# Plant Disease Identification On Multispectral Image Of Leaves Using CNN.

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#### **ABSTRACT:**

For any developing country ,agriculture is it's backbone. Farmers must be equipped with the most up-to-date technology and methodologies to obtain the highest yield of their crops. Artificial intelligence has a wide range of uses in a variety of industries. Artificial intelligence can be a big help in managing agricultural illnesses because of the ability to spot problems, provide acceptable causes for them, and establish effective treatments for them. The suggested system gives a brief introduction of Artificial Intelligence application in agriculture, its procedures, and the numerous ways for detecting diseases in crops, as well as recommendations for how to combat them. Convolutional Neural Networks are used for image processing.

## I. INTRODUCTION:

Agricultural and industrial techniques have advanced to new heights in terms of development, as well as in terms of its adverse effects. Agriculture is a basic requirement for all living things, but not to it's fullest. Various techniques of cultivating agriculture fields have evolved over time, with the chemical process playing a significant part. Both natural and man-made factors might have an impact on the leaves. Damage to the leaves has a direct impact on the final result. Man-made factors have a bigger impact on the plant and its leaf spoilage. Industrial techniques using

various processes is used through all sectors for succeed in various fields, and agriculture is no exception. The goal is to identify the plant's disease, which necessitates first recognizing its numerous plant species, then classifying and comparing them to healthy plants. The unhealthy plants can be screened using the comparison, and the name of the disease can then be determined, as well as methods for combating the predicted ailment.

Artificial intelligence (AI) plays a significant role in the advancement of industry. Drones using artificial intelligence will be extremely useful in observing wider agricultural fields and acquiring a large - scale dataset in a short period of time. The major goal is to collect diseased plants while ignoring areas where no plants exist. To analyze data, a CNN model is employed for supervised learning. A single variety of plant species is identified and forecasted by the previous conclusions, but this technique aids in the identification and prediction of multiple species at once.

# II. LITERATURE SURVEY:

(i)The ultimate goal of this study is to use Artificial Intelligence to anticipate plant disease. Artificial intelligence sensors could identify plant disease, pests, and malnutrition. Drone-based photos can be used to monitor crops and examine fields. Image sensing and analysis are used to distinguish between infected and non-diseased portions of the leaves. Plants that have

been affected are harvested. After that, they're taken to the lab. Agribot or Agbot is also used to assist farmers in reducing physical labour and increasing crop efficiency. The image processing method can be utilised to locate the impacted area as well as the leaf's colour difference. The quickest way to identify plant illness is with the use of a microscope. Convolutional Neural Network(CNN) is used in image recognition and used in provide finite diagnosis.(ii) Deep Neural Networks have been used in a variety of fields. A mapping between input and output is provided by neural networks. The input is in the form of an image, and the result is crop disease. The nodes of the neural network produce numeric results from the output edge , which would then be used as inputs in the input edge. During the training process, Deep Neural Networks are trained by mapping the parameters. They begin by examining the leaf's hue. This is based on a dataset in which leaves have been separated by removing all background color. (iii) Various diseases, such as fungus and bacteria, harm crops, and the symptoms of the disease have an impact on agriculture. Leaf discoloration is first signal of the damaged plant. Pictures are first be taken using a digital camera or imaging device. Then, from the raw image, eliminate the noise. The second phase is image pre-processing, which involves removing undesirable aberrations. Image segment would be the third phase, which separates the picture from the background. Feature extraction is the fourth step. The classifying process is the last phase. The classifier's goal is to recognize photos by sorting them based on the feature vector acquired in the fourth phase. (iv) The accuracy and reliability of these processes will be increased by the use of technology in the detection and analysis. This technology also includes Visualization techniques. ML and DL are the diverse methods which helps exerts to analyze the plant disease. CNN (Convolutional Neural Networks) helps to determine the differences in the natural plants. The sick plants are identified by pixel-wise operations which is used classify the disease. The swelling(Moisture content), burning sensation, disease and pest along with soil analysis is detected using ANN(Artificial Neural Networks). The dataset of the plant leaf, disease and soil images are trained in MATLAB tool and classified into various clusters. CNN (Convolutional Neural Networks) is used for analyze accurately. CART (Classification and

Regression Tree) in machine learning is used to predict the condition of the plants in future. The feature extraction is GLCM texture extraction and edge detection for moisture content level. (vi) This system is used for detecting multiple disease of a plant varieties. This system can be done by giving inputs which are captured by the cameras in-built in the autonomous rover. The GPS location also recorded in the rover to make a map of the farm and checked by the robot. The images are classified under various varieties using deep learning algorithms. CNN is used for image classification. On testing they recorded the accuracy of 93.21% was obtained from VGG16 and 95.24% from InceptionResNetV2 which are deep learning model's architecture. (vii) In this paper, they proposed a vision based automatic detection of plant disease detection using Image Processing Technique. Image processing algorithms are developed to detect the plant infection or disease by identifying the color feature of the leaf area. K mean algorithm is used for color segmentation and GLCM is used for diseases classification. Vision based plant infection showed efficient result and promising performance.(viii) In this project, image processing which can extract the image properties or useful information from the image. The main aim of Machine Learning is to understand the training data and fit the training data into models that should be useful to the people. So it can assist in good decisions making and predicting the correct output using the large amount of training data. (ix) This paper proposes an enhanced k-mean clustering algorithm to predict the infected area of the leaves. A color-based segmentation model is defined to segment the infected region and placing to its relevant classes. Disease detection involves steps like image acquisition, image pre-processing, image segmentation, feature extraction and classification. Our project shows the affected part of the leaf in percentage.(x) This paper presents a neural network algorithmic program for image segmentation technique used for automatic detection still as the classification of plants and survey on completely different disease classification techniques that may be used for plant leaf disease detection. Image segmentation, that is a very important fact for malady detection in plant disease, is completed by victimization genetic algorithmic program.

# III. PROPOSED METHODOLOGY:

In several situations, detecting plant diseases efficiently remains a big challenge. A major danger to food security and agriculture is plant disease. The use of deep learning technologies and recent advances in computer vision have opened the way for modern plant disease prediction and identification. The major purpose of this study is to create a trained model that can both detect the crop disease and provide information on how to prevent it from spreading further. This could aid farmers in implementing the necessary action to enhance plant health, resulting in higher yields and output.

The suggested system makes use of artificial intelligence (AI), convolutional neural networks (CNN), and deep learning (DL). Artificial intelligence (AI) refers to a computer's capability to perform that would normally need human intelligence and discernment. Drones are utilized in this technology to gather photos, which serve as the project's dataset. The dataset includes the images of different category of plants and its different types of leaves. Each plant leaves are further classified based on number of diseases that can be predicted in each plant. The dataset is loaded on to the prediction model where the images are categorized and labialized. Table 1 explains the category of plants associated according to its disease. Further it is preprocessed based on image color and size. The image which does not match the preprocessing are considered as unwanted screening other than leaves. These images are taken out of dataset and the rest id continued with the prediction model. A convolutional neural network (CNN) is a sort of artificial neural network that is used for data analysis and supervised learning. Image processing, natural language processing, and other cognitive tasks can all benefit from CNNs. Predictive modeling is a mathematical process used to predict future events or outcomes by analyzing patterns in a given set of input data. It is a crucial component of predictive analytics, a type of data analytics which uses current and historical data to forecast activity, behavior and 'trends. The Xception model is trained on over a million photos from the ImageNet collection by CNN. It can also be used to get picture characterization information. Deep learning (DL) is a machine learning and artificial intelligence (AI) technique that mimics how humans acquire knowledge. For categorization, CNN's features are fed into a traditional machine learning classifier. This system, which is written in Python, detects the disease and suggests ways to improve the plant's condition. Through the deployment of CNN models, an accuracy of 89 % was obtained in predicting plant disease from a sample image given by the user.



Fig. 1. Working flow of the proposed system

## IV. IMPLEMENTATION:

Plant disease prediction is based on CNN, which forecasts diseases in plants depending on the diseases dataset provided. The disease identification database is gathered from farmers and uploaded as the dataset. It is then assigned to each plant, and the data is divided accordingly. In the split data, 80 percent of the dataset is used for training and the remaining 20% is used for testing.

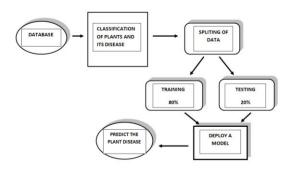


Fig 2: Proposed architecture

The overall proposed system is classified into three modules

- 1. Preprocessing and Normalizing the dataset
- 2. Implementing the Xception model.
- 3. Building CNN model

# A. PREPROCESSING AND NORMALIZING THE DATASET

Based on the specific species of plants, more than 37 classes were created. The photos, with the exception of the plant leaf species, have been preprocessed. Choosing a time series normalization approach is difficult.

| PREDICTION INDEX | DISEASE NAME   |
|------------------|--|
| 0                | 'AppleApple_scab'                                    |
| 1                | 'AppleBlack_rot'                                     |
| 2                | 'AppleCdear_apple_rust'                              |
| 3                | 'Applehealthy'                                       |
| 4                | 'Blueberry_healthy'                                  |
| 5                | 'Cherry_(including_sour)Powdery_m ildew'             |
| 6                | 'Cherry_(including_sour)healthy'                     |
| 7                | 'Corn_(maize)Cercospora_leaf_spot<br>Gray_leaf_spot' |
| 8                | 'Corn_(maize)Common_rust_'                           |
| 9                | 'Corn_(maize)Northern_Leaf_Blight                    |
| 10               | 'Corn_(maize)healthy'                                |
| 11               | 'GrapeBlack_rot_'                                    |
| 12               | 'GrapeEsca_(Black_Measles)'                          |
| 13               | 'GrapeLeaf_blight_(Isariopsis_Leaf<br>Spot)'         |
| 14               | 'Grape_healthy'                                      |
| 15               | 'OrangeHaunglongbing_(Citrus_gre ening)'             |
| 16               | 'PeachBaterial_spot'                                 |
| 17               | 'Peachhealthy'                                       |
| 18               | 'Pepper,_bell_Bacterial_spot'                        |
| 19               | 'Pepper,_bellhealthy'                                |
| 20               | 'PotatoEarly_blight'                                 |
| 21               | 'PotatoLate_blight'                                  |
| 22               | 'Potatohealthy'                                      |
| 23               | 'Raspberry_healthy'                                  |
| 24               | 'Soyabean_healthy'                                   |
| 25               | 'SquashPowdery_mildew'                               |
| 26               | 'StrawberryLeaf_scorch'                              |
| 27               | 'Strawberryhealthy'                                  |
| 28               | 'TomatoBacterial_spot'                               |
| 29               | 'TomatoEarly_blight'                                 |

| 30 | 'TomatoLate_blight'                             |
|----|---|
| 31 | 'TomatoLeaf_Mold'                               |
| 32 | 'TomatoSeptoria_leaf_spot'                      |
| 33 | 'TonatoSpider_mites Two-<br>spoted_spider_mite' |
| 34 | 'TomatoTarget_Spot'                             |
| 35 | 'TomatoTomato_Yellow_Leaf_Curl<br>_Virus'       |
| 36 | 'TomatoTomato_mosaic_virus'                     |
| 37 | 'Tomatohealthy'                                 |

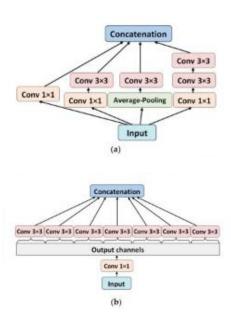
Table 1: Class and their disease

Datasets are taken with multiple categories such as Apple, Blueberry, Cherry, Grape, Peach, Pepper, Raspberry, Potato, Soy bean, Strawberry, Tomato, Orange and Corn. Totally 11 species are trained as healthy datasets that helps to identify even the healthy leaves if given as datasets. Some of the leafs such as apple, corn , grape which have four different classification of diseases are categorized into 4 different layers and sample leaf is identified and predicted according to those multiple layers. The sample diseased leaf is compared and the types of disease are identified. Leaves of cherry, peach and strawberry has two different diseases whereas pepper and potato has three different diseases. Leaves of Blueberry, Orange, Raspberry, Soy Bean, squash has only one type of disease to be predicted. The highest species identified is tomato which has nine different types of diseased leaves and the identification of sampled diseased leaf is done by referring all the respective nine layers.

### B. IMPLEMENTING THE XCEPTION MODEL.

Xception is a hypothesis based on the Inception module, which provides cross-channel and spatial connections within CNN extracted features that can be decoupled fully. Figure (a) shows the generic Inception module from Inception v3, which uses cross-channel correlations by splitting input data in four ways to convolution size of 1 1 and average pooling, then mapping correlations to convolution size of 3 3 and forwarding them for concatenation. The notion is turned into the Xception module, as depicted in Figure, according to Inception (b) Following data input, discrete convolution sizes of 3 3 without average pooling are produced just using one size of 1

1 convolution, which are applied in non-overlapping regions of the output channels before being combined. The Xception module is robust, stronger than the Inception module, and can operate correlations of cross-channels and spatial relations with maps fully decoupled



## C. BUILDING CNN MODEL

When using convolution layer in the Xception architecture, there is a layer after the input layer that generates convolutional kernels and calculates multiple feature maps to display the input data's features. The first convolution using detection models by convolutional kernels would be used to collect the major feature map, which is then fed into the activation function calculation. The convolution kernels are divided into all sections of the incoming data to create each feature map. The absolute results of the feature extraction are created by the various convolution kernels; theoretically, the position I j) of a feature value in the feature map as the kth layer dictates the lth, which is computed as where weight vector is defined as Wvl.

$$s_{i_{jk}}^l = W \nu_k^l C_{ij}^l + B_v l_k$$

k and Bvl k, set for the bias value of the kth filter of the lth layer, for C l i,j as the center of input patch on (i, j) position of the lth layer. In sharing the feature map of S 1 i,j,k, it creates the calculation of the Wvl k kernel.

## V. EXPERIMENTAL RESULTS:

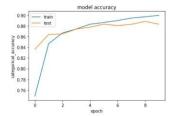


Fig 3 The accuracy of the trained model

This graph shows the information about the accuracy of the trained data. The blue line indicates training model and the red line indicates the test. In training, when the epoch is at level 0, the accuracy acquired was 75%. And it gradually increases up to the level of 84%. When the epoch reaches 100, it graduates up to the level of 86%. When the epoch is from 200-800, the categorized accuracy reaches the level of 90%. In testing, when the epoch is at the initial level 0, the accuracy is 84%. And then it slightly increases up to the level of 86% accuracy. When the epoch is 100, the accuracy is 86%. And then the accuracy decreases till the epoch level of 200. Then, the accuracy level graduates till the level of 300. Then, it slightly increases at the accuracy if 88% till epoch level of 500. up to the epoch level of 600, the accuracy decreases up to 85%. Then it slightly increases up to 88%. At last, when the epoch level reaches 800, the accuracy slightly decreases up to the level of 85%.

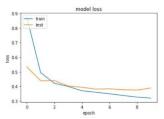


Fig 4 The model loss of the trained model

This graph shows the information about the model loss of the trained data. The blue line indicates the train and the red line indicates the test. In raining model, the loss level reaches high when the epoch is at level 0. And the level of loss slightly decreases up to the loss of 0.5 till the epoch reaches 100. And till the level of 200, it slightly decreases up to 0.4 level of loss. And till the level of 400, the loss level slightly graduates till 0.4 of level loss. And when the epoch level reaches the level of 800, the loss level deceases and it reaches the level of 0.3. and in testing, when the epoch is at the initial

level, the loss level reaches 0.55. and the loss level slightly decreases up to 0.45 when the epoch reaches 100. And then the loss slightly increases, until the epoch level of 200. Then the loss level graduates, up to the epoch level of 800.

## VI. CONCLUSION AND FUTURE SCOPE:

The main goal of this project is to examine various plant species in order to predict plant diseases and to see how this approach may be improved in the future to attain greater accuracy. The survey covers over the stages involved in image processing techniques pre-processing, such segmentation, including extraction of features, and classifications based on plant diseases. In a computer vision system, deep learning techniques are crucial. Integrating image processing and deep learning approaches in a disease prediction system has shown to have significant potential. For the project's future scope, it might be deployed as an app and used on a regular basis.

## VII. REFERENCES:

- (i) George E Meyer, Joao Camargo Neto, David D Jones and Timothy W Hindman." Intensified fuzzyclusters for classifying plant, soil, and residue regions of interest from color images". Computers and electronics in agriculture, (2004):161–180
- (ii) Jayme Garcia Arnal Barbedo. "Plant disease identification from individual lesions and spots using deeplearning". Biosystems Engineering, (2019):96–107.
- (iii) Sabine D Bauer, Filip Kor'c and Wolfgang F"orstner. "The potential of automatic methods of classification to identify leaf diseases from multispectral images". Precision Agriculture, (2011):361–377.
- (iv) Camargo and JS Smith. "Image pattern classification for the identification of disease causing agents inplants". Computers and Electronics in Agriculture, (2009):121–125.
- (v) Gittaly Dhingra, Vinay Kumar, and Hem Dutt Joshi. "A novel computer vision based neutrosophicapproach for leaf disease identification and classification". Measurement, (2019):782–794.
- (vi) MA Ebrahimi, MH Khoshtaghaza, Saeid Minaei, and B Jamshidi. "Vision-based pest detection based onsym classification method". Computers and Electronics in Agriculture, (2017): 52–58.
- (vii) Konstantinos P Ferentinos. "Deep learning models for plant disease detection and diagnosis". Computersand Electronics in Agriculture, (2018): 311–318.

- (viii) Guillermo L Grinblat, Lucas C Uzal, M´onica G Larese, and Pablo M Granitto. "Deep learning for plantidentification using vein morphological patterns". Computers and Electronics in Agriculture, (2016): 418–424.
- (ix) Zahid Iqbal, Muhammad Attique Khan, Muhammad Sharif, Jamal Hussain Shah, Muhammad Habib urRehman, and Kashif Javed. "An automated detection and classification of citrus plant diseases usingimage processing techniques": A review. Computers and electronics in agriculture, (2018):12–32.
- (ix) Zahid Iqbal, Muhammad Attique Khan, Muhammad Sharif, Jamal Hussain Shah, Muhammad Habib urRehman and Kashif Javed. "An automated detection and classification of citrus plant diseases using image processing techniques": A review. Computers and electronics in agriculture, (2018):12–32.
- (x) Muhammad Sharif, Muhammad Attique Khan, Zahid Iqbal, Muhammad Faisal Azam, M Ikram UllahLali and Muhammad Younus Javed. "Detection and classification of citrus diseases in agriculture basedon optimized weighted segmentation and feature selection". Computers and electronics in agriculture, (2019):220–234.
- (xi) Sethy, P.K., Barpanda, N.K., Rath, A.K., Behera, S.K. "Deep feature based rice leaf disease identification using support vector machine". Comput. Electron. Agric. (2020):105-527.