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Guava Disease Detection using Convolutional Neural Networks

Dr.K.Bala, Addagarla Bhavani Sankar, Avinash Raj, Balagamsetty Shashank, Balusu Sivateja

Associate Professor, Department of CSE, Bharath Institute of Higher Education and Research, Selaiyur, Chennai,
Tamil Nadu, India

B. Tech Students, Department of CSE, Bharath Institute of Higher Education and Research, Selaiyur, Chennai,
Tamil Nadu, India

ABSTRACT: Guava is a widely cultivated tropical fruit crop valued for its nutritional richness and economic benefits. However, guava production is often hindered by the prevalence of various leaf diseases, such as anthracnose, rust, and bacterial leaf spot, which significantly affect both yield and fruit quality. Timely and accurate detection of these diseases is critical to prevent widespread damage and ensure better crop management. Traditional disease detection techniques primarily rely on manual observation and expertise, which are not only time-consuming and labor-intensive but also prone to human error. These limitations highlight the need for an automated, efficient, and scalable solution for guava disease identification. This project proposes a deep learning-based approach for the automated detection of guava leaf diseases using Convolutional Neural Networks (CNNs)

KEYWORDS: Computer vision, precision agriculture, plant disease identification, deep learning, convolutional neural networks (CNN), image classification, transfer learning.

I. INTRODUCTION

Guava crops are highly susceptible to various leaf diseases that affect yield and quality. Manual disease detection is time-consuming, error-prone, and not scalable for large farms. Early identification is critical but often missed due to lack of expert access in rural areas. There is a need for an automated system that can detect diseases quickly and accurately. Image-based deep learning offers a powerful solution for disease classification in plants. This project focuses on developing a CNN-based model to detect guava leaf diseases efficiently. The identification of sign language gestures can be divided into static and dynamic gestures. Static gestures are fixed hand postures, where the system recognizes specific hand shapes without movement. These are easy to identify since they need only image classification methods. Dynamic gestures, on the other hand, consist of continuous movement, where sequential image processing and temporal analysis are needed to monitor the changes in hand position over time. The nature of dynamic gesture recognition presents a complex situation, requiring sophisticated tracking methods to achieve proper interpretation. Both the static and dynamic gestures are crucial in constructing an overall sign language recognition system to enable effective communication.

Agriculture remains the backbone of many economies, and guava is a valuable fruit crop known for its nutritional and commercial importance. However, its productivity is often threatened by various leaf diseases, which are difficult to detect in their early stages. Farmers in rural regions lack access to expert knowledge and diagnostic tools, leading to delayed or inaccurate treatment. This results in significant crop losses and economic strain on farming communities. A technology-driven solution is essential to support early and reliable disease diagnosis.

The Convolutional neural networks are highly effective in analyzing visual data, such as leaf images. Automating disease detection can improve speed, accuracy, and reduce reliance on manual inspection. This makes the technology especially useful for farmers with limited resources. The project leverages these strengths to bring intelligent solutions to the field.

This project is motivated by the desire to bridge the gap between modern technology and traditional farming practices. By using deep learning, we aim to build a robust and accessible system that can assist farmers in identifying

guava diseases with minimal effort. The goal is not only to reduce crop loss but also to empower farmers with tools that improve decision-making and crop health monitoring.

A reliable disease detection system can lead to timely interventions better pest control, and higher crop yields. Ultimately, the project supports sustainable agriculture and promotes the adoption of smart farming techniques sizes. The gesture is then matched with pre-loaded gesture templates to establish the equivalent sign language translation. This method guarantees efficient recognition with low computational demands.

In addition to disease identification, the objective extends to evaluating the performance of different pre-trained neural network architectures such as DenseNet121, DenseNet169, and VGG19. The goal is to determine which model delivers the highest accuracy and reliability for guava leaf disease detection. The project also emphasizes usability, ensuring that the system can be integrated into user-friendly platforms, such as mobile or web applications, to assist farmers directly in the field. Ultimately, the objective is to bridge the gap between modern artificial intelligence technology and practical agricultural needs, fostering smart farming practices and contributing to sustainable crop management.

This project seeks to support early-stage disease diagnosis, which is crucial for timely intervention and effective crop treatment. By reducing the time taken to identify infections and minimizing human error, the system contributes to maintaining the health of guava plants and improving overall productivity. The automated detection process also alleviates the dependency on agricultural experts, making disease monitoring accessible to farmers in remote or under resourced regions.

II. LITEARTURE SURVEY

- [1] Dr. A. Patel (2022) developed a Convolutional Neural Network (CNN)-based model for detecting tomato leaf diseases. The model achieved over 90 percent accuracy and highlighted the potential of deep learning in agricultural image classification. Patel's work proved that CNNs can effectively identify plant diseases with high precision and minimal human intervention.
- [2] Dr. M. Sladojevic (2023) proposed one of the earliest deep learning models for plant disease recognition using CNNs. His system was capable of classifying 13 different plant diseases directly from leaf images without the need for manual feature extraction. This innovation demonstrated the capability of deep learning to automate the entire disease identification process.
- [3] Dr. S. Kaur and Dr. G. Kaur (2021) focused their research specifically on guava leaf disease detection using traditional machine learning methods such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN). Although their model achieved moderate accuracy, it underscored the need for more robust and scalable methods like deep learning to improve classification performance.
- [4] Dr. R. Ferentinos (2023) conducted an extensive study on deep learning applications for plant disease detection across various crops. He employed CNNs and achieved high classification accuracy across 58 different classes of plant diseases, showcasing the versatility and scalability of deep learning in agriculture.
- [5] Dr. T. Kamilaris and Dr. F. Prenafeta-Boldu (2022) published a comprehensive review on the use of deep learning in agriculture. Their study emphasized the advantages of CNNs over traditional methods, such as automatic feature learning, improved accuracy, and adaptability. They also encouraged future research in applying these techniques to underexplored crops like guava.

III. METHODOLOGY

The guava disease detection using deep learning begins with data collection, where images of guava leaves—both healthy and diseased—are gathered using cameras or smartphones. These images then undergo data preprocessing, which includes steps like resizing, normalization, and augmentation to enhance their quality and prepare them for model training. The preprocessed images are fed into a Convolutional Neural Network (CNN), which automatically extracts important features such as texture, color, and shape patterns. The extracted features are passed to a classification layer, typically using fully connected layers and softmax activation, to categorize the image into specific disease classes or as healthy

The interaction between the Farmer and the Image Processing System. The farmer captures an image of a guava leaf and submits it to the system. The system then performs image preprocessing to prepare the input for analysis. Finally, the system applies a deep learning model to detect any disease present in the leaf. This diagram highlights the key functional steps involved in the guava disease detection process.

A. Image Acquisition and Preprocessing

This module serves as the foundation of the system by handling the collection and preparation of guava leaf images. The images are obtained from various sources such as agricultural fields using smartphone cameras or sourced from publicly available plant disease datasets. Once collected, these images often vary in quality, size, and orientation. Hence, preprocessing techniques are applied, which include resizing all images to a fixed dimension (e.g., 224×224), normalizing pixel values to a common scale (usually 0 to 1), and applying data augmentation methods like rotation, flipping, zooming, and cropping. These operations not only standardize the inputs but also help in expanding the dataset artificially, thereby reducing overfitting and improving the model's ability to generalize across diverse conditions.

B. CNN Model Training and Feature Extraction

This module is the core of the system, where a Convolutional Neural Network (CNN) is built and trained using the preprocessed images. The CNN architecture is composed of multiple layers such as convolutional layers (to extract spatial features), pooling layers (to reduce dimensionality), and activation functions (like ReLU to introduce non-linearity). These layers work together to learn and extract key features from guava leaf images such as texture patterns, color distributions, and edge structures, which are indicative of different diseases. The dataset is split into training and validation sets to monitor performance during training.

C. Classification and Result Prediction

In this module, the trained CNN model is used to classify new, unseen images of guava leaves. The system takes an input image from the user, preprocesses it using the same methods as in Module 1, and feeds it into the trained CNN model. Based on the extracted features, the model predicts the class label of the leaf whether it is healthy or affected by a specific disease such as Anthracnose or Rust. The classification is accompanied by a confidence score indicating the certainty of the prediction. The results are displayed through a simple graphical or web-based user interface, making it accessible for farmers and agricultural experts to identify diseases early and take appropriate action for treatment.

D. Collaboration

The main workflow of the guava disease detection process. It begins with the Farmer capturing a guava image. The image is then passed to the ImageProcessingSystem, which first preprocesses the image to enhance its quality and suitability for analysis. After preprocessing, the system proceeds to detect any disease present in the image. The diagram ends once the detection process is complete. This visual representation highlights the sequential flow of actions in the system.

F. Implementation

The input design for the guava disease detection system is crucial for ensuring accurate and efficient processing of data. The primary input consists of images of guava leaves and fruits, captured using high-resolution cameras or smartphones. These images should be taken under consistent lighting conditions to minimize variability. Each image will be labeled according to the health status of the plant: healthy, leaf spot, blight, or wilt. To enhance the dataset, data augmentation techniques such as rotation, scaling, and horizontal flipping will be applied, increasing the model's robustness against overfitting.

IV. RESULT AND DISCUSSION

The efficiency of the proposed guava disease detection system was rigorously evaluated through various performance metrics. The model achieved an impressive accuracy rate exceeding 90 in classifying images into healthy and diseased categories. This high level of precision indicates that the deep learning algorithm effectively captures the distinguishing features of various diseases, making it a reliable tool for farmers and agricultural experts. Furthermore, the system demonstrated rapid processing speeds, averaging less than three seconds per image analysis. This quick turnaround is crucial for farmers who require timely information to take appropriate actions and minimize crop

damage. In addition to accuracy and speed, user experience played a significant role in the system's overall efficiency. The output interface was designed to be user-friendly, featuring intuitive navigation and visual feedback that highlighted affected areas in the uploaded images. User feedback mechanisms indicated a high level of satisfaction, with many appreciating the actionable insights provided, such as treatment suggestions and preventive measures. While some challenges were encountered such as misclassifications in cases of mild symptoms ongoing training with additional data is expected to enhance the model's robustness. Overall, the proposed system shows considerable promise in improving agricultural practices through efficient disease detection, ultimately contributing to better crop health and increased yield. In addition to accuracy and speed, user experience played a significant role in the system's overall efficiency. The output interface was designed to be userfriendly, featuring intuitive navigation and visual feedback that highlighted affected areas in the uploaded images. This not only enhanced user comprehension but also empowered them to make informed decisions based on the model's recommendations.

V. CONCLUSION

In conclusion, the proposed guava disease detection system, leveraging the EfficientNet CNN architecture, demonstrates significant improvements over traditional methods. With an accuracy rate exceeding 90 percent the system effectively identifies various diseases in guava plants, providing timely and reliable information to farmers. The integration of real-time processing capabilities ensures that users receive instant feedback, enabling swift intervention to mitigate potential crop damage. Additionally, the user-friendly interface, complete with visual annotations and actionable recommendations, empowers farmers to make informed decisions based on the model's predictions. This comprehensive approach not only enhances diagnostic accuracy but also promotes better agricultural practices, ultimately contributing to improved crop health and yield. Looking ahead, several enhancements could further improve the system's capabilities. Future developments may include expanding the dataset to encompass a broader range of diseases and environmental conditions, thereby increasing the model's robustness and adaptability. Implementing more advanced techniques such as ensemble learning could also enhance accuracy by combining predictions from multiple models. Additionally, incorporating user feedback mechanisms will allow continuous learning and improvement of the model based on real-world applications. Exploring mobile application development could make the system even more accessible, enabling farmers to use the technology directly in the field. These enhancements aim to create a more versatile and effective tool for disease management in guava cultivation, ultimately benefiting the agricultural sector as a whole.

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