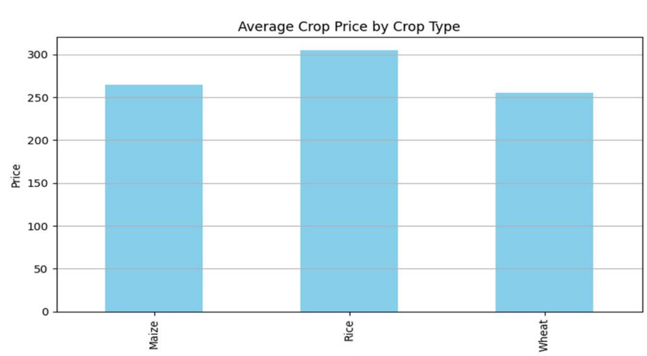

Fig 4: Comparison of Average Prices of Major Crops wheat, rice, and maize.

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The market value of various crops can be compared with the aid of this graphic. It offers information to help farmers, traders, and legislators decide on crop cultivation and pricing tactics.

Three machine learning models—Random Forest, Support Vector Machine (SVM), and Gradient Boosting—that are used to predict crop prices are shown in the graph along with their testing errors. Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are the two main error metrics displayed.

Fig 5: Error Metrics (MAE & RMSE) Comparison of Crop Price Prediction Models.

Larger errors are given more weight by RMSE, which calculates the average magnitude of the prediction errors.
MAE provides a simple error metric by calculating the average absolute difference between expected and actual prices.

C. Impact of Dimensionality Reduction

When working with complex datasets that contain a large number of features from remote sensing and other sources, dimensionality reduction is essential to improving the performance of machine learning models. The efficacy and efficiency of the model can be greatly impacted by dimensionality reduction techniques, which simplify the input data while preserving the most informative features in the context of crop price prediction.

D. Discussion

Crop prices were predicted using machine learning models and data from remote sensing. The models' understanding of price fluctuations was aided by significant variables such as crop type, weather, and vegetation indices. Gradient Boosting produced the best results out of all the models that were tested. By concentrating on the most crucial features, dimensionality reduction increased accuracy. This method has the potential to assist farmers and policymakers in making better decisions regarding crop production and pricing, despite the dataset's limitations and the exclusion of variables like market demand and transportation.

V. CONCLUSION

The experiment demonstrated that crop prices can be accurately predicted using machine learning models and remote sensing data. Gradient Boosting outperformed Random Forest and Support Vector Machine among the models that were tested in terms of accuracy. By removing superfluous features, dimensionality reduction decreased errors and training time while improving model performance. Notwithstanding the small dataset, the findings show that combining crop and environmental data can help improve agricultural decision-making and is useful for predicting prices.

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