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Mobile-based leaves disease diagnosis and prediction system Using Deep Learning

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Abstract: Agriculture is important for India. Plant diseases pose significant threats to global food security, leading to substantial crop yield losses. Early and accurate disease detection is crucial for timely intervention and effective management. This paper presents a novel mobile-based system that leverages advanced deep learning techniques to diagnose and predict plant leaf diseases. The system utilizes a Convolutional Neural Network (CNN) model trained on a large dataset of images capturing various plant diseases. Users can capture images of diseased leaves using their mobile devices and upload them to the system. The CNN model analyzes the images, identifies the specific disease, and provides a detailed diagnosis along with recommended treatment options. By empowering farmers with real-time disease information, this system aims to enhance agricultural productivity and sustainability. Plant diseases remain a significant challenge in agriculture, causing substantial crop yield losses and economic burdens. Early and accurate disease diagnosis is critical for timely intervention and effective management strategies. This research presents a mobile-based system that integrates advanced deep learning techniques to automatically detect and predict plant leaf diseases.The system leverages a Convolutional Neural Network (CNN) model, specifically designed to extract relevant features from images of diseased leaves. The CNN model is trained on a diverse dataset comprising imag of various plant species and their associated diseases. By analyzing the input images, the model can accurately classify the disease and provide a detailed diagnosis. To enhance user accessibility and convenience, the system is implemented as a mobile application. Farmers can capture images of affected leaves using their smartphones and upload them to the application. The system processes the images, performs disease detection and prediction, and presents the results in an easy-to-understand format. Additionally, the application provides recommendations for suitable treatments, such as specific pesticides or fungicides, to mitigate the impact of the disease. By empowering farmers with timely and accurate disease information, this mobile-based system aims to improve agricultural practices, reduce crop losses, and contribute to sustainable agriculture.JEL Classification Number: I10, C88, L86.

I. INTRODUCTION

Plant diseases significantly threaten global food security, leading to substantial crop yield losses, economic damages, and challenges for farmers worldwide. Timely and accurate disease detection is critical for effective management and mitigation of these impacts. However, traditional methods of diagnosing plant diseases often depend on expert knowledge, time-intensive laboratory tests, and manual observation, which can delay intervention and are not always accessible to farmers in remote areas. To overcome these challenges, automated disease detection systems are gaining traction as a reliable solution. Recent advancements in deep learning, especially Convolutional Neural Networks (CNNs), have brought transformative changes to image classification and object detection tasks. CNNs excel at analyzing complex visual patterns, enabling precise identification of plant diseases from leaf images. These capabilities make CNNs a perfect fit for addressing the limitations of traditional approaches. This research focuses on the development of a mobile-based system that leverages advanced deep learning techniques to detect and predict plant leaf diseases with high accuracy. By utilizing smartphones, a ubiquitous tool among farmers, the system empowers users to capture images of diseased leaves effortlessly and upload them for analysis. The integration of deep learning with mobile technology aims to deliver a user friendly, accessible, and efficient solution, bridging the gap between advanced technology and agricultural needs. This approach not only enhances agricultural practices but also contributes to global efforts toward sustainable farming and food security

II. LITERATURE REVIEW

Harshavardhan Reddy G. Agri Engineering (2021) [1] titled "A Mobile-Based System for Detecting Plant Leaf Diseases Using Deep Learning," focuses on the use of deep learning techniques for automated plant disease detection using mobile devices. The survey explores them potential of such systems in addressing the challenges faced by farmers in early disease detection and management. Deep Learning for Plant Disease Detection the survey delves into the application of deep learning models, particularly Convolutional Neural Networks (CNNs), for accurately identifying plant diseases from images of infected leaves. Mobile-Based Implementation the emphasis is on developing mobile applications that can leverage the power of deep learning to provide real-time disease diagnosis directly to farmers in the field. Benefits of Early Detection the survey highlights the importance of early disease detection in preventing significant crop losses and reducing the need for excessive pesticide use. Anushka Bengal 2022 [2], titled "POTATO LEAF DISEASE DETECTION. AND CLASSIFICATION USING CNN," focuses on the application of Convolutional Neural Networks (CNNs) for automated detection and classification of potato leaf diseases. The survey highlights the challenges faced by farmers in accurately identifying diseases like early blight and late blight, which can significantly impact crop yields. CNN-Based Disease Detection the survey explores the use of CNNs as a powerful tool for analysing images of potato leaves and differentiating between healthy and diseased leaves. Improved Accuracy the proposed CNN based system aims to achieve higher accuracy in disease detection compared to traditional methods. Potential Benefits the successful implementation of such a system could help farmers make timely interventions, reduce crop losses, and optimize pesticide usage. Kamal K.C et.al. [3] described Continuous monitoring and visual examination of the field by the human sometimes leads to error. It detects the plant disease using depth wise separable convolution based on leaves images. leaves images. To increase the productivity and improve the plant health based on the characteristics such as colour, shape and size. Vimal K et.al. [4] In this paper detect the disease from rice plant. The disease affected leaves and stems images can be taken from the rice field. For feature extraction the pretrained deep convolution (SVM) network (CNN) has been used and the classification of disease use Support vector Machine. The disease affected rice plant given as an input to every layer of CNN. The features can be obtained from the final layer of CNN are given to disease classification. Mokhtar, U. et.al [5] find the two types of disease on tomato plant perform binary classification using kernel-based function with SVM on 200 RGB images. I. Steinwart and A. Christmann [20] describe about the Support vector machines (SVMs) and artificial neural network are commonly used for detecting plant diseases. Jayme G.A. et.al. [6] developed CNN using neural network toolbox for transfer learning data. CNN model trained with three different levels. For training the data 80% of sample data were used and for data validation 20% of data were used. Kamlesh et.al. [14] plant protection can be achieved by hyper spectral imaging. The precise and detailed information about an object can be extracted from hyper spectral imaging. D. A. Sheikh et.al [15] describes the image processing technique processes the images which are captured by the camera. The converted image sends to RF module. Through this PC connected to robot. The pesticides can be automatically where it is needed. Konstantinos P et.al [7] Machine learning related application achieved plant illness diagnosis. ANN refers large number of processing layers for deep learning. Convoluted neural network worked as a tool in deep learning. The complex process like pattern recognition for large amount of data can be modelled by CNN. Zahid Iqbala et.al. [8] explains automatic detection of citrus plant disease and classification by the image preprocess, image analysis, pattern extraction, pattern selection and classification methods. Otsu thresholding technique on affected image for background removal during segmentation. To improve the accuracy of classification of diseases using support vector machine (SVM).For segmentation k-mean clustering technique is used. Infected plant images can be divided into many clusters. Each cluster has a different set of pixel values. Srdjan Sladojevic et.al. [9] developed a model for leaf image classification, the plant disease recognition using deep convolution network. By distinguish the plant leaves from their surroundings to recognize various types of plant leaf diseases from the developed model. The plant disease detection from leaf images can be automated by deep learning. . The network can be trained by learn the features of leaf images which distinguish one class from others. Starting from the first convolution layer to the fifth convolution layer, the features can be learned like parts of leaves and shapes are displayed to construct the feature map. Varalakshmi [10] identified the disease infected leaves with the help of automated system by processing the leave images captured by camera. For better disease classification the Active contour edge detection can be used to achieve better results. Active contour edge detection combined with multiclass Support vector machines. Zahid Iqbal et.al. [11] explains automatic detection of citrus plant disease and classification by the image preprocess, image analysis, pattern extraction, pattern selection and classification methods. Otsu thresholding technique on affected image for background removal during segmentation. 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III. METHODOLOGY

The methodology encompasses the basic system model outlined in Figure 1: Representation of Framework, as • • Customer Workflow: The customer journey begins with login or registration, followed by searching for items. Once items are found, they can be added to the cart. When ready, the customer places an order, proceeds to payment, and finally logs out. Admin Workflow: The admin, after login or registration, has the capability to look up orders. The system then displays the items available in the carts, facilitating order management and delivery coordination. The admin can then log out. And second diagram shows Figure 2: System Architecture, which represents the system operates with a clear customer-centric approach. Users can either register a new account or log in with an existing one. They can then browse and search for products, adding desired items to their cart. The system provides flexibility by allowing users to view their cart, remove items, and search for additional products. Once ready, users proceed to checkout and complete their purchase. The system also includes an admin panel for managing orders and inventory

IV. RESULTS AND DISCUSSION

4.1 Login Page

Secure authentication mechanisms are implemented to ensure that only authorized healthcare professionals can access the platform. Each user has a detailed profile that includes their specialization, experience level, and professional credentials.

4.1.1 Community Forum and AI Query Solver

The community forum allows users to post questions, share case studies, and engage in discussions. The AI query solver assists users by providing instant responses to medical queries, drawing from the platform's extensive repository of blogs and news articles.

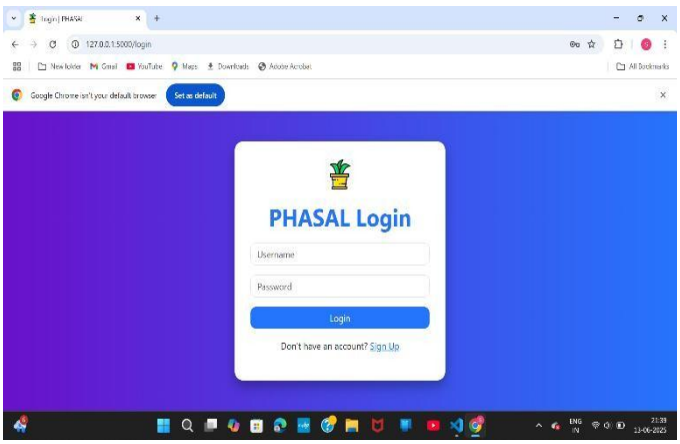


Fig.1. login page

4.1.2 Upload Image

This section enables users to publish and access the latest news and blog posts related to healthcare.

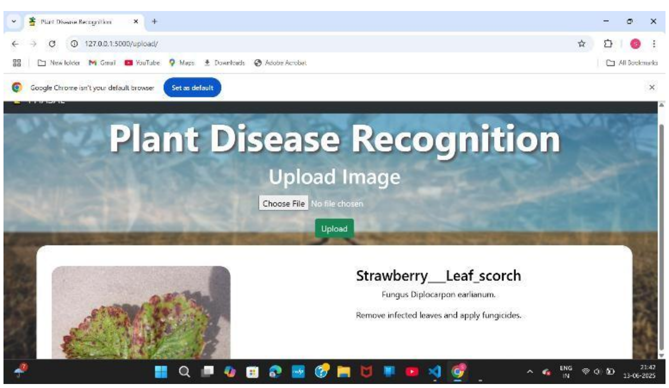


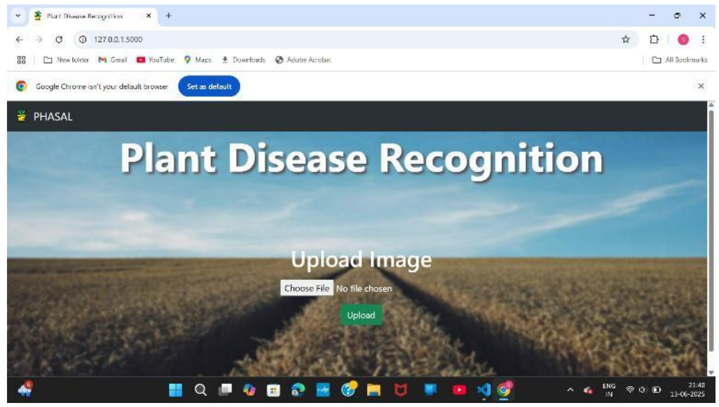
Fig.2. Highlights of the Features

4.1.3 Continuous Integration/Continuous Deployment (CI/CD)

The platform employs CI/CD pipelines to ensure rapid and reliable deployment of updates and new features. This approach minimizes downtime and ensures that users have access to the latest functionalities.

Fig.3. Personal Dashboard and Activity Log

Importance of User Experience (UX)



User Experience (UX) plays a pivotal role in the success of healthcare collaboration tools. Healthcare professionals, often working in high-pressure environments, need tools that are intuitive and easy to navigate. Complex or cluttered interfaces can lead to frustration and reduce efficiency, which could negatively impact patient care.

For example, a real-time dashboard displaying patient records, communication threads, and task updates must prioritize clarity. Features like drag-and-drop task assignments or color-coded alerts for emergencies can enhance usability. Designing for speed and simplicity ensures that healthcare workers can focus more on patient care rather than troubleshooting technical issues.

Accessibility is essential in creating inclusive tools that cater to a diverse group of healthcare professionals. Incorporating multi-language support allows professionals from various linguistic backgrounds to collaborate effectively. For instance, an Indian hospital might benefit from a tool that supports regional languages like Hindi, Tamil, or Bengali alongside English.

Voice-activated commands are another valuable feature. Surgeons or nurses who are physically occupied can issue commands or retrieve information hands-free. Additionally, compatibility with screen readers, high-contrast modes for visually impaired users, and large font options can make the platform usable for everyone, including individuals with disabilities.

System Architecture:

The system architecture comprises three main layers: 1. User Layer Mobile App: The user interacts with the system through a mobile application. The app allows users to capture images of plant leaves using their smartphone's camera. Image Processing: The captured images are pre-processed to enhance image quality and extract relevant features. 2. Application Layer Android Platform: The mobile application is developed using the Android platform, ensuring compatibility with a wide range of Android devices. Cloud Servers: The system utilizes cloud servers to store and process the images. This enables scalability and accessibility from anywhere with an internet connection. 3. DL Layer Intermediate Representation Mode: The pre-processed images are converted into a suitable intermediate representation format for the CNN model. Workflow • Image Capture: The user captures an image of a diseased plant leaf using the mobile app. • Image Preprocessing: The captured image is pre-processed to enhance image quality and extract relevant features. • Feature Extraction: The pre-processed image is fed into the CNN model, which extracts features from the image. • Disease Prediction: The extracted features are used to predict the disease type using the trained CNN model. • Disease Information: The system provides information about the predicted disease, including its symptoms, causes, and management strategies. Figure 1: Representation of Framework 4.1 Model: • • • • Seller Module: This module allows nursery owners or sellers to manage their inventory, add new plants, update prices, and keep track of sales. It provides an easy interface for managing products and ensuring accurate listings for customers. Customer Module: The customer module allows users to browse available plants, compare products, and make purchases online. Customers can create accounts, view purchase history, and track the status of their orders without needing to visit nurseries physically. Management Module: This module helps in handling the overall operations of the nursery, such as stock management, order processing, and customer service. It simplifies the coordination between different departments and ensures smooth functioning of the system. Delivery Module: The delivery module is designed to track orders and manage deliveries. It ensures that customers receive their purchases on time, and allows both sellers and customers to view delivery status in real-time.

V. LIMITATION AND CHALLANGES

Limitations:

• Dependence on Internet Connectivity: The system requires reliable internet access. Poor or intermittent connectivity can disrupt operations.

• Limited Accessibility in Rural Areas: In areas with inadequate digital infrastructure, potential users may face challenges in adopting the system.

• Technical Knowledge Requirement: Users, including nursery staff, may need training to effectively use the system, especially if they are not tech-savvy.

• Initial Development Cost: Designing and implementing the system might involve significant upfront costs for development and hosting.

• Maintenance and Updates: Regular maintenance, updates, and bug fixes are required, which might add ongoing operational costs.

• Integration Challenges: Difficulty in integrating with existing tools, such as inventory or financial management systems, may hinder efficiency.

• Data Loss Risks: Without proper backups, system failures or server issues could lead to loss of critical data.

Challenges:

1] Ensuring Data Security: Protecting sensitive user information, including uploaded leaf images, account details, and system analytics, from cyber threats is critical. Implementing robust encryption, secure storage, and secure communication protocols is essential but challenging.

2] System Scalability: As the user base grows, the system must efficiently handle a large volume of uploaded images and requests without compromising performance or accuracy. Scaling cloud resources for storage and processing can be resource-intensive.

3] Dataset Quality and Diversity: Training the model requires a diverse and high-quality dataset representing various plant species, diseases, and environmental conditions. Gathering and maintaining such a dataset is time consuming and resource-intensive.

4] Integration with Farming Practices: Integrating the system with existing agricultural tools or frameworks used by farmers, such as crop management systems, may be complex. Ensuring compatibility and seamless operation is a challenge.

5] Limited Internet Access: The system’s reliance on internet connectivity for uploading images and processing can limit its usability in remote rural areas with poor network coverage.

6] Real-Time Processing Challenges: Providing quick, accurate diagnoses and recommendations while maintaining computational efficiency can be challenging, especially on mobile devices with limited processing power.

7] Cross-Device Compatibility: Ensuring the mobile application works seamlessly across various operating systems, device configurations, and screen sizes adds to the complexity of development.

VI. SUMMARY AND COCLUSIONS

The mobile-based leaf disease diagnosis and prediction system ensures secure and private storage of user data, including uploaded images and analysis results, in an organized manner. It empowers farmers to diagnose plant diseases anytime, anywhere, without the need for expert visits or laboratory tests. Users can capture and upload images of affected leaves for analysis, boosting their confidence in leveraging technology for disease management. The system enhances accessibility and convenience by providing real-time diagnoses and treatment recommendations. It also offers feedback options, enabling continuous improvement and a better user experience.

VII. REFERENCES

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