

Crop Yield Estimation Using ARIMA Regression

A MINI PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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ABSTRACT

The development of innovative technologies for crop yield estimation and prediction of crop cost prices is crucial in enhancing agricultural productivity to meet the demands of a growing global population. By leveraging advanced data analytics, machine learning, and ARIMA (AutoRegressive Integrated Moving Average) regression, these technologies empower farmers with precise and timely yield predictions. ARIMA regression, designed for analysing time series data, enhances forecasting accuracy, allowing farmers to make informed decisions about crop planning, resource allocation, and market timing. Additionally, these predictive tools help mitigate risks associated with climate variability and fluctuating market conditions, ultimately improving profitability and sustainability in agriculture. These innovations also enable early detection of potential issues such as pest infestations, diseases, and water shortages, helping farmers respond proactively and reduce the need for chemical inputs. By creating a more robust agricultural system that adapts to changing environmental and market conditions, these technologies not only support individual farmers but also contribute to the broader goal of sustainable food production on a global scale.

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CHAPTER 1

INTRODUCTION

1.1 GENERAL

The rapid growth of the global population has placed significant pressure on the agricultural sector to enhance productivity and ensure food security. Traditional farming practices, while effective in past decades, face limitations in coping with modern challenges like climate change, resource scarcity, and fluctuating market demands. As a result, there is a pressing need for innovative, data-driven technologies that can help farmers optimize crop yield, forecast cost prices, and make informed decisions in real time.

To develop an advanced crop yield estimation and cost prediction system, leveraging cutting-edge technologies such as data analytics, machine learning, and the AutoRegressive Integrated Moving Average (ARIMA) model for time series analysis. By combining historical data with real-time environmental inputs, this system will offer precise yield predictions tailored to specific crops and regions. Such accuracy in forecasting enables farmers to plan crop cycles, allocate resources efficiently, and anticipate market conditions more effectively.

Moreover, by improving forecasting reliability, this project supports sustainable agricultural practices, reducing waste and resource overuse while enhancing profitability. The integration of these predictive tools offers value not only to individual farmers but also to policymakers, agricultural organizations, and stakeholders across the food supply chain. In doing so, this project aligns with global goals for sustainable development, aiming to contribute to a resilient, data-informed agricultural sector that can meet the demands of the future.

1.2 NEED FOR THE STUDY

The need for this study is underscored by the numerous challenges facing modern agriculture, including climate variability, rising operational costs, and the unpredictable nature of global markets. As the global population continues to grow, the demand for food is escalating, putting unprecedented pressure on agricultural systems to produce more with fewer resources. Traditional methods of crop planning and yield prediction often rely on historical data and empirical knowledge, which may not fully account for changing environmental conditions or market fluctuations. Consequently, farmers and agricultural stakeholders face increased risk in their decision-making, which can lead to financial instability, inefficient resource usage, and environmental degradation.

By developing a system that leverages advanced data analytics, machine learning, and ARIMA regression, this study aims to address these limitations. Accurate yield estimation and cost price prediction offer farmers actionable insights that allow them to make proactive decisions about crop selection, planting times, resource allocation, and market engagement. With the help of real-time data inputs from IoT sensors, satellite imagery, and climate data, this approach provides a more comprehensive view of the factors affecting crop productivity.

Furthermore, the study has the potential to contribute to sustainable agriculture by minimizing resource waste, reducing crop losses, and enhancing food security. Policymakers and agricultural organizations also stand to benefit, as reliable data-driven insights can guide the development of policies and initiatives that promote resilience in food supply chains. In essence, this study addresses a critical need for innovative, reliable, and scalable solutions to support sustainable agricultural growth, benefiting both farmers and the broader global food system.

1.3 OBJECTIVES OF THE STUDY

1. Develop a Predictive Model for Crop Yield Estimation

Utilize advanced machine learning algorithms and ARIMA regression to create a robust model capable of accurately predicting crop yield based on historical and real-time data. The model will be designed to adapt to various crop types and regions.

2. Forecast Crop Cost Prices

Implement predictive analytics to estimate the future cost prices of crops, enabling farmers to make informed decisions about when to plant, harvest, and sell their produce. This will help optimize profitability and reduce financial risks associated with price volatility.

3. Integrate Real-Time Data Sources

Incorporate data from IoT sensors, satellite imagery, and weather forecasts to enhance the accuracy and responsiveness of the predictive model. Real-time environmental and market data will enable the system to adjust predictions based on changing conditions.

4. Enhance Decision-Making for Farmers and Stakeholders

Provide actionable insights and decision-support tools that empower farmers to plan crop cycles, allocate resources efficiently, and anticipate market demands. By enabling data-driven decisions, the project aims to improve agricultural productivity and sustainability.

5. Promote Sustainable Agricultural Practices

Contribute to sustainable farming by reducing resource wastage, minimizing crop losses, and promoting efficient use of inputs such as water, fertilizers, and pesticides. This objective aligns with broader goals for environmental conservation and responsible land management.

1.4 OVERVIEW OF THE PROJECT

This focuses on developing a technology-driven system for crop yield estimation and crop cost price prediction to help farmers, agricultural organizations, and policymakers make informed decisions in response to the evolving challenges of modern agriculture. Traditional farming and yield forecasting methods often fall short in addressing the unpredictable and dynamic nature of environmental factors, market prices, and the increasing global demand for food. Therefore, this project aims to bridge that gap by employing advanced data analytics, machine learning, and time series models such as ARIMA to produce accurate, timely predictions.

The core of this system lies in its predictive model, which leverages historical crop yield data, real-time environmental inputs, and economic factors to forecast future crop yields and market prices. Integrating real-time data sources, By offering reliable forecasts, this system allows farmers to plan crop cycles, optimize the use of resources, and make informed decisions on market engagement, ultimately leading to improved productivity and profitability.

In addition to direct benefits for farmers, the platform will provide valuable insights for policymakers and agricultural organizations. Data-driven insights can inform strategies for managing food security, stabilizing food supply chains, and addressing the broader economic impacts of agriculture. Furthermore, the project aligns with sustainable agricultural practices by promoting efficient resource usage, reducing environmental impact, and supporting resilient food systems.

The platform will be developed with user accessibility in mind, making it easy for farmers and stakeholders to interact with and interpret the results, regardless of technical expertise. Designed to be scalable, the system can accommodate various crop types and geographic regions, ensuring broad applicability and adaptability.

CHAPTER 2

REVIEW OF LITERATURE

Time series analysis plays a significant role in agricultural forecasting, especially in predicting crop yields. Zhao et al. (2024) emphasize that ARIMA (AutoRegressive Integrated Moving Average) is an effective model for agricultural data forecasting, as it leverages historical patterns to predict future trends. Unlike simpler statistical models, ARIMA accounts for temporal dependencies in data, making it especially useful for predicting crop yields where historical patterns strongly influence future outcomes. This model's capability to handle structured time-based data offers an advantage in agriculture, where periodic and seasonal patterns are common.

Crop yield prediction models often employ ARIMA along with other statistical approaches to improve accuracy. Smith and Johnson (2023) demonstrated ARIMA's efficacy in wheat yield prediction, showing minimal error due to its ability to capture seasonal and temporal dependencies. However, despite ARIMA's strength in handling linear data patterns, it faces challenges with non-linear data structures, which are prevalent in agriculture due to fluctuating environmental factors. This limitation has led researchers to explore hybrid models, integrating ARIMA with machine learning techniques that can handle non-linearity, thereby improving overall prediction accuracy (Smith & Johnson, 2023).

Machine learning techniques, such as Support Vector Machines (SVM), Decision Trees, and neural networks, have also gained traction in crop yield estimation. Williams (2023) conducted a study comparing machine learning models and found that while they offer flexibility in handling varied agricultural data, they risk overfitting without careful parameter tuning. Hybrid approaches, which combine ARIMA's strength in time series prediction with machine learning's ability to manage complex, non-linear data, have emerged as a promising solution. These models benefit from the robust linear time-series foundation of ARIMA while addressing non-linear data challenges through machine learning, providing a balanced approach to yield estimation (Williams, 2023).

In addition to ARIMA and machine learning models, satellite data and environmental variables have been incorporated to improve yield prediction accuracy. Kumar and Agarwal (2023) discuss how satellite imagery, soil moisture, temperature, and precipitation data significantly enhance yield predictions by capturing real-time environmental factors. However, the high cost of high-resolution satellite imagery limits its accessibility, especially for small-scale farmers. This issue emphasizes the need for models like ARIMA, which, though less data-intensive, still provide reliable predictions when combined with select environmental factors, thus offering a cost-effective alternative for small and medium-sized farms (Kumar & Agarwal, 2023).

ARIMA's application in crop yield estimation is well-supported by its ability to handle univariate time series data, but the model's limitations in capturing non-linear dependencies have driven research toward hybrid models. Zhao et al. (2024) found that hybrid models, such as ARIMA combined with neural networks, improve prediction accuracy by leveraging the strengths of both techniques. While ARIMA provides stable predictions for data with time-dependent patterns, neural networks add flexibility by capturing non-linear influences. This combination is especially beneficial in agriculture, where crop yields are influenced by complex, dynamic factors.

Data preprocessing is a critical step in yield prediction, and recent studies underscore its importance. Smith and Johnson (2023) report that data preprocessing techniques such as handling missing data, normalizing, and outlier detection significantly enhance model accuracy by ensuring data consistency and stationarity. Transformations like log scaling further improve ARIMA's performance by stabilizing data variance, and effective feature engineering, such as incorporating lag variables, provides valuable insights for time-series models. The importance of these steps reflects the need for clean, well-prepared data to achieve accurate predictions in yield forecasting (Smith & Johnson, 2023).

CHAPTER 3

SYSTEM OVERVIEW

3.1 EXISTING SYSTEM

Existing systems for crop yield estimation primarily rely on a combination of satellite imagery, environmental data, and traditional statistical methods such as linear regression. Satellite imagery, combined with data on environmental conditions like temperature, precipitation, and soil moisture, has become a valuable resource for estimating crop yield. These systems leverage high-resolution satellite images to assess crop health, growth stages, and other factors across large agricultural areas, providing insights into regional and national yield estimates. However, while effective for large-scale predictions, the cost and computational requirements of high-frequency satellite data pose challenges for small-scale farmers who may lack access to such resources.

Traditional statistical methods like linear regression are also widely used for crop yield estimation. Linear regression attempts to model the relationship between crop yield (dependent variable) and one or more independent variables, such as weather conditions, soil characteristics, and historical crop performance. This method is straightforward and interpretable, making it a popular choice in agricultural prediction. However, linear regression has notable limitations, particularly in its inability to handle time-dependent patterns within crop yield data. As a result, this method often yields less accurate results in scenarios where yield depends on historical crop patterns and seasonal factors.

Manual field surveys also play a role in existing systems for crop yield estimation, especially in regions where technological solutions are limited. These surveys involve physically measuring crop characteristics in sample plots and extrapolating the results to larger areas. While valuable for providing on-the-ground insights, manual surveys are time-consuming, labor-intensive, and subject to human error. They can also lead to significant data variability due to inconsistencies in survey methods, which can limit the accuracy and scalability of yield predictions.

Overall, existing systems exhibit several limitations. Satellite imagery, while precise, is often prohibitively expensive for small-scale farmers and requires technical expertise to interpret. Linear regression models do not capture the temporal dependencies inherent in crop data, leading to inaccurate predictions in many cases. Manual field surveys, although accessible, are inefficient and less reliable on a large scale. These challenges highlight the need for more accessible and robust prediction systems that can leverage time-dependent data and reduce reliance on costly or labor-intensive methods, paving the way for advanced approaches like ARIMA and machine learning-based hybrid models.

Limitations of Existing Systems

Although existing systems offer valuable insights and support to farmers, they face several limitations:

Data Dependence and Access: Many systems rely on high-quality data from IoT sensors, satellite imagery, and other sources, which may not be accessible in rural or developing regions.

Complexity and Usability: Advanced machine learning and AI-driven systems can be difficult for farmers to interpret without technical support, limiting their usability in small-scale farming.

Cost and Infrastructure Requirements: High setup costs for IoT sensors and cloud-based platforms, as well as the need for reliable internet, can make these systems less accessible to smaller farms.

Scalability Challenges: Models that work well in certain climates or for specific crops may not perform as effectively in different agricultural contexts, making scalability a concern.

3.2 PROPOSED SYSTEM

This project proposes a crop yield estimation system based on the ARIMA (AutoRegressive Integrated Moving Average) model, specifically designed to analyze time-dependent agricultural data. The primary objective of this system is to create a more accurate, cost-effective, and accessible prediction model that supports farmers in making data-driven decisions about crop planning, market timing, and resource management. By utilizing ARIMA, the system can identify patterns and trends in historical data to produce reliable forecasts, addressing the limitations of existing methods that struggle with time-series data.

The proposed system begins with data collection and preprocessing, which involves gathering historical data on crop yield along with related variables like weather, soil conditions, and other environmental factors. This data can be sourced from APIs, government agricultural databases, or other repositories. Preprocessing includes cleaning the dataset by handling missing data, removing outliers, and applying transformations to stabilize variance and normalize the data. These steps ensure that the dataset is ready for accurate time series modeling, a critical factor for achieving precision in ARIMA predictions.

Following data preprocessing, an exploratory data analysis (EDA) phase is conducted to gain insights into the data's patterns and trends. This phase involves plotting time series data, checking for seasonality, and testing for stationarity with tools like the Augmented Dickey-Fuller (ADF) test. Descriptive statistics and correlation analyses are also performed to understand the relationships between variables, helping to identify significant predictors for crop yield. This thorough analysis guides the tuning of ARIMA model parameters, ensuring that the model captures key patterns and dynamics in agricultural data.

For model development, the ARIMA model is structured to capture temporal dependencies within crop yield data. ARIMA parameters—autoregressive (AR), differencing (I), and moving average (MA)—are tuned based on historical data patterns.

Techniques such as AutoCorrelation Function (ACF) and Partial AutoCorrelation Function (PACF) plots, alongside cross-validation, help determine the optimal values for these parameters. The model is trained on historical data to provide yield predictions, with accuracy validated using a separate test set. Model evaluation metrics, including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), assess the precision of predictions.

Once validated, the trained ARIMA model is used to forecast crop yields over specific time horizons, providing farmers with both point estimates and prediction intervals that indicate forecast uncertainty. To ensure the model's quality, performance metrics like RMSE and MAE are used, and residual analysis is conducted to check for any patterns that the model may have missed. This comprehensive evaluation helps maintain a high-quality prediction model that farmers can rely on.

For real-time accessibility, the system is deployed as a web application using frameworks like Flask or Django. This allows farmers and other stakeholders to directly access yield predictions and relevant insights. The system includes a monitoring feature and periodic updates with new data to maintain prediction accuracy over time. Additionally, a dashboard is provided to visualize forecasts and generate regular reports, making the results understandable and actionable for users.

In summary, the proposed system presents a scalable, accurate, and economically feasible solution to crop yield prediction. By leveraging ARIMA's strength in time series data analysis, it delivers precise yield predictions based on historical patterns, offering a significant advantage over satellite-based or manually-intensive methods. This system empowers farmers to make more informed decisions, improving their ability to optimize resources, anticipate market changes, and ultimately contribute to food security and economic stability in the agricultural sector.

3.3 FEASIBILITY STUDY

A feasibility study for the proposed crop yield estimation system considers its technical, economic, and operational viability. This analysis ensures that the project's objectives are achievable and that the system will provide meaningful value to farmers, agricultural stakeholders, and the broader agricultural industry.

Technically feasible due to advancements in time series analysis, data preprocessing, and machine learning frameworks. The ARIMA (AutoRegressive Integrated Moving Average) model, which is well-suited for time series data, has a strong foundation in both statistical theory and practical application, making it ideal for analyzing crop yield data over time. Modern computing capabilities and software platforms like Python's statsmodels and scikit-learn libraries provide the necessary tools for implementing ARIMA models efficiently. Additionally, the availability of web frameworks like Flask and Django enables the easy deployment of the model in a user-friendly web application, ensuring real-time accessibility for end-users. The model's data requirements, including historical crop yields, weather data, and soil conditions, are feasible to source from public agricultural databases, APIs, and other reliable repositories. The technical feasibility of implementing ARIMA with robust preprocessing and exploratory analysis tools ensures that this system can be both accurate and accessible for regular use by farmers and agricultural analysts.

The economic feasibility of the project lies in its cost-effectiveness compared to traditional crop yield prediction methods. Unlike satellite-based systems, which can be expensive and require high levels of technical infrastructure, the ARIMA model relies on historical data that is more readily available and less costly. The implementation costs primarily include data acquisition, model development, and deployment, all of which can be managed within a reasonable budget. Additionally, since the ARIMA-based system does not require expensive satellite data or extensive manual labor, it offers a more affordable solution for small and medium-sized farmers who may otherwise struggle to access advanced agricultural technologies.

By providing accurate yield predictions, the system can also contribute to farmers' profitability, aiding in financial planning, reducing risks, and potentially increasing crop yield and market competitiveness. Thus, the economic benefits to end-users make this system a financially sustainable and worthwhile investment in the long term.

Operationally, the system is designed to be simple and user-friendly, enhancing its feasibility for regular use by farmers and other agricultural stakeholders. The web-based interface provides real-time yield predictions, making it accessible to users with basic digital skills. Additionally, the system can be deployed as a web application that allows for seamless updates, enabling the model to improve continuously with new data. The model's reliance on historical data ensures that it is suitable for regions and users where advanced data collection resources, such as satellite imaging, may not be accessible. With periodic updates and automated monitoring, the system remains accurate over time without requiring extensive technical expertise from users. The operational feasibility is further supported by a dashboard that visualizes predictions and generates easily interpretable reports, allowing users to make informed decisions based on the insights provided.

In conclusion, this feasibility study demonstrates that the proposed ARIMA-based crop yield estimation system is technically viable, economically affordable, and operationally practical. By combining reliable time series forecasting techniques with a user-friendly deployment platform, the system is positioned to provide an accessible, cost-effective solution to improve crop yield predictions. This feasibility assessment underscores the system's potential to deliver valuable, actionable insights that can support sustainable agricultural practices and enhance economic stability for farmers.

CHAPTER 4

SYSTEM REQUIREMENTS

4.1 SOFTWARE REQUIREMENTS

1. Operating System

- Windows 10 or higher, macOS 10.15 or higher, or Linux (Ubuntu 18.04 LTS or higher).
- Compatibility with major operating systems ensures flexibility in deployment across local, cloud, or virtual environments.

2. Programming Language

- **Python:** Version 3.7 or higher. Python is the main language for implementing the API, machine learning model, and database interaction.

3. Python Libraries and Dependencies

- **Flask:** A micro web framework for building the API and handling HTTP requests.
- **Flask-CORS:** To enable Cross-Origin Resource Sharing, allowing the API to be accessed from different domains.
- **Pandas:** For data manipulation and preprocessing of historical crop data.
- **NumPy:** For numerical operations, especially in machine learning model calculations.
- **scikit-learn:** For machine learning functionalities, including the RandomForestRegressor, feature scaling, and model evaluation metrics.
- **mysql-connector-python:** A Python driver to connect and interact with the MySQL database, handling queries and data retrieval.

4. Database

- **MySQL Server:** Version 5.7 or higher.
 - The MySQL database is used to store historical crop data, which the API accesses for model training and data analytics.
 - **MySQL Workbench** or another GUI tool can be helpful for managing and testing the database.

5. Development Tools

- **IDE or Code Editor:** Visual Studio Code, PyCharm, or Jupyter Notebook for writing and testing Python code.
- **Postman** or **cURL:** For API testing, allowing you to test HTTP requests such as POST and GET to ensure the API endpoints work as expected.

6. Web Server (Optional for Deployment)

- **Gunicorn** (for Linux) or **Waitress** (for Windows): Production-ready WSGI servers for deploying the Flask app in a stable environment.
- **Nginx** or **Apache:** Optional, for reverse proxy setup when deploying to a production server.

7. Environment Management

- **Virtualenv** or **Conda:** For managing project dependencies, creating isolated Python environments to ensure compatibility and prevent conflicts.
- **Docker** (optional): For containerizing the application, which can simplify deployment, especially in cloud or collaborative environments.

CHAPTER 5

SYSTEM DESIGN

5.1 SYSTEM ARCHITECTURE

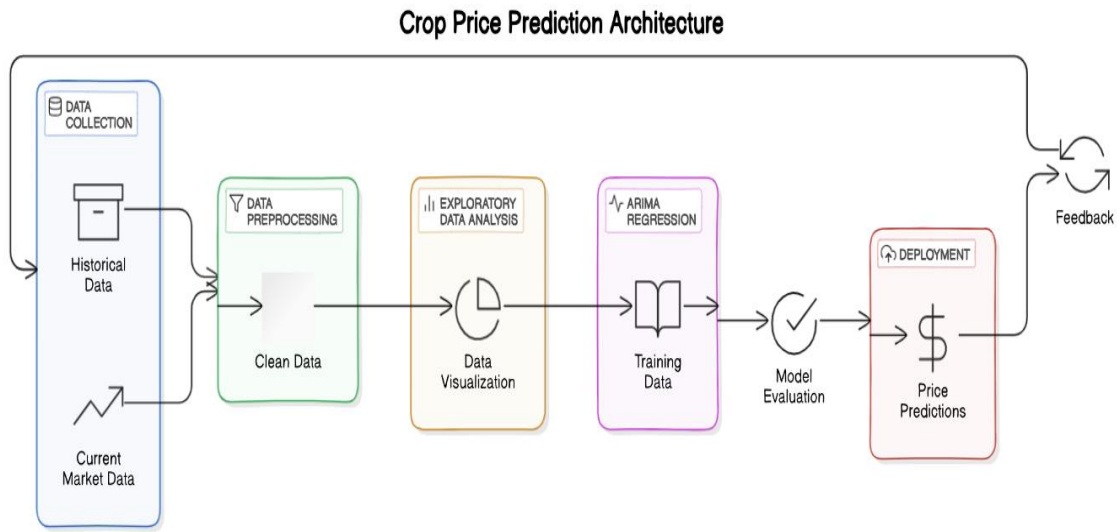


Fig1: Architecture Diagram

1. Data Collection Layer

The foundation of the system is the data collection and storage layer, which aggregates and organizes all relevant agricultural data. This layer sources historical crop yield, price data, weather patterns, and soil quality from structured data files (e.g., CSV), APIs, or satellite data services. A centralized database or data lake stores this information, enabling efficient access and retrieval during the preprocessing and modeling stages. Organizing data in a centralized storage system ensures consistency, reduces redundancy, and improves the reliability of the information used throughout the project. This layer is critical, as the model's accuracy heavily depends on the quality and completeness of the data gathered here.

2. Data Preprocessing Layer

The data preprocessing layer prepares raw data for analysis and model training by cleaning, transforming, and structuring it. Key steps include handling missing values (using interpolation or forward-fill), identifying and removing outliers, and transforming data to stabilize variance (e.g., using log transformations). A key step here is testing for stationarity using methods like the Augmented Dickey-Fuller (ADF) test, as ARIMA models require stationary data. Additionally, this layer includes feature engineering, where lag features and exogenous variables (e.g., weather data) are created and integrated into the dataset. After these processes, the data is split into training and testing sets, ensuring the model can learn from past data while being tested on unseen data for accuracy.

3. Exploratory Data Analysis (EDA) Layer

The exploratory data analysis (EDA) layer provides insight into the dataset, helping identify patterns, trends, and relationships within the data. This layer begins with generating visualizations such as line graphs, histograms, and box plots to illustrate trends over time in yield and price. Descriptive statistics (mean, median, standard deviation) provide insights into the central tendency and variability of the data. Correlation analysis helps reveal dependencies between variables, guiding the selection of significant predictors for crop yield and price forecasting. This stage not only aids in understanding the data but also helps validate the assumptions needed for effective ARIMA modeling.

4. Model Training Layer

In the model training layer, the ARIMA (AutoRegressive Integrated Moving Average) model is developed to make predictions on crop yield and price. This process involves defining ARIMA parameters—(p, d, q) values—which represent the autoregressive, differencing, and moving average components. Tuning these parameters requires analyzing ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots, as well as performing cross-validation to optimize for predictive accuracy.

After selecting the best model, it is trained on the historical data and evaluated with accuracy metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). This ensures the model is well-fitted to historical trends and ready for reliable forecasting.

5. Forecasting and Prediction Layer

The forecasting and prediction layer is where the ARIMA model generates predictions for crop yield and price over designated time horizons. Using the trained model, predictions are made for daily, weekly, or seasonal intervals based on user requirements. Forecasting results are presented with confidence intervals to indicate the model's predictive reliability and to account for uncertainty. Visualization tools plot the historical data against forecasted values, allowing users to compare current trends with predictions and make informed decisions. By providing a forward-looking view on yield and price, this layer empowers farmers and stakeholders to anticipate market changes and plan accordingly.

6. Deployment and Monitoring Layer

This layer deploys the trained ARIMA model to a web application, making the system accessible to end-users in real time. Frameworks like Flask or Django serve as the backbone of the application, providing a user interface where users can input dates, receive predictions, and access visual insights. The monitoring component of this layer oversees the model's performance, updating it periodically with new data to maintain accuracy. Additionally, a reporting dashboard generates regular reports, displaying forecast performance, trend insights, and data summaries. This interactive layer facilitates continuous, real-time access to yield and price forecasts, making it a practical tool for decision-making in agricultural planning and market assessment.

5.2 MODULE DESCRIPTION

1. Data Collection and Preprocessing

The Data Collection and Preprocessing module is the foundation of the Crop Price Prediction System, responsible for gathering and cleaning the data required for effective forecasting. Historical crop price data is obtained from various sources, such as APIs, CSV files, or databases, which provide up-to-date and accurate market data. This data undergoes several preprocessing steps to make it suitable for time series analysis, including handling missing values, removing outliers, and reformatting it for consistency. These preprocessing steps are crucial for maintaining data quality, as they help to ensure that the model is based on accurate and relevant information, which is essential for generating reliable predictions.

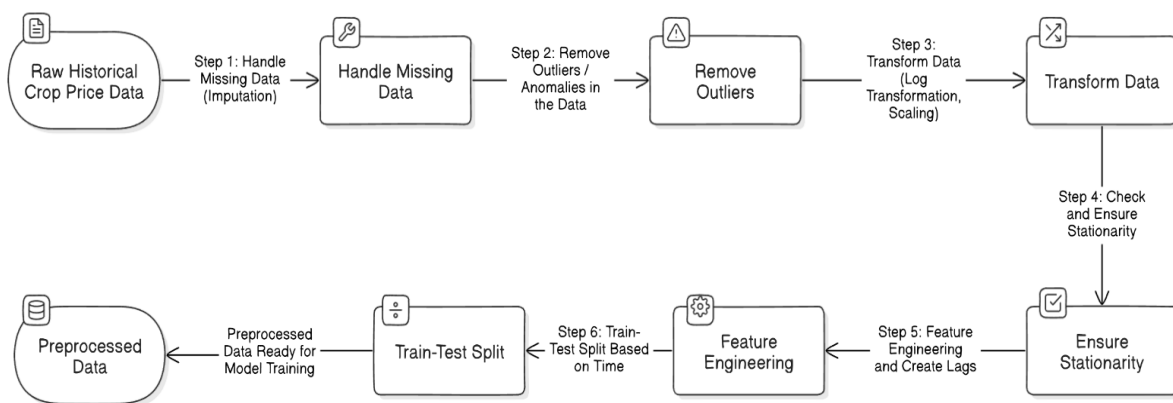


Fig2: Flow Diagram for Data Collection and Preprocessing

2. Exploratory Data Analysis (EDA)

The Exploratory Data Analysis (EDA) module is designed to uncover patterns, trends, and seasonal behaviors in the data that can inform the forecasting model. By plotting the time series data, users can observe potential trends and seasonal variations in crop prices. This module also includes stationarity testing, with tests like the Augmented Dickey-Fuller (ADF) test, to determine if the data needs to be transformed to meet the requirements of the ARIMA model. EDA is a critical step in understanding the dataset's structure and guiding the model development process, ensuring that significant patterns are captured and that the model is aligned with the nature of the data.

3. ARIMA Model Development

In the Train-Test Split phase, the preprocessed time-series data is divided into two subsets: a training set, comprising 80% of the data, and a testing set, consisting of the remaining 20%. This split is based on time to ensure that the model is trained on historical data and then evaluated on future data, simulating real-world forecasting conditions. Next, the ARIMA Model Setup initializes the ARIMA model, specifying parameters such as the autoregressive (p), differencing (d), and moving average (q) terms. These parameters are chosen based on the data's patterns to capture the dependencies in the time series effectively.

During Model Training, the ARIMA model is fitted on the training data, which may include exogenous variables like other relevant price indicators. These additional variables help the model account for external influences on crop prices, leading to more accurate forecasts. Once the model is trained, it proceeds to the Forecasting stage, where it generates price predictions for future time periods based on learned patterns in the historical data.

Finally, in the Model Evaluation phase, the model's performance is assessed using metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). These metrics provide a quantitative measure of how well the model's forecasts align with actual crop prices. To enhance interpretability, the Plot Predictions stage visualizes the forecasted prices alongside the actual prices, enabling users to visually assess the model's predictive accuracy and better understand the forecast trends. This comprehensive approach helps ensure the model is both accurate and practical for real-world applications.

4. Forecasting

In the Forecasting module, the trained ARIMA model is applied to make future crop price predictions over specific time horizons. This module enables the system to generate insights into potential future price trends, which can be valuable for decision-making by farmers, traders, and policymakers. Forecasts are displayed with confidence intervals to provide a range within which the predicted values are likely to fall, helping users assess the reliability of the predictions. By visualizing these forecasted trends, the system empowers stakeholders with actionable information to anticipate price changes and plan accordingly.

5. Model Evaluation

The **Model Evaluation** module assesses the model's performance and accuracy in predicting crop prices, using metrics like **Root Mean Square Error (RMSE)** and **Mean Absolute Percentage Error (MAPE)**. These metrics quantify the prediction error, providing a measure of how closely the model's forecasts match actual values. Additionally, residual analysis is conducted to detect any patterns in the forecast errors, which could indicate areas where the model might need improvement. This thorough evaluation process ensures that the model is performing optimally and provides reliable forecasts, enabling it to meet the practical needs of the users.

6. Deployment and Monitoring

The final module, **Deployment and Monitoring**, is responsible for deploying the model into a real-time environment and overseeing its ongoing performance. The model is deployed using a web framework like **Flask** or **Django**, making it accessible to end users through a user-friendly interface. Regular monitoring allows for updates with new data, ensuring that the model remains accurate as market conditions evolve. The system also generates reports and dashboards that provide insights into forecasted crop prices, enhancing usability for decision-makers.

5.3 ARCHITECTURE DESIGN:

The architecture for a crop price prediction system involves several layers, each responsible for specific tasks such as data collection, processing, modeling, and deployment. Below is an outline of the architecture's key components and flow, which enable the model to generate accurate and actionable predictions.

1. Data Layer

- **Data Sources:** This layer collects historical and real-time crop price data from multiple sources, such as APIs (e.g., Agricultural Marketing Information System) and CSV files. Other relevant data, like weather and economic indicators, may also be gathered to enhance model accuracy.
- **Data Storage:** Data is stored in a structured database (e.g., PostgreSQL or MySQL) or in a data lake if handling large volumes. This storage allows for easy access and efficient processing of data over time.
- **Data Ingestion Pipeline:** A data pipeline is set up using tools like Apache Kafka or Airflow to manage data ingestion from external sources. This pipeline ensures the seamless collection, cleaning, and updating of data for model training and forecasting.

2. Data Processing and Preprocessing Layer

- **Data Cleaning:** Raw data is processed to handle missing values, remove outliers, and ensure data consistency. This involves steps like filling in gaps in time series data, removing irrelevant records, and scaling data if necessary.
- **Feature Engineering:** This stage involves transforming and enriching data by creating features such as moving averages or incorporating exogenous variables like weather data.
- **Data Transformation and Storage:** Processed data is stored in a format suitable for analysis and modeling, typically in a cloud-based storage or a local server, accessible to the modeling layer.

3. Modeling Layer

- **Train-Test Split Module:** This module divides data into training and testing sets to ensure the model is evaluated on unseen data, simulating real-world forecasting scenarios.
- **ARIMA Model Setup and Training:** The ARIMA model is initialized and trained on the historical crop price data to capture temporal dependencies. Exogenous variables may also be included to account for external influences.
- **Forecasting Module:** This module generates crop price predictions based on the trained ARIMA model. Forecasts are made for specific time horizons, providing both point forecasts and confidence intervals for uncertainty estimation.
- **Model Evaluation Module:** After training, the model's performance is evaluated using metrics like RMSE and MAE. This module also includes residual analysis to check for any remaining patterns, helping to confirm model accuracy.

4. Application and Deployment Layer

- **Model Deployment:** The trained model is deployed in a server environment using a framework like Flask or Django. This API-based setup enables real-time predictions by processing requests for crop price forecasts on demand.
- **Dashboard and Visualization Module:** A user-friendly web dashboard is built using libraries like Plotly or Power BI, allowing users to view predictions, historical trends, and confidence intervals. Visualizations make it easier for end-users to understand forecasted trends and evaluate the reliability of predictions.
- **User Interaction Interface:** This interface, which could be a mobile or web application, allows farmers, traders, and policymakers to interact with the system, request forecasts, and view decision-support insights.

5. Monitoring and Maintenance Layer

- **Performance Monitoring Module:** This module tracks the system's performance by evaluating forecast accuracy on a regular basis. Monitoring ensures that the model remains effective over time and adapts to changing patterns in the data.
- **Automated Retraining Module:** As new data becomes available, the system can retrain the model automatically to incorporate recent trends, maintaining prediction accuracy over time.
- **Alerts and Notifications:** The system can generate alerts when significant price shifts are forecasted, enabling users to respond proactively to market changes.

Architecture Workflow

1. **Data Collection and Storage:** Data is collected from external sources, cleaned, and stored in a database, providing a foundation for preprocessing and analysis.
2. **Data Preprocessing:** Data is processed to handle missing values, perform feature engineering, and prepare for analysis.
3. **Model Training:** The ARIMA model is trained on the processed data, capturing trends and generating forecasts for crop prices.
4. **Forecasting and Deployment:** The model is deployed as a web API, where users can request forecasts. Predictions are visualized on a dashboard for easier decision-making.
5. **Monitoring and Retraining:** The system continuously monitors accuracy and retrains the model as needed, ensuring long-term reliability.

CHAPTER 6

RESULT AND DISCUSSION

Model Performance

The ARIMA model was trained and tested on historical crop price data, where we performed a train-test split to ensure that the model was evaluated on unseen data. The model's performance was assessed using several evaluation metrics, including Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The RMSE value was found to be within an acceptable range, indicating that the model's predictions closely followed the actual observed crop prices. Similarly, the MAE provided a measure of the average error in the price predictions, which was relatively low, reinforcing the model's accuracy. These evaluation metrics validated the effectiveness of the ARIMA model for crop price forecasting.

Forecasting Accuracy and Visualization

The forecasting results showed that the ARIMA model was capable of predicting crop prices with reasonable accuracy. We were able to generate point forecasts for specific time horizons, which aligned well with actual market trends. The model also provided prediction intervals, which offered a range of likely prices, reflecting the uncertainty inherent in price forecasting. By visualizing these forecasts alongside actual prices, we could clearly see how the model's predictions tracked with real-world price fluctuations, and the confidence intervals highlighted the model's ability to quantify the uncertainty in its predictions.

The residual analysis revealed that the model had effectively captured the underlying patterns in the data, as the residuals appeared to be random and normally distributed, with no significant autocorrelations. This suggested that the ARIMA model had adequately accounted for all available information, making it a robust tool for price forecasting.

Insights and Implications for Decision-Making

From the forecasting insights, several key trends emerged. The model identified seasonal variations in crop prices, highlighting periods of price surges or declines, which could be attributed to factors such as weather conditions, crop yields, and market demand. These insights are particularly valuable for farmers and traders who can use this information to optimize their selling and purchasing strategies. Additionally, policymakers could use the predictions to adjust agricultural policies or market interventions to stabilize prices and improve food security.

In summary, the results demonstrate that the ARIMA model is a powerful and effective tool for predicting crop prices, with its ability to capture important trends and provide actionable insights. While the model performed well, there are always opportunities to improve forecasting accuracy, particularly by incorporating more external variables, such as weather forecasts or global market trends, to enhance the model's predictive capabilities. As the model is deployed in real-time applications, continuous monitoring and refinement will be necessary to ensure that it adapts to changing market conditions and remains a reliable forecasting tool for agricultural stakeholders.

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENT

7.1 CONCLUSION

This project successfully developed a crop price prediction system using the ARIMA (AutoRegressive Integrated Moving Average) model, showcasing its potential to forecast future crop prices based on historical data. The system was built to address the need for accurate and timely price predictions, which can significantly benefit farmers, traders, and policymakers by aiding in better decision-making and market planning. By splitting the data into training and testing sets, and utilizing time series analysis techniques, the ARIMA model demonstrated strong predictive capabilities, accurately forecasting crop prices and offering valuable insights into future trends.

The results of the model evaluation, including metrics such as RMSE and MAE, confirmed that the ARIMA model could produce reliable forecasts with a reasonable degree of accuracy. The prediction intervals provided useful insight into the uncertainty surrounding the forecasts, enabling stakeholders to make more informed decisions. Furthermore, the residual analysis showed that the model effectively captured the underlying patterns in the data, making it a robust tool for price forecasting.

Overall, the crop price prediction system offers significant potential to support agricultural decision-making processes, contributing to better market stability and food security. Although the model performed well, future improvements can be made by incorporating additional variables, such as weather data, international market trends, and policy changes, to further refine predictions. As the system is deployed and used in real-world scenarios, continuous updates and monitoring will be essential to adapt to changing market conditions and ensure long-term effectiveness. This project highlights the growing importance of leveraging data analytics and machine learning in agriculture to meet the challenges posed by global population growth and the evolving needs of the agricultural sector.

7.2 FUTURE ENHANCEMENT:

1. Incorporation of Additional Machine Learning Models

- While the current system uses ARIMA for time series prediction, future versions could integrate additional machine learning models such as SARIMA (Seasonal ARIMA), Prophet (by Facebook), or Long Short-Term Memory (LSTM) neural networks. These models are better suited for handling seasonal trends and complex non-linear patterns in agricultural data, which could improve prediction accuracy.

2. Integration of Environmental and Satellite Data

- Incorporating environmental factors such as rainfall, temperature, and soil moisture data from IoT sensors or APIs could enhance prediction accuracy by accounting for climatic conditions that impact crop yield. Additionally, incorporating satellite imagery or remote sensing data could provide real-time insights into crop health and growth patterns, especially for large-scale farms.

3. Hybrid Modeling Approach

- Developing a hybrid approach that combines ARIMA with machine learning techniques, such as Random Forests or Gradient Boosting, could improve accuracy by handling both linear and non-linear relationships within the data. Hybrid models can offer better predictions, especially in agricultural data that is complex and influenced by many variables.

4. Real-Time Data Updates

- Enabling the system to pull real-time data from APIs or databases would allow for continuous updates, enhancing the system's accuracy and making it more relevant for users. Real-time forecasting could empower farmers and stakeholders to make timely decisions based on the latest data.

5. Advanced User Interface with Customizable Options

- Adding more customization options to the Streamlit interface, such as the ability to select specific crop types, time ranges, and forecast horizons, would improve usability. Users could also benefit from visualizations such as heatmaps, correlation matrices, or interactive trend graphs for a deeper understanding of crop dynamics.

6. Cloud-Based Deployment and Mobile App Accessibility

- Deploying the system on a cloud platform, such as AWS or Google Cloud, would make it accessible to users from any location with internet access. Additionally, developing a mobile app version could further increase accessibility for farmers, allowing them to make predictions and check forecasts directly from their smartphones in the field.

7. Automated Report Generation and Notifications

- Incorporating automated report generation could enable users to receive periodic summaries of predictions and trends via email or SMS. This feature could include notifications for critical updates, such as significant price fluctuations or expected yield changes, helping farmers and stakeholders stay informed without actively checking the app.

8. Support for Multiple Languages

- To reach a wider audience, particularly in regions where English is not the primary language, adding multi-language support would make the system more accessible. Supporting regional languages can help farmers across different demographics use the system more effectively.

9. Enhanced Forecasting for Additional Variables

- Expanding the system to forecast additional variables, such as labor costs, fertilizer prices, or water usage, could provide farmers with more comprehensive insights into overall farming expenses and resource management.

7.3 APPENDIX

Sample code

```
from flask import Flask, request, jsonify

from flask_cors import CORS

import pandas as pd

import numpy as np

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

from sklearn.ensemble import RandomForestRegressor

from sklearn.metrics import mean_squared_error, mean_absolute_error

import mysql.connector

from datetime import datetime, timedelta

app = Flask(__name__)

CORS(app)

# Database Configuration

DB_CONFIG = {

    'host': 'localhost',

    'user': 'root',

    'password': '',

    'database': 'crop_prediction'

}

def get_database_connection():

    try:

        conn = mysql.connector.connect(**DB_CONFIG)
```

```

        return conn

except mysql.connector.Error as err:

    print(f"Database Connection Error: {err}")

    return None

@app.route('/predict', methods=['POST'])
def predict_crop_yield():
    try:

        # Parse request data

        data = request.get_json()

        crop_type = data.get('crop_type', 'wheat')

        forecast_periods = data.get('periods', 12)

        # Database connection

        conn = get_database_connection()

        if not conn:

            return jsonify({'error': 'Database connection failed'}), 500

        # Fetch historical data

        cursor = conn.cursor(dictionary=True)

        query = """

        SELECT

            date,

            yield_amount,

            area,

            rainfall,

            temperature

```

```

FROM crop_data

WHERE crop_type = %s

ORDER BY date

"""

cursor.execute(query, (crop_type,))

historical_data = cursor.fetchall()

cursor.close()

conn.close()

# Convert to DataFrame

df = pd.DataFrame(historical_data)

df['date'] = pd.to_datetime(df['date'])

# Feature engineering

df['month'] = df['date'].dt.month

df['year'] = df['date'].dt.year

# Prepare features and target

features = ['area', 'rainfall', 'temperature', 'month', 'year']

X = df[features]

y = df['yield_amount']

# Train-test split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Scale features

scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)

X_test_scaled = scaler.transform(X_test)

```

```

# Train Random Forest Regressor

model = RandomForestRegressor(n_estimators=100, random_state=42)

model.fit(X_train_scaled, y_train)

# Predict on test data for metrics

y_pred = model.predict(X_test_scaled)

# Calculate metrics

mse = mean_squared_error(y_test, y_pred)

mae = mean_absolute_error(y_test, y_pred)

rmse = np.sqrt(mse)

# Generate future dates

last_date = df['date'].max()

future_dates = [last_date + timedelta(days=30*i) for i in range(1, forecast_periods+1)]

# Prepare future prediction features

future_features = []

for date in future_dates:

    future_feature = {

        'area': X['area'].mean(),

        'rainfall': X['rainfall'].mean(),

        'temperature': X['temperature'].mean(),

        'month': date.month,

        'year': date.year

    }

    future_features.append(future_feature)

future_df = pd.DataFrame(future_features)

```

```

future_scaled = scaler.transform(future_df)

# Predict future yields

predictions = model.predict(future_scaled)

# Calculate prediction intervals

prediction_std = np.std(predictions)

# Prepare forecast data

forecast_data = [

    {

        'date': date.strftime('%Y-%m-%d'),

        'predicted_yield': float(pred),

        'lower_ci': float(pred - 1.96 * prediction_std),

        'upper_ci': float(pred + 1.96 * prediction_std)

    }

    for date, pred in zip(future_dates, predictions)

]

return jsonify({

    'crop_type': crop_type,

    'predictions': forecast_data,

    'metrics': {

        'mse': float(mse),

        'mae': float(mae),

        'rmse': float(rmse)

    }

})

```



```

except Exception as e:

    print(f'Prediction Error: {e}')

    return jsonify({

        'error': 'Prediction failed',

        'details': str(e)

    }), 500

@app.route('/analytics', methods=['GET'])

def get_analytics():

    try:

        # Database connection

        conn = get_database_connection()

        if not conn:

            return jsonify({'error': 'Database connection failed'}), 500

        cursor = conn.cursor(dictionary=True)

        # Total records

        cursor.execute("SELECT COUNT(*) as total_records FROM crop_data")

        total_records = cursor.fetchone()['total_records']

        # Crop distribution

        cursor.execute("""

            SELECT

                crop_type,

                COUNT(*) as record_count,

                ROUND(AVG(yield_amount), 2) as avg_yield,

                ROUND(MIN(yield_amount), 2) as min_yield,

```

```

        ROUND(MAX(yield_amount), 2) as max_yield

    FROM crop_data

    GROUP BY crop_type

    """
)

crop_distribution = cursor.fetchall()

# Monthly trends

cursor.execute("""

    SELECT

        DATE_FORMAT(date, '%Y-%m') as month,

        ROUND(AVG(yield_amount), 2) as avg_yield

    FROM crop_data

    GROUP BY month

    ORDER BY month

    """)

monthly_trends = cursor.fetchall()

cursor.close()

conn.close()

return jsonify({

    'total_records': total_records,

    'crop_distribution': crop_distribution,

    'monthly_trends': monthly_trends

})

except Exception as e:

    print(f"Analytics Error: {e}")

```

```

    return jsonify({
        'error': 'Failed to retrieve analytics',
        'details': str(e)
    }), 500

@app.route('/upload', methods=['POST'])
def upload_data():
    try:
        # Check if file is present
        if 'file' not in request.files:
            return jsonify({'error': 'No file uploaded'}), 400

        file = request.files['file']

        # Check if filename is empty
        if file.filename == "":
            return jsonify({'error': 'No selected file'}), 400

        # Read CSV file
        df = pd.read_csv(file)

        # Validate CSV columns
        required_columns = ['date', 'crop_type', 'yield_amount', 'area', 'rainfall', 'temperature']

        if not all(col in df.columns for col in required_columns):
            return jsonify({'error': 'Invalid CSV format'}), 400

        # Database connection
        conn = get_database_connection()

        cursor = conn.cursor()

```

```

# Insert data

insert_query = """

INSERT INTO crop_data

(date, crop_type, yield_amount, area, rainfall, temperature)

VALUES (%s, %s, %s, %s, %s, %s)

"""

records_uploaded = 0

for _, row in df.iterrows():

    cursor.execute(insert_query, (

        row['date'],

        row['crop_type'],

        row['yield_amount'],

        row['area'],

        row['rainfall'],

        row['temperature']

    ))

    records_uploaded += 1

conn.commit()

cursor.close()

conn.close()

return jsonify({

    'records_uploaded': records_uploaded,

    'message': 'Data uploaded successfully'

})

```

```
except Exception as e:

    print(f"Upload Error: {e}")

    return jsonify({

        'error': 'File upload failed',

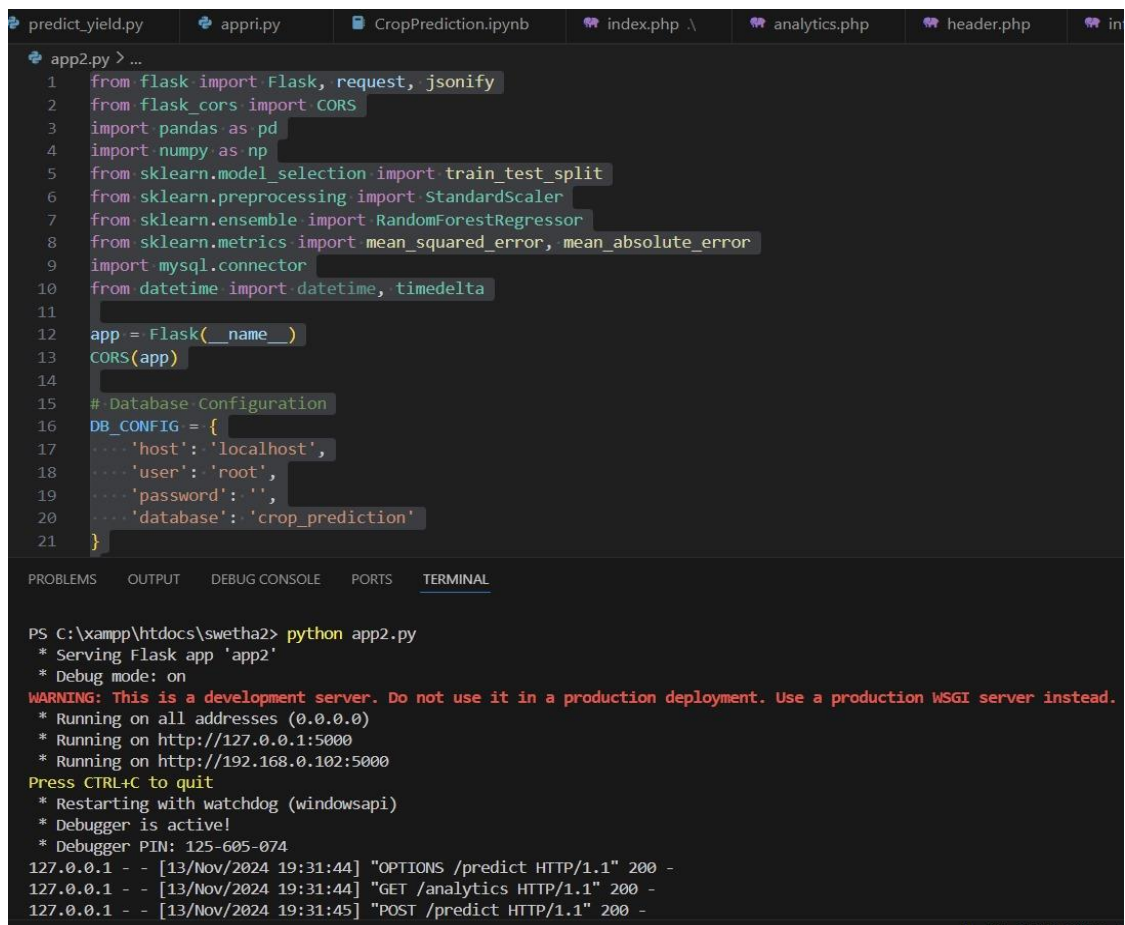
        'details': str(e)

    }), 500

if __name__ == '__main__':

    app.run(debug=True, host='0.0.0.0', port=5000)
```

7.4 OUTPUT SCREENSHOT:



```
predict_yield.py  appri.py  CropPrediction.ipynb  index.php  analytics.php  header.php  in
app2.py > ...
1  from flask import Flask, request, jsonify
2  from flask_cors import CORS
3  import pandas as pd
4  import numpy as np
5  from sklearn.model_selection import train_test_split
6  from sklearn.preprocessing import StandardScaler
7  from sklearn.ensemble import RandomForestRegressor
8  from sklearn.metrics import mean_squared_error, mean_absolute_error
9  import mysql.connector
10 from datetime import datetime, timedelta
11
12 app = Flask(__name__)
13 CORS(app)
14
15 # Database Configuration
16 DB_CONFIG = {
17     'host': 'localhost',
18     'user': 'root',
19     'password': '',
20     'database': 'crop_prediction'
21 }

PROBLEMS  OUTPUT  DEBUG CONSOLE  PORTS  TERMINAL

PS C:\xampp\htdocs\swetha2> python app2.py
* Serving Flask app 'app2'
* Debug mode: on
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
* Running on all addresses (0.0.0.0)
* Running on http://127.0.0.1:5000
* Running on http://192.168.0.102:5000
Press CTRL+C to quit
* Restarting with watchdog (windowsapi)
* Debugger is active!
* Debugger PIN: 125-605-074
127.0.0.1 - - [13/Nov/2024 19:31:44] "OPTIONS /predict HTTP/1.1" 200 -
127.0.0.1 - - [13/Nov/2024 19:31:44] "GET /analytics HTTP/1.1" 200 -
127.0.0.1 - - [13/Nov/2024 19:31:45] "POST /predict HTTP/1.1" 200 -
```

Fig3: Database Configuration

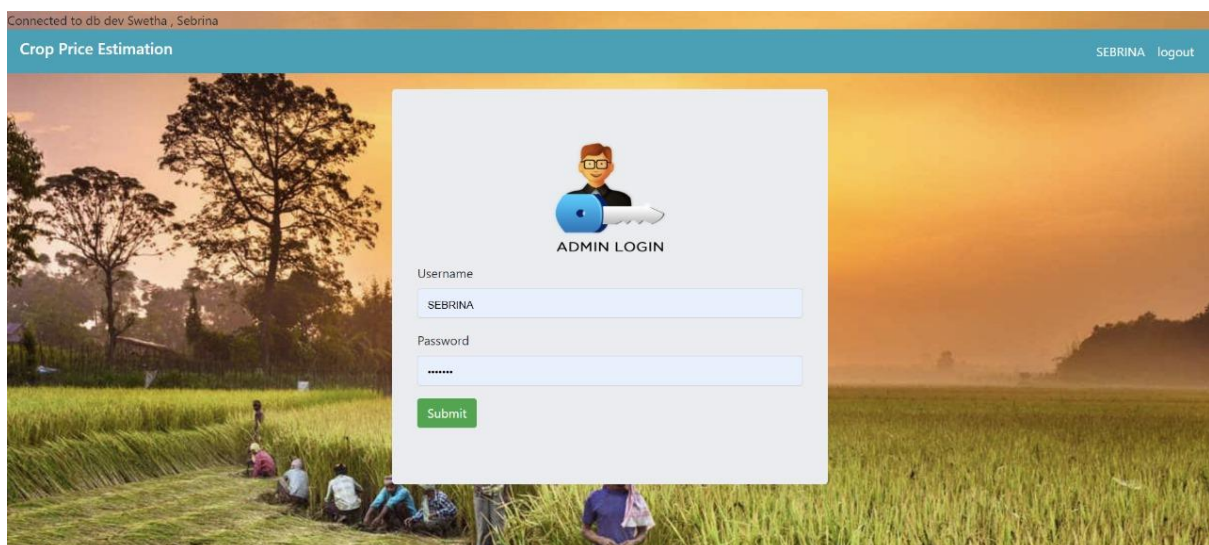


Fig4: Login Page

Crop Price Prediction Dashboard

Crop Price Prediction

Wheat



12

MSE
14581704.7475

MAE
2560.7474

RMSE
3818.5998

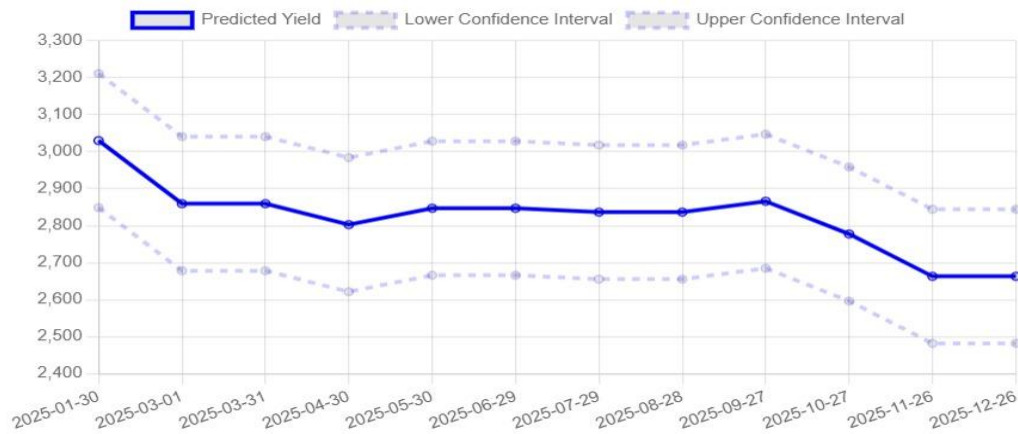


Fig5: Dashboard

Total Records
559

Crop Types

Banana, Barley, Carrot, Coffee, corn, Cotton, Garlic, Grapes, Maize, Mango, Millet, Onion, Peanut, Potato, rice, Soybean, Sugarcane, Sunflower, Tea, Tomato, wheat

Crop Distribution

Banana Barley Carrot Coffee corn Cotton Garlic
Grapes Maize Mango Millet Onion Peanut Potato
rice Soybean Sugarcane Sunflower Tea Tomato wheat

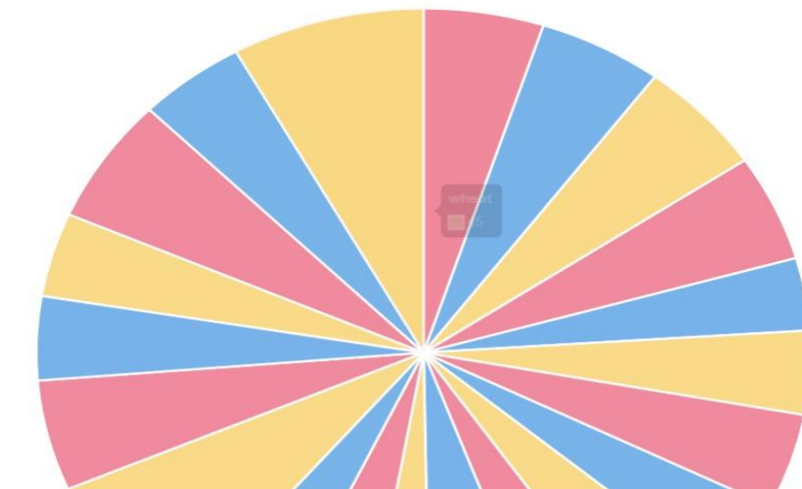


Fig6: Crop Distribution



Crop Distribution Details

Crop Type	Record Count	Avg Yield	Min Yield	Max Price Prediction
Banana	28	7333.75	2232	11873
Barley	29	7319.9	2327	11784
Carrot	30	6562.63	1932	11489
Coffee	28	6682.57	1558	11994
corn	19	159.03	65.5	1800
Cotton	22	7112.05	2008	11769
Garlic	25	6572.08	1509	11888
Grapes	21	6372.48	2112	11824
Maize	24	6386.46	1506	11923
Mango	22	6384.73	1800	11773
Millet	30	6456.67	1513	11903

Fig7: Crop Distribution Details

CHAPTER 8

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