Crop Prediction System Project

Submitted in partial fulfillment of the requirements of the degree

BACHELOR OF ENGINEERING IN COMPUTER ENGINEERING

By

Riya Lasi / 42

Mahek Kataria / 38

Rahul Kithani / 40

Manish Motwani / 31

Name of the Mentor

Prof. Sujata Khandaskar

Vivekanand Education Society's Institute of Technology,

An Autonomous Institute affiliated to University of Mumbai

HAMC, Collector's Colony, Chembur,

Mumbai-400074

University of Mumbai (AY 2024-25)

CERTIFICATE

This is to certify that the Mini Project entitled **"Crop Prediction System Project "** is a bonafide work of **Riya Lasi (42),Mahek Kataria (38), Rahul Kithani (40) , Manish Motwani (31)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **"Bachelor of Engineering"** in **"Computer Engineering" .**

(Prof.________________)

Mentor

(Prof.________________)

Head of Department

(Prof.____________)

Principal

Mini Project Approval

This Mini Project entitled “Prakruti-Parv:A Wildlife Conservation Project” by **Riya Lasi (42),Mahek Kataria (38), Rahul Kithani (40) , Manish Motwani (31)** is approved for the degree of **Bachelor of Engineering** in **Computer Engineering.**

Examiners

1………………………………………
(Internal Examiner Name & Sign)

2………………………………………
(External Examiner name & Sign)

Date:

Place:

Contents

ABSTRACT

The Crop Prediction System is an innovative tool designed to assist farmers in making informed decisions about which crops to plant based on a range of environmental and soil parameters. By analyzing critical factors such as soil composition, temperature, phosphorus content, sulfur content, and potassium levels, the system provides accurate predictions tailored to local conditions. This data-driven approach helps optimize crop selection, ensuring better yields, sustainable farming practices, and improved resource management.

With a user-friendly interface, the system allows farmers to input specific data about their land, while the underlying algorithm analyzes the information to recommend suitable crops. The system empowers farmers to enhance productivity by aligning crop choices with the natural capabilities of the land, minimizing risks, and maximizing output. By integrating scientific data into everyday farming practices, this crop prediction system aims to promote agricultural sustainability and improve food security.

ACKNOWLEDGEMENTS

We would like to express our sincere gratitude to Vivekanand Education Society's Institute of Technology for their support throughout our project. Their assistance in gathering project-related information was invaluable. We are delighted to extend our heartfelt appreciation to Prof.Sujata Khandaskar , our TE Mini-Project Mentor, for her generous assistance and valuable advice in developing the project synopsis. Her guidance and suggestions were instrumental in our project's development.

Our profound thanks go to Dr. (Mrs.) Nupur Giri, the Head of the Computer Department, and Dr. (Mrs.) J.M. Nair, our Principal, for granting us the opportunity to undertake this project. Their support was essential in successfully completing both the project synopsis and project review.

We would like to express our deep gratitude to all the teaching and non-teaching staff for their unwavering encouragement, support, and selfless assistance throughout the project. Their contributions were indispensable to our project's success.

LIST OF FIGURES:

LIST OF TABLES:

1.INTRODUCTION:

1.1 Introduction:

Farmers often face challenges in selecting the right crops for their land due to insufficient and generalized soil data, leading to poor yields and inefficient resource use.Traditional methods rely on outdated or broad data that do not consider the specific conditions of the soil, resulting in suboptimal crop choices. This project is designed to solve this problem by providing a precise, data-driven approach to crop selection. .This innovative solution not only improves agricultural productivity and sustainability but also empowers farmers with the information they need to make informed decisions, ultimately leading to better yields and more efficient resource management. The system can accurately predict the most suitable crops for specific soil condition

1.2 Motivation:

Our motivation for developing the Crop Prediction System arises from the need to support farmers in making informed decisions amidst increasingly unpredictable environmental conditions. In today's evolving agricultural landscape, many farmers lack access to reliable tools that help predict optimal crops based on essential factors like soil quality, nutrient levels, and climate conditions. This gap often leads to lower yields, inefficient resource use, and unsustainable practices. Additionally, the demand for technology-driven solutions that enhance productivity while promoting sustainability is growing. Traditional crop selection methods, based on experience and intuition, are no longer adequate in addressing modern agricultural challenges. The Crop Prediction System addresses these issues by integrating advanced data analytics with a user-friendly interface, offering farmers tailored crop recommendations based on soil characteristics, temperature, and nutrient levels. This approach enables farmers to maximize yields, improve resource management, and adopt sustainable farming practices, fostering a more resilient agricultural future.

1.3 Problem Statement and Objectives:

In agriculture, making the right crop selection is crucial for maximizing yield and ensuring sustainable farming practices. Farmers often struggle to select the most suitable crops for their fields due to a lack of precise and actionable soil data. Traditional methods rely on broad, outdated information, leading to poor crop choices, reduced yields, and inefficient use of resources. This lack of specificity in soil analysis and crop prediction can result in economic losses and unsustainable farming practices. To address these challenges, there is a need for a more accurate, data-driven system that considers real-time soil conditions and provides tailored crop recommendations..

1.4 Organization of Report:

Chapter 1: Introduction

The first chapter introduces the core concept of the "Crop Prediction System" project, aimed at supporting farmers in optimizing crop selection and enhancing agricultural sustainability. It explores the motivation behind the development of the system, highlighting the challenges farmers face in making informed crop decisions due to varying soil conditions, nutrient availability, and climate factors. The chapter presents a clear problem statement, addressing the need for technology-driven solutions to improve crop productivity and resource management. It also outlines the specific objectives of the project, focusing on how the system integrates soil analysis, temperature, and nutrient data to provide tailored crop recommendations that empower farmers to make informed decisions and embrace sustainable farming practices.

Chapter 2: Literature Review

This chapter reviews existing literature and technologies related to crop prediction, precision agriculture, and sustainable farming. It examines relevant studies, research papers, and current systems to identify existing methods for soil analysis and crop recommendations. The review highlights gaps in current technologies and the challenges farmers face, which the Crop Prediction System aims to address. It also emphasizes the need for innovation and collaboration among agricultural stakeholders to improve decision-making and promote sustainable farming practices.

Chapter 3: Project Implementation

This chapter focuses on the technical implementation of the Crop Prediction System. It outlines the architectural framework, including the design processes and algorithms used for analyzing soil conditions, nutrient levels, and environmental factors to recommend suitable crops. The chapter discusses the software components that enable the platform's key features, such as data input, crop prediction, and user-friendly interfaces for farmers. It concludes with experimental findings, an analysis of results, and discussions on potential future improvements to enhance the system's accuracy and its impact on sustainable farming practices.

2.LITERATURE SURVEY:

2.1 Survey of Existing System:

Sr No	Name of author	Date of Publication	Key Takeaways	Limitations
1.	Muhammad Ashfaq,Imran Khan ,Abdulrahman Alzahrani,Muhammad Usman Tariq, Humera khan and Anwar Ghani	18 March 2024	The study focuses on enhancing wheat yield prediction by using machine learning (ML) models and integrating a diverse set of data sources, including climate, satellite, soil, and socioeconomic information. By analyzing data from 2017 to 2022 for the Multan region in Pakistan, the research compares the effectiveness of different ML techniques.	1.Data Quality: Accuracy depends on the completeness and quality of historical data 2.Regional Focus: Results may not generalize to other regions with different conditions. 3.Model Complexity: Random Forest is computationally intensive and less interpretable. .
2.	M.Kalimuthu, P.Vaishnavi, M.Kishore	2020	This research presents a crop prediction model using the Naive Bayes classifier, leveraging climatic and soil parameters like temperature, humidity, and moisture for accurate crop yield forecasts. A mobile application is also developed to aid farmers in making informed decisions based on real-time data inputs, enhancing agricultural efficiency and sustainability.	1. The model's accuracy is constrained by the quality and granularity of input data, such as inconsistent climatic and soil information. 2.The Naive Bayes classifier's assumption of feature independence may not fully capture the complex relationships between agricultural factors.

3.	Akash Mondal, Saikat Banerjee	29 october 2021	The study tracks changes in irrigated croplands in Zhangjiakou, China, from 1987 to 2015 using remote sensing data. It finds that irrigated areas in the semi-arid Bashang region increased by 7.55%, while those in the mountainous Baxia region decreased slightly by 0.60%. Irrigated croplands peaked in 2000 and then declined due to policies promoting drought-resistant farming. The study highlights the need for better water resource management and suggests its methods could support agricultural policy adjustments in similar regions.	1.Historical Data Accuracy: Dependence on historical data, which may be incomplete or inconsistent. 2.Generalizability: Findings may not be applicable to other regions with different climatic and geographical conditions. 3.Remote Sensing Challenges: Difficulty in distinguishing small irrigated plots mixed with rainfed croplands.
4.	Zijuan zhu, Zengxiang,lijun zuo, feifei sun, tianshi oan,Jun li	June 25,2021	The study tracks changes in irrigated croplands in Zhangjiakou, China, from 1987 to 2015 using remote sensing data. It finds that irrigated areas in the semi-arid Bashang region increased by 7.55%, while those in the mountainous Baxia region decreased slightly by 0.60%.Irrigated croplands peaked in 2000 and then declined due to policies promoting drought-resistant farming. The study highlights the need for better water resource management and suggests its methods could support	1.Historical Data Accuracy: Dependence on historical data, which may be incomplete or inconsistent. 2.Generalizability: Findings may not be applicable to other regions with different climatic and geographical conditions. 3.Remote Sensing Challenges: Difficulty in distinguishing small irrigated plots mixed with rainfed croplands.

			agricultural policy adjustments in similar regions	

Table 1. Literature Survey

2.2 Limitation Existing system or Research gap

Existing crop detection systems face several critical limitations that hinder effective agricultural management. One significant issue is inaccurate crop identification, as many current methods rely on manual inspection or outdated techniques, leading to errors in recognizing various crop species and diagnosing diseases. This can result in decreased crop yields and increased economic losses for farmers.

Additionally, fragmented monitoring and data collection systems lead to incomplete or inconsistent information regarding crop health and environmental conditions, which obstructs timely decision-making and efficient resource allocation.

Moreover, many disease detection systems are limited in their effectiveness, often failing to accurately identify symptoms and lacking the ability to provide reliable, real-time alerts for farmers. Public engagement also poses a challenge, with educational resources and outreach efforts frequently poorly integrated, which diminishes their effectiveness in informing and empowering farmers about sustainable practices and disease prevention strategies.

Finally, fundraising platforms for agricultural initiatives often exhibit inefficiencies, with disjointed efforts and limited tools for tracking donations and investments, resulting in inadequate financial support for vital agricultural development projects. These gaps highlight the need for improved approaches in crop detection and management systems.

2.3Mini Project Contribution

The crop detection mini project addresses significant limitations in existing agricultural systems through several innovative contributions. First, it enhances crop identification by developing a reliable model that improves the accuracy of recognizing various crop species and detecting diseases, reducing reliance on manual inspection and outdated methods.

Additionally, the project promotes user engagement by allowing farmers and agricultural stakeholders to share their experiences and insights regarding crop management, fostering a collaborative environment for knowledge exchange.

Furthermore, it focuses on improving disease detection methods, refining the accuracy and reliability of identifying and reporting crop health issues. The integration of educational resources within the platform aims to raise awareness about best practices in crop management and sustainable agriculture.

3.PROPOSED SYSTEM:

3.1 Introduction:

The proposed system for crop detection addresses critical challenges in modern agriculture by integrating advanced technologies to enhance crop management and disease prevention. Utilizing deep learning models, the platform improves the accuracy of crop species identification and enables timely detection of diseases through a PyTorch-based neural network. This empowers farmers and agricultural stakeholders to make informed decisions, optimize yields, and mitigate losses caused by crop diseases.

In addition to crop identification and disease detection, the system offers a comprehensive repository of educational resources aimed at enhancing farmers' knowledge of best practices in crop management and sustainable agriculture. The platform also facilitates data-driven insights and analytics, allowing users to track crop health trends over time. By providing these tools and resources, the crop detection system ensures that users can actively improve their agricultural practices and contribute to sustainable farming initiatives.

3.2 Architectural Framework / Conceptual Design

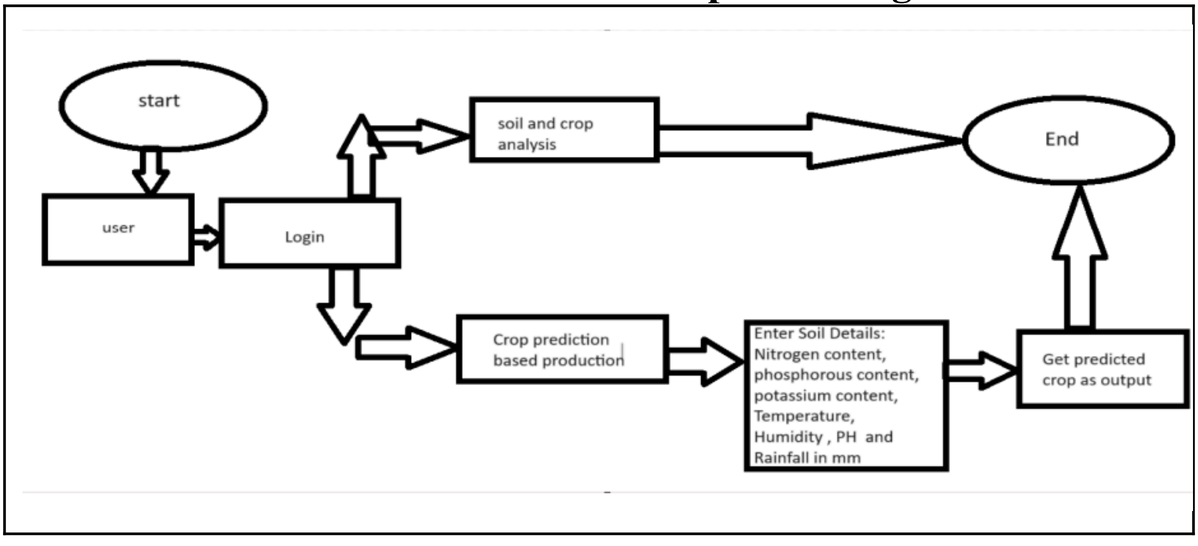

Figure 1.Architectural FrameWork

3.3Algorithm and Process Design

1.User Authentication:

- Implement a secure login system to protect user data and ensure authorized access.
- Allow users to create accounts and manage their profiles, including the ability to upload images and track detection results.

2.Crop Identification:

- Utilize a deep learning model (e.g., ResNet50 or EfficientNet B5) trained on a diverse dataset of crop images.
- Process uploaded images through the model to identify crop species and assess their health status, providing detailed information on potential diseases and treatment options.

3.Disease Detection:

- Develop algorithms to analyze images for symptoms of common crop diseases.
- Use the model to generate alerts based on detected disease patterns, enabling farmers to take timely actions.

4.Data Analytics and Reporting:

- Implement analytics to track user activity and crop health trends over time.
- Provide reports on crop health, disease outbreaks, and yield predictions to help farmers make informed decisions.

5.Educational Resource Management:

- Curate and categorize educational materials, including articles, videos, and best practices related to crop management and disease prevention.
- Implement a user-friendly interface for easy access to these resources, facilitating knowledge sharing among users.

6.Data Storage and Management:

- Utilize MongoDB for storing user data, crop information, disease records, and educational resources.

- Design efficient schemas to ensure optimal data retrieval and management, supporting the overall functionality of the system.

7.User Feedback and Iteration:

- Implement a feedback mechanism for users to report issues or suggest improvements.
- Use this feedback to iteratively enhance the model and user experience based on real-world usage and requirements.

3.4Methodology Applied:

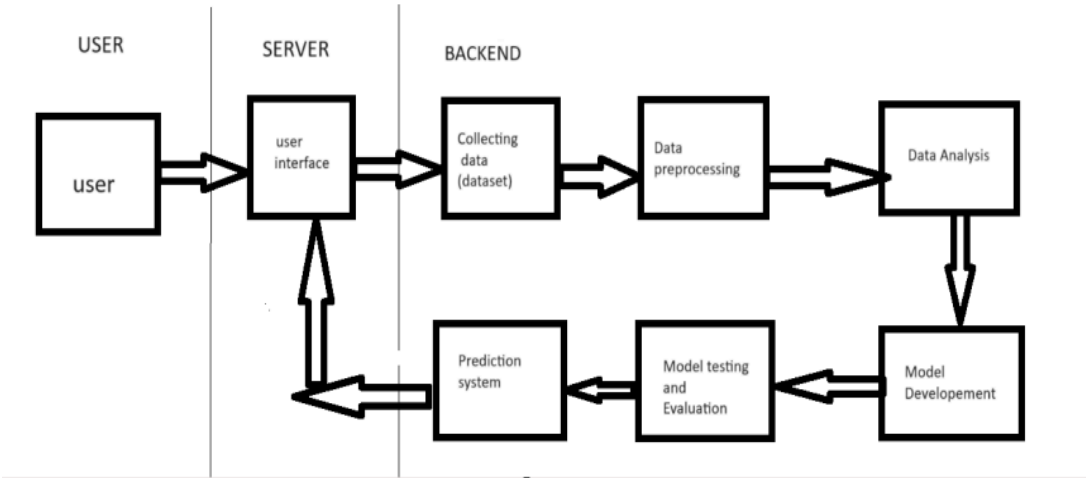

Figure 2 .Methodology Diagram

The project methodology for the crop detection system involves several key components across frontend and backend development. For the frontend, a responsive user interface has been designed using React, enhancing accessibility and user experience for farmers and agricultural stakeholders. Redux is utilized for effective state management, while Axios enables seamless API integration for data fetching and submission.

On the backend, RESTful APIs have been built with Express for user authentication and data handling, complemented by a custom Flask API that connects with a PyTorch model for crop classification and disease detection. The system allows users to upload images of crops, which are then analyzed by the model to identify crop types and detect potential diseases.

Database management is conducted using MongoDB, with carefully designed schemas for users, crops, disease records, and alerts to ensure efficient data handling. This enables streamlined access to information and facilitates data-driven decision-making for improved crop management.

Additionally, a deep learning model has been developed with PyTorch to classify crop species from user-uploaded images and analyze data for disease symptoms, facilitating timely interventions and enhancing agricultural productivity. This comprehensive methodology supports the overall goals of the project and enhances its effectiveness in precision agriculture and sustainable farming practices.

3.5 Hardware and Software Specifications

- **Hardware:**

1. Computer: 4GB RAM / 256GB SSD

- **Software:**

1. Frontend Technologies:
    A. HTML5
    B. CSS
    C. JavaScript
    D. React.js
2. Backend Technologies:
    A. Flask
    B. Node.js
    C. Express.js
3. Database Management:
    A. MongoDB
4. Machine Learning Libraries and Frameworks:
    A. Powerbi
    B. Python
    C. Sci-kit learn
    D. Numpy
    E. Pandas
    F. Matplotlib
    G. Seaborn

3.6 Experiment and Results for Validation and Verification

Crop Detection and Disease Identification Model:
We evaluated the performance of crop detection and disease identification models using two neural network architectures: EfficientNet B5 and ResNet50, trained on a dataset of approximately 50,000 images. The comparison focused on model accuracy, training time, and generalization ability on unseen crop data.

1. EfficientNet B5:

★ **Training Process:** Trained for 12 epochs, taking about 4 hours and 20 minutes, optimizing 28,652,232 parameters.

★ **Training Accuracy:** Achieved 85% training accuracy, demonstrating effective learning of complex crop features and diseases.

★ **Test Accuracy:** Reached 87% test accuracy on a 2,000-image test set, indicating good generalization to unseen crop data.

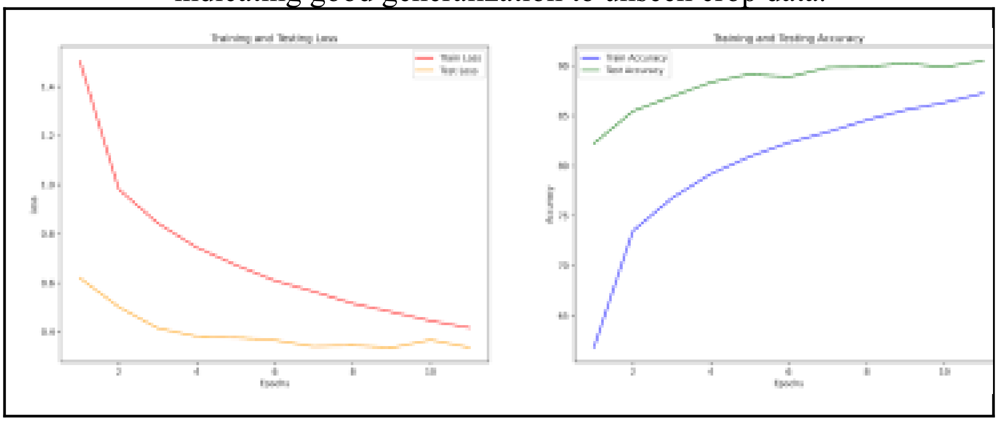

Figure 3. EfficientNet B5 Graphs

2. ResNet50:

★ **Training Process:** Trained for 10 epochs in 25-30 minutes, optimizing 23,819,480 parameters.

★ **Training Accuracy:** Achieved 92% training accuracy, outperforming EfficientNet B5 in crop feature extraction.

★ **Test Accuracy:** Attained 90% test accuracy on the test set, showing a strong balance between speed and accuracy for real-time crop detection and disease identification.

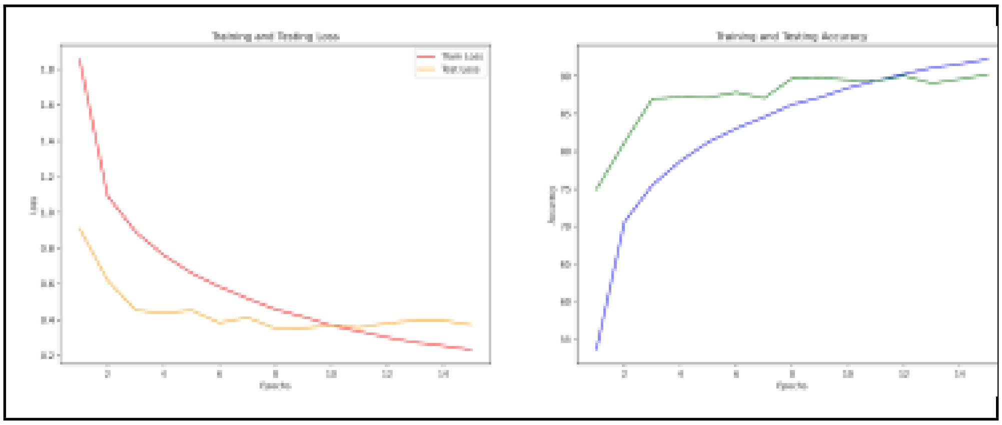

Figure 4. ResNet50 Graphs

Crop Disease Classification Model:

Model Architecture: The crop disease classification model is a multi-class classifier built using the ResNet101 architecture, selected for its deep layers and ability to capture subtle variations in crop diseases. The dataset consisted of 5,000 images representing five major crop diseases.

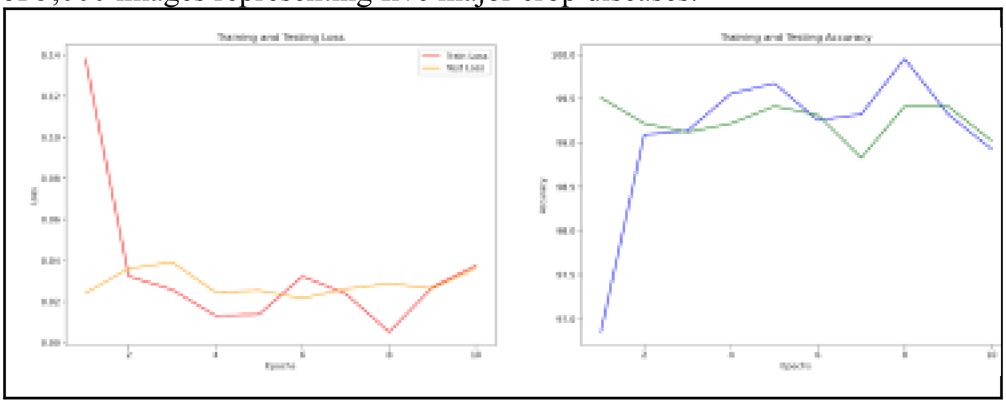

Figure 5.Crop Disease Classification Model

Training:

- **Total Training Images:** 1,000 per disease class
- **Batch Size:** 32
- **Optimizer:** Adam with a learning rate of 0.001
- **Loss Function:** Cross Entropy
- **Training Epochs:** 10
- **Training Accuracy:** 97%

Testing:

- **Total Testing Images:** 500 per disease class
- **Test Accuracy:** 95%

Implementation:

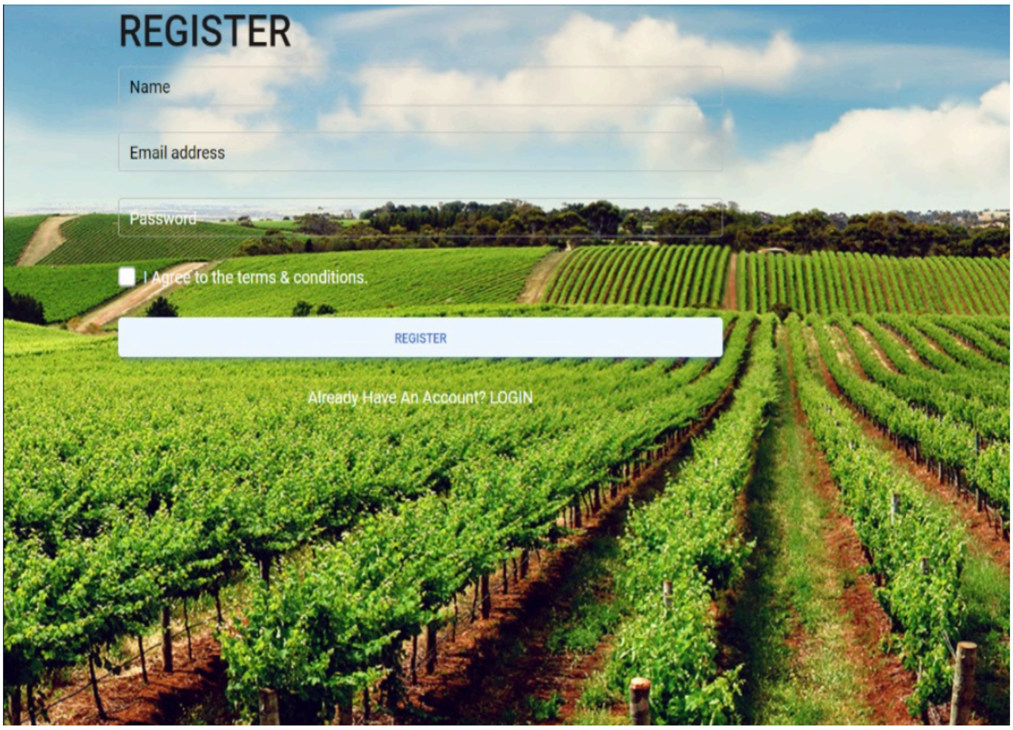

Figure 6. Register Page

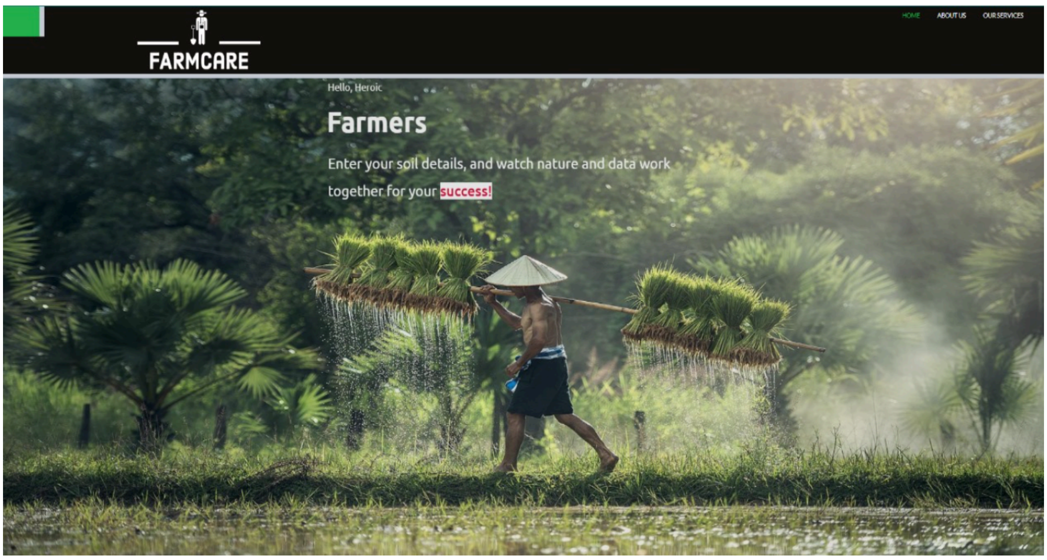

Figure 7. Home Page

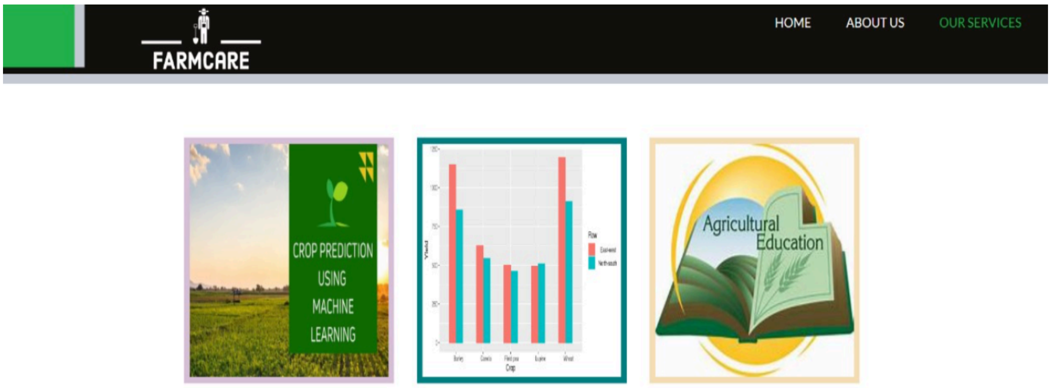

Figure 8. Our Services

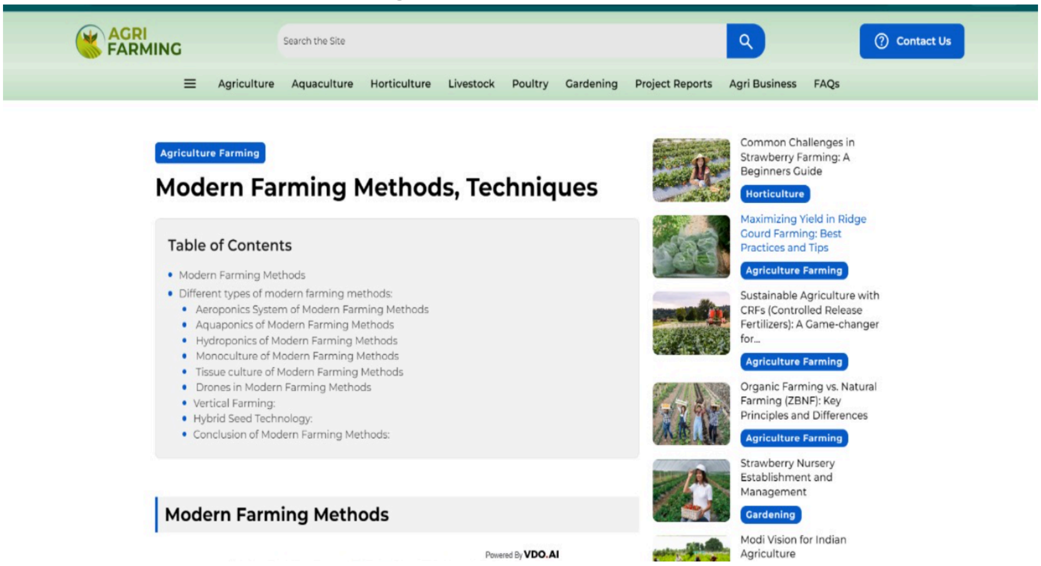

Figure 9. Contact Us

3.7 Result Analysis and Discussion

Result Analysis of Crop Detection and Disease Identification Model

:

Factors of Comparison	EfficientNetb5	ResNet50
Model Architecture	Compound scaling with depth, width, and resolution.	Deep residual network with shortcut connections.
Training Time	Four hours and third minutes approx.	20-30 minutes approx.
Model Complexity	More complex architecture requiring more computational resources.	Less complex; efficient in resource usage.
Test Dataset Size	1520 images approx	1520 images approx
Inference Speed	Slightly slower inference time due to complexity.	Faster inference, suitable for

		real-time applications.
Train accuracy	86 %	93 %
Test accuracy	89%	90%

Table 2. Comparison of EfficientNet B5 vs ResNet50

Discussion on Crop Detection and Disease Identification Model :

Model Accuracy: ResNet50 outperformed EfficientNet B5 with higher training accuracy (93% vs. 86%) and slightly better test accuracy (90% vs. 89%), demonstrating stronger learning ability for crop detection and disease identification. This suggests ResNet50 is more effective in distinguishing different crop types and detecting diseases with minimal errors.

Generalization: Both models displayed good generalization capabilities, with a small difference in test accuracy, indicating that neither model overfit the data. This means both are reliable for accurately identifying crops and diseases in new, unseen data.

Training Time: EfficientNet B5 required significantly longer training time (4.5 hours vs. 20-30 minutes for ResNet50), without substantial accuracy improvement. This makes ResNet50 a more efficient choice for applications that require rapid model deployment, especially in dynamic agricultural environments.

Model Suitability: ResNet50 is more practical for real-time crop detection and disease identification due to its faster training time and strong accuracy, making it ideal for large-scale agricultural use. EfficientNet B5, while slower, could be considered for specialized cases where marginally higher accuracy is preferred.

Crop Disease Classification Model:

The model's high accuracy demonstrates strong classification capability, with only a slight difference between training (99%) and testing accuracy (98%). This suggests that the model generalizes well to unseen data, avoiding overfitting. The consistently low loss values further confirm that the model learned effectively from the dataset. Overall, the model proves to be highly reliable for detecting crop diseases and identifying various crop types, making it suitable for practical applications in precision agriculture and sustainable farming practices. This performance ensures that the system can assist farmers in optimizing crop management and improving yield outcomes.

3.8 Conclusion and Future Work

In conclusion, the Crop Detection System project aims to provide a comprehensive platform for agricultural efficiency by integrating advanced technologies for crop identification, disease detection, soil analysis, and yield prediction. By leveraging deep learning models and user-friendly interfaces, the project enhances awareness and facilitates active participation in precision agriculture. The collaborative nature of the platform fosters a community of users dedicated to improving crop management and boosting agricultural productivity.

Looking ahead, we recognize that there is still significant work to be done. Our primary focus will be on creating and facilitating end-to-end project capabilities, including fundraising mechanisms and payment gateway integration. We also aim to enhance community involvement features, encouraging users to share their knowledge and contribute to sustainable farming practices. Additionally, we will explore and implement advanced deep learning techniques and models to improve the accuracy and effectiveness of crop detection and disease diagnosis. These developments will help us build a more robust platform that meets the evolving needs of modern agriculture and food security initiatives.

4. REFERENCES

1. Sun, Y., Li, J., Zhang, Z., Wang, H., Chen, L., & Zhang, Y. (2024). Identification of crop diseases in the field environment based on the improved YOLOv5 model. *Remote Sensing*, 16(9), 1535. https://doi.org/10.3390/rs16091535
2. Gupta, R., Kumar, A., Sood, H., & Mishra, A. (2020). Crop health monitoring using image processing. *International Journal of Science Technology & Engineering*, 7(1), 004.
3. Sharma, P., Joshi, R., & Bhattacharya, D. (2022). A literature review of computer vision techniques in precision agriculture. *Materials, Methods & Technologies*, 16. ISSN 1314-7269.
4. Hernandez, A., Miao, Z., Vargas, L., Dodhia, R., Arbelaez, P., & Lavista Ferres, J. M. (2024). PyTorch-Agriculture: A collaborative deep learning framework for crop disease detection. *arXiv:2405.12930v3* [cs.CV]. https://arxiv.org/abs/2405.12930
5. Kumar, A., Singh, B., & Yadav, P. (2024). Factors influencing wheat yield prediction using machine learning in Northern India. *The Journal of Precision Agriculture*. https://doi.org/10.1002/jpa.22638
6. Bhargava, M. D., & Jain, K. (2021). Plant behavior in response to environmental stress. *Academic Press*.
7. Li, W., & Wagner, M. (2014). SOP: A model of automatic memory processing in crop behavior. In *Information processing in plants* (pp. 1-21). *Plant Science Press*.
8. Joshi, S. N. (2015). The science of plant disease and health: Challenges, opportunities, and global perspectives. *Frontiers Media SA*.
9. Mehta, K., Ayele, E., Meratnia, N., & Havinga, P. (2018). Crop disease detection technologies—a survey. *MDPI Sensors*, 14, 1474. https://www.mdpi.com/1424-8220/18/5/1474
10. Patel, E., Kar, D., & Singh, A. (2018). Spotting crop diseases in action: Augmenting UAVs with automatic detection in near real time. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.
11. Singh, A., Nguyen, T. H., Sinha, A., Plumptre, A., Joppa, L., & others. (2017). Predicting crop yield for agricultural efficiency. *IBM Journal of Research and Development*, 3–1.

12. Venter, O., Brodeur, N. N., Nemiroff, L., Belland, B., Dolinsek, I. J., & Grant, J. W. A. (2006). Threats to crop productivity in Canada. *Bioscience*, American Institute of Biological Sciences, 903–910.
13. Innes, R., & Frisvold, G. (2009). The economics of crop diseases. *Annual Reviews*, Annu. Rev. Resour. Econ., 485–512.
14. Runge, M. C. (2011). An introduction to adaptive management for crop health. *US Department of Agriculture*, 220–233.
15. Beaudrot, L., Ahumada, J., O'Brien, T. G., & Jansen, P. A. (2019). Detecting crop health declines through UAV monitoring: An evaluation of the Tropical Agriculture Assessment and Monitoring protocol. *Oryx*, Cambridge University Press, 126–129.
16. Islam, S. B., & Valles, D. (2020). Identification of diseased crops in Texas from drone images using deep neural networks for precision agriculture. In *2020 10th Annual Computing and Communication Workshop and Conference (CCWC)* (pp. 537–542).