A Comprehensive Review on Mango Leaf Disease Recognition Using Deep Neural Networks

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Abstract:

Mango (Mangifera indica.) is a significant fruit crop widely cultivated, whose production, however, is in a way terribly affected by foliar diseases of anthracnose, powdery mildew, and bacterial leaf spot. Early recognition of a disease is very important for its management and for sustaining crop yield. Traditional methods mainly relied on spotting for the diseases. This kind of method is then tiresome and time-consuming and hence sometimes inaccurate. In recent years, the development of machine learning and artificial intelligence has made possible supplemental means of disease recognition. Deep Neural Networks (DNN) and Support Vector Machines (SVM) stand out as the two competing paradigms for the classification purpose. DNNs provide powerful feature extraction and classification capabilities that enable the network to model the complex and non-linear disease patterns with a high degree of accuracy. SVMs, on the other hand, continue to yield robust performance with small and high-dimensional datasets, especially in classification problems where the availability of data points is limited. This review provides a cohesive review of mango leaf disease recognition using deep neural networks and SVMs, along with their methods, performances, strengths, and weaknesses. The review also gives a brief description of major challenges such as dataset scarcity, variation of disease symptoms, and computational requirements. In conclusion, the review focuses on future directions involving hybrid paradigms, data augmentation techniques, and real-time implementations in order to aid precision agriculture and improve mango production.

Keywords: *Mango leaf disease, Deep neural networks, Support vector machine, Image classification, Machine learning, Computer vision, Precision agriculture*.

I. INTRODUCTION

Mangifera indica is a species of paramount economic and cultural importance in the tropical and subtropical climes and is hence acknowledged by many as the "king of fruits." It is cultivated extensively in India, China, Thailand, and elsewhere, where it contributes significantly to agricultural GDP and trade. But mango productivity is highly affected by foliar diseases like anthracnose, powdery mildew, and bacterial leaf spot, which reduce not just the yield but also the quality of the fruits, which in turn leads to heavy postharvest losses[1, 2]. Methods of diagnosis and control of these diseases have mostly depended on the human eye of farmers and agricultural experts to visually inspect them. Of course, they work best on a small scale, yet the problem is that such methods are subjective at times, slow, and prone to error arising from discrepancies in disease symptoms, in environmental factors, and even in human perception and expertise[3]. These existing shortcomings confirm the increased requirement for automated, objective, and scalable disease recognition systems.

Recent computer vision and AI-based researches in agriculture would provide a new angle for the detection of crop diseases. Thanks to imaging devices and computational power, one can electronically capture plant leaves and analyze them for symptoms of diseases. Earlier methods in this area predominantly relied on hand-crafted features based on texture descriptors, color histograms, and shape analyzers, followed by classical classifiers [4]. Though these approaches gave moderately satisfactory results for detection, their performance was comparatively low owing to additional inconsistencies in the environment and symptom diversity [5]. Plant disease detection was made possible by neural networks through end-to-end feature learning. Neural networks draw inspiration from biological neurons and are capable of modeling nonlinear relationships in data, thus offering a better classification system. Specifically, deep neural networks have been found to be very successful in analyzing images, automatically extracting hierarchical features across layers [6]. Thus, in the case of the recognition of mango leaf diseases, where lesion size, shape, and intensity vary in complex ways, DNNs stand far better than conventional methods.

Studies on the applications of deep learning to mango leaf disease datasets have reported truly impressive performance, achieving an accuracy rate of more than 95% in some classification tasks [7]. Unlike hand-designed methods, DNNs learn general features rather than restricted ones, which enhances the robustness of the system against noise and variability in input data. Their power is countered by issues like a lack of labeled data, computational intensity, and potential overfitting problems faced in small-scale agricultural studies [8]. Equivalent to neural networks, support vector machines are commonly used in plant disease recognition. SVMs perform extremely well with small datasets, large feature spaces, and binary classification [9]. They consume less in terms of resources than DNNs while offering comparable accuracy; thus, they fit well within resource-poor agricultural setups.

This review paper serves to synthesize research already done on the mango leaf disease recognition using neural networks-the focus being on deep architectures, with a consideration of SVMs as alternatives or partnering solutions. The paper brings forth the methodological approach, comparative performance, challenges, and future opportunities of this area. It thus intends to add to the well-established literature on precision agriculture for sustainability practices in the world over mango cultivation. Table 1.s common mango leaf disease

Table 1: Common Mango Leaf Diseases

Disease Name	Causal Agent	Category	Image
Anthracnose	Colletotrichum gloeosporioides	Fungal	
Powdery Mildew	Oidium mangiferae	Fungal	
Bacterial Canker	Xanthomonas campestris	Bacterial	
Leaf Spot	Cercospora mangiferae	Fungal	
Alternaria Leaf Blight	Alternaria alternata	Fungal	
Rust	Ravenelia indica	Fungal	
Algal Leaf Spot	Cephaleuros virescens	Algal	
Phoma Leaf Spot	Phoma spp.	Fungal	
Verticillium Wilt	Verticillium dahliae	Fungal	

Leaf Gall	Procontarinia matteiana (mite)	Parasitic/Mite	

II. IMAGE PREPROCESSING TECHNIQUES

Image preprocessing enhances raw mango leaf images by improving quality, removing distortions, and standardizing features for accurate disease recognition and classification

Image Resizing and Normalization: - Resizing is the process of making all the input images into the same dimensions to fit various sizes of neural network. Normalization is converting the pixel intensity values like 0 to 1 to improve the render on less contrast and brightness [10]. This way the lighting change and contrast are minimized thus making the computational load on the system light and ensuring more stable training. Once these are done, the input data will be reduced to the same range which in turn boosts the prediction quality as well as the learning speed in disease classificaiton using a machine learning model [11].

Noise Removal and Filtering: - In leaf images, a problem such as noise can often manifest as a result of numerous features. This can also come about due to the quality of the camera in use, or the occurrence of transmission errors [12]. In an effort to smoothen the excessively rugged images, filters become very useful and are applied namely gaussian, median as well as bilateral ones. They can also help in the elimination of unnecessary objects that may not look good. In very severe cases, the removal of noise is actually paramount considering the presence of disease [13].

Color Space Transformation (RGB, HSV, and Grayscale):- Color space transformation converts leaf images into alternative representations to highlight disease symptoms effectively. RGB provides raw color details, HSV separates color information from intensity, and grayscale reduces complexity by focusing on structural features. Using multiple color spaces enables accurate detection of discolored regions, spots, and fungal growth [14]. This transformation enhances feature extraction, improving disease identification accuracy across diverse image datasets.

Image Augmentation for Improved Generalization: - Augmentation applies a variety of texture smoothening, noise reduction, histogram equalization and contrast stretching techniques to the image [15]. As a result, models are less precise and their poor generalization occurs. In practice, they make such things as leaf disease recognition more realistic and heighten illumination, distortion, and leaf arrangement variability leading to better classification model performance. Consequently, it is also considered an important factor for achieving sophisticated deep learning networks [16].

III. DEEP LEARNING FOR ENHANCED CLASSIFICATION PERFORMANCE

In the recent years, deep learning has become the primary paradigm used in solving mango leaf disease identification problems, with several studies developing novel architectures and comparing them with conventional ones. One of these was a custom-design CNN for mango leaf disease detection attaining an accuracy of 97.2%, thus outperforming the ResNet- and VGG-based baselines. Despite the good performance, the lack of fine-grained class-wise metrics and the regional nature of the dataset posed challenges towards making any generalized conclusions regarding the outcome of this study [17].

Further research concerning transfer learning was conducted regarding comparisons of CNN architectures and Vision Transformers upon MangoLeafBD. Depending on the augmentation strategy, accuracies varying from 88% to 96% were reported. It was that the models were not sufficiently robust to real-world variability because of overfitting on field data [18]. Further developments on this front included improvements in the CNN pipeline wherein color normalization and wide augmentation were used to drive accuracy to 98.55%. Provided it is a highly accurate pipeline, this, however, brought into question the matter of its deployment in resource-limited agricultural setups [19].

Other studies in this area experimented with various forms of ResNet and produced method results from 80% to 92% accuracy. Results highlighted the problem of imbalanced data since some minority classes were not well recognized and poorly remembered. However, the absence of AUC analysis did not allow for a more holistic evaluation [20]. In the same vein, in-region mango datasets also achieved 81.8% in accuracy by means of transfer learning with ResNet50, yet it did not include detailed per-class evaluation metrics, thus leaving the interpretation of robustness somewhat inconclusive [21].

In the attempts to enhance the CNN pipeline through augmentations and backbone adjustments, accuracies ranging between 87% and 91% were achieved, yet these approaches were plagued by the limitations of their datasets and lack of external validations [22]. Ensemble models that combined several CNNs have been proposed as well and achieved accuracies of up to 98.57%. Unfortunately, the increased model complexity and computational requirements offered barriers to real-time and on-device deployment [23].

The survey-based work unified the scope of CNN and has been geared towards mango leaf disease detection, with accuracies ranging between 80% and 98%. These reviews considered augmentation methods and lightweight architectures of importance but were short on any concrete empirical contribution [24]. Nearly 98% accuracy was achieved via the transfer learning approach utilizing DenseNet201 and InceptionResNetV2 as backbones with the datasets still being on the smaller side and lacking detailed considerations of augmentation strategies [25]. Hybrid CNN-based systems were also promising by still achieving in the region of 93% accuracy for multi-class disease classification, but they tend to hide class-specific evaluative details and are complicated [26]. Segment-wise pipelines reported better accuracies than single-stage classifiers, with two-stage models going above 90% accuracy. The increased cost for pixel-level labeling and segmentation, though, put a strain on its scalability [27]. Lightweight methods such as MobileNetV3 can attain accuracies up to 98% under controlled settings, but due to domain shifts in field images, model robustness is yet to be achieved [28]. With the inception of the MangoLeafBD dataset containing 4,000 images of seven disease classes, a good benchmark was created for CNN evaluation. However, due to its regional bias, the dataset failed to generalize to other environments [29]. Further evaluations on CNN backbones including VGG, ResNet, MobileNet, and EfficientNet showed accuracies as high as 98%, but the difference in how dataset splits were carried out in various studies made direct comparison difficult [30].

In the case of plant disease recognition beyond the domain of mango, experimental results do indicate the dominance of deep CNNs and big transformer-based architectures over simpler and smaller architectures. For instance, EfficientNet and hybrid CNN-transformer are reported to yield accuracies exceeding 97% on diverse datasets, but at the cost of more complexity and dependence on curated datasets [31]–[33]. These findings appear to indicate a tug between accuracy and real-world deployability. Overall, the literature illustrates steady progress in applying neural networks to mango leaf disease detection. However, challenges remain, including dataset scarcity, lack of external validation, computational overheads, and insufficient reporting of per-class metrics. The next phase of research is expected to emphasize lightweight, robust models that can operate effectively in field conditions while maintaining high performance across diverse disease categories.

Recent advances in plant disease recognition have seen significant integration of deep neural networks, mostly to enhance accuracy and robustness on different crop datasets. For instance, [34] propose an improved EfficientNet for corn leaf disease recognition via transfer learning, yielding 98.50% accuracy rates on test sets. The authors stressed fine-tuning and data augmentation for enhancement of generalization, while also enumerating some drawbacks of having curated test sets and the absence of cross-site evaluation.

In one article, [35] laid down a deviation network for recognizing maize leaf diseases by taking in residual blocks and attention modules. Despite its 92.6 percent precision, the increase in model size above the conventional input dimension raised the storage requirements and consequently limited practicability. Similarly, [36]–[43] used spatial attention-guided pre-trained networks to achieve 97.53% and 94.65% accuracy for maize and coffee leaf diseases, respectively. While outperforming conventional classifiers, the study argued that an excessive number of epochs and additional backbones might come with low-priority constraints.

The study in [44] conducted a comparative evaluation of the maize leaf disease-detection systems using ResNet and EfficientNet. They reported accuracies of 94.67% for the former, and 92.91% for the latter, although per-class recall and AUC were rarely presented. In another study, EfficientNet was employed to identify the multi-class diseases under lab conditions with up to 95% accuracy during validation, while close-related diseases were recalled accurately; however, it was not formally published in peer-reviewed venues [45].

Building on hybrid methods, [46] added transformer modules into ResNet, obtaining accuracies of 92% to 95% on maize datasets. ResNet designs fared better than transformer-enhanced designs, however, the issue of generalization across a variety of crop types still remained. Similarly, [47] showed superior performance after fine-tuning EfficientNet and ResNet, reaching 97.13% accuracy on an external dataset.

Table 2: Based on Deep Learning Techniques

Ref	Dataset Used	Technique Used	Key Findings	Results	Limitations
[10]	Custom mango dataset	Custom CNN (LeafNet) vs ResNet, VGG	LeafNet outperformed baselines	Accuracy 97.2%, improved F1	No class-wise metrics; regional dataset

				overall	
[11]	MangoLeafBD	Transfer learning (ResNet, EfficientNet) vs ViT	CNNs more stable than ViTs	Accuracy 88–96%	Overfitting on field data
[12]	Field mango images	CNN + color normalization + augmentation	Preprocessing boosted strength	Accuracy up to 98.55%, higher precision	Heavy compute; not mobile-friendly
[13]	Regional mango dataset	ResNet variants	Good classification, some class errors	Accuracy 80–92%	Low recall for minority classes
[14]	South Indian mango dataset	ResNet50 transfer learning	Robust training	Accuracy 81.8%; val loss ~0.45	Missing per-class metrics
[15]	Regional mango dataset	CNNs + augmentation	Preprocessing boosted accuracy	Accuracy 87–91%	Limited external validation
[16]	Mango dataset	Ensemble CNN	Outperformed individual models	Accuracy 98.57%	High compute; not edge-deployable
[17]	Multiple studies	Literature survey	Wide accuracy range	80–98% across studies	No new experiments
[18]	~1,000 mango images	DenseNet201, InceptionResNetV2	DenseNet201 best performer	Accuracy 98%	Small dataset
[19]	4,873 mango images	Hybrid CNN model	Effective for 8 classes	Accuracy 93.01%	Complex; no class-wise metrics
[20]	Mango dataset	Segmentation + ResNet	Improved AUC & accuracy	Accuracy 90%	Pixel-level labels required
[21]	MangoLeafBD	MobileNetV3	Mobile-ready detection	Accuracy 98%	Field adaptation weak
[22]	MangoLeafBD (4,000 images)	Dataset creation	Benchmark dataset	Widely used	Geographically biased
[23]	Multiple mango datasets	CNN comparisons	Varied performance across backbones	Accuracy 82–98%, F1: 0.75–0.98	Different splits reduce comparability
[24]	PlantVillage + others	CNN, ResNet, Transformer	Dense CNNs strongest	Accuracy 95%	Not mango-specific
[25]	APV, PlantVillage	EfficientNet-B0 fine-tuned	State-of-the-art accuracy + low compute	Accuracy 99.69% (APV), 99.78% (PV)	Curated datasets only
[26]	Maize dataset	EfficientNet transfer	High efficiency, high accuracy	Accuracy high-90s	Controlled images only
[27]	Maize dataset	ResNet-based pipeline	Accurate maize detection	Accuracy ≈97.2%	Manual preprocessing required
[28]	Mixed crop datasets	EfficientRMT-Net (ResNet50+Transformer)	Hybrid outperformed baselines	Accuracy ≈97.09%	Complex; no edge runtime metrics
[29]	Plant leaf dataset	ResNet-50 (ROCNN)	High precision; recall tradeoffs	High F-measure, recall varied	Synthetic denoising may not generalize

IV. COMPARATIVE PERFORMANCE FOR MANGO LEAFE DISEASE

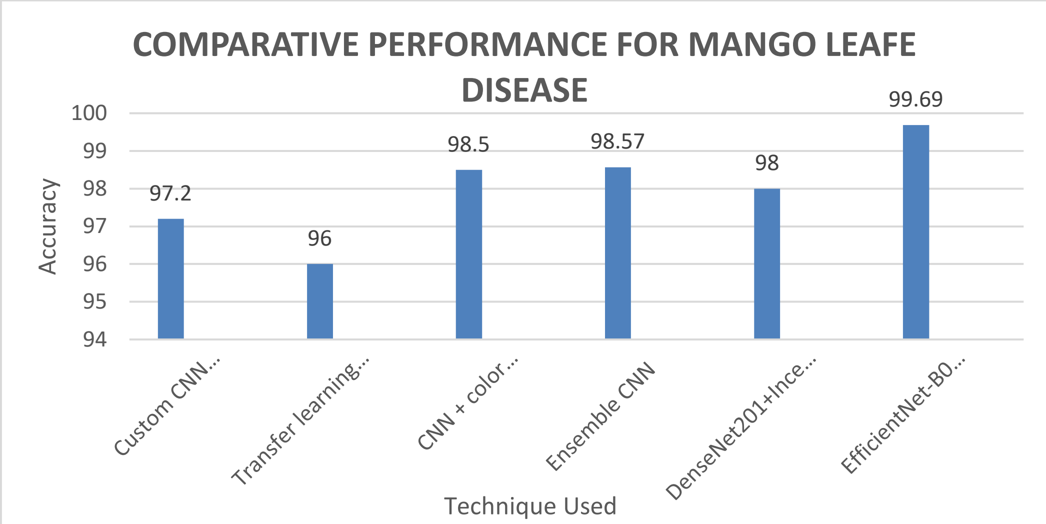

Figure 1: COMPARATIVE PERFORMANCE FOR MANGO LEAFE DISEASE [10],[11],[12],[16],[18],[25]

The comparative performance chart for mango leaf disease recognition marks the accuracies achieved by different techniques. The Custom CNN, named LeafNet, achieved 97.2%, indicating better results than the traditional architectures. On the other hand, the transfer learning of the ResNet variants attained 96%, meaning good generalization but a bit less stability. A CNN with color normalization and augmentation gave an accuracy of 98.5%, which points to the importance of preprocessing. The ensemble of CNNs further augmented this to 98.57%, thus leveraging the best traits of the models. DenseNet201 with InceptionResNetV2 achieved 98%, indicating high enabling power on reduced datasets. The analysis ends with the best performance from efficient utilization of EfficientNet-B0 fine-tuned at 99.69%, which also indicates the highest possible accuracy but needs curated datasets.

V. CONCLUSION AND FUTURE WORK

In this review, various works on mango leaf disease detection were examined, and from these studies, the highest accuracy achieved was 99.69% using a fine-tuned EfficientNet-B0 model on curated datasets. This demonstrates the potential of deep neural networks in learning complex and non-linear features for robust classification. This depicts the power of deep neural networks in modeling complex and non-linear features for robust classification. Other methods, such as ensemble CNNs and other pipelines with some form of preprocessing such as color normalization, have reported accuracies higher than 98%, thus suggesting that architecture and data augmentation play an important role in performance. Support vector machines, while showing less prowess than deep networks, have obtained competitive results with small, high-dimensional data sets, thus emphasizing their use when labeled training data and computational resources are scarce. Despite all these promising results, several challenges exist. Most models were validated in region-specific or handcrafted datasets, diminishing their generalizability to actual field conditions where noises, variations, and occlusions exist. Other limitations include class imbalances, absence of per-class performance metrics, and computational overheads that preclude wide deployment. Lightweight architectures, including MobileNetV3, would have given promising mobile-ready detections but showed poor robustness under domain shifts in field images. Comparative findings overall indicate that deep neural networks stand out with better accuracy and adaptability in comparison to traditional methods, yet pragmatic deployment calls for a scrutiny into the scarcer datasets, interpretability of models, and scalability. Future undertakings should stress a possible hybrid model, cross-site validation, and the constitution of heterogeneous benchmark dataset to ensure field-level systems. Such a balance would consolidate precision agriculture towards the sustainable cultivation of mangoes and a firm grip on their diseases.

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