

A Comprehensive Review of Machine Learning Techniques for Mango Leaf Disease Detection

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Abstract:

Mango is nationally and globally an important fruit-bearing crop and population friendly-prone to various fungoidal leaf diseases that obstruct production and yield. Timely and accurate detection of diseases followed by adequate treatment reduces loss. This review, therefore, investigates image processing methods and machine learning approaches, specifically a Neural Network Ensemble (NNE) and Support Vector Machine (SVM), for recognition of mango leaf diseases. The approach used HSV color transformation, K-means clustering, and Gray-Level Co-occurrence Matrix (GLCM) for feature extraction, whereas classification was employed by SVM. The system had an averaging accuracy of 80% for four common diseases: Dag, Golmachi, Moricha, and Shutimold. This paper thereby presents machine learning in smart agriculture as a promising tool, efficient for plant disease detection as an alternative to manual detection.

Keywords: Mango Leaf Disease , Image Processing ,Neural Network Ensemble, Support Vector Machine, Feature Extraction, Smart Agriculture

I. INTRODUCTION

Mango is considered the king of fruits by botanists-and thus represents an extremely important tropical fruit in the economy and for cultivation throughout Asia, Africa, and Latin America [1]. In countries like India, Bangladesh, and Pakistan, the cultivation of mangoes, in fact, forms a major share of agricultural income and foreign exchange revenue. Production and mango quality are indeed much affected due to the occurrences of a range of diseases, the leaf being usually the first noticeable symptom of plant health problem [2]. It has been reported that mango leaf diseases, such as Anthracnose, Powdery Mildew, Mango Malformation, Bacterial Canker, Red Rust, and Shutimold, cause significant yield losses. For example, the worldwide crop damage caused by Anthracnose can go up to 39%, whereas Mango Malformation has been noted to affect more than 50% of the trees in some regions. These diseases impair the photosynthetic capacity of leaves, inhibit fruit growth, and in extreme instances, result in premature fruit drop or death of the tree [3].

The conventional modes of disease identification depend on visual inspection by an expert agriculturist. These traditional methods are time-consuming, highly subjective, and often inaccurate, especially during early infections or in large-scale farming fields [4]. With an ever-increasing food demand and decreasing agricultural labor, plant disease detection has to be automated, scalable, and accurate. Agricultural diagnosis mainly has been a diagnostic specialty on the manual side until the recent advances in applied imaging and machine learning. These can classify diseases by leaf color, texture, and shape to enable an early solution and better crop management [5]. The purpose of this review is to study the developments in mango leaf disease recognition techniques, particularly those that rely on neural networks and support vector machines to automate and improve the diagnosis of mango diseases [6].

A. Image Processing Techniques in Leaf Disease Recognition

Early detection systems and plant leaf disease classification in image processing bear huge importance, since with mango, for example, which requires very early intervention to prevent huge-scale yield losses. Image processing, in the setting of an automated mango leaf disease recognition system, is the first stage wherein raw visual data are prepared for successful classification using machine learning [7]. This section presents a big picture of common image processing techniques used in their identification, particularly in color space conversions, segmentation methods like K-means clustering, and some necessary preprocessing techniques.

Mostly, image processing starts with image acquisition. In order to maintain data quality, the raw images are enhanced with preprocessing techniques to improve their quality and remove noise. Some examples of preprocessing include resizing, color balancing, contrast adjustment, and noise filtering [8]. Such processes maintain the standard data format and reduce

variations induced by environmental factors outside the scene. Image preprocessing techniques involve color space conversions. While the standard RGB color space is most widely used, it is not always adequate to capture perceptual differences. To detect mango leaf diseases, conversion of RGB images to more perceptually relevant spaces such as HSV (Hue, Saturation, Value) or Lab color space has been found useful [9].

After the color conversion process, segmentation is applied to differentiate the area affected by disease on one side and the healthy parts of the leaf on the other [10]. One of the comprehensible unsupervised segmentation methodologies used in this domain is k-means clustering. It classifies the pixels on the basis of the feature similarity (for instance, color intensity) so that infected regions stand out clearly. In this regard, K-means clustering is useful in breaking down an image into meaningful clusters, thus reducing the complexity of the input data and helping to concentrate on the areas that may contain disease-relevant information [11]. Morphological operations and edge detection methods like Sobel or Canny filters may then be applied to further process the segmentation to crisp up the final outline of the diseased spots and hence help in accurate localization of the regions. Features are then extracted from these regions, where texture, statistic, and shape features are used to train the classifiers, such as support vector machines or neural networks [12].

Collectively, the image processing steps aim to transform unstructured image data into structured, meaningful representations that can be directly considered by machine learning algorithms. The accuracy of disease classification majorly depends on the quality and the method of preprocessing and segmentation employed, respectively. When image quality improves and with increasing diversity, so do the techniques that accommodate the latest ones such as deep feature maps and adaptive thresholding. In general, image processing still acts as the backbone of automatic leaf disease identification systems. It promotes better accuracy for classification and real-time application scaling for smart agriculture, thus becoming indispensable for future prospects in crop disease management [13].

Table:1 Common Mango Leaf Diseases with Symptoms and Causes

Disease Name	Symptoms	Causes
Anthrachnose	Dark, sunken lesions on leaves; black spots may coalesce and cause leaf drop	<i>Colletotrichum gloeosporioides</i> (fungus)
Powdery Mildew	White, powdery fungal growth on leaf surface; leaf curling or distortion	<i>Oidium mangiferae</i> (fungus)
Mango Malformation	Deformed leaf structures; twisted and bunched young leaves	<i>Fusarium mangiferae</i> (fungus), hormonal imbalance
Bacterial Canker	Water-soaked, dark, raised lesions on leaf veins; cracking and gum exudation	<i>Xanthomonas campestris</i> pv. <i>mangiferaeindicae</i> (bacterium)
Red Rust	Reddish-orange spots; velvet-like pustules that may turn black over time	<i>Cephaleuros virescens</i> (alga)
Shutimold	Sooty black mold on leaves, often seen after insect infestation (ants, aphids)	<i>Capnodium spp.</i> (fungal mold growing on insect honeydew)
Golmachi	Circular, oily dark green spots turning brown; may be surrounded by yellow halos	Fungal infection (less studied)
Moricha Disease	Brown-black patches with rough texture; premature leaf drying	Likely due to fungal pathogens

II. LITERATURE REVIEW

A. CNN for Automatic Feature Extraction

S. I. Ahmed *et al.* [1] (2022) **propose** the MangoLeafBD dataset comprising over 4,000 labeled mango leaf images across seven disease categories, enabling CNNs to automatically learn robust feature hierarchies for disease classification. Their work removes the need for handcrafted features and supports end-to-end CNN training. However, **limitations** arise in cross-variety adaptability and environmental variability.

R. A. Rizvee *et al.* [2] (2023) **propose** LeafNet, a custom CNN trained to detect Anthracnose and Powdery Mildew by automatically learning spatial and texture features from leaf images. It achieves high accuracy and bypasses the need for manual feature engineering. Nonetheless, **limitations** exist in generalizing across noisy backgrounds and field images.

V. Krishna Pratap and N. Suresh Kumar [3] (2024) **propose** a deep learning approach using transfer learning with CNN models (VGG16, MobileNet, EfficientNet) to extract automatic features from mango leaf datasets. They report excellent

performance in disease identification without preprocessing. However, environmental diversity and complex symptoms introduce **limitations**.

P. D. Rinanda *et al.* [4] (2024) **propose** comparative CNN-based architectures (VGG16, InceptionV3, standard CNN) for classifying mango leaf diseases, validating CNN's ability to learn features from raw images. Their work confirms CNN's effectiveness even with simple architectures. Still, shallow networks show **limitations** in deep texture discrimination.

Y. Ünal and M. Türkoğlu [5] (2025) **propose** a deep feature extraction framework using DenseNet201, ResNet18, and SqueezeNet to support mango disease classification with machine learning classifiers. CNNs outperform manual feature pipelines with accuracy near 98%. Yet, performance drops in limited sample scenarios show **limitations**.

S. Sharma *et al.* [6] (2025) **propose** CNN architectures such as AlexNet, VGG19, and DenseNet121 for automatic disease detection in mango leaves, finding DenseNet121 most effective. Their CNN models extract multi-level deep features for precise classification. Nonetheless, mobile deployment reveals **limitations** in computational demand.

V. Gautam *et al.* [7] (2024) **propose** an ensemble of CNN models using stacked deep features to classify mango leaf diseases, achieving better performance through diversity in feature representation. Their model automatically combines complementary features learned across CNN variants. However, ensemble complexity poses **limitations** in real-time deployment.

S. Mustofa *et al.* [8] (2023) **propose** CNN-based deep learning models as the preferred strategy for plant disease classification, including mango leaf recognition, due to their automated feature extraction capability. The study presents various hybrid CNN variants showing strong classification outcomes. Despite success, dataset imbalance and high training cost are **limitations**.

Farhan Bin *et al.* [9] (2025) **propose** a hybrid CNN-transformer model where CNN handles low-level local feature extraction while transformers address global dependencies. Their dual-architecture approach improves interpretability and disease differentiation. Still, performance on low-resolution field images shows **limitations**.

A. Preeya V. [10] (2024) **propose** a multi-objective CNN architecture optimized using pigeon-inspired algorithms to enhance classification accuracy and feature richness. The CNN learns mango leaf patterns automatically from enhanced segmented images. However, model tuning dependency introduces **limitations** in dynamic field environments.

B. Transfer Learning for Small Agricultural Datasets

Dhawan *et al.* [11] (2023) suggested that the pretrained model ResNet18, which should be fine-tuned using 2,000 or so mango leaf images. The method gives a 99.88% accuracy and lesser overfitting. Transfer learning thus allowed the model to efficiently extract features even with a meager number of samples. However, when the images contain a lot of background noise, the system underperforms.

Rajbongshi *et al.* [12] (2023) They put forth DenseNet201 and InceptionV3, transfer learning-based models for multi-class mango leaf disease recognition. The pretrained models worked with over 97% accuracy on a rather small dataset. Still, imbalanced data and classes that are poorly represented impacted classification stability.

Salamai *et al.* [13] (2023) Propose DenseNet78, an efficient compact CNN architecture improved by transfer learning. Their model can maintain very high accuracy (~99.47%) and is memory-efficient, which is crucial for mobile deployment. Still, the system loses accuracy under low-light and blurring conditions.

Puranik *et al.* [14] (2024) This MobileNetV3 model opens all doors for edge deployment. The model was finely tuned on MangoLeafBD with garnering of high accuracy at minimal computational expense, basically transferable to smartphones. However, unchanging factors of illumination in images brought in prediction errors.

Gautam *et al.* [15] (2024) Propose an ensemble of pre-trained CNNs that includes ResNet50 and DenseNet121, with training done on MangoLeafBD. Such an ensemble approach improves robustness and generalization on small datasets; however, computational complexity becomes an inhibitor for real-time applications.

Bin *et al.* [16] (2025) The design assigns the extraction of local features via CNN and modeling of long-range dependencies via transformer to the hybrid CNN-transformer. Trained with a transfer learning approach, the model is highly accurate, interpretable; however, large model size and high latency limit on-device use.

Ünal and Türkoğlu [17] (2025) Fine-tune lightweight models such as SqueezeNet and Xception to detect mango diseases. An accuracy of above 98 percent was attained using minimal computational resources. However, the performance suffered during variations in natural lighting and overlapping leaves.

Pratap and Kumar [18] (2024) present adaptive transfer learning with VGG16 and GoogleNet for the detection of common and rare diseases. Training transfer learning has accelerated convergence and has reduced overfitting on small datasets. Yet, because of the seasonal variance of disease symptoms, there has been an effect on the accuracy of detection.

Mustofa et al. [19] (2023) proposed a benchmarking study on deep learning approaches using transfer learning for the detection of plant leaf diseases. They cited the success of transfer-learned CNNs on small datasets such as MangoLeafBD, stating efficiency. Nevertheless, challenges related to cross-region generalization of the model remain.

C. Based on Hybrid DL Approaches (CNN + RNN, CNN + Attention)

Mohapatra et al. [20] (2022) The method consists of four stages for mango-leaf disease identification-preprocessing, segmentation using Otsu, feature extraction (ULBP, GLCM, color, pixel), and classification through AOCDO-optimized RNN. One consideration is that while the hybridized DOX optimization maximizes the accuracy of the system, it infinitely limits the complexity and computational load.

Rajpoot et al. [21] (2022) Present an automated system for mango leaf disease detection based on BBHE for preprocessing and CNN for classification; the system reaches an accuracy of 99.21%. While the detection in its early stage is effective, the system will face limitation in real-world image noise and leaf occlusion.

A. Umamageswari et al. [22] (2022) Propose the detection of leaf diseases using FCM segmentation, SIFT feature extraction, and LSTM classification, tested on an 8000-image Kaggle dataset. Though limited by the dependency on expert databases and image quality, model performance is reported to reach 96% accuracy across multiple classes of diseases.

S. Maheswaran et al. [23] (2022) Propose an AI-based system of image processing and CNN for the detection of groundnut leaf diseases, such as rust and leaf spot, attaining an accuracy of 96.50%. Though the system is effective and scalable, the performance of the model in the field could vary depending on the prevailing conditions and image qualities, thus forming a limitation.

Dhivyaa C. R et al. [24] (2022) Propose DCRDB-MLFD-BiLSTM: a novel model that combines dilated convolution and residual dense blocks to realize robust detection of cassava leaf diseases with a 95.49% F1-score. Though effective across multiple datasets, the model's complexity and computational cost remain a limitation for real-time field deployment.

Pal et al. [25] (2022) Propose a lightweight MobileNet V2 + LSTM hybrid model for citrus leaf disease classification, achieving 93.28% accuracy and enabling offline use in remote areas. A limitation arises while suitable for mobile deployment, as the model accuracy may fall with diverse pest types and low-quality image inputs.

Hritwik Ghosh et al. [26] (2023) Present a comparative study of ML (RandomForest, KNN) and DL (AlexNet, ResNet50, EfficientNet-B0) models for mango leaf disease detection using a custom dataset. In the DL domain, unsurprisingly, superior accuracy is yielded. The study, however, yields the important conclusion that, except for the application domains requiring heavy computational demands, the performance of any model is heavily dependent on preprocessing and tuning.

Redwan Ahmed Rizvee et al. [27] (2023) Propose LeafNet, a CNN-based model trained on region-specific mango leaf images from Bangladesh to detect seven common diseases with 98.55% average accuracy. It outperforms models such as AlexNet and VGG16; however, its limitation remains in being a region-specific model, which may hamper its ability to generalize across different climatic conditions.

Varun Kumar et al. [28] (2023) present a coconut leaf disease classification model in general terms which proved extremely accurate in the weathering of different parameters: precision (94.79–97.00%), recall (95.10–96.41%), and the F1-score (95.29–96.08%). Indeed, its performance on 4,940 images gave 95.74% accuracy, proving that the model might work very well under different situations, though its performance would definitely vary with the diversity of the real-world data, considered to be a limitation.

Isha Gupta et al. [29] (2023) Offer a four-stage classification system for mango leaf diseases, solving the problems of overfitting, complexity, and feature dimensionality. The set had 1,536 images taken from a Kaggle dataset. The model gave an accuracy of 97.9% and a sensitivity of 96.2%, while the lack of diversity in its data set may restrict its ability to be applied in compound real-world situations, considered as a limitation.

S. Jain et al. [30] (2023) came up with a hybrid deep learning-based classification solution that coupled a customized SVM and SGD for identifying mango leaf diseases using the Harumanis Mango Leaves 2021 dataset. This model has an accuracy of 97.7%, but given that the model depends on handcrafted hybridization, its application to diverse disease patterns may be less adaptable.

J.Kaur et al. [31] (2023) [presented] a method based on artificial neural networks for early detection of mango crop diseases by utilizing high-resolution images and contrast enhancement preprocessing to detect very small disease blobs. Such an approach improves upon the traditional CNNs whose low-resolution inputs limit accuracy while improving the reliability of subtle infection patterns in datasets.

D. Lita Pansy et al. [32] (2023) propose UAV-based hyperspectral imaging system employing MD-FCM for clustering and XCS-RBFNN for classification to detect mango leaf diseases and pest attacks with high spatio-temporal accuracy. Using apply and newly enhanced segmentation, feature selection by LFD-BOA as a technical method allows the system to gain better performance than other older methods.

Amit Kumar Pathak. et al. [33] (2024) Describe a CNN-deep-learning-based model trained through the most advanced preprocessing techniques, data augmentation, and hyperparameter tuning, capable of classifying eight classes of mango leaf diseases with 99% accuracy. It will be integrated into an Android app for Mango-SCN, thereby allowing people to more easily access and manage diseases both practically for experts and farmers.

D. Banerjee et al. [34] (2025) Considered a CNN classification model, trained on 10,380 images of mango leaves, that achieves 97.10% accuracy and balanced F1-scores for Red Rust, Black Tip, and Bacterial Canker. Having precision and recall higher than 96% for most of their classes, the model generalizes well and is useful for agricultural disease timely intervention.

Srinivas Aluvala et al. [35] (2025) Proposed a CNN-based model to classify ten intensity scales (1–91%) of Gummosis severity in mango leaves using a 12,405-image dataset with an overall accuracy of 92.62% and 99% for Gummosis stage detection. The method can give precisions from 96.15% to 98.31%, with strong F1-scores and uniform support across scales. It has been shown to be highly successful and has been suggested as a framework to annihilate severity-level classification from crop disease management.

Table 2: Comparative Analysis of Mango Leaf Disease Detection Techniques

Ref	Techniques Used	Feature Selection	Dataset Used	Key Findings	Results	Limitations
Mohapatra et al. [20] (2022)	Otsu + AOCDO-RNN	ULBP, GLCM, Color, Pixel	Not specified	Hybridized DOX optimization boosts accuracy	High accuracy	High computational complexity
Rajpoot et al. [21] (2022)	BBHE + CNN	Not specified	Not specified	Effective early-stage detection	Accuracy: 99.21%	Sensitive to image noise and occlusion
Umamageswari et al. [22] (2022)	FCM + SIFT + LSTM	SIFT	Kaggle (8000 images)	Multi-class detection performance	Accuracy: 96%	Dependent on expert datasets and image quality
Maheswaran et al. [23] (2022)	CNN	Not specified	Not specified	Effective for groundnut disease	Accuracy: 96.5%	Performance may vary in field conditions
Dhivyaa C. R et al. [24] (2022)	DCRDB–MLFD–BiLSTM	Not specified	Multiple datasets	Robust detection with F1-score of 95.49%	F1-score: 95.49%	Complex and computationally intensive
Pal et al. [25] (2022)	MobileNet V2 + LSTM	Not specified	Not specified	Lightweight and supports offline use	Accuracy: 93.28%	Degrades with low-quality images
Ghosh et al. [26] (2023)	RF, KNN, AlexNet, ResNet50, EfficientNet	Not specified	Custom dataset	DL models outperform ML; preprocessing crucial	DL more accurate	High computation requirements

Rizvee et al. [27] (2023)	LeafNet (CNN)	Not specified	Bangladesh-specific images	Detects 7 diseases better than AlexNet/VGG16	Accuracy: 98.55%	Region-specific; limited generalization
Varun Kumar et al. [28] (2023)	CNN	Not specified	4940 images	Strong metrics across diverse conditions	Accuracy: 95.74%	Real-world diversity may affect performance
Isha Gupta et al. [29] (2023)	4-stage classification system	Not specified	Kaggle (1536 images)	Solves overfitting & feature dimensionality issues	Accuracy: 97.9%, Sensitivity: 96.2%	Dataset lacks diversity
Jain et al. [30] (2023)	Hybrid DL (SVM + SGD)	Not specified	Harumanis Mango 2021	Combines handcrafted and deep learning	Accuracy: 97.7%	Less adaptable to new/unseen disease patterns
J. Kaur et al. [31] (2023)	ANN + Contrast Enhancement	Not specified	High-res image dataset	Detects subtle infections using high-resolution images	Improved over standard CNNs	Requires high-res images
Lita Pansy et al. [32] (2023)	UAV + MD-FCM + XCS-RBFNN	LFD-BOA	Hyperspectral UAV imagery	High spatio-temporal detection accuracy	High accuracy	High system complexity
Pathak et al. [33] (2024)	CNN + Data Augmentation + Tuning	Not specified	8 disease classes	Integrated into Mango-SCN Android App	Accuracy: 99%	Dataset lacks diversity
Banerjee et al. [34] (2025)	CNN	Not specified	10,380 images	Balanced F1-scores; detects Red Rust, Black Tip, etc.	Accuracy: 97.1%	Complex and computationally intensive
Aluvala et al. [35] (2025)	CNN	Not specified	12,405 images	Classifies 10 severity stages of Gummosis	Accuracy: 92.62%, Stage Acc: 99%	Requires high-res images

III. ROLE OF FEATURE EXTRACTION USING GLCM IN DISEASE CLASSIFICATION

The gray-level co-occurrence matrix is a strong texture-based feature extraction method, widely employed for image processing in plant pathology for disease classification. The GLCM considers the spatial relationship between pixels by registering how often a pixel of a certain gray-level intensity is found neighboring some other pixel, thus recording meaningful texture patterns in the image [14]. This matrix is generated for some set of predefined orientations and distances, most commonly at 0°, 45°, 90°, and 135° angles. After that, features like contrast, correlation, energy (uniformity), homogeneity, and entropy are extracted from GLCM to study the texture of plants' leaf surfaces, both healthy and diseased, thereby providing meaningful classification model-based pattern recognition [15].

GLCM increases performances of machine learning and deep learning classifiers in terms of mango leaf disease detection. For instance, powdery mildew and anthracnose can change the surface texture of the leaf, with areas affected possibly being highlighted by GLCM features [16]. High contrast levels may represent lesion or irregularities, and high entropy values could indicate randomness in the infected regions. Such features, when given as inputs to classifiers such as Random Forest, Support Vector Machines, or hybrid CNN-based classifiers enhance their classification accuracy by providing discrimination at texture levels beyond what RGB values alone can provide [17]. Moreover, GLCM is computationally inexpensive and can be easily combined with other feature extraction techniques such as color histograms or shape descriptors to create stronger feature vectors. In general, GLCM systems measure subtle changes in texture, thus playing a crucial role in disease diagnosis systems and becoming one of the indispensable tools for automated plant disease recognition pipelines [18].

IV. MACHINE LEARNING CLASSIFIERS IN PLANT PATHOLOGY

Being effective tools in plant pathology, ML classifiers have brought revolutions in the detection, diagnosis, and treatment of plant diseases. Climate change, pathogen evolution, and the soaring demand for crops pose many threats to agriculture,

making early and accurate disease detection vital. In contrast, the traditional manual inspection offers limited speed, makes subjective judgments, and is prone to errors. Conversely, ML classifiers automate disease diagnosis, making it data-driven, precise, efficient, and scalable [19]. Among widely used classifiers in the literature, SVM, RF, k-NN, DT, and NB have shown great ability to classify different plant diseases either from leaf images, spectral data, or molecular information. They learn patterns from labeled datasets, extracting essential features such as color, texture, and shape to classify them into categories representing healthy or diseased. SVM is considered quite effective for binary classification problems and performs well with high dimensional data. Being an ensemble learning method, RF achieves improvements in accuracy and reduces overfitting by aggregating the predictions of several decision trees [20]. Although k-NN is simple and effective for smaller datasets, it can be computationally expensive for larger ones. NB can be utilized for the probabilistic classification problems where independence is expected among features. ML classifiers in plant pathology have been successfully applied to crop diseases like wheat, rice, maize, mango, tomato, and apple [21]. Also, when they are integrated with image processing and feature extraction techniques such as LBP, HOG, and GLCM, classifier performances are further improved [22]. However, their success majorly depends on the quality of the dataset, class balance, and feature engineering. Lately, ML approaches have been combined with deep learning to design efficient hybrid models with improved accuracy for complex classification problems [23]. However, even with promising results, issues such as dataset variability, generalizability of models across different regions, and computational cost, etc., still remain unresolved. Resolving these issues using improved algorithms, transfer learning, and real-time deployment strategies in the very near future can lead to an accelerated adaptation of ML classifiers in precision agriculture. Thus, ML-based plant disease classification ensures sustainable agriculture through timely intervention, thereby mitigating yield loss and minimizing chemical usage, thus contributing to food security on a global scale [24].

V. COMPARATIVE ANALYSIS OF MLDR SYSTEM PERFORMANCE AND ACCURACY

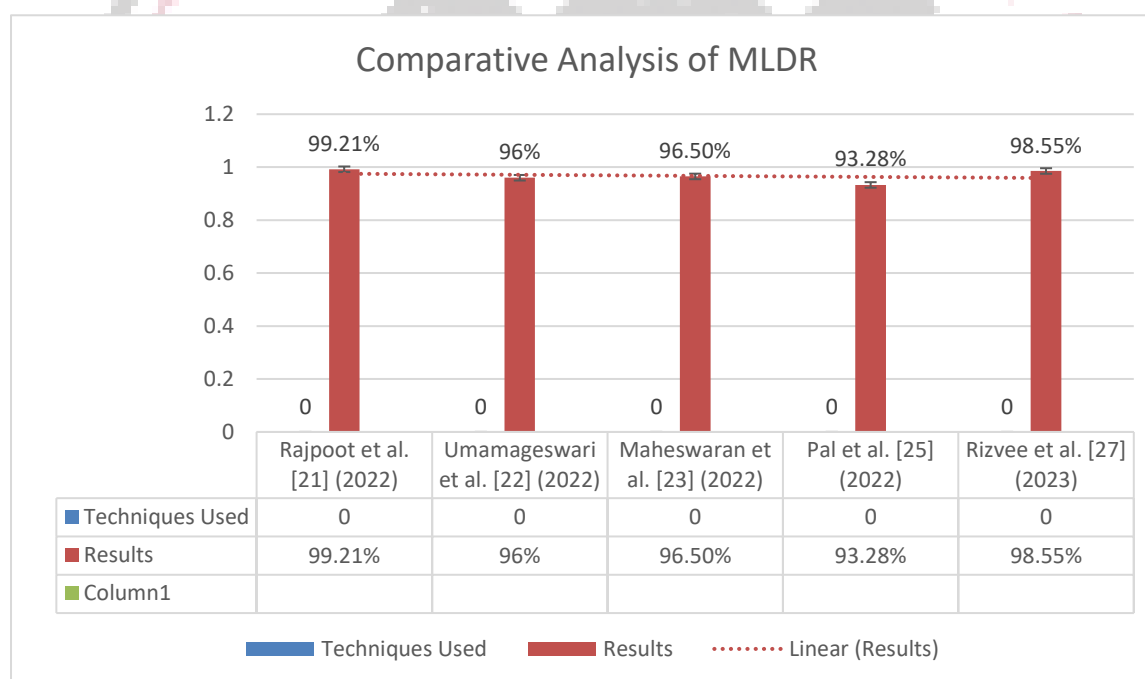


Fig. 1: Comparative Analysis of MLDR System Performance and Accuracy

VI. LIMITATIONS

Many datasets become region-specific or are built in fully controlled environments, which limits a model's ability to generalize under varying environmental conditions or mango varieties [25]. Deep CNN and hybrid models require high computational power and memory, hindering implementation on low-end devices or in the field. Models may overfit on limited datasets: they learn the training too well but do not do the same with new or noisy data. With poor-quality images (e.g., blurry, under/overexposed, or occluded leaves), detection accuracy drops, with such images being so common in real-world setup [26]. Annotated datasets need an expert, especially one capable of making differentiation between diseases showing similar visual symptoms. It is always a tedious and error-prone task. Due to their lack of explainability, CNN-based models do not offer agricultural experts or farmers the possibility of trusting the predictions in the presence of transparent reasoning [27].

VII. CONCLUSION

This review highlights the efficiency of machine learning systems in diagnosing mango leaf diseases. Combining NNE and SVM classifiers with strong image processing and feature extraction techniques allows the system to reliably detect the diseases. The results prove that the methodology can be successfully applied in real agricultural settings, where timely identification of diseases greatly helps to increase productivity and reduce crop losses. Expanding the dataset and introducing additional disease types would eventually improve the scalability and accuracy of the model. In future research, one may compare color- with texture-based features to improve classification accuracy further.

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