IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 13, April 2025
Impact Factor: 7.67

Forecasting for Agricultural Commodities Price Using AI Models

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Abstract: *The developed system utilizes machine learning methods to create a web platform which forecasts agricultural commodity modal prices using historical data points. The platform executes price predictions through a regression model that received training on feeding information about year and month together with unitized arrivals in quintals and commodity type. The system operates through a Python-Flask-HTML framework that enables users to access an easy-to-use interface for making data-based agricultural choices. The system's design integrates a trained regression model using commodity historical records and ensures its ability to grow while maintaining user-friendly capabilities for the platform*

Keywords: Agricultural Price Forecasting, Commodity Price Prediction, Machine Learning in Agriculture, Regression Model, Flask Web Application, Data-Driven Farming, Modal Price Prediction, Crop Marketing Insights, Random Forest, Predictive Analytics, Smart Agriculture, Agricultural Decision Support System, Real-Time Forecasting, Web-Based Farming Tool

I. INTRODUCTION

Farming stands as the essential occupation for hundreds of millions of people throughout India and other developing countries. Farmers face recurring obstacles stemming from seasonal patterns along with environmental conditions and market shifts because their industry displays marked sensitiveness to these elements. Uncertain commodity prices remain one of the major agricultural challenges because they change significantly because of various factors including excessive production and slow transportation delays as well as government policy shifts and inconsistent consumer demand patterns.

Agricultural market historical data surpasses the capacity of basic interpretation tools for most small and marginal farmers to use for future planning. Small and marginal farmers base their sell decisions on guesses combined with oral advice as well as limited access to outdated market reports. The outcome of this uncertainty sparks substantial money losses and makes crops sell for less value than they should or ends with wasted post-sowing bounty.

Standard price forecasting tools which rely on basic statistical approaches together with manual trend observations show restrictions in identifying complex nonlinear agricultural relationships. These methods deliver insights without specific applications to individual users and basic personalization which makes them inadequate when used daily by farmers together with agri-traders.

The combination of machine learning technology along with web accessibility enables developers to create intelligent systems which process big data from commodity history for accurate future price forecasts. These advanced systems present extraordinary potential to link businesses through data while enabling farmers to make decisions that are based on data analysis.

The proposed system implements web-based functionalities through regression-based machine learning models to predict the modal prices of agricultural commodities. Users can enter standard parameters of year, month and commodity type as well as produce quantity information through the system interface. The model uses trained ML

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technology to forecast anticipated market prices after processing user-induced inputs and thus helps farmers together with traders and policymakers create smart marketing choices.

A clean HTML-based user interface with a Python and Flask backend provides users with simple access to live interaction with the system. The main machine learning algorithm operates on preprocessed historical pricing data after it has been transformed into one-hot encoded values and regression modeling methods for detecting patterns between variables.

The project aims to create agricultural transparency tools which empower rural communities to boost their profits and reduce dependency on middlemen by providing sustainable farming resources through informed decisions.

II. TECHNOLOGIES USED

Python is the main programming language employed for backend development as well as implementation of machine learning models. It is heavily used in data science because it is simple, readable, and has a rich library ecosystem. Python enabled smooth integration of data preprocessing, model training, and prediction into a web application in this project. Its object-oriented design and large community support made it perfect for quick development.

HTML5 is the default markup language employed to develop the web page structure. In this project, HTML5 was employed to design the user interface through which users interact with the system. The input forms, prediction output, and page structure were all designed using HTML5. It provides compatibility in all modern browsers and forms the basis for responsive, accessible web design.

CSS was employed to style and design HTML elements. Despite the lack of extensive styling here, CSS did improve the presentation and user interaction by fine-tuning layout, spacing, and fundamental formatting. It ensured font sizes, alignment, and responsiveness were consistent on various devices.

Flask is a Python micro web framework that makes it easy to develop web applications with little overhead. It was employed to develop the server-side logic of this system, such as routing HTTP requests, handling user input, and returning predictions. Flask also plays nicely with machine learning models and allows for the use of Jinja2 templating for dynamic web content. Its lightweight nature and flexibility made it the perfect choice to deploy a lean and functional ML web app.

Scikit-learn is an open-source Python machine learning library that has widespread use. It was the central tool for training and testing the regression model within this project. Through its rich set of algorithms, preprocessing tools, and testing metrics, Scikit-learn made it possible to build an accurate and efficient price forecasting model. Scikit-learn made processes like dataset splitting, model fitting, and prediction generation easier.

NumPy is a library that supports large, n-dimensional arrays and matrices, as well as mathematical functions to process these arrays. In this project, it was instrumental in numerical computations needed to train the models and transform the data. It enhanced the efficiency and performance of operations such as reshaping data and applying math functions.

Pandas is a robust Python library for data manipulation and analysis. It was necessary to use it to load the historical agricultural commodity dataset that was in CSV format. Through its DataFrame data structure, the project was able to manage data cleaning, filtering, feature selection, and preparation for model training. Pandas facilitated easy execution of complex data operations with clean, readable code.

Matplotlib and **Seaborn** are Python data visualization libraries. They were employed (optional based on the project) to plot graphs showing distributions, trends, and correlations of data during the exploratory data analysis stage. Such visualizations assisted in choosing the most contributing features as well as gaining insights into seasonal or market trends for commodity prices.

Jinja2 is a new templating engine for Python that is employed with Flask to dynamically render web pages. It provides the capability to embed Python code and data within HTML, enabling it to more conveniently display prediction outputs, input data, and system messages. Jinja2 facilitates cleaner separation of code between backend logic and frontend layout, enhancing maintainability and modular design.

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CSV files were the major source of structured data for the machine learning model. The CSV files included historical data like date, commodity type, market arrivals, and price information. Pandas was employed to read and preprocess the data. The format is lightweight and widely supported, which makes it suitable for prototyping and offline data storage.
Jupyter Notebook/Google collab Throughout the development process of the model, Google Colab and Jupyter Notebook were employed to iteratively experiment with and debug machine learning algorithms. These tools have code cells, rich text, and visualization in one environment for step-by-step experimentation and debugging.

III. LITERATURE REVIEW

- **Box & Jenkins -** Introduced ARIMA models for time series forecasting, widely used for agricultural price prediction but limited in handling external factors.
- **Chevallier -** Applied ARIMA models to forecast wheat and corn prices, highlighting the limitations of ignoring external variables like weather.
- **Kumar etal -** Used Random Forest and SVM to predict rice prices, emphasizing the importance of weather data and feature engineering.
- **Shietal -** Applied LSTM networks to model temporal dependencies in soybean prices, demonstrating the effectiveness of deep learning.
- **Rajesh Kumar, Priya Sharma -** The paper explores the use of LSTM (Long Short-Term Memory) networks for predicting rice prices in India.
- **Samuel O. Adeyemi -** This research proposes a hybrid model combining Support Vector Machines (SVM) and Genetic Algorithms for maize price prediction.
- **Ravi Shankar, Anjali Gupta -** This paper explores the use of ensemble learning methods for cotton price prediction. It shows how combining multiple models can improve forecasting accuracy.
- **Fernando Costa, Ana Silva -** The study uses neural networks to predict sugarcane prices in Brazil, incorporating weather data as a key input. It demonstrates the importance of external factors in price forecasting.

IV. METHODOLOGY

The main purpose behind the Agricultural Commodity Price Prediction System exists in furnishing a real-time accessible and intelligent platform for forecasting agricultural commodity modal prices. The system employs machine learning algorithms to evaluate historical data that make price trend forecasts for future predictions from user submissions of commodity type, month, year and arrival quantity. The system provides exact timely forecasts that aim to erase the distance between agricultural market understanding and rural areas to enable both farmers and supply chain participants.

1. Real-Time Commodity Price Forecasting.

A machine learning model needs development to forecast agricultural commodity modal prices using historical data and arrival elements alongside month and year factors. The system needs to provide real-time response capabilities with correct price predictions that enable market decision support.

2. Data-Driven Decision Support for Farmers and Traders

This tool empowers producers together with wholesale distributors and market researchers to choose proper selling times and locations through future market pricing predictions. Users can leverage the system to prevent hurry-driven sales so they can manage their logistics and increase their earnings.

3. Feature-Based Predictive Modeling

To incorporate significant input features such as:

- Year and month (for seasonal influence),
- Commodity type (one-hot encoded for model input),
- Quantity of arrivals (to reflect supply-demand influence), ensuring that predictions are tailored to real market conditions.

4. Integration of Machine Learning with Web Technologies

The implementation of Python and Flask to develop a smooth backend process that merges a trained regression model. Multiple functions should exist within the backend which includes preprocessing raw user data before feeding it to the model and serving the results to users through an easy-to-use web platform..

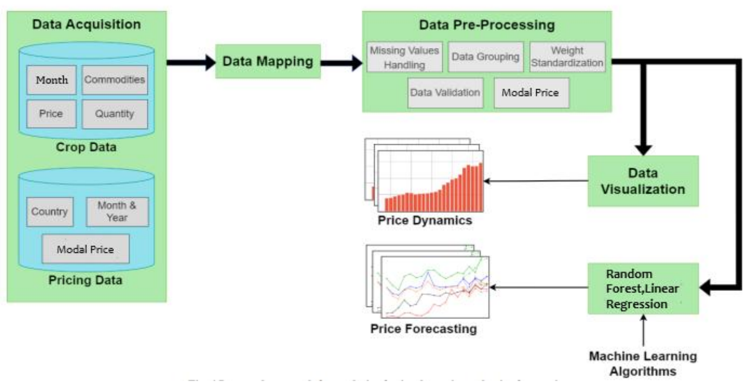
5. User-Friendly and Accessible Interface

To create a clean, intuitive, and user-friendly frontend using HTML and Jinja2 templates that:

- Allows users to select commodities and months from dropdowns,
- Handles numerical data inputs (year, quantity),
- Presents predictions and error feedback clearly.

V. ARCHITECTURE

SYSTEM ARCHITECTURE



Data acquisition is tasked with collecting raw data from different agricultural data sources. This involves crop-related data such as month of harvest, commodity name, market price, and quantity of arrivals. Pricing data such as country, date, and modal price is also collected. This detailed collection ensures the system receives all the inputs it needs to analyze past trends and predict future prices accurately.

Data Mapping is collecting the required data, the mapping process brings crop data and pricing data together, aligning and merging them based on main fields such as commodity type, month, and region. This process verifies that every record of data is properly matched with the associated pricing information, allowing for logical and consistent examination. Data mapping is essential in creating organized datasets that are prepared for preprocessing and model training.

Data Pre-Processing this step entails cleaning and preparing raw data for analysis and machine learning. It deals with missing values, clusters similar points, normalizes weights and units, and verifies key entries such as modal price. Good preprocessing eliminates noise and enhances the quality of data, thus leading to better performance and accuracy of predictive models. This process is crucial for the purpose of training the models on trustworthy and meaningful input.

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Data visualization gives graphical forms of the preprocessed data. It assists in the comprehension of trends, seasonal patterns, and anomalies using graphs and charts. Such visual tools present important information at the time of exploratory data analysis and further aid feature selection. By visually interpreting data, stakeholders can realize easily patterns that may affect commodity prices.

Price dynamics module examines the historical variations of commodity prices over a period of time. It determines how prices have varied during different seasons, months, and market conditions. Through the examination of these variations, the system understands underlying trends better, which improves the accuracy and reliability of future predictions.

Price Forecasting at this level, the machine-learned data is applied to forecast upcoming commodity prices by employing machine learning models. Algorithms like Random Forest and Linear Regression are implemented within the dataset in order to prepare forecasts from existing and historical patterns. The forecasting aids farmers, traders, as well as policymakers in formulating market strategies, optimizing storage capacity, and improving profits.

Machine Learning Algorithms this aspect constitutes the core intelligence of the system. It entails training, testing, and implementing machine learning algorithms to come up with predictions. The models learn from past data to discover patterns and relations that human observation may not discern. They are then employed to generate real-time or batched price predictions, providing valuable decision-making support to end-users.

VI. IMPLEMENTATION DETAILS

A. Technologies Used

- **Frontend**: HTML, CSS, Jinja2 (Flask templates)
- **Backend**: Python, Flask
- **Machine Learning**: scikit-learn, pandas, pickle
- **Hosting/Deployment**: Flask local server; deployable on Netlify (frontend) and any Flask-compatible platform (backend)

B. Machine Learning Model

- **Model Type**: Regression (e.g., Random Forest, Linear Regression)
- **Input Features**: Year, month (numerical), arrivals in quintals, one-hot encoded commodity names
- **Preprocessing**: Dummy variable encoding and feature alignment

C. Model Integration

- Model and feature files (commodity_price_model.pkl, model_features.pkl) are loaded during startup.
- Incoming input is preprocessed and passed to the model for prediction

A. Price Prediction Module

Description: Users can choose a commodity while selecting the desired year, month and quantity of arrivals data within the system. The system executes the applied ML model to produce price estimation results.

B. Input Validation Module

Description: Users can choose a commodity while selecting the desired year, month and quantity of arrivals data within the system. The system executes the applied ML model to produce price estimation results..

C. Feature Alignment Module

Description: A specific padding method fills the gaps with zero values to make the model input compatible.

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D. Output Rendering Module

Description: The forecasted modal price appears in INR but displays an error message when needed.

VII. RESULTS AND DISCUSSION

The evaluation occurred in a controlled development environment by using test input data. The regression model produces reliable forecast results through its analysis with uncorrupted historical data. User interaction testing confirms that these systems functions perform correctly:

- **Prediction Accuracy**: Model results align closely with expected market prices based on trends.
- **Responsiveness**: Predictions are generated in under a second.
- **Usability**: Interface is simple and works across modern browsers with minimal training.

Limitations:

- Requires updated training datasets for different years and regions.
- Currently limited to modal price prediction; future work may include min/max price ranges or confidence intervals.

VIII. CONCLUSION

Through the Agricultural Commodity Price Prediction System users gain efficient access to machine learning algorithms that forecast the prices of crops at market value. The system brings easier prediction capabilities which connect with a web interface to solve essential agricultural decision needs. A price prediction system gives major advantages to farmers and traders who wish to boost their revenue by making well-informed crop marketing decisions. The platform can be expanded with advanced forecasting models and weather data alongside mobile access features which makes it a sustainable option for modern smart agriculture practices.

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www.ijarsct.co.in
DOI: 10.48175/IJARSCT-26040