RESEARCH ARTICLE Agricultural Science Digest, Volume 45 Issue 6: 1004-1010 (December 2025)

Convolutional Neural Networks for the Intelligent and Automated Detection of Mango Leaf Disease to Enhance Crop Health Management

Shivam Dinkar[1], K. Jayapriya[2], Niveditha Pallerla[3], Kunal D. Jadhav[4], Anil R. Shet[5]

10.18805/ag.DF-717

ABSTRACT

Background: Mango leaf diseases reduce fruit yield and quality, requiring early detection for effective management. Traditional methods rely on manual inspection, which is slow, subjective and error-prone. Deep learning, especially Convolutional Neural Networks (CNNs), offers automation but faces challenges. These include class imbalance, poor dataset generalization and limited real-world scalability. This study develops a robust CNN model to improve mango leaf disease classification.

Methods: A dataset of 2,494 mango leaf images from the Mendeley database was used. Images were categorized into anthracnose, bacterial canker, cutting weevil, dieback and healthy. Preprocessing involved image resizing, normalization and data augmentation to enhance model performance. The dataset was split into 80% training, 10% validation and 10% testing. A six-layer CNN with ReLU activation, max-pooling, dropout (0.5) and fully connected layers was trained for 25 epochs. The model used Adam optimizer and categorical cross-entropy loss.

Result: The model achieved 98.03% training accuracy and 97.77% validation accuracy over 25 epochs. It had a low validation loss (0.0485), indicating good generalization. The confusion matrix showed high precision and recall across all classes. The overall classification accuracy was 96.53%, with a macro-average F1-score of 96.57%. Anthracnose and Dieback were perfectly classified. Bacterial canker had a lower precision (0.8500), suggesting minor misclassifications. AUC analysis showed good disease separation, with Cutting Weevil achieving the highest AUC (0.72). This CNN model can automate mango disease detection, reducing reliance on manual inspections. It can be useful for smart farming systems and mobile applications for real-time disease diagnosis. Future work will focus on expanding the dataset, optimizing for mobile use and integrating environmental factors for better disease prediction.

Key words: Agriculture, Convolutional neural networks, Mango leaf disease, Mendeley, Smart detection.

INTRODUCTION

Mangoes are a popular fruit all over the world due to their richness in nutrients as well as the delicious taste that they possess. Pests, along with diseases, result in the loss of 30-40% of the crop (Mia *et al*., 2020). Pathogens that attack mango plants cannot be identified by manual checking and, hence, become less accurate. Farmers cannot easily identify different illnesses that damage mango plants, which results in a decreased mango fruit output. The numerous illness7es wreak havoc on the mangoes' harvesting, resulting in irregularly coloured black patches. These dots appear on the leaf surface or inside early fruit (Kabir *et al*., 2020; Singh *et al*., 2019). In their early stages, these disorders need to be identified and treated (Liu *et al*., 2019).

These illnesses are caused by disease-causing agents like mushrooms, bugs, bacteria, fungi and viruses that cause the death of plants. Plant identification is a process that involves consulting agricultural professionals who regularly inspect each plant. This makes farmers' workloads heavy since they have to follow the body of the plant, resulting in wasting a lot of time (Trang *et al*., 2019). Mango production is still being plagued by numerous leaf diseases such as Anthracnose, Bacterial Canker, Cutting Weevil and Dieback. These diseases can lead to significant reductions in yields

[1]Department of Forestry, College of Agriculture, Raipur Indira Gandhi Krishi Vishwavidyalaya, Raipur-492 012, Chhattisgarh, India.
[2]Department of Bachelor of Business Administration, K S Rangasamy College of Arts and Science, Thiruchengodu-637 215, Namakkal, Tamil Nadu, India.
[3]Pharmacy Manager, Crawford Pharmacy of Pleasanton, Texas, USA.
[4]Department of Lifelong Learning and Extension, University of Mumbai, Mumbai-400 020. Maharashtra, India.
[5]Department of Biotechnology, Karnatak Lingayat Education Technological University, Hubballi-580 031, Karnataka, India.

Corresponding Author: Shivam Dinkar, Department of Forestry, College of Agriculture, Indira Gandhi Krishi Vishwavidyalaya, Raipur-492 012, Chhattisgarh, India.
Email: shivamdinkar1997@gmail.com
ORCIDs: 0009-0008-3364-4917, https://orcid.org/0000-0003-3264-8883

How to cite this article: Dinkar, S., Jayapriya, K., Pallerla, N., Jadhav, K.D. and Shet, A.R. (2025). Convolutional Neural Networks for the Intelligent and Automated Detection of Mango Leaf Disease to Enhance Crop Health Management. *Agricultural Science Digest.* **45(6):** 1004-1010. doi: 10.18805/ag.DF-717.

Submitted: 23-01-2025 **Accepted:** 05-11-2025 **Online:**18-11-2025

and quality, posing serious threats to worldwide mango production. For proper management approaches and reducing crop damage, these diseases must be diagnosed early and well identified with minimum mistakes. Traditional methods of disease detection depend on the help provided by agriculture bodies, but this has been limited due to a lack of infrastructure as well as human capital (Swetha *et al*., 2016). Machine learning algorithms, together with visual computing techniques, can also support the development of intelligent systems for identifying leaf diseases in plants.

Machine learning, particularly deep learning with neural systems, has gained prominence due to the advancements in computer processors and devices primarily used in agriculture. The advancement of computer technology will facilitate monitoring and controlling plant disease symptoms by farmers. Previous studies have demonstrated that image recognition may be used to detect plant illness in maize, apples and various other stable and sick plants (Kumar *et al*., 2021; Hai and Duong, 2024; Lugito *et al*., 2022). In the past few years, there has been a growing interest in employing current technology, like CNNs, to automate illness diagnosis in agriculture. CNNs, a deep learning algorithm based on human vision, have shown amazing achievement in photo recognition applications such as plant disease classification. The main purpose of this study is to investigate the role played by CNNs in the early detection and classification of mango leaf diseases. In order for us to develop an accurate system that can differentiate between diverse leaf conditions, we should train our CNN models on a set of images depicting different disease symptoms on mango leaves.

Mango leaf disease research and approaches are presented in this section. The learning processes for identifying automatic leaf diseases in mango species are determined Several studies (Cho *et al*., 2024; AlZubi, 2023; Wasik and Pattinson, 2024) argue that machine learning is the best approach for detecting diseases in fish, plants and animals as well as manufacturing industry (Porwal, 2024). Pratap and Kumar (2024) detected chilli leaf illness using methods like K-nearest neighbors (KNN), Artificial Neural Network algorithms (ANN), Picture editing procedures, as well as K-means clustering. Although K-means clustering is simple, it may be difficult to set up. Altalak *et al*. (2022), Deep learning combined with manual characteristics can improve plant leaf classification. Their approach combines CNN with a support vector machine (SVM) and leaves segmentation for classification. However, in noisy datasets with overlapping classes, SVM may not work effectively. Ding (2023) used a CNN-based LeNet to identify plant illnesses, with GoogleLeNet delivering faster results but risking overfitting. Zhang *et al*. (2023) employed image processing and statistical approaches to identify plant diseases using the YOLOv3 model. While YOLOv3 is quick and accurate, it may have localization mistakes and poorer recall than sensors with two stages.

Singh *et al*. (2019) proposed an automatic web-based disease of leaves segmentation solution based on a neural network. The proposed system was separated into four base radial functions: First, photos of mango leaves are captured in real-time with a web-enabled digital camera. Second, the pictures were pre-processed with a “scale-invariant feature transform technique” and features were extracted. Third, a bacterial foraging optimisation approach was employed to improve the NN’s training by focusing on the most distinctive properties. The radial basis function NN was utilized to recover the damaged area in mango leaf images. For anthracnose (fungal) infection, the test results also revealed high accuracy of the suggested system. Mia *et al*. (2020) proposed an NNE for MLDR that can aid in the quick and accurate diagnosis of diseases. A classification model generated training data, which included pictures of leaves inflicted with different illnesses. The project developed an ML system for automatically uploading new images of diseased leaves and correlating them with training data to detect mango leaf diseases. Research findings showed that this method successfully identified and classified the ailment under investigation with an average rating of 80%.

Nagaraju *et al*. (2020) presented a V2IncepNet, which combines the best design features from Inception module. Basic traits are accumulated by VGGNet module, while high-dimensional features are extracted using Inception module for image categorization. Pham *et al*. (2020) came up with an artificial neural network (ANN) technique in 2020 for identifying early tissue disorders on the leaves wherein only small spots are visible at higher resolutions. Following this, all affected blobs across the entire dataset were separated through a contrast enhancement technique after preprocessing stage. Kumar *et al*. (2021) developed a new CNN design in 2021 for spotting mango anthracnose disease. It was tested using a “real-time dataset” retrieved from “farms across Karnataka, Maharashtra and Delhi”. Both photographs of healthy as well as diseased leaves of mango trees are included. In their study, Sujatha *et al*. (2017) made use of artificial neural networks (ANNs) to identify early mango leaf diseases. The damaged leaf’s image was captured with a digital camera at a constant distance and with acceptable light. The image obtained with the digital camera was pre-processed with reduced noise using an average filter, colour transformation and histogram adjustment.

Research gap

In the existing literature, few research studies have been conducted on mango leaf disease detection using ML models. Most existing studies rely on complex models that require high computational resources. Additionally, small datasets and limited real-world adaptability affect model performance. There is a need for a lightweight and efficient CNN-based model that can accurately classify mango leaf diseases with minimal computational requirements.

Objective of research

This study employs a Sequential CNN with convolutional, max-pooling and fully connected layers to classify mango

leaf diseases. A preprocessed image dataset (including resizing, noise reduction and augmentation) is used to train the model with categorical cross-entropy loss and the Adam optimizer. The model achieves high classification accuracy, effectively distinguishing between healthy and diseased leaves despite variations in lighting, texture and background. This lightweight CNN model can be used for real-time disease detection and is suitable for mobile applications and smart farming. Early diagnosis helps prevent crop loss and improves mango yield and quality.

MATERIALS AND METHODS

Deep neural networks within machine learning's "deep learning" sphere discern complex data. Deep learning can process various kinds of data such as text, audio, video pictures time series sensors and IOT data. Image processing is a typical use case for deep learning techniques like (CNN). A CNN model can be trained to discriminate disease-infected and healthy leaves from mangoes with high accuracy using a dataset that comprises photos of both types of leaves. The techniques include four major steps. The first step is to collect data and the second is to design an appropriate model. The third phase is data training, with the last step being model testing.

Dataset

The Mendeley database provided this study's training dataset. The collection contained 2494 images of mango leaves grouped into five categories: Anthracnose, cutting weevil, bacterial canker, dieback and healthy (Fig 1).

Image preprocessing, labelling and training dataset

Image pre-processing was utilised to improve or modify the raw images required to run the CNN classifier. To ensure consistency, photos must be resized and rescaled because image sizes might vary between sources. Because larger-sized pictures demand additional processing resources, this step is critical for preserving accuracy and accelerating the training process. Before data is sent across the network, it must be standardised to a uniform size and format. The photos used in this investigation were shrunk to 256×256×3 and then transformed to grayscale. Following adjusting the size, the mango leaf pictures were input and labelled with the appropriate health phrase. Using the training and test datasets, five classes were identified.

The dataset was divided into three sets: training, validation and test. The divisions were as follows: 80% training, 10% validation and 10% testing. Data augmentation was done to the training set. This covers both random horizontal and vertical flips and rotations. The photos were normalised by adjusting the values of the pixels to the [0, 1] range.

Model architecture

The TensorFlow Keras API was used to create the neural network model, which is formed up of a succession of convolutional layers and layers with maximum pooling (Fig 2). The last layers are completely linked (dense) layers for categorization.

- The input layers resize photos to 256×256 pixels and normalises pixel values.
- Convolutional layers with various sizes of filters (64, 256, 512) and kernel dimensions (3×3) were used. Nonlinearity was introduced using ReLU activation functions (Table 1).
- Max-pooling layers (2, 2) were included after every layer of convolution to minimise spatial dimensionality.
- The flattened layer converts 2D feature maps into 1D vectors for completely linked layers.
- Before the final output layer, 64-unit dense layers with ReLU activation were added. The output layer is made



Fig 1: Images of mango plant leaves categorised into anthracnose, bacterial canker, cutting weevil, die back and healthy.

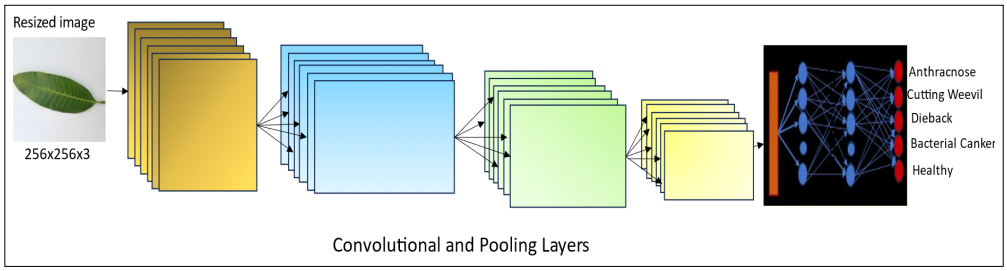


Fig 2: Model architecture includes convolution, pooling layers, flattening and dropout parameters.

up of neurons equivalent to the number of classes (5 in this example), as well as a function of softmax activation for multiclass classification.

- The training consisted of 25 epochs and a batch size of 32. Training progress, involving accuracy and validating accuracy, was tracked and documented for future study.

Convolution operations traverse an input picture or feature map using filters, often known as kernels. Each level extracts information from overlapping parts. The procedure entails mathematical operations such as dividing filter components by input picture elements and summing the results. A two-dimensional convolution process is represented by an input picture (I) and a kernel (K) in the following manner:

$$S_{(i,j)} = \sum_{p=0}^{m-1} \sum_{q=0}^{n-1} I_{(i=p,\, j+q)} K_{(p.q)}$$

Where,

m and n= The kernel (K) coordinates.

i and j= The image (I) coordinates.

To decrease computational difficulty and overfitting risk, the model has a max pooling layer. The layer that is fully connected classifies photos based on the patterns learnt in preceding layers. The Fully Connected Layer, which includes a Softmax function, predicts and provides probabilities to classes, guaranteeing that incoming data is classified accurately and interpretably. The softmax function converts the numerical numbers of neurons in the preceding layer (y1, y2, y3, …yn) into probabilities (P1, P2, P3, …Pn) given n.

$$P_k = \frac{e^{yk}}{\sum_{j=1}^{n} e^{yj}}$$

Where,

y_k= The value in numbers of the j^{th} neuron in the preceding layers.

P_k= The probability of class k after applying softmax.

Converts an input into an array with one dimension. It does not have any settings. To summarise, the method begins with an input pattern of (32, 256, 256, 3) for a batch of 32 256×256-pixel photos with three colour channels. The model is made up of convolutional, max-pooling and dense layers, resulting in a total of 2,125,061 trainable parameters. This architecture's purpose is most likely picture classification, in which a model trains to extract characteristics and forecast depending on the classes supplied.

Evaluation parameters

CNN are evaluated using a variety of critical criteria to measure their performance in addressing certain problems. Here are some common assessment parameters for CNNs:

A confusion matrix is a visual depiction of the model's performance for each class, showing true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN).

Predicted values.			
		Positive	Negative
Actual values	Positive	TP	FN
	Negative	FP	Tn

Accuracy is the percentage of photos that are correctly categorised. Although it might be deceptive for imbalanced datasets, this metric is simple yet effective.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision is a percentage of positive instances that are positive as compared to those expected. demonstrates the model's ability to prevent false positives.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall the proportion of genuine positive cases which are accurately detected. displays the model's ability to recognise genuine positives.

$$\text{F1 - Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

Results and Discussion

The researchers created CNN architectures to detect illnesses in mangoes by analysing a data set of healthy and sick leaves. On the training dataset, the CNN model achieved remarkable performance metrics, including a loss of 0.059 and an accuracy of 98.03%. It also had a validation loss of 0.0485 and an accuracy of 97.77% (Fig 3). These measurements, when evaluated against a separate validation dataset, show the model's ability to apply its learnt patterns to new, previously unknown data. Although there is a little decrease in accuracy when compared to the training set, validation performance remains remarkable, confirming the model's usefulness in detecting illnesses in mangoes *via* image analysis.

Fig 4 depicts the forecasts and accompanying confidence scores for several occasions. The model regularly performs well across classes. However, minor differences in accuracy and confidence ratings provide important information about its capacity to differentiate across classes.

The confusion matrix analyses the model's classification accuracy for five particular categories: Anthracnose, Bacterial Canker, Cutting Weevil, Dieback and Healthy. Each row in the matrix contains the actual labels for classes and each of the columns represents the anticipated labels for the class (Fig 5).

The CNN designs have been tested for their ability to detect sick leaves in diverse photos, demonstrating their potential for disease diagnostics and plant health. The model correctly detected both damaged and healthy leaves, indicating its capacity to distinguish healthy from ill mango leaves.

The performance metrics (Table 2) illustrate the classification model's capacity to distinguish between pathological and healthy states. When the accuracy scores are examined, it is clear that Anthracnose, Cutting Weevil and Die Back illnesses received a score of 1.0000, indicating that all occurrences categorised were properly anticipated. However, the accuracy of sores was somewhat

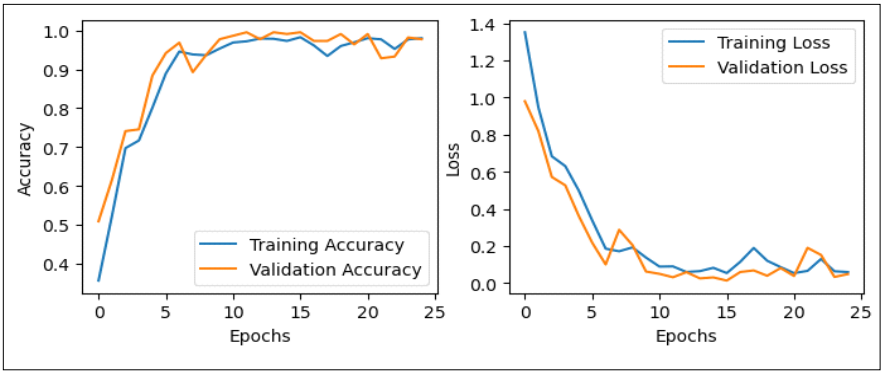


Fig 3: Performance of accuracy and loss over epochs.

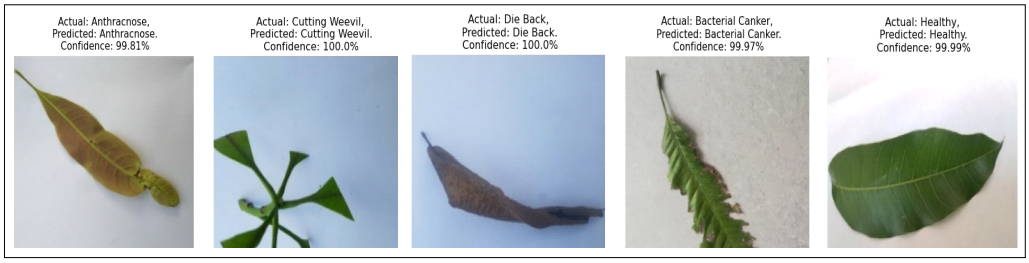


Fig 4: Actual and predicted sick pictures using the proposed CNN model.

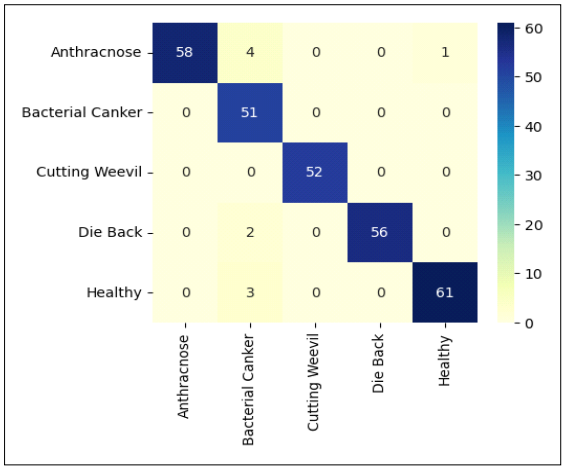


Fig 5: The confusion matrix includes both actual and expected labels.

Table 1: Hyperparameters of the convolutional neural network (CNN) model.

Parameter	Description
No. of convolution layer	6 with different filter sizes (64, 256, 512)
No. of max pooling layer	6 with a pool size of (2, 2)
Dropout rate	0.5
Network weight assigned	Uniform
Activation function	Relu
Epoch	25
Batch size	32
Image size	256×256×3 pixels

lower (0.8500) for Bacterial Canker, suggesting that only a small proportion of cases diagnosed as sores might be false positives. Both Bacterial Canker and Cutting Weevil had recall scores of 1.0000, suggesting that the model could recognise each case.

Anthracnose achieved a slightly reduced recall of 0.9206, indicating that the model did not identify all picture occurrences. All classes did well on the F1-Score, which takes recall and precision into consideration; Cutting Weevil received 1.000, while Die Back received a high score of 0.9825. The average weighted metrics show how reliable the model is with total accuracy being 96.53%. This implies that the model can accurately identify events in the medical environment while maintaining recall and precision.

The graph illustrates the performance of a classifier on various diseases as well as on one healthy class. Each illness has an Area Under Curve (AUC) displayed which means the higher AUC value indicates better separation of diseased plants from healthy ones. For instance, Anthracnose had an AUC value of 0.65, showing a high false positive rate (FPR) or true positive rate (TPR), depending on classification threshold choice (Fig 6). On the other hand, Cutting Weevil had a greater AUC value of 0.72 suggesting higher discrimination between these two classes than all other classes combined together.

On comparing the CNN model developed in this study with previous research, the accuracy obtained here demonstrates superior performance. The proposed CNN model achieved an overall accuracy of 96.53%, outperforming several existing models for mango disease detection. Gulavnai and Patil (2019) achieved an accuracy

Table 2: Matrices after classification.

	Precision	Recall	F1-score	Support
Anthracnose	1.0000	0.9206	0.9587	63
Bacterial canker	0.8500	1.0000	0.9189	51
Cutting weevil	1.0000	1.0000	1.0000	52
Die back	1.0000	0.9655	0.9825	58
Healthy	0.9839	0.9531	0.9683	64
Accuracy			0.9653	288
Macro avg	0.9668	0.9679	0.9657	288
Weighted avg	0.9699	0.9653	0.9660	288

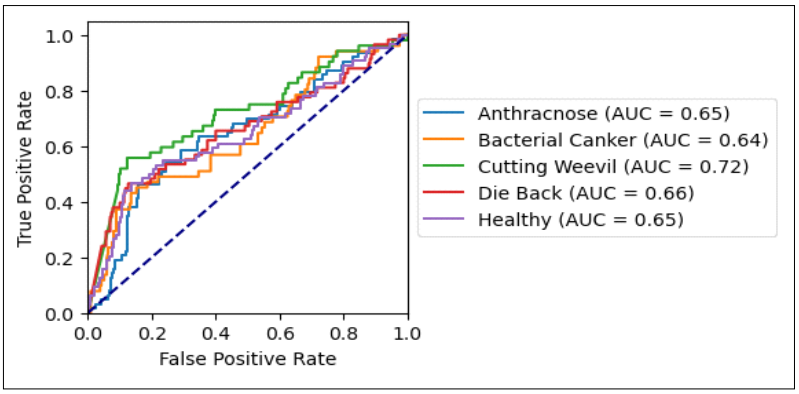


Fig 6: ROC (AUC) curve for diseased and healthy leaves of mango.

of 91% with their CNN model for recognizing four mango diseases. Similarly, the CNN-based model by Sharma *et al*. (2022) identified three mango disease classes-Anthracnose, Powdery Mildew and Red Rust, along with healthy leaves, achieving an accuracy of 90.36% using a dataset from Sher-e-Kashmir University of Agricultural Sciences and Technology, Jammu. In contrast, the neural network ensemble (NNE) proposed by Mia *et al*. (2020) detected mango diseases with only 80% accuracy. Meanwhile, Rao *et al*. (2021) employed transfer learning and deep neural networks to recognize Bacterial Canker in mangoes, achieving a recall value of 82% on a self-acquired dataset. However, their model exhibited 99% overall accuracy in distinguishing three mango diseases from healthy leaves.

CONCLUSION

The proposed CNN model effectively detects mango leaf diseases, achieving 96.53% accuracy after 25 epochs. High precision and recall values indicate strong model reliability across different disease categories. The confusion matrix confirms the model's ability to distinguish between healthy and diseased leaves, making it a valuable tool for early disease detection. This study highlights the potential of deep learning in precision agriculture. By enabling early and accurate disease diagnosis, the model can help farmers reduce crop losses, minimize pesticide use and improve mango production. Policymakers and agricultural extension services can integrate such AI-based solutions into disease management programs to support sustainable farming practices.

Future research should focus on expanding the dataset to include more disease variations, environmental conditions and geographical locations. Additionally, integrating statistical hypothesis testing, such as t-tests or ANOVA, would further validate the model's superiority over traditional methods. Exploring hybrid models, transfer learning and multimodal approaches could enhance classification accuracy and adaptability for real-world agricultural applications.

ACKNOWLEDGEMENT

Funding

This research received no external funding.

Disclaimers

The views and conclusions expressed in this article are solely those of the authors and do not necessarily represent the views of their affiliated institutions. The authors are responsible for the accuracy and completeness of the information provided but do not accept any liability for any direct or indirect losses resulting from the use of this content.

Authors' contributions

All authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all the aspects of this work.

Data availability

The data analysed/generated in the present study will be made available from corresponding authors upon reasonable request.

Availability of data and materials

Not applicable.

Use of artificial intelligence

Not applicable.

Declarations

Authors declare that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

The authors declare that they have no conflict of interest.

REFERENCES

Altalak, M., Ammad uddin, M., Alajmi, A. and Rizg, A. (2022). Smart agriculture applications using deep learning technologies: A survey. *Applied Sciences*. **12(12):** 5919.

AlZubi, A.A. (2023). Artificial intelligence and its application in the prediction and diagnosis of animal diseases: A review. *Indian Journal of Animal Research*. **57(10):** 1265-1271. doi: 10.18805/IJAR.BF-1684.

Cho, O.H., Na, I.S. and Koh, J.G. (2024). Exploring advanced machine learning techniques for swift legume disease detection. *Legume Research.* **47(7):** 1221-1227. doi: 10.18805/LRF-789.

Ding, B. (2023). Lenet: Lightweight and efficient lidar semantic segmentation using multi-scale convolution attention. arXivpreprint arXiv. 2301.04275.

Gulavnai, S. and Patil, R. (2019). Deep learning for image based mango leaf disease detection. *International Journal of Recent Technology and Engineering*. **8(3S3):** 54-56.

Hai, N.T. and Duong, N.T. (2024). An improved environmental management model for assuring energy and economic prosperity. *Acta Innovations*. **52(5):** 9-18. https://doi.org/10.62441/ActaInnovations.52.2.

Kabir, R., Jahan, S., Islam, M.R., Rahman, N. and Islam, M.R. (2020). Discriminant Feature Extraction using Disease Segmentation for Automatic Leaf Disease Diagnosis. In: Proceedings of the International Conference on Computing Advancements. (pp. 1-7).

Kumar, P., Ashtekar, S., Jayakrishna, S.S., Bharath, K.P., Vanathi, P.T. and Kumar, M.R. (2021). Classification of mango leaves infected by fungal disease anthracnose using deep learning. In 2021 5th International Conference on Computing Methodologies and Communication (ICCMC). *IEEE.* (pp. 1723-1729).

Liu, L., Li, J. and Sun, Y. (2019). Research on the Plant Leaf Disease Region Extraction. In Proceedings of the 2019 International Conference on Video, Signal and Image Processing. (pp. 49-54).

Lugito, N.P.H., Djuwita, R., Adisasmita, A. and Simadibrata, M. (2022). Blood pressure lowering effect of *Lactobacillus*-containing probiotic. *International Journal of Probiotics and Prebiotics*. **17(1):** 1-13. https://doi.org/10.37290/ijpp2641-7197.17:1-13.

Mia, M.R., Roy, S., Das, S.K. and Rahman, M.A. (2020). Mango leaf disease recognition using neural network and support vector machine. *Iran Journal of Computer Science*. **3(3):** 185-193. https://doi.org/10.1007/s42044-020-00057-z.

Nagaraju, Y., Sahana, T. S., Swetha, S. and Hegde, S. U. (2020). Transfer learning based convolutional neural network model for classification of mango leaves infected by anthracnose. In 2020 IEEE International Conference for Innovation in Technology (INOCON). *IEEE.* (pp. 1-7).

Pham, T.N., Van Tran, L. and Dao, S.V.T. (2020). Early disease classification of mango leaves using feed-forward neural network and hybrid metaheuristic feature selection. *IEEE Access*. **8:** 189960-189973.

Porwal, S., Majid, M., Desai, S.C. Vaishnav, J. and Alam, S. (2024). Recent advances, challenges in applying artificial intelligence and deep learning in the manufacturing industry. *Pacific Business Review (International)*. **16(7):** 143-152.

Pratap, V.K. and Kumar, N.S. (2024). Deep learning based mango leaf disease detection for classifying and evaluating mango leaf diseases. *Fusion: Practice and Applications*. **15(2):** 261-261.

Rao, U.S., Swathi, R., Sanjana, V., Arpitha, L., Chandrasekhar, K. and Naik, P.K. (2021). Deep learning precision farming: Grapes and mango leaf disease detection by transfer learning. *Global Transitions Proceedings*. **2(2):** 535-544. https://doi.org/10.1016/j.gltp.2021.08.002.

Sharma, A., Bijral, R.K., Manhas, J. and Sharma, V. (2022). Mango leaf diseases detection using deep learning. *International Journal of Knowledge Based Computer Systems*. **10(1):** 40-44.

Singh, U.P., Chouhan, S.S., Jain, S. and Jain, S. (2019). Multilayer convolution neural network for the classification of mango leaves infected by anthracnose disease. *IEEE Access*. **7:** 43721-43729.

Sujatha, S., Saravanan, N. and Sona, R. (2017). Disease identification in mango leaf using image processing. *Advances in Natural and Applied Sciences*. **11(6 SI):** 1-8.

Swetha, K., Venkataraman, V., Sadhana, G.D. and Priyatharshini, R. (2016). Hybrid approach for anthracnose detection using intensity and size features. In 2016 IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR). *IEEE.* (pp. 28-32).

Trang, K., TonThat, L., Thao, N.G.M. and Thi, N.T.T. (2019). Mango Diseases Identification by a Deep Residual Network with Contrast Enhancement and Transfer Learning. In: 2019 IEEE Conference on Sustainable Utilization and Development in Engineering and Technologies (CSUDET). *IEEE.* (pp. 138-142).

Wasik, S. and Pattinson, R. (2024). Artificial Intelligence Applications in Fish Classification and Taxonomy: Advancing our Understanding of Aquatic Biodiversity. *Fish Taxa*. **31:** 11-21.

Zhang, Y., Wang, M., Zhao, D., Liu, C. and Liu, Z. (2023). Early weed identification based on deep learning: A review. *Smart Agricultural Technology*. **3:** 100123.