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Ensembled AttenNet: A Novel Deep Learning Approach for Mango Leaf Disease Detection

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Short Running Title: Attention-based CNNs for Mango leaf Disease Detection

Abstract:
Agriculture is severely threatened by plant diseases, which can result in poor quality and quantity of food. Because of the rapid spread of plant diseases and the vast areas affected, it is difficult to control them effectively. Several leaf diseases affect the mango industry particularly severely, reducing fruit yields and quality. In order to prevent and treat these diseases effectively, it is crucial to identify them quickly and correctly. In this study, attention methods and multi-scale feature fusion will be used to improve automatic detection of mango leaf diseases. To extract the features, we use a pretrained VGG16 model. A number of common diseases were evaluated, including anthracnose, bacterial canker, weevils, dieback, gall flies, powdery mildew, sooty mold, and healthy leaves. Data used for classification comes from Kaggle's MangoleafBD dataset. In order to train and test the model, 4000 images were used. In addition to cross-validation methods, precision, recall, and F1 metrics are used to measure model resilience. An accuracy of up to 99% was achieved with the model. This model provides better results than state-of-the-art models.

Keywords: Plant disease detection, Mango leaf disease, Deep learning in agriculture, Convolutional Neural Network (CNN), Attention Mechanism, MangoleafBD dataset, Early disease identification, Mango crop quality improvement

1. Introduction:

Mango plants (Mangifera indica) are tropical fruit crops grown in many countries worldwide, and one of the most economically important tropical crops. There is, however, an important point to keep in mind: mango trees are highly susceptible to various diseases caused by fungal, bacterial, and viral agents[1][2]. Without detection or accurate diagnosis, these diseases can cause significant yield losses, negatively impacting the livelihoods of farmers and the overall mango industry[3]. Detecting and managing these diseases in a timely manner is essential for preventing crop losses and maintaining fruit quality. An automated disease detection system is necessary in order to mitigate the challenges associated with manual inspection, which is time consuming and error-prone[4]. In their article, the authors discuss infections caused by fungi, specifically Anthracnose[5]. Identifying illnesses is conducted using CNN and Alexnet. The mango leaves used in the dataset were collected from the GBPUAT field site.The authors of study investigated three diseases: bacterial canker, scab, and powdery mildew [6]]. Alexnet model is trained and tested to detect diseased or healthy leaves. In this study, mango leaves are considered as the dataset. Based on the proposed model, the accuracy is 89%. Based on CNN algorithms, the authors develop a mechanism for detecting Anthracnose [7]. The dataset used was mango fruit. Separating the sick mangoes is the main objective. The accuracy of the method is 70%.A study has been conducted on anthracnose, red rust, and powdery mildew [8]. In order to detect and classify leaf diseases, the authors proposed a model based on CNNs. Leaves make up the dataset under consideration. A CNN is trained to diagnose and characterize diseases of leaves. A CNN-based model has an accuracy of 90.36%. Researchers in [9] used AlexNet deep learning architecture with particle swarm optimizer to detect plant diseases. They trained on a public database of 25 classes of five crops to determine which leaves were healthy and which were diseased. As a result of combining AlexNet with PSO, accuracy was enhanced by 3.23% to 98.83%. In order to detect Apple leaf diseases, the authors used a Multistep Optimization Resnet[10]. A total of 9,118 images were used for training and 2,279 images for verification. Precision, recall, and F1-score were calculated as 0.9557, 0.9558, and 0.9557, respectively. Convolutional neural networks and support vector machines are proposed for MobileNetV2 based on crossover-based levy flight distributions. According to the study results, it demonstrated 99.43% accuracy, 98.03% precision, 99.56% recall, and 95.67% F1 scores [11]. In the study[12], an ensemble architecture was employed to combine the best deep learning models, resulting in an accuracy of 97.31% in validating the models. From images of coffee leaves, deep features are extracted using transfer learning and convolutional neural networks (CNNs). A combination of deep learning and artificial intelligence would provide a promising alternative for identifying plant diseases due to their ability to learn from complex patterns [13]. As a community, we need open datasets, comparative analytic tools, and reproducible research methodologies to maximize both scientific labor and collaborative synthesis. It is vital that experimental methods are open and rigorous, and that novice researchers are urged to adhere to ethical standards and innovate responsibly[14]. A CNN variant model such as ResNet50, DenseNet201, EfficientNetB4, and InceptionV3 was proposed to detect between two classes[15]. Based on the results of DenseNet201 and EfficientNetB4, the results are the best with accuracy of 97.97%[15]. An apple leaf disease detection method based on Multistep Optimization Resent is described in[16]. During training, 9,118 images were used, while 2,279 images were used for verification. A mean precision, recall, and F1-score of 0.957, 0.958, and 0.957, respectively, was obtained. Mango trees can suffer damage from a number of diseases, including Anthracnose, Bacterial Flower Disease, Golmachi, Moricha, Shutimold, Bacterial Black Spot, Apical Bud Necrosis, Red Rust, Lichens, Powdery Mildew, Root Rot, and Damping Off[17]. Several pathogens, including bacteria, viruses, fungi, parasites, and sometimes even unfavourable environmental conditions, can cause such diseases[18]. In most cases, human intelligence is insufficient to identify the exact cause of illness. In the past, farmers followed specialists' observations of diseased plants, or experts came to the farm and advised them, who would then protect the plants from disease [19]. Machine learning is one of the subcategories of artificial intelligence. It involves designing and learning systems, predicting results, and analyzing previous experiences. The collection of data is the first step in the learning process, which is comparable to personal experience. A machine learning approach has recently been used to detect disease in plants based on the processing of photos. ESDNN (Ensemble Stacked Deep Neural Network) is a recent technique that can be used to classify mango leaf diseases [20]. Additionally, in [11], 380 color images representing healthy and diseased mango trees were analyzed using a pretrained MobileNetV2+SVM model. There were a number of different techniques used to augment the data in order to improve generalization and the learning stage. According to [21] using color and ultraviolet (UV) images, an LDA model can detect anthracnose in Sugar mango fruits. According to the authors, UV-A light may be useful for detecting the disease at an early stage and LDA may be useful for discriminating mangoes with anthracnose.

Sr#	Writer	Methods	Dataset	Acc.	Contribution
01	[22]	Ensemble and transfer learning	Rice leaf	98%	Provided a new ensemble model.
02	[23]	Combination (CNN, ViT)	WRCD, RLDD, Plant village	-	Proposed a lightweight deep learning approach combining CNN and ViT.
03	[23]	YOLOv5, U2 Net, ViT	PlantDoc, PlantVillage	90.8%	Stage classification techniques on apple leaf disease.
04	[24]	DLMC-Net	Citrus, Cucumber, Grapes, Tomato	93.56% (Citrus), 92.34% (Cucumber), 99.50% (Grapes), 96.56% (Tomato)	A deeper lightweight multi-class classification model.
05	[25]	EANet, MaxViT, CCT, PVT	Multi class tomato diseases	97% (MaxViT)	Accumulate varying degrees of interest in job changes.
06	[20]	Vision Transformer	Plant Village	96.71%	Higher accuracy than traditional CNN.
07	[26]	RSNSR-LDD, DDN	PlantVillage, Grape 400	97.19%, 99.37%, 99.06% (PlantVillage), 96.88%, 97.12%, 95.43% (Grape400), 100%	A new super-resolution network (DDN)-based leaf disease detection network (RSNSR-LDD) (grape leaf rot) is proposed.

Methodology:

A deep learning model for kidney disease must go through several steps before it can be deployed in the clinic (Fig. 1). Data acquisition, pre-processing, data selection, model training, validation, and testing, as well as evaluation and interpretation are all steps in this process. The following section will provide detailed instructions for each step

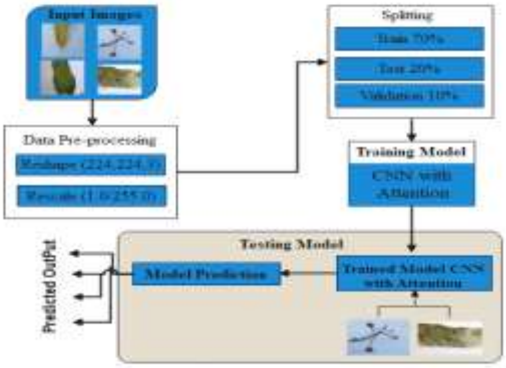


Figure 1:Model Architecture

2.1 Data collection:

In order to apply deep learning to mango diseases, data must first be gathered. When building a deep learning model, a large set of medical images is generally required. In order for an algorithm to remain accurate and general, high-quality data must be used to train it. When multiple modalities, machines, and imaging parameters are used in multiple experiments, bias can be reduced, but the model's convergence can also be impaired. A model's success depends on its developers understanding the domain in which it will operate, and obtaining as much data as they can from the domain as possible. Here are the basic steps for deep learning, which lay the foundation for the rest of the process. A balanced dataset of 4000 data images was collected, classified, and used for training The classes are divided equally: Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, Sooty Mould, as shown in fig.2. Open data collection is a category on Kaggle that researchers can use to download these data sets.

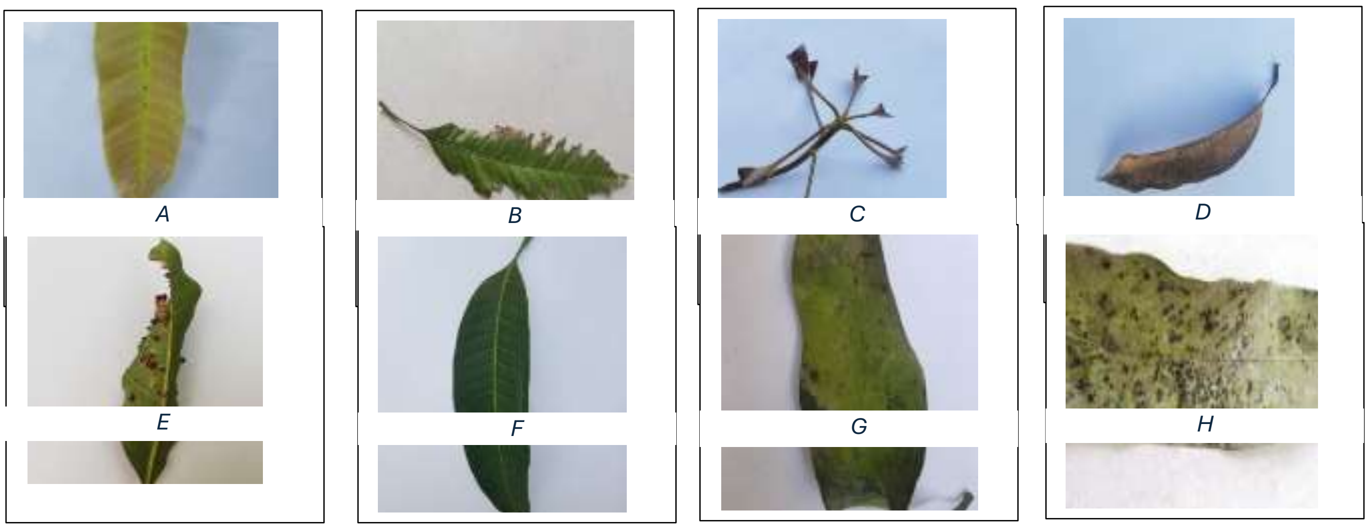


Figure 2:Classification of Dataset (A) Anthracnose,**(B) Bacterial Canker,(C) Cutting Weevil, (D) Die Back, (E) Gall Midge, (F) Healthy,(G) Powdery Mildew, (H) Sooty Mould**

2.2. Data pre-processing
The second step of deep learning is data preprocessing. In this step, the dataset is cleaned and prepared. The quality of the data plays an important role in improving the accuracy of the algorithm. Preprocessing techniques include normalizing images, registering images, and reducing noise. The labeling of data is another aspect of data preprocessing. It is common for labels to take different forms in various types of learning tasks. When data is labeled, each image in a dataset is classified into a class or category, such as in the classification of kidney diseases. A generative model that uses self-supervised learning does not require an additional label.

2.3. Data augmentation
Another important aspect of data preprocessing is data enhancement. A data augmentation technique involves modifying existing data using methods such as rotation, scaling, and cropping in order to reduce overfitting. Several generative adversarial networks have been demonstrated to generate synthetic images that are of high authenticity, showing their potential for enhancing data.

2.4. Feature Extraction:
Deep learning uses the best and most reliable technique for extracting features, called a CNN, to solve different shortcomings of machine learning feature extraction. Knowledge is learned through layers. In order to learn something, you need to go through layers. In the process of matching and extracting data, filtering mechanisms are used.

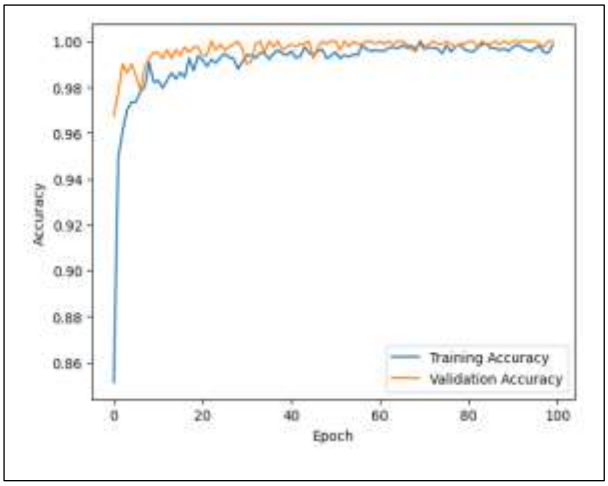
2.5. Dataset Partitioning and Model Selection Methodology:
Cross validation on a dataset divided into K values is performed by dividing the dataset into K values, where K + 1 must be found in the following division. It is recommended that K value be set at 10. This is according to the study researcher. There are 10 subsets of the 4000 data in a total dataset. There are 400 data points in each fold. The cross-validation is 10-fold when K = 10. Upon conclusion of this routine activity, 0.8% of the problems have been solved (3200 mango leasf images) Perform to the best of your abilities, and a further 0.2% (800 mango leaf images) are still to be resolved. This is how the system is verified. Using any input device, the first step in this model design is to acquire images. A preprocessing step followed the acquisition of the images. The images were then prepared for analysis by using the preprocessing steps. To extract features with neural networks using preprocessed images, preprocessed images were included in the Ensembled model, which includes CNN with attention. According to the study, 0.25 and 0.5 dropout percentages were used in each layer, and the best results were obtained with 0.5 dropout percentage. An analysis of the image is then done to determine which extractions are most appropriate to represent the image. A feature extraction is based on extracted data used during training and testing for identification. The result of training a knowledge base is shown in Fig.1 by the classification of images into syndromes associated with them.

Evaluation Techniques:
This study utilized multiple techniques during the development process, as well as at the end, in order to assess how well the structure worked. Based on four evaluation metrics, the confusion matrix report assesses the prototype's acquisitions: F1-score, Precision, Recall, and Accuracy. Research was conducted by measuring the outcome of an evaluation developed by

domain experts of a prototype. The objective testing of an artifact has been done through the use of experimental analysis. Ultimately, the results of this evaluation indicate the model has practical application.

2. Experimental Results and Discussion:

Through the customization of several parameters, experiments were conducted to find an efficient model. An analyzer should consider five parameters: the color of a dataset, the number of epochs, the augmentation, the optimizer, and the dropout. Compared with a non-augmentation image, an augmented RGB colored image showed a 15% improvement in accuracy. As part of the training process, three epochs were performed, 50, 100, to determine the performance of this new model. Nevertheless, 100 epochs were the most effective for the model. It was found that the training accuracy at the 100th epoch was 0.9987, which was the highest ever Fig 3 shows the model's accuracy rates during training and validation, and Figure 4 shows the model's loss statistics.



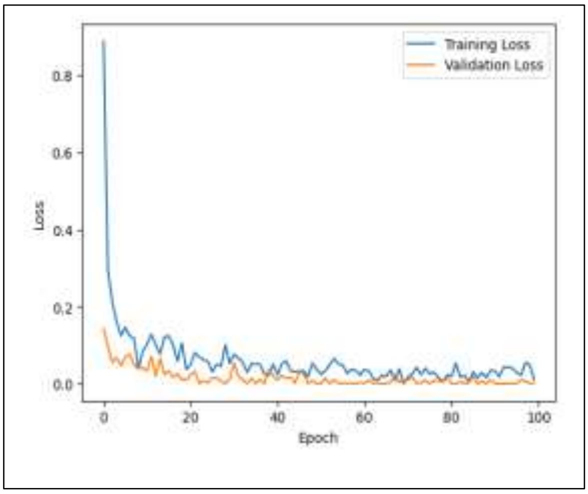


Figure 3: Training and validation Accuracy

Figure 4: Training and validation Loss

Model evaluation

This study evaluated the accuracy and effectiveness of the developed machine learning models using performance metrics By measuring metrics such as accuracy, recall, precision, and F1-score, valuable insight was gained into the classifiers' performance. The evaluation was based on a confusion matrix illustrated in figure 5. This analysis was conducted to comprehensively examine the classification results based on the confusion matrix. True positives (TP) reflected instances that were correctly classified as positive, while true negatives (TN) represented instances that were incorrectly classified as negative. A false positive (FP) is a prediction which was incorrectly classified as a positive; a false negative (FN) is a prediction which was incorrectly classified as a negative. According to the evaluation approach, the model's accuracy and efficiency in detecting kidney disease at an early stage could be evaluated effectively.

Accuracy:

This ratio can be used to determine whether the prediction accuracy of output cases compared to all data cases is high or low.

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

Confusion Matrix:

Using the model generated, figure 5 below demonstrates how the model performs when attempting to classify data.

Precision:

The precision of a data collection system is a performance metric for the quality of the samples being collected. In mathematics, a fraction is defined as a difference between an observation that was predicted and one that was observed to be positive. As a result, precision is a measurement of how accurately our model predicts positive results (i.e., how many actual positives there are). Precision of model show in figure. 6

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall:

Referring to recall, these metric measures whether the data was retrieved correctly. This is also known as sensitivity, and it indicates the percentage of correctly predicted positives compared to the total number of positives. Consequently, recall gives an indication of how many actual positives were captured in the model (total). The model's recall can be seen in figure 6.

$$\text{R} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

F1-Score:

By using this metric, you can measure the accuracy of your tests. A weighted average of the F1 score is used to calculate recall and precision. It should be valid even when the distribution is uneven, as it aims to strike a balance between precision and recall..

$$\text{F1} - \text{score} = 2 \cdot \frac{\text{P} \cdot \text{R}}{\text{P} + \text{R}}$$

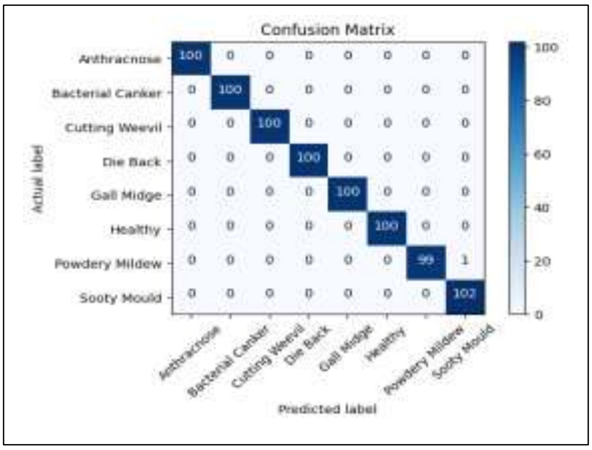


Figure 5: Confusion Matrix

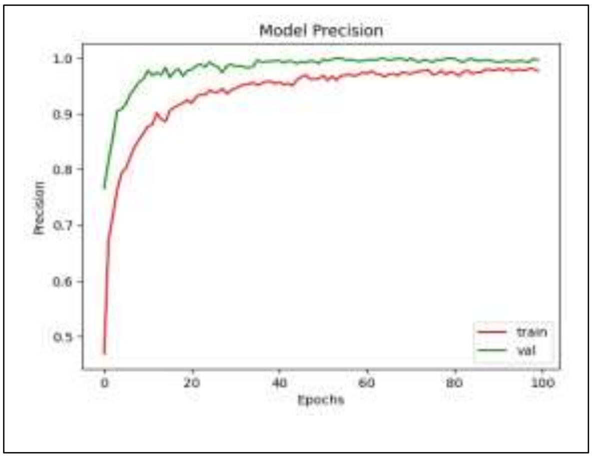


Figure 6: Precision

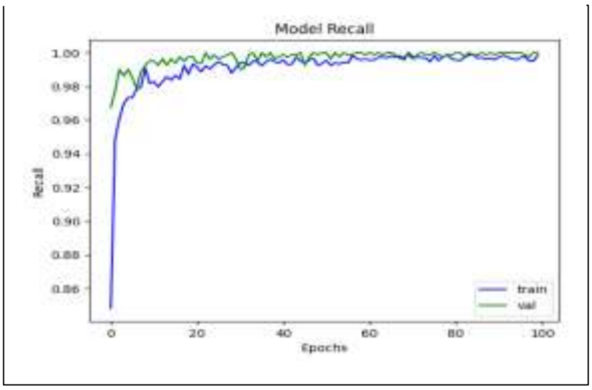


Figure 7: Recall

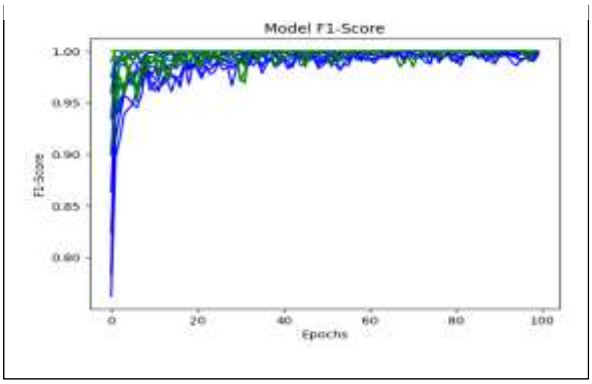


Figure 8: F1-Score

3. Conclusion

Plant diseases must be detected early in order to be effectively controlled and improved crops can be produced. As a result, this study developed a deep learning model that accommodates multiscale feature fusion and attention mechanisms with the objective of classifying mango leaf diseases efficiently. Last but not least, we aimed to develop a model that is exceptionally accurate at distinguishing healthy mango leaves from diseased mango leaves, while keeping computation efficiency in mind. Our first step is to train the simplest CNN model with its variant, VGG16, in order to detect diseases. Based on the performance results, the model with VGG16 was accurate for classifying diseased and healthy mango leaves at 97%. The multiscale feature fusion approach is incorporated into the model to enhance the model results further and go beyond the existing model. By utilizing these methods, the model is better able to focus on disease-specific areas of the leaf and capture detailed multiscale information for a more accurate representation of leaf features. Through both multiscale feature fusion and the attention mechanism, the accuracy of the model was improved from 97.15% to 99.15%. Based on the proposed method, it was possible to identify localizations with symptoms of diseases more accurately and to process feature data more reliably, resulting in greater accuracy and reliability in classification.

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5. Data Availability:

Data is publicly available on Kaggle,
https://www.kaggle.com/datasets/aryashah2k/mango-leaf-disease-dataset

6. Conflicts of Interest:

The authors declare no conflicts of interest.

References

P. Mm and B. Chelliah, "Mango leaf disease identification and classification using a CNN architecture optimized by crossover-based levy flight distribution algorithm," Neural Comput. Appl., vol. 34, pp. 1–14, 2022, doi: 10.1007/s00521-021-06726-9.

S. I. Ahmed et al., "MangoLeafBD: A comprehensive image dataset to classify diseased and healthy mango leaves.," Data Br., vol. 47, p. 108941, Apr. 2023, doi: 10.1016/j.dib.2023.108941.

A. Picon, M. Seitz, A. Alvarez-Gila, P. Mohnke, A. Ortiz-Barredo, and J. Echazarra, "Crop conditional Convolutional Neural Networks for massive multi-crop plant disease classification over cell phone acquired images taken on real field conditions," Comput. Electron. Agric., vol. 167, p. 105093, 2019, doi: https://doi.org/10.1016/j.compag.2019.105093.

D. U. Singh, S. Chouhan, S. Jain, and S. Jain, "Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease," IEEE Access, vol. 7, 2019, doi: 10.1109/ACCESS.2019.2907383.

S. Arya and R. Singh, "A Comparative Study of CNN and AlexNet for Detection of Disease in Potato and Mango leaf," in 2019 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT), 2019, pp. 1–6. doi: 10.1109/ICICT46931.2019.8977648.

U. Sanath Rao et al., "Deep Learning Precision Farming: Grapes and Mango Leaf Disease Detection by Transfer Learning," Glob. Transitions Proc., vol. 2, no. 2, pp. 535–544, 2021, doi: https://doi.org/10.1016/j.gltp.2021.08.002.

S. Wongsila, P. Chantrasri, and P. Sureephong, “Machine Learning Algorithm Development for detection of Mango infected by Anthracnose Disease,” in 2021 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunication Engineering, 2021, pp. 249–252. doi: 10.1109/ECTIDAMTNCON51128.2021.9425737.

M. Mohapatra, A. K. Parida, P. K. Mallick, and N. Padhy, “Mango Leaf Disease Detection Based on Deep Learning Approach,” in 2022 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC), 2022, pp. 1–7. doi: 10.1109/ASSIC55218.2022.10088323.

A. M. Iliyasu, A. S. Benselama, D. K. Bagaudinovna, G. H. Roshani, and A. S. Salama, “Using Particle Swarm Optimization and Artificial Intelligence to Select the Appropriate Characteristics to Determine Volume Fraction in Two-Phase Flows,” Fractal Fract., vol. 7, no. 4, 2023, doi: 10.3390/fractalfract7040283.

H. Yu et al., “Apple leaf disease recognition method with improved residual network,” Multimed. Tools Appl., vol. 81, no. 6, pp. 7759–7782, 2022, doi: 10.1007/s11042-022-11915-2.

M. Prabu and B. J. Chelliah, “Mango leaf disease identification and classification using a CNN architecture optimized by crossover-based levy flight distribution algorithm,” Neural Comput. Appl., vol. 34, pp. 7311–7324, 2022, [Online]. Available: https://api.semanticscholar.org/CorpusID:246196192

D. Novtahaning, H. A. Shah, and J.-M. Kang, “Deep Learning Ensemble-Based Automated and High-Performing Recognition of Coffee Leaf Disease,” Agriculture, vol. 12, no. 11, 2022, doi: 10.3390/agriculture12111909.

Y. Shou et al., “Heavy metals pollution characteristics and risk assessment in sediments and waters: The case of Tianjin, China,” Environ. Res., vol. 212, p. 113162, 2022, doi: https://doi.org/10.1016/j.envres.2022.113162.

D. S. J. Ting, C. S. Ho, R. Deshmukh, D. G. Said, and H. S. Dua, “Infectious keratitis: an update on epidemiology, causative microorganisms, risk factors, and antimicrobial resistance.,” Eye (Lond)., vol. 35, no. 4, pp. 1084–1101, Apr. 2021, doi: 10.1038/s41433-020-01339-3.

A. Chaturvedi, S. Sharma, and R. R. Janghel, “Detection of external defects in tomatoes using deep learning,” J. Ambient Intell. Humaniz. Comput., vol. 14, no. 3, pp. 2709–2721, 2023, doi: 10.1007/s12652-023-04514-y.

H. Yu et al., “Apple leaf disease recognition method with improved residual network,” Multimed. Tools Appl., vol. 81, no. 6, pp. 7759–7782, 2022, doi: 10.1007/s11042-022-11915-2.

N. Rahaman et al., “A Deep Learning Based Smartphone Application for Detecting Mango Diseases and Pesticide Suggestions,” vol. 13, 2023, doi: 10.12785/ijcds/XXXXXX.

L. Molina-Cárdenas et al., “First Report of Mango malformation disease caused by Fusarium proliferatum in Mexico.,” Plant Dis., Jun. 2022, doi: 10.1094/PDIS-05-22-1213-PDN.

R. Garg, A. K. Sandhu, and B. Kaur, “A Systematic Analysis of Various Techniques for Mango Leaf Disease Detection,” in 2023 International Conference on Disruptive Technologies (ICDT), 2023, pp. 349–354. doi: 10.1109/ICDT57929.2023.10150878.

V. Gautam, R. K. Ranjan, P. Dahiya, and A. Kumar, “ESDNN: A novel ensembled stack deep neural network for mango leaf disease classification and detection,” Multimed. Tools Appl., vol. 83, no. 4, pp. 10989–11015, Jun. 2023, doi: 10.1007/s11042-023-16012-6.

L. Ramírez Alberto, C. Eduardo Cabrera Ardila, and F. Augusto Prieto Ortiz, “A computer vision system for early detection of anthracnose in sugar mango (Mangifera indica) based on UV-A illumination," Inf. Process. Agric., vol. 10, no. 2, pp. 204–215, 2023, doi: https://doi.org/10.1016/j.inpa.2022.02.001.

A. A. Ahad, M. Sanchez-Gonzalez, and P. Junquera, "Understanding and Addressing Mental Health Stigma Across Cultures for Improving Psychiatric Care: A Narrative Review.," Cureus, vol. 15, no. 5, p. e39549, May 2023, doi: 10.7759/cureus.39549.

Y. Borhani, J. Khoramdel, and E. Najafi, "A deep learning based approach for automated plant disease classification using vision transformer," Sci. Rep., vol. 12, no. 1, p. 11554, 2022, doi: 10.1038/s41598-022-15163-0.

S. Sharma, J. Mohler, S. D. Mahajan, S. A. Schwartz, L. Bruggemann, and R. Aalinkeel, "Correction: Sharma et al. Microbial Biofilm: A Review on Formation, Infection, Antibiotic Resistance, Control Measures, and Innovative Treatment. Microorganisms 2023, 11, 1614," Microorganisms, vol. 12, no. 10, 2024, doi: 10.3390/microorganisms12101961.

A. Yasmin, A. Basunia, M. Rahim, M. Haque, and M. Hossain, "Mokter Hossain et al 2023 Minor fruit vol 9 2 16," vol. 9, pp. 141–148, 2023.

W. Chen and Y.-C. Huang, "Letter to the editor regarding Li et al. (2022) Identifying ecosystem service bundles and the spatiotemporal characteristics of trade-offs and synergies in coal mining areas with a high groundwater table, Liu et al. (2021) Ecosystem service multifunctionality assessment and coupling coordination analysis with land use and land cover change in China's coastal zones, and Zhang et al. (2021) Spatial relationships between ecosystem services and socioecological drivers across a large-scale region: A case study in the Yellow River Basin," Sci. Total Environ., vol. 829, p. 154717, 2022, doi: https://doi.org/10.1016/j.scitotenv.2022.154717.