A Novel Exploration of Plant Disease and Pest Detection Using Machine Learning and Deep Learning Algorithms

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Abstract
Agriculture plays a vital position inside the Indian economic system. Farmers, who account for 58 percent of the population, rely on it for their living. Each and everyday farmer face different problems due to pests It is hard to discover the ailment manually via the use of manpower. It creates a notable effect within the agriculture field and reduces cultivation. The researcher planned to discover the pests and disorder inside the agriculture discipline through the use of cutting-edge technology. With the help of agriculture expert, the disorder is easily recognized via system mastering algorithm and as compared with manual method. Hence, images are taken from the agriculture field and processed with image processing techniques. The model is trained using a machine learning technique, and an image from the dataset is processed to perceive pest and disease. These techniques assist in detecting plant disease to boom the yield of cultivation. This survey describes the current challenges to be resolved via the usage of the current advanced Machine Learning approach and takes a look at in fact about numerous systems for disease identification and classification is also achieved.

Keywords: Machine learning, plant leaf disease detection, Identification, classification

Introduction

One of the best essential sources of human sustenance on Earth is thought to be farming. It is vital to the economy of the country. It plays a primary part in the economy of every country. A farmer's financial growth depends on the eminence of the products that they produce, which depends on the plant's growth and the yield they get. Pests are the important threats to the growth of crops. It has an effect on the healthy yield of crops and thereby lessens the production. It is a matter of concern to protect these crops as agriculture is a fundamental part of the country. Detection of pests in plants plays an active role. Smart cultivation is significant for handling the difficulties of agricultural creation regarding efficiency, natural effect, food security and manageability. In the nations like India, where half of the labor force is related to farming however just have the 17.35 % of the Gross Domestic Product that is excessively less as related to manpower connected. Indian food production is affected by numerous factors such as weather, historical, geographical, natural and political. Agriculturalists normally notice symptoms of disease on plants. Professionals can either diagnose the ailment themselves or rely on laboratory tests. In India, naked eye monitoring by a professional is a common method for disease detection. The costs of consulting qualified experts are considerable and making it on time in a remote place is impossible. Monitoring is a risky part of pheromone- based pest control systems. Consequently, a method for former disease identification is necessary.

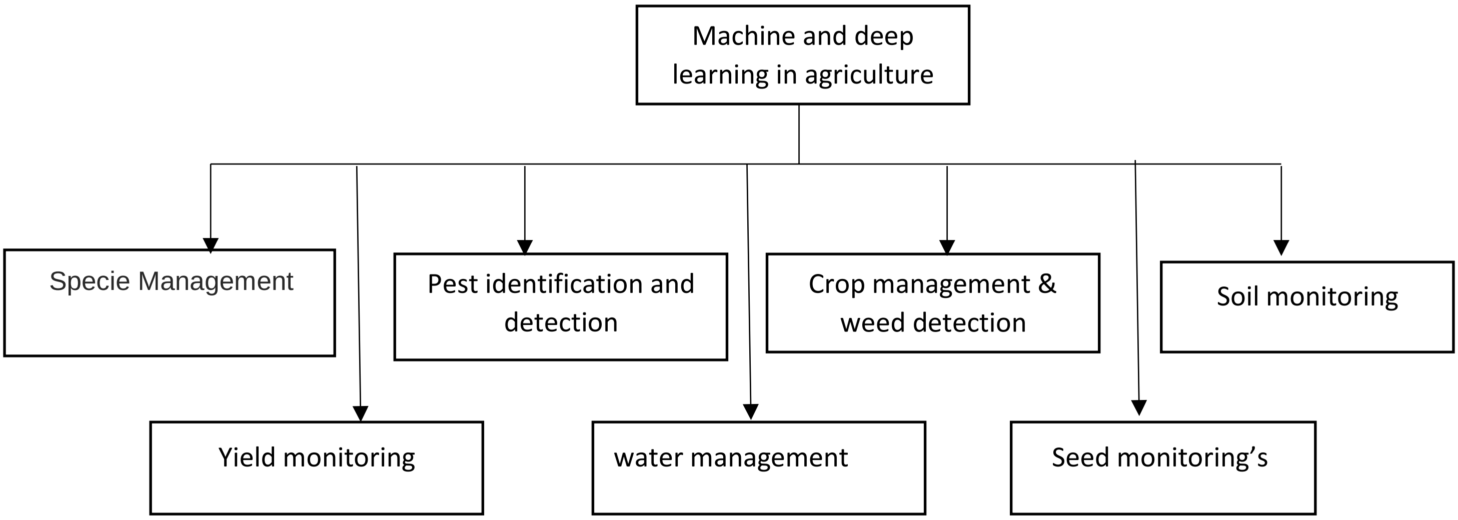

Fig 1. Machine learning and deep learning applications in agriculture

Monitoring plays a significant role in pheromone-based pest control strategies. In commonly used trap-based environments Pest tracking, digital images collected are processed for identifying and counting pests by human experts. Manual Counting is labor-intensive, slow, costly and often error-prone, preventing real-time efficiency from being achieved. Our purpose is to apply current system learning techniques to the pest identification and counting of pests, successfully putting off peoplefrom the loop to attain a totally computerized, pest monitoring system. Utilizing a variety of image processing techniques including segmentation, classification, type and as a result, leaf ailments is been detected early and crop output can be enhanced. Figure 1 shows how AI techniques are used in agriculture.

Inexperience farmers might also threat to choose wrongly for pest identification and insecticides. This brings the environment down and cause unnecessary economic loss. To overcome this problem the image processing techniques are mostly used in pest detection and identification which is shown figure 2.

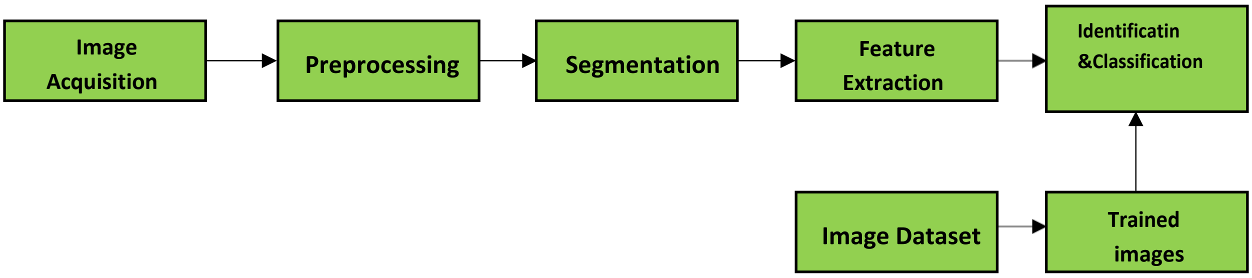

Fig 2. Method for pest identification and classification

LITERATURESURVEY

R.Sujatha et al. [1] has considered the effectiveness of machine learning procedures to find plant disease. Plants are essential because they are humanity's primary source of energy due to their rich nourishing and medicinal values. Due to leaf diseases, these rich nutritional and medicinal values get affected more. Identification of leaf diseases is so critical in the agricultural sectors. For the identity of leaf disorder, diverse Machine learning (ML) strategies in addition to Deep learning (DL) strategies are developed and examined through numerous researchers. The strategies are extremely useful in leaf sickness detection and additionally compare the best among these two techniques. Generally Machine learning classifiers are Linear-SVM,SGD, RF and deep learning classifiers are Inception-v3, VGG-19 and VGG-16. Initially the author collects the leaf disease datasets from the farm area and analyses those data using both ML and DL algorithms. Using these classifiers, foliage infections are detected. The author explains that Deep Learning functions in a comparable way to the human brain's neural structure, with layers and optimizers that assist in constructing a dependable model with high precision. The researchers compare the results obtained through both machine learning (ML) and deep learning (DL) techniques to conclude that Deep Learning results are considerable in comparison with ML.

SouravKumarBhoietal.[2]Machine learning is used to investigate facts and learn from them. Whereas deep learning evolved from machine learning that addresses various datasets in a more compatible manner. This proposed model is based on the scope of the dataset and deeper into the network. The citrus leaf disease dataset is where the work flow is shown and predictions were made using the ML and DL classifiers for the multi-elegance classification approach. Citrus fruits are acknowledged for their immune assist to people. There are various categories of citrus fruits such as pummelo, sweet oranges, lemons etc. Citrus fruits are high in flavonoids, antioxidants, and polyphenols, which aid in the treatment of diseases such as Alzheimer's, cardiovascular, leukemia , Parkinson's , and others. The citrus leaves were captured with a DSLR at a resolution of 72dpi and a size of 256 * 256 pixels. Citrus leaves and fruits that are both diseased and healthy are included in the dataset. In order to create a model and predict the class for the testing dataset using the training dataset, ML and DL algorithms has been developed. Images are sent into the system, which creates a vector of values that can be used for extensive machine learning processing after that. This embedded works faster, but there is no demand for an internet connection. The hyper plane-based technique was optimized to cope with a multiclass environment after the early phases were depicted in binary categorization. Linear, polynomial, sigmoid functions and radial basis functions and are among SVM functions.

HaoxuYangetal.[3] have proposed the experimental investigation and estimation of extensive residual network mostly built agricultural disease detection using AI in intelligent farm devices. In agricultural crop enterprise, pest and disorder control had been a great priority problem. Because of exceptional advancements in the discipline of computer vision-based agricultural pest identification, artificial intelligence is being used, which increasingly more researchers shift their focus from machine learning to deep learning techniques. This paper investigates about use of a novel deep learning version WRN to address the challenge of CV-based automatic disease detection. Initially, the researchers created a large commercial agricultural disorder image dataset including over 36000 pieces of disease as well as common types of diseases in tomato, raspberry, corn, potato, and apple. Within the Tensor Flow deep-learning framework, the researchers examined and evaluated the broad residual networks approach utilizing the Tesla K80. In the analysis procedure, the researchers discovered that WRN indicates a terrific effect for identify of agricultural diseases. This research demonstrates how the WRN model can be used to diagnose agricultural disorders.

Dipika Harpale et al. [4] has proposed an image analysis and machine attempting to learn approach to identifying plant syndromes. The android-primarily based application is designed to enable agronomists to detect plant disease via importing a leaf image to the machine. The OpenCV after which the image type to be able to discover the disease of plant is completed using machine learning. Image recognition represents one of the most significant image processing programmers, which is an important tool for early disease detection in crop production. The Gaussian filtering for image pre-processing and CNN to recognize the nature of leaf syndrome. If the image is detected as abnormal defected area is assessed and pesticides are suggested through vendors or on-line stores.

Muammer TÜRKOĞLU et al. [5] The accurate detection of plant diseases is critical to avoiding yield loss and decreased amounts of agriculture products. In order to resolve such glitches, machine learning is a technique that may be utilized. Modern deep learning techniques, which are primarily utilised in image processing, are now being applied to offer numerous new precision agriculture strategies. Deep feature extraction, which is classified by SVM, KNN approaches and extreme learning machine is used to extract the features (ELM). The tests were processed using data from Turkey containing images of disease and pest images. Performance evaluation is done for F1-score, accuracy and sensitivity. Deep data acquisition and transfer analysis outperform multiple rule sets in terms of overall performance for monitoring environmental disorders and pests. Finally, ResNet50 features with SVM classifier shows a better accuracy score than ResNet101, Squeeze Net, Alex Net, InceptionResNetV2, Google Net.

ThenmozhiKasinathanetal.[6]The agriculture division has a significant opportunity to enhance demand for food and supplies by producing healthy meals. Pest detection in crops is a tough challenge for farmers as a major part of the plants which are affected to the best is lessened because of the pest attack. The Wang and Xie dataset is analyzed, with classification of nine and 24 insect classes using feature descriptors and machine learning methodologies. 9-fold cross-validation was used to improve the visibility of the categorization models. With nine and 24 class insects, the CNN Model achieved maximum classification rates of 91.5 and 90 percent, respectively. SVM, KNN ANN, and Naive Bayes are some of the machine learning algorithms used to classify shape information derived from image processing techniques. CNN models were employed in insect classification to evaluate the accuracy of the classification with other methods. Higher accuracy was attained using CNN, which can be useful for identifying insects based on their classes and families. Finally, the results show that the CNN model has the highest classification accuracy in the Wang and Xie datasets, with 91.5 percent and 90 percent, respectively.

Harshal Waghmare et al. [7] As a result, one of the emerging domains is leaf-based disease detection in plants. Leaf texture analysis and pattern recognition method proposed for Detection of plant disease using opposite color LBP. This paper focuses mostly focus Grape's plant leaf disease finding system. A single plant leaf is used as input, and segmentation is performed. With a segmented leaf image, the high pass filter is used to detect leaf disease. The unique fractal based texture feature is recovered using a segmented leaf texture. Each disease contains a different texture. The retrieved texture pattern is separated using Multiclass SVM. The two most widespread diseases affecting raspberry plants are downy mildew and black rot. With 450 photos of grape leaves (160 healthy leaves and 290 damaged leaves), the multiclass SVM was utilized to analyse them. The multiclass SVM classifier shows the accuracy of 89.3%. The accuracy of Decision Support Systems (DSS) is 96.66 % when combined with the multiclass SVM.

ShanwenZhangetal.[8]AlexNet is one of the versions proposed in this paper to become aware of the plant disease. The experiment was carried out to diagnose the cucumber disease with datasets of six similar cucumber leaf diseases (600 cucumber diseased with 100 normal leaves were collected). The data is collected with resolutions of 2456×2058 pixels for cucumber plant from Yangling agricultural high-tech 100 usual leaves were collected industrial, China. The disease leaf is segmented using K-means clustering algorithm. The experiment is carried out with different algorithm AlexNet model, world-wide pooling PDCNN,DCNN. There are three improvements to the GPDCNN. The dilated convolutional layer recovers spatial resolution while increasing the convolution receptive field without increasing computing complexity or losing discriminant formation. GPDCNN shows better learning and higher recognition ratecomparede to DCNN, AlexNet.

Mohit Agarwal et.al. [9] Tomato is the most essential vegetable cultivation in India. The several machine learning techniques like naive bayes ,SVM, 3decision trees, logistic regression and various features extraction techniques are used to identify the tomato with 9 kinds of leaf disease. CNN base deep learning neural network is proposed with 8 hidden layers. The dataset consists of ten classes of tomato disease. The traditional ML methods of k-NN give great accuracy of 94.9% , VGG16 pretrained models obtained accuracy of 93.5%. These models were implemented to a CNN model that had been trained and tested on a dataset. When compared to VGG16, Inception-V3, and Mobile Net, give accurate information tends to increase with epoch count, with the best showing at 5000 epochs with a 98.4 percent accuracy. The diverse assessment metrics which include - accuracy, confusion matrix, bear in mind, precision, F1-score, and so forth used to examine the overall performance of the proposed algorithm. The actual photograph taken from the agriculture subject via cell with a purpose to identify the multi-crop plant sickness is pick out with the tough dataset of seventeen disease with five crops of rape-seed, wheat, corn, rice, wheat, barley etc.

ArtzaiPiconet.al.[10]The actual image taken from the agriculture subject via mobile with a purpose to identify the multi- crop plant sickness is pick out with the tough dataset of seventeen disease with four or five crops of barley rice, corn, wheat and rape-seed. Crop ID is sent to the convolutional neural network, which incorporates crop-conditional CNN architecture with contextual category metadata. The suggested solution includes integrated contextual meta-data to supplement the image info that is sent into the classification system with crop information.

Sanjeevi Pandiyan et.al [11] Agriculture is the foremost part of India. Most of the plant leaf is infected due to the bacteria, micro-organisms viruses, fungi and cause several disease. The authors proposed IoT based novel method to increase the accuracy for apple plant leaf disease identification. The system takes input of non-objective leaf with disease and without disease. The database compares the input leaf image to the one which was before entry non-objective leaf without disorder image. The image is fine-tuned by using the image converter in order to save the image in right format. The Heterogeneous IoT detection (HIoTD) and secure identification and isolation (SII) techniques is used to differentiate a variety of multiple leaf diseases. The results of the experiments show that the proposed method helps to distinguish a high-detection ratio with a revealing behavior of Recall (95 percent), Precision (83.2 percent), Accuracy (98.55 percent), and F-measure (86 percent).

ChangjianZhouet.al[12] The crop disease identification plays a major role. It is difficult to find with the support of staff to minimize the plant disease. This research, a rebuilt residual dense network model for tomato leaves is proposed Deep residual networks and dense networks provide advantages in terms of increasing accuracy and decreasing training parameters combines with the hybrid deep learning model. The dataset contains more than 13,000 images with 9 classes of different tomato leaf diseases. The different deep convolutional neural networks of Alexnet, Inception network, Residual network, dense network results are compared with the proposed system. The RRDN produced a higher accuracy of 95%.

Waleej Haider et.al [13]The crop disease plays a vibrant role in the food production field due to less sharing of knowledge among the cultivators. It leads to a decrease the agriculture production. The research has been started with the support of the framer, agriculture expert are the platform. To identify the disease, the research study suggested various disease detection categorization methods and approaches based on machine learning algorithms. In this paper the wheat crop is selected for disease identification. The model contains image-based disease detection is done by the Convolution Neural Network and Symptom based disease classification is done by using decision tree. The 2324 symptom-based dataset was taken as the samples to detect disease the as the testing data. The dataset contains 18 sets of labeled diseases. Some species, such as common bunt, fusarium head blight, sooty head moulds which cause disease. The repeated process of data restoration and outcome confirmation used by agricultural professionals to improve performance. When compared to the traditional algorithm, the suggested algorithm has an accuracy of 98 percent.

Davoud Ashourloo et.al [14] Wheat is one of the major productions in India. The use of spectral vegetation indices to regulate disease severity detection is based on the various disease stages and disease indicators on plant attributes (SVIs). To classify the disease and its symptoms, various machine learning strategies are used. The RGB Digital photos of infected leaves are collected for analysis. These datasets are utilized with the GPR, SVR, and PLSR for disease detection. By using these algorithms, the prediction is done to recognize the symptom of plant disease. A non-imaging spectroradiometer was used to measure the leaves of various diseases symptoms in the electromagnetic range of 350 to 2500 nm. The different sizes of the sample dataset used to train the model. Each algorithm determines the coefficient R2 value and root mean square error. The thirty iterations are done with three methods. The best model is preferred built on the R2 and RMSE. The PLSR shows lower performance compared to SVR and GPR.

XihaiZhanget.al[15]The number of network parameters has been lowered in order to increase maize leaf disease detection accuracy. This research proposes improvements to the GoogLeNet and Cifar10 models. Nine kinds of maize images are used to train and test by adjusting the parameters. After the one hundred thousand iterations are classified by the three classifiers contain both test accuracy and test loss. Both states are stable as the top - 1 evaluates the accuracy approaches one and the loss goes to zero. The Cifar10 model contains two completely coupled layers of Relu function and dropout operation. The model's maximum testing accuracy is 97.8 percent. The experiment used four pooling combinations of three convolutions: Max/Max/Ave, Max/Ave/Ave, Ave/Ave/Ave and Max/Max/Max. Both accuracy and loss are measured after every twenty iteration. GoogLeNet and Cifar10, two upgraded deep CNNs models, achieved great identification precision of 98.9% and 98.8%, respectively, and reduced convergence iterations.

Prince Samuel S et.al [16] Due to a shortage of labour, interest, and other natural constraints, farming is becoming exceedingly challenging. This Paper suggests a Survey of various methods of Crop selection, seeding of crop , weed detection and observing the system that increase the Productive output. In olden days the weed was removed manually, with pesticide. The normal plantal so gets affected of using pesticide and it is the long process. Due to the lack of labour the IoT based smart agriculture is established.The image is taken and trained with different algorithms using machine learning and Artificial Intelligence. The weed image is taken and it processed by image processing technique. The image's features are extracted and classified. The three different techniques are used which is knowledge flow, knowledge base and realized input. The multiple sensors is used to learn the input data in agriculture field and stored in the plant database. The independent robot has been designed to detect the weed and leaf's are recognized using the image processing .The cloud-based architectures are used to detect the weed. Initially it happens with the support of human support. The advanced techniques like drones are used to distinguish the weeds and planting the seed. The aerial image of the agriculture field, arm based robot and multipurpose agriculture robot are used to perceive the early disease in the leaf, Monitoring, Spraying, and yield assessing. To instruct the chatbot, the artificial neural network algorithm is used for all data. The system design and the process of the algorithm was not explained clearly. Furthermore, in recent years, drones have been built to identify pests and weeds, and to reduce stress in agricultural activities, computer vision technology has been used in the automation of sprayers.

Chiranjeevi Muppala et.al [17] This paper discussed with the detection of moths using deep neural network in the paddy field. Detection of the pest in the early stage can easily avoid the fast spread in agriculture field. The pests are trapped with light source with funnel attached with plastic container. The trapped pest image is captured with camera. The contrast enhancement technique is used to improve the image's quality. The DHO technique is used to boost image contrast. The goal of the FAPG filter is to eliminate the contrast-enhanced image's undesired impulsive sounds. It was done with two steps, which are pixel inspection, and replacement. Multilevel Otsu thresholding was designated to separate the multiple objects. SAR algorithm with Optimized DNN was proposed. The different number of hidden layers are considered, and the weight matrix must be carefully chosen to reduce the DNN's mean absolute error (MAE). SAR was utilised. After evaluating performance parameters such as PSO, GWO, CII of DHO, WOA algorithms, PSNR, and AMBE, The DHO classifier was selected to enhance contrast of the image. The proposed technique achieved 97.85 % precision with 98.29 % recall, F1 score and FNR of 98.30 %, 98.75 %, 0.0125 % respectively using the correct optimization techniques in the insect testing phase. DNN-SAR shows the highest accuracy compere to ResNet50, GoogleNet, Alexnet.

A.Ramcharan et.al [18] The authors introduces a deep learning-based image-based cassava disease identification method. A deep convolutional neural network is used to train a dataset of cassava illness photos to detect two types of insect damage and threediseases.Accuracyratesforthebest-trainedmodelsexceeded93%.Themodelistrainedwith11,670imagesofcassava diseases. The images are taken with genotypes and stages of maturity. Finding disease and type of pest damage is unique dependingonthesymptom.Thedatasetshavebeenannotatedwithsixlabelsbasedoncassavadisease professionals'in-field diagnoses. Tensorflow was used to effectively implement the Inception model and Inception v3. Inception utilises the GoogLeNet model with a variety of philosophies to upgrade networks to enhance performance with a slight increase in the computing cost and a substantial benefit if the amount of memory or processing power available is limited. The performance is tested using a training model that uses 10% of the dataset to test trainee steps while the other 90% is divided into distinct testing and training data set configuration. The precision is determined by the number of samples. We contrasted the effectiveness of three architectures for training the final layer of the CNN model Inception v3 procedure such as support vector machines (SVM), the originalinceptionsoftmaxlayer,andknnclosestneighbourforalldatasets(knn).Theaccuracyofthel eafisbasedoncorrect classification of the from 73% to 91%. The overall accuracy ranges from 80% to93%.

ching-ju chen et.al[19] Artificial intelligence and the Internet of things(AIoT) is work along with environmental sensors used to identify a pest with a mobile application. In smart agriculture, artificial intelligence and Internet of Things (AIoT) technology are collaborating in deep learning. The real-time image recognition system 687 images of image data for Tessara to map apillosa are collected from the drone and mobile application.The image of the pest is labeled to train the data and the imgaug library is used to escalate the accuracy. The image contains GPS information to share the locality of the hassle. The image pre-processing was used to increase the training samples using the grayscale, sobel edge detection, and color features enhancement. The pest is identified with the different viewing directions are left, right, abdominal views, and back view. To increase the number of images used, sample segmentation and image augmentation methods are used to enhance the precision of the pest image. The field collects four different sensors with six different types of environmental data. The LORA module sends the data to the cloud database. The server station has acknowledged once it receives thedata.Thedataarecollectedeveryonehouroncefromtheenvironmentalfield.Withinsixmonthsof time,12,960sets of datawerecollectedfromtheenvironment.Sensorsareusedtoidentifythepestwhichcausesdamagein the cultivation field. Images are collected by using drones and mobile application(mAP)is uploaded in the cloud to recognize the pest along with the location. The YOLOv3 model is used to classify the pest and extract their features with 90%accuracy.

DimuthuLakmalet.al[20]RiceisoneoftheprimaryproductionswithintheAsiancountries.Amach inelearningtechnique was proposed in this paper to find the brown plant hopper in the paddy field. The machine learning and satellite remote sensing data is user to find the hopper in the field. It processes under the two phases are and Ratio and standard difference indices and time series classification based. The area has to decide to study the data. The texture of the image are obtained by using the GLCM technique. The sum variance is calculated the values are obtained in data range of the selected pixel. The whole dataset contains 4650 pieces of information, with 465 items validated in each iterationandtrainedwith4185 data points. The CNN that was used to classify the time series. The pre-processing is done by using four steps are 1) improving the geocoding of images 2) time series comparisons are done by normalize the value 3) remove speckle noises 4) subset with a GLMC. Planet Scope multi-spectral band file is used in brown plant hopper attack detection to calculate standard difference and ratio indices. Red,Green,NIR and Blue are the four spectral bands in the multi-spectral band file. The equation is used to calculate the conventional difference indices and proportion indices values. The convolution neural network is cultivated which produced the accuracy of 96.20%. The SVM Model is used for classification.The model trained with more datasets will improve the accuracy. The suggest approach works better to find the disease in the paddy field.

Huiqun Hong et.al [21] Tomato is one of the main productions in china. During the growth the plant get affected by the disease and the pest. The deep learning plays a vital role which used to diagnosis the disease and pest. The size of data, computation cost, and time are reduced using the transfer learning. The five convolutional neural network Xception, Densenet_Xception, ResNet 50, MobileNet, ShuffleNet. The dataset which contains both disease and healthy leafs. The tomato leaf contains 9 common diseases, based on it contain 18 classifications based on the disease and pest. Using image augmentation, the number of photos needed to train the model has increased to 13112 images. These five deep CNN models are used to train and test the dataset Densenet_Xception shows the highest accuracy of 97.10%.The same approach is further implemented using the smart phone for assisting the tomato pest control.

Liu Liu et.al [22]have dealt with a multi-class pest monitoring using deep learning based automatic approach. It works based on two stage deep learning are hybrid global and local activated feature. The CNN based model is mainly used for exact detection of the pest with 88.6k images. The global activated process is used to find the many tiny pest using many pyramids level. It mainly works on the depth and spatial level activation. The activation of deepness is calculated using the W*H*C which is evaluated from CNN block of 3D Feature extraction and generate with the lower dimensional feature. In the same way spatial level activation which takes one*one size of kernel to diminish input features and produced the output of 2D spatial activation vector. Local activated region proposal network are used to localize pest was developed under the two motivation. The first stage contains standard RPN to find the pest location using sliding window. The local spatial positions mainly for the pest region classification based on the shape and color of the pest. The samples are predicted by using the bounding box method. The binary classification system in which pests are classified using localized boxes. The pest severities are estimated with the multi-class classification ask are do me with MeanSquareError(MSE).Analysis is done with 88.6K images dataset 16 pest categories. All the three concepts are work under the Inception, ResNet50 and proposed novel method of deep learning LARPN's). LARPNs are more effective in automatic pest monitoring.

Quoc Bao Truong et.al [23] This paper proposed to find the pest using the two methods. Pomelo is the kind of citrus fruit the pest is affected in body, leaves, and fruits. The pest mainly the growth and yield of the pest. The pre-processing is done by transfer the to HSV from RGB colorspace. The quality of the image is enhanced by a 3x3mask.The candidate area is extracted from the original image by using the morphological operation.The colormoments, correlograms are used to extract the color feature. Zernike moments are used for shape moments to extract the feature which converts the RGB to grayscale done by the radial polynomial. Model is trained by using the SVM Train() function with labels, accuracy determined with Evaluate Classification Problem() function. The SVM Predict() for classify and detect the object. The model is trained with 1,840 objects. One of the most powerful approaches for pattern categorization and image processing is the Convolutional Neural Network (CNN). A CNN is composed of at least yet another pair of maximum pooling and convolutional layers. Higher layers work on a lower resolution for a more complex part of the inputs. Data are trained with the labels for input pattern to the output response. It works as an iterative process to get the response of intermediate and final features of the neuron. Data augmentation is used to escalate the training samples by simple horizontal reflection and rotation augmentation The deep learning model in the proposed solution has the highest efficiency of 99.35%.

Rui Li et.al [24]Pest segmentation and tracking is one of the most difficult tasks in agriculture. The CNN method for the pest localization and acceptance is not satisfied. The CNN method employs a data augmentation technique to address this issue. A device called pest intelligent gathering equipment is used to collect the data for the wheat and rice plants. The 4400 pictures were used to randomly divide the dataset in to other both validation and training subsets. Labels and bounding boxes have been added to the set of data. The convolutional neural network (CNN) is part of ANN which automatically extract the 2Dobject for object recognition and detection. Performance is enhanced via data augmentation techniques of pest localization and detection are trainset (Rotation, Multiscale), test time augmentation. The average precision is calculated for DAG-CNN, HR, FPN and non-maximum suppression (NMS). The proposed system improves the of 81.4% mean Average Precision (mAP).

Dhapitha Nesarajan et.al [25] The coconut is one of the main productions in srilanka. This paper's main objective was to develop a method for pest attack and nutritional shortage in coconut plant. Automatic identification, rather than human monitoring, may be a more efficient and effective way to detect sickness. The dataset is prepared by collecting the image of healthy and unhealthy leaf using the digital camera person-processing is done to improve the correctness of the dataset image and reduce its complexity. K-means clustering is used to identify nutrition deficiency by segmentation. The affected leaves are identified and feature is extracted for the further process. The support vector machine is a popular technique for classifying leaves. The CNN model of VGG-16, ResNet50, and EfficientNet-B0 is used for classification. EfficientNetB0 model shows the highest accuracy used to predict the nutrient deficiency. Once the pest and nutrition deficiency is identified it recommends the pesticides and fertilizers. Opencv is used for plant monitoring. The mobile application used to identify the pest disease. The major drawbacks in the previous research is the lack of monitoring the plant from initial stage to until the disease fully recovered. This approach aids inexperienced farmers in increasing output. The SVM and CNN mainly used for the classification which shows the better accuracy.

Waleej Haider et.al [26] Agriculture research has done in which yield is decrease due to the disease, agriculture field, lack of knowledge, method of agriculture and irrigation. The researcher has proposed various technique to identify the disease using the numerous machine learning techniques to identify the wheat disease. Due to this approach the agriculture experts are not required to verify the identification results. The wheat disease are identified under symptoms and physical parts. There are several disease are under this two category. New Model has been proposed to discover the type of the pest. It consist of two kinds of the datasets are symptom-based text and Image based datasets. The model works under two side as left and right. The left side in which the disease is classified based on the symptoms. The image-based disease categories is shown on the right side. In the data acquisition process the data are acquired from the survey, interview, online and the queries. The unwanted noise are removed using the data pre-processing. The features have to extract and classification is done by using the decision tree used for discrete-valued function. The information gain, entropy are calculated for 2324 symptoms using symptom-based text data. The CNN is implemented for the image-based dataset with 9340 images. The decision tree, support vector machine, naive bayes, ADA-Boost classifier is implemented and estimate with the suggested CNN Model which shows the high accuracy. Proposed model which displays greater accuracy when compared to the conventional approach.

Deepaet.al[27]This article outlines various machine learning algorithms for locating pests. The plants are affected by the pest. Several machine learning approaches are used to categorize the type of pest. The disease is unique for different kinds of the plant. The automated identification of the plant disease is done by machine learning techniques. The plant leaves are affected due to the environmental and climate change.The images in the dataset are pre-processed and the features retrieved from an agricultural field. The SVM is used to classify the data once it has been clustered. The binary classifier are uses the hyper plane. Multiclass classification is achieved for one to one or one to many mapping. The pest are classified as different classes. This automatic detection help the farmers to improve the production with free of pest.

Kirti et.al [28] Esca is a fungal disease that affects grape plants and is marked by a dark streak on the leaves. This leaf is fallen prematurely and take into account as the unhealthy leaf. From the village, the dataset is gathered which contain 1807 images contain both healthy and unhealthy images. The deep learning method is used to find the disease. The affected part which contains reddish or brownish color patches are presented in the veinor edge of the leaf. The image is processed in which RGB is converted to HSV conversion. The K-means cluster is used to extract saturation component which forms the cluster. The deep neural network ResNet50 is used to classify the data. It takes the segmentation as the input for the further classification. The logic is performed using the matlab with some deep Learning toolbox. The image is extracted with k-means. The classification is done for both segment and no segment leaf in which accuracy is calculated. The accuracy is calculated and compared with various papers. The categorization was determined by dividing the data set into of 70:30and80:20. This proposed system shows the better accuracy when compare to the existing systems.

Yong AI et.al [29] The pest detection is the major role in the agriculture field. Early identification and detection of pest which automatically reduce the economic loss. The dataset is together from the public competition the 28 plant disease from 10 crops. The convolution neural network solves the problem of too many parameters and improves image stability. The most used convolution neural networks are LeNet-5, ALexNet, Inception Network, Residual network. IoT based detection is happen with the support of sensors and cameras which is placed in the mountain to capture the image. The image information is learned from the deep learning neural network from the collected image to identify the pest. The basic model isInception-ResNet-v2,while the hybrid model doesnot have a hybrid network but does have the depth benefit of a residual network.The residual unitil improves accuracy but doesnot fix the problem in the beginning. The image is pre-processed to improve model consistency; the neural network is not trained using the transfer learning approach. The pretrained model is loaded, the parameter are fix properly in the convolution and the connection layer. Following model-based training, classification and recognition on the test set are completed. This model shows the overall accuracy of 86.1%. The accuracy have to improve by increase the number of crops and disease.

Dhapitha Nesarajanet.al [30] have propounded models to find the disease and harm pest affected in the coconut tree. The image was collected from a digital gadget that has been pre-processed to improve accuracy and simplify the dataset. K-means, the edge detection method, mountain clustering and the Otsu method are used for segmentation. The maximum value is set to identify the affected area in the plant. Feature is extracted using the image segmentation. To improve accuracy, the suggested approach considers the colour and shape of the leaf. Following the extraction of features classification techniques include both the testing and training processes. In order to distinguish between healthy and unhealthy leaves, an SVM classifier is used. The training dataset is split with 4classes which is processed with multiclass classification. The CNN architecture used to find the nutrient deficiency detection. SIFT is the OpenCV used for plant monitoring. With the help of mobile App, the disease is identified by reading the sample from the given image. The SVM and CNN classifier shows very high accuracy. The drawback in the previous research has been overcome by monitoring from initial until fully recovers. This system increases the productivity and increase the profit

RESULTS AND DISCUSSIONS

Table 1: Techniques used for disease/pest detection in plants and their Results

Year	**Researchers**	**Dataset**	**Algorithm**	**Results/Conclusion**
2021	R.Sujatha et al.	Citrus leaf	Squeeze net (SN), (L-SVM). Random Forest	In comparison, the algorithm scored 76.8% for RF, 86.5 % for SGD, and 87% for SVM. It is best to use a machine learning algorithm. SVM works well with a wide range of data, and there is less of a risk of overfitting. The time it takes to complete an operation is relatively short. Cost-effective computing with normalized statistics.The computation is quicker and the results converge as quickly as possible due to how stochastic gradient descent operates. Random forest, on the other hand, performs admirably in a non-linear structure, controls outliers andoverfits with more precision.
2021	Sourav Kumar Bhoi et al.	Rice	UAV based computer vision system and AI mechanism to Pest detection using tags, confidence value and threshold	Different pests generate tags with confidence values. The greatest confidence values for pestidentification are attained when the pest belongs to a tag with a maximum confidence value and a confidence threshold of75%.
2019	Haoxu Yang et al.	10 varieties of crops with 35 diseases. The crops such as tomato, grape, corn and citrus are the thirty six thousand image as data sets	WRN model, Google Net Inception	The innovative end-to-end method implemented for automatically detecting multiple classes insects. The neural network is used to trained, evaluate and analyse to determine the accuracy to the best model for the plant tomato, potato and corn

				models.
2019	Muammer TÜRKOĞLU et al.	Apricot, Walnut, Peach, Cherry	ResNet50, ResNet101, InceptionV3, Inception ResNetV2, Squeeze Net, Alex Net, Google Net, VGG16 and VGG19	Finally ResNet50 features with SVM classifier shows a better accuracy score than all other algorithm.
2020	Thenmozhi Kasinathan et al.	Various Insect Dataset	ANN, SVM, NB, KNN and CNN model.	For large insect datasets, the pest identification technique of the convolutional neural network (CNN) model was used to detect pests with classlabels.Definitive resultsprovedthat the CNN model for 9 and24 classes of insects shows a supreme classification accuracy of 91.5% and 90%.
2016	Harshal Waghmare et al.	Grape plant	Multiclass SVM, %. Decision Support Systems	The multiclass SVM shows accuracy of 89.3%.The DSS is integrated and it shows accuracy of 96.66%
2019	Shanwen Zhang et al	Cucumber leaf	GPDCNN, DCNN, Alexnet	GPDCNN shows better result than DCNN, Alex Net. This model increase the learning and higher recognition rate.
2019	Artzai Picon et.al	barley, corn, rice Wheat and rape-see	crop conditional CNN architecture	This approach obtained an BAC of 0.98, which was greater to the other approaches and classifier errors of 71%.
2020	Sanjeevi Pandiyan et.al	Apple leaf Disease	Advanced segmented dimension extraction (ASDE), Heterogeneous IoT detection (HIoTD), Secure Identification and Isolation (SII)	The experiment shows the higher accuracy of 98.55%
2021	Changjianet.al	Tomato plant Leaf	residual dense restructured deepnetwork	The RRDN produced higher accuracy of 95% compare to other model like Deep CNN, ResNet50, DenseNet121.
2021	Waleej Haider et.al	Wheat leaf	Expert Opinion Tree and CNN	The proposed model shows higher accuracy related to the traditional algorithm
2016	Davoud Ashourloo et.al	Wheat	PLSR, Gaussian process regression,ν	PLSR shows lower performance compared to

			support vector regression	SVR and GPR
2018	Xihai Zhang et.al	Maize	Google Net and Cifar10	Model received to the high identification accuracy of 98.9 and 98.8 percent respectively.
2020	Chiranjeevi Muppala et.al	paddy	search and rescue optimization (DNN-SAR), ResNet50, Google Net, Alexnet	The proposed method accomplished precision of 98.29% in insect detection.
2017	A.Ramcharanet.al	Cassava	The support vector machines (SVM) ,inception softmax layer, and knn nearest Neighbour (knn)	Overall accuracy range from 80% to 93%
2020	ching-ju chen et.al	Fruits tree(Tessaratoma papillosa)	YOLOv3	Attained overall accuracy 90%
2019	Dimuthu Lakmal et.al	Brown Planthopper in paddyfield	SVM and convolution neuralnetwork	CNN produced overall efficiency of 96.20%.
2020	Huiqun Hong et.al	Tomato plant	Xception Densenet_Xception, ResNet 50 , MobileNet, ShuffleNet	Densenet_Xception shows the maximum accuracy of97.10%
2019	Liu Liu et.al	16 type of pest	Inception, ResNet50 ,Local activated Region Proposal Network	LaRPN shows better result
2018	Quoc Bao Truong et.al	Pomelo Leaf	shallow architecture and deep architecture	Deep architecture shows the best approach with the highest accurateness of 99.35%
2019	Rui Li et.al	Wheat And Rice Plant	DAG-CNN, HR, FPN and non-maximum suppression (NMS)	The main focus of this research could enable pest detection and identification for intelligent prediction.
2020	Dhapitha Nesarajan et.al	Coconut plant	SVM and CNN	SVM and CNN used as the best method of the classifier
2021	Deepa et.al	Tomato leaf	Multiclass SVM	SVM Shows better accuracy
2021	Kirti et.al	Grape leaf	Deep neural network ResNet 50	Proposed system shows better accuracy
2019	Mohit Agarwal et.al	Tomato plant	Decision Trees , support vector machine (SVM), Logistic Regression, CNN, naive bayes	CNN Shows better accuracy of 98.4% with 18160 images
2020	Yong AI et.al	10 crops with 27 disease images	LeNet-5, AlexNet, Inception Network, Residual network	Inception-ResNet-v2 shows the accuracy of 86.1%

2020	Dhapitha Nesarajan et.al	Coconut plant	SVM and CNN	SVM shows the accuracy of 93.54% and CNN shows the accuracy of 93.72%

The multiple categorization approaches are utilised to identify the pest and illness utilising machine learning and deep learning techniques. The numerous image processing with machine learning techniques utilised in various articles are surveyed, and their accuracy is compared.. Figure 2 elucidates the accuracy level of different classifiers and other kinds of methods used disease recognition. Based on the dataset the accuracy is shown fig 3.

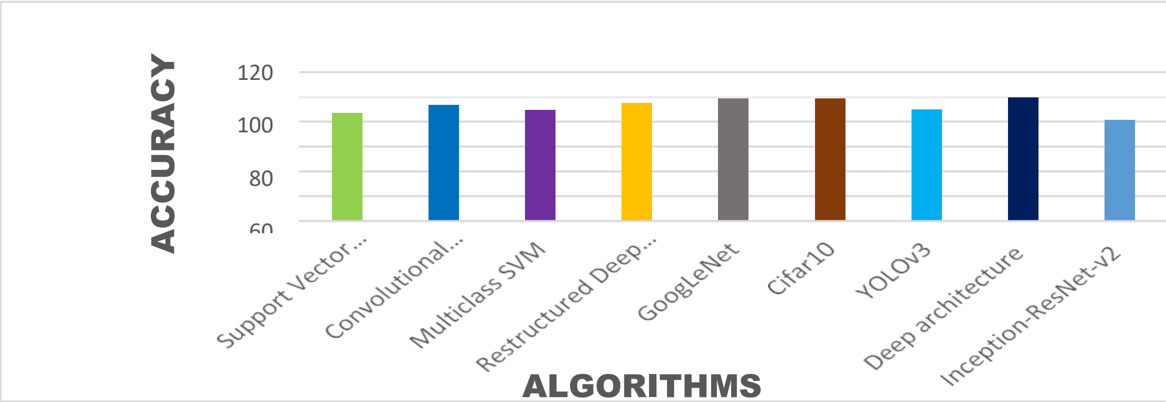

Fig 3. Accuracy Level comparison of different Techniques

CONCLUSION

In this study, we give a survey on different agriculture product diseases detection and classification with advanced machine learning techniques. This will make any future studies in this area for development easier to demonstrate. The model is trained with sufficient data is passed as the input to identify the plant disease. The pest disease are identified and classified with high accuracy. The more machine learning algorithms can be verified in this field to get more enhanced and exact results. The algorithms discussed in this research assist scientists in overcoming a variety of issues that directly or indirectly impact farmers. There are various methods for disease detection and classification is automatic or computerised but still there is lack in this research topic. The future work is done to made research in advanced algorithm to improve accuracy.

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