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Artificial Intelligence in Agriculture for Leaf Disease Detection and Prediction: A Review

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Abstract

Gross Domestic Product (GDP) of nations mostly depends on agriculture sector. Use of engineering technology for farmers and rural development playing important role in 21th century. Technology such as Deep Learning, Machine Learning and Artificial Intelligence are preferred for leaf disease detection. In the growing stages of crops control on leaf diseases are most important step. The disease detection and analysis at early stage for unhealthy leafs with solution always support of agriculture development. Our survey largely focus on related tools, technology, and different deep learning model. The improvement in percentage of accuracy is target and main goal for leaf diseases detection. The main approach is predict accurate type of disease occurred on tomato, soyabean and grapes leaf at early stage. Our study aim to address the issue using the Deep Learning (DL) techniques. Real time gathering of diseased leaf images and process using Convolution Neural Network (CNN) are the crucial step in proposed research. Convolution Neural Networks detect the diseased leaf and provide the analysis over it with better accuracy on real datasets. An agriculture surveying for disease detection playing unique role for farmer's community. Ultimately all this supports and helps for increase the profit in the agriculture which always motivate the farmers for farming.

Keywords: *Convolution Neural Network (CNN), Deep Learning, Artificial Intelligence, Machine Learning*

1. Introduction

Agriculture field is unique source of wealth and its development essential for farmers. The major issue facing by farmers are due to different diseases occurred on crops. The detection and analysis of diseases is major concern for maximum productivity of food in the agriculture. Due to the lack of infrastructure and technology, the major issue occurs in the food safety, therefore detections of crop diseases are very crucial in coming days. The identification of diseases is need for yield estimation, food security and disease management [1].

Asian farmers cultivates oryza sativa (rice) which always increase 2.5 percent every year. The challenges faced by farmers is infection of plant with different diseases. Due to this influenced there is 37 percent loss in the production. The use of deep learning technology to identify this diseases during harvesting get benefited by attainting better yield. The study of various classifiers and use of it for identification of oryza sativa (rice) disease support for increase the production [2]. The identification of different category of disease mostly brown color spot and rice cracks. The good precision using the auto weight allocation in deep learning architecture for oryza sativa (rice) is achieved. The various techniques like preprocessing, classification, segmentation, feature extraction are considered for final results [2].

Now smart technique provide the automatic diagnosis of corn disease which prevent several types of crop losses. Deep convolution neural network (DCNN) method used for corn leaf recognition. The graphic processing unit improved the performance with hyper-

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parameter tuning with pooling combination settlements [3]. The CNN block with hardware Intel movidus and raspberry pi 3 recognition of corn leaf diseases. The entire system model running on smart device and artificial agriculture drones which acquired the accuracy 88.46% [3].

Maize crop is major food category which affected due to leaf blight disease. Training the large images with high accuracy is the targeted output of CNN, which is detecting and identify of maize trees. The CNN not depends on specific features , it has effect of identification and target to recognition, detection and segmentation .[4] A target detection multi scale method used to perform sampling for the images. The Convolution Neural Network (CNN) used for extractions images features in the classification and regression [4].

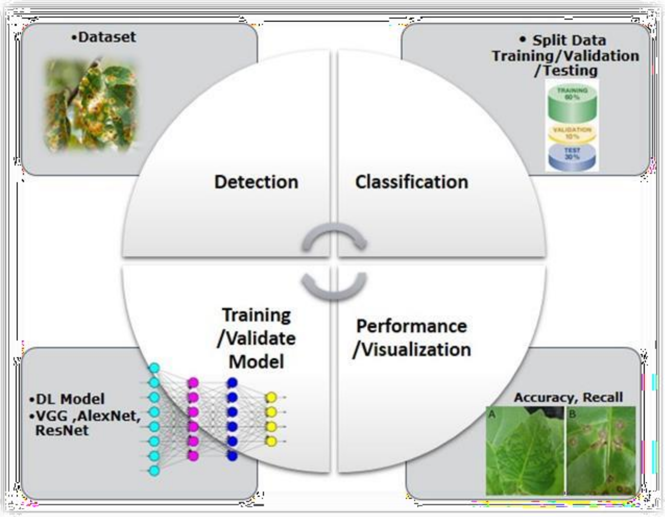

Fig 1. Process Flow of Leaf Disease Detection

The huge volume of datasets increase performance of learning algorithm and reduced the over fitting. The collection of real time datasets as input to training model is a difficult and challenging task. Therefore, use of augmentation techniques increase the change in training data at great extents. Deep learning augmentation techniques are possible to use for different operation on images. The image cropping, flipping, rotation, transformation, noise rejection, color augmentation are the important steps. The new approach of neural style transfer (NST) and generative adversarial networks (GANs) supporting for image processing [5].

The use of small number of dataset in CNN classification is a difficult and expensive task. This approach can be handle with transfer learning which recognized and applying knowledge to solve the manual label data issue [6].

2. Background

There are many Deep Learning (DL) of Convolution Neural Network (CNN-Based) architecture such as Google Net, AlexNet, (VGG16), ResNet, SqueezeNet, etc. The different data sets i.e. Plant Village Net, ResNet34, DenseNet-121, ImageNet, real, small and large image datasets are available. The below table show the details of datasets, architecture model networks and its accuracy. [Table 1]

The early stage crop disease detection and prediction in the precision agriculture improved rapidly with use for digital camera, computer vision and deep learning. A ResNet34 model is novel way for crops disease detection with open available datasets [1].

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The serial combination of two classifier, and hybrid combination of three classifier in parallel with an individual classifier including features like color, texture and shape [7].

Table: 1 Different Category of Datasets with Networks/Model and Accuracy

S.N	Category of Datasets	Networks/ Model	Accuracy (%)
1	50,000 In-Field Crop Disease Samples [1]	Convolutional Neural Network, (ResNet34)	99.40
2	2462 Images ((https://challenger.ai/)) [10]	Deep Convolutional Neural Networks (DCNN), DenseNet-121	93.71
3	Plant Village [11]	Convolutional Neural Network, ImageNet	98.98
4	Images Captured Dataset [3]	Convolutional Neural Network	88.46
5	Crop Pest Dataset [12]	Deep Convolutional Neural Networks (DCNN), GoogLeNet ,ResNet101	96.67,90.46
6	Plant Village Computer-Assist Diagnosis [13]	Multi-Layer Perceptron, and Support Vector Machine	94.35
7	Plant Village [14]	Deep Learning, VGG16, InceptionV3 & MobileNet	91.2
9	Plant Village [15]	Machine Learning (ML) Convolution Neural Network	98.7
10	Mobile captured 1747 On-field Images [16]	Computer Vision with Deep Learning	95.24
11	Public Dataset,47363 Images 27 Diseases [17]	Convolutional Neural Network, Inception-ResNet-v2	86.1
13	600 Images [18]	Convolutional Neural Network	93.7
14	4923 Images ,Camera-Assisted Disease Diagnosis [19]	Convolutional Neural Networks, F-RCNN,	95.75
15	Small Datasets 124 Images [20]	Deep Learning, Transfer Learning	95
16	Real Dataset, 194 Banana Tier Samples [21]	Deep Learning, Mask R-CNN	96.5
17	10 Disease Classes [22]	Convolutional Neural Network, F-CNN	98.6
18	3663 Images, GPU Tesla [23]	Convolutional Neural Network	87.1
19	14,725 images [24]	Convolutional Neural Network, StridedNet, LeNet, and VGGNet	95.4
20	13,842 Sugarcane Image [25]	Deep Learning	0.95
21	Dataset with 40 Classes [26]	Convolutional Neural Network, AlexNet, ResNet, GoogLeNet and VGGNet	95.97
22	1200 Plant Village [27]	CNN, AlexNet, GoogleNet, VGG16, ResNet101,DensNet201	96, 96.4, 96.4, 92.1, 93.6
23	39 Different Classes, Image Augmentation [28]	Deep Convolutional Neural Networks (DCNN)	96.46
24	13,689 Images Dataset [29]	Deep Convolutional Neural Networks (DCNN), AlexNet	97.62
25	Mobile Devices Captured 2,756 Images.[30]	Deep Learning, Transfer Learning	93

In the pre-processing phase removal of noise and artifacts form input image are important, same subjected to obtained segments using piecewise fuzzy C-means

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clustering. In the feature extraction phase each segment extracted texture features, which consist of histogram of oriented gradients, information gain, and entropy.[8] The texture features subjected to classification phase, which uses deep belief network (DBN).The Rider-CSA is integrating the rider optimization algorithm (ROA) and Cuckoo Search (CS) same used for training the DBN [8]. The parameter such as maximal accuracy, sensitivity and specificity improved with use of CSA-DBN [8].

DenseNet-121 deep convolution network used for identification of apple leaf disease, with regression, multi-label classification and loss function methods. In the apple leaf image data set, images of six apple leaf diseases, used for data modeling and method evaluation [9].

Plant Village (PV) is famous dataset collected for automatic plant disease identification system. In the PV there are 38 crops disease pairs, with 26 crops diseases and 14 crops plants. One more dataset IPM and Bing which having 119 images from only retrieves 64 and 121 images from expected in the Bing. In the IPM 38 crops diseases pair in PV, the IPM test set allows to evaluate 19 pair while Bing test set allows to evaluate 26 pairs [31].

The tomato plant diseases such as bacterial wilt, leaf mold and grey spot are detected. The Convolutional neural networks (CNN) has good performance to detect disease, recognition and image classification of disease plant. The sample plant village datasets with size of the pixel of sample images is 256 * 256. The class label late blight, septoria leaf-spot and spider-mites-two spot with average accuracy is 90.20%. The use of different class label of datasets increase the performance of accuracy is possible [32].

The features of disease images shows different types of pattern into the leaf region. Deep Learning techniques initially localizes the leaf region by utilization of color image. The performance of model analyzed using plant village databases of potato, tomato and pepper leaf using a multi- layer perceptron and support vector machine (SVM). The model gives better performance and accuracy 94.35% with area under curve 94.7% [33].

The detection and identification of disease from different plant leaf is advance research on field of agriculture. Artificial Intelligence based approach for image processing with high computing power provide growth and protection to the plant. The number of AI techniques for detecting and classifying plant disease like Neural Network, Logistic regression, Decision Tree, Support Vector Machine, k-Nearest Neighbors(k-NN),Naive Bayes and Deep Convolution neural Network (Deep CNN) [15].

Plant village dataset contain 39 classes of different crops like apple potato, corn, grapes etc. where 10 classes of tomato classes. The machine learning methods gives accuracy 94.9% with k-NN and VGG16 having accuracy 93.5&. To increase the machine learning accuracy with CNN, image pre-processing used with accuracy 98.7% [15].

The popular Convolution Neural Network (CNN) model AlexNet and GoogleNet used for prediction of classes of different plant images from plant village datasets. Use of pre-trained model like AlexNet and VGG (Visual Geometry Group) for classification of 25 different plant and 58 distinct classes are combined. The accuracy of model is 99.53% with VGG pre-trained model but very poor accuracy for images from different datasets [15].

The maximum micro diseases on plant not visible at early stage, which causes bacteria and viruses effect on crops. Artificial Intelligence is novel technology if field of agriculture for disease detection with better and improved efficiency [34]. Computer vision and Convolutional Neural Network (CNN) algorithms based image processing with train model VGG-16 architecture gives the excellent accuracy [34].

The public dataset comes from AI Challenger Competition in 2018 with 27 disease image of 10 crops. The model Inception-ResNet-v2 selected for training. The relu activation function used with accuracy 86.1% in this model. The pre-trained model with real public dataset having best accuracy, the goal of proposed system improvement the accuracy greater than 86.1% [35].

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One more database having 600 images i.e. 200 images of unique crops variety which labeled with 10 kinds of crops diseases. The crop variety with having two classes i.e. healthy crop and rusty crop. The CNN filter and pooling types with different size for max pooling size of 32* 32*3 and accuracy is 92%. The average size of pool 64* 65*3 and accuracy 93.7 % which better as compared to machine learning and features extraction model.[36].The prepared 600 images database obtained result with improvements in feasibility and performance of CNN as compared to machine learning model [36].

Tomato plant diseases namely Phoma Rot, Leaf Miner, and Target Spot. The dataset of 4923 images of diseased and healthy tomato collected for detection and identify using Convolution Neural Network. The F-RCNN trained detection model produced confidence score 80% and transfer learning accuracy is 95.75%. The automated detection and recognition system implemented on actual datasets with accuracy 91.67% for tomato plant leaf disease detection [37].

The transfer learning approach with feature extraction build the identification system for mildew disease. As the deep learning is fast speed and better accuracy model algorithm for agriculture crop disease detection. The novel result achieved from the experiment i.e. accuracy is 95%, precision 90.50%,the recall94.50 and f1 score of 91.75% [6]. The new image database prepared using sensors with resolution range from 1 to 24 Mpixel from smartphone, compact cameras, DSLR Camera. The prepared dataset having 500 images of healthy and unhealthy of different specimen, disorder, code and samples [38].

3. Architecture and Methodology

Deep Learning based detection techniques provide the opportunity in the precision agriculture. For, high performance and better accuracy deep convolution neural network (DCNN) training model required with huge datasets and high configuration computing system. In the future cloud based solution always successful, beneficial and effective, which easily deployed remotely at any location [3]. The below figure shows the structure for leaf disease detection [Figure-2]

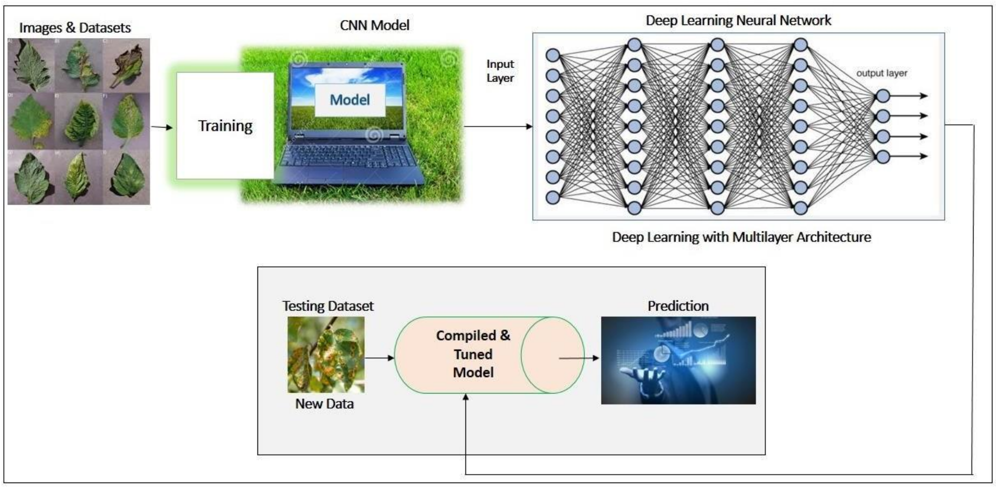

Fig 2. Proposed Convolution Neural Network (CNN) Structure for Leaf Disease Detection

A deep learning(DL) based Multi-Context Fusion Network (MCFN) extract highly discriminative and visual features from 50,000 disease sample collected from field.

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The Multi-Context Fusion Network (MCFN) have developed in IoT agriculture for precise crop disease detection, which improved recognition performance [1].

The VGG16 is simple and widely used architecture for the ImageNet, it take input images and return a vector of class. The 16 Convolution layer are used to extract features from the ImageNet for images. The last softmax layer used for classification, Relu activation function applied for every convolution layer. Deep CNN which is special Feed forward Neural Network which take the input images. The features of input images automatically extracted by convolution layers [15].

The images which are the input to CNN Deep Learning algorithm are resize to fixed size. The CNN take the images of fixed size and applied to the image processing filter. The role of convolution filter here to extract the important feature from training dataset [15].

The CNN based model approach having three convolution and three max pooling layers followed by two fully connected layer. The model over the pre-trained model i.e. MobileNet, VGG16 and InceptionV3 and [14].

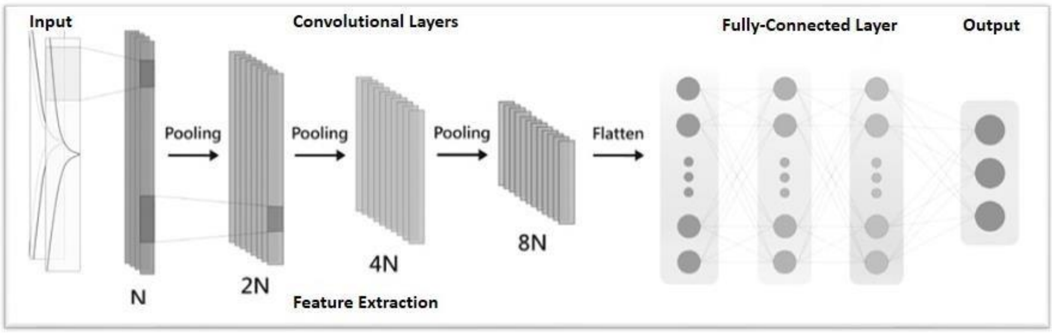

Fig. 3 Pictorial Representation of the Proposed Convolution Network

In the architecture of Convolution Neural Network (CNN) consists of convolution layers, pooling layers, full connected layers and dense layers below are the details of layers [39].

Convolution Layer: The extraction of specific features from images is main role of convolution layers. The repeated use of convolution layers helps for better features extraction of input images [39] With below equation, features extraction (H_i) of multiple layers in CNN calculated.

$$H_i = \varphi(H_{i-1} W_i + b_i)$$

Where, H_i-Feature map, W_i –Weight, bi is offset and φ – Rectified linear unit (Relu)

Pooling layers: Pooling layers is important building block of Convolution Neural Network (CNN). It reduce the spatial size of convolved features, also decease the computational power required for image processing. The max pooling and average pooling is types of pooling, where max pooling returns maximum value of images and average pooling returns average value of image portion.

Fully-connected layers: The special purpose of fully- connected layers is use the extracted features for image classification. The Softmax function conduct the prediction of previous layer extracted feature of images. Softmax is activation function in the output layers for multiclass classification

Neural network layer based classifier as a multilayer perceptron model (MLP) used for two-class classification. The model with nonlinearity, which introduced by a rectified linear unit (Relu) activation in the entire vectors. A classification using support vector

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machine (SVM) having higher flexibility of class separation. The SVM fundamental as a [33].

$$Minimize \frac{1}{2}\sum_{j=1}^{n} W_1^2 + C\sum_{j=1}^{N}\zeta_j$$

The performance specification for segmentation evaluation are measured with F1 score, accuracy matrix, and operating characteristic curve (ROC), along with area under curve. The evaluation metrics are measure the classifier performance as

F1 Score: The test accuracy measured using F1 Score. It is harmonic mean between precision and recall. The F1 Score range are 0 and 1.The performance of model depend on F1 Score and it can balance using precession and recall.

Precision: Precision support to find number of correct positive divided predicted positive by classifier.

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

Recall: It is calculated as correct positive divided by all related samples

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Feature extraction in the segmentation convert image into vector of fixed features. The adopted features in system are color, texture and shape. The color adopted methods define mean, standard deviation and sleekness which extracted two color space RGB and HSV. The GLCM (gray-level co-occurrence matrix) used for texture feature extraction in the color image. This method used for plant disease recognition.[7] One more approach for collection of dataset using mobile phone camera, where total one thousand images taken in real field. In the captured image contain seventeen types of diseases with five crops (wheat, barley, corn, rice, and rape-seed)[40]

Deep Neural Network method used to validate the hypothesis, here a balance accuracy is 92% for smaller crop and 93% for single multi-crop model. In this techniques, CNN architecture that combine crop identification, weather condition, geographical location categorical metadata.[40]

4. Conclusion

In our survey paper, we have studied about different types of leaf diseases occurred on plants. The accuracy and performance parameter found on real image dataset is not sufficient and good for leaf disease detection. So our proposed work increase the accuracy of diseases detection on leafs and it is crucial for agriculture development. The major focus of research for advancement in agriculture. Improve the performance parameter with suitable model for farmers. The collection of real images from the field in agriculture and prepared datasets. The collected images apply as input for Convolution Neural Network (CNN) is a target for future works.

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