PLANT HEALTH DETECTION USING CNN

Mayank Sharma[1]
MTech, Computer Science & Engineering R.D. Engineering College, Ghaziabad, India
Prof. Dr. Manish Kumar[2]
Professor, Dept. of Computer Science & Engineering R.D. Engineering College, Ghaziabad, India

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Abstract :

Plant leaves development is pretentious by pests, ailment, and nutrient rudiments. All these paucities can decline the performance of the crop. Therefore, exposure from the symptom caused by these entities has to determine correctly and therefore we need agricultural/horticultural or botanical experts. However, using the convolutional neural network the classification carried out using convolutional layer or techniques like mean shift image, canny edge detection, contour edge, region of interest, high-level synthesis, gray level co-occurrence matrix (GLCM), hue saturation value deficiency in the growth of plants can be spotted or revealed. Consequently, using the convolutional neural network vide Inception-ResnetV2 and ReLu we able to achieve the results as the health status of the plant in the different diagnostic ranges as Specimen 1 is 2.36% unhealthy and lies to the diagnostic category of resistant likewise specimen 2 is 31.54% unhealthy as lies to the category of moderately susceptible, specimen 3 is 0.00% unhealthy and lies to the category of resistant and specimen 4 is 11.23% unhealthy and lies to the category of moderately resistant.

Keywords : Plant Disease, Neural Network, Convolutional Neural Network, Gray Level Cooccurrence Matrix.

1. INTRODUCTION

Plant growth and development is influenced by several factors, including the availability of sufficient water, sunlight and nutrients. Plants need thirteen essential nutrients to thrive and survive a deficiency of one or more of these thirteen nutrients can inhibit plant growth or even damage the plant itself. Nutrition can be divided into two types, namely macro nutrients and micro nutrients [1] even they need a protection from various ailments like fungi, insects and animals.

Macro nutrients consist of Nitrogen, Potassium, Phosphorus, Sulfur, Magnesium and Calcium while micronutrients consist of Boron, Iron, Zinc, Copper, Manganese, Molybdenum, and Chlorine. Plants need large amounts of macro nutrients to survive while micro nutrients are only needed in small amounts [1]. Deficiency of these nutrients can inhibit plant growth and can also spread to other plants planted on the same land. This can be treated if nutritional deficiencies are detected quickly.

The physical condition of plant leaves can be used as an indicator of macro nutrient deficiency, including leaf size and leaf color. So far, to determine the nutritional condition of the plant, it has been carried out by manual examination, namely by looking at the condition of the plant leaves one by one the symptoms of deficiencies that arise. However, this cannot be done effectively with large numbers of plants. This method will take a lot of time and effort; therefore in this study the authors propose a nutrient deficiency detection method in plants using an artificial neural network.

Several previous studies have discussed the detection of nutritional deficiencies, namely the detection of calcium deficiency in greenhouses using machine vision techniques based on changes in temporal, color and morphology of plants [2], detection of sulfur deficiency in plants potatoes using optical sensors [3] and prediction of nutritional content macro and micro-nutrients in sub-Saharan African soils using spatial data and a principal component analysis (PCA) approach [4].

Artificial neural network (ANN) is a computation system inspired by biological neural networks that are part of the animal brain. This system learns progressively to perform a task by considering the examples given. ANN changes the input by entering it through a series of hidden layers, each layer consisting of a series of neurons where each neuron is connected to all neurons in the previous layer. In the last layer, there is an output layer that represents the predicted results. The approach of the artificial neural network method that will be used in this study is the convolutional neural network (CNN).

Convolutional neural network (CNN) consists of a series of convolutional layers, pooling layers, and fully connected layers. CNN has two components, namely feature extraction and classification, at the feature extraction stage a series of convolution and pooling operations will be carried out where the features of an image are detected then fully connected layers will work as a classifier for the extracted features, and determine the probability in the image. as a result of predictions.

The CNN architecture that will be used in this study, namely Inception-ResnetV2 and ReLu, is a CNN architecture that receives models as comprising of ranges 0 - 10 % Resistant,11 – 30 % Moderately Resistant, 31 – 60 % Moderately Susceptible in ImageNet Large Scale Visual Recognition Challenge (ILSVRC) dataset. Inception-ResnetV2 combines the methods found in previous research, namely the inception module which allows to carry out several convolution processes in parallel [5] and residual blocks to simplify the optimization process during training and reduce training, test errors in architecture with a number lots of layers [6]. In the implementation of Inception-ResnetV2 the author uses the transfer learning method. Transfer learning is a learning method where a system that has been developed previously is reused for different problems [7].

2. LITERATURE REVIEW

Macro Nutrient Deficiency: Nutritional deficiency is a condition that occurs when plants do not get adequate amounts of macro nutrients or micro nutrients, where macro nutrients consist of nitrogen, potassium, phosphorus, sulfur, magnesium and calcium while micro nutrients consist of boron, iron, zinc, copper. , manganese, molybdenum, chlorine; Deficiency of macro nutrients can affect plant growth and development as well as plant quality. In addition, these substances are needed in larger quantities than micro nutrients because macro nutrients are the main substances used in the development of plant cells and tissues [8]. To detect nutritional deficiencies, analysis of plant leaves can be carried out. Through the condition of the leaves it can be estimated what nutrients are absorbed in sufficient quantities by the roots of the plant, symptoms of deficiency can be observed from the color and size of the leaves [9].

Macro Nutrition	Symptoms
Nitrogen (N)	• The leaves are light yellow • The leaves are yellow or purple
Potassium (K)	• Leaf edges are brown • Poor quality of flowers and fruit
Phosphorus (F)	• Slow leaf growth • The leaves are yellow • Color yellow between nerve plant
Magnesium (Mg)	• Leaves fall early • Reddish brown leaf color

Table 1: Symptoms of macro nutrient deficiency

CONVOLUTIONAL NEURAL NETWORK *:* Convolutional neural network or also known as CNN is a development method of traditional artificial neural network architecture, the general structure of CNN can be seen in Figure 1.

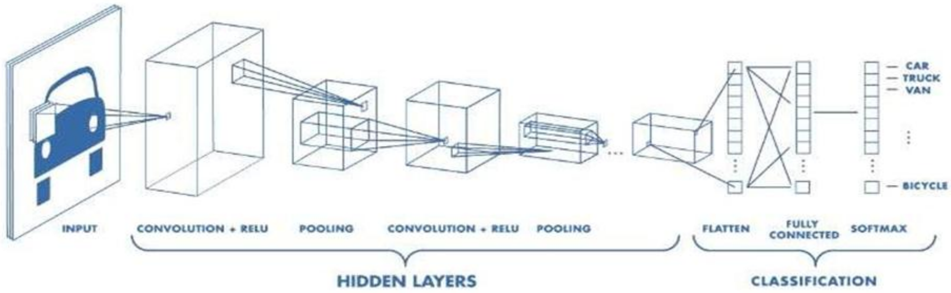

Figure 1: CNN Architecture [24]

In CNN, convolution operations are used instead of the matrix multiplication operation in general and the weight value on CNN is not a scalar value but a small matrix which is also called a kernel or filter. The components on CNN are as follows:

Convolutional Layer*:* Convolutional layer functions to extract features from an input image. In the convolutional layer, a convolution process is carried out on the data using filters to produce a feature map as can be seen in Figure 2 and then an activation function is used to produce non-linear convolution results, CNN generally uses the ReLU function.

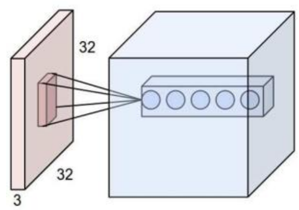

Figure 2: Convolution process [25]

Pooling Layer*:* Pooling layer or also called down-sampling layer is used to reduce the dimensions of the data and aims to reduce the number of parameters and computations on CNN. Pooling can reduce the time needed in the training process and also reduce over fitting. An illustration of the pooling process can be seen in Figure 3.

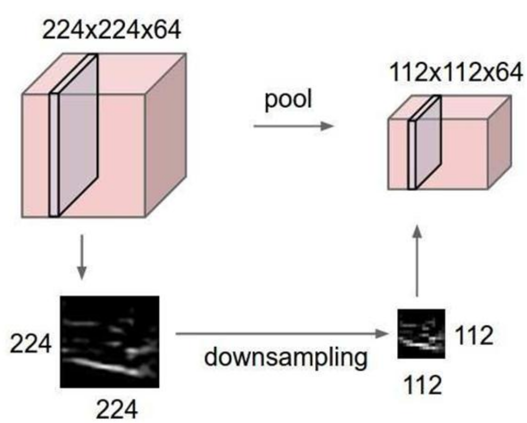

Figure 3: The pooling process [26]

Fully Connected Layer: Fully connected layer generally used in CNN final layers. In the fully connected layer, all neurons will be connected to one another, such as in a feed forward neural network and a classification process is carried out, the results of which will be output from CNN. The illustration of the fully connected layer can be seen in Figure 4.

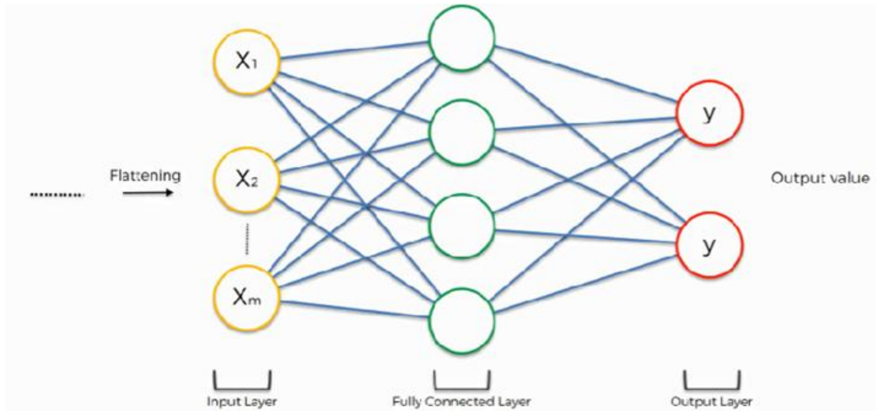

Figure 4: Fully connected layer

INCEPTION-RESNET V2: Inception-Resnet V2 is a CNN architecture created by Google and is a development of the previous CNN architecture, Inception. The Inception Resnet V2 architecture uses two concepts that were initiated in previous research, namely the inception module which allows to carry out several convolutional processes in parallel [28] and residual connections which allow the training process in deep neural networks without a decrease in accuracy caused by degradation. The structure of the Inception-Resnet V2 architecture can be seen in Figure 5.

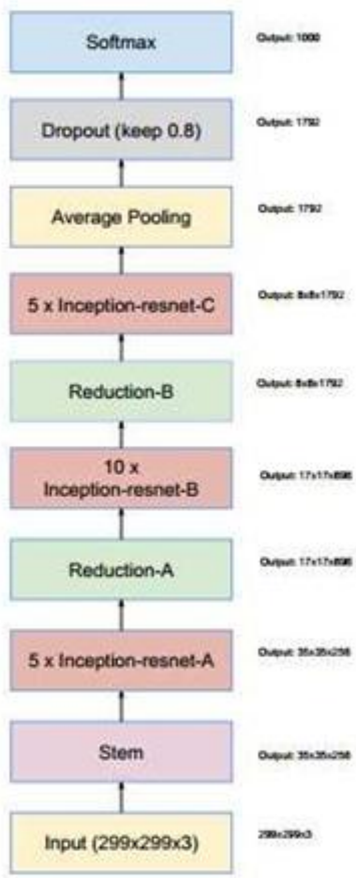

Figure 5: Inception-ResnetV2 architectural structures

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3. PROPOSED METHODOLOGY

This section proposes a method for the identification of nutrient deficiencies and health status in various plants. This method includes initial image processing including data preparation, preprocessing, feature extraction, and identification of nutrient deficiencies and to find out the state of leaf either its healthy or not with the percentage of healthiness.

- **DATA PREPARATION**

This stage produces 3 (three) levels pre-processing, feature-extraction and classification which is obtained in this study via planting independently and in consultation with agricultural experts at Uttar Pradesh, India, the appropriate leaf image data were divided into two, first training data and secondly testing data. The way of taking leaf images in this study is depicted in the diagram stage in Figure 6.

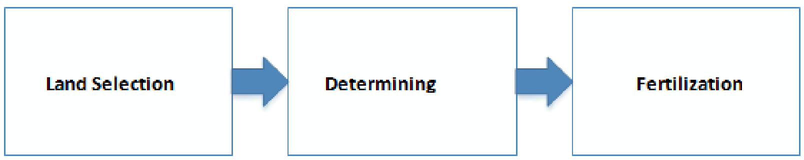

Figure 6: Image capture diagram of Plant leaves

The main topic of this research, as previously described, is the development of a nutrient deficiency detection or the health status system in plants. This research has three main problems. The first problem is how to detect nutritional conditions in plants using deep learning methods through various kinds of images with different characteristics. Second, how to get high accuracy in detecting the nutritional condition of plants. The third problem is how to implement nutrient detection methods in plants into an application prototype. Answering the main problem above, detection of nutritional conditions in plants can be done using a deep learning architecture, namely InceptionResnet V2. Increasing the accuracy value can be done by using the transfer learning method, which means that the model used has been through training using the plants leaves dataset. The results of the detection of the above plant nutritional conditions will then be implemented into a python-based application prototype using the Linux platform. This study offers a solution which is a summary of the answers to the problems described above. Detection of nutritional conditions in plants and the level of deficiency can be done with the Inception-Resnet V2 model which is implemented into an application prototype. The thinking framework or methodology diagram can be seen in Figure. 6.

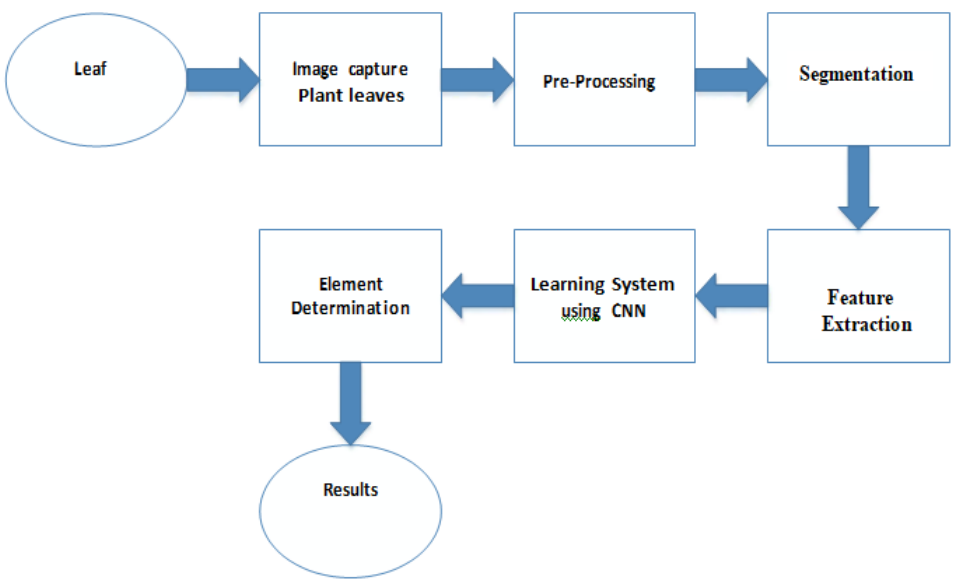

Figure 6 Block Diagram of the System Design

4. SIMULATION AND RESULTS

The results of data preparation in this study obtained 69 images of various leaves consisting of 23 images of nutrient deficiency. Each data was divided into two groups, the first group consisted of 16 training data on each nutrient deficiency and the second consisted of 7 test data on each leaf image of nutrient deficiency in leaves. The training leaf data and the test leaf data obtained in this study have differences. The training data is the result of image data from leaves that has been validated by botany experts, while the test data obtained is data that has not been validated for nutrient deficiency in leaves using Inception-ResnetV2 and ReLu. Both data were obtained through independent planting by researchers as described in the previous chapter. The results obtained at the time of data preparation are an image including resistant, moderately resistant and moderately susceptible the samples are depicted in Figure 7.

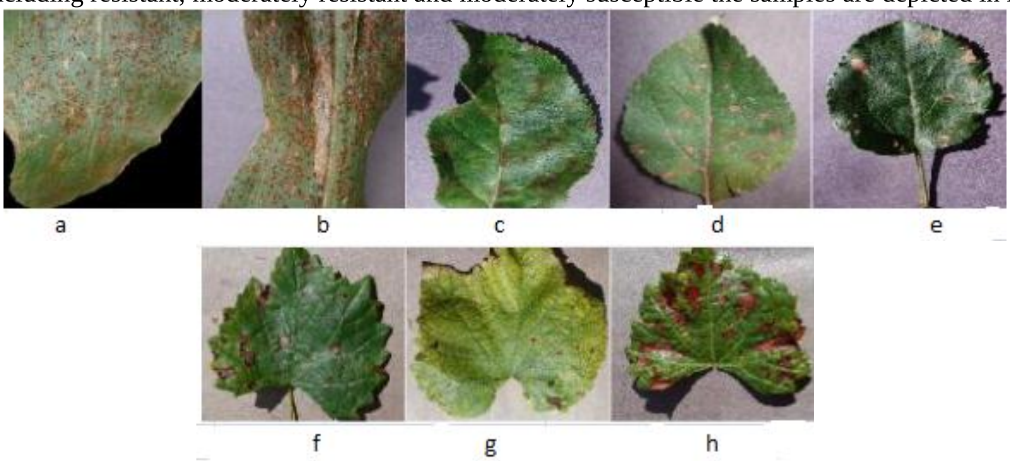

Figure 7: Samples from Data Set

Preparation of the initial data produced in this study is a picture of various plants that is still complete with its attributes, including leaves, stalks, fruit, and so on. This makes it more difficult for an image to be analyzed for leaf color because the background in the image is often the dominant one as in Figure 7. The analysis carried out in an automatic system for nutrient deficiencies or health status is through leaves, so that plants other than leaves will be eliminated. The process of removing noise in leaf images is done manually using image editing tools by removing attributes other than the observed leaf image. To uniform the accuracy of the training and testing leaf data, it is replaced with white or black so that the base image results are zero. Image editing results can be presented in accordance with Figure 7. After the cropping process is carried out on the training data and testing data, a leaf analysis is carried out which is obtained from the results of independent planting by researchers in the form of elements as resistant, moderately resistant and moderately susceptible.

Mean Shift Image: A convolutional layer consists of neurons arranged in such a way as to form a filter with length and height (pixels). For example, the first layer in the feature extraction layer is usually a convolutional layer with a size of 5x5x3. Length 5 pixels, height 5 pixels, and thickness/amount 3 pieces according to the channel of the image. These three filters will be shifted to all parts of the image. Each shift will be carried out a "dot" operation between the input and the value of the filter to produce an output or what is commonly referred to as an activation map or feature map using mean shift image the below figure depicts the scenario of mean shift image.

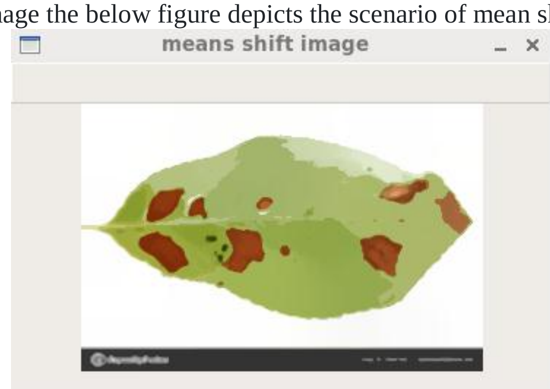

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Figure 7 Convolutional Layer based Mean Shift Image

Canny Edge Detection : Image processing is a general term for a variety of techniques that exist to manipulate and modify images in various ways. Image processing is an important part that underlies various real applications, such as pattern recognition, distance sensing via satellite or aircraft and machine vision. Edge detection in an image is a process that produces the edges of image objects and is the first step to enclosing information in the image. Canny is known as the optimal edge detection; this algorithm provides a low error rate, localizes edge points and provides one response for one edge the below figure depicts the same.

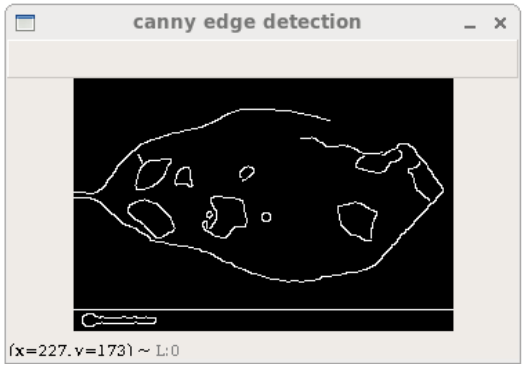

Figure 8 Convolutional Neural Network based Canny Edge Detection

Contour Edge: Large intensity gradients may be more suitable for edges than small intensity gradients. It is not much in the case of specifying a threshold at which a given intensity switches the gradient from conforming to an edge to not doing so. Contour Edge therefore uses thresh-holding with hysteresis. Thresh-holding with hysteresis requires two thresholds namely high and low. Assuming that the important edges must be along a continuous curve in the image allows us to follow the faint part of a certain line and to get rid of some noisy pixels which are not lines but have produced a large gradient. Therefore start by applying a threshold high boundary. It marks out the edges can be pretty sure the original. Starting from this, using previously obtained directional information, the edges can be traced through the image. While tracing the edges, applying the lower bound, it is possible to trace the faint part of the edge while finding the starting point. After this process is complete the binary image has each pixel marked as either an edge pixel or a non-edge pixel. From the complementary output of the tracing edge step, a binary edge map is obtained. in this way it can also be treated as a set of edge curves, which after further processing can be represented as polygons in the image domain.

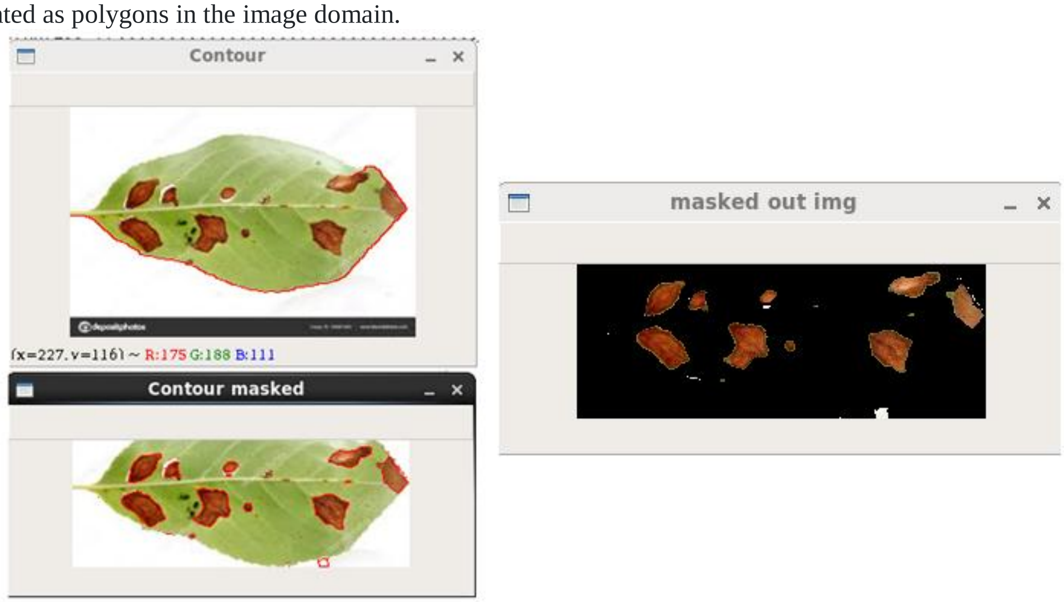

Figure 9 Edge Detection using Contour Edge CNN

Region of Interest : CNN uses filters (also known as kernel , feature detectors), to detect features, such as borders, present throughout the image. A filter is simply a matrix of values, called weights, that are trained to detect certain features. Filters move across each part of the image to check if the feature it is meant to detect is present. To provide a value that indicates how certain a certain feature is present, the filter performs a convolutional operation, which is an element-wise product and adds up between two matrices. When the features are present in the image part, the convolution operation between the filter and the image part produces real numbers with high value. If the feature is missing, the resulting value is low. In the image below, filters trained to detect the plus sign are skipped over a portion of the image. Since that part of the image contains the same added value that the filter is looking for, the result of the convolution operation is a large number. But when the same filter / kernel passes through parts of the image with very different sets of edges, the output is small convolution, meaning that there is no strong presence of plus signs and element-wise products and the sum will result in zero or very less values. So we need a number of feature detectors to detect various curves / edges of the image. The result of passing through this filter throughout the image is an output matrix called the region of interest or convoluted feature that stores this filter convolution across different parts of the image. Now that we have multiple filters, we're producing 3D output: one 2D feature map per filter. The filter must have the same number of channels as the input image so that element-wise multiplication can occur. Additionally, filters can be shifted over the input image at varying intervals, using step values. The step value determines by how much the filter should move at each step. The below figure depicts the region of interest.

Figure 10 Convolutional Operation using Region of Interest.

High-Level Synthesis : High Level Synthesis elevate the intensity of generalization and notion stage to an acerbated high level arrangement on convolutional layers and depiction the brighter and crystal clear image using hardware acceleration forming and delivering to diagnose for further findings using ReLU.

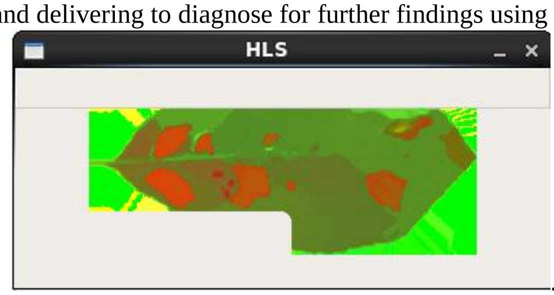

Figure 11: HLS Accelerated Image

Gray Level Co-Occurrence Matrix (GLCM): After the image's shape characteristic value is taken, and then what will be taken is the texture feature value using the Gray Level Co-Occurrence Matrix (GLCM) method. The input to the GLCM process is a gray scale image. The image will later be converted into a GLCM matrix, which is a matrix that represents the proximity relationship between pixels in the image in various directions and spatial distances that produce feature values with the desired level of difference. This study used 4 GLCM matrices in determining the value of texture features in mangrove fruit images, namely GLCM with a spatial distance of 1 and an angle of 0 °, GLCM with a spatial distance of 1 and an angle of 45 °, GLCM with a spatial distance of 1 and an angle of 90 °, and GLCM with a spatial distance of 1 and an angle of 45 °. 1 spatial distance and 135 ° angle. The value of feature extraction taken is entropy, contrast, correlation, energy, and homogeneity. Each value from the feature extraction will produce 4 GLCM matrices, where each matrix produces 5 texture features, so the total is 20 features. However, the statistical value of the GLCM matrix for each feature is taken, so that there are 5 features that will be extracted and used as input to the ELM. The values of the extraction features are obtained using the CNN function. GLCM spatial distance. Image: grayscale image for which the GLCM value will be calculated. The value of the extraction features of the GLCM can be seen in table 1.

0.5592	0.3254	0.9499	0.2717	0.9163
0.5581	0.3176	0.952	0.274	0.9201
0.5565	0.3211	0.9521	0.2684	0.9198
0.5562	0.322	0.9516	0.2755	0.9195
0.5564	0.3304	0.9502	0.2705	0.9154
…	…	…	…	…
0.4207	0.2071	0.9584	0.5543	0.9555

Table 1 Value of the extraction feature of the GLCM

Hue Saturation Value: HSV is a method for color feature extraction. HSV consists of three parameters such as Hue, Saturation, and Value. HSV is an alternative representation of the color that comes from the red, green, and blue intensity of the RGB color space. A pixel in this color space is defined by hue (H), saturation (S), and value (V). Hue represents true colors, such as red, violet, and yellow. Hue is used to differentiate colors and define reddish (reddish), greenish (greenish), etc. from light. Statement saturation the slightest bit of white is given to the color. Value is an attribute the amount of light received by the eye regardless of color. A hue value between 0 and 1 means that the color is between red through yellow, green, cyan, blue and magenta and back to red. Saturation value between 0 to 1 means the color is gray to not white. Score a value between 0 to 1 means a brighter color using Inception-ResnetV2 and ReLu.

Figure 12: Hue Saturated Value

Based on above scenario the four different leaves are evaluated using the proposed scheme and the results are produced as under:-

PARTICULAR	PERIMETER	TOTAL AREA	INFECTED AREA	% OF INFECTION REGION
	**701.92**	**18875.00**	**338.50**	**11.36%**

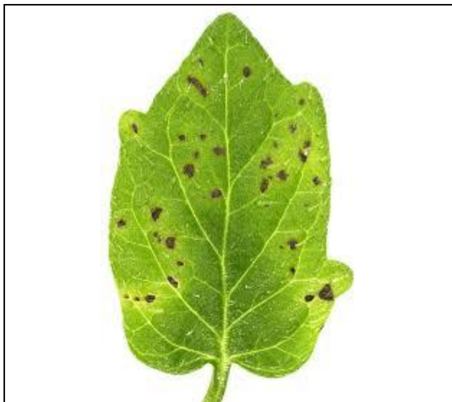	**1544.66**	**163**	**52**	**31.54%**
	**626.44**	**14310.00**	**0.03**	**0.00%**
	**787.02**	**26066.00**	**2676.50**	**11.23%**

Table 2: Results using proposed scheme

In context to above mentioned examinations the proposed scheme can appraise that the specimen No.1, 2, 4 were infected with ailment and are unhealthy leaves while specimen No.3 is healthy leaves due to non-occurrence of any ailment.

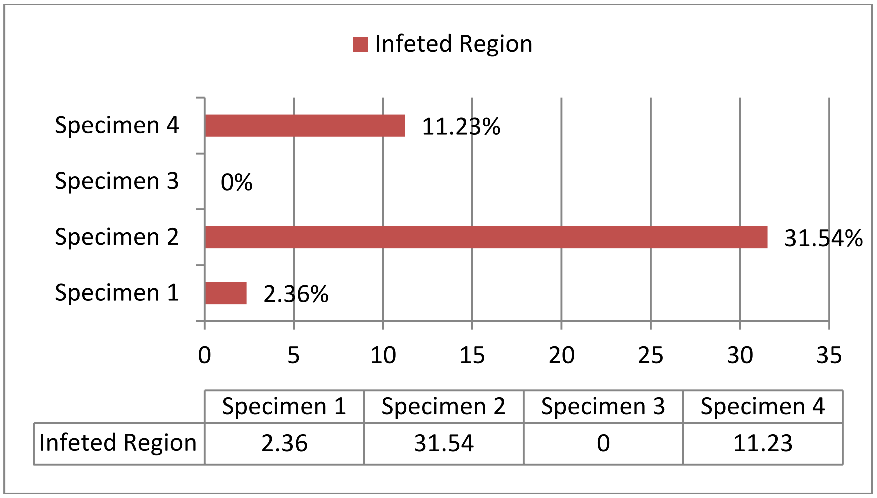

Figure 13: Chart Depicting Health Status of Specimen Leaves using Proposed Scheme.

- **Diagnostics Range**

The below mentioned range elaborates the health status of the leaf by which the results can be classified into four major categories as under:-

1. *0-10% Resistant*
2. *11– 30% Moderately Resistant*
3. *31 –60% Moderately Susceptible*
4. *61-100% Susceptible*

The above is the rational analysis which represents the condition of plant leaf.

Particular	% Infected Region	State (Health Status)
Specimen 1	2.36%	*Resistant*
Specimen 2	31.54%	Moderately *Susceptible*
Specimen 3	0.00%	*Resistant*
Specimen 4	11.23%	*Moderately Resistant*

Table 3: Health Status as Result Achieved by Proposed Scheme

5. CONCLUSION AND FUTURE SCOPE

Conclusion: This research deals with the classification of health and other deficiencies in plants with distinguishing features of as resistant, moderately susceptible, resistant and moderately resistant as mentioned in diagnosed range. However, using the convolutional layer and techniques using mean shift image, canny edge detection, contour edge, region of interest, high-level synthesis, gray level co-occurrence matrix (glcm), hue saturation value we are able to conclude that the difference is deficiency the growth of plants is possible because of the pattern The spots on each leaf can be patterned with color. The spots appear more comprehensive and dominant on the leaf body, the spots tend to point towards the leaf body to reveal the ribs are found unevenly on leaves and tend to be more colored the value of spot spots on each nutrient deficiency and the health of leaves was successfully distinguished by using Gray Level Coocurance matrix. The results of the classification using an convolutional neural network vide Inception-ResnetV2 and ReLu whereas in table 4.3 the sample results are depicted as ready reference.

Future Scope: This research still allows for further research to be carried out, including:

1. It is also necessary to determine the age of the leaves used in the classification because it affects the color that dominates the texture of the leaves, such as leaves the older ones are predominantly yellow or purple, if so adults will turn green.
3. The system developed by this writer still works offline, where identification is done on images outside the direct retrieval process. It needs to be integrated with the camera and mobile phone media so that the system can work simultaneously online and real time.

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