DAYANANDA SAGAR UNIVERSITY

SCHOOL OF ENGINEERING

Devarakaggalahalli, Harohalli
Kanakapura Road, Ramanagara - 562112, Karnataka, India

Bachelor of Technology
in
COMPUTER SCIENCE AND ENGINEERING

Major Project Report

Transforming Agriculture with AI, collaborative solutions and Image based diagnosis

Batch: 43

By

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Under the supervision of
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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING,
SCHOOL OF ENGINEERING
DAYANANDA SAGAR UNIVERSITY,

(2023-2024)

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Department of Computer Science & Engineering
Devarakaggalahalli, Harohalli, Kanakapura Road, Ramanagara - 562112
Karnataka, India

CERTIFICATE

This is to certify that the Major Project work titled **“Transforming Agriculture with AI, collaborative solutions and Image based diagnosis”** is carried out by **Aravind Bhat (ENG20CS0038)** bonafide students eight semester of Bachelor of Technology in Computer Science and Engineering at the School of Engineering, Dayananda Sagar University, Bangalore in partial fulfillment for the award of degree in Bachelor of Technology in Computer Science and Engineering, during the year **2023-2024**.

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1.

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DECLARATION

I, **Aravind Bhat (ENG20CS0038)** are students of seventh semester B. Tech in **Computer Science and Engineering**, at School of Engineering, **Dayananda Sagar University**, hereby declare that the Major Project titled **“Transforming Agriculture with AI, collaborative solutions and Image based diagnosis”** has been carried out by me and submitted in partial fulfilment for the award of degree in **Bachelor of Technology in Computer Science and Engineering** during the academic year **2023-2024.**

Student

Signature

Name: Aravind Bhat

USN: ENG20CS0038

Place: Bangalore
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TABLE OF CONTENTS

NOMENCLATURE USED

AI	Artificial Intelligence
ML	Machine Learning
GUI	Graphical User Interface
ResNet	Residual Network
DB	Database
DLCNN	Deep Learning Convolutional Neural Network
CUDA	Compute Unified Device Architecture
OTP	One Time Password

LIST OF FIGURES

ABSTRACT

My project represents a holistic approach to agricultural innovation, recognizing that success in farming extends beyond mere diagnosis of plant diseases. It acknowledges the interconnectedness of various factors affecting agricultural outcomes, including market access, social dynamics, and environmental sustainability. By deploying cutting-edge technologies and data-driven insights, your platform empowers farmers to make informed decisions and adapt to changing conditions effectively. Moreover, it fosters a sense of community and collaboration among farmers, researchers, and industry experts, creating a vibrant ecosystem of knowledge sharing and collective problem-solving. Through collaborative efforts and community engagement, your project aspires to bridge the gap between traditional farming practices and modern agricultural solutions, ensuring that farmers have access to the resources and support they need to thrive in a rapidly evolving agricultural landscape. Ultimately, your project is not just about revolutionizing farming practices; it is about empowering farmers, strengthening communities, and building a more sustainable future for agriculture.

CHAPTER 1 INTRODUCTION

This project endeavors to develop an integrated platform that transcends traditional agricultural practices, aiming to comprehensively address the multifaceted challenges [8],[9],[10],[11],[14] faced by farmers. The core concept involves farmers uploading images of agricultural issues, triggering a collaborative process where volunteers propose solutions within a three-week timeframe, subject to public approval. This innovative platform goes beyond conventional farming approaches by incorporating advanced tools for plant disease diagnosis [1],[2],[3] leveraging technology to bridge the gap between farmers and consumers. By fostering direct connections and community-driven solutions the project seeks to unite diverse farming communities and pioneer sustainable agricultural practices.

The overarching objective is to empower farmers with cutting-edge solutions while promoting inclusivity and community engagement. With an emphasis on problem-solving through public funding, this initiative envisions a dynamic ecosystem where collective efforts lead to innovative solutions for the challenges plaguing the agricultural sector [12],[13],[15]. Through this collaborative model, the project aspires to create a resilient and adaptive agricultural landscape that not only addresses current issues but also anticipates and mitigates future challenges. Ultimately, the project aims to revolutionize farming practices, strengthen community bonds, and foster a sustainable and innovative approach to agriculture.

1.1 SCOPE

The project's scope is vast, integrating advanced tools like ResNet for precise plant disease diagnosis. It fosters community-driven solutions by allowing volunteers to propose timely interventions for farmer-uploaded issues. The direct links established between farmers and consumers enhance transparency in the agricultural supply chain. Leveraging public funding for innovative problem-solving underscores the potential for broader societal impact. Overall, the project envisions a transformative impact on agriculture by embracing technology, community engagement, and transparency, with the ultimate goal of addressing critical challenges faced by farmers.

1.2 Social impacts:

1. **Empowering Farmers:** The project empowers farmers by providing them with a platform to diagnose plant diseases, make informed decisions, and connect directly with consumers. This empowerment contributes to the socioeconomic upliftment of farmers, enhancing their role in the agricultural value chain.

2. **Community Collaboration:** The volunteer collaboration platform fosters a sense of community-driven problem-solving. Volunteers can contribute their expertise, and farmers benefit from a collective effort to address challenges. This collaborative approach strengthens community bonds and encourages knowledge-sharing.

3. **Market Access for Farmers:** The integrated farmer-consumer portal improves market access for farmers. By directly connecting with consumers, farmers can better showcase their produce, negotiate fair prices, and establish a more transparent and efficient agricultural market.

4. **Rural Development:** Through strategic partnerships and continuous feedback mechanisms, the project contributes to rural development. It facilitates the adoption of sustainable farming practices, introduces technological advancements, and enhances the overall quality of life in rural communities.

5. **Global Knowledge Exchange:** Research publications and knowledge sharing contribute to a global exchange of agricultural insights. The project becomes a part of the broader scientific community, encouraging similar initiatives worldwide and fostering a collaborative approach to addressing global agricultural challenges.
6. **Environmental Sustainability:** By promoting early disease diagnosis and sustainable farming practices, the project indirectly contributes to environmental sustainability. Reduced reliance on pesticides, optimized resource usage, and improved farming techniques align with broader goals of environmental conservation.

CHAPTER 2 PROBLEM DEFINITION

The agricultural sector is confronted with multifaceted challenges, chief among them being the persistent menace of plant diseases and the restricted access to markets faced by farmers. This situation is compounded by the absence of a centralized platform that could facilitate seamless communication and collaborative problem-solving. Farmers, dispersed across diverse regions, often lack the means to share their challenges efficiently or tap into collective knowledge for effective solutions.

In response to these pressing issues, our project proposes a transformative solution that encompasses plant disease diagnosis and the establishment of direct links between farmers and consumers. By leveraging advanced technologies such as machine learning for disease identification and fostering community-driven solutions, we aim to bridge the existing gaps in the agricultural landscape. The central tenet of the project involves dedicated volunteers contributing verified solutions within a defined timeframe, thereby cultivating a sense of collective responsibility and collaboration.

Crucially, the project is underpinned by a community-centric approach, where public funding becomes the driving force behind innovative problem-solving. This model not only empowers farmers with valuable insights and solutions but also nurtures a resilient and interconnected agricultural ecosystem. The creation of a centralized platform acts as a catalyst for positive change, fostering sustainability, strengthening community ties, and heralding a new era of dynamic and responsive agriculture.

CHAPTER 3 LITERATURE SURVEY

[1] Vinod Kumar, Hrithik Arora, and Jatin Sisodia et al introduced a ResNet-based approach for Detection and Classification of Plant Leaf Diseases, published in the proceedings of the International Conference on Computing Communication Control and Automation. Their study demonstrated that by fine-tuning parameters and employing techniques like learning rate scheduling, gradient clipping, and weight decay, ResNet achieved remarkable accuracy of 99% in image classification tasks, surpassing other models. This research underscores the effectiveness of ResNet architectures in accurately identifying and classifying plant diseases, showcasing their superiority over traditional methods.

[2] G.P. Saradhi Varma, Satti R.G. Davuluri et al introduced a novel approach titled "ResNet-based modified Red Deer Optimization with DLCNN classifier for plant disease identification and classification" at the International Conference on Computing Communication Control and Automation in 2023. Their study, utilizing ResNet and DLCNN classifier, focused on plant disease identification and classification using datasets from Plant Village and Rice Plant Disease. Implemented through Anaconda Distribution software in Python, their system incorporated training and testing processes to evaluate performance metrics, achieving a notable 93% accuracy in disease detection and classification. The research underscores the importance of automated methods in addressing challenges associated with manual crop disease inspection, emphasizing the critical role of early disease detection in global food production and quality maintenance.

[3] Smitha Pad Shetty and Ambika et al introduced a novel approach for plant leaf disease detection utilizing the Leaky Rectilinear Residual Network (LRRN) model, evaluated against existing methodologies such MF3 R-CNN, OMN-CNN, and CNN-VGG19. Their proposed model achieved remarkable performance metrics, including an accuracy of 94.56%, precision of 93.48%, recall of 93.12%, F1-score of 93.82%, and specificity of 92.58%. The study underscores the significance of leveraging advanced deep learning techniques to enhance disease detection in plants. By surpassing previous methods, the LRRN model demonstrates superior effectiveness in identifying and classifying plant leaf diseases, thereby advocating for its adoption in precision agriculture practices.

[4] Muhammad Shoaib, Bilal Shah, Syed Ehsan-ul-Haque et al conducted a thorough investigation on plant disease detection using advanced deep learning techniques, specifically focusing on ResNet technology. They emphasized the importance of developing generalizable models capable of detecting diseases across various plant species and highlighted the necessity of accessible datasets for training and evaluating machine learning and deep learning models in this field.

[5] Kalpana Chowdary and Jude Hemanth et al explored the effectiveness of DenseNet-121, ResNet-50, and VGG-16 in the early diagnosis and classification of plant diseases in crops. Their study revealed that DenseNet-121 outperformed ResNet-50 and VGG-16, as well as Inception V4, in terms of classification accuracy, sensitivity, specificity, and F1 score. DenseNet-121 demonstrated reduced training complexity and achieved remarkable results, with a classification accuracy of 99.81% and an F1 score of 99.8%. This research underscores the significance of implementing advanced deep learning technologies, for accurate and efficient plant disease identification in agriculture.

[6] Nindra Chandu and N. Bharatha Devi conducted a comparative study published in Eur. Chem. Bull. 2023, examining ResNet and Support Vector Machine (SVM) for plant disease detection. The study detailed ResNet's algorithm steps, highlighting the importance of data normalization and feature selection. Furthermore, it emphasized the critical role of timely disease detection in preventing plant bacteria harm and enhancing economic outcomes.

[7] The document, authored by Dr. T. Praveen Blessington, Bhargav Krishnan, Yash Bharne, Kartiki Khoje, and Prathamesh Padwal from Zeal College of Engineering and Research, discusses leaf disease detection using deep learning techniques, published in the International Journal of Creative Research Thoughts (IJCRT). Their research aims to enhance agricultural productivity by automating plant disease recognition. The proposed method involves employing a ResNet model, which exhibits superior performance compared to other deep learning models. Through the utilization of image processing and Convolutional Neural Networks (CNN), early detection and identification of leaf diseases can significantly reduce crop losses and improve yield. The study underscores the importance of technology integration in agriculture for early disease detection and mitigation. The project design to facilitate effective leaf disease detection.

CHAPTER 4 PROJECT DESCRIPTION

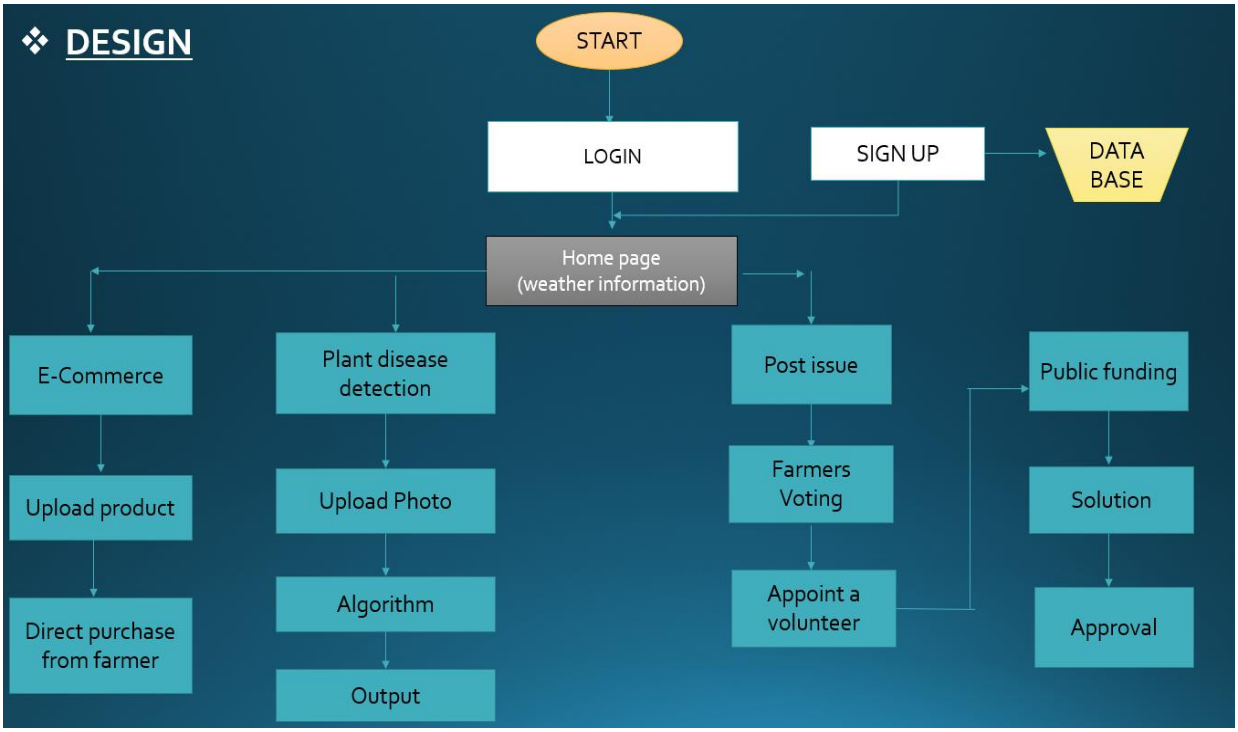

Figure 4.1: Design of the project

Website Design Overview:

The design of our farmers' website is focused on providing a comprehensive platform that addresses key challenges faced by the agricultural community. The site is structured around three core functionalities: E-commerce, Plant Disease Detection, and Post-Issue Resolution.

4.1 PROPOSED DESIGN

1) E-commerce Section:

In the E-commerce section, farmers can seamlessly upload details of their agricultural products. This includes images, descriptions, and relevant information. Consumers, including fellow farmers and buyers, can browse through the listings and make direct purchases, fostering a direct farmer-to-consumer connection. This feature not only facilitates efficient trade but also empowers farmers by broadening their market reach.

2) Plant Disease Detection:

The Plant Disease Detection module integrates cutting-edge technology to address crop health concerns. Farmers can upload images of their crops afflicted by diseases. Behind the scenes, a ResNet model processes these images, accurately diagnosing the plant diseases. The predicted results are then communicated back to the farmers, enabling them to take timely and informed action to mitigate the impact on their crops. This technology-driven approach enhances agricultural productivity and contributes to sustainable farming practices.

3) Post-Issue Resolution:

The Post-Issue Resolution division is designed to foster a collaborative community where farmers can collectively address challenges. Farmers facing issues in their fields can post them on the platform. A unique aspect of this feature is the incorporation of a democratic voting system. Fellow farmers can vote on the severity and importance of the posted issues. The platform then appoints a volunteer based on these votes. The selected volunteer takes responsibility for resolving the posted issue. The resolution process is public-funded, allowing the agricultural community to support and collectively invest in addressing critical problems. Once the volunteer successfully resolves the issue and gains approval from the community, it is documented as a successful case study, contributing valuable knowledge to the farming community.

4.2 ASSUMPTIONS AND DEPENDENCIES

- **Smartphone Adoption:** Assuming widespread access to smartphones is fundamental, as the mobile application relies on this. It influences the ease of use and accessibility of the platform for both farmers and volunteers.
- **Algorithm Performance:** The success of the plant disease diagnosis system heavily depends on the continuous improvement and reliable performance of the underlying machine learning algorithms. Regular updates are critical for maintaining accuracy.
- **Server Reliability:** The reliability and availability of the project's servers are essential dependencies. Any disruptions or technical issues with servers could impede the overall functionality of the platform and user experience

CHAPTER 5 REQUIREMENTS

5.1 FUNCTIONAL REQUIREMENTS

- **User Authentication and Authorization:** Users should be able to register and log in with secure authentication. Different user roles (farmers, consumers, volunteers) with appropriate permissions.

- **E-commerce Module:** Farmers can upload product details, including images, descriptions, and pricing. Consumers can browse products, add them to a cart, and make direct purchases. Secure payment gateway integration for online transactions.

- **Plant Disease Detection:** Farmers can upload images of crops with diseases. Integration with a CNN model for disease prediction. Provide accurate and timely results of disease detection to farmers.

- **Post-Issue Resolution:** Farmers can submit agricultural issues with relevant details. Implement a democratic voting system for the community to prioritize issues. Selection of volunteers based on community votes for issue resolution. Public funding mechanism for issue resolution projects.

- **Community Engagement:** Discussion forums for farmers to interact, share knowledge, and seek advice. Notification system for updates on posted issues, resolutions, and community discussions. User-friendly interfaces for easy navigation and interaction.

5.2 Software Requirements

i. Frontend Tools and libraries:

- React: Library for web user interfaces.

- Bootstrap, Tailwinds: Frontend development framework.

- Font Awesome, Hero icons: Library for icons which can be used in frontend.

ii. Backend Tools and libraries:

- Node.js: Used to create server-side web application
- MongoDB: Database to store the data.
- Flask: Framework used for developing web application using Python.
- Socket.IO: Used for real time communication.

5.3 Hardware Requirements

- Operating System: Compatible with major operating systems (Windows, macOS, Linux)
- Processor: Dual-core or higher
- RAM: Minimum 4GB (8GB recommended)
- Storage: Sufficient disk space for development tools, libraries, and datasets
- Web Browser: Latest versions of popular browsers (Chrome, Firefox, Safari)
- Payment Processing: Integration with payment gateways may require compliance with their specific system requirements

CHAPTER 6 METHODOLOGY

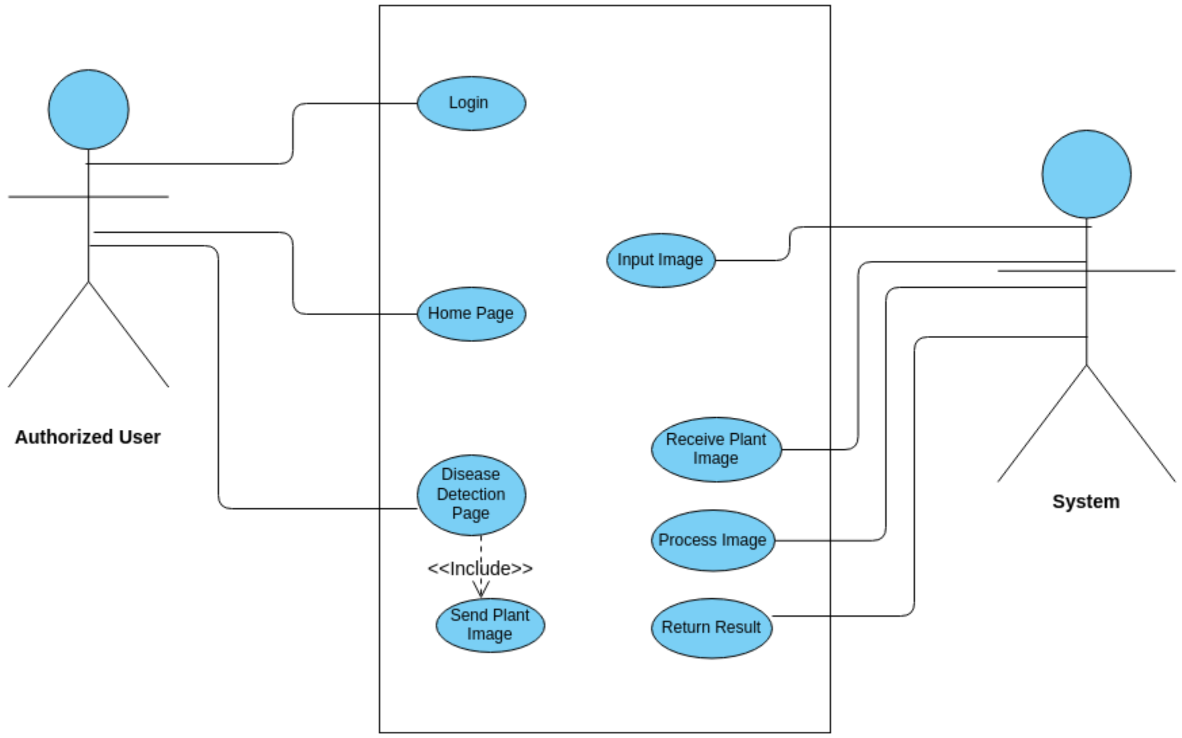

Figure 6.1: Plant Disease Detection Use Case Diagram

The use case diagram for plant disease detection outlines the various interactions between actors and the system to achieve specific goals in identifying and managing plant diseases. The primary actors involved are the "User" and the "System." The "User" interacts with the system to perform tasks such as uploading images of plants, accessing information about diseases, and receiving diagnosis results. The "System" encompasses the functionalities responsible for image processing, disease identification, and providing recommendations or treatment options.

The key use cases depicted in the diagram include "Upload Image," where the user submits images of diseased plants for analysis; "Identify Disease," which involves the system analyzing the uploaded images to detect and classify plant diseases accurately enabling users to retrieve detailed information about identified diseases, including symptoms, causes, and recommended treatments; and "Provide Recommendations," where the system suggests appropriate actions or treatments based on the diagnosed disease. Additionally, the diagram illustrates the relationship between these use cases, highlighting the flow of interactions between the user and the system. It emphasizes the user-centric approach of the system, focusing on delivering a seamless experience for users seeking assistance in detecting and managing plant diseases effectively.

Conducted research on existing literature and studies related to agricultural innovation, AI in farming, and collaborative platforms for farmers. Designed the high-level architecture and system flowcharts for the Transforming Agriculture with AI project, incorporating information gathered from the provided project report to understand objectives, scope, and requirements.

Tools used**:**

- Node.js (Backend)
- Fast API (Model Deployment)
- CUDA (GPU Acceleration)
- torch summary (Model Summary)
- Matplotlib (Data Visualization)

CHAPTER 7 EXPERIMENTATION

The experimental pipeline begins with the meticulous preparation and preprocessing of data, where essential libraries like PyTorch and torchvision are imported to handle deep learning functionalities and image processing tasks. The New Plant Diseases Dataset is structured meticulously, ensuring the seamless organization of images into training and validation sets. Leveraging the ImageFolder class from torchvision. datasets, diverse plant diseases and healthy specimens are curated for augmentation using techniques like random rotation, bolstering the model's resilience to various environmental conditions. Moving on to model architecture and training strategies, ResNet-9 emerges as the cornerstone, renowned for its efficacy in image classification tasks. This architecture, comprising convolutional layers and residual blocks, is initialized with random weights and accelerated through GPU training using CUDA, optimizing performance with the Adam optimizer and a One Cycle learning rate scheduler. Hyperparameter tuning becomes paramount, where a systematic exploration of parameters like learning rate and weight decay is conducted across multiple experiments, aiming to maximize accuracy while mitigating overfitting risks. Following training, model evaluation ensues, rigorously assessing performance metrics like accuracy, precision, recall, and F1-score to provide a comprehensive understanding of the model's strengths and weaknesses in classifying plant diseases and healthy specimens, thus informing agricultural management practices effectively.

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1. Data Preparation and Preprocessing

The experimental pipeline commences with the importation of essential libraries, including PyTorch for deep learning functionalities and torch vision for image processing tasks. We meticulously set up the data directories, adhering to the structure of the New Plant Diseases Dataset. Leveraging the Image Folder class from torch vision. datasets, we meticulously organize the dataset into training and validation sets, each containing images of diverse plant diseases and healthy specimens. To augment the training data and enhance the model's robustness, we employ a series of data augmentation techniques such as random rotation. This preprocessing step is pivotal in ensuring that the model generalizes well to unseen data and exhibits resilience to various environmental conditions.

2. Model Architecture and Training Strategies

The cornerstone of our experimentation lies in the utilization of the ResNet-9 architecture, renowned for its efficacy in image classification tasks. Comprising a series of convolutional layers, residual blocks, and a classifier, ResNet-9 serves as the backbone of our deep learning model. We initialize the model with random weights and seamlessly transfer it to the GPU for accelerated training using CUDA, thus capitalizing on the computational prowess of modern graphics processing units. To optimize the model's performance and foster efficient convergence, we employ the Adam optimizer with a One Cycle learning rate scheduler. Throughout the training process, we meticulously monitor both training and validation losses, alongside accuracy metrics, to gauge the model's efficacy and identify potential areas for improvement.

3. Hyperparameter Tuning and Optimization

Hyperparameter tuning plays a pivotal role in fine-tuning the model's parameters to achieve optimal performance. We embark on a systematic exploration of hyperparameter space, varying key parameters such as the learning rate, weight decay, and gradient clipping threshold across multiple experiments. Leveraging techniques such as grid search or random search, we meticulously evaluate different combinations of hyperparameters, seeking to maximize the

model's accuracy on the validation set while mitigating the risk of overfitting. This iterative process of hyperparameter optimization is crucial in refining the model's architecture and enhancing its predictive capabilities.

4. Model Evaluation and Performance

Metrics Following the training phase, we rigorously evaluate the model's performance on the validation set, employing a suite of performance metrics to assess its efficacy. In addition to accuracy, we compute metrics such as precision, recall, and F1- score to provide a comprehensive understanding of the model's strengths and weaknesses. By analyzing these metrics, we gain valuable insights into the model's ability to correctly classify plant diseases and healthy specimens, thereby facilitating informed decision-making in agricultural management. practices.

CHAPTER 8 RESULT ANALYSIS

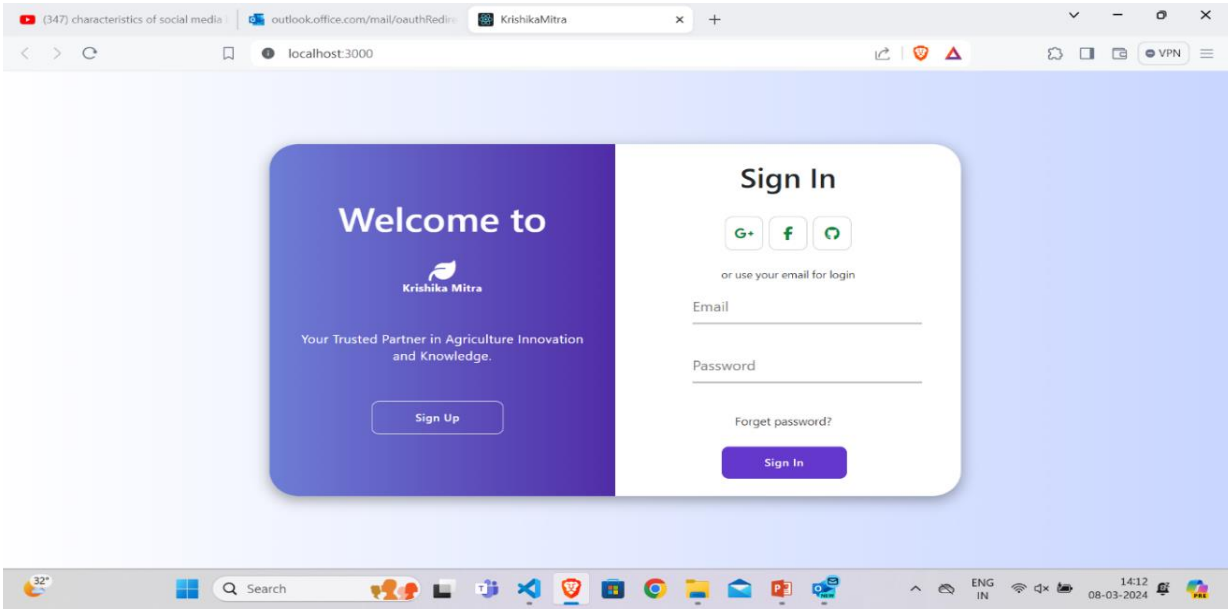


Figure 8.1-signin Page

The Figure 8.1, "login page" of an app is its main screen, serving as the initial point of entry for users, providing navigation and access to key features and content.

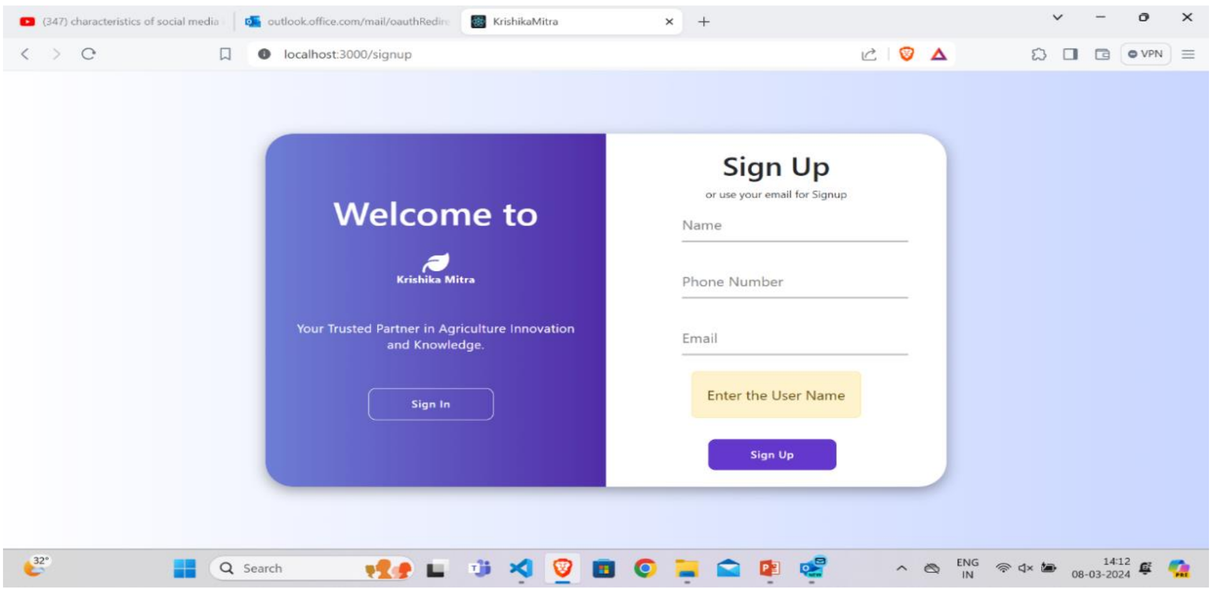


Figure 8.2-Signup Page

The Figure 8.2, "signup page" takes the credentials and save the user information in database

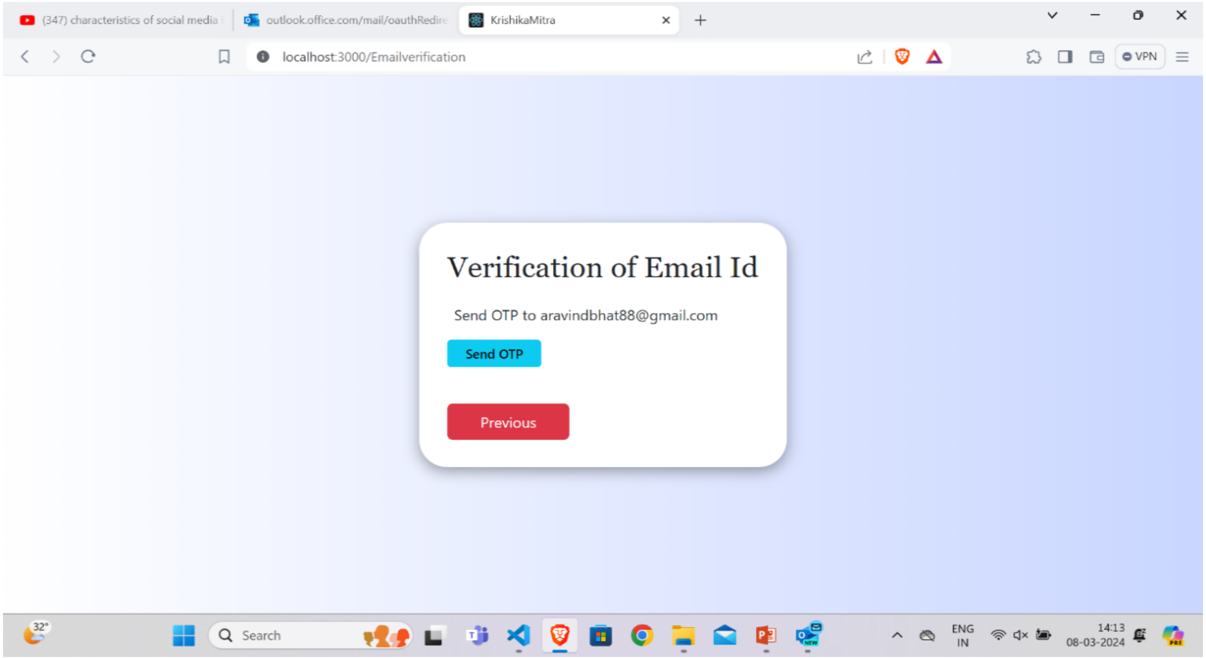


Figure 8.3 -Email verification Page

The Figure 8.3 describes the following details:

- It sends the OTP to the given email address

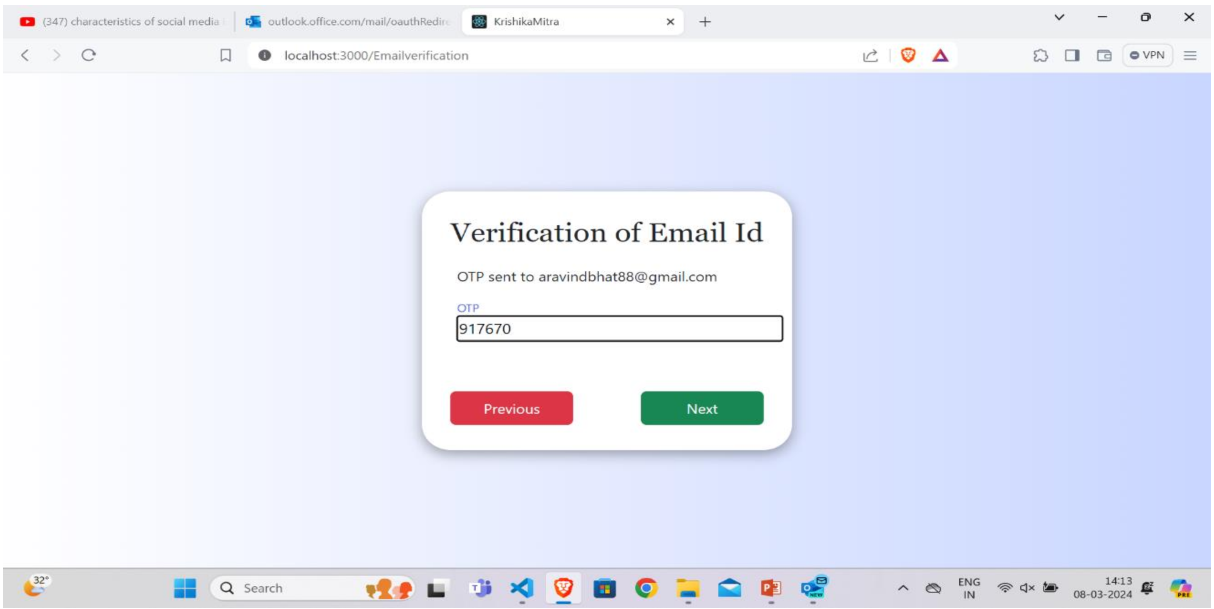


Figure 8.4-Email verification Page

The Figure 8.4 give the following details of:

- Checks whether the inserted OTP is correct or not

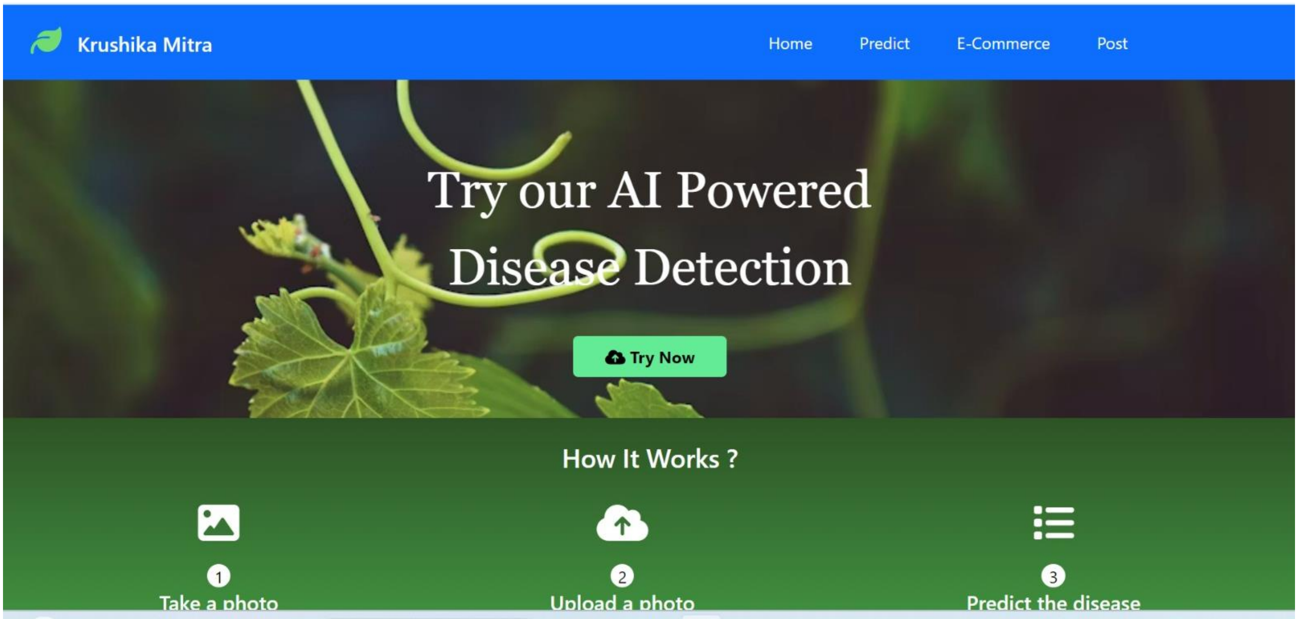
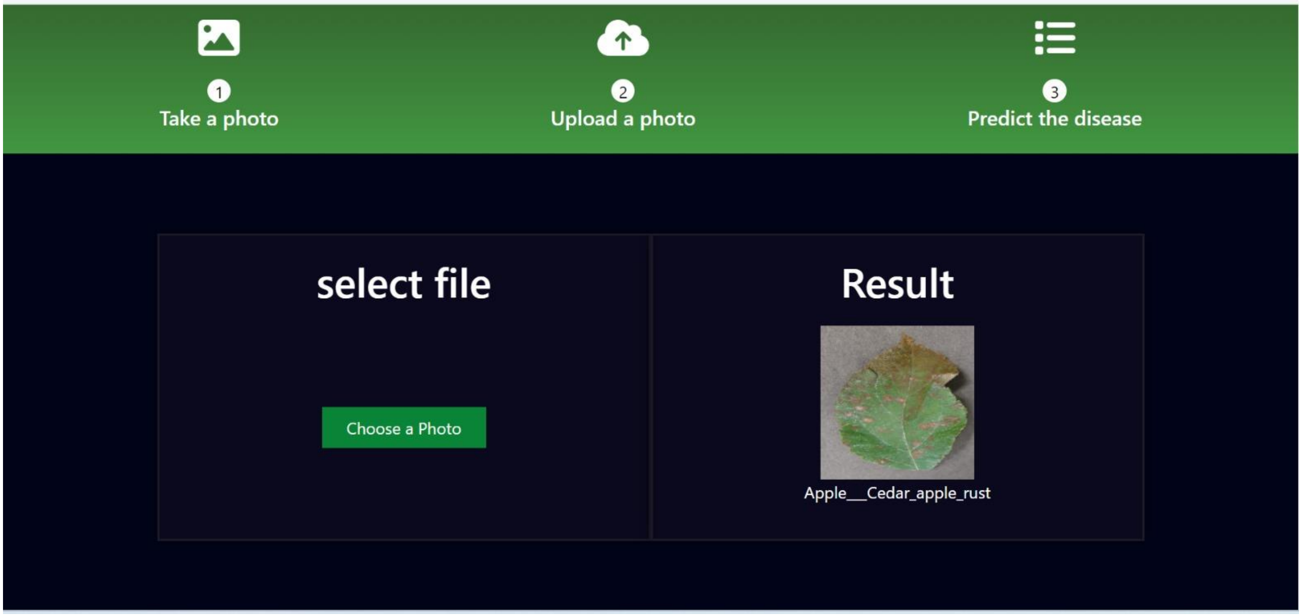


Figure 8.5-Select and upload Image

In Figure 8.5, we can select and upload the image.



8.6- Output

In Figure 8.6, shows the generated output after predicting the disease.

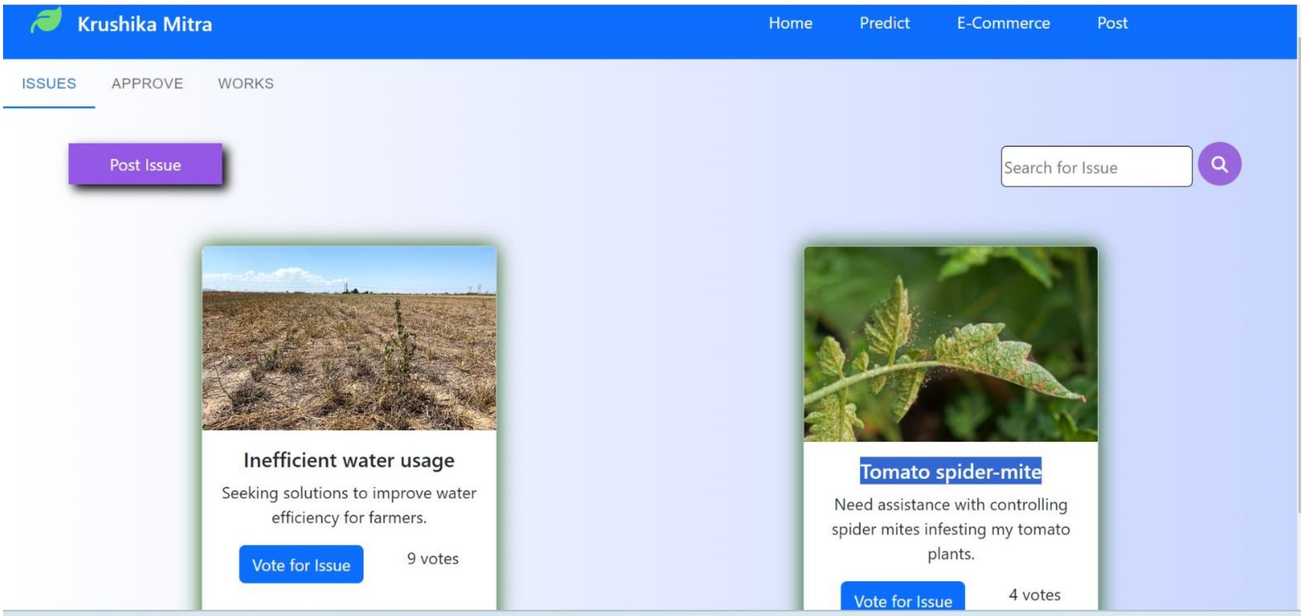


Figure 8.7-Post Issue

Figure 8.7, farmers can upload the image regarding the difficulties they placed.

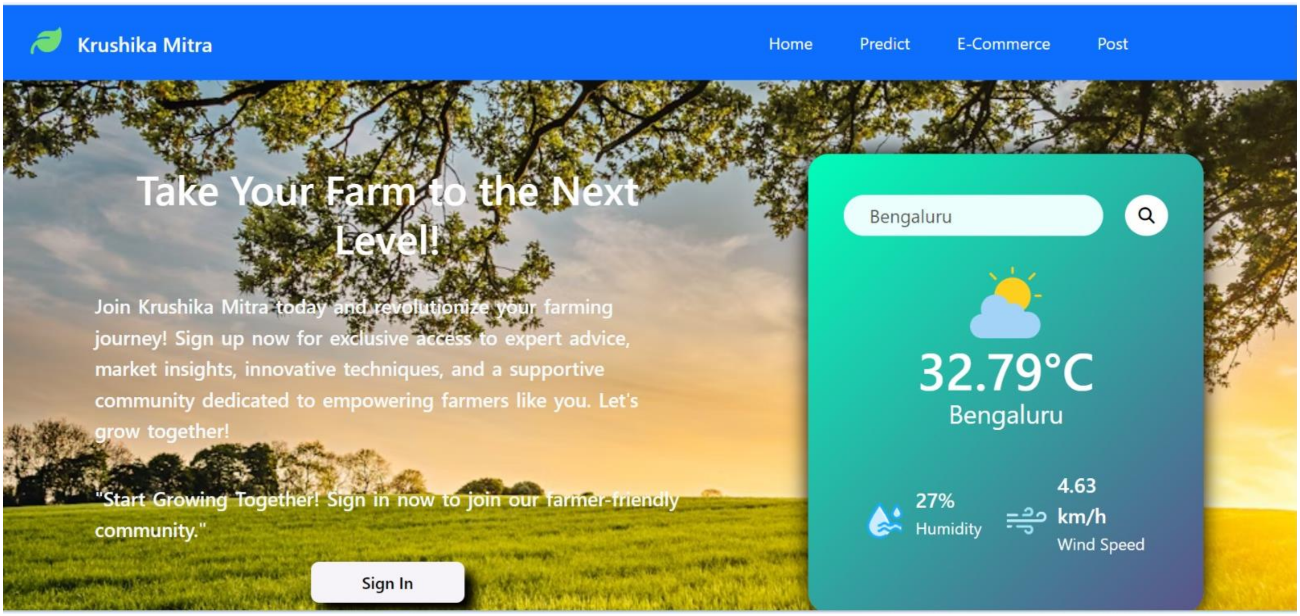


Figure 8.8-Weather Forecast

Figure 8.8, display's the weather forecast.

CHAPTER 9 CONCLUSION

In conclusion, my experimentation endeavors to advance the state-of-the-art in plant disease classification through a rigorous and systematic approach. By meticulously designing experiments, optimizing hyperparameters, and evaluating model performance, we aim to develop a robust and reliable deep learning model for agricultural applications. Looking ahead, future research directions may involve exploring novel architectures, integrating multi-model data sources, and deploying the model in real-world agricultural settings to assess its scalability and practical utility. Through continuous innovation and collaboration, we strive to revolutionize crop health management practices and contribute to the global sustainability of agricultural systems.

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