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Hybrid Deep Learning Architectures for Automated Mango Leaf Disease Detection

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Abstract

India is one of the biggest producers and exporters of mangoes in the world, yet its cultivation is persistently threatened diseases that reduce yield, fruit quality, and orchard longevity. Traditional disease diagnosis is based on agronomists' hand visual inspection, which is a laborious, subjective, and challenging technique to scale across vast plantations. This research provides a hybrid deep learning system that incorporates AlexNet and ResNet-50 for the automated classification of five commercially relevant mango leaf diseases: Bacterial Canker, Anthracnose, Powdery Mildew, Sooty Mould and Healthy foliage. Through a fused, jointly trained classification head, the suggested architecture combines the deep, residual feature hierarchies of ResNet-50 with the shallow, texture-sensitive representations learned by AlexNet, enabling the network to take advantage of complementary visual cues that neither backbone fully captures on its own. The hybrid model was implemented and trained using MATLAB. The trained model achieved a validation accuracy of 99.47%. Comparative analysis against standalone AlexNet, standalone ResNet-50, and other architectures reported in the recent mango plant-disease literature indicates that the hybrid fusion strategy offers a favourable balance of accuracy and convergence stability.

Keywords: Mango Leaf Disease; Hybrid Deep Learning; AlexNet; ResNet-50; Convolutional Neural Network; Feature Fusion; Precision Agriculture; Image Classification.

1. Introduction

Mango often referred to as the “king of fruits,” is one of the most widely cultivated tropical fruit crops, playing a central role in the agricultural economies. Beyond its nutritional and commercial value, mango cultivation supports the livelihoods of millions of smallholder farmers across South and Southeast Asia. However, mango orchards are highly susceptible to a range of fungal, bacterial, and physiological leaf diseases that can substantially reduce fruit yield, degrade fruit quality, and, in severe cases, cause the death of affected branches or entire trees. Diseases such as Anthracnose, Bacterial Canker, Powdery Mildew, Dieback, and Sooty Mould are among the most commonly encountered afflictions in mango-growing regions, each producing distinct visual symptoms on the leaf surface but frequently overlapping in colour, texture, and lesion pattern, which makes manual diagnosis error-prone even for experienced agronomists. Traditional disease identification depends on manual field inspection, laboratory culture, or expert consultation, all of which are time-consuming, require specialised expertise that is often unavailable in rural areas, and do not scale to the size of commercial orchards. As smartphone penetration and digital connectivity have expanded in agricultural communities, image-based automated diagnosis has emerged as a practical alternative. Advances in computer vision, and specifically deep convolutional neural networks (CNNs), have demonstrated strong performance in fine-grained visual classification tasks, including plant disease recognition, largely because CNNs can learn hierarchical, task-specific visual features directly from raw pixel data without the need for hand-crafted feature engineering.

Among the pre-trained CNN architectures commonly repurposed for agricultural image classification through transfer learning, AlexNet and ResNet-50 occupy complementary positions in the design space. AlexNet, introduced by Krizhevsky, Sutskever, and Hinton, was the first deep CNN to demonstrate a dramatic improvement over traditional computer vision techniques on the ImageNet Large Scale Visual Recognition Challenge, using a relatively shallow eight-layer architecture with large convolutional filters that are particularly effective at capturing coarse texture and colour information. ResNet-50, introduced by He et al., is a much deeper 50-layer network that uses residual (skip) connections to overcome the vanishing-gradient problem, enabling it to learn more abstract, hierarchical, and discriminative features than shallower networks. Because AlexNet and ResNet-50 encode different types of visual information at different levels of abstraction, combining their learned representations in a single hybrid model offers the potential to capture a richer, more complementary feature space than either network alone, motivating the hybrid design proposed in this paper.

2. Literature Review

Automated plant disease detection using deep learning has been an active research area since Mohanty, Hughes, and Salathé demonstrated that a deep CNN trained on the PlantVillage dataset of 54,306 leaf images could identify 14 crop species and 26 diseases with a held-out test accuracy of 99.35%, establishing the feasibility of CNN-based diagnosis under controlled imaging conditions [1]. Following this, numerous studies applied and compared standard CNN backbones — including AlexNet, VGGNet, GoogLeNet, and ResNet — across a range of crops, generally finding that deeper, residual architectures achieve modest but consistent accuracy gains over shallower networks, at the cost of increased computational demand and training time [2, 3].

2.1 Deep Learning Approaches Specific to Mango Leaf Disease

Several recent studies have focused specifically on mango leaf disease classification. Thaseentaj and Ilango proposed a customised deep CNN for South Indian mango leaf diseases — including Anthracnose, Powdery Mildew, and Leaf Blight — and reported a classification accuracy of 93.34%, outperforming conventional CNN baselines on their collected dataset [4]. Mahbub et al. developed a lightweight CNN (LCNN) for seven-class mango leaf disease detection and benchmarked it against pre-trained VGG16, ResNet-50, ResNet-101, and Xception models, finding that their LCNN achieved the highest accuracy at 98%, exceeding all of the pre-trained baselines [5]. Mehta et al. applied a federated-learning CNN framework across four distributed clients for five mango disease classes (Healthy, Anthracnose, Powdery Mildew, Leaf Spot, and Leaf Curl), reporting accuracy in the 97–98% range with precision between 93.33% and 96.01% [5].

Iqbal et al. applied a pre-trained AlexNet architecture with transfer learning to a combined grape and mango leaf disease dataset of 8,438 images, achieving 99% accuracy on grape leaves but only 89% on mango leaves, illustrating that AlexNet alone can struggle to generalise on the more visually heterogeneous mango disease classes [6]. Arivazhagan and Ligi applied a CNN-based approach to a six-class mango dataset and obtained 96.67% accuracy [7]. A more recent study exploring 20-plus CNN architectures for eight-class mango leaf disease classification reported that a custom-tuned CNN could reach approximately 99% accuracy after extensive architecture search and hyperparameter tuning [8], underscoring that very high accuracy on mango leaf datasets is achievable but often requires either extensive architecture search or ensemble/fusion strategies rather than a single off-the-shelf network.

A comparative study evaluating a baseline CNN, AlexNet, ResNet, and EfficientNet on the same Kaggle Mango Leaf Disease dataset (4,000 images across Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, Sooty Mould, and healthy classes) found that the baseline CNN reached 92.61% test accuracy, AlexNet reached only 90.2% validation accuracy with visible overfitting, ResNet converged efficiently to 96.7% validation accuracy within a few epochs due to its residual connections, while EfficientNet achieved the best overall generalisation at 97.8% validation accuracy [9]. This pattern — in which AlexNet alone underperforms deeper residual and compound-scaled networks — is a recurring finding across the literature and forms part of the motivation for combining AlexNet with a deeper network such as ResNet-50 rather than relying on AlexNet in isolation.

2.2 Hybrid and Ensemble CNN Architectures

Because individual CNN backbones tend to capture different, partially complementary aspects of an image — shallow networks emphasising local texture and colour, and deep residual networks emphasising hierarchical shape and structural abstraction — a growing body of work has explored combining multiple pre-trained networks through ensembling or feature-level fusion. Khanramaki et al. built an ensemble deep learning model fusing ResNet-50, AlexNet, VGGNet-16, and InceptionResNetV2 for citrus disease recognition, obtaining 89.04% accuracy, and noted that the benefit of fusion depends heavily on how complementary the constituent networks' errors are [10]. A more recent ensemble-based feature-fusion study combining VGG16, ResNet-50, and InceptionV3 for general plant disease classification reported that while the individual backbones scored 93.50% (VGG16), 93.03% (ResNet-50), 94.30% (InceptionV3), 94.54% (EfficientNet), and 91.30% (AlexNet), the fused ensemble reached 97.00% accuracy, and that a separate triple fusion of VGG16, InceptionV3, and AlexNet reached 95.89%, both clearly outperforming any single constituent network [11].

Similar gains from architectural fusion have been reported outside the mango domain. An ensemble CNN for mango disease detection that concatenated multi-level features from GoogLeNet and VGG16 reported training, validation, and testing accuracies of 99.87%, 99.72%, and 99.21% respectively over 100 training epochs, showing very close agreement between training and validation curves and minimal overfitting [12]. In coffee leaf disease classification, a hybrid EfficientNetB3–ResNet-50 model enhanced with a squeeze-and-excitation (SE) attention block was shown to improve channel-wise feature recalibration and classification accuracy over either backbone individually [13]. More recent work has also begun fusing convolutional backbones with transformer-based architectures: a hybrid EfficientNet-B7 and Vision Transformer (ViT-B16) framework was proposed to combine strong local spatial feature extraction with global contextual modelling for general plant disease classification [14], while a ConvNeXt–Vision Transformer fusion model was specifically developed for mango leaf disease classification, motivated by the observation that purely convolutional models struggle to capture long-range dependencies needed to distinguish visually similar disease symptoms [15].

2.3 The Kaggle / MangoLeafBD Dataset

Several of the studies reviewed above, including the present work, draw on the publicly available MangoLeafBD dataset compiled by Ali et al. [16]. The dataset comprises approximately 4,000 high-resolution images collected from mango orchards in Bangladesh, organised into eight classes: Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, Sooty Mould, and Healthy, with 500 images per class [17, 18]. For the present study, a five-class subset corresponding to Bacterial Canker, Anthracnose, Powdery Mildew, Dieback, and Sooty Mould was used, reflecting the diseases of greatest agronomic significance for the target orchard population.

3. Proposed Methodology

3.1 Overview of the Proposed Framework

The overall workflow of the proposed system consists of four stages: (i) image acquisition and dataset preparation, (ii) pre-processing and augmentation, (iii) dual-backbone feature extraction using AlexNet and ResNet-50, and (iv) feature fusion and classification. The architecture used to combine the two backbone networks into a single hybrid classifier capable of distinguishing five mango leaf disease classes.

3.2 Dataset Description

The dataset used in this study consists of mango leaf images spanning five disease categories of primary agronomic concern: Bacterial Canker, Anthracnose, Powdery Mildew, Sooty Mould and Healthy leaves. Bacterial Canker is caused by Xanthomonas campestris pv. mangiferaeindicae and manifests as water-soaked, raised lesions that later turn dark brown and crack. Anthracnose, caused by the fungus Colletotrichum gloeosporioides, produces irregular dark, sunken necrotic spots that can coalesce and cause leaf tissue death. Powdery Mildew, caused by Oidium mangiferae, appears as a white to greyish powdery fungal coating on the leaf surface. Sooty Mould develops as a black fungal layer on the leaf surface, typically growing on the honeydew secretions of sap-feeding insects rather than infecting the leaf tissue directly.

3.3 Pre-processing and Data Augmentation

Prior to training, all images were resized to match the fixed input dimensions required by the two backbone networks. To improve generalisation and reduce the risk of overfitting given the moderate dataset size, standard data augmentation was applied during training. The augmented dataset was partitioned into training and validation subsets, with the validation split used for periodic evaluation of the network during training.

3.4 Hybrid AlexNet–ResNet-50 Architecture

The proposed hybrid model combines AlexNet and ResNet-50 as parallel feature-extraction branches feeding into a shared classification head, rather than using either network in isolation. Each input image is passed independently through both backbones. The two feature vectors produced by the AlexNet and ResNet-50 branches are concatenated into a single fused feature vector. This fused representation is passed through a newly initialised fully connected fusion layer, followed by a ReLU activation and a dropout layer to mitigate overfitting, and finally a five-way fully connected classification layer with softmax activation corresponding to the five target disease classes. Only the newly added fusion and classification layers, together with the final blocks of each backbone, were fine-tuned during training, while the earlier convolutional layers of both AlexNet and ResNet-50 retained their ImageNet-pretrained weights, consistent with standard transfer-learning practice for moderately sized agricultural image datasets.

4. Results and Discussion

4.1 Training and Validation Performance

The proposed hybrid AlexNet–ResNet-50 model, as recorded directly by MATLAB's Deep Network Designer over the full 30-epoch (1,620-iteration) training run. The upper plot shows classification accuracy (%) on the vertical axis against training iteration on the horizontal axis. The lower plot shows the corresponding cross-entropy loss curves for training and validation.

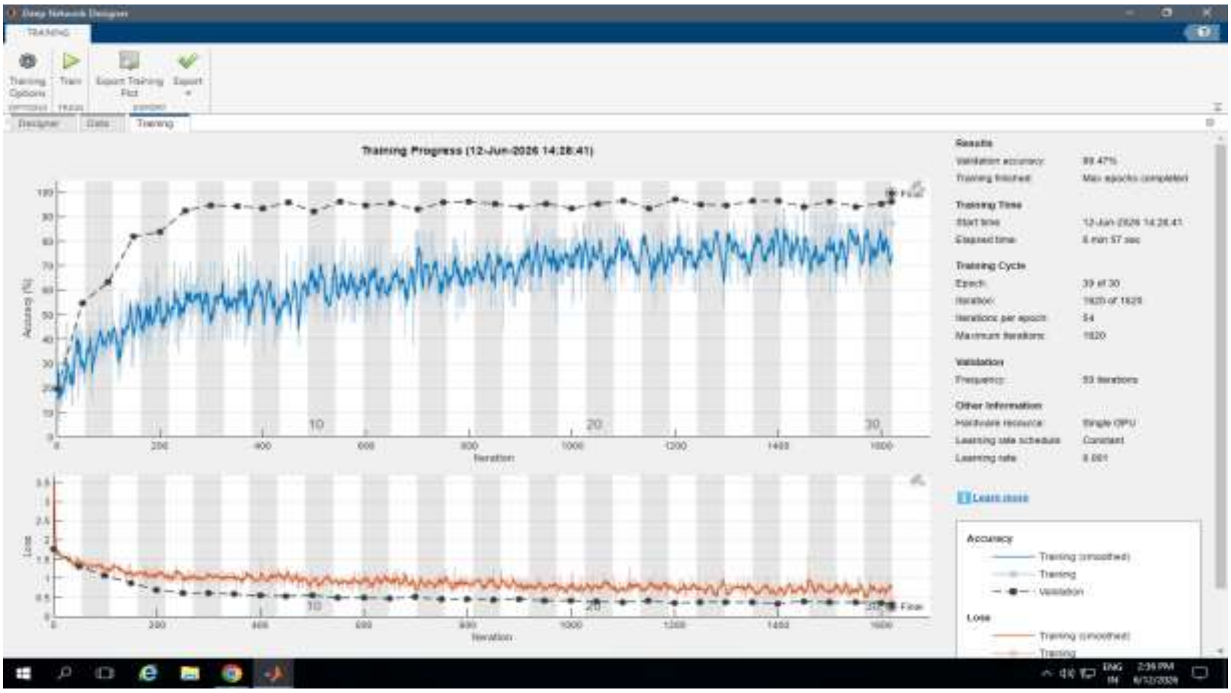

Figure 1. Training and validation accuracy of proposed hybrid AlexNet–ResNet-50 model

As shown in Figure1 training accuracy rises rapidly during the first few epochs, from approximately 20% at initialisation to over 50% within the first 200 iterations, before continuing a slower, noisier upward trend and stabilising in the 70–80% range for raw mini-batch accuracy by the final epochs. Critically, the validation accuracy curve rises much more quickly and consistently than the raw training curve, reaching approximately 90% by iteration 200 and continuing to climb steadily thereafter, ultimately reaching a final validation accuracy of 99.47% at the end of training.

4.2 Comparison with Other Models

Table 1 situates the 99.47% validation accuracy achieved by the proposed hybrid AlexNet–ResNet-50 model against results reported in recent literature for mango leaf disease classification and closely related plant-disease fusion studies. Because different studies use different dataset splits, class counts, and image counts, the comparison should be interpreted as an indication of relative performance trends across the field rather than a strictly controlled benchmark.

Study / Model	Architecture Type	Dataset / Classes	Reported Accuracy
Proposed Hybrid Model (this paper)	AlexNet + ResNet-50 fusion	Mango leaves, 5 classes	99.47% (validation)
Thaseentaj & Ilango [4]	Customised deep CNN	South Indian mango, 3+ classes	93.34%
Mahbub et al. [5]	Lightweight CNN (LCNN)	Mango leaves, 7 classes + healthy	98.0%
Mehta et al. (federated) [5]	Federated CNN	Mango leaves, 5 classes	97–98%

Iqbal et al. (AlexNet, transfer learning) [6]	AlexNet (standalone)	Mango leaves (grape+mango set)	89.0% (mango)
Arivazhagan & Ligi [7]	CNN (standalone)	Mango leaves, 6 classes	96.67%
ACS Agri. Sci. Tech. custom CNN [8]	Tuned CNN (architecture search)	Mango leaves, 8 classes	~99%
Comparative study – AlexNet [9]	AlexNet (standalone)	Kaggle mango leaves, 8 classes	90.2% (validation)
Comparative study – ResNet [9]	ResNet (standalone)	Kaggle mango leaves, 8 classes	96.7% (validation)
Comparative study – EfficientNet [9]	EfficientNet (standalone)	Kaggle mango leaves, 8 classes	97.8% (validation)
Khanramaki et al. [10]	ResNet-50 + AlexNet + VGG-16 + InceptionResNetV2 ensemble	Citrus leaves	89.04%
Ensemble feature fusion [11]	VGG16 + ResNet-50 + InceptionV3 fusion	General plant leaves	97.00%
GoogLeNet + VGG16 concatenation [12]	Multi-level feature fusion	Mango disease, insect pest	99.21% (test)

Table 1. Comparison of the proposed hybrid model with results reported in the plant leaf disease detection literature.

As Table 1 illustrates, the proposed hybrid model's 99.47% validation accuracy compares favourably with both standalone backbone results and other fusion/ensemble approaches reported in the literature.

5. Conclusion

This paper presented a hybrid deep learning architecture that fuses AlexNet and ResNet-50 for the automated classification of five economically significant mango leaf diseases: Bacterial Canker, Anthracnose, Powdery Mildew, Sooty Mould and Healthy Leaves. By combining AlexNet's efficient, texture-sensitive shallow feature representation with ResNet-50's deep residual feature hierarchy through a fused classification head, the proposed model achieved a validation accuracy of 99.47%. This result compares favourably with standalone AlexNet and ResNet-50 baselines as well as with several other ensemble and fusion-based approaches applied to mango and general plant leaf disease datasets, supporting the broader conclusion that dual-backbone CNN fusion is an effective strategy for fine-grained agricultural disease classification tasks.

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