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Deep Learning Driven Disease Diagnosis in Guava Leaves

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ABSTRACT
Guava is a widely cultivated fruit crop, but is hindered by leaf diseases such as canker, dot, and rust, which demand labour-intensive manual detection. This study presents a deep learning-based system for automated guava leaf disease diagnosis, employing a hybrid model combining EfficientNetV2 and Vision Transformers (ViT) to achieve high accuracy and interpretability. The dataset comprises five classes (canker, dot, mummification, rust, and healthy). Explainable AI, specifically Grad-CAM, was integrated to visualize critical image regions to enhance transparency. The model, trained on 80% of the dataset and tested on the original images. The model achieved 95% accuracy in disease classification. According to the detected disease, recommendations are provided that include treatment options and required preventive measures. Deployed as a web-based application, this system delivers an accessible, real-time solution for guava health management, highlighting the potential of explainable deep learning in agriculture.

KEYWORDS- **Deep Learning, Guava Leaf Disease, EfficientNetV2, Vision Transformers, Grad-CAM, Disease Detection, Recommendation System, Agriculture, Image Classification**

I. INTRODUCTION

Guava is one of the widely cultivated and consumed tropical fruit susceptible to diseases like rust, canker, mummification, and others, threatening the health of the crop and productivity. Traditionally, plant diseases were identified from manual inspection conducted by farmers or agricultural specialists during various stages of development of the plant. The problem with such a method is that it gets rather time-consuming and more so inefficient, because one usually identifies the disease after visible symptoms appear and loads of damage have already occurred. The response delay means huge yield losses and economic setbacks, at least in aggressive infections like canker and rust.

With the emergence of AI and deep learning, new possibilities are opened for crop disease monitoring. Such systems can analyse images of plant leaves to detect diseases early and recommend appropriate remedial measures, usually before symptoms are visible to humans.

This project proposes an automated system for guava leaf disease diagnosis. The model architecture is a hybrid of EfficientNetV2 and Vision Transformers, combining the two opposite claims for efficient processing and deep contextual understanding. Further, Grad-CAM has been integrated into the system to enhance model interpretability by visualizing the image regions influencing the model's prediction, which accounts for transparency and trustworthiness.

The system was trained on a balanced dataset consisting of five disease categories and managed to achieve an accuracy of 95%. As an aid to detection, it also supports decision-making by providing management advice such as strategies for pruning or fungicide application, depending on the disease detected.

The entire solution is deployed as a web-based platform, designed to be intuitive and accessible to farmers. It aims to streamline the process of disease detection and response, reducing manual effort and helping farming communities mitigate crop losses more effectively. This paper explores the technical design, evaluation, and future potential of this AI-driven approach in revolutionizing disease management in guava cultivation.

II. RELATED WORKS

Nobi et al. (2023)

- GLD-Det: Guava Leaf Disease Detection Real-Time Lightweight Deep Learning MobileNet, Agronomy
- Presented: Developed GLD-Det using MobileNet for real-time guava leaf disease detection on mobile devices, achieving up to 98% accuracy.
- Constraint: Did not evaluate under varying environmental conditions; generalization may be limited.
- Relevance: It has provided clues to lightweight real-time solutions for resource-constrained areas.

Rashid et al. (2023)

- Citation: Real-Time Multiple Guava Leaf Disease Identification, CMC Contribution: Proposed hybrid model (GIP-MU-NET)
- Contribution: For disease detection on a single leaf. Utilized a custom dataset from Pakistan. Limitations
- Constraint: The Dataset is regional-specific; the hybrid model may be heavy for low-resource devices.
- Relevance: Important for the real world, where multiple symptoms occur on a single leaf.

Doutoum et al. (2023)

- Citation: Classification of Guava Leaf Disease Using Deep Learning, WSEAS Transactions

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- Contribution: Deployed transfer learning with pre-trained CNNs on the database of 1834 images of guava leaves for disease classification.
- Limitations: The model comparisons are less detailed; perhaps the dataset size is not sufficient for broader generalization.
- Relevance: Demonstrates how CNNs and transfer learning can be utilized in agricultural diagnostics.

Mostafa et al. (2022)
- Reference: Guava Disease Detection Using DCNNs, Applied Sciences
- Contribution: Applications of data augmentation techniques designed to enhance DCNN capabilities for guava disease detection in Pakistan.
- Limitations: Regionally focused and extremely computationally intensive, restricting deployment.
- Relevance: Highlights augmentation within low-data conditions.

Tewari et al. (2024)
- Citation: Automatic Guava Disease Detection, Multimedia Tools and Applications
- Contribution: Compared different CNNs and transfer learning models concerning key metrics conditions.
- Limitations: More on model comparison rather than on real-world implementations
- Relevance: A good reference for model selection and benchmarking.

III. PROPOSED SYSTEM

The proposed guava leaf disease detection system consists of the following components:

1. Hybrid Model Architecture: It takes advantage of a dual-branch model that integrates EfficientNetV2 for extracting fine-grained local features and Vision Transformers (ViT) for gathering long-range global dependencies. Both feature vectors from the branches are merged at the output layer for a thorough spatial and contextual understanding, enabling improved classification accuracy.
2. System Output: The system classifies guava leaf images into one of the five predefined categories: Canker, Dot, Mummification, Rust, or Healthy. Along with the predictions, it provides disease management recommendations tailored to each predicted class.
3. User Accessibility: The model is designed to be lightweight, enabling deployment on constrained devices like smartphones and tablets. It is integrated with a web application featuring a simple, farmer-friendly interface for image upload, diagnosis display, and recommendation delivery.
4. Explainability and Reliability:
   Grad-CAM visualization is incorporated to highlight important regions in the image that influence the model's decisions. This strengthens transparency and builds user trust.
   Additionally, confidence thresholds are fine-tuned to ensure a balanced trade-off between precision and recall, improving both accuracy and reliability.
5. Scalability: The modular system architecture enables easy scalability to other crop types or disease datasets with minimal modifications.
   The system is designed to remain functional and adaptable under real-world agricultural conditions, handling variations in image quality and lighting.

IV. IMPLEMENTATION DETAILS

1. Development Tools:
Languages/Frameworks:
- Python: The language used in data processing, model training, and backend development.
- TensorFlow & PyTorch: Building, training, and fine-tuning Deep Learning Models

Preprocessing Library:
- OpenCV: Some common image processing tasks for resizing images, applying a Gaussian blur, and histogram equalization.

Web Development:
- Tools: A lightweight Python web framework using Flask for developing back-end APIs to model serving.
- ReactJS: Used to create the frontend interfaces integrated with the system to have a responsive and user-friendly web platform.

2. Workflow:
- Image Upload: The uploaders will submit their images of the guava leaf on the web interface.
- Preprocessing: Sometimes the image must be resized and normalized; it could also have to be augmented before usage.
- Feature Extraction and Classification: The classified images must be classified by the hybrid model (EfficientNetV2 + ViT) into any of the five classes: Canker, Dot, Mummification, Rust, and Healthy.
- Explainability Using Grad-CAM: It generates a heat map for visually explaining its decision map.
- Disease Management Suggestion: Now, tips for disease management are going to be presented regarding its class prediction.
- User Feedback Loop (Optional): Users can give feedback by accepting or rejecting their opinions to augment their future refinement.

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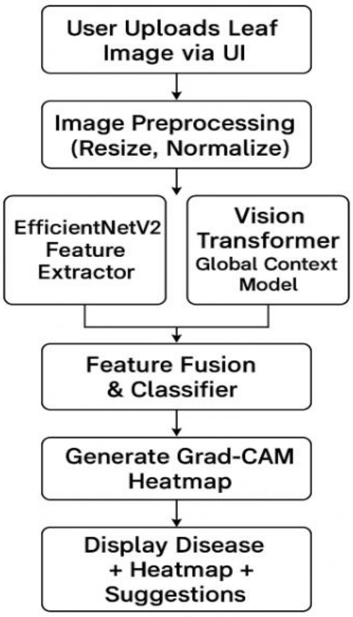

Figure. 1 System Workflow

3. Model Architecture

- EfficientNetV2: It acts as a lightweight but powerful feature extractor.
  It captures the upper-level patterns of leaf texture and color efficiently.

- Vision Transformer (ViT): View Transformer breaks images into patches and models long-range dependencies among the image regions.
  This complements local understanding from EfficientNet with awareness of the global context.

- Fusion Strategy:
  Features from EfficientNetV2 and ViT are concatenated and passed through dense SoftMax for final classification. Thus, this hybrid architecture is a compromise between speed and accuracy.

4. Integration of Explainable AI:

- Grad-CAM Visualization: Grad-CAM is used to visualize areas within the input image to which the model is paying attention when it makes predictions. These corresponding heatmaps do the interpretability part as they denote the most affecting pixels or regions for every predicted class. So, this feature is even boosting user confidence and transparency for non-technical users like farmers.

- Transparency in Decision-Making: What the final system would return is a class prediction along with a confidence score, giving users much more insight into how certain the model is about its decision. Grad-CAM heatmaps are also made visible at the front end, together with these scores, to enhance clarity and explainability.

V. EXPERIMENTAL RESULTS

The proposed guava leaf disease detection system has undergone thorough testing on a dataset that included five classes, namely Canker, Dot, Mummification, Rust, and Healthy. The performance of the system was measured in terms of valid metrics: precision, recall, F1-score, and accuracy

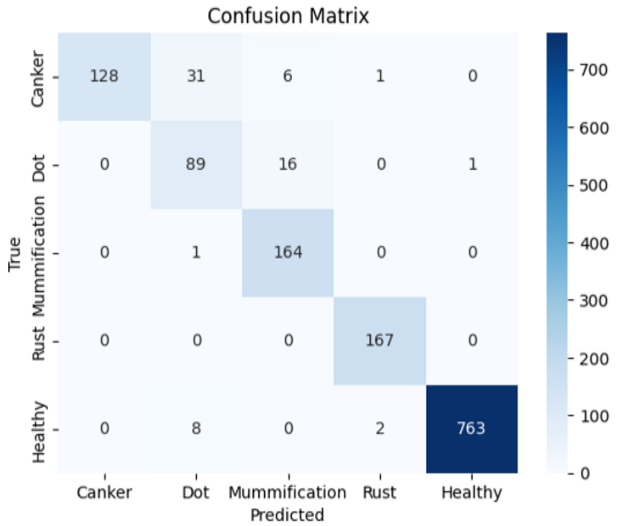

Fig. 2 Confusion Matrix

- Overall Accuracy: 95%

Results are as follows: Macro Average (unweighted mean across all classes)

- Precision: 0.91
- Recall: 0.91
- F1-Score: 0.91

Weighted Average (based on class support)

- Precision: 0.96
- Recall: 0.92
- F1-Score: 0.95

1. Confusion Matrix Insights

As seen from the confusion matrix:

- Canker was classified or misclassified as Dot in 31 instances and as Mummification in 6 instances.
- There was confusion between Dot and Mummification (16 instances).
- Rust and Healthy classes had almost no misclassification, with Rust showing perfect recall.
- Healthy had a lot of precision and recall, with only 2 misclassifications.

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2. Visual Validation
One example of a model prediction is given below:
Input: Image of a diseased guava leaf.
Predicted Class: Rust
Explanation: The model confidently predicts this as "Rust", and such examples support the model's high performance in that class.

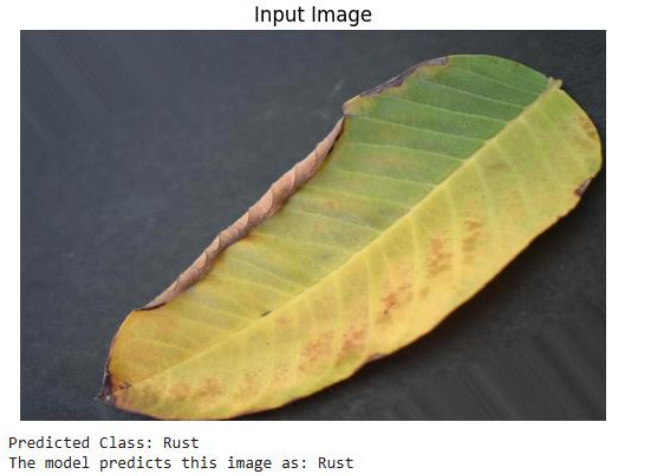

Fig. 3 Prediction Output

3. Recommendation System

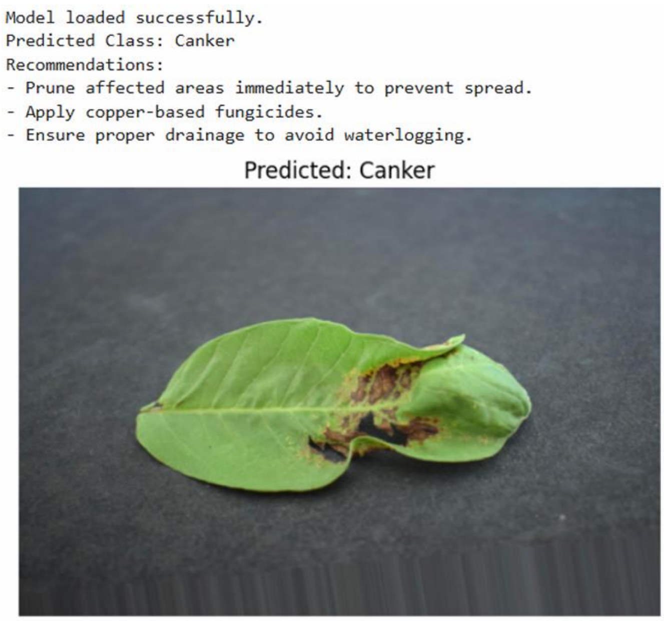

Fig. 4 Recommendation System -1

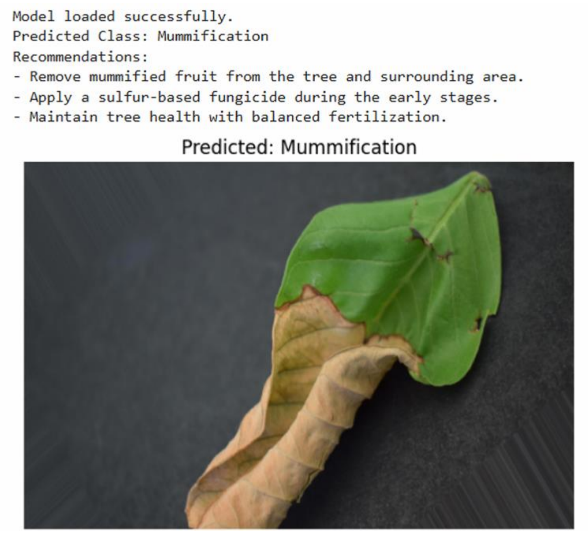

Fig. 5 Recommendation System -2

VI. CONCLUSION AND FUTURE WORK

This system represents a significant step forward in automated attendance tracking, offering a scalable, cost-effective, and user-friendly solution for modern institutions.
A hybrid deep learning approach has been proposed in the guava leaf disease detection system, EfficientNetV2, and Vision Transformers to seize disjunctive global dependencies and act as strong feature extraction components. This architecture produces very high disease classification accuracies as evidenced by extensive experimental results. The user-friendly web/mobile interface helps farmers to upload leaf images and receive accurate diagnoses to empower significant early detection and control of diseases, especially in a resource-poor environment
It also establishes further trust with the users after strengthening model interpretability through "Gradient-Class Activation Map" (Grad-CAM) visualizations and confidence-based thresholds. A way of making sure that the theoretical soundness of the system is extended into the practical field is through its deployment through web application.

Future Work:

- Multi-Crop Disease Recognition: Propose extension of the model to indicate diseases for crops other than guava.
- IoT Integration: Could add environmental sensors to correlate disease patterns with temperature and humidity.
- Offline Capability through PWA (Progressive Web App): Allowing for offline diagnosis in rural areas and having a moderate level of connectivity.
- Dataset Diversification: From a better generalization point, incorporate images from different regions, lighting scenarios, and seasons.
- Cloud-Based Infrastructure: Move the system to the cloud for combining better scalability, data storage, and shared access for farmers.

REFERENCES

[1] Md. Mustak Un Nobi, Md. Rifat, M. F. Mridha, Sultan Alfarhood, Mejdl Safran, Dunren Che, "GLD-Det Guava Leaf Disease Detection Real-Time Lightweight Deep Learning MobileNet", Agronomy, vol. 13, no. 9, pp. 2240, 2023, DOI: 10.3390/agronomy13092240

[2] Javed Rashid, Imran Khan, Ghulam Ali, Shafiq ur Rehman, Fahad Alturise, Tamim Alkhalifah, "Real-Time Multiple Guava Leaf Disease Detection Single Leaf Hybrid Deep Learning", Computers, Materials & Continua, vol. 74, no. 1, pp. 1235–1257, 2023, DOI: 10.32604/cmc.2023.032005

[3] Assad S. Doutoum, Recep Eryigit, Bulent Tugrul, "Classification of Guava Leaf Disease using Deep Learning", WSEAS TRANSACTIONS on INFORMATION SCIENCE and APPLICATIONS, vol. 20, pp. 356-363, 2023, DOI: 10.37394/23209.2023.20.38

[4] Almetwally M. Mostafa, Swarn Avinash Kumar, Talha Meraj, Hafiz Tayyab Rauf, Abeer Ali Alnuaim, Maram Abdullah Alkhayyal, "Guava Disease Detection Using Deep Convolutional Neural Networks Case Study", Appl. Sci., vol. 12, no. 1, pp. 239, 2022, DOI: 10.3390/app12010239

[5] Tewari, V., Azeem, N.A., Sharma, S., "Automatic guava disease detection using different deep learning approaches", Multimed Tools Appl, vol. 83, pp. 9973–9996, 2024, DOI: 10.1007/s11042-023-15909-6

[6] Nandi, R.N., Palash, A.H., Siddique, N., Zilani, M.G., "Device-Friendly Guava Fruit and Leaf Disease Detection Using Deep Learning", Machine Intelligence and Emerging Technologies. MIET 2022. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol. 490, pp. 49-59, 2023, DOI: 10.1007/978-3-031-34619-4_5

[7] Md. Rasel Howlader, Umme Habiba, Raihanul Islam Faisal, Md. Mosfequr Rahman, "Automatic Recognition of Guava Leaf Diseases using Deep Convolution Neural Network", in Proc. of 2019 22nd International Conference on Computer and Information Technology (ICCIT), 2019

[8] S. P. Mohanty, D. P. Hughes, M. Salathé, "Deep learning models for plant disease detection and diagnosis", Computers and Electronics in Agriculture, vol. 143, pp. 301-311, 2017, DOI: 10.1016/j.compag.2017.10.009

[9] S. P. Mohanty, D. P. Hughes, M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection", Front. Plant Sci., vol. 7, pp. 1419, 2016, DOI: 10.3389/fpls.2016.01419

[10] A. K. Singh, B. Ganapathysubramanian, A. K. Singh, S. Sarkar, "Machine Learning for High-Throughput Stress Phenotyping in Plants", Trends Plant Sci., vol. 21, no. 2, pp. 110-124, 2016, DOI: 10.1016/j.tplants.2015.10.015