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A Comprehensive Survey on Machine Learning and Deep Learning Techniques for Crop Disease Prediction in Smart Agriculture

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ABSTRACT

Diseases caused by bacteria, fungi, and viruses are a problem for many crops. Farmers have challenges when trying to evaluate their crops daily by manual inspection across all forms of agriculture. Also, it is difficult to assess the crops since they are affected by various environmental factors and predators. These challenges can be addressed by employing crop disease detection approaches using artificial intelligence-based machine learning and deep learning techniques. This paper provides a comprehensive survey of various techniques utilized for crop disease prediction based on machine learning and deep learning approaches. This literature review summarises the contributions of a wide range of research works to the field of crop disease prediction, highlighting their commonalities and differences, parameters, and performance indicators. Further, to evaluate, a case study has been presented on how the paradigm shift will lead us to the design of an efficient learning model for crop disease prediction. It also identifies the gaps in knowledge that are supposed to be addressed to forge a path forward in research. From the survey conducted, it is apparent that the deep learning technique shows high efficiency over the machine learning approaches, thereby preventing crop loss.

INTRODUCTION

Advancements in Information and Communication Technologies (ICT) and the Internet of Things (IoT) have revolutionized the agricultural industry by shaping the traditional method of farming in a smarter way to maximize yield and increase food production (Fountas et al. 2015). Smart farming involves the coagulation of different technologies, namely wireless sensors connected to the Internet of Things, robotics, artificial intelligence, and cloud computing (Wolfert et al. 2017). Agriculture plays a vital role in promoting the growth and economy of a country. In India, agriculture plays a significant role in meeting the expanded food demand raised by the population. However, crops are prone to diseases due to various fungi, bacteria, and viruses (Vishnoi et al. 2021). Crops infected by these disease-causing organisms are supposed to be detected and treated in time (Chen et al. 2020a). If they are left undetected, it may dwindle food production. This may also worsen the food supply chain, which degrades the performance of agricultural activity (Li et al. 2021). The traditional methods of manual inspection are not conducive, even for small-scale farmers.

Food loss per year accounts for nearly 37%, which has to be substantially reduced (Tiwari et al. 2021). This also results in financial losses for the farmers. Traditionally, farmers rely on suggestions from experts when samples of infected crops are taken as specimens or a personal visit is needed. This process is tedious since it requires finding an expert and supervision. Sometimes, the findings may not be reliable or effective (Bera et al. 2019). Therefore, it is essential to detect and treat crop diseases precisely. This challenge motivates the researchers to design an automatic, reliable, and efficient method to detect crop diseases (Hang et al. 2019). To assist in the process of detecting and classifying crop diseases, image processing techniques play a prominent role. The image processing technique involves different stages, namely acquisition, pre-processing, segmentation, feature extraction, selection, and classification. The major advantage of image processing techniques involves the use of threshold methods, region methods, and color detection to diagnose and detect crop diseases (Ganatra et al. 2018). Most of the techniques face limitations in accuracy, which need to be improved. The major problem with utilizing these techniques is the manual generation of feature parameters that are supposed to be alleviated (Yuan et al. 2021). Several researchers and academicians have contributed a lot to identifying and classifying crop diseases. Some of the commonly used artificial intelligence-based approaches are machine learning and deep learning.

The most popular technique used for crop disease detection is the convolutional neural network. More than machine-learning models, deep learning acts as a state-of-the-art technology. The major advantages of using convolutional neural networks are zero human supervision, automatic feature extraction, high accuracy, less computation, and handling large datasets (Khan et al. 2021). Building an automated recognition system benefits amateurs and professional experts in identifying the conditions of the crop by its appearance and features while determining the disease. Various methods based on perception, non-linearity, and configurations have been surveyed. This survey provides a comprehensive review of crop diseases utilizing machine learning and deep learning techniques. It focuses on the type of crop, datasets, models utilized, and performance parameters for classification. The work also involves the classification of several image-processing algorithms that perform crop disease detection and classification.

Motivation

Crop yield is mainly affected by several environmental factors or pathogens. Timely diagnosis and detection of crop diseases can provide protection, thereby reducing the food and financial losses incurred. Hence, it is essential to design a methodology that would detect, predict, or forecast crop diseases. When faced with a wide variety of datasets, parameters, hardware configurations, and experimental conditions, it can be challenging to select the most appropriate model to use for machine learning, deep learning, or artificial intelligence research. Therefore, researchers need to conduct a comprehensive analysis to identify a reliable model for data processing, prediction, and categorization of crop diseases. This motivates us to carry out an extensive survey corresponding to crop disease detection and prediction based on machine and deep learning techniques that have been proposed.

Major Contributions

The main aim of this survey is to carry out a comprehensive analysis of machine learning and deep learning techniques utilized for crop disease prediction. The major contributions of this survey are as follows:

- To identify various types of image segmentation methods that act as a base for detecting and classifying crop disease.
- A comparative analysis with a summary and insights into various techniques applied to various crops are presented.
- Performance investigations based on various methods of machine and deep learning techniques are performed.
- Research gaps and case studies have been presented that would shed light on how the learning approach would lead us into the future.

Organization of the Survey

This survey has been organized as follows: Section 1 defines the introduction; Section 2 provides the classification of machine learning and deep learning techniques utilized for agricultural crop diseases; Section 3 provides the performance investigations in terms of parameters and models on crop disease prediction using machine and deep learning techniques; section 4 provides the case studies to evaluate the survey and presents the research gaps; and section 5 provides the conclusion and the future scope.

PAST STUDIES

Computer Vision

Computer vision can be described as the coagulation of various techniques to obtain, process, scrutinize, and gain insights from complex, high-dimensional data (Jähne et al. 1999). Computer vision involves signal processing, image processing, and pattern recognition. One of the major important processes of image processing involves image segmentation. To analyze and detect crop diseases, images are scanned, and the regions that are affected are segmented for further processing (Kaur et al. 2014). Images are segmented into various parts based on features such as pixel intensity, color, and texture. Image segmentation techniques can be broadly classified into edge-based segmentation, region-based segmentation, and hybrid segmentation (Zaitoun et al. 2015). Some of the important image segmentation-based approaches utilized in both machine and deep learning techniques are classified along with their advantages and limitations in Table 1.

Classification of Machine Learning Models for Crop Disease Prediction

Agriculture has become a hot spot for research since it has been influenced by the use of modern technologies like IoT, Artificial Intelligence (AI), and cyber connectivity (Tamsekar et al. 2019). Smart Agriculture offers the utilization of high-end applications by way of data acquisition obtained from multiple sources, namely sensors, cameras, robots, and drones. Machine learning techniques have opened a wide arena of opportunities that offer applications based on analyzing various features and constraints, giving rise to an insight that would rectify traditional problems like manual

Table 1: Classification of crop disease segmentation approaches.

Image Segmentation Approaches	Advantages	Limitations
Region-based Segmentation (Singh et al. 2019)	Enables us to select among the automated and collective images. Provides a trustworthy performance.	Consumes huge amounts of memory and storage
Edge-based Segmentation (Badage et al. 2018)	It is good for images to have better contrast between objects	Inadequate in case of faulty detection or with a huge number of edges
Threshold-based Segmentation (Singh et al. 2017)	Robust and less cost topologically Suitable for real-time scenarios	Highly sensitive to noise.
Clustering-based Segmentation (Zhang et al. 2019)	Divides images into homogenous regions utilized for real-time problems to be solved.	Produces clusters of similar sizes
Watershed-based Segmentation (Yu et al. 2023)	Output is reliable	Involves highly complex gradient computation
Neural Network-based Segmentation (Senthilk et al. 2009)	Utilized for making decisions Accuracy is high	Training is highly difficult

inspection, fault diagnosis, disease detection, the severity of disease, and prediction. This section provides a classification of traditional methods of machine learning that have been applied to various crop diseases.

Singh and Kaur (2019) proposed plant disease detection based on region-based segmentation and a KNN classifier. Their methodology utilized the Grey-Level Co-occurrence Matrix (GLCM) technique to analyze textural features, achieving 97% accuracy in detecting leaf miners, mosaic viruses, and whiteflies in plant leaves. Chopda et al. (2018) developed a plant disease detection model for cotton crops using a decision tree classifier. Sharma et al. (2018) introduced an artificial neural network-based approach for predicting potato late blight disease based on weather parameters, achieving an accuracy of 90%. Gadekallu et al. (2021) proposed a novel principal component analysis whale optimization-based neural network model for classifying tomato plant diseases using the GPU. Their model achieved a training accuracy of 99% and a testing accuracy of 86%. Rumpf et al., 2010) proposed early identification and classification of sugar beet diseases based on support vector machines and spectral vegetation significance, achieving an accuracy of 97%. However, their methodology suffered from target class overlap. Bhatia et al. (2020) presented a powdery mildew disease prediction model using the hybrid support vector machine logistic regression model, with an accuracy of 92.37%. Still, they indicated the need for further performance improvement. Nababan et al. (2018) developed a disease detection system for oil palm using a Naive Bayes classifier based on expert system technology, achieving an

Table 2: Comparative analysis of machine learning models utilized for crop disease prediction.

Author	Machine Learning Model	Merits	Demerits
(Gadekallu et al. 2021)	PCA-Whale Optimization Algorithm (WOA)	Dimensionality has been greatly reduced	Their model considers only the linear relationship between the data
(Geetha et al. 2020)	Random Forest (RF)	Since it uses a bagging technique the accuracy and reliable	Training time for the dataset is quite high
(Resti et al. 2022)	Multimodal Naïve Bayes (MNB) and KNN	Easy to implement	The success rate of MNB and KNN highly depends on data
(Hatuwal et al. 2020)	Convolutional Neural Network (CNN)	Performs multiclass classification	Suffers from repeated training of data which possess high computation time.
(Kaur et al. 2020)	Support Vector Machine (SVM) &	Reduces redundancy and improves accuracy	Fewer features are considered
Chaudhari et al. 2020)	K-means Clustering and Support Vector Machine (SVM)	Identifies the symptom-wise banana leaf diseases	Accuracy has to be improved
(Dang-Ngoc et al. 2021)	Hierarchical Support Vector Machine (HSVM)	Diseased main leaf regions are segmented automatically	Low quantity Dataset
(Mojumdar et al. 2021)	K-means clustering, GLCM & Support Vector Machine (SVM)	Extracted features will determine and classify healthy or sick using SVM	Classification Accuracy needs to be improved
(Nirmal et al. 2022)	Support Vector Model	Distinguishes healthy and unhealthy leaves effectively	Utilized fewer samples of data, which needs to be improved

accuracy rate of 80%. However, precision improvement was identified as a major disadvantage. Geetha et al. (2020) proposed an effective crop prediction model based on a random forest algorithm that does not require large datasets for classification.

Chauhan & Deepika (2020) introduced a maize disease detection system using a random forest classification algorithm for three variants of diseases. Their model achieved an accuracy of 80.68% but exhibited limitations in handling large datasets effectively. Resti et al. (2022) proposed a corn plant disease and pest detection system using multimodal Naive Bayes and a k-nearest neighbor classifier. Their work achieved an accuracy of 99.54% for KNN and 92.72% for MNB, but heavily depended on the size and quantity of the data. Hatuwal et al. (2020) presented a plant disease detection system using convolutional neural networks with features extracted using the Haralick texture feature algorithm. Their CNN model achieved a higher accuracy of 97.89% compared to conventional approaches like random forest, support vector machine, and k-nearest neighbors but suffered from repeated training and high computation time. Table 2 provides a comparative analysis of machine learning models for various crops, including their advantages and limitations.

Comparative Analysis of Deep Learning Models on Crop Disease Prediction

Deep learning is a subcategory of machine learning that follows the exact functioning of the human brain. Deep learning trains itself based on the artificial neural network model (Kaur et al. 2021). Typically, it can be described as a multi-layer perceptron that consists of layers that are hidden and can perform feature extraction and find its relevance to gain data insights (Shinde & Shah. 2018). The major advantage of the deep learning model is that it performs feature extraction automatically for classification (Sarangi et al. 2021). It performs many levels of training in a hierarchical order. The most widely used methodology for deep learning models is convolutional neural networks (Li et al. 2021). This model can be used to process large amounts of heterogeneous data. It includes three types of activation functions, namely sigmoid, tanH, softmax, and ReLu functions (Dhar et al. 2021). The model consists of a convolution layer, a pooling layer, a fully connected layer, and a drop-out layer. It is composed of three layers, namely the input, hidden, and output layers (Sarwinda et al. 2021). This section provides a comparative analysis of various works carried out by researchers based on deep-learning models for crop disease prediction.

The paddy crop disease detection and classification system proposed by Haridasan et al. (2023) uses deep learning. The system they developed had a 91.45% success rate in classifying data. However, overfitting of the data occured in the tuning parameter. Arun Malik et al. (2022) designed and evaluated a hybrid method for detecting sunflower leaf disease by using a deep-learning approach. Their model achieved an accuracy of 89.2%. Due to unorganized data, high computation time was exhibited.

A deep-learning architecture based on generative adversarial networks was suggested by Habin Jin et al. (2022) to identify diseases in grape leaves with an accuracy of 86.36%. However, their model suffered from class imbalance, which needed a data augmentation technique. Upadhyay & Kumar (2022) created a rice plant disease detection system based on a convolutional neural network approach with an accuracy of 99.7%. The major advantage was that it efficiently processed huge datasets, and hence, no manual feature extraction method was required.

Feng Jiang et al. (2020) created a deep learning model based on a support vector machine and convolutional neural networks for detecting four kinds of rice leaf diseases. They achieved a high accuracy of 96.8%. However, CNN suffered from problems such as optimal neurons and low data samples. Yun Zhao et al. (2022) proposed a plant disease classification model based on the fusion of the inception and residual structures and an embedded attention mechanism called RIC-Net. It achieved an accuracy of 99.55% by detecting diseases in corn, potatoes, and tomatoes. However, their proposed methodology had to be tested by using real-time datasets, which should be large.

Using an enhanced DenseNet (DenseNet Network), Jiang et al. (2023) proposed a rice disease deep detection model with a 99.4% average classification accuracy. Using a conditional generative adversarial network (C-GAN), Amreen et al. (2021) presented a deep-learning approach to tomato plant disease detection by creating synthetic images of tomato plant leaves with an accuracy of 99.51 percent. The main benefit of their approach was that overfitting was eliminated through the use of C-GAN for data augmentation. However, the generator and the discriminator competed with each other, making the training unstable and slow.

To detect plant diseases with thermal images, Bhakta et al. (2023) developed a novel modified deep convolutional neural network. To lessen the computational burden and the overfitting issue in the case of a short dataset, they proposed using three convolutional layers. Their approach had a 97.5% success rate. To evaluate the efficacy of their model, it must be applied to a sizable data set. Using a convolutional neural network on mobile devices hosted in a Platform-as-a-Service (PaaS) cloud, Lanjewar & Panchbhai (2023) developed a method for predicting the presence of disease in tea leaves.

The accuracy of their model was 100 percent. A key issue was the need to append healthy tea leaf data within the dataset.

Ozguven & Adem (2019) came up with the automatic detection and classification of leaf spot disease in sugar beet using the deep learning model and achieved an accuracy of 95.48%. However, accuracy needed to be improved further. Xu et al. (2023) came up with a deep-learning model for wheat leaf disease identification. Their methodology was experimented with using the wheat data obtained from the Henan Province of China. Their methodology achieved a classification accuracy of 98.83%; however, the number of samples utilized was not comprehensive.

Noah Bevers et al. (2022) created a transfer learning-based convolutional neural network for soybean plant disease detection with an accuracy of 96.8%. However, their methodology suffered from the omission of data-augmented images, which diminished the overall performance. A rE-GoogLeNet convolutional neural network model for detecting rice leaf diseases in the wild was proposed by Le Yang et al. (2023). Their methodology achieved an accuracy rate of 99.58%, which was a 1.72% improvement over the GoogLeNet model. However, the major drawback was that their model was computationally more intensive.

For accurate sugarcane leaf disease diagnosis, Li et al. (2022) presented a lightweight vision transformer based on shuffle convolution with an accuracy of 98.84%. For accurate diagnosis of grape leaf disease and pests, Lu et al. (2022) proposed a ghost-convolution enlightened transformer hybrid model with an accuracy of 98.14 percent. However, processing the limited data required by the model was laborious.

Lamba et al. (2023) presented a new hybrid model (GCL) based on a network structure. The GCL combined the generative adversarial network (GAN) with a convolutional neural network (CNN) and a long short-term memory network (LSTM) for dataset segmentation. Their methodology achieved an accuracy of 97%. However, the major drawback was that it used very limited data for classification. A hybrid classification model based on modified feature-weighted fuzzy clustering (MFWFC) was proposed by Senthilkumar and Prabhusundhar (2023). Their model achieved an accuracy of 93.57%. However, there were too many classification algorithms used in the system, making it excessively complicated.

Zhang et al. (2023) proposed using multi-channel automatic orientation recurrent attention networks for tomato leaf disease detection. Their model achieved an accuracy of 96.47% with the PlantVillage dataset. However, their model posed limitations since they used small datasets. Using a refined swin transformer and a limited data set, Wang et al. (2022) presented a method for the practical recognition of cucumber leaf diseases. Their methodology achieved an accuracy of 98.97%. However, training time was quite high. Singh et al. (2023) came up with a novel framework for potato leaf disease detection using a deep learning model and achieved an accuracy of 97.2%. The major advantage of their proposed methodology was that it was computationally fast since an additional transition layer was added. However,

Table 3: Comparative analysis of deep learning models utilized for crop disease prediction.

Author	Deep Learning Model	Merits	Demerits
(Haridasan et al. 2023)	SVM, CNN	It is efficient since the dataset contains more dimensions	Classification accuracy needed to be improved
(Haibin Jin et al. 2022)	GANs	Multi-feature fusion mechanism captures the fine-grained features	Model suffers from class imbalance
(Jiang et al. 2023)	DenseNet + Adabound Algorithm + Channel Attention (Squeeze and Extraction)	A variety of features are considered for the classification	Computational time is quite high
(Amreen et al. 2021)	Conditional Generative Adversarial Networks	Prevented the problem of overfitting	Training the model becomes unstable and slow.
(Bhakta et al. 2023)	Modified Deep CNN + Thermal Imaging	Reduces the computation overhead and overfitting	The model has to be validated using large datasets
(Lanjewar & Panchbhai 2023)	CNN + PaaS Cloud	Reduces the computation overhead and overfitting	The dataset is not perfect since healthy tea leaves are not included.
(Noah Bevers et al. 2022)	Transfer Learning + CNN	Transfer learning boosted the performance of the CNN	Omitted Large Features that are highly needed.
(Senthilkumar et al. 2023)	Hybrid Classifier Model	Handles dynamic arrival of data	Design is complex
(Mahum et al. 2023)	Densely Connected Convolutional Neural Network – 201	Complexity is reduced by decreasing parameters.	Their method has to be evaluated by using large datasets.

their model suffered from an overfitting problem. Mahum et al. (2023) proposed a cotton leaf disease detection system using deep neural networks. Their proposed methodology achieved an accuracy of 99.37%. However, it suffered from weak learning when explicit regularisation was explained, which was one of the major drawbacks. Table 3 provides a comparative analysis of deep-learning models for crop disease prediction.

PERFORMANCE EVALUATION OF VARIOUS WORKS OF MACHINE LEARNING AND DEEP LEARNING TECHNIQUES ON CROP DISEASE PREDICTION

This section gives a summary and insights into the results of a performance evaluation of the parameters used in machine learning and deep learning models for crop disease detection. Table 4 provides a comparative analysis of machine learning models utilized for crop disease prediction.

Summary and Insights on Machine Learning Models on Crop Disease Prediction

Most of the machine learning utilized for crop disease prediction involves the use of Support vector machines (Rumpf et al.2010, Bhatia et al. 2020, Kaur et al. 2020, Chaudhari et al. 2020, Orin et al. 2021, Dang et al. 2021, Genitha et al. 2019, Mojumdar et al. 2021, Nirmal et al. 2022, Kilaru et al. 2021, Mohanty et al. 2022), the K-Nearest Neighbour algorithm (Singh et al. 2019, Resti et al. 2022), the Decision Tree (Chopda et al. 2018), the Artificial Neural Network (Sharma et al. 2018), the Random Forest algorithm (Geetha et al. 2020, Chauhan et al. 2021), and Naive Bayes (Resti et al. 2022, Hatuwal et al. 2020). Among these methods, the support vector machine is more utilized since it addresses misclassifications. In the case of a large number of properly labeled items in a dataset, supervised learning algorithms such as SVM followed by KNN perform better by yielding a good result. These two algorithms succeeded then and there with the use of a random forest algorithm. The utilization of neural network-based optimization methods outperforms all the above-mentioned algorithms in terms of accuracy, precision, recall, and F1 scores. For potato crops, works based on KNN and ANN can be used.

Among these, KNN performs at par with an accuracy of 97%. The major difference between KNN and ANN is the number of points selected or the number of data or features selected for classification. Random forest algorithm performs much better than SVM since it accepts the data as they are, whereas SVM considers the distance between the data or the feature. The accuracy of the random forest algorithm is similar to that of the SVM. The training time taken by the random forest is comparatively lower than that of the SVM.

Performance Evaluation of Deep Learning Models on Crop Disease Prediction

Table 4: Performance evaluation of machine learning models on crop disease prediction.

Reference	Machine Learning Model/Algorithm	Dataset	Crop/Plant	Tool	Performance Metric and Result
(Singh & Kaur 2019)	Grey Level Co-occurrence Matrix (GLCM)-Texture Analysis; K-means Clustering-Region based Segmentation; KNN Classifier for disease prediction	PlantVillage Dataset	Potato leaves	MATLAB	Accuracy 97%
(Bhatia et al. 2018)	SVM-Noise Removal using Adaptive Sampling Noise Reduction (ANR) method; Logistic Regression-Classification.	Tomato Powdery Mildew Disease (TPMD) dataset	Tomato	R Studio 1.1.463	Accuracy-92.37%
(Chauhan & Deepika 2021)	Label finding, Gradient Calculation, random forest classifier	Corn Dataset	Maize	Python, Pandas Package	Accuracy-80.68%
(Hatuwal et al. 2020)	Haralick Texture Feature Algorithm, Convolution Kernel, Max Pooling, ReLu	Kaggle PlantVillage Dataset	Apple, cherry, Grape, Peach, Pepper, Strawberry	Google Colab	Accuracy-97.89%
(Kaur et al. 2020)	SVM, Decision Tree, NB, KNN	Citrus disease dataset	Citrus	MATLAB (R 2019)	Accuracy 90.4%
(Kilaru et al. 2021)	YOLO + Discrete Wavelet Transform + SVM, DarkNet Architecture	Kaggle PlantVillage Dataset	Maize	Matlab	SVM and its variants perform much better
(Mohanty et al. 2022)	Histogram of Oriented Gradients (HOG), Logistic Regression, Support Vector Machine, Random Forest	Kaggle PlantVillage Dataset	Tomato	Numpy, Open CV	Accuracy-73%

This section provides a performance evaluation of deep-learning models for crop disease prediction. For deep learning, from the standpoint of recognition accuracy, it has gone beyond finding the correlation and inter-class and intra-class correlation between the datasets. Some of the deep learning models involve transfer learning, reinforcement learning, and so on. Table 5 provides a comparative analysis of the deep-learning models utilized for crop disease prediction.

Summary and Insights on Deep Learning Models on Crop Disease Prediction Convolutional Neural Network

In CNN, the number of parameters to learn and the computation time are reduced. Also, the number of features generated gets summed up and is robust (Haridasan et al. 2023). To identify complex features, several layers of convolution with distinct kernel sizes can be utilized (Arun Malik et al. 2022). The Otsu-based thresholding technique is highly efficient since it facilitates effective noise removal, thereby benefiting automatic feature extraction, which reduces the computational overhead (Upadhyay & Kumar 2022). The degradation problem caused by an increase in the network depth between the convolutional layers of a residual structure in Inception-based convolutional neural networks with an incorporated modified convolutional block attention module (CBAM) (Yun Zhao et al. 2022) has been solved. Too many parameters, a huge model size, and a lengthy training period are problems that the Inception architecture aims to address. Because of this, the network architecture can autonomously choose superior characteristics, simplifying network parameters and computations.

DenseNet

The combination of DenseNet and the channel attention mechanism squeeze-and-excitation helps us to strengthen the features that are favorable while rejecting the unfavourable ones (Jiang et al. 2023). The use of DenseNet with more transition layers reduces the computation time taken for training the model. The utilization of Softmax functions

Table 5: Comparative analysis of deep learning models utilized for crop disease prediction.

Reference	Deep Learning Model/ Algorithm	Dataset	Crop/Plant	Tool	Performance Metric and Result
(Haibin et al. 2022)	VGG16 and InceptionV1	Plant Village public dataset	Grape	TensorFlow; CuDNN Computational Library	Accuracy of VGG16 and InceptionV1 achieve 96.13%
(Jiang et al. 2023)	DenseNet network (DenseNet), Adabound algorithm	Public dataset	Rice	Pytorch	The average CA 99.4%
(Bhakta et al. 2023)	VGG-16, VGG-19, Resnet50 and Resnet101,svm,LR	Open environment	Plant disease	Python with Keras; TensorFlow	95% accuracy and high precision 97.5%
(Lanjewar & Panchbhai 2023)	ResNet50, Xception, and NASNetMobile	Mendeley data website	Tea leaf	Python	Recognition accuracy is 100%
(Xu et al. 2023)	VGG-19, ZFNet, GoogLeNet, Inception-V4	Open-source databases	Wheat leaf	Keras 2.2.4 Frame, TensorFlow GPU 1.14.0; python 3.7; CuDNN 7.0	The overall CA was 98.83%, and the maximum testing accuracy was 99.95%
(Le Yang et al. 2023)	rE-GoogLeNet convolutional neural network	Public dataset PlantVillage	Rice leaf	TensorFlow 2.3 Python 3.7	Accuracy-99.58%
(Li et al. 2023)	Shuffle-convolution-based lightweight vision transformer	public dataset Plant Village,	Sugarcane leaf diseases	PyTorch 1.10	Accuracy-98.84%
(Lamba et al.2023)	LSTM + CNN + GAN	Mendeley, Kaggle, UCI, and GitHub	Paddy diseases	Google Colab	Accuracy-97%
(Wang et al. 2022)	Swin Transformer and GAN	Chinese dataset	Cucumber	Anaconda framework-PyTorch 1.7.0	Accuracy-98.97%
(Singh et al. 2023)	CNN	Google images	Cotton	Python 3.10.9, libraries: OpenCV, Keras, Tensorflow, Numpy, Matplotlib	Accuracy-99.39%
(Mahum et al. 2023)	DenseNet-201	Plant Village Dataset	Potato leaf	Python framework with Keras v0.1.1 library	Accuracy -97.2%

benefits multi-class cataloging. However, the class imbalance problem can be solved by using data augmentation or oversampling of data (Mahum et al. 2023). Utilization of conditional generative adversarial networks along with the DenseNet121 model generates synthetic images that yield high accuracy.

Transfer Learning Methods

The combination of VGG-16 and MobileNet (Arun Maliket al. 2022), which is an ensemble model, yields more accuracy and eradicates the traditional problems of learning like overfitting, gradient problems, huge data processing, and

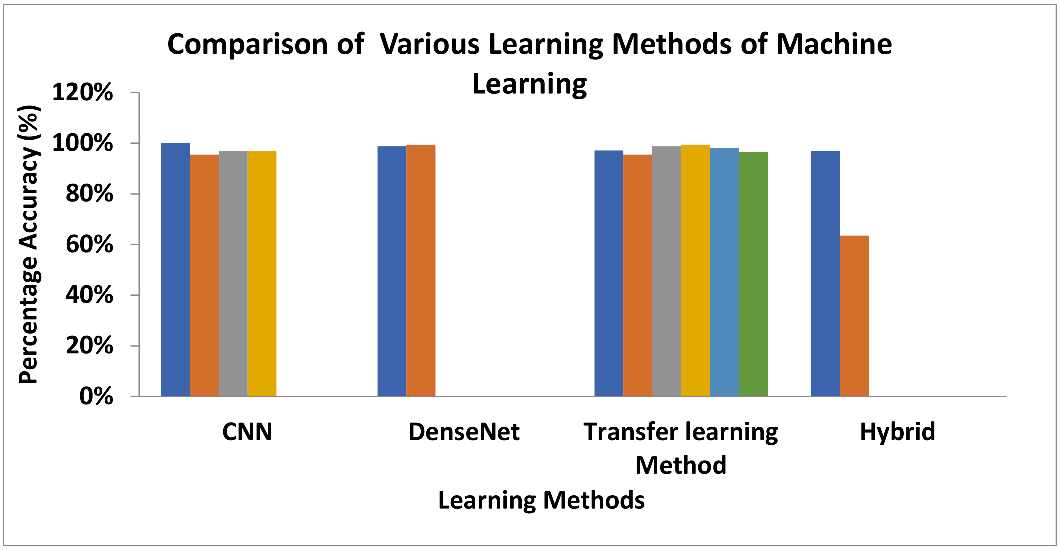

Fig. 1: Comparison of various machine learning strategies.

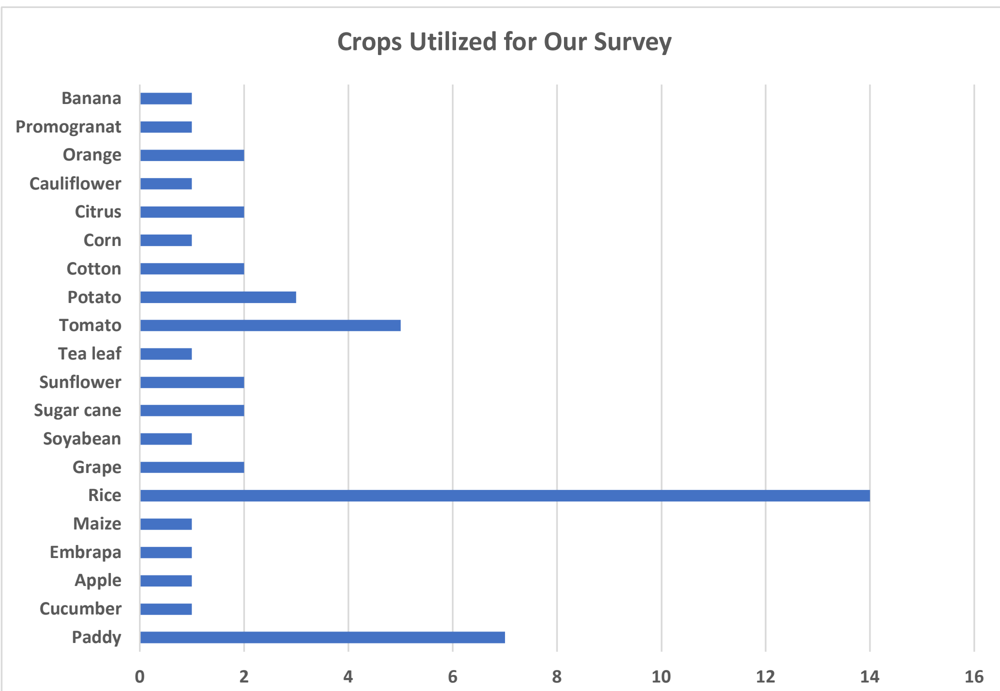

Fig. 2: Crops utilized for our survey.

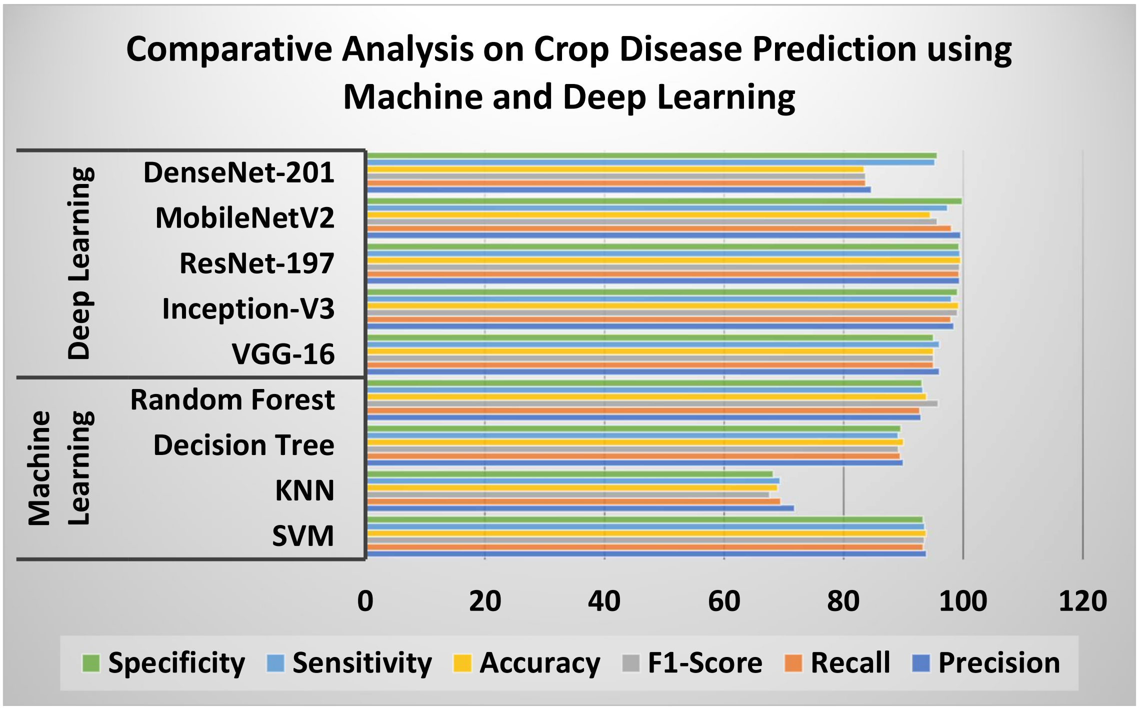

Fig. 3: Comparative analysis of crop disease prediction using machine and deep learning models.

less training time. Similarly, the combination of VGG-16 and Inception V1 provides a higher accuracy of 96.13% (Haibin et al. 2022). GANs are highly attractive to researchers due to the following reasons: 1) They can process huge datasets. 2) Different numbers of parameters and computation sizes can be varied. 3) Hyperparameter selection is easy, and it can be used for multiple-tuning training, which consumes very little time. The work proposed by (Xu et al. 2023) has made a great impact and contains a coagulation of two parallel CNNs. It consists of a residual channel attention block (RCAB), a feedback block (FB), elliptic metric learning (EML), and CNN, achieving a higher accuracy of 99.95%. The major use of EML is that it can be used to distinguish and alleviate recurring features. To extract the deep semantic features of an image, transformer-based deep learning models can be adapted. Images with low resolution and complex backgrounds can use these transformer-based approaches for disease detection. The horizontal patching of features from the low-level to the high-level convolution layer is an example of how the combination of convolution and transformer makes deep semantic feature extraction possible (Lu et al. 2022). An asymptotic non-local means algorithm and a multi-channel automatic orientation recurrent attention network (Zhang et al. 2023) can be used together to get rid of background noise and pull out useful information for diagnosing and classifying diseases. The approach is effective at pinpointing infected areas and determining disease variance across and within population groups.

Hybrid Methods

A combination of CNN, GANs, and LSTM performs better; however, an increase in the dataset and the generation of new images for feature extraction are computationally difficult (Lamba et al. 2023). The hybrid classifier model (Senthilkumar & Prabhusundhar 2023) provides a great achievement in meeting the goals of increasing the size of the dataset, the training time taken by the model, and the size of the window utilized for pre-processing. This can be used for prediction. Deep CNN: DCNN models, namely ResNet50, Xception, and NASNetMobile, achieved 100% accuracy (Lanjewar & Panchbhai 2023). Fig. 1 provides a comparative analysis of different types of methodologies for machine learning strategies. Fig. 2 provides a comparison of the various crops utilized for our survey. Fig. 3 provides the comparison analysis of crop disease prediction classification accuracy based on deep and machine learning models.

CASE STUDIES

Due to the advancements of technology, IoT, or machine intelligence, has been made viable, thereby connecting physical objects to the internet and facilitating aid for farmers.

This section also provides an analysis of different scenarios that can be solved by using deep learning techniques.

Scenario 1: Among all the models surveyed, provide a comparative analysis of the accuracy of various machine and deep learning models based on different crop diseases. From the analysis, please provide an overview and comment on its efficiency.

Answer: Fig. 4 provides a comparative analysis of various machine and deep learning models developed for various crop diseases.

From Fig. 4, it is apparent that more than the machine learning models, deep learning models outperform. Of all the models surveyed, it is identified that VGG19 (Xu et al. 2023) has been applied for disease detection on cotton crops, providing an accuracy of 100%. NASNetMobile (Lanjewar & Panchbhai 2023) provides an accuracy of at most 99%. NASNetMobile has been applied for tea leaf disease detection. From the Fig., it is identified that RESNET employed in NASNetMobile provides the highest accuracy along with the VGG19 model. Of the remaining DenseNet models (Jiang et al. 2023, Noah et al. 2022), RESNET152V2 (Singh et al. 2023) provides the highest accuracy of more than 99%. These approaches can be utilised to test other crop diseases such as maize, cotton, jute, fruits, and vegetables.

Scenario 2: India is the largest exporter of the commercial crop 'cotton.' Cotton suffers from a wide variety of diseases, which degrade the growth of the farmer's economies of the farmers. Is there any model that possibly detects and classifies, giving a classification accuracy of, at most, 100% performance? The model developed should be able to process a large amount of data.

Answer: By collecting a large number of data from the agricultural department in Salem, Tamil Nadu. A dataset has been processed by using data transformation, data cleaning, data reduction, and data processing steps.

It is then fed into the model of RESNET152V2, which is a transfer learning model consisting of a data augmentation pattern classification with more than 22 types of diseases. Their proposed model (Singh et al. 2023) has utilized three convolutional hidden layers that can be used to identify cotton diseases through four different feature labels. The architecture of the proposed model is depicted in Fig. 5. The model can achieve a classification accuracy of 99.39%. Their proposed model consists of an input layer where the cotton leaves are fed as input, which is then processed to obtain an RGB image. This is then fed into the convolution layer, which consists of a leaky reactivation layer unit along with the max pooling function, which contains a dimensionality reduction from 128 × 128 dimensions to 126 × 126, 63 × 63, and 30 × 30 dimensions, which then gets connected to the fully connected layer of 64 features, and finally, the 22 classes of features can be obtained.

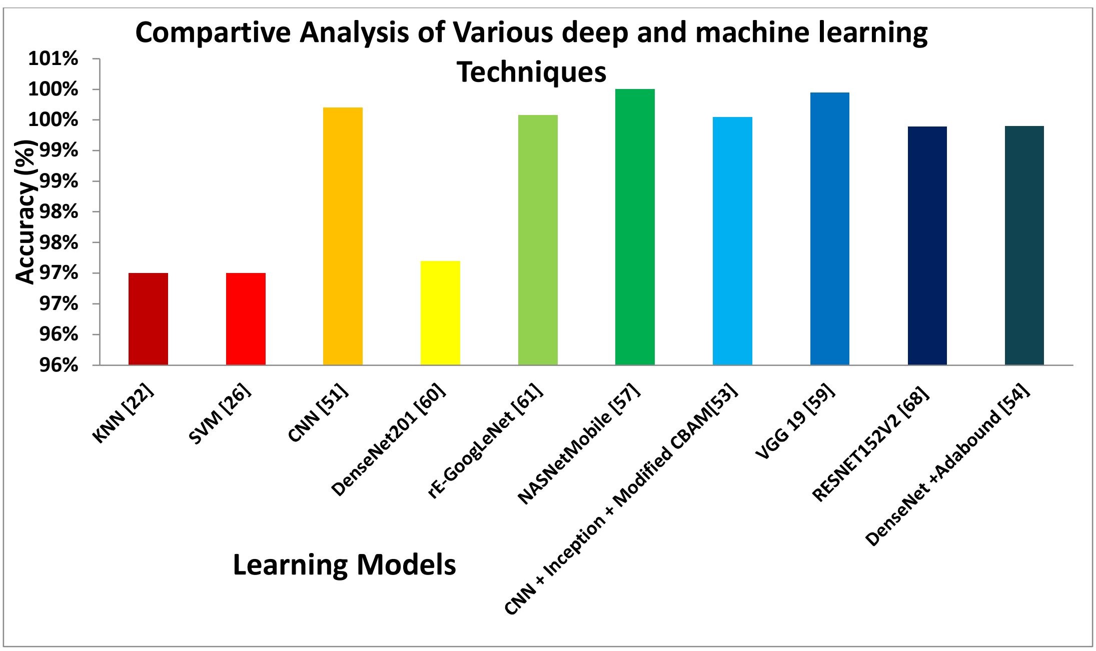

Fig. 4: Comparative analysis of various machine and deep learning models.

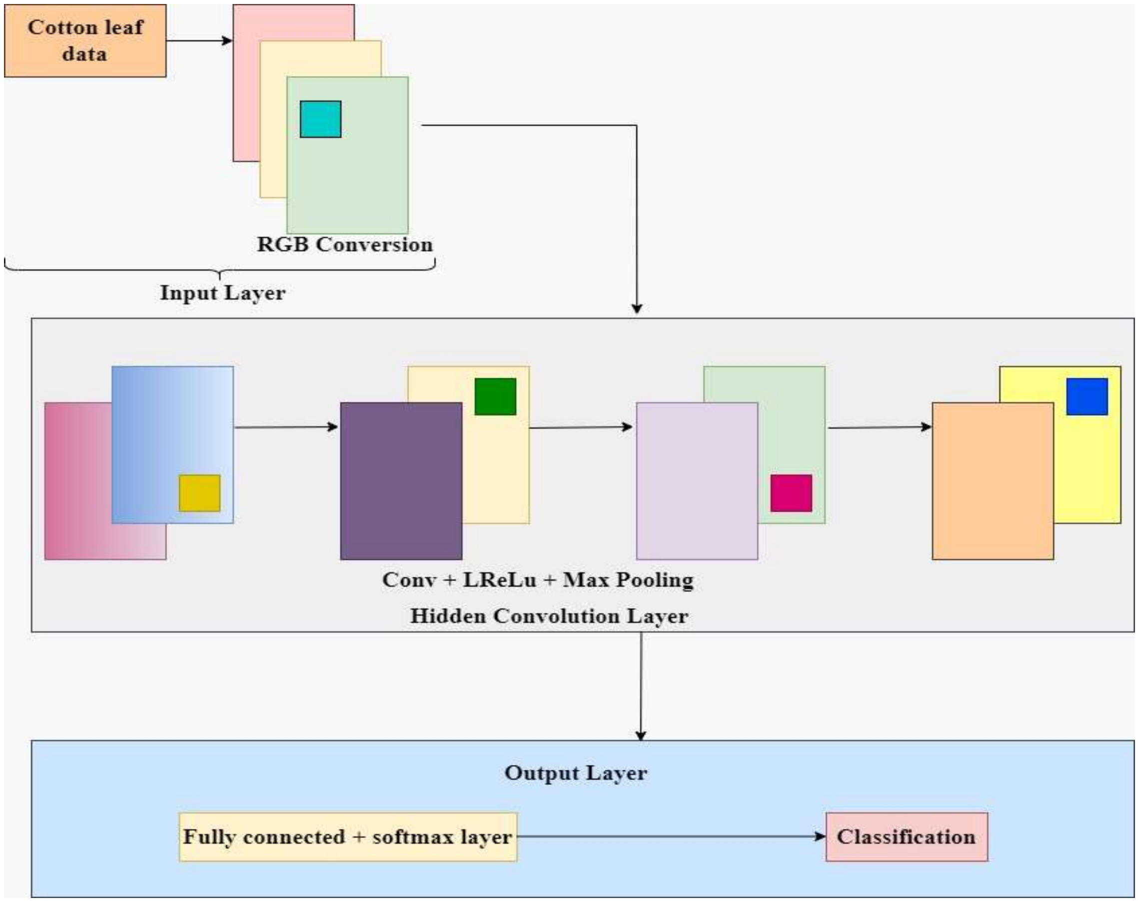

Fig. 5: Deep learning model case study for the scenario.

Table 6: Comparison of Deep Learning Models based on precision, size, and speed.

Model	Precision	Size	Speed
VGG16 + Inception (Haibin et al. 2022)	96.13%	240 MB	60FPS
C-GAN (Amreen et al. 2021)	99.10%	180MB	120FPS
LSTM + CNN + GAN (Lamba et al. 2023)	97%	58MB	210FPS
YoLO-MobileNetv3 (Maski et al. 2021)	98.39%	11.52MB	244FPS
YOLOv4 (Liu et al. 2020)	95%	236MB	62FPS
Tiny-YOLOv4 (Bochkovskiy et al. 2020)	96.71%	33.4MB	220FPS
YOLO-Fastest (Redmon et al. 2018)	92.38%	1.3MB	230FPS

Scenario 3: Viruses that affect papaya cause a ringspot on its leaves, which has to be detected. Hence, to reduce the damage, what are the hybrid methods that can provide the most classification with higher accuracy? The major requirements are speed and data size.

Answer: The major requirement of the deep learning model is that it has to alleviate the problem of overfitting due to the huge size of the data. Hence, a based architecture, along with the concept of bounding box approaches, increases the speed and supports huge data sizes. Hence, YOLO with NCNN can process 236 megabits of data. Some of the hybrid models that can handle large data sets are given in Table 6 as follows:

Scenario 4: How to address the problems of image resolution; class imbalance, and insufficient data size while designing a learning model for crop disease identification and classification?

Answer: To address the problem of image resolution or faded image classifications, conditional generative adversarial networks can be utilized (Amreen et al. 2021). C-GANs provide synthetic images, which help in classification and accuracy. To address the problem of class imbalance, data augmentation approaches like position and color augmentation can be utilized (Bhakta et al. 2023). To achieve better performance DenseNet architecture or YOLO backbone architectures can be utilised to improve classification accuracy.

RESEARCH GAPS AND INSIGHTS

1. Utilization of seasonal and geographical data for crop yield estimation based on GIS technology is yet to be investigated (Haridasan et al. 2023).
2. Automatic feature extraction-based techniques have to be developed (Upadhyay & Kumar 2022).
3. To address the problem of overfitting while making a model to learn, it is necessary to devise a new data augmentation technique that would cater to various needs (Singh et al. 2023).
4. While training a model, the inter-class and intra-class similarities can cause confusion, which is supposed to be addressed (Yun Zhao et al. 2022).
5. Investigation on faster-RCNN and Updated-RCNN-based deep learning models that are supposed to be investigated against various crops for disease detection has not been explored yet (Ozguven & Adem 2019).
6. Severity assessment, along with disease detection, is an area that is supposed to be explored (Jiang et al. 2023).
7. Base model architectures and frozen-core training approaches in the case of transfer learning approaches are yet to be explored and investigated.
8. To prevent the network model from the problem of overfitting conditional generative adversarial network (C-GAN) is utilized as a data augmentation technique that can enhance the size of the dataset (Amreen et al. 2021).
9. Segmentation-based lightweight-based model to address crop disease detection and its severity is an emerging area (Li et al. 2023).
10. Recognition of multiple diseases on a single leaf is supposed to be investigated further (Wang et al. 2022).

CONCLUSION AND FUTURE WORK

In this paper, several works by various authors on machine learning and deep learning techniques for crop prediction are surveyed. A comparative analysis based on performance parameters, type of model, datasets, and tools for crop disease detection catering to various requirements is investigated. Research gaps have been identified concerning various machine learning models and different learning methods. Moreover, a comparison table of various learning strategies has been formulated, which acts as a backbone for future researchers.

Future work should involve federated learning-based deep learning models that can be applied to the detection, prediction, and classification of crop diseases. Neural Architecture Search Network Mobile searches for the best possible algorithm, which has to be utilized for modeling an effective learning technique. Multi-scale feature extraction techniques to enhance the process of feature extraction will provide efficient detection of the diseased images. Deep CNN-based models can provide more stability and reliability for better performance results. Deep Convolutional Extreme Learning Machine models (DC-ELM) improve training speed by removing convergence and alleviating the requirement for multiple iterations to change the hidden layer weights. Devising the best optimizer according to the requirements provides an improvement in the performance of the classifier.

REFERENCES

Abbas, A., Jain, S., Gour, M. and Vankudothu, S. 2021. Tomato plant disease detection using transfer learning with C-GAN synthetic images. Comput. Electron. Agric., 187: 0168. https://doi.org/10.1016/j.compag.2021.106279

Arun Malik, A., Vaidya, G., Jagota, V., Eswaran, S., Sirohi, A., Batra, I., Rakhra, M. and Evans Asenso. 2022. Design and evaluation of a hybrid technique for detecting sunflower leaf disease using a deep learning approach. J. Food Qual., 20: 700.

Badage, A. 2018. Crop disease detection using machine learning: Indian agriculture. Int. Res. J. Eng. Technol., 5(9): 866-869.

Bera, T., Das, A., Sil, J. and Das, A.K. 2019. A survey on rice plant disease identification using image processing and data mining techniques. Technologies, 365–376. https://doi.org/10.1007/978-981-13-1501-5_31

Bhakta, I., Phadikar, S., Majumder, K., Mukherjee, H. and Sau, A. 2023. A novel plant disease prediction model based on thermal images using modified deep convolutional neural network. Precision Agric., 24(1): 23-39. https://doi.org/10.1007/s11119-022-09927-x

Bhatia, A., Chug, A. and Singh, A.P. 2020. Hybrid SVM-LR classifier for powdery mildew disease prediction in tomato plants. 7th Int. Conf. Signal Process. Integr. Networks (SPIN), pp. 218–223. IEEE Publ. https://doi.org/10.1109/SPIN48934.2020.9071202

Bochkovskiy, A., Wang, C.Y. and Liao, H.Y.M. 2020. Yolov4: Optimal speed and accuracy of object detection. arXiv, 2: 109.

Chaudhari, V. and Patil, M. 2020. Banana leaf disease detection using K-means clustering and Feature extraction techniques. In Int. Conf. Adv. Comput. Commun. Mater. (ICACCM), 2020 (pp. 126-130. IEEE Publ. https://doi.org/10.1109/ICACCM50413.2020.9212816

Chauhan, M. and Deepika, S. 2021. Detection of maize disease using random forest classification algorithm. Turk. J. Comput. Math. Educ., 12: 715-720.

Chen, J., Zhang, D. and Nanehkaran, Y.A. 2020a. Identifying plant diseases using deep transfer learning and enhanced lightweight network. Multimedia Tools Appl., 79(41-42): 31497-31515. https://doi.org/10.1007/s11042-020-09669-w

Chopda, J., Raveshiya, H., Nakum, S. and Nakrani, V. 2018. Cotton crop disease detection using decision tree classifier. Int. Conf. Smart City Emerg. Technol., 1112: 85371. https://doi.org/10.1109/ICSCET.2018.8537336

Dang-Ngoc, H., Cao, T.N.M. and Dang-Nguyen, C. 2021. Citrus leaf disease detection and classification using hierarchical support vector machine. Electr. Electron. Eng., 21: 69-74. https://doi.org/10.1109/ISEE51682.2021.9418680

Dhar, P., Dutta, S. and Mukherjee, V. 2021. Cross-wavelet assisted convolution neural network (AlexNet) approach for phonocardiogram signals classification. Biomed. Signal Process. Control, 63: 102142. https://doi.org/10.1016/j.bspc.2020.102142

Feng Jiang, F., Lu, Y., Chen, Y., Cai, D. and Li, G. 2020. Image recognition of four rice leaf diseases based on deep learning and support vector machine. Comput. Electron. Agric., 179: 2020.105824. https://doi.org/10.1016/j.compag.2020.105824

Fountas, S., Carli, G., Sørensen, C. G., Tsiropoulos, Z., Cavalaris, C., Vatsanidou, A., Liakos, B., Canavari, M., Wiebensohn, J. and Tisserye, B.A. 2015. Farm management information systems: Current situation and future perspectives. Comput. Electron. Agric., 115: 40-50. https://doi.org/10.1016/j.compag.2015.05.011

Gadekallu, T.R., Rajput, D.S., Reddy, M.P.K., Lakshmanna, K., Bhattacharya, S., Singh, S., Jolfaei, A. and Alazab, M. 2021. A novel PCA–whale optimization-based deep neural network model for classification of tomato plant diseases using GPU. J. Real-Time Image Process., 18(4): 1383-1396. https://doi.org/10.1007/s11554-020-00987-8

Ganatra, N. and Patel, A. 2018. A survey on disease detection and classification of agriculture products using image processing and machine learning. Int. J. Comput. Appl., 180(13): 1-13.

Geetha, V., Punitha, A., Abarna, M., Akshaya, M., Illakiya, S. and Janani, A. P. 2020. An effective crop prediction using a random forest algorithm. In Int. Conf. System, Comput., Autom. Networking (ICSCAN), 2020, pp. 1-5. IEEE Publ. https://doi.org/10.1109/ICSCAN49426.2020.9262311

Genitha, C., Dhinesh, E. and Jagan, A. 2019. Detection of leaf disease using principal component analysis and linear support vector machine. Adv. Comput., 11: 350-355. https://doi.org/10.1109/ICoAC48765.2019.246866

Jin, H., Li, Y., Qi, J., Feng, J., Tian, D. and Mu, W. 2022. GrapeGAN: Unsupervised image enhancement for improved grape leaf disease recognition. Comput. Electron. Agric., 198: 2022.107055. https://doi.org/10.1016/j.compag.2022.107055

Hang, J., Zhang, D., Chen, P., Zhang, J. and Wang, B. 2019. Classification of plant leaf diseases based on improved convolutional neural network. Sensors, 19(19): 4161. https://doi.org/10.3390/s19194161

Haridasan, A., Thomas, J. and Raj, E.D. 2023. Deep learning system for paddy plant disease detection and classification. Environ. Monit. Assess., 195(1): 120.

Hatuwal, B.K., Shakya, A. and Joshi, B. 2020. Plant leaf disease recognition using random forest, KNN, pp. 13-19. SVM and CNN.

Jähne, B., Haussecker, H. and Geissler, P. Eds.. 1999. Handbook of computer vision and applications, 2. Academic Press.

Jiang, M., Feng, C., Fang, X., Huang, Q., Zhang, C. and Shi, X. 2023. Rice disease identification method based on attention mechanism and deep dense network. Electronics, 12(3): 508. https://doi.org/10.3390/electronics12030508

Kaur, A., Guleria, K. and Kumar Trivedi, N.K. 2021. Feature selection in machine learning: Methods and comparison. Adv. Comput. Innov. Technol. Eng., 21: 789-795. https://doi.org/10.1109/ICACITE51222.2021.9404623

Kaur, B., Sharma, T., Goyal, B. and Dogra, A. 2020. A Genetic Algorithm based Feature Optimization method for Citrus HLB Disease Detection using Machine Learning. Smart Syst. Invent. Technol., 32: 1052-1057. https://doi.org/10.1109/ICSSIT48917.2020.9214107

Kaur, D. and Kaur, Y. 2014. Various image segmentation techniques: A review. Int. J. Comput. Sci. Mobile Comput., 3(5): 809-814.

Khan, R.U., Khan, K., Albattah, W. and Qamar, A.M. 2021. Image-based detection of plant diseases: From classical machine learning to the deep learning journey. Wireless Commun. Mobile Comput., 1: 1-13. https://doi.org/10.1155/2021/5541859

Kilaru, R. and Raju, K.M. 2021. Prediction of maize leaf disease detection to improve crop yield using machine learning based models. Comput. Sci. Technol., 17: 212-217. https://doi.org/10.1109/ICRTCST54752.2022.9782023

Lamba, S., Baliyan, A. and Kukreja, V. 2023. A novel GCL hybrid classification model for paddy diseases. Int. J. Inf. Technol., 15(2): 1127-1136. https://doi.org/10.1007/s41870-022-01094-6

Lanjewar, M.G. and Panchbhai, K.G. 2023. Convolutional neural network based tea leaf disease prediction system on smart phone using paas cloud. Neural. Comput. Appl., 35(3): 2755-2771. https://doi.org/10.1007/s00521-022-07743-y

Le Yang, X.Y., Zhang, S., Long, H., Zhang, H., Xu, S. and Liao, Y. 2023. GoogLeNet based on residual network and attention mechanism identification of rice leaf diseases. Comput. Electron. Agric., 320: 107543.

Li, L., Zhang, S. and Wang, B. 2021. Apple leaf disease identification with a small and imbalanced dataset based on lightweight convolutional networks. Sensors, 22(1): 173. https://doi.org/10.3390/s22010173

Li, S., Wang, L., Li, J. and Yao, Y. 2021. Image classification algorithm based on improved AlexNet. In J. Phys. Conf. Ser., 1813: 012051.

Li, X., Li, X., Zhang, S., Zhang, G., Zhang, Muqing, & Shang, H. 2023. SLViT: Shuffle-convolution-based lightweight vision transformer for effective diagnosis of sugarcane leaf diseases. J. King Saud Univ. Comput. Inf. Sci., 35(6): 101401. https://doi.org/10.1016/j.jksuci.2022.09.013

Liu, J. and Wang, X. 2020. Tomato diseases and pests detection based on improved Yolo V3 convolutional neural network. Front. Plant Sci., 11: 898. https://doi.org/10.3389/fpls.2020.00898

Lu, X., Yang, R., Zhou, J., Jiao, J., Liu, F., Liu, Y., Su, B. and Gu, P. 2022. A hybrid model of ghost-convolution enlightened transformer for effective diagnosis of grape leaf disease and pest. J. King Saud Univ. Comput. Inf. Sci., 34(5): 1755-1767. https://doi.org/10.1016/j.jksuci.2022.03.006

Mahum, R., Haris, M., Zaib-Un-Nisa, M., Muhammad, A., Falak, S.K., Muhammad, S., Saipunidzam, M. and Iskander, T. 2023. A novel framework for potato leaf disease detection using an efficient deep learning model. Hum. Ecol. Risk Assess. Int. J., 29(2): 303-326.

Maski, P. and Thondiyath, A. 2021. Plant disease detection using advanced deep learning algorithms: A case study of papaya ring spot diseaseVision Comput., 47: 49-54. https://doi.org/10.1109/ICIVC52351.2021.9526944

Mohanty, R., Wankhede, P., Singh, D. and Vakhare, P. 2022. Tomato plant leaves disease detection using machine learning. Appl. Artif. Intell. Comput., 311: 544–549, 2022. https://doi.org/10.1109/ICAAIC53929.2022.9793302

Mojumdar, M.U. and Chakraborty, N.R. 2021. Orange and Orange leaves diseases detection using Computerized Techniques. Comput. Commun. Networking Technol., 62: 1-4. https://doi.org/10.1109/ICCCNT51525.2021.9579964

Nababan, M., Laia, Y., Sitanggang, Delima, Sihombing, O., Indra, E., Siregar, S., Purba, W. and Mancur, R. 2018. The diagnosis of oil palm disease using Naive Bayes Method based on Expert System Technology. J. Phys. Conf. Ser., 1007(1): 012015. https://doi.org/10.1088/1742-6596/1007/1/012015

Nirmal, M.D., Jadhav, P. and Pawar, S. 2022. Pomegranate leaf disease classification using feature extraction and machine learning.

Smart Electron. Commun., 11: 619-626. https://doi.org/10.1109/ICOSEC54921.2022.9951907

Noah Bevers, N., Sikora, E. J. and Hardy, N.B. 2022. Soybean disease identification using original field images and transfer learning with convolutional neural networks. Comput. Electron. Agric., 203: 107449. https://doi.org/10.1016/j.compag.2022.107449

Orin, T.Y., Mojumdar, M.U., Siddiquee, S. M. T. and Chakraborty, N. R. 2021. Cauliflower leaf disease detection using computerized techniques. Comput., Commun. Autom., 218: 730-733. https://doi.org/10.1109/ICCCA52192.2021.9666437

Metin, O.M. and Adem, K. 2019. Automatic detection and classification of leaf spot disease in sugar beet using deep learning algorithms. Physica. Part A, 2019: 122537.

Redmon, J. and Farhadi, A. 2018. Yolov3: An incremental improvement. arXiv, 027: 67.

Resti, Y., Irsan, C., Putri, M. T., Yani, I., Ansyori, A. and Suprihatin, B. 2022. Identification of corn plant diseases and pests based on digital images using multinomial naïve Bayes and K-nearest neighbor. Sci. Technol. Indonesia, 7(1): 29-35. https://doi.org/10.26554/sti.2022.7.1.29-35

Rumpf, T., Mahlein, A.K., Steiner, U., Oerke, E.C., Dehne, H.W. and Plümer, L. 2010. Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance. Comput. Electron. Agric., 74(1): 91-99. https://doi.org/10.1016/j.compag.2010.06.009

Sarangi, P. K., Guleria, K., Prasad, D. and Verma, D.K. 2021. Stock movement prediction using neuro-genetic hybrid approach and impact on growth trend due to COVID-19. Int. J. Networking Virtual Organisations, 25(3/4): 333-352. https://doi.org/10.1504/IJNVO.2021.120172

Sarwinda, D., Paradisa, R.H., Bustamam, A. and Anggia, P. 2021. Deep learning in image classification using residual network (ResNet) variants for detection of colorectal cancer. In. Procedia Comput. Sci. 5th Int. Conf. Comput. Sci. Comput. Intell., 179: 423-431. https://doi.org/10.1016/j.procs.2021.01.025

Senthilk, N. and Rajesh, R. 2009. Edge detection techniques for image segmentation- A survey of soft computing approaches. Int. J. Recent Trends Eng. Technol., 1(2): 250-254.

Senthilkumar, T.P. and Prabhusundhar, P. 2023. Prediction of rice disease using modified feature-weighted fuzzy clustering (MFWFC) based segmentation and hybrid classification model. Int. J. Syst. Assur. Eng. Manag., 15: 131-148 https://doi.org/10.1007/s13198-022-01835-7

Sharma, P., Singh, B.K. and Singh, R.P. 2018. Prediction of potato late blight disease based upon weather parameters using artificial neural network approach. Comput. Commun. Networking Technol., 3: 1-13. https://doi.org/10.1109/ICCCNT.2018.8494024

Shinde, P. P. and Shah, S. 2018. A review of machine learning and deep learning applications. In 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA) (pp. 1-6). IEEE.

Singh, J. and Kaur, H. 2019. Plant disease detection based on region-based segmentation and KNN classifier. In Proceedings of the International Conference on ISMAC in Computational Vision and Bio-Engineering 2018 (ISMAC-CVB), pp. 1667-1675. Springer International Publishing.

Singh, J. and Kaur, H.2019. Plant disease detection based on region-based segmentation and KNN classifier. In Proceedings of the International Conference on ISMAC in Computational Vision and Bio-Engineering 2018 (ISMAC-CVB), pp. 1667-1675. Springer International Publishing.

Singh, P., Singh, P., Farooq, U. 2023. CottonLeafNet: cotton plant leaf disease detection using deep neural networks. Multimed Tools Appl. (2023).

Singh, V. and Misra, A. K. 2017. Detection of plant leaf diseases using image segmentation and soft computing techniques. Information processing in Agriculture, 4(1): 41-49.

Tamsekar, P., Deshmukh, N., Bhalchandra, P., Kulkarni, G., Hambarde, K. and Husen, S. 2019. Comparative analysis of supervised machine learning algorithms for GIS-based crop selection prediction model. In Computing and Network Sustainability: Proceedings of IRSCNS 2018.

Tiwari, V., Joshi, R. C. and Dutta, M. K. 2021. Dense convolutional neural networks based multiclass plant disease detection and classification using leaf images. Ecological Informatics, 63: 101289.

Upadhyay, S.K., Kumar. 2022. A novel approach for rice plant diseases classification with deep convolutional neural network. Int. j. inf. tecnol., 14: 185-199.

Vishnoi, V. K., Kumar, K. and Kumar, B. 2021 Plant disease detection using computational intelligence and image processing. J. Plant Dis. Prot., 128(1): 19-53.

Wang Fengyi, Yuan Rao, Qing Luo, Xiu Jin, Zhaohui Jiang, Wu Zhang, Shaowen Li. 2022. Practical cucumber leaf disease recognition using improved Swin Transformer and small sample size, Computers and Electronics in Agriculture, 107163.

Wolfert, S., Ge, L., Verdouw, C. and Bogaardt, M. J. 2017. Big data in smart farming–a review. Agricultural systems, 153: 69-80.

Xu, Laixiang, Bingxu Cao, Fengjie Zhao, Shiyuan Ning, Peng Xu, Wenbo Zhang, Xiangguan Hou. 2023. Wheat leaf disease identification based on deep learning algorithms, Physiological and Molecular Plant Pathology, 101940.

Yu, Y., Wang, C., Fu, Q., Kou, R., Huang, F., Yang, B. and Gao, M. 2023. Techniques and challenges of image segmentation: A review. Electronics, 12(5): 1199.

Yuan, Y., Chen, L., Wu, H. and Li, L. 2021. Advanced agricultural disease image recognition technologies: A review. Inf. Process. Agric., 19: 534-546.

Yun Zhao, Cheng Sun, Xing Xu, Jiagui Chen. 2022. RIC-Net: A plant disease classification model based on the fusion of Inception and residual structure and embedded attention mechanism, Computers and Electronics in Agriculture, 2021.106644.

Zaitoun, Nida M., and Musbah J. Aqel. 2015.Survey on image segmentation techniques.Procedia Computer Science, 797-806.

Zhang Yukai, Shuangjie Huang, Guoxiong Zhou, Yahui Hu, Liujun Li. 2023. Identification of tomato leaf diseases based on multi-channel automatic orientation recurrent attention network, Computers and Electronics in Agriculture, 205: 107605.

Zhang, S., You, Z. and Wu, X. 2019. Plant disease leaf image segmentation based on superpixel clustering and EM algorithm. Neural Computing and Applications, 31: 1225-1232.