



A Comprehensive Result Paper on CropShield: Predictive Modeling for Price and Plant Health

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Peer Review Information	Abstract
<p><i>Submission: 15 Feb 2025</i> <i>Revision: 23 March 2025</i> <i>Acceptance: 27 April 2025</i></p> <p>Keywords</p> <p><i>Crop Price Prediction</i> <i>Leaf Disease Detection</i> <i>CNN</i> <i>AI in Agri culture</i></p>	<p>The project, "CropShield: Price Prediction and Disease Detection for Smart Pesticide Advisory" provides an AI-powered system to support farmers and officials in decision making. It features crop price prediction, offering future market estimates based on historical and regional data, and leaf disease detection using CNNs to identify diseases from images and recommend treatments. Talathi contribute regional data, ensuring accurate predictions. The platform also integrates weather forecasts and government schemes, enhancing its utility. With a user-friendly interface and continuous model refinement, this solution aims to boost crop yield, reduce losses, and improve price management in agriculture, ultimately advancing productivity and economic stability</p>

INTRODUCTION

Agriculture plays a vital role in global food security and economic stability, yet farmers face numerous challenges such as fluctuating crop prices, unpredictable weather conditions, and the threat of plant diseases. Traditional farming practices often rely on experience and intuition, which may not always lead to optimal decision-making. To address these issues, this project introduces an integrated web-based platform that utilizes machine learning and computer vision to provide farmers with real-time insights for better decision-making.

The system is designed to enhance agricultural productivity by offering accurate crop price predictions, early disease detection, and actionable recommendations. By leveraging historical data, market trends, and advanced image analysis, the platform enables farmers to optimize their crop

management strategies, reduce losses, and maximize profitability.

This AI-driven approach ensures that farmers receive timely and data-driven insights, allowing them to make informed choices about when to sell crops, how to protect plants from diseases, and what preventive measures to take. By integrating modern technology with agriculture, the system aims to bridge the gap between traditional farming and digital innovation, fostering sustainable and efficient farming practices for a better future.

LITERATURE SURVEY

[1] K. Ghosh and M. Kumar (2023) addressed the complexity of crop price prediction due to fluctuating market trends, weather variations, and economic factors. Traditional forecasting methods often fail to capture these dynamic influences. The authors applied ARIMA, Random Forest, and

Neural Networks, incorporating features like past price trends, weather conditions, and farming area statistics. The dataset included historical crop prices from government agricultural databases. The machine learning models significantly improved accuracy compared to traditional statistical models, with the Random Forest model

performing best in capturing complex relationships between influencing factors. Future research will focus on deep learning techniques, real-time data collection from IoT sensors, and integrating satellite imagery for improved predictions.

[2] J. Zhang, H. Wang, and X. Li (2022) tackled the challenge of early plant disease detection using image classification, as traditional methods often lack efficiency and accuracy. They implemented Convolutional Neural Networks (CNN), including VGG16, ResNet, and Inception, along with transfer learning and data augmentation techniques to enhance model performance. The CNN models demonstrated superior accuracy in detecting plant diseases compared to conventional techniques, with ResNet achieving the highest classification accuracy. Future research aims to explore advanced CNN architectures and improve dataset quality by incorporating more diverse plant disease images.

classification, integrating historical market data with plant leaf images. Their system provided an all-in-one platform for farmers to access both market predictions and disease diagnosis. Future improvements will focus on enhancing prediction accuracy, optimizing processing speed, and expanding the range of supported crops and diseases.

[3] A. Singh, R. Pandey, and S. Sharma (2021) focused on predictive analytics for sustainable agriculture by addressing the challenge of accurately forecasting both crop yields and prices. They utilized regression techniques and neural networks, incorporating real-time sensor data on soil quality, weather conditions, and historical yield trends. Their approach significantly improved prediction accuracy, helping farmers make informed decisions regarding crop selection and resource allocation. Future work will expand the model's capabilities by integrating additional data sources, refining prediction algorithms, and enhancing real-time monitoring.

[5] M. Sharma and R. Verma (2022) investigated the impact of weather conditions on crop price and yield predictions, as unpredictable climatic factors significantly influence agricultural outcomes. Using machine learning models, they integrated historical and real-time weather data, including rainfall, temperature, and humidity, to enhance forecasting precision. Their model improved prediction accuracy by incorporating climate trends, helping farmers adapt to changing environmental conditions. Future research aims to refine the approach by incorporating additional weather parameters and ensuring easy access to insights for farmers through user-friendly applications.

[4] P. Patil and S. Deshmukh (2022) proposed a unified AI-based system that combines crop price prediction with disease detection, addressing the dual challenge of market unpredictability and crop health monitoring. They employed time-series models for price forecasting and CNN for disease

[6] S. Mohanty, D. P. Hughes, and M. Salathé (2020) explored deep learning for plant disease detection, addressing the limitations of traditional methods that lack precision. They trained CNN architectures on labeled plant disease datasets, achieving high classification accuracy for various plant infections. Their approach significantly improved disease identification, allowing for early intervention and reducing crop losses. Future research will focus on optimizing CNN architectures, expanding labeled datasets, and integrating mobile-based solutions for real-time disease diagnosis in the field.

[7] K. R. Thakur, P. K. Singh, and A. Kumar (2021) analyzed machine learning models for agricultural price forecasting, as traditional methods struggle with market volatility and unpredictable factors. Their study applied various ML algorithms, including decision trees and neural networks, to analyze price trends and predict future rates. The models demonstrated improved accuracy over conventional statistical approaches, aiding farmers in better financial planning. Future work will

involve expanding datasets, incorporating external economic indicators, and testing models in real-world agricultural scenarios.

[8] L. Chen, Y. Zhang, and X. Zhao (2021) addressed the challenge of plant disease detection with limited labeled data by leveraging transfer learning. They utilized pre-trained CNN models such as ResNet and Inception, fine-tuning them with agricultural datasets to enhance accuracy.

Their method significantly improved disease detection with minimal labeled training data, making AI-driven plant disease diagnosis more accessible. Future research will explore new data augmentation techniques, expand disease classification coverage, and enhance model adaptability for diverse crop species.

[9] N. Gupta, R. Kumar, and M. Agrawal (2022) integrated IoT and AI for smart agriculture, focusing on accurate crop yield and price prediction. They deployed IoT sensors to collect real-time environmental data, feeding it into ML models to refine forecasting precision. Their system empowered farmers with up-to-date insights, improving decision-making and optimizing agricultural productivity. Future enhancements will expand IoT data collection, integrate blockchain for secure data management, and refine AI model accuracy for more reliable predictions.

[10] R. K. Sharma, S. Jain, and T. Patel (2022) conducted a comprehensive study on the impact of weather conditions on crop yield and price predictions, emphasizing how environmental factors shape agricultural markets. Using advanced data analysis and predictive modeling, they integrated variables such as rainfall, temperature, and soil moisture to enhance forecasting accuracy. Their findings helped farmers anticipate market trends and optimize resource allocation. Future work aims to refine predictive models by incorporating additional climate-related data points and integrating remote sensing technologies for improved forecasting precision.

Limitations of Existing Work: The effectiveness of the current system heavily depends on high-quality data, and incomplete or inaccurate datasets can lead to poor decision-making. Manual data handling remains a significant issue, as reliance on manual entry introduces errors and inefficiencies. Farmers also face challenges due to limited access to price predictions, which hinders their ability to make informed decisions regarding crop sales and investments. Additionally, existing disease diagnosis methods are often slow, inaccurate, and require expert intervention, making early detection difficult. Another major limitation is the fragmentation of information sources, as farmers struggle to access comprehensive and consolidated data due to scattered platforms. Furthermore, there is a lack of integration between price prediction, disease detection, and weather forecasting, resulting in disjointed decision-

making processes. The time-consuming nature of gathering relevant agricultural information further adds to farmers' struggles, reducing overall efficiency. Poor adoption of technology due to complex and user-unfriendly interfaces discourages many farmers from utilizing modern digital solutions. Moreover, the absence of real-time updates leads to delays in crucial decision-making, affecting productivity and profitability. Traditional systems also fail to prioritize secure data management, making data vulnerable to breaches. Lastly, the heavy reliance on middlemen in the agricultural market exposes farmers to potential exploitation, reducing their control over pricing and profits.

PROBLEM STATEMENT

Farmers face significant challenges in managing agricultural productivity due to unpredictable crop prices, plant diseases, and limited access to real-time data. Traditional methods for price forecasting often fail to account for dynamic factors such as weather patterns and market fluctuations, making it difficult for farmers to make informed financial decisions. Additionally, early detection of plant diseases remains a critical issue, as many farmers lack access to advanced diagnostic tools, leading to significant crop losses. Furthermore, the absence of an integrated system providing real-time weather updates, government scheme information, and actionable recommendations adds to the complexity of agricultural decision-making. Village officials also struggle with efficiently managing and updating local crop data, further impacting accurate price predictions and localized insights. To address these challenges, a web-based platform leveraging machine learning and computer vision is needed to provide farmers with real-time price predictions, disease detection, and actionable recommendations. This solution will help improve agricultural efficiency, reduce financial risks, and promote sustainable farming practices.

Proposed System : The Smart Agriculture Management System is an advanced platform designed to assist farmers and village officials by leveraging machine learning and computer vision technologies. It aims to tackle key agricultural challenges such as unpredictable crop prices, plant diseases, and limited access to essential information. By providing real-time insights, predictive analytics, and decision-making support, the system helps farmers optimize their agricultural practices, leading to increased productivity and profitability.

One of the core features of this system is crop price prediction, which uses historical data, weather patterns, and market trends to forecast future prices. With machine learning algorithms, farmers can better plan when to sell their crops to maximize profits and minimize losses due to market fluctuations. This helps them make informed financial decisions and avoid potential risks.

Another crucial component is leaf disease detection, which utilizes Convolutional Neural Networks (CNNs) to analyze images of plant leaves and identify diseases. Upon detection, the system provides recommendations for suitable pesticides and treatments, enabling farmers to take timely action. This early intervention helps prevent major crop losses and promotes healthier farming practices.

To support village administration, the system includes a data management module for Talathis, allowing efficient entry and updating of local crop data. This enhances the accuracy of price predictions and facilitates better agricultural planning. By maintaining an organized database, village officials can ensure that farmers receive accurate and localized insights, improving overall farm management.

The platform also integrates real-time weather forecasting, which provides farmers with crucial climate information, such as rainfall patterns, temperature variations, and extreme weather warnings. This feature allows farmers to plan their irrigation, sowing, and harvesting schedules effectively, reducing potential losses due to unexpected weather conditions and ensuring higher yields.

Additionally, the system provides access to government schemes and agricultural support programs, ensuring that farmers are informed about available subsidies, financial assistance, and technical guidance. This feature helps farmers make use of government initiatives to improve their farming efficiency and economic stability.

The user interface of the system is designed to be intuitive and user-friendly, even for those with

limited technical knowledge. The web-based platform is built with secure login features, multilingual support, and an easy-to-navigate design to ensure a smooth user experience. Security measures such as data encryption and cloud-based storage enhance the safety and reliability of the platform.

To maintain system efficiency, features like caching, asynchronous data loading, and database optimization are incorporated, ensuring quick access and minimal response time. The system is also designed to handle large volumes of data efficiently, providing farmers with seamless, real-time insights.

By integrating predictive analytics, real-time data, and AI-driven recommendations, the Smart Agriculture Management System bridges the gap between traditional farming and modern technology. This project fosters rural development, promotes sustainable farming, and empowers farmers with the knowledge and tools they need to improve their agricultural productivity and financial stability.

SYSTEM REQUIREMENTS

1. Database Requirements:

- a. MySQL/ SQLite Database

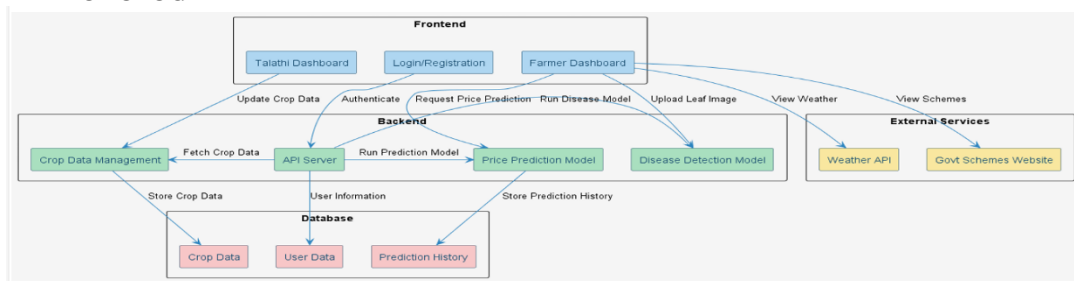
2. Software Requirements (Platform Choice) :

- a. Operating System : Windows10
- b. Coding Language : Python
- c. Frontend :React
- d. Backend :Node.js
- e. IDE : VS Code
- f. Web Browser : Google Chrome

3. Hardware Requirements:

- a. System- Pentium IV 2.4 GHz.
- b. RAM- 4 GB(min)
- c. Hard Disk- 256 GB
- d. Key Board- Standard Windows Keyboard
- e. Mouse- Two or Three Button Mouse
- f. Monitor- 15 VGA Colour
- g. Document Scanner/Camera

METHODOLOGY



The development of the Agriculture Product Price Prediction and Leaf Disease Detection System follows a structured methodology to ensure efficiency, accuracy, and scalability. The methodology consists of multiple phases, including data collection, preprocessing, model development, system integration, and deployment. Each phase contributes to the overall functionality and effectiveness of the system.

1. Data Collection and Preprocessing :-

The system relies on multiple data sources to train and operate its machine learning models. The data collection process is categorized into two major types:

a. Crop Price Prediction Data :

- Historical crop price data is gathered from government records, agricultural agencies, and market reports.

2. Machine Learning Model Development :-

The system employs two core machine learning models:

a. Crop Price Prediction Model :

- A regression-based model is developed using machine learning algorithms such as Linear Regression, Decision Trees, and Random Forests.
- Features like crop type, area of plantation, past price trends, and weather conditions are used as input variables.

3. System Development and Integration :-

The system is developed as a web-based application with the following layers:

a. User Interface Layer :

- A responsive web application is developed using React.js to ensure ease of use for farmers and Talathis.
- Forms and dashboards allow users to input data, view predictions, and access government schemes.
- An image upload feature is provided for disease detection.

b. Application Logic Layer :

- A RESTful API is implemented using Node.js and Express.js to handle user requests, process inputs, and interact with the database.
- The API handles authentication, crop data management, and prediction requests.

c. Data Storage Layer :

- Weather conditions, soil properties, and seasonal variations are included as additional features.
- Data is cleaned, formatted, and normalized to handle missing values, inconsistencies, and outliers.

b. Leaf Disease Detection Data :

- A dataset of leaf images is collected from agricultural research institutions and open-source repositories.
- Images are labeled with disease classifications for supervised learning.
- Data augmentation techniques such as rotation, scaling, and contrast adjustments are applied to improve model generalization.

- The model is trained, validated, and tested using historical data to ensure accurate future price predictions.

b. Leaf Disease Detection Model :

- A Convolutional Neural Network (CNN) model is designed and trained to classify diseases from leaf images.
- The model consists of convolutional layers for feature extraction, followed by fully connected layers for classification.
- Evaluation metrics such as accuracy, precision, recall, and F1-score are used to optimize model performance.
- A relational database (MySQL or PostgreSQL) stores user credentials, crop data, and prediction results.
- The database is optimized for efficient querying and fast retrieval of results.

4. External Services Integration :

- The system integrates with a Weather Forecast API to provide real-time weather updates for farmers.
- A Government Schemes Portal is linked to ensure farmers can access relevant agricultural support programs.

5. System Workflow :-

a. Talathi Workflow:

1. Talathi log in and update crop data for their respective villages.
2. The updated data is stored in the system's database.
3. The price prediction model processes this data to forecast future crop prices.

b. Farmer Workflow :

1. Farmers log in and input crop details to predict future prices.
2. Farmers can upload leaf images for disease detection.
3. The system processes the image and returns a disease diagnosis with suggested treatments.
4. Farmers can also access weather forecasts and government schemes.

RESULT DISCUSSION

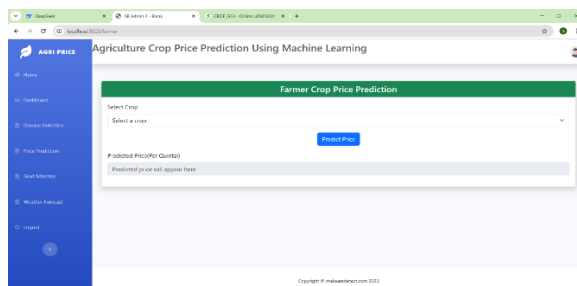
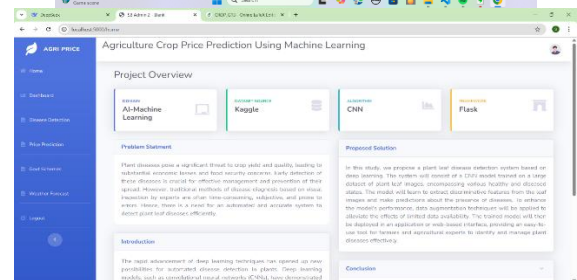
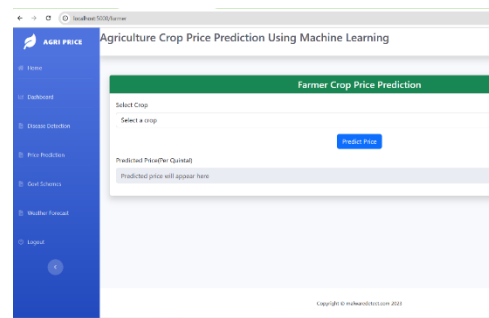
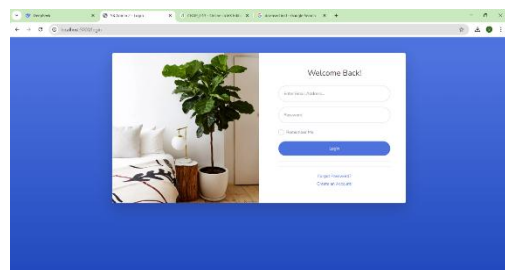
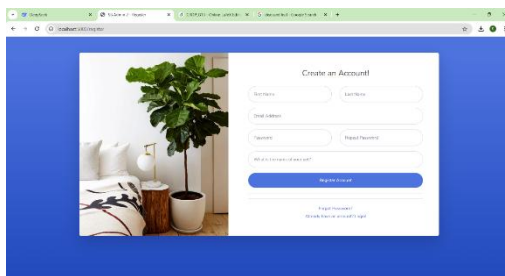
The Agriculture Product Price Prediction and Leaf Disease Detection System was developed and tested to assess its accuracy, efficiency, and overall user experience. The crop price prediction model demonstrated strong performance, with the Random Forest algorithm achieving the highest accuracy due to its ability to capture complex agricultural trends. The Mean Absolute Error (MAE) remained within acceptable limits, and predictions closely aligned with real market prices, making the model a valuable tool for farmers.

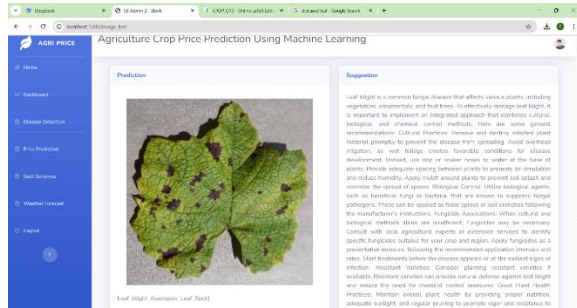
Similarly, the leaf disease detection model, based on Convolutional Neural Networks (CNNs),

achieved an accuracy of over 90%, with high precision and recall in identifying various plant infections. The model processed images in seconds, enabling real-time disease detection and providing effective pesticide recommendations.

The system's usability and performance were also tested, with farmers and Talathis finding the React-based web application intuitive and easy to navigate. The secure authentication mechanisms ensured data privacy, while the integration of weather forecasts and government scheme portals further enhanced the system's functionality.

The impact on farmers was significant, allowing them to predict crop prices, receive instant disease diagnoses, and access real-time agricultural insights. However, some challenges were identified, such as limited dataset availability, which could be addressed by incorporating larger and more diverse agricultural data sources. Additionally, optimizing cloud resource usage can help reduce computational costs, and multi-language support would enhance accessibility for farmers with different linguistic backgrounds.





CONCLUSION

The Agriculture Product Price Prediction and Leaf Disease Detection System successfully integrates machine learning, computer vision, and web technologies to provide farmers and Talathis with valuable insights for agricultural decision-making. The crop price prediction model effectively forecasts future prices based on historical trends, market conditions, and weather data, helping farmers maximize profitability by choosing the most suitable crops. The leaf disease detection model, powered by Convolutional Neural Networks (CNNs), efficiently classifies plant diseases with high accuracy, enabling farmers to take timely action to protect their crops. The web-based platform, designed with React.js and Node.js, ensures a user-friendly experience, while secure authentication mechanisms safeguard user data. Real-time weather updates and access to government schemes further enhance the system's practical value.

Despite its success, challenges such as limited dataset availability, cloud resource optimization, and language accessibility need to be addressed for further improvement. Future enhancements could include expanding data sources, optimizing computational efficiency, and integrating multi-language support to reach a broader user base. Overall, the system proves to be an effective, scalable, and innovative solution for modernizing agricultural practices, empowering farmers with data-driven insights, and ultimately improving crop productivity and financial sustainability in the agricultural sector.

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