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Machine Learning Techniques for Crop Disease Detection using IoT

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ABSTRACT

Crop disease detection is essential in agriculture to improve crop yield. Human health is also affected when infected products are consumed in food intake. Thus, it is important to detect diseases in the beginning phases so that agricultural products can maintain the quality of the products. Several algorithms and techniques have been developed for the machine learning to detect the disease on crops in the techniques used are image processing, segmentation, and classification. IoT based image processing and Machine Learning approaches are necessary for the detection of crop disease. Various sensors collect the real-time data of different parameters like humidity, temperature, rainfall, etc. This research highlights the detailed survey and analysis of machine learning algorithms & comparison of various techniques for the detection of crop disease..

KEYWORDS: Machine Learning; crop detection; Raspberry Pi, IoT, OpenCV,K-means, CNN

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I. INTRODUCTION

Agriculture plays an important role in the economies of all countries. Many factors affect agricultural products and degrade their quality like weather conditions, low-quality seeds and unavailability of resources at a particular time. Earlier, the farmers were performing the diagnosis manually and by checking the crops at some intervals. The areas of the crop that remain unchecked always lead to more damage in many areas of crop. The diagnosis process requires the complete checking of the soil, the condition of the crop, and the effect of weather on the soil. It becomes easier to detect the disease of the crops in the early stages using image processing, segmentation, pattern recognition, and texture analysis. The image processing technique is more commonly utilized for the recognition and classification of disease among crops. In image processing systems, the images of the affected areas of crops are given as input. After that, various image processing techniques are applied to the affected area of the crop to get the affected area separate like cropping and segmentation. This process requires complete deep analyzing of the images first and then selecting the appropriate algorithm accordingly. Here, the selection of an algorithm plays an important role in the final results because the way of working of each algorithm is different for a variety of images.

The input images are required to be of better quality so that images can be analyzed properly and correct classification and detection can be made. IoT sensor network has become popular in industry usage and normal day-to-day life to increase crop yield production and its quality. Conventional techniques for detecting diseases include direct visual analysis by visual identity of disease symptoms appearing on crop or chemical strategies. AI approach helps to find the crop disease in the underlying stages. The researchers developed techniques to capture good-quality images with professional cameras. The images of the affected areas of the crop can be taken manually, or drones can be used to capture the images from different angles of the crop. Figure 1 below shows the segmentation and hybrid feature extraction for different diseases. The crop diseases are detected & measured in terms of accuracy in detecting the correct disease classification. The disease in the crops differs in color, size, shape, and texture of the outer surface. This can be analyzed by the image processing system efficiently with the utilization of machine learning algorithms and image processing techniques.

Various researches are using the online available images of affected areas of crops. Many websites play a major role as a large source of the database information can be retrieved from sources such as Kaggle and Google Dataset, etc. [3].

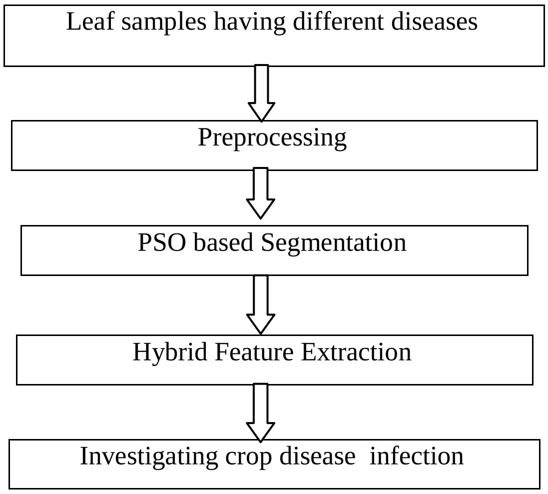

Figure 1: Segmentation & Hybrid Feature Extraction

Deep learning is a useful technology to improve automated methods to detect crop disease and achieve higher performance. Deep learning architectures are being developed by researchers for default feature extraction and illness classification. This work performs a thorough analysis of different traditional machine learning and in depth learning structures for crop disease recognition utilizing RGB and spectral imaging techniques (such as hyperspectral and multispectral approaches). Below Figure 2 shows some of the several disease diagnostic techniques used in this research.

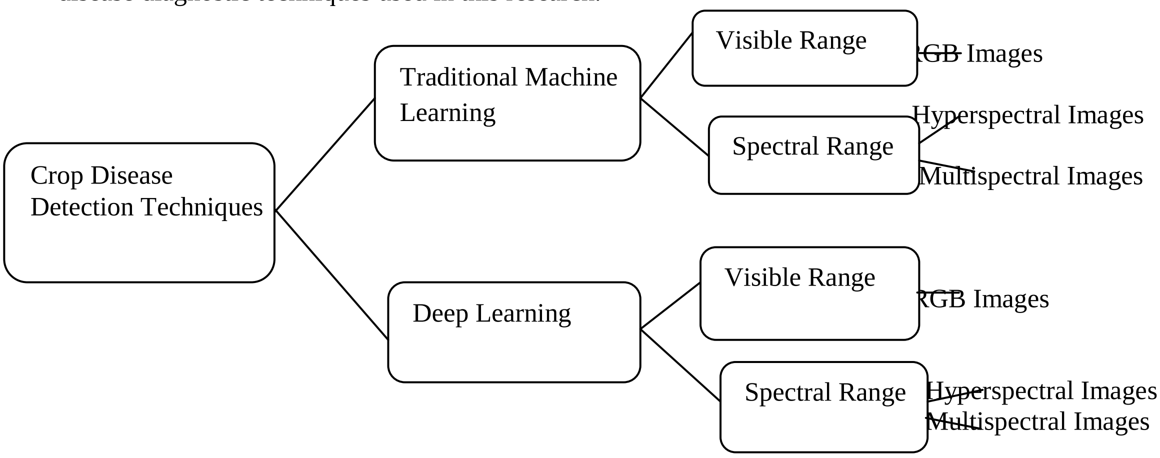

Figure 2: Crop Disease Detection Techniques

The work flow is detailed as follows. Section 2 describes the disease classification research done in previous years & has been highlighted in the Literature review. Section 3 highlighted the results achieved by various researchers using different techniques related to cropping disease detection. A comprehensive evaluation of machine learning techniques for disease diagnosis is given in Section 4. The traditional machine learning methods based on RGB are reviewed in Section 4.1 and The spectral pictures utilized in crop disease detection are described in Section 4.2, Section 5 focuses on the work with deep learning architectures as it is applied to visible light and spectral pictures. Section 6 presents the conclusion.

II. REVIEW OF LITERATURE

Peer-reviewed &refereed journal papers have been studied for review of literature &have been listed as below:

Pinto et al.[1] Proposed an approach to detect and classify the disease in the sunflower crop using image processing. The research was carried out using the leaf images of the crop that were taken using a high-resolution digital camera. The prepared dataset is first pre-processed, and then k-means grouping was applied to detect the affected part of the leaf from the disease. Machine Learning algorithms are implemented to classify the images (in light of their texture and color) using the MATLAB programming language. The research also presented the result comparison of these algorithms based on the accuracy of these Machine Learning algorithms namely Multi-class Support Vector Machine (MC-SVM), K-Nearest Neighbour (k-NN), Naive Bayes (NB), and Multinominal Logistic regression (MLR). The results showed that MLR is the best classifier algorithm having an average accuracy of 92.57%

Ferentinos[5] presented a model using the convolutional neural network to detect the disease from crop images. The images considered were of both diseased and healthy crops for preparing the model. The dataset (containing 87,848 images) is related to 25 different types of crops and contained 58 unique sets of combinations of crops. The proposed model achieved a success rate of 99.53% in identifying combinations. The results made the proposed model more useful in providing early warning notification, and the approach can further be extended for integrating the disease identification system for plants.

Moghadam et al.[6] proposed a technique using Machine Learning and hyperspectral imaging to recognize the Tomato Spotted Wilt Virus (TSWV) in the capsicum crops. Based on the features, State Vector Machine (SVM) classifier was trained for differentiating between the inoculated and healthy crops. The results show about 90% accuracy using the proposed technique.

Fuentes et al. [7] presented the deep learning-based mechanism that helped in detecting pests as well as diseases in the tomato crop. This was done with the help of captured images with different resolutions using Faster Convolutional Neural Network, Single Shot Multi-box Detector, and Region-based Fully Convolutional Network. These conditions are dependent on time, season, and place. The aim of the data annotation process is to label the class as well as the area of the tainted districts in the image and proceeded with data augmentation. R-CNN method was then used for the recognition of objects & SSD and R-FCN techniques were applied. This led to resultant AP (average precision) enhanced to 80%.

Mohanty et al. [8] detected crop diseases with the help of deep learning from images & utilized the total dataset of 54306 images (of both the healthy and the diseased crop leaves).Both the model improvement just as the expectations were done on these downscaled pictures. This was done on three distinct renditions of the dataset. These versions are a color plant, Grayscale crop plant, and the segmented crop & trained with the deep convolutional neural network. As a result, they were getting 99.35% accuracy. Their model correctly classifies the diseases acro prop and also checked the performances of AlexNet and GoogLeNet.

Priyanka and Kumar [9] concluded that harvest diseases may prompt extreme farming yield. Various systems were proposed to recognize crop afflictions. The image used is preprocessed& then applied for K means gathering get the polluted piece of the leaf. The polluted part is presented to morphological taking care of to expanding the corrupted area. SVM classifier is used to perceive and arrange the contaminations reliant upon the isolated component.

Sujatha et al. [10] presented a survey on the recognizable proof of plant infections utilizing image processing methods. Computer vision techniques were used to identify the diseases. The results were compared with different approaches like SVM and Neural Network for disease detection and classification. This approach provides an optimal solution for crop diseases.

Elangovan [11] proposed that Classification is performed using a support vector regression approach to automatically detect crop diseases. Module identification included Bacterial Blight, Cercospora spot, black Roland, and Alternaria Spot diseases on the crop. Molecular techniques were used for disease detection. K-means clustering is used to segment the diseased part of the crop.

Vamsidhar et al. [12] Proposed the division method for the programmed identification and characterization of plant leaf diseases. The preparation set is utilized for preparing the and preparing set is utilized for testing the calculations. SVM has shown better results in distinguishing proof and grouping of contagious infections on oat crops though NN has shown better arrangement in parasitic illness ID.

Joshi and Jadhav [13] proposed a new technique to diagnose and classify diseases related to rice. They have identified and classified these diseases. Various features were extracted based on the shape of the rice. Using MDC and K-NN techniques, these retrieved characteristics were then merged and categorized. The overall accuracy of work is around 89.23% in the use of MDC and 87.02% in the use of K-NN.

Biswas et al. [14] proposed the system that was utilized in classifying the diseases affecting the grapes. The disease recognition is done with the assistance of picture handling and AI algorithms & uses the Random forest approach and GLCM features method. The performance of work is compared with the machine learning approaches like PNN, BPNN, and SVM. The SVM approach achieved the highest accuracy of around 86%.

Aggarwal et al. [15] suggested a Random Forest approach used to measure risk to improve the performance of any application related to the risk. Integration of the framework and the Random Forest approach is presented to predict software errors in the error dataset. According to the modules presented, software error prediction and testing using a predicted approach have proven to be very effective.
Aggarwal et al. [16] proposed a soft computing method in whichthe Biological approach is used w on soft computing methods to minimize the risk in the related application.The development of narrative architectures and designs for software risk management utilizing soft computing and a naturally inspired approach is the main emphasis of the project. The Simulated Biological Response approach is used to manipulate multiple parameters in a flavor of soft computing-based optimization.

III. COMPARISON OF LITERATURE WORK

Table 1: Analysis of Techniques used for Crop Disease Detection

S.No.	Researcher/year	Techniques/ tools/ Algorithms used	SummaryAnalysis	Paper referred
1.	Pinto et al. (2016)	MC-SVM, k-NN, NB, MLR	Multinominal Logistic Regression (MLR) with textural features is found to be the best classifier	[1]
2.	Ferentinos (2018)	Convolutional neural network	Concluded that the convolutional neural network is suitable for detecting plant diseases by analyzing simple leaf images.	[5]
3.	Moghadam et al. (2017)	SVM, Machine learning, and hyperspectral imaging	An SVM classifier with a radial basis function kernel performed better to segment grapevines.	[6]
4.	Fuentes et al. (2017)	R-CNN, SSD, and R-FCN	Technique-based data annotation and augmentation techniques are used to generate better results. Results showed that the resultant AP (Average Precision) is more than 80%	[7]
5.	Mohanty et al. (2016)	Convolutional neural network, AlexNet, and GoogLeNet	99.35% accuracyachieved. DA deep convolutional neural network is found to be very effective with smaller feature spaces.	[8]
6.	Priyankha and Kumar (2017)	HOG algorithm, Segmentation and SVM classifier, K-means clustering	Image processing is utilized to ID and characterize sicknesses in a precise way. The SVM classifier can characterize the crop disease.	[9]
7.	Sujithra et al.(2020)	Support Vector Machine, Neural Network	The generalized square distance technique is used thegrapefruituitdataset to classify the disease in leaves to achieve better performance.	[10]
8.	Elangovan (2017)	RGB Image, Segmentation, Pre-processing, SVM classifier	SVM classifier is found to be very effective with smaller feature spaces. The system has an accuracy of 91.27% and the Precision value is 88.11%	[11]
9.	Vamsidhar et al. (2019)	Image processing, CBIR, SVM, Plant Disease, ANN	SVM showed better results in the identification of fungal diseases on crops.	[12]
10.	Joshi and Jadhav (2016)	MDC (Minimum Distance Classifier), K-NN (k-Nearest Neighbor classifier)	In extraction, shading, and zone astute shape highlights have been separated and utilized as a contribution to the classifier having better results.	[13]
11.	Biswas et al. (2016)	Random forest approach, GLCM features method	Random Forest is the best classification approach to extract GLCM features for background partition and disease classification	[14]

12.	Aggarwal et al. (2021)	Random forest approach	RF approach is used to measure risk to improve the performance of any application related to risk	[15]
13.	Aggarwal et al. (2020)	Soft computing methods	A biological approach is used along with g soft computing methods to minimize the risk in the related application	[16]

IV. MACHINE LEARNING FOR CROP DISEASE DETECTION

Machine learning is popular due to its techniques and practical applications related to various fields. Machine Learning is used for four purposes such as detection or identification, Quantification, classification, and prediction [4]. In identification/detection, the machine algorithms are used to detect the object or particular required part in images or objects. For example, identifying the affected area on the crop or finding the water area from satellite images. In quantification, the one Learning algorithms are utilized to measure the quantity of the objects that are detected. The classification works by clarifying the images or objects into different categories based on dataset properties and features.

The prediction algorithms of machine learning are useful in predicting the early notifications for crop disease based on current environment settings and features of the crops. These algorithms are Logistic Regression (LR), Naive Bayes (NB), Support Vector Machine (SVM), Ensemble Techniques, Clustering Algorithms, K-Nearest Neighbour (KNN), etc.

4.1 Machine learning with RGB images

Earlier research highlighted various disease detection systems and Each of them offered a different suggestion on how to classify, segment, etc.

Sharif et al. [17]have proposed an algorithm that uses three different datasets to find lesions on citrus fruits and leaves. On the pre-processed images, an optimal weighted segmentation algorithm was used. The best features were chosen using a hybrid feature selection technique after being generated from the color and texture features to create a cod book. A multiclass SVM was used for the classification, and it achieved an average accuracy of 92 %.

Ali et al. [18] Presented a system for visual symptom-based diagnosis and classification of citrus illnesses.The segmentation of the contaminated area in photos was done using the distance between colors. The method was tested on classifiers like SVM, K-nearest neneighbor(KNN), boosted tree, and bagged tree while utilizing LBP and color information. The researchers used disease level classification alongside picture level classification and reported effective disease level classification using color characteristics. Overall accuracy and sensitivity ratings of 99.7% and 99.7%, respectively, were reported. There were 199 photos in the database.

Islam et al. [19] Proposed using pictures from the plant village dataset to classify potato illnesses. Using masks created using the LBP color model, the authors segmented the images. The paper reported an accuracy of 95% using 10 texture color features. While there are many photos of potato leaves in the plant village dataset, the study only used 300 of them for its experimental purposes.

Hassanien et al. [20] Employed an improved moth-flame method based on rough sets to find the illnesses (such as early blight and powdery mildew) in tomato leaves.The infected tomato leaves were classified using the SVM algorithm and a feature selection technique. The effectiveness of the moth flame optimization technique was compared to that of particle swarm optimization and genetic algorithms in the study (GA).The classification accuracy improved by 6% using the suggested feature selection strategy.

Singh et al. [21] proposed automatic leaf disease identification and classification, and image segmentation algorithms based on GA are suggested for five different classes: bacterial disease on rose, bacterial disease on bean leaves, sunburned lemon leaves, early scorch on banana leaves, and beans with fungal disease.

Four texture features were obtained using a matrix of color co-occurrences.

SVM and the minimal distance criteria (MDC) were used to classify the data.

Classification accuracy was attained for MDC with K-means, MDC with the suggested GA, and SVM with the proposed GA, respectively, at 86.54 %, 93.63 %, and 95.71 %.

Phadikar et al. [22]classified the four rice illnesses leaf brown spot, leaf blast, sheath rot, and bacterial blight using Fermi energy-based segmentation techniques.

The infection's color, shape, and location were employed as features, and the rough set theory was applied to choose the most noticeable aspects.The classification of the rice illnesses was done with 92.29% accuracy using a rule-based classifier.The proposed method achieved an overall accuracy of 80.39 % and 94.21 %, respectively, when compared to the benchmark UCI dataset and existing feature selection and classification strategies.

Johannes et al. [23]described a technique based on statistical analysis and the identification of a candidate hotspot for three wheat diseases—Septoria, rust, and tan spot—in actual field settings.The study presented two segmentation options:
1) utilizing manually created masks; 2) utilizing visual characteristics and simple linear repetitive clustering (SLIC).Using local descriptors, the illness candidate regions were collected and assessed.The algorithm was reported by the authors to be effective on a variety of crops and pests, and it was implemented in a mobile application.

The various research projects using machine learning techniques on RGB photos are summarised in Table 2 below. The crops used, various pre-processing and segmentation techniques used, pertinent extracted features and classifiers, and the performance metric used are all listed in the table.

Table 2. Comparative analysis of RGB images using machine learning algorithms

Crop	Dataset (no. of images)	Pre-processing method	Segmentation method	Extracted features	Classifier	Evaluation metric	Paper referred
Citrus	citrus disease image gallery 1000	Hybrid contrast stretching technique	Enhanced weighted segmentation	Color, textural, and geo metric features	Multi class SVM	Average accuracy =92.4%	[17]
Citrus	199 images	Image enhance mentand color transformation	Color difference-based algorithm	color histogram, LBP	KNN, SVM, boosted tree, and bagged tree	Sensitivity=99.7% Accuracy=99% AUC=1.0	[18]
Potato	300 images	-	Masks based on LBP color space	Color and texture	SVM	Accuracy=95%	[19]
Tomato	200 images	Noise removal and image resizing	Gaussian mixture-based segmentation	A rough set of textural designs using moth flame optimization	SVM	Accuracy=91.5, Precision=91.5, Recall=91.5%	[20]
Rose, bean, lemon, and banana	25 images for each class	Clipping, image smoothing, and contrast enhancement	GA	Color co-occurrence matrix: local homogeneity,	1. SVM,K-means clustering	Accuracy:1)86.54% 2) 93.63% 3) 95.71%	[21]
Rice	500 images	Not specified	Fermi Energy -based Region detection	C Color, shape, and position	Rule-based classifier	Classification accuracy=92.29%	[22]
Wheat	3,637 images	Color constancy	SLIC and manual-generated masks	Visual features and use of statistical inference model	Meta classifier	AUC>0.8	[23]

4.2 Machine Learning with Spectral Images

Numerous imaging methods, such as hyperspectral, multispectral, thermal, fluorescence imaging, etc., that can record and use information outside of the visible spectrum have significantly advanced different areas of plant disease detection [18].The most common imaging techniques that can offer both spatial and spectral information about plants, which is particularly helpful for evaluation, are hyperspectral and multispectral imaging. The work done with hyperspectral and multispectral imaging techniques is the main focus of this study. The multispectral methodology gathers spectral information in relatively broad wavebands, whereas the hyperspectral method acquires spectral information from a wider spectral range with narrower wave bands. Rich spectrum information in spectral imaging aids in the potential disease detection even before outward signs of the disease arise.

Bauriegel et al. [24] analyzed that under rather realistic circumstances, hyperspectral pictures were used to evaluate the wheat to find fusarium early. Stage 75 is the best stage for disease identification during the development period scaled by BBCH, according to Principal Component Analysis (PCA), which was used to discover four spectral bands that assisted in the classification.The measure of the sickness was examined using the spectral angle mapper (SAM).

Barbados et al. [25] Used Fusarium head blight on wheat kernels were detected using hyperspectral imaging.The algorithm's result was an index showing the likelihood that the kernel will be contaminated. More than 91% classification accuracy was attained by the algorithm.

Li et al. [26]analyzed that with a 93 % accuracy rate, the study examined the hyperspectral pictures using PCA, band ratio, and a straightforward thresholding procedure. Only 270 samples total from the study's experimentation were used.

Huang et al. [27]analyzed that rice leaf folder was found using hyperspectral reflectance To analyze the reflectance measured from rice plants and the affected canopy during the booting stage, a linear regression model was developed. Based on spectral indices, the model was able to identify a leaf roll rate and disease scale.The root means square error (RMSE) method was used to examine it, and the authors recommended employing hyperspectral reflectance to find the rice leaf folder.

Zhang et al. [28] studied that to find powdery mildew, researchers analyzed the spectral reflectance of winter wheat.The authors investigated hyperspectral reflectance to identify winter wheat powdery mildew. In a laboratory setting, the reflectance of healthy and sick leaves was studied. Remarkable spectral changes in the visible and near-infrared region were discovered. Fisher's linear discriminate analysis (FLDA) is used to categorize damage into three categories: normal, minor, and heavy. The study found that FLDA was successful for the discrimination analysis of severely damaged leaves and that PLSR performed better than MLR for disease severity.

Rumpf et al. [29]employed SVM to identify and categorize sugar beet diseases before the appearance of symptoms in hyperspectral reflectance. With a 97 % accuracy rate, the work distinguished between healthy and diseased leaves, and it achieved more than 86 % accuracy for multiclass classification.

Shi et al. [30] to identify and categorize pests and illnesses in winter wheat, a kernel discriminant method based on spectral vegetation indices has been presented.Redundancy in the spectral vegetation indices was eliminated using independent t-tests and correlation analysis, and a Gaussian kernel function was utilized for discriminant analysis.The algorithm successfully distinguished between healthy and damaged leaves at the canopy level with an accuracy at the leaf level of 82.9 % (slight), 89.2 % (moderate), and 87.9 % (severe).

An overview of the various research using machine learning techniques on spectral pictures is described in Table 3 below.

Table 3. Comparative Study of Machine Learning Algorithm On Spectral Images

Crop	Disease	Imaging Technology	Model/ Technique	Evaluation Metric	Paper referred
Wheat	Head blight	Hyperspectral Imaging	1) SAM 2) Head blight index	Accuracy: 91%	[24]
Wheat	Fusariumhead blight	Hyperspectral Imaging	Morphological operations	Accuracy>91%	[25]
Orange	8 most common defects	Hyperspectral Imaging	Thresholding, band ratio, and PCA	Accuracy=94%	[26]
Rice	Rice leaf folder	Hyperspectral reflectance	Linear regression	RMSE: 0.059-leaf roll rate and 0.22-infestation scale	[27]
Winter wheat	Powdery mildew	Hyperspectral reflectance	1) MLR 2) PLSR 3) FLDA	PLSR-(RMSE)=0.23 R^2 = 0.8 FLDA-accuracy=90%	[28]
Sugar beet	leaf spot, leaf rust	Hyperspectral reflectance	SVM: Binary classification	Accuracy: 1)97% 2)86%	[29]
Winter wheat	Yellow rust, aphid,and powdery mildew	Hyperspectral reflectance	Kernel discriminant analysis	82.9 %(slight), 89.2 % (moderate), and 87.9 % represent the total accuracy of occurrence at the leaf level (severe)	[30]

V. DEEP LEARNING FOR CROP DISEASE DETECTION

Deep learning in computer vision technology has advanced significantly with recent advancements in fields like artificial intelligence, processor technologies, image processing, and supporting software. It is used in various industries for both supervised and unsupervised pattern identification and classification. It is now a very powerful research topic. It is also used in the agricultural sector to address numerous problems with food production. Plant disease detection can benefit from deep learning's capabilities. Convolutional Neural Network (CNN) is one of the well-known deep learning architectures since it can extract features from the data while building the model [42].

Deep learning architectures require huge datasets for their training to extract features effectively.However, there are very few large and disparate datasets accessible in the domain of plant disease recognition.The concept of transfer learning is being used to somewhat address these difficulties.Using a model that has already been trained on a sizable dataset for a new, related job is called "transfer learning."[33-34].

5.1 Deep learning with RGB images

Many methods of diagnosing plant diseases based on the depth of functional information in visual band images have been developed in recent years and are detailed below.

Jiang et al. [31] Used a Multibox single shot (SSD) detector to detect apple disease. The authors have proposed an in-depth SSN (DCNN) model based on SSD-based rainbow integration and VGGNet integration. The model provided 78.80 % which means average accuracy and visibility speed of 23.13 frames per second (FPS). The study also revealed that the model could identify multiple infections in the same infected image**.**

Selvaraj et al. [32] proposed utilizing DCNN to identify observable banana diseases and insect indications on diverse banana plant segments.The authors applied transfer learning and offered six models (each for a different portion of a banana plant) and 18 classes.The classification was performed using the ResNet50, InceptionV2, and MobileNetV1 models.For quick object detection, the SSD model was used with MobileNetV1.These experiments show how real-time applications, such as the detection of plant diseases, can make use of the SSD's capability.

Barbados et al. [33]utilized lesions and spots on leaves to detect plant diseases using a pre-trained network called GoogLeNet.Segmenting original photos into distinct lesions and spots while taking into account five various indications and symptoms, such as scattered small, scattered large, isolated, extensive, and powdery, was required for the task.When compared to the original photos, the study found that incorporating lesions and spots enhanced accuracy.This study had the benefit of spotting many illnesses on a single leaf.

Geetharamani et al. [34] Proposed the13 distinct plant leaves from the plant village dataset were divided into 39 classes using DCNN.By employing data augmentation, the authors claimed to have improved the model's performance from 91.43% to 97.87 %.They used a variety of epochs, batch sizes, and dropouts train their model.This study demonstrated how data augmentation improves recognition performance.

Coulibaly et al. [35] Proposed employing visual geometry group-16 (VGG16) transfer learning to detect mildew disease in millet crops.Even with a limited data set, the model performed well, achieving 95 % accuracy, 90% precision, 94% recall, and 91.75% F1 score.

Picon et al. [36] Deployed DCNN to classify crop diseases in the wild. For the illness categorization of three wheat diseases for photos obtained in real-world settings, the system used a deep residual neural network (ResNet) with improvements in augmentation strategies and tile cropping. With advances in confidence estimation, super pixel segmentation, and artificial background, training, the method produced an improved average balanced accuracy of 0.84 (ResNet) compared to 0.78 (classical approach).On the pilot test, the model also received a balanced accuracy score of 0.96.

Hu et al. [37] Suggested uses a low shot learning method to identify diseases in tea leaves.Tea leaf diseases were identified using a mixture of conditional deep convolutional generative adversarial networks and VGG16, with an average classification accuracy of 90%. SVM was used to segregate the disease spots using color and texture features. The research on plant disease recognition using deep learning architectures for analyzing RGB photos is summarized in Table 4 below.It highlights the crops used, different CNN models, and the work's evaluation measures.

Table 4: Comparative study of Deep Learning Algorithm on RGB images

Crop Type	Model	Dataset/ Images used	Evaluation metric	Paper Referred
Banana	CN (ResNet50, InceptionV2, andMobileNetV1)	30,952	Accuracy: 70%to99%	[31]
Millet	CNN(VGG16)	124	Accuracy=95% Precision=90.50% Recall=94.50% F1-score=91.75%	[32]
Apple	CNN(GoogleNet inception module)	26370	mAP =78.80%	[33]
14 crops	GoogLeNet	46400	Accuracy>75%	[34]
13 crops	CNN	55,448 without augmentation 61,486 with augmentation	Accuracy= 96.46%	[35]
Wheat	CNN(ResNet)	8,178	Balanced accuracy > 0.96 (improvement from 0.78 to 0.87 for exhaustive testing)	[36]
Tea	C-DCGAN and VGG16	120	Average accuracy=90%	[37]

5.2 Deep learning with spectral images

In-depth reading is often used in RGB images. However, one of the most effective research sites for diagnosing plant diseases is using in-depth reading of multispectral and hyperspectral data. Among the various thinking techniques, hyperspectral imaging is the most widely used method in the field of deep learning structures. However, various challenges, such as the size of the data, the increase in calculation time due to multi-dimensional data, noise in certain bands, the need for adequate training labeled data testing, and the possibility of a major error, need to be addressed. while using hyperspectral data for in-depth reading.

Nagasubramanian et al. [38] proposed 3D DCNN to enhance its performance in hy-perspectral data.The 3D DCNN model was combined with saliency map-based visualization and hyperspectral data in this study to identify charcoal rot in soybean crops.The model got a 0.87 F1-score and 95.73 % classification accuracy using hyperspectral stem images.The model classified data using wavelengths in the near-infrared (NIR) region.

Polder et al.[39]reported a technique for identifying illnesses inflicted on potato plants by the potato virus Y (PVY) using modified fully CNN on hyperspectral pictures.On two rows, the study trained the network for actual field tests, and on two more rows, it was validated.When compared to a conventional disease evaluation, the precision and recall were greater than 0.78 and 0.88, respectively.

Wang et al.[40]developed an integrated approach based on generative adversarial nets for early detection of the tomato spotted wilt virus utilizing hyperspectral imaging, which segmented the plant, classified the spectrum, and classified the image (GANs).Before the onset of symptoms, the approach could identify infected plants and classify the pixels as background, infected plant, or healthy plant without the need for hyperspectral bands. At the plant level, the authors reported 96.25 % accuracy.

Zhang et al. [41] DCNN and hyperspectral unmanned aerial vehicle (UAV) images are presented for automatic yellow rust disease recognition using spectral and spatial information. Inception-ResNet layers were suggested in the work, and it indicated an overall accuracy of 0.85.

VI. CONCLUSION

This research work provides a comprehensive overview of current work done on plant disease detection using a variety of imaging techniques combined with conventional machine learning and in-depth architectural studies. CNN models have replaced Plant Disease Learning Models as they offer the highest accuracy levels and a wide range of diagnostics for plant species and diseases. However, they need great model training details to achieve high accuracy and precision. The work also highlights the shortage of publicly available data sets, the lack of images captured under natural conditions, and the resulting limitations.

The use of various imaging modalities for the detection of early detection of disease is also highlighted in the study. Among the many photography techniques, RGB imaging is the most popular method. However, it does not detect pre-existing symptoms. The use of hyperspectral and multispectral images can be used to achieve this pre-symptomatic diagnosis. However, there are problems that need to be addressed such as the challenges of processing high-volume data, the maximum amount of time required for calculation, the sounds in the spectral band, the good band selection, etc.

With the advancement in the technology of thought sensors, GPUs, and computer vision, it can be expected that soon, smartphones with sophisticated built-in sensors and in-depth learning structure may be used for real-time, accurate, and early detection. with a wide variety of plants and diseases to control economic and agricultural losses.

REFERENCES

[1]. Pinto, L.S., Ray, A., Reddy, M.U., Perumal,P.,and Aishwarya,P., ‘Crop disease classification using texture analysis’, 2016 IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology, Bangalore, India,pp. 825-828, 2016.

[2]. Goyal, L., Sharma, C., M., Singh, A., ‘Leaf and Spike Wheat Disease Detection & Classification using an Improved Deep Convolutional Architecture, Informatics in Medicine Unlocked (science direct)’, Vol. 5, pp.750-761, 2020.

[3]. Tripathi, M., and Maktedar,D., ‘Recent machine learning-based approaches for disease detection and classification of agricultural products, in Conf. 2016 International Conference on Computing, Communication Control and automation, Greater Noida, India, pp. 1-6, 2016.

[4]. Wu, Ju., Li, B., and Wu, Z., ‘Detection of Crop Pests and Diseases Based on Deep Convolutional Neural Network and Improved Algorithm’,Proceedings of the 2019 4th International Conference on Machine Learning Technologies, Coimbatore, India,Vol. 7, pp-20-27,ACM, ISBN 978-1-4503-6323-5/19/06, 2019

[5]. Ferentinos,K.P., ‘Deep learning models for crop disease detection and diagnosis’, Computers and Electronics in Agriculture(Elsevier), Vol. 145, pp. 311-318, 2018.

[6]. Moghadam, P., Ward, D., Goan, E., Jayawardena, S., Sikka, P., and Hernandez, E., ‘Crop Disease Detection Using Hyperspectral Imaging’, 2017 International Conference on Digital Image Computing: Techniques and Applications, Sydney, NSW, pp. 1-8, 2017.

[7]. Fuentes, A., Yoon, S., Kim, S., and Park, D., ‘A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition’, Sensors, Vol. 17, No. 9, pp. 20-24, 2017.

[8]. Mohanty, S.P, Hughes, D.P., and Salathe,M., ‘Using Deep Learningfor Image-Based Plant Disease Detection’, Frontiers in Plant Science, vol. 7,2016.

[9]. Priyankakha, J.J, and Kumar, K.S., ‘Crop Disease Identification Using a Feature Extraction HOG Algorithm’, Asian Journal of Applied Science and Technology, vol. 1, Issue 3, pp. 35-39, 2017.

[10]. Sujithra, J., and Ukrit, M.F., ‘A review on crop disease Identification and Classification through leaf Images’, European Journal of Molecular & Clinical Medicine, vol. 07, Issue 09, pp. 1168-1183, 2020

[11]. Elangovan, K., ‘Crop Disease Classification Using Image Segmentation and SVM Techniques’, International Journal of Computational Intelligence Research, Vol. 13, No. 7, pp. 1821-1828, 2017.

[12]. Vamsidhar, E., Rani, P.J., and Babu, K.R., ‘Plant Disease Identification and Classification using Image Processing’, International Journal of Engineering and Advanced Technology, Vol. 8, Issue 3S, pp. 442-446, 2019.

[13]. Joshi, A.A., and Jadhav,B.D., ‘Monitoring and controlling rice diseases using Image processing techniques’, 2016 IEEE International Conference on Computing, Analytics and Security Trends, 2016.

[14]. Biswas, S., Saunshi, A., Sarangi, S., and Pappula,S., ‘Random forest-based classification of diseases in grapes from images captured in uncontrolled environments, 2016 IEEE 13th International Conference on Signal Processing, 2016.

[15]. Aggarwal, A., Dhindsa, K. S., and Suri, P. K., ‘Performance-Aware Approach for Software Risk Management Using Random Forest Algorithm’, International Journal of Software Innovation, Vol 9, No.1, pp.12-19, 2021.

[16]. Aggarwal, A., Dhindsa, K. S., and Suri, P. K., ‘Design for Software Risk Management Using Soft Computing and Simulated Biological Approach’, International Journal of Security and Privacy in Pervasive Computing, Vol. 12, No. 2, pp. 44-54, 2020.

[17]. M. Sharif, M. A. Khan, Z. Iqbal, M. F. Azam, M. I. U. Lali, and M. Y. Javed, “Detection and Classification of Citrus Diseases in Agriculture Based on Optimized Weighted Segmentation and Feature Selection,” Computers and Electronics in Agriculture,Vol.150,pp.220-234,July2018.

[18]. H. Ali, M. I. Lali, M. Z. Nawaz, M. Sharif, and B. A. Saleem, “Symptom Based Automated Detection of Citrus Diseases UsingColorHistogramandTexturalDescriptors,”ComputersandElectronicsinAgriculture,Vol.138,pp.92-104,2017.

[19]. M.Islam,A.Dinh, K.Wahid, and P.Bhowmik,“Detection of Potato Diseases Using Image Segmentation and Multiclass Support Vector Machine,”IEEE 30th Canadian Conferenceon Electricaland Computer Engineering, pp.1-4, 2017

[20]. A. E. Hassanien, T. Gaber, U. Mokhtar, and H. Hefny, “An Improved Moth Flame Optimization Algorithm Based on Rough Sets for Tomato Diseases Detection,”Computers and Electronicsin Agriculture,vol.136,pp.86-96,2017.

[21]. V.SinghandA.K.Misra,“Detection of Plant Leaf Diseases Using Image Segmentation and SoftComputingTechniques,”Information Processingin Agriculture,Vol.4, No.1, pp.41-49,2017.

[22]. S.Phadikar,J.Sil, and A.K.Das,“Rice Diseases Classification Using Feature Selection and Rule Generation Techniques,”Computers and Electronics in Agriculture, Vol.90,pp. 76-85,2013.

[23]. A. Johannes, A. Picon, A. Alvarez-Gila, J. Echazarra, S. Rodriguez-Vaamonde, A. D. Navajas, et al., “Automatic Plant Disease Diagnosis Using Mobile Capture Devices, Applied on a Wheat Use Case,” Computers and Electronics in Agriculture, Vol.138, pp.200-209, 2017.

[24]. E. Bauriegel, A. Giebel, M. Geyer, U. Schmidt, and W. B. Herpich, “Early Detection of Fusarium Infection in Wheat Using Hyper-Spectral Imaging,”Computers and Electronics in Agriculture,Vol.75,No.2,pp.304-312, 2011.

[25]. J.G.Barbedo, C.S.Tibola, and J.M.Fernandes,“Detecting Fusarium Head Blight in Wheat Kernels Using Hyperspectral Imaging,” Biosystems Engineering, Vol. 131,pp.65-76,2015.

[26]. J.Li,X.Rao, and Y.Ying, “Detection of Common Defectson Oranges Using Hyperspectral Reflectance Imaging,” Computers and Electronics in Agriculture, Vol.78, No. 1,pp.38-48,2011.

[27]. J. Huang, H. Liao, Y. Zhu, J. Sun, Q. Sun, and X. Liu, “Hyperspectral Detection of Rice Damaged by Rice Leaf Folder,” Computers and Electronics in Agriculture, Vol.82,pp. 100-107,2012.

[28]. J. C. Zhang, R. L. Pu, J. H. Wang, W. J. Huang, L. Yuan, and J. H. Luo, “Detecting Powdery Mildew of Winter Wheat Using Leaf Level Hyperspectral Measurements,”Computers and Electronics in Agriculture,Vol.85,pp.13-23,2012.

[29]. T. Rumpf, A. K. Mahlein, U. Steiner, E. C. Oerke, H. W. Dehne, and L. Plümer, “Early Detection and Classification of Plant Diseases with Support Vector Machines Based on Hyperspectral Reflectance,” Computers and Electronics in Agriculture, Vol.74,No.1,pp.91-99,2010.

[30]. Y.Shi,W.Huang,J.Luo,L. Huang,andX. Zhou,“Detection and Discrimination of Pests and Diseases inWinterWheat Based on Spectral Indices and Kernel Discriminant Analysis,” Computers and Electronics in Agriculture, Vol. 141, pp.171-180,2017.

[31]. M. G. Selvaraj, A.Vergara, H. Ruiz, N. Safari, S. Elayabalan, W. Ocimati, et al., “AI-Powered Banana Diseases and Pest Detection,”Plant Methods,Vol. 15,No.1, 92,2019.

[32]. S.Coulibaly, B.Kamsu-Foguem, D.Kamissoko, and D.Traore,“Deep Neural Networks with Transfer Learning in Millet Crop

Images," Computers in Industry,Vol.108, pp.115-120,2019.

[33]. 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,"IEEEAccess,Vol.7,pp.59069-59080,2019.

[34]. J. G. A. Barbedo, "Plant Disease Identification from Individual Lesions and Spots Using Deep Learning," Biosystems Engineering,Vol.180,pp.96-107,2019.

[35]. G.Geetharamani and A.Pandian,"Identification of Plant Leaf Diseases Using a Nine-Layer Deep Convolutional Neural Network," Computers and Electrical Engineering, Vol. 76,pp. 323-338,2019.

[36]. A. Picon, A. Alvarez-Gila, M. Seitz, A. Ortiz-Barredo, J. Echazarra, and A. Johannes, "Deep Convolutional Neural Networks for Mobile Capture Device-Based Crop Disease Classification in the Wild,"Computers and Electronics in Agriculture, Vol.161,pp.280-290, 2019.

[37]. G.Hu,H.Wu,Y.Zhang, and M.Wan,"ALow Shot Learning Method for TeaLeaf's Disease Identification,"Computers and Electronics in Agriculture, Vol.163,104852, 2019.

[38]. K. NagaSubramanian, S. Jones, A. K. Singh, S. Sarkar, A. Singh, and B. Ganapathy Subramanian, "Plant Disease Identification Using Explainable 3D Deep Learning on Hyperspectral Images," Plant Methods, Vol. 15, No. 1, pp. 91-98,2019.

[39]. G. Polder, P. M. Blok, H. A. de Villiers, J. M. vander Wolf, and J. Kamp, "Potato Virus Y Detection in Seed Potatoes Using Deep Learning on Hyperspectral Images," Frontiers in Plant Science, Vol. 10,pp. 200- 209,2019.

[40]. D. Wang, R. Vinson, M. Holmes, G. Seibel, A. Bechar and S. Nof, "Early Detection of Tomato Spotted Wilt Virus by Hyperspectral Imaging and Outlier Removal Auxiliary Classifier Generative Adversarial Nets,"Scientific Reports, Vol.9,pp. 4370-4377,2019.

[41]. X.Zhang, L.Han,Y.Dong,Y.Shi,W.Huang,and L.Han,"A Deep Learning-Based Approachfor Automated Yellow Rust Disease Detection from High-Resolution Hyperspectral UAV Images," Remote Sensing, Vol. 11, No. 13, pp. 1448-1554, 2019.

[42]. Mishra, M., Choudhury, P. and Pati, B., "Modified ride-NN optimizer for the IoT based plant disease detection,"Journal of Ambient Intelligence Human Computing12(Springer),pp. 691-703,https://doi.org/10.1007/s12652-020-02051-6, 2021