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Deep Learning based Image Segmentation and Classification of Lychee leaf Diseases

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ABSTRACT

Agriculture plays a vital role in sustaining global food security, and early detection of plant diseases is essential to minimize crop losses and improve yield quality. This paper presents a Django-based intelligent system for automated detection and severity analysis of lychee leaf diseases using deep learning and computer vision techniques.

The proposed system utilizes a Convolutional Neural Network (CNN) trained on a multi-class dataset consisting of ten categories, including Anthrax Leaf, Bituminous Leaf, Curl Leaf, Deficiency Leaf, Dry Leaf, Felt Leaf, Fungal Leaf Spot, Healthy Leaf, Leaf Blight, and Leaf Gall. The model achieves accurate classification of leaf conditions from uploaded images. To enhance interpretability, the system integrates an OpenCV-based segmentation module that isolates diseased regions by applying HSV color space thresholding. The segmented output highlights healthy leaf areas in green and infected regions in blue over a black background.

Furthermore, the system computes the disease progression percentage by calculating the ratio of infected pixels to total leaf pixels, providing quantitative insight into disease severity. The application is deployed using Django, offering a user-friendly interface that supports image upload, prediction display, segmentation visualization, and personalized user history tracking through authentication.

Experimental results demonstrate that the system effectively combines classification accuracy with visual and numerical analysis, making it a practical decision-support tool for farmers and agricultural experts. The integration of machine learning, image processing, and web technologies provides a scalable and real-time solution for smart agriculture.

1.INTRODUCTION

Agriculture remains one of the most critical sectors for sustaining human life and economic stability, especially in countries where farming is a primary occupation. Among various agricultural challenges, plant diseases significantly affect crop yield, quality, and overall productivity. Lychee, being a valuable fruit crop, is highly susceptible to various leaf diseases such as Leaf Blight, Fungal Leaf Spot, Anthrax, and Nutrient Deficiency. Early and accurate detection of these diseases is essential to prevent large-scale crop damage and to ensure effective treatment.

Traditionally, disease identification in plants relies on manual inspection by farmers or agricultural experts. However, this approach is time-consuming, subjective, and often inaccurate, particularly in rural areas where expert knowledge may not be readily available. With the advancement of artificial intelligence and computer vision, automated plant disease detection systems have emerged as a promising solution to overcome these limitations.

In recent years, Deep Learning techniques, especially Convolutional Neural Networks (CNNs), have shown remarkable performance in image classification tasks, including plant disease detection. These models can automatically extract complex features from leaf images and classify them into multiple disease categories with high accuracy. However, most existing systems focus only on classification and fail to provide insights into the severity or spread of the disease, which is crucial for decision-making in agriculture.

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To address this limitation, this work proposes an intelligent web-based system for Lychee Leaf Disease Detection and Severity Analysis. The system integrates a CNN-based classification model with an image segmentation module developed using OpenCV. While the CNN predicts the disease class, the segmentation module identifies infected regions on the leaf and visually highlights them. Additionally, the system calculates the disease progression percentage by analyzing the proportion of infected pixels, providing a quantitative measure of disease severity.

The proposed system is implemented using the Django framework, enabling real-time interaction through a user-friendly web interface. It allows users to upload leaf images, view predictions, visualize segmented outputs, and track their analysis history through a personalized account system. This integration of deep learning, image processing, and web technologies creates a comprehensive and scalable solution for smart agriculture.

Overall, the system aims to assist farmers, researchers, and agricultural experts by providing an accurate, fast, and accessible tool for early disease detection and monitoring, thereby contributing to improved crop management and reduced agricultural losses.

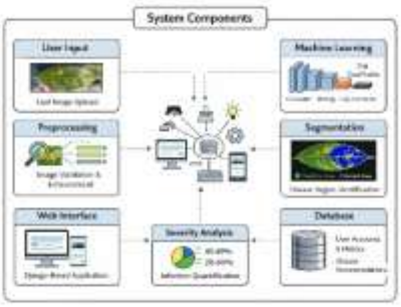

Figure.1 :system components

2.LITERATURESURVE

Mohanty et al. [1] utilized deep learning techniques, particularly Convolutional Neural Networks (CNNs), for plant disease detection using leaf images. Their study demonstrated that deep CNN models such as AlexNet and GoogLeNet achieved an accuracy of over 99% on a large plant disease dataset. Similarly, Ferentinos [2] applied deep learning models on plant leaf datasets and reported high classification accuracy of 99.53% using CNN architectures, proving the effectiveness of deep learning in agricultural applications.

Sladojevic et al. [3] developed a plant disease recognition system using deep neural networks and achieved an accuracy of 96.3% across multiple plant species. Their approach focused on automatic feature extraction, eliminating the need for manual intervention. On the other hand, Pujari et al. [4] employed image processing techniques using color, texture, and shape features combined with machine learning classifiers such as Support Vector Machines (SVM), achieving reliable performance in disease detection.

In addition to classification, segmentation techniques have also been explored. Revathi and Hemalatha [5] used image segmentation methods based on color transformation and thresholding to identify diseased regions in cotton leaves. Their results showed improved visualization of infected areas, although the system lacked quantitative severity analysis. Likewise, Singh and Misra [6] applied K-means clustering for segmenting diseased regions, which provided better region separation but suffered from sensitivity to noise and lighting conditions.

Recent studies have attempted to integrate classification with severity estimation. However, most existing systems focus either on classification accuracy or segmentation visualization, with limited work addressing both simultaneously in a real-time web-based environment. Therefore, there is a need for a comprehensive system that combines deep learning-based classification, precise segmentation, and disease progression analysis, which is addressed in the proposed work.

3.PROPOSED SYSTEM

The proposed system is a web-based intelligent application designed for automated detection and severity analysis of lychee leaf diseases using deep learning and image processing techniques. The system integrates a Convolutional Neural Network (CNN) for disease classification with an OpenCV-based segmentation module to identify infected regions on leaf images

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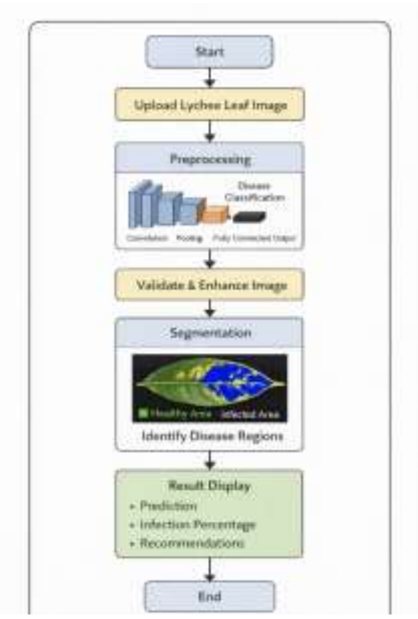

Figure 3:Deep Learning Pipeline for Lychee Leaf Disease Identification

Initially, the user uploads an image of a lychee leaf through a user-friendly web interface developed using the Django framework. The system first performs validation using basic image processing techniques to ensure that the uploaded image contains a leaf. Once validated, the image is passed to the trained CNN model, which classifies it into one of the predefined disease categories, including Anthrax Leaf, Bituminous Leaf, Curl Leaf, Deficiency Leaf, Dry Leaf, Felt Leaf, Fungal Leaf Spot, Healthy Leaf, Leaf Blight, and Leaf Gall.

Following classification, the system applies image segmentation using HSV color space thresholding to distinguish between healthy and diseased regions. The background is removed and displayed in black, while healthy leaf areas are highlighted in green and infected regionmarked in blue. This visual representation enhances interpretability and allows users to easily identify affected areas.

In addition to visual analysis, the system calculates the disease progression percentage by computing the ratio of infected pixels to the total leaf pixels. This provides a quantitative measure of disease severity, enabling better decision-making for treatment and crop management. Furthermore, the system includes a user authentication module, allowing multiple users to create accounts and maintain personalized prediction histories. Each user's uploaded images, predictions, and infection percentages are securely stored in a database using SQLite. The system also provides disease-specific recommendations and treatment suggestions based on the predicted class.

Overall, the proposed system offers a comprehensive solution by combining classification, segmentation, severity estimation, and user interaction in a single platform. It is scalable, efficient, and suitable for real-time agricultural applications, assisting farmers and researchers in early disease detection and management.

4.RESULTS DESCRIPTION

The proposed system was evaluated using a dataset of lychee leaf images containing ten different classes, including both healthy and diseased categories. The Convolutional Neural Network (CNN) model demonstrated high classification performance, accurately identifying various leaf diseases such as Anthrax Leaf, Fungal Leaf Spot, Leaf Blight, and others. The model achieved reliable prediction confidence levels, indicating its effectiveness in distinguishing between multiple disease classes.

In addition to classification, the segmentation module successfully identified and highlighted infected regions on the leaf images. The system was able to clearly separate the background, healthy leaf areas, and diseased portions using HSV-based color thresholding. The segmented output displayed a black background, green regions representing healthy leaf areas, and blue regions indicating infected portions. This visual representation improved the interpretability of the results and allowed users to easily understand the extent of disease spread.

Furthermore, the system computed the disease progression percentage by calculating the ratio of infected pixels to the total leaf area. The results showed that the system could effectively quantify the severity of infection, providing values such as 20–60% for moderately affected leaves and higher percentages for severely infected samples. This numerical output complements the visual segmentation and helps in making informed decisions regarding treatment.

The web-based implementation using Django enabled real-time interaction, allowing users to

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upload images, view predictions, and analyze results instantly. The integration of user authentication ensured that each user could maintain a personalized history of predictions. Experimental observations indicate that the system performs well under normal lighting conditions and with clear leaf images. However, slight variations in lighting and background complexity may affect segmentation accuracy, suggesting scope for further improvement using advanced deep learning-based segmentation models.

Overall, the results demonstrate that the proposed system effectively combines classification, segmentation, and severity estimation into a single platform, making it a practical and efficient tool for disease monitoring and management.

Figure 3. Web interface for proposed lychee leaf disease classification system.

5.CONCLUSION

In this work, a comprehensive web-based system for lychee leaf disease detection and severity analysis has been developed using deep learning and image processing techniques. The proposed system successfully integrates a Convolutional Neural Network (CNN) for accurate disease classification with an OpenCV-based segmentation module for identifying infected regions on leaf images. The system not only classifies diseases into multiple categories but also provides a visual representation of affected areas and computes the disease progression percentage, offering both qualitative and quantitative insights.

The implementation using the Django framework enables real-time interaction through a user-friendly interface, allowing users to upload images, view predictions, and maintain personalized analysis history. Experimental results demonstrate that the system performs effectively in detecting diseases and estimating their severity under standard conditions. The combination of classification, segmentation, and severity estimation makes the system a practical tool for assisting farmers and agricultural experts in early disease detection and decision-making.

However, the system has certain limitations, such as sensitivity to lighting conditions and background variations, which may affect segmentation accuracy. These challenges can be addressed in future work by incorporating advanced deep learning-based segmentation models and expanding the dataset for better generalization. Overall, the proposed system provides a scalable and efficient solution for smart agriculture and has the potential to be extended to other crops and disease detection applications.

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