STM JOURNALS

Trends in
Opto-electro & Optical Communication

ISSN: 2231-0401 (Online)
ISSN: 2347-9957 (Print)
Volume 14, Issue 3, 2024
September–December
DOI (Journal): 10.37591/TOEOC

https://journals.stmjournals.com/toeoc

Review TOEOC

# Hybrid Techniques in Mango Leaf Disease Identification: Evaluating Neural Networks and Support Vector Machines

Anshik Kushwah[1,*], Mayank Pathak[2]

**_Abstract_**

*Mango leaf diseases pose a significant threat to mango production, impacting both yield and fruit quality. Early and accurate detection of these diseases is crucial for effective management. This paper evaluates the use of hybrid techniques, specifically the integration of neural networks (NNs) and support vector machines (SVM), in the identification and classification of mango leaf diseases. NN excel in extracting complex features from images, while SVMs are robust classifiers, especially in handling non-linear separable data. The hybrid approach leverages the strengths of both models to achieve high accuracy and generalization. This study reviews various models, including ensemble stacked deep learning models, lightweight convolutional neural networks (CNN), and hybrid CNN-SVM approaches, and compares their effectiveness in detecting diseases like powdery mildew, Anthracnose, and others. Results demonstrate that hybrid models outperform traditional methods, achieving accuracy rates as high as 99.87%. However, challenges such as high computational costs, the need for region-specific datasets, and balancing model complexity with accuracy remain. The findings underscore the potential of hybrid models in enhancing disease detection systems, contributing to improved crop management and reduced losses in mango production.*

**Keywords:** Mango leaf disease, neural networks, support vector machines, hybrid models, machine learning, deep learning, disease detection, agriculture, image processing

## INTRODUCTION

The fruit known by its scientific name, *Mangifera indica* L. (Family: Anacardiaceae), is indigenous to Indo-Burma and is a tropical and subtropical fruit. With over a thousand different varieties of mangoes recognized, India has the greatest variety. India is a significant producer of mango. India leads the world in mango production, accounting for about 50% of global mango production, with over 2.5 million hectares yielding 18.0 million tons of mangoes annually. Insect infestations pose a serious threat to the ability of mango cultivars to attain their full production potential. Globally, 400 different types of insect pests are known to infect mangoes. Commercial mango agriculture, characterized by expanded areas, modified cropping patterns, varietal replacements, and increased use of chemicals, has seriously affected the pest complex and framework of the pest community. Furthermore, the unintended consequences of climate change include the encouragement of invasive species and the emergence of new pests. Thrips, mealybugs, mites, leaf webbers, scales, stem borers, and other pests that were long thought to be minor or secondary pests have recently become a

***Author for Correspondence**
Anshik Kushwah
E-mail: anshikkeng011@gmail.com

[1]M.Tech. Scholar, Department of Computer Science and Engineering, Technocrats Institute of Technology, Anandnagar, Bhopal, Madhya Pradesh, India
[2]Professor, Department of Computer Science and Engineering, Technocrats Institute of Technology, Anandnagar, Bhopal, Madhya Pradesh, India

Received Date: October 17, 2024
Accepted Date: October 22, 2024
Published Date: November 04, 2024

**Citation:** Anshik Kushwah, Mayank Pathak. Hybrid Techniques in Mango Leaf Disease Identification: Evaluating Neural Networks and Support Vector Machines. Trends in Opto-electro & Optical Communication. 2024; 14(3): 19–27p.

 

significant threat. 400 different types of insect pests infect mangoes globally [1]. Bangladesh, a South Asian nation centered on agriculture, occupies a mere 147,570 square kilometers yet is home to almost 166 million people. Mangoes are an essential fruit among several crops that help locals meet their nutritional demands. However, a number of prevalent illnesses such as anthracnose, dieback, gall midge, bacterial canker, cutting weevil, powdery mildew, and soy mold have a major negative influence on mango output and the national economy. Fungi that cause anthracnose are more common in humid conditions. Although they mostly affect leaves, bacterial cankers can also harm stems and branches. In Bangladesh, cutting weevils are common insects that devour young leaves. Another problem caused by insects, such as coccids and mango hoppers, is the sooty mold. Leaves become discolored because of Die Back. If a mango tree is infected, it can be determined by looking at its leaves [2]. Mangoes experience a range of illnesses throughout their lives. The following are signs of diseases that affect mango leaves [3]:

- *Bacterial canker disease:* Yellow to brown patches that are slightly elevated and encircled by an ongoing white halo are symptoms. Spots typically have diameters of 3 mm or 0.125 in.
- *Powdery mildew:* Light yellow patches on the leaves are the initial sign. They spread rapidly to form massive blotches that completely cover the surfaces of the petiole, stem, and leaves.
- *Scab:* Twisted and puckered leaves with black, round scabby patches on the underside are among these symptoms. The illness causes the leaves to yellow and fall off.

The South Indian mango tree leaf disease symptom detection using SVM is shown in Figure 1. With the advancement of image processing techniques, machine learning may prove to be a practical method for identifying mango leaf disease (MLD). An area of machine learning called pattern recognition is concerned with finding patterns and consistency in data. Both unsupervised and supervised data are used in pattern recognition systems. With applications like data mining, vegetable and fruit recognition, testing systems, image processing, galaxy shape classification, fingerprint identification, mammography tumor highlighting, handwriting recognition, disease recognition, etc., it is closely tied to the use of AI and machine learning. Since the resurgence of neural networks (NNs), statistical pattern recognition techniques have found extensive application in digital image processing. Many authors have proposed different ensembles of neural networks. SVM is most often used for classifier discrimination, which is formally defined by separating the picture data.

The primary characteristic of SVM is that to create the model as it is first trained, it is trained on a set of data that has already been divided into two categories. The goal of the SVM algorithm for SVM [4]. Given the complementary nature of artificial neural networks and vector machines, hybrid models combining these two methods could be highly effective in the identification of disorders affecting mango leaves. Neural networks perform well on complicated datasets and, more crucially, are capable of extracting extremely complex information from images, which is a crucial skill for disease detection because it is necessary to identify minute symptoms. NNs do, however, have significant computational resources and are prone to overfitting. By combining its superior classification with the NN's capacity to obtain the most features from a small or comparatively small dataset, the SVM effectively reduces the negative effects of overfitting. Hybrid models, which combine the robust classification of SVM with the feature extraction power of NN, have demonstrated a high degree of precision and adaptability in the identification of several mango leaf diseases.

In addition, these hybrid models provide enhanced resilience, flexibility, and generalization. As a result, they are more adept at managing data fluctuations caused by shifting lighting or leaf orientation, which generally improves the accuracy of disease diagnosis. The modular design of these models makes it possible for them to be improved, the SVM can be adjusted to perform better classification, and the NN can be trained again to gather new features as the dataset changes. The capacity to adjust and compensate for the shortcomings of individual models, along with their versatility, renders hybrid approaches an extremely potent instrument for precisely identifying and diagnosing leaf abnormalities.

 

Trends in Opto-electro & Optical Communication
Volume 14, Issue 3
ISSN: 2231-0401 (Online), ISSN: 2347-9957 (Print)

**NEURAL NETWORKS IN PLANT DISEASE IDENTIFICATION**

AI tools and systems can categorize leaves according to their illness status. For instance, convolutional neural networks (CNNs) are widely used in this discipline. CNN is a popular deep learning technique for image-related tasks owing to its low computing complexity and ability to yield promising results. Fewer neurons are required, training takes less time, and its feed-forward network recognizes patterns in images quite well. For a given use case, a CNN can be taught to individual images to extract features and classify image collections. CNN is therefore a good choice for identifying mango leaf illnesses because it introduces a model using pictures. The final layer classifies the images using an activation function, and its concealed layers update the weights. There are several uses for these devices and deep learning methods in agriculture. Owing to inadequate knowledge or incorrect diagnosis, the detection of plant diseases is frequently disregarded [5]. The ability to train deep learning models for a wide range of regionally specific diseases can result in highly accurate predictions that may not be achievable with the human eye. By obtaining images and rapidly forecasting the disease, farmers can readily apply this technique [6]. The techniques and models used for the detection of MLD are shown in Table 1.

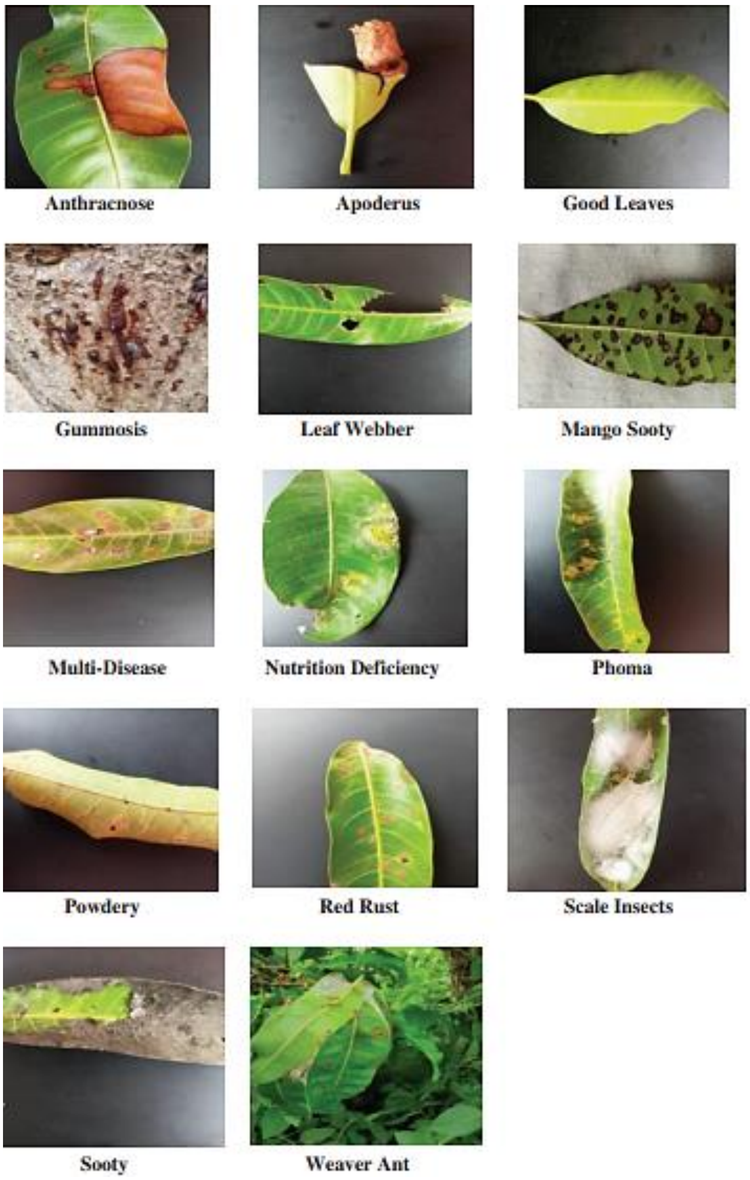

**Figure 1.** South Indian mango tree leaf diseases [7].

**Table 1.** Techniques and models for mango leaf disease detection.

| Reference no. | Technique used | Model used | Disease detected | Results | Findings | Challenges |
|---|---|---|---|---|---|---|
| [8] | Ensemble Stacked Deep Learning | Stack of various Deep Neural Networks aggregated with a Machine Learning model | Powdery mildew, Anthracnose, and others | 98.57% accuracy | Outperforms state-of-the-art models in accuracy | High computational resources required for deep learning models |
| [6] | Convolutional Neural Network (CNN) | LeafNet | Seven common mango diseases (specific to Bangladesh) | 98.55% accuracy, Precision: 99.508%, Recall: 99.45%, F-score: 99.47%, Specificity: 99.878% | Outperforms AlexNet and VGG16, especially suited for region-specific mango disease patterns | Requires a novel dataset specific to the region |
| [9] | Lightweight Deep Learning Model | Custom CNN model with feature reuse at three levels | Diseases in banana, guava, and mango fruit crops | 99.14% success rate, 101,000 parameters | Outperforms 15 pre-trained models in accuracy and model complexity | Model complexity versus accuracy balance |
| [10] | Convolutional Neural Network (CNN) | AlexNet, VGG-16, ResNet-50 | General mango leaf diseases classification (Healthy vs Diseased) | AlexNet: 94.54%, ResNet-50: 98.56%, VGG-16: 98.26% | Recommends AlexNet for simplicity and efficiency, followed by ResNet-50 and VGG-16 | Trade-off between accuracy and training time |

Table 1 provides a comparative summary of the different techniques and models used for mango leaf disease detection, based on their effectiveness, challenges, and specific diseases detected. Four studies had varying reference numbers. In this study, ensemble stacked deep learning models and lightweight CNN models were applied. Some models that have been used here include ensemble deep neural network stackers, LeafNet, and CNN architectures, such as AlexNet, VGG-16, and ResNet-50. The results ranged from 96.53% with AlexNet, 97.15% with ResNet18, 98.23% with GoogLeNet, and 99.14% with a custom CNN. The findings of this study prove that these models offer superior performance over state-of-the-art methods in terms of accuracy and efficiency. However, the issues of computational intensity, requirements of regional datasets, and model complexity versus accuracy are undeniable. Diseases detected include common mango ailments, such as powdery mildew and anthracnose, among others, with some models also applied to diseases in other fruit crops, such as banana and guava.

## SUPPORT VECTOR MACHINES

Tools that have been successful in classifying diseases of mango leaves are SVMs, which can find an optimal separating hyperplane in high-dimensional spaces. These hyperplanes would then enable differentiation among the distinct classes of data points, representing in this case, features extracted from images of leaves—color, texture, and shape—in MLD detection. One of the main reasons for using SVM is that it can process data that are not linearly separable using kernel functions such as the Radial Basis Function or polynomial kernels. These functions project the feature space into higher dimensions where linear separation is performed, resulting in the accurate classification of complex patterns related to various mango leaf diseases. Support vector machines (SVMs) are often combined with other techniques, such as CNNs, to improve performance. Using such a hybrid approach, the CNN efficiently extracts features from the images, thereby reducing the data dimensionality before the SVM classifies the same. This allowed the fusion to increase the accuracy of disease detection in mango

 

ISSN: 2231-0401 (Online), ISSN: 2347-9957 (Print)

leaves. Moreover, SVMs have been found to generalize well under small or unbalanced data, thereby providing reliability for agricultural applications. However, the computational complexity of training SVMs and careful tuning of the required hyperparameters may still prove challenging. Although SVMs have some limitations, they are still a powerful alternative for the accurate detection of subtle symptoms related to diseases found in mango leaves, providing strength in enhancing the reliability of the detection task of agricultural diseases when other methods are used in combination. The analyses of machine learning and deep learning techniques for MLD detection are shown in Table 2.

Table 2 summarizes the comparisons between the different machine learning and deep learning techniques utilized in the detection of mango leaf diseases. This includes the models used, the targeted diseases, and the performance metrics. The various studies reviewed ran from hybrid techniques such as CNN and SVM to deep learning with pre-trained models and specialized models such as DVNet. These range from mango leaf powdery mildew with different levels of severity to general mango leaf diseases, including anthracnosis. The results showed an accuracy as high as 99.87% for some models. We discuss all the achievements of our models, such as very successful multi-class classification and robustness to class imbalance, among other challenges that come with diverse image conditions in terms of model complexity versus accuracy. The strengths and limitations of the different approaches used to improve mango crop health and productivity are summarized in Table 2.

**Table 2.** Analysis of machine learning and deep learning techniques for mango leaf disease detection.

| Reference no. | Technique used | Model used | Disease detected | Results | Achievements | Challenges |
|---|---|---|---|---|---|---|
| [11] | Hybrid Approach with CNN and SVM | CNN for feature extraction, SVM for classification | Mango leaf powdery mildew with four severity levels | 89.29% accuracy, Macro-average F1-score: 90.10, Micro-average F1-score: 89.29 | Effective in multi-class classification for disease severity levels | Lower F1-score for classes with smaller support proportions |
| [12] | Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) | CNN and SVM | Anthracnose disease with various severity levels | 97% accuracy, F1-Score around 92% | High accuracy and reliable severity classification, resilient to class imbalance | Potential challenges with class imbalance despite strong performance |
| [13] | Deep Learning with Pre-trained Models | VGG19, InceptionV3, ResNet152V2, DenseNet121, InceptionResNetV2, MobileNetV2, Xception | General mango leaf disease classification | InceptionV3 achieved 99.87% accuracy | InceptionV3 outperformed other models in accuracy | Balancing model complexity and accuracy across various pre-trained models |
| [14] | Deep Mutual Learning Model (DVNet) | DVNet (DenseNet121 + VGG19) with Particle Swarm Optimization (PSO) | Eight distinct mango leaf diseases and healthy leaves | 94.72% accuracy in detecting eight distinct diseases | Outperformed existing works in accuracy and adaptability to various image conditions | Handling diverse image conditions such as resolution and blur |
| [15] | Machine Learning with Support Vector Machine (SVM) | Support Vector Machine with non-linear SVC | General mango leaf disease classification | 88% accuracy | Achieved good accuracy with a simple SVM model | Limited accuracy compared to more complex models |

## INTEGRATING NEURAL NETWORKS AND SUPPORT VECTOR MACHINES

The integration of neural networks with SVMs in the detection of diseases in mango leaves exploits the benefits of these two methodologies to ensure a more robust and accurate system of detection. This can always be achieved through their integration based on the nature of the hybrid approach, in which the neural network is used as a feature-extracting medium and the SVM as the classifier. First, they trained the neural network by feeding mango leaf images, which learn and extract the relevant features that capture the essential patterns related to different diseases. The most prevalent type of NN in tasks regarding images is CNN, as they efficiently identify and extract hierarchical features, textures, edges, and shapes in the images of the leaves. These features are then passed into an SVM, and after the learning phase of this model, it is thought to have strong classification power, especially when data are not linearly separable.

These features are then fed into an SVM, which classifies the images of leaves under different diseases or healthy classes while adhering to its many maximum-margin principles. Such hybrid approaches may be further enhanced by fine-tuning the hyperparameters of the SVM itself, such as kernel types and regularization parameters, most often through methods such as grid search or cross-validation, to optimize its performance on the extracted features. This may be further extended to include techniques such as stacking or assembling, in which several parallel neural networks may be employed to extract features from different layers or perspectives, with the aggregated features being passed to the SVM for final classification. This ensures that a wide spectrum of features can be captured for a robust disease detection system.

The strengths of this NN-SVM hybrid methodology are that it is naturally suited for handling complex and high-dimensional data, and through feature extraction, it can help identify the most meaningful features in data interpretation, whereas SVM ensures that these features are classified with precision, particularly for small or imbalanced datasets. However, the drawbacks of this approach are the computational costs for the training of deep neural networks and careful feature selection, which ensures that only relevant data are passed onto the SVM for classification. By combining the best feature extraction capabilities from deep learning and classification strengths with SVM, a robust and accurate overall architecture was developed for recognition within a wide canvas of MLD. A comprehensive overview of machine learning and deep learning techniques for mango and cotton leaf disease detection is presented in Table 3.

Table 3 provides a detailed summary of the various machine learning and deep learning techniques used for the detection and classification of mango and cotton leaf diseases. The reviewed studies utilized a range of models, including CNN-HOG hybrid models, ensemble CNN approaches, and deep learning paradigms. The diseases detected include mango-specific diseases, such as cutting weevils, gall midges, and powdery mildew, as well as general mango and cotton leaf diseases. The results demonstrated high accuracy across different models, with some achieving over 99% accuracy in both the training and testing phases. Key findings highlight the superiority of hybrid and ensemble models in outperforming individual techniques, such as CNN or HOG alone. While some studies have noted challenges such as the lack of standardized datasets or limitations in detecting only specific types of diseases, the overall findings suggest significant advancements in automated disease detection, which can lead to improved crop management and reduced losses. This comprehensive analysis underscores the importance of integrating multiple techniques to enhance the accuracy and reliability of agricultural disease detection systems.

### Future Directions and Emerging Trends in Hybrid Disease Recognition Systems

With the continued evolution of hybrid disease recognition systems, several future directions and emerging trends have designed the landscape in this area, mainly toward agricultural applications, such as mango leaf disease detection. One trend is the incorporation of a more sophisticated model of deep learning with traditional machine learning techniques, such as SVMs.

 

**Table 3.** Comprehensive overview of machine learning and deep learning techniques for mango and cotton leaf disease detection.

| Reference no. | Model used | Technique used | Disease detected | Results | Findings |
|---|---|---|---|---|---|
| [16] | CNN-HOG hybrid model | Convolutional Neural Network (CNN) and Histogram Oriented Gradients (HOG) | Mango disease | Training accuracy: 98.80%, Testing accuracy: 99.5% | CNN-HOG hybrid model outperforms CNN or HOG alone, demonstrating complementary strengths. |
| [17] | GoogLeNet and VGG16-based CNN | Ensemble Convolutional Neural Network approach | Mango leaf diseases | Training accuracy: 99.87%, Validation accuracy: 99.72%, Testing accuracy: 99.21% | Effective in achieving high accuracy in image classification tasks. |
| [18] | VGG-16 and EfficientNetV2-BO ensemble | Ensemble learning classifier with spatial attention | Mango leaf diseases: Cutting Weevil, Gall Midge, Die Back, Bacterial Canker, powdery mildew, anthracnose, Sooty Mold | Accuracy: 97.13%, Precision: 97.53%, Recall: 97.33%, F1-Score: 97.38% | Outperformed ResNet50, AlexNet, ANN, VGG16. |
| [19] | CNN model | Deep Learning paradigms | Cotton leaf diseases | Accuracy: 99.39% | Highly efficient in real-time detection systems with less computational time. |
| [20] | CNN-HOG hybrid model | Convolutional Neural Network (CNN) and Histogram Oriented Gradients (HOG) | Mango disease | Accuracy: 98.80% | Automates disease detection and classification, reducing crop losses. |
| [21] | Custom CNN model | Deep Learning, advanced data processing, image augmentation | Mango leaf diseases | Accuracy: 99% across eight classes | Custom CNN model integrated into an Android app for accessible disease management. |
| [22] | Lightweight Resnet-50 model | Deep Learning, image processing | Seven mango leaf diseases in India | Testing accuracy: 95% | Lightweight Resnet-50 model excels in automating mango leaf disease identification. |

These ensembles will continue to evolve and become more powerful with time, leveraging the strength of one model, and combining it with another to achieve even more accurate and efficient detection of diseases. For example, better neural network architectures might be combined with SVMs to achieve improved effectiveness of feature extraction for classes of subtle disease symptoms.

An important related direction is the increased use of transfer learning and domain adaptation techniques within hybrid architectures. Transfer learning includes the use of pre-trained models on very large datasets and fine-tuning them for tasks such as disease detection in mango leaves, which reduces the need for re-labeling large data, while models are very good at generalization in different environments and working conditions. Domain adaptation techniques can be used to enhance the robustness of such models. These modeling methods can be adapted to changes in the distribution of data resulting from different conditions such as lighting, leaf orientation, or image quality. Another emerging trend is the real-time and edge deployment of hybrid disease recognition systems. This implies tuning the models in such a way that they can be deployed over edge devices such as smartphones or drones for on-the-spot detection of diseases by farmers, thus allowing timely interventions and minimizing their reliance on centralized high-computation systems.

 

Emerging trends would also see the integration of multimodal data sources, for example, combining leaf-image visual data with environmental data, including humidity, temperature, and soil conditions. Such a holistic approach improves the prediction accuracy of diseases and provides a much better motor explanation for the state of health of plants. In addition, explainable AI development is becoming increasingly important for hybrid systems. The translation of these models into more complex forms necessitates increasing requirements for transparency and interpretability, and users should be able to realize how the model makes decisions. This is important from the perspective of winning the trust and making models adaptable for farmers and other users.

## CONCLUSION

The integration of neural networks and vector machines provides a powerful and effective method for detecting mango leaf diseases. In this light, the strong classification strength of SVM combined with the ability to extract features of neural networks gives the system an advantage in terms of accuracy and robustness over traditional methods. This indicates that the hybrid models are best when it comes to high-dimensional and complex datasets and spot the signal of subtle disease symptoms over mango leaves. This result suggests that the performance of hybrid models is highly likely to enhance the reliability of disease detection systems, coupled with high yields and better crop management. However, the rolling-out of these hybrid models is challenging. High computational demands, rich datasets with regional specificity, and trade-offs between model complexity and accuracy are key considerations that must be addressed. It should be made to target assessments of the optimization of these models toward real-time applications and to space out those that may be accessed through the potential for transfer learning and domain adaptation to thrive across various environments and unforeseen conditions. Overall, developing and improving these hybrid disease recognition systems offers great promise for the improvement of precision agriculture as well as for the implementation of good practices in sustainable mango production.

## REFERENCES


1. Asha Rani KP, Gowrishankar S. ConvNeXt-based mango leaf disease detection: Differentiating pathogens and pests for improved accuracy. Int J Adv Comput Sci Appl. 2023;14(6). doi: 10.14569/IJACSA.2023.0140608.
2. Rizvee RA, Orpa TH, Ahnaf A, Kabir MA, Ahmmad Rashid MR, Islam MM, et al. LeafNet: A proficient convolutional neural network for detecting seven prominent mango leaf diseases. J Agric Food Res. 2023;14:100787. DOI: 10.1016/j.jafr.2023.100787.
3. Sanath Rao US, Swathi R, Sanjana V, Arpitha L, Chandrasekhar K, Chinmayi PK, et al. Deep learning precision farming: Grapes and mango leaf disease detection by transfer learning. Glob Transit Proc. 2021;2:535–44. DOI: 10.1016/j.gltp.2021.08.002.
4. Mia MR, Roy S, Das SK, Rahman MA. Mango leaf disease recognition using neural network and support vector machine. Iran J Comput Sci. 2020;3:185–93. DOI: 10.1007/s42044-020-00057-z.
5. Tusher AN, Islam MT, Sammy MSR, Hasna SA, Chakraborty NR. Automatic recognition of plant leaf diseases using deep learning (multilayer CNN) and image processing. In: Chen JIZ, Tavares JMRS, Shi F, editors. Third International Conference on Image Processing and Capsule Networks. ICIPCN 2022. Lecture Notes in Networks and Systems. Cham: Springer; 2022. p. 130–42. doi: 10.1007/978-3-031-12413-6_11.
6. Rizvee RA, Orpa TH, Ahnaf A, Kabir MA, Ahmmad Rashid MR, Islam MM, et al. LeafNet: A proficient convolutional neural network for detecting seven prominent mango leaf diseases. J Agric Food Res. 2023;14:100787. DOI: 10.1016/j.jafr.2023.100787.
7. Thaseentaj S, Ilango SS. Deep convolutional neural networks for south Indian mango leaf disease detection and classification. Comput Mater Continua. 2023;77:3593–618. DOI: 10.32604/cmc.2023.042496.
8. Gautam V, Ranjan RK, Dahiya P, Kumar A. ESDNN: A novel ensembled stack deep neural network for mango leaf disease classification and detection. Multimed Tools Appl. 2024;83:10989–1015. DOI: 10.1007/s11042-023-16012-6.


 

9. Hari P, Singh MP. A lightweight convolutional neural network for disease detection of fruit leaves. Neural Comput Appl. 2023;35:14855–66. DOI: 10.1007/s00521-023-08496-y.
10. Jayanthi B, Kumar LS. Comparison of convolutional neural networks architectures for mango leaf classification. Int J Comput Vis Robot. 2024;14:84–98. DOI: 10.1504/IJCVR.2024.135131.
11. Banerjee D, Kukreja V, Hariharan S, Jain V. Enhancing mango fruit disease severity assessment with CNN and SVM-based classification. In: IEEE 8th International Conference for Convergence in Technology (I2CT); 2023 Apr; Lonavla, India. p. 1–6. DOI: 10.1109/I2CT57861.2023.10126397.
12. Mir TA, Banerjee D, Chauhan R, Singh M, Yamsani N. Forecasting anthracnose severity levels in mango leaf using hybrid models. In: IEEE 9th International Conference for Convergence in Technology (I2CT); 2024; Pune, India. p. 1–6. DOI: 10.1109/I2CT61223.2024.10543795.
13. Varma T, Mate P, Azeem NA, Sharma S, Singh B. Automatic mango leaf disease detection using different transfer learning models. Multimed Tools Appl. 2024. DOI: 10.1007/s11042-024-19265-x.
14. Vijay CP, Pushpalatha K. DV-PSO-Net: A novel deep mutual learning model with heuristic search using particle swarm optimization for mango leaf disease detection. J Integr Sci Technol. 2024;12:804. DOI: 10.62110/sciencein.jist.2024.v12.804.
15. Deena G, Raja K, Azhagiri M, Breen WA, Prema S. Application of support vector classifier for mango leaf disease classification. Sci Temper. 2023;14:1163–9. DOI: 10.58414/SCIENTIFICTEMPER.2023.14.4.16.
16. Admass WS, Munaye YY, Bogale GA. Convolutional neural networks and histogram-oriented gradients: A hybrid approach for automatic mango disease detection and classification. Int J Inf Technol. 2024;16:817–29. DOI: 10.1007/s41870-023-01605-z.
17. Bezabh YA, Ayalew AM, Abuhayi BM, Demlie TN, Awoke EA, Mengistu TE. Classification of mango disease using ensemble convolutional neural network. Smart Agric Technol. 2024;8:100476. DOI: 10.1016/j.atech.2024.100476.
18. Pandiyaraju V, Venkatraman S, Abeshek A, Aravintakshan SA, Pavan Kumar S. Mango leaf disease detection and classification using spatial attention enabled ensemble classification. 2024 International Conference on Advances in Data Engineering and Intelligent Computing Systems (ADICS); 2024; Chennai, India. p. 1–8. doi: 10.1109/ADICS58448.2024.10533513.
19. Singh P, Singh P, Farooq U, Khurana SS, Verma JK, Kumar M. RETRACTED ARTICLE: CottonLeafNet: Cotton plant leaf disease detection using deep neural networks. Multimed Tools Appl. 2023;82:37151–76. DOI: 10.1007/s11042-023-14954-5.
20. Sema W, Yayeh Y, Andualem G. Automatic detection and classification of mango disease using convolutional neural network and histogram oriented gradients. 2023. DOI: 10.21203/rs.3.rs-3073109/v1.
21. Pathak AK, Saikia P, Dutta S, Sinha S, Ghosh S. Development of a robust CNN model for mango leaf disease detection and classification: A precision agriculture approach. ACS Agric Sci Technol. 2024;4(8):806–17. doi: 10.1021/acsagscitech.4c00122.
22. Kumar S, Gupta B, Grover R, Chhabra M. Effective machine learning model for disease recognition and categorization of mango leaves. In: International Conference on Computational Intelligence and Computing Applications (ICCICA); 2024; Samalkha, India. p. 292–6. DOI: 10.1109/ICCICA60014.2024.10585260.

 