IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 13, No. 3, September 2024, pp. 2498~2505
ISSN: 2252-8938, DOI: 10.11591/ijai.v13.i3.pp2498-2505

A survey of detecting leaf diseases using machine learning and deep learning in various crops

Thilagaraj Thangamuthu[1], Abdul Kareem[2], Varuna Kumara[2], Utkrishna Udesh Naik[3], Sanjana Poojary[3], Bharath Raju[3]

[1]Department of Artificial Intelligence and Machine Learning, Moodlakatte Institute of Technology, Kundapura, India
[2]Department of Electronics and Communication Engineering, Moodlakatte Institute of Technology, Kundapura, India
[3]Department of Computer Science and Engineering, Moodlakatte Institute of Technology, Kundapura, India

Article Info

Article history:

Received Jan 9, 2024
Revised Feb 12, 2024
Accepted Mar 4, 2024

Keywords:

Agricultural productivity
Convolutional neural networks
Deep learning
Machine learning
Plant leaf disease

ABSTRACT

For agricultural productivity and food security to be guaranteed, early detection and treatment of illnesses are crucial. Machine learning (ML) and deep learning (DL) approaches can be used to precisely and successfully identify plant leaf diseases. A heterogeneous dataset comprising photos of both healthy and diseased leaves such as bacterial blights, fungal infections, and viral manifestations provides the foundation for the model building and training. Accuracy, precision, recall, and F1-score are the measures used to assess the model's performance. ML techniques are helpful in the identification and extraction of pertinent information from plant leaf pictures, whereas DL techniques in general, and convolutional neural networks (CNN), in particular, are remarkable at learning complex hierarchical representations. Therefore, DL architectures like CNN are utilized in conjunction with ML approaches like support vector machines (SVM), decision trees, and random forests to extract complicated patterns and attributes from leaf pictures. This research provides an extensive analysis of the performance and application of DL and ML approaches recently applied to the early identification of leaf diseases in different crops.

Corresponding Author:

Thilagaraj Thangamuthu
Department of Artificial Intelligence and Machine Learning, Moodlakatte Institute of Technology
Kundapura, Karnataka 576217, India
Email: thilagaraj@mitkundapura.com

1. INTRODUCTION

The global food security is under an increasing threat from widely emerging plant diseases. To increase agricultural productivity and ensure food security, early diagnosis of plant diseases is essential. The conventional methods of detection of plant diseases include visual observation, microscopy, mycological analysis, and biological diagnostics. These methods are of a time-consuming and labor-intensive nature. As a result, there is a lot of research being done on the application of machine learning (ML) and deep learning (DL) approaches to the early identification of plant diseases, and this trend seems highly promising.

For the early diagnosis of plant leaf diseases, traditional ML approaches are frequently used for extracting features and classification. DL techniques have recently attracted attention as a potential tool for learning intricate hierarchical representations. Hence, to provide a comprehensive framework for plant leaf disease identification, this study makes use of the synergies between DL and ML techniques.

The detection and extraction of relevant information from photographs of plant leaves is made easier by ML techniques. Combining DL and convolutional neural networks (CNN) which excel at learning intricate hierarchical representations creates a potent model that can identify minute patterns that point to a variety of plant diseases. The proposed technique holds the potential for the non-invasive, precise, and instantaneous diagnosis of plant leaf diseases, facilitating resource allocation and timely interventions. As precision agriculture gains traction, the combination of ML and DL in disease identification offers a transformative possibility for resilient and sustainable crop management.

In this paper, we intend to bring out a comprehensive survey of the ML techniques, DL techniques, and a combination of ML and DL techniques in the early detection of plant leaf diseases. This survey critically examines the state-of-the-art technologies and expresses informed views and will definitely provide guidance and ideas for future developments of the application of ML and DL techniques in the early detection of plant leaf diseases. This will increase the crop yield to achieve food security.

2. LITERATURE REVIEW

The application of ML techniques and DL techniques for early detection of leaf diseases is studied in the literature. The comparison of the performance of those approaches is presented in Table 1 (see in Appendix). The table compares methods, algorithms, and accuracy for various leaf diseases.

2.1. Performance of machine learning models

Various ML models are implemented to detect leaf disease [1]–[8]. The support vector machine (SVM), random forest (RF), linear regression, decision tree (DT), and k-nearest neighbour (KNN) algorithms exhibited strong performance. The review findings indicate that the SVM method is capable of accurately detecting and classifying plant diseases with remarkable accuracy. This model undergoes testing on numerous types of leaves and various diseases affecting leaves.

2.2. Performance of deep learning models

Several methods cited in papers [9]–[35], derived from pre-existing DL models, exhibited robust performance in this challenge. This study introduces contemporary and superior solutions. The following deep algorithms shown strong performance in detecting leaf diseases: CNN, Inception V4, DenseNet-121, ResNet-50, InceptionResNet V2, EResNet-50, VGG16, R-CNN, EfficientNet, GoogleNet, ant colony optimization with convolution neural network (ACO-CNN), and generative adversarial network (GAN). The VGG16 algorithm performs well with the highest accuracy. It has been noted that significant deep-learning algorithms are being used to identify leaf diseases.

2.3. Performance of a combination of machine learning and deep learning models

The integration of ML and DL models was applied in this contest, as described in [36]–[42]. The performance of the artificial neural network (ANN), KNN, and CNN models was commendable when handling various leaf datasets containing diverse illnesses. The combined models outperform other approaches. The combined models perform well with good accuracy in dealing with different leaf datasets with multiple diseases [43]–[50]. Therefore, it can be said that the combined models outperform ML and DL models in terms of accuracy when it comes to removing intricate patterns and features from leaf pictures.

3. POTENTIAL AREAS OF RESEARCH

In the previous sections, the authors of this work have identified some opportunities that they believe have not received much attention from researchers. There is limited discourse on the real-time surveillance of the initial symptoms of illnesses before their widespread dissemination across the entire plant. There is limited study on integrating various tracking and testing duties into a single system to lower expenses, enhance technology accessibility for farmers, and provide ease. Most studies on models for detecting plant diseases examine two-dimensional images taken from plant samples. When dealing with fruit samples, the use of single-input cameras or a two-dimensional view can be problematic due to the spherical or cylindrical shape of most fruits. Hence, there are a lot of research opportunities on sensor technology. Additionally, advances in DL and ML can be used to create algorithms that more accurately detect leaf illnesses early on.

4. CONCLUSION

The study of DL and ML techniques for the accurate and dependable early detection of plant leaf diseases is compared in this work. It is discovered that while DL approaches in general and CNN, in particular, are amazing at learning complex hierarchical representations, using ML techniques for obtaining and choosing features improves the model's selective abilities. The system is capable of learning hierarchical properties because DL techniques more particularly, CNN are combined with ML techniques. This allows the system to be extremely accurate in identifying and classifying various plant leaf diseases. The survey's findings demonstrate how effective it is to combine DL and ML models for early leaf disease identification.

APPENDIX

Table 1. Comparison of ML and DL techniques for early detection of leaf diseases (*continue…*)

Author	Work carried	Methods and algorithms	Plant name and diseases identified	Accuracy (%)
Ramesh *et al*. [1]	The gathered datasets of healthy and diseased leaves are subjected to a RF collective training procedure. Features of an image are extracted using the histogram, which is a representation of an oriented gradient. Large-scale plant disease detection through the use of ML to train vast amounts of publicly accessible data sets.	RF, SVM, KNN, Naïve Bayes (NB), CART	Papaya leaf-brown spot	RF-70.14 %, SVM-40.33%, KNN-66.76%, NB-57.61%, CART-64.66%
Oo and Htun [2]	The experimental findings unequivocally establish that the suggested methodology adeptly discerns and categorizes four prevalent plant leaf ailments: cercospora leaf spot, powdery mildew, bacterial blight, and rust.	SVM, KNN, and ensemble classifier (EC)	Rose-bacterial blight, powdery mildew, cercospora leaf spot and rust	SVM-98.2%, KNN-80.02%, EC-84.6%
Mokhtar *et al*. [3]	The gabor wavelet change method is used to extract relevant features from tomato leaf pictures. This is carried out in conjunction with the application of different kernel functions through SVM. Finding and classifying the particular type of illness affecting tomato plants is the aim.	SVM	Tomato leaf-bacterial blight and cercospora leaf spot, powdery mildew and rust.	SVM-99.5%
Sandhu and Kaur [4]	These disease detection techniques exhibit high efficiency and accuracy, enabling them to effectively operate the created system for leaf disease detection, despite certain restrictions.	SVM, NB	Various plants and diseases	SVM-86%, NB-79%
Iqbal and Talukder [5]	A dataset comprising 450 images of both healthy and diseased potato leaves is used for image segmentation. The dataset was sourced from the free-to-use plant village database. To distinguish between healthy and diseased leaves, seven classifier approaches are used.	RF, logistic regression (LR), KNN, DT, NB, LDA, and SVM	Potato leaf-late blight, early blight	RF-97%, LR-94%, KNN&DT-91%, NB-84%, LDA-78%, SVM-37%
Islam *et al*. [6]	Multiclass SVM for picture segmentation.	SVM	Potato leaf-late blight, early blight	SVM-95%
Ahmed *et al*. [7]	Four ML methods have been evaluated and compared for the detection of illnesses in rice leaves. To varying degrees, the algorithms correctly anticipated the rice leaf diseases.	LR, KNN, DT, NB	Rice leaf-bacterial blight, brown spot, leaf smut	DT-97%
Mohan *et al.* [8]	The task can be divided into two primary categories: recognizing paddy disease and signs of plant diseases. The first step in the disease diagnosis procedure is to use an AdaBoost classifier and Haar-like features to identify the rice plant's affected area.	SIFT feature & classifier-SVM & KNN	Paddy (rice)-and multiple diseases	KNN-93.33%, SVM-91.10%
Andrew *et al*. [9]	Plant disease identification efficiency with pre-trained models based on CNN. Their focus was on optimizing the hyperparameters of popular pre-trained models such as ResNet-50, DenseNet-121, VGG-16, and Inception V4. The well-known PlantVillage dataset, which includes 54,305 picture samples of various plant disease species in 38 classifications, was used for the tests.	Inception V4, DenseNet-121, ResNet-50, VGG-16	Apple, tomato, and grape leaves, multiple diseases	V4-99.78%, VGG16-84.27%, ResNet50-99.83%, DenseNet121-99.81%
Sladojevic *et al.* [10]	The novel approach to training and the methodology employed enables a rapid and effortless application of the system in practical settings. The model that has been suggested can distinguish between 13 different types of plant diseases when compared to healthy leaves. Additionally, it is capable of differentiating between the surroundings and the leaves of plants.	CNN	13 different plant leaves	CNN-96.3%
Joshi and Bhavsar [11]	Detection of nightshade crop leaf disease detection.	DL algorithms	Multiple plants and diseases	Accuracy not mentioned
Srinidhi *et al*. [12]	The classification is performed with high accuracy, categorizing the diseases into 4 distinct classes. This work uses data enrichment and image annotation techniques, namely flipping, blurring, and canny edge detection, to improve the apple leaf disease dataset.	CNN-EfficientNetB7, DenseNet	Apple leaf-multiple diseases	EfficientNetB7-99.8%, DenseNet-99.75%
Monigari *et al*. [13]	By using 20639 images from 15 folders showing both healthy and damaged leaves from plants, then CNN was trained. With the use of leaf photo analysis, this research aims to develop a more advanced and accurate method for understanding plant illnesses.	CNN	Tomato-late blight, septoria, pepper-bacterial spot, potato-early and late blight	CNN -90%
Krishnamoorthy *et al*. [14]	A CNN model called InceptionResNetV2 is used in conjunction with the transfer learning technique to reliably detect diseases in images of rice leaves. By modifying several hyperparameters, the foundational CNN model was made more accurate.	CNN model-Inception ResNetV2	Rice leaf-leaf blast, bacterial blight, and brown spot	Inception ResNetV2-95.67%

Table 1. Comparison of ML and DL techniques for early detection of leaf diseases

Author	Work carried	Methods and algorithms	Plant name and diseases identified	Accuracy (%)
Deng *et al*. [15]	The smartphone app, along with a software system comprising servers and clients, offers precise and effortless recognition of rice diseases. An inherent constraint of the ensemble model is the presence of numerous parameters, which might potentially impact the speed of identification.	ResNet-50, ResNeXt-50, DenseNet-121, ResNeSt-50, and SE-ResNet-50	Rice leaf- false smut, neck blast, rice leaf blast, sheath blight, bacterial stripe, brown spot	DenseNet-121, SE-ResNet-50, and ResNeSt-50 performed well with accuracy–98%
Myna *et al*. [16]	Healthy and sick leaves are inputs and the afflicted photos are classified into five distinct categories. The proposed methodology utilizes various stages, including preprocessing, feature extraction, training, testing, and classification.	DL algorithm - VGG16	Cabbage leaf and 5 diseases	VGG16-92%
Bari *et al*. [17]	The faster R-CNN technique incorporates a sophisticated region proposal network (RPN) architecture that accurately determines the placement of objects to produce potential regions. Three different rice leaf diseases might be automatically diagnosed with the use of the suggested DL-based method.	Faster R-CNN algorithm	Rice leaf-rice blast, brown spot and hispa	R-CNN for rice blast–98.09%, Brown spot–98.85%, Hispa–99.17%
Vasantha *et al*. [18]	Using a variety of ML techniques and comparing several algorithms to identify the crop disease kind based on image data, this system provides possible solutions. Furthermore, it shows freshly introduced methodologies and performance measures.	ML and DL algorithms	Rice leaf-brown spot, leaf blast, sheath blight, sheath rot, bacterial leaf blight, leaf Smut	CNN–highest accuracy
Tejaswini *et al*. [19]	This work aids farmers by identifying illnesses in rice leaves, hence promoting robust crop production. When it comes to performance, DL models outperform conventional ML techniques.	5-layer convolution, VGG-16, VGG19, Xception, Resnet	RICE leaf- brown spot, leaf blast, hispa	5-layer convolution model-78.2%
Rajeena *et al*. [20]	By modifying the variables, the suggested study uses EfficientNet to improve the accuracy of the maize leaf disease database. Tests utilizing DenseNet and ResNet on the test dataset validate the accuracy and resilience of this method.	EfficientNet-based DL framework	Corn leaf-rust, gray leaf spot, blight	EfficientNet-98.85%
Goyal *et al*. [21]	A new DL model that successfully divides wheat diseases into ten different classifications.	Deep convolution architecture	Wheat leaf-8 diseases	Average accuracy of the proposed model-98.62%.
Jiang *et al*. [22]	The data enrichment and image annotation techniques are used in this study to construct the apple leaf disease dataset. The dataset consists of laboratory photographs as well as complicated images captured in real-world situations.	SSD, VGG-Net, INAR-SSD, CNN	Apple leaf-alternaria leaf spot, brown spot, mosaic, grey spot, rust	INAR-SSD-78.80%
Zhang *et al*. [23]	Empirical studies demonstrate that recognition accuracy can be enhanced by augmenting the diversity of pooling operations, incorporating a rectified linear unit (ReLU) function and dropout operations, and iteratively adjusting the model parameters.	GoogLeNet, Cifar10 model	Maize leaf-8 diseases	GoogLeNet-98.9%, Cifar10-98.8%
Sahasra *et al*. [24]	The methodologies utilized to categorize distinct diseases for leaf disease identification. It also discusses the pre-processing technique used for the automatic identification of leaf diseases and the algorithm used for picture segmentation.	VGG16	Apple and tomato –bacterial spot, early and late blight	VGG16-99.99%
Khan *et al*. [25]	The technique of transfer learning is utilized to initialize the parameters of the suggested deep model. Data augmentation methods like translation, rotation, reflection, and scaling were used to reduce overfitting.	CNN	Apple leaf-8 diseases	CNN-97.18%
Yan *et al*. [26]	An improved model that makes use of the VGG16 architecture to precisely identify illnesses in apple leaves was provided in this study. To reduce the number of parameters, a pooling layer with global averages is used in place of the fully connected layer, and a batch normalization layer is added to accelerate convergence.	CNN based on VGG-16	Apple leaf-scab, frog eye spot, and cedar rust	VGG16-99.01%.
Fuentes *et al*. [27]	A technique for annotating classes locally and globally, as well as augmenting data aiming to enhance accuracy and minimize the occurrence of false positives.	Faster R-CNN, region-based fully convolutional network (R-FCN), and SSD	Tomato leaf–8 diseases	Not specified
Zhong and Zhao [28]	Employed ACO-CNN to distinguish between infected and uninfected leaves.	ACO with CNN, GAN, CNN, SGD	Apple leaf-7 diseases	ACO-CNN–99.98%, CNN-99.97%, GAN-99.6%, SGD-85%

Table 1. Comparison of ML and DL techniques for early detection of leaf diseases

Author	Work carried	Methods and algorithms	Plant name and diseases identified	Accuracy (%)
Malvade *et al*. [29]	A novel approach is presented, utilizing pre-trained CNN models, to automatically detect and categorize biotic stressors in paddy crops from field photos. An empirical assessment of the best CNN models employing transfer learning to learn based on ImageNet weights is also included in the planned study.	Inception-V3, VGG-16, ResNet-50, DenseNet-121 and MobileNet-28	Paddy (rice)-brown spot, hip, and leaf blast	ResNet-50–92.61%
Mohanty *et al*. [30]	DL models can be trained on increasingly bigger, publicly available image datasets, providing a clear route towards widespread, smartphone-assisted crop disease diagnosis.	AlexNet, GoogLeNet	14 crops and 26 diseases	AlexNet-85.53%, GoogLeNet-99.34%
Mohameth *et al*. [31]	"Smartphone-assisted disease diagnosis" is a breakthrough made possible by the combination of sophisticated cell phones with computer vision via DL.	VGG16, ResNet 50, Google Net	13 crops and multiple diseases	VGG16-97.82%, ResNet50-95.38%, Google Net-95.3%.
Lee *et al*. [32]	A novel method utilizing RNN has been developed to autonomously identify diseased areas and extract pertinent characteristics for illness categorization. In addition, they examine the focal point of attention acquired by our RNN.	InceptionV3, GoogleNet, Seq-RNN	Multiple crops and 20 diseases	InceptionV3-98.05%, GoogleNet-99.17%, Seq-RNN–98.17%
Moganarengam and Vignesh [33]	Classification is conducted by analyzing the leaf's characteristics, such as colour and form, to categorize diseases into several types, including healthy, bacterial spot, and leaf mould.	CNN and DenseNet 201	38 crops and multiple diseases	DenseNet 201-95%
Jeon and Rhee [34]	Using the CNN model, a unique leaf categorization method was created. Using GoogleNet, two models were built by changing the network depth. The degree of damage to the leaves or discoloration was taken into account to evaluate each model's performance.	GoogleNet, variant of GoogleNet	Multiple crops and diseases	GoogleNet – 99.6 %, variant of GoogleNet-99.8%
Sladojevic *et al*. [35]	A novel method involving classifying leaf images using deep neural networks.	CNN	13 crops and multiple diseases	CNN-96.3%
Sarkar *et al*. [36]	A system employing an analysis of colour, edges, and texture features using SVM and ANN.	SVM and ANN	Rice leaf - blight	SVM-92.4%, ANN-99.5%
Shrivastava and Patidar [37]	This work also looks at the challenges and limitations associated with using ML and DL to diagnose plant diseases. These challenges include issues with data accessibility, imaging quality, and the capacity to discriminate between plants that are ill and healthy.	ML and DL algorithms	Multiple datasets and diseases	ML and DL algorithms progress discussed
Shoaib *et al*. [38]	Models for identifying nutritional deficiencies.	ANN, SVM, KNN, and fuzzy classification (FC)	Multiple plants and diseases	ANN-99%, SVM-97%, KNN-99 %, FC-99%
Ngongoma *et al*. [39]	Many diseases harm leaves' chlorophyll, which results in dark or black patches on the leaf's surface. They can be found using ML techniques, feature extraction, picture preprocessing, and image segmentation. For feature extraction, the grey level co-occurrence matrix is employed.	CNN and SVM	Multiple crops and diseases	CNN-97.7%, SVM-80%
Jubaer *et al*. [40]	To obtain an accurate diagnosis, linked or related plant ailments were gathered. The good results obtained with minimal computing resources demonstrated the algorithm's efficiency in identifying and categorizing leaf diseases. It is possible to use more algorithms to improve the categorization accuracy.	ML and DL algorithms	Multiple plants and diseases.	Many algorithms with accuracies
Sawarkar and Kawathekar [41]	The method of detecting diseases involves acquiring images, pre-processing images, segmenting pictures, extracting features, and classifying pictures. Investigating methods to protect rose plants from various diseases is the goal of this work.	ML and DL algorithms	ROSE leaf-black spot, powdery mildew, anthracnose	Recommended model-SVM
Nikith *et al*. [42]	This research examines and presents three distinct models capable of detecting eight different leaf diseases.	CNN, SVM, KNN	Soyabean leaf- 7 diseases	CNN-96%, SVM-76%, KNN-64%
Singh and Misra [43]	The subsequent two phases are added in succession after the segmentation step. The green pixels that predominate are identified in the first phase. Following this, the green-dominated pixels are masked using Otsu's approach to establish the appropriate threshold values.	Proposed model	Potato leaf– 7 diseases	Proposed model–94%
Naikwadi and Amoda [44]	It includes a summary of the several disease classification schemes that can be used to find plant leaf diseases. Plant leaf disease identification relies heavily on image segmentation, which is accomplished through the use of a genetic algorithm.	SVM and K-Means	Rose and beans leaves-bacterial, lemon-sun burn, banana-scorch and fungal	Proposed algorithm with average accuracy-97.6%.

Table 1. Comparison of ML and DL techniques for early detection of leaf diseases

Author	Work carried	Methods and algorithms	Plant name and diseases identified	Accuracy (%)
Kulkarni *et al*. [45]	Based on generated data sets, several ML algorithms are used to discern between wholesome and unwholesome leaves. The several stages of implementation, including feature extraction, dataset construction, classifier training, and classification.	Statistical image processing and ML model	20 different diseases of 5 common plants	Proposed model average accuracy-93%.
Elfatimi *et al*. [46]	Provided a method for classifying leaf diseases in beans and identifying and describing the optimal network architecture, including hyperparameters and optimization algorithms.	MobileNet, MobileNetV2	Beans leaf-angular leaf spot, bean rust	Proposed model 92% to 97%
Bansal *et al*. [47]	Presented a collection of pre-trained DL models and evaluated their efficacy on a dataset comprising photographs of apple leaves.	CNN	Apple leaf-multiple diseases	Proposed model-90%
Paymode and Malode [48]	Predicting the kind of illness that will affect tomato and grape leaves in their early stages is the main objective. The multi-crops leaf disease is detected through the CNN methods.	CNN based VGG16 model	Tomato and grape-9 diseases	Proposed model (grapes-98.40%, Tomatoes-95.71%)
Orillo *et al*. [49]	The effective implementation of a MATLAB programme involved utilizing image processing and a backpropagation neural network to accurately identify illnesses in rice leaves.	ANN	Rice leaf -bacterial leaf blight and rice blast	Proposed model-100%
Liu *et al*. [50]	To identify diseases in apple leaves, the task entails generating a sufficient number of abnormal pictures and designing a new architecture for a deep CNN inspired by AlexNet.	CNN	Apple leaf-alternaria leaf spot, mosaic, rust, brow spot	Proposed model-97.62%

REFERENCES

[1] S. Ramesh *et al*., "Plant disease detection using machine learning," in *2018 International Conference on Design Innovations for 3Cs Compute Communicate Control (ICDI3C)*, 2018, pp. 41–45, doi: 10.1109/ICDI3C.2018.00017.

[2] Y. M. Oo and N. C. Htun, "Plant leaf disease detection and classification using image processing," *International Journal of Research and Engineering*, vol. 5, no. 9, pp. 516–523, 2018, doi: 10.21276/ijre.2018.5.9.4.

[3] U. Mokhtar, M. A. S. Ali, A. E. Hassenian, and H. Hefny, "Tomato leaves diseases detection approach based on support vector machines," in *2015 11th International Computer Engineering Conference: Today Information Society What's Next?*, 2016, pp. 246–250, doi: 10.1109/ICENCO.2015.7416356.

[4] G. K. Sandhu and R. Kaur, "Plant disease detection techniques: a review," in *2019 International Conference on Automation, Computational and Technology Management (ICACTM)*, 2019, pp. 34–38, doi: 10.1109/ICACTM.2019.8776827.

[5] M. A. Iqbal and K. H. Talukder, "Detection of potato disease using image segmentation and machine learning," in *2020 International Conference on Wireless Communications Signal Processing and Networking*, 2020, pp. 43–47, doi: 10.1109/WiSPNET48689.2020.9198563.

[6] M. Islam, A. Dinh, K. Wahid, and P. Bhowmik, "Detection of potato diseases using image segmentation and multiclass support vector machine," in *IEEE 30th Canadian Conference on Electrical and Computer Engineering*, 2017, pp. 1–4, doi: 10.1109/CCECE.2017.7946594.

[7] K. Ahmed, T. R. Shahidi, S. M. I. Alam, and S. Momen, "Rice leaf disease detection using machine learning techniques," in *2019 International Conference on Sustainable Technologies for Industry 4.0 (STI)*, 2019, pp. 1–5, doi: 10.1109/STI47673.2019.9068096.

[8] K. J. Mohan, M. Balasubramanian, and S. Palanivel, "Detection and recognition of diseases from paddy plant leaf images," *International Journal of Computer Applications*, vol. 144, no. 12, pp. 34–41, 2016, doi: 10.5120/ijca2016910505.

[9] J. Andrew, J. Eunice, D. E. Popescu, M. K. Chowdary, and J. Hemanth, "Deep learning-based leaf disease detection in crops using images for agricultural applications," *Agronomy*, vol. 12, no. 10, 2022, doi: 10.3390/agronomy12102395.

[10] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep neural networks based recognition of plant diseases by leaf image classification," *Computational Intelligence and Neuroscience*, vol. 2016, pp. 1–12, 2016, doi: 10.1155/2016/3289801.

[11] B. M. Joshi and H. Bhavsar, "Deep learning technology based night-CNN for nightshade crop leaf disease detection," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 11, no. 1, pp. 215–227, 2023.

[12] V. V. Srinidhi, A. Sahay, and K. Deeba, "Plant pathology disease detection in apple leaves using deep convolutional neural networks apple leaves disease detection using EfficientNet and DenseNet," in *2021 5th International Conference on Computing Methodologies and Communication (ICCMC)*, 2021, pp. 1119–1127, doi: 10.1109/ICCMC51019.2021.9418268.

[13] V. Monigari, G. K. Sri, and T. Prathima, "Plant leaf disease prediction," *International Journal for Research in Applied Science and Engineering Technology*, vol. 9, no. 7, pp. 1295–1305, 2021, doi: 10.22214/ijraset.2021.36582.

[14] N. Krishnamoorthy, L. V. N. Prasad, C. S. P. Kumar, B. Subedi, H. B. Abraha, and S. V. E., "Rice leaf diseases prediction using deep neural networks with transfer learning," *Environmental Research*, vol. 198, 2021, doi: 10.1016/j.envres.2021.111275.

[15] R. Deng *et al*., "Automatic diagnosis of rice diseases using deep learning," *Frontiers in Plant Science*, vol. 12, pp. 1–15, 2021, doi: 10.3389/fpls.2021.701038.

[16] A. N. Myna, M. K., M. K., R. H. S., and Y. D. Jain, "Classification and detection of cabbage leaf diseases from images using deep learning methods," *Automation, Control and Intelligent Systems*, vol. 11, no. 1, pp. 1–7, 2023, doi: 10.11648/j.acis.20231101.11.

[17] B. S. Bari *et al*., "A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework," *PeerJ Computer Science*, vol. 7, pp. 1–27, 2021, doi: 10.7717/PEERJ-CS.432.

[18] S. V. Vasantha, B. Kiranmai, and S. R. Krishna, "Techniques for rice leaf disease detection using machine learning algorithms," *International Journal of Engineering and Technical Research*, vol. 9, no. 8, pp. 162–166, 2021.

[19] P. Tejaswini, P. Singh, M. Ramchandani, Y. K. Rathore, and R. R. Janghel, "Rice leaf disease classification using CNN," *IOP Conference Series: Earth and Environmental Science*, vol. 1032, no. 1, pp. 1–14, 2022, doi: 10.1088/1755-1315/1032/1/012017.

[20] F. Rajeena P. P, A. S. U, M. A. Moustafa, and M. A. S. Ali, "Detecting plant disease in corn leaf using EfficientNet architecture an analytical approach," *Electronics*, vol. 12, no. 8, pp. 1–18, 2023, doi: 10.3390/electronics12081938.

[21] L. Goyal, C. M. Sharma, A. Singh, and P. K. Singh, "Leaf and spike wheat disease detection & classification using an improved deep convolutional architecture," *Informatics in Medicine Unlocked*, vol. 25, pp. 1–8, 2021, doi: 10.1016/j.imu.2021.100642.

[22] P. Jiang, Y. Chen, B. Liu, D. He, and C. Liang, "Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks," *IEEE Access*, vol. 7, pp. 59069–59080, 2019, doi: 10.1109/ACCESS.2019.2914929.

[23] X. Zhang, Y. Qiao, F. Meng, C. Fan, and M. Zhang, "Identificbiation of maize leaf diseases using improved deep convolutional

neural networks," *IEEE Access*, vol. 6, pp. 30370–30377, 2018, doi: 10.1109/ACCESS.2018.2844405.
[24] T. Sahasra, S. K. S, S. M. S, and P. R. Devi, "Leaf disease detection using deep learning," in *2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 2021, pp. 1797–1804, doi: 10.1109/ICESC51422.2021.9532909.
[25] A. I. Khan, S. M. K. Quadri, S. Banday, and J. L. Shah, "Deep diagnosis: a real-time apple leaf disease detection system based on deep learning," *Computers and Electronics in Agriculture*, vol. 198, 2022, doi: 10.1016/j.compag.2022.107093.
[26] Q. Yan, B. Yang, W. Wang, B. Wang, P. Chen, and J. Zhang, "Apple leaf diseases recognition based on an improved convolutional neural network," *Sensors*, vol. 20, no. 12, pp. 1–14, 2020, doi: 10.3390/s20123535.
[27] A. Fuentes, S. Yoon, S. C. Kim, and D. S. Park, "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition," *Sensors*, vol. 17, no. 9, pp. 1–21, 2017, doi: 10.3390/s17092022.
[28] Y. Zhong and M. Zhao, "Research on deep learning in apple leaf disease recognition," *Computers and Electronics in Agriculture*, vol. 168, pp. 1–6, 2020, doi: 10.1016/j.compag.2019.105146.
[29] N. N. Malvade, R. Yakkundimath, G. Saunshi, M. C. Elemmi, and P. Baraki, "A comparative analysis of paddy crop biotic stress classification using pre-trained deep neural networks," *Artificial Intelligence in Agriculture*, vol. 6, pp. 167–175, 2022, doi: 10.1016/j.aiia.2022.09.001.
[30] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers in Plant Science*, vol. 7, pp. 1–10, 2016, doi: 10.3389/fpls.2016.01419.
[31] F. Mohameth, C. Bingcai, and K. A. Sada, "Plant disease detection with deep learning and feature extraction using plant village," *Journal of Computer and Communications*, vol. 08, no. 06, pp. 10–22, 2020, doi: 10.4236/jcc.2020.86002.
[32] S. H. Lee, H. Goëau, P. Bonnet, and A. Joly, "New perspectives on plant disease characterization based on deep learning," *Computers and Electronics in Agriculture*, vol. 170, pp. 1–8, 2020, doi: 10.1016/j.compag.2020.105220.
[33] V. Moganarengam and S. P. Vignesh, "Plant disease classification using CNN and DenseNet, a comparative study," *International Research Journal of Engineering and Technology (IRJET)*, vol. 8, no. 11, pp. 236–240, 2021.
[34] W. S. Jeon and S. Y. Rhee, "Plant leaf recognition using a convolution neural network," *International Journal of Fuzzy Logic and Intelligent Systems*, vol. 17, no. 1, pp. 26–34, 2017, doi: 10.5391/IJFIS.2017.17.1.26.
[35] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep neural networks based recognition of plant diseases by leaf image classification," *Computational Intelligence and Neuroscience*, vol. 2016, pp. 1–11, 2016, doi: 10.1155/2016/3289801.
[36] C. Sarkar, D. Gupta, U. Gupta, and B. B. Hazarika, "Leaf disease detection using machine learning and deep learning: review and challenges," *Applied Soft Computing*, vol. 145, 2023, doi: 10.1016/j.asoc.2023.110534.
[37] G. Shrivastava and H. Patidar, "Rice plant disease identification decision support model using machine learning," *ICTACT Journal on Soft Computing*, vol. 12, no. 3, pp. 2619–2627, 2022, doi: 10.21917/ijsc.2022.0365.
[38] M. Shoaib *et al.*, "An advanced deep learning models-based plant disease detection: a review of recent research," *Frontiers in Plant Science*, vol. 14, pp. 1–22, 2023, doi: 10.3389/fpls.2023.1158933.
[39] M. S. P. Ngongoma, M. Kabeya, and K. Moloi, "A review of plant disease detection systems for farming applications," *Applied Sciences*, vol. 13, no. 10, pp. 1–28, 2023, doi: 10.3390/app13105982.
[40] M. A. Jubaer, M. N. Hasan, M. Mustavi, M. T. Shahriar, and T. Ahmed, "Potato leaf disease detection using image processing," *International Journal of Education and Management Engineering*, vol. 13, no. 4, pp. 9–18, 2023, doi: 10.5815/ijeme.2023.04.02.
[41] V. Sawarkar and S. Kawathekar, "A review: rose plant disease detection using image processing," *IOSR Journal of Computer Engineering (IOSR-JCE)*, vol. 20, no. 4, pp. 15–19, 2018, doi: 10.9790/0661-2004031519.
[42] B. V. Nikith, N. K. S. Keerthan, M. S. Praneeth, and D. T. Amrita, "Leaf disease detection and classification," *Procedia Computer Science*, vol. 218, pp. 291–300, 2022, doi: 10.1016/j.procs.2023.01.011.
[43] V. Singh and A. K. Misra, "Detection of plant leaf diseases using image segmentation and soft computing techniques," *Information Processing in Agriculture*, vol. 4, no. 1, pp. 41–49, 2017, doi: 10.1016/j.inpa.2016.10.005.
[44] S. Naikwadi and N. Amoda, "Advances in image processing for detection of plant diseases," *International Journal of Application or Innovation in Engineering & Management (IJAIEM)*, vol. 2, no. 11, pp. 168–175, 2013.
[45] P. Kulkarni, A. Karwande, T. Kolhe, S. Kamble, A. Joshi, and M. Wyawahare, "Plant disease detection using image processing and machine learning," *Computer Vision and Pattern Recognition*, pp. 1–13, 2021.
[46] E. Elfatimi, R. Eryigit, and L. Elfatimi, "Beans leaf diseases classification using MobileNet models," *IEEE Access*, vol. 10, pp. 9471–9482, 2022, doi: 10.1109/ACCESS.2022.3142817.
[47] P. Bansal, R. Kumar, and S. Kumar, "Disease detection in apple leaves using deep convolutional neural network," *Agriculture*, vol. 11, no. 7, pp. 1–23, 2021, doi: 10.3390/agriculture11070617.
[48] A. S. Paymode and V. B. Malode, "Transfer learning for multi-crop leaf disease image classification using convolutional neural network VGG," *Artificial Intelligence in Agriculture*, vol. 6, pp. 23–33, 2022, doi: 10.1016/j.aiia.2021.12.002.
[49] J. W. Orillo, J. D. Cruz, L. Agapito, P. J. Satimbre, and I. Valenzuela, "Identification of diseases in rice plant (*oryza sativa*) using back propagation artificial neural network," in *2014 International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)*, 2014, pp. 1–6, doi: 10.1109/HNICEM.2014.7016248.
[50] B. Liu, Y. Zhang, D. J. He, and Y. Li, "Identification of apple leaf diseases based on deep convolutional neural networks," *Symmetry*, vol. 10, no. 1, pp. 1–16, 2018, doi: 10.3390/sym10010011.

BIOGRAPHIES OF AUTHORS

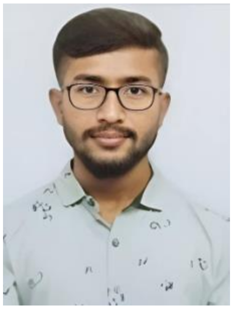
Dr. Thilagaraj Thangamuthu is currently working as an associate professor and head in the Department of Artificial Intelligence and Machine Learning, Moodlakatte Institute of Technology, Kundapura, India. Ph.D. from Bharathiar University, Coimbatore. He has 14 years of Teaching experience; He has published around 12 papers in national and international conferences and journals. His research areas are machine learning and educational data mining. He can be contacted at email: thilagaraj.t@gmail.com.

Dr. Abdul Kareem holds a Doctor of Philosophy from St Peter's Institute of Higher Education and Research, Chennai, India. He also received his B.Tech. and M.Tech. from Kannur University, India in 2003 and Visvesvaraya Technological University, Belagavi, India in 2008 respectively. He is currently the Principal and a Professor of Electronics and Communication Engineering at Moodlakatte Institute of Technology, Kundapura, India. His research interests are in artificial intelligence, machine learning, control systems, and microelectronics. He has published over 15 papers in international journals and conferences. He is a senior member of IEEE. He can be contacted at email: afthabakareem@gmail.com.

Varuna Kumara is a research scholar in the Department of Electronics Engineering at JAIN Deemed to be University, Bengaluru, India. He also received his B.E. and M.Tech. from VTU, Belagavi, India. He is currently serving as an assistant professor of Electronics and Communication Engineering at Moodlakatte Institute of Technology, Kundapura, India. His research interests are in artificial intelligence, signal processing, and control systems. He can be contacted at email: varunakumara@mitkundapura.com.

Utkrishna Udesh Naik is currently a student, pursuing his final year of Engineering in the Department of Computer Science and Engineering at Moodlakatte Institute of Technology, Moodlakatte, Kundapura, Udupi, Karnataka, India. He is an active researcher in machine learning and applications. He is a student member of IEEE. His research interests include artificial intelligence, machine learning, and data mining. He can be contacted at email: tkrishnanaik416@gmail.com, utkrishnanaik416@gmail.com.

Sanjana Poojary is currently a student, pursuing her final year of Engineering in the Department of Computer Science and Engineering at Moodlakatte Institute of Technology, Moodlakatte, Kundapura, Udupi, Karnataka, India. She is an active researcher in deep learning and applications. She is the student research coordinator of Moodlakatte Institute of Technology. Her research interests include artificial intelligence, machine learning, and fuzzy logic. She can be contacted at email: sanjanapoojaryg@gmail.com.



Bharath Raju is currently a student, pursuing his final year of engineering in the Department of Computer Science and Engineering at Moodlakatte Institute of Technology, Moodlakatte, Kundapura, Udupi, Karnataka, India. He is an active researcher in deep learning and applications. His research interests include artificial intelligence, machine learning, and support vector machines. He can be contacted at email: bharath.r32@outlook.com.