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Review Of Deep Learning-Based Multi-Class Classification of Mango, Guava, And Pomegranate Leaf Diseases

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***Abstract*—Early identification of plant diseases is crucial to maintaining agricultural productivity and preventing economic losses. In recent years, the emergence of deep learning has made it possible to design efficient image-based systems capable of diagnosing diseases across different crops. This review presents an analytical overview of the techniques applied to the multi-class classification of mango, guava, and pomegranate fruit and leaf diseases. It compiles information on existing public datasets, preprocessing methods, and deep learning architectures such as convolutional neural networks (CNNs), transfer learning models, and object detection approaches like YOLO. It also considers privacy-oriented methods such as federated learning. The study compares reported accuracies, computational complexity, and generalization capabilities while noting persistent gaps, including the absence of large cross-domain datasets and limited deployment on low-cost hardware. The observations summarized here aim to guide future research toward developing explainable, lightweight, and scalable deep learning solutions for disease detection in horticultural crops.**

***Index Terms*—Plant disease detection, Deep learning, multi-class classification, Mango, Guava, Pomegranate , Federated learning**

I. INTRODUCTION

Agriculture remains the foundation of India's economy, with horticultural crops such as mango (Mangifera indica), guava (Psidium guajava), and pomegranate (Punica granatum) serving as vital contributors to both domestic and export markets. These fruit crops, however, are vulnerable to a variety of foliar and fruit diseases that can drastically affect yield quality and quantity, ultimately impacting farmer income and national productivity [1]. In tropical and subtropical regions, diseases such as anthracnose (Colletotrichum gloeosporioides), powdery mildew (Oidium mangiferae), and bacterial leaf spot commonly attack mango leaves, leading to dark lesions, defoliation, and reduced photosynthetic activity [3]. Guava trees face similar threats, including algal leaf spot (Cephaleuros virescens), guava rust, and wilt, which result in discoloration and early leaf fall [4]. Pomegranate crops often suffer from cercospora leaf spot and bacterial blight, both of which can cause extensive damage to leaves and fruits [5]. Traditionally, disease identification has relied on visual inspection by farmers or experts. While this approach can be effective for small orchards, it becomes inefficient and error-prone in largescale operations. Moreover, early-stage symptoms are often subtle and can be misdiagnosed even by trained observers. These challenges highlight the need for automated, accurate, and scalable solutions for early disease detection. Recent developments in artificial intelligence (AI) and deep learning have revolutionized crop disease diagnosis. Convolutional Neural Networks (CNNs) can automatically learn hierarchical visual features from images, allowing accurate classification of disease types [6]. Popular architectures such as VGG16, ResNet50, and InceptionV3 have demonstrated robust performance in identifying plant diseases, while object detection frameworks like YOLOv5 extend these capabilities to real-time localization of infected regions [7]. Furthermore, the introduction of Federated Learning (FL) has enabled collaborative model training across multiple farms without centralized data transfer, enhancing privacy and scalability. Despite these advancements, several challenges persist. These include interclass similarity, where visually distinct diseases appear similar, and intra-class variability, where the same disease presents differently under varying environmental conditions. Additional issues such as class imbalance and poor generalization under diverse lighting and backgrounds also affect performance. Addressing these issues is crucial for building reliable and deployable disease recognition systems. This review consolidates and critically examines existing deep learning methods for multi-class classification of leaf diseases in mango, guava, and pomegranate crops. It discusses the datasets, architectures, and evaluation metrics used across studies, while identifying research gaps that hinder large-scale deployment.

1.1. Importance of Disease Detection in Mango, Guava, and Pomegranate

Mango plantations are prone to fungal and bacterial diseases such as Anthracnose, Powdery Mildew, and Bacterial Canker. Guava crops are affected by Wilt, Algal Leaf Spot, and Anthracnose, while Pomegranate often suffers from Bacterial Blight and Cercospora Leaf Spot [8?]. These diseases directly impact fruit yield and quality, leading to post-harvest losses and reduced export potential. Automated disease detection can help farmers respond promptly, minimize chemical usage, and improve sustainability.

1.2. Limitations of Traditional Detection Methods

Manual inspection is the most common method for identifying plant diseases in the field. However, it is timeconsuming, subjective, and unsuitable for large orchards. Additionally, inconsistent lighting, background clutter, and human fatigue contribute to misclassification of early symptoms. These limitations necessitate automated systems capable of high accuracy under diverse environmental conditions.

1.3. Advances in Deep Learning for classification of plant diseases

Recent advances in computer vision have made deep learning a transformative tool for agriculture [13]. CNN architectures such as VGG16, ResNet50, and InceptionV3 have achieved high classification accuracy in plant disease recognition [12]. Detection frameworks like YOLOv5 enable localization of diseased regions in real time, while Federated Learning facilitates decentralized model training across farms without data sharing [9]. Hybrid models combining CNN with classifiers like Random Forest (RF) and Support Vector Machine (SVM) have also improved performance for small datasets [11].

1.4. Need for a Comprehensive Review

Although individual studies have addressed disease detection in mango, guava, and pomegranate, few have compared their performance or evaluated multi-crop adaptability. Existing literature rarely discusses trade-offs between model complexity, computational efficiency, and deployment feasibility—factors essential for real-world agricultural use.

II. RELATED WORKS

Deep learning has rapidly evolved as a practical and reliable approach for plant disease classification, replacing earlier manual and rule-based techniques. Traditional image analysis methods often relied on handcrafted texture or color features, which performed inconsistently under variable field conditions. Recent research demonstrates that neural network architectures, especially convolutional models, can extract subtle image patterns to achieve highly accurate disease recognition. This section reviews key studies focusing on mango, guava, and pomegranate leaf disease detection.

2.1. Guava Leaf Disease Detection

Guava trees are vulnerable to several leaf infections, including anthracnose (Colletotrichum gloeosporioides), algal leaf spot (Cephaleuros virescens), rust, and wilt. These diseases cause visible changes in color, texture, and shape, often making manual diagnosis difficult. Sanap et al. [9] introduced GuavaCareNet, a federated CNN model trained on distributed farm datasets. Their method preserved data privacy while maintaining strong accuracy (approximately 96) across multiple categories. The approach highlights how federated architectures can support collaborative learning without the need for centralized data collection. Chaskar et al. [21] developed a CNN-based framework for general crop leaf disease detection.

Figure 1: Guava Leaf Diseases: Anthracnose, Algal Leaf Spot, and Rust (Sample Image)

2.2. Mango Leaf Disease Detection

Mango crops frequently suffer from fungal and bacterial diseases such as anthracnose, powdery mildew, bacterial canker, and leaf blight. These infections lead to black spots, powdery coatings, or necrotic edges, which degrade leaf photosynthesis. Researchers have explored various CNN architectures to classify these diseases with high precision. Patil et al. [12] applied transfer learning using ResNet50 and achieved accuracy above 95. In another study, Deshmukh and Patil [3] integrated YOLOv5 for real-time detection, enabling field-level monitoring on edge devices.

Figure 2: Mango Leaf Disease: Anthracnose caused by Colletotrichum gloeosporioides (Sample Image)

2.3. Pomegranate Leaf Disease Detection

Pomegranate plants are susceptible to cercospora leaf spot (Cercospora punicae), bacterial blight (Xanthomonas axonopodis), and alternaria leaf spot, among others. These conditions produce irregular dark patches or oily lesions, often spreading from leaves to fruits. Gokhale et al. [11] developed a hybrid classifier combining CNN and Random Forest, which improved precision and recall compared to single-model CNNs. Other researchers [?] combined CNNs with Support Vector Machines (SVM) for secondary classification, allowing better handling of small, imbalanced datasets.

Figure 3: Pomegranate Leaf Disease: Cercospora Leaf Spot (Sample Image)

2.4. Transfer Learning, Object Detection, and Federated Models

Due to the limited size of agricultural datasets, transfer learning has become a common strategy for training deep models efficiently. Pre-trained networks such as ResNet, InceptionV3, and DenseNet have been adapted for plant disease recognition by fine-tuning on leaf images [13]. Beyond classification, object detection frameworks such as YOLO and Faster R-CNN have been used to identify infected leaf regions precisely. Meanwhile, federated learning frameworks [7] have enabled multi-location model training without the need for direct data sharing, which supports privacy and scalability.

2.5. Comparative Studies and Open Challenges

Several comparative analyses have benchmarked popular architectures across different fruit species. Figure 4 shows a performance summary of representative deep learning models. Although CNN-based and hybrid approaches perform well, major challenges remain particularly in handling class imbalance, inter-class similarity, and variation in lighting or image quality. Explainability also remains an emerging concern, as most deep models function as "black boxes" without offering clear visual reasoning for their predictions.

III. DATASETS AND PREPROCESSING

Several datasets have been used in literature to train and validate leaf disease classifiers. One of the widely adopted datasets is MangoLeafBD, which consists of approximately 4,000 images of mango leaves across seven disease categories, including healthy samples [14]. Another mango dataset from Mendeley offers 2,336 processed leaf images and 12,730 augmented variants [15]. For guava, the GLDAD dataset categorizes leaf images into classes such as anthracnose, scorch, rust, and yellowing (66,000 images) [16]. A combined guava leaf + fruit dataset includes 3,432 real images with leaf diseases like cancer, rust, anthracnose, and dot [17]. In pomegranate, researchers collected 1,245 leaf images covering healthy, Alternaria, and bacterial blight classes [18], while another study used 201 images for disease classification on pomegranate leaves [19]. To support multispecies models, the PlantDoc dataset offers 2,598 annotated leaf disease samples across 13 plant species and 17 disease classes [20].

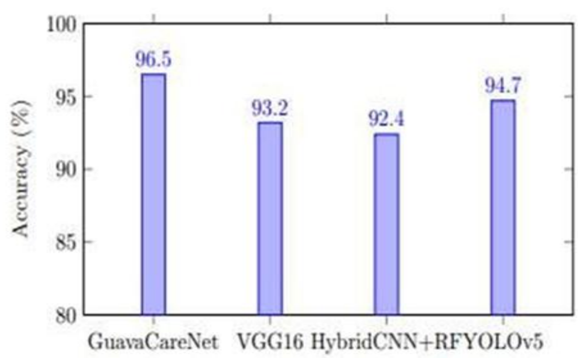

Figure 4: Accuracy comparison of deep learning models across mango, guava, and pomegranate leaf datasets

3.1. Common Preprocessing Techniques
Resizing: Input images are resized (e.g., 224×224 or 256×256) to match CNN model requirements.
Normalization: Pixel values are scaled to [0, 1] or standardized using dataset mean and variance.
Data Augmentation: Random rotations, flips, zoom, and brightness/contrast adjustments are used to increase dataset diversity.

Segmentation:
In some studies, leaf segmentation is performed to isolate diseased regions. The proposed system follows a multi-model strategy that processes image data from mango, guava, and pomegranate leaves independently before integrating the results into a unified classifier. Each crop-specific dataset undergoes preprocessing, splitting, and model training in parallel. After training and evaluation, the best performing models are combined into an ensemble to generate the final classification output. This approach leverages the unique visual characteristics of each crop while ensuring that the overall system generalizes effectively across different fruit species.

IV. METHODOLOGY

The proposed methodology adopts a modular pipeline for end-to-end plant leaf disease classification. It is structured into four major stages, as illustrated in Figure 5.

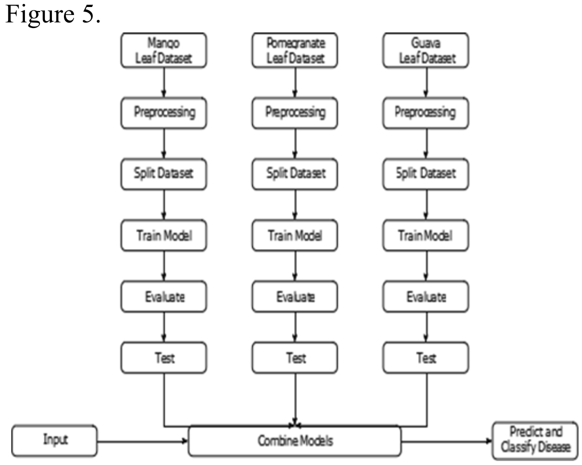

Figure 5: Proposed Multi-Model Architecture

1. Image Acquisition:
High-quality images of mango, guava, and pomegranate leaves affected by various diseases were collected from publicly available repositories such as MangoLeafBD, GLDAD, and PlantDoc. The inclusion of multiple datasets ensures diversity in lighting, background, and disease severity conditions.

2. Preprocessing:
Each image was resized to a uniform resolution of 224 × 224 pixels and normalized to improve numerical stability during training Data augmentation techniques such as random rotation, flipping, brightness

adjustment, and contrast enhancement were applied to mitigate overfitting and improve model robustness.

3. Feature Extraction:
Deep features were extracted using a pre-trained ResNet50 network, which captures hierarchical spatial representations of the leaf texture and color distribution. The network's convolutional layers were fine-tuned on crop-specific datasets to adapt to subtle variations among disease categories.

4. Multi-Head Classification:
The extracted features were fed into three separate classification heads, each corresponding to one crop type. Each head was optimized independently using softmax activation to produce multi-class probability outputs. The results were later combined in a weighted fusion stage to generate the final disease class prediction. This modular design allows reusability of pre-trained weights while supporting scalability for additional crop species. It also enables integration with federated learning frameworks, where each model head can be trained on decentralized data sources without compromising privacy. The entire pipeline is designed for deployment on edge devices to support real-time diagnosis in agricultural setting s.

V. FUTURE WORK

Although deep learning has significantly improved the accuracy of plant disease classification, its practical implementation in agricultural environments still faces several barriers. Future research should aim to make these systems more accessible, transparent, and adaptable to real-world farming conditions. First, there is a growing need to develop multi-crop, unified models capable of identifying both crop species and disease categories within a single network. Such models could drastically reduce the need for crop-specific training data and improve scalability across different regions. Second, researchers should focus on building larger, standardized datasets that capture seasonal variations, natural lighting conditions, and real field backgrounds. Datasets collected from different geographical zones would help improve the generalization capability of deep learning architectures. Third, incorporating explainable AI (XAI) mechanisms can enhance farmers' trust in model predictions. Visualization techniques such as Grad-CAM and feature attribution methods can help illustrate which leaf areas influence a model's decision, making the diagnosis more interpretable. Fourth, the design of lightweight and energy-efficient models is essential for deployment on mobile or edge devices. Compressed networks and model quantization can enable real-time disease detection without requiring high-end GPUs. Finally, the integration of Internet of Things (IoT) and remote-sensing technologies with deep learning pipelines can create holistic crop health monitoring systems. By combining ground-level leaf analysis with aerial imagery from drones or satellites, researchers can establish early warning systems for large-scale disease outbreaks. Overall, the next stage of research should move toward creating sustainable, privacy-preserving, and farmer-friendly intelligent systems that can operate effectively in resource constrained environments.

VI. CONCLUSION

This review examined the progress of deep learning techniques in the multi-class classification of leaf diseases in mango, guava, and pomegranate crops. The studies discussed demonstrate that architectures such as CNNs, transfer learning models, and federated frameworks have achieved promising results for image based disease identification. However, most of these solutions are evaluated under controlled conditions, which limits their usability in real-world agricultural settings. A key observation from the literature is that model performance heavily depends on dataset diversity and preprocessing quality. While high accuracies are frequently reported, issues like class imbalance, limited generalization, and lack of interpretability remain unresolved. These limitations point toward the need for more inclusive datasets and transparent model designs.

In conclusion, deep learning continues to hold immense potential for transforming plant disease management. Its success, however, will depend on the development of explainable, lightweight, and easily deployable systems that bridge the gap between research prototypes and field applications. By addressing the existing challenges, future frameworks can contribute to more sustainable and data-driven agricultural practices, ultimately empowering farmers with accurate and timely decision-support tools. across diverse environments article.

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