

“Deep Learning for Identification of Plant Nutrient Deficiencies”

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ABSTRACT

The purpose of this project is to detect the nutrient deficiency in plants just by simply capturing the image of leaves of the plants. Here we used the image analysis method for identifying nutrient deficiencies in plant based on its leaf. First, we divide an input leaf image into small blocks. Second, each block is fed to a set of convolutional neural networks (CNNs). Each CNN is specifically trained for a nutrient deficiency and is used to decide if a block has any symptom of the corresponding nutrient deficiency or not. Next, the responses from all CNNs are integrated to produce a single response of block using a winner-take-all strategy. Finally, using a multi-layer perception the responses from all blocks are integrated into one to produce a final response for the whole leaf. Here the group of plants with complete nutrients were studied. A dataset consisting leaf images was collected and used for experimentation

I. INTRODUCTION

In the developing world, technology plays a vital role in all sectors. Indian economy mainly dependent on agriculture. we are still using traditional methods in the agricultural practices. Identifying nutrient deficiency in plants is still difficult for farmers and consume more time, work and cost. If it is identified wrongly then the product yield, money and time will be lost. In general ,we identify the nutrient deficiency through agricultural laboratories and experienced people(farmers). The prediction of nutrient deficiencies manually may go wrong due to several environmental conditions. The nutrient deficiency in crops mainly appear in their leaves, stem, flowers, fruits, etc. Here in this project we are using the leaf for identifying the nutrient deficiency in plants. Generally a plant should need almost twelve nutrients for its efficient growth. They are Nitrogen, Phosphorous, Potassium, Magnesium, Sulphur, Molybdenum, Zinc, Boron, Copper, Calcium, Iron, Chloride. Generally, the nutrient deficiencies are identified in

the leaves of the plants by the symptoms like reduction in leaf size, color, distorted edges, necrosis, black spots etc., The farmer needs to uproot the entire plant and test the defected plant in the corresponding laboratory to identify the appropriate nutrient deficiencies , which takes more time and cost consuming. This project help us to identify and analyze the effects of particular nutrient deficiency and it also help the plant attempt to survive from the deficiency.

II. LITERATURE SURVEY

[1] **A. Camargo, J.S. Smith:** The emergence and development of plant diseases and pest outbreaks has become more common nowadays, as factors such as climate and environmental conditions are more unsettled than ever. The rate of spread of disease depends on current crop conditions and susceptibility to infection (Lucas et al., 1992). When plants become diseased, they can display a range of symptoms such as coloured spots, or streaks that can occur on the leaves, stems, and seeds of the plant. These visual symptoms continuously change their color, shape and size as the disease progresses. a banana leaf infected with Black Sigatoka (*Mycosphaerella fijiensis* Morelet) at various stages of infection. Fig. 1(a) shows stage 1, which is the first external symptom of the disease. It appears as a small whitish or yellow coloured spot that also resembles the first stage of the Yellow Sigatoka disease (*Mycosphaerella musicola* Mulder). These symptoms can only be observed on the underside of the leaf. In the next stage, stage 2, symptoms appear as stripes, generally brown in color and visible on the underside of the leaf, as illustrated in Fig. 1(b). Stage 3 symptoms, Fig. 1(c), differ from stage 2 in that stripes becomes longer, wider and under certain conditions, such as with weak inoculums and unfavorable climatic conditions, can reach lengths of 20 or 30 mm. Stage 4 symptoms, appear on the underside as a brown spot and on the upper side as a black spot. Stage 5 is when the elliptical spot is totally black and has

spread to the underside of the leaf. It is surrounded by a yellow halo with the centre beginning to flatten out. In stage 6, Fig. 1(d), the Centre of the spot dries out, turns light grey, and is surrounded by a well-defined black ring which is in turn surrounded by a bright yellow halo. These spots remain visible after the leaf has dried out, because the ring persists (Orjeda, 1998).

[2] **Jayme Garcia Arnal Barbedo:** The whitefly is a small insect that feeds from the sap of a wide variety of plants (Flint, 2002). According to Martin and Mound (2007), there are more than 1500 identified species of whiteflies. This is one of the main pests that affect agriculture, with damages coming both from sap loss and from the transmission of a variety of diseases carried by the whiteflies. In order to reduce the losses caused by whiteflies, two kinds of actions are normally carried out: 1) monitoring crops in order to detect infestations as soon as possible, so control measures can be implemented more effectively; 2) research on more effective means to monitor crops and control the pest. In both cases, counting the number of insects (nymphs and adults) is a fundamental part of the process. The most direct way of measuring whitefly infestation is to manually identify and count the insects inside a selected region. In general, this approach does not require sophisticated apparatus and, more importantly, relies on the remarkable human ability to resolve ambiguities and unclear situations, even under far from ideal conditions. On the other hand,

human beings are susceptible to physiological and psychological phenomena that may be important sources of error: fatigue, visual illusions, boredom, among others. Also, humans are usually much slower than machines in performing simple tasks like counting. Two main strategies for automatically counting whiteflies can be found in the literature, one using sticky traps, and the other using plant leaves directly.

III. IMPLEMENTATION

3.1: CONVOLUTIONAL NEURAL NETWORK

A convolutional neural network consists of an input layer, hidden layers and an output layer. In any feed-forward neural network, any middle layers are called hidden because their inputs and outputs are masked by the activation function and final convolution. In a convolutional neural network, the hidden layers include layers that perform convolutions. Typically this includes a layer that does multiplication or other dot product, and its activation function is commonly ReLU. This is followed by other convolution layers such as pooling layers, fully connected layers and normalization layer

Step1: convolutional operation:

The first building block is convolution operation. In this step, we will touch on feature detectors, which basically serve as the neural network's filters.

The Convolution Operation

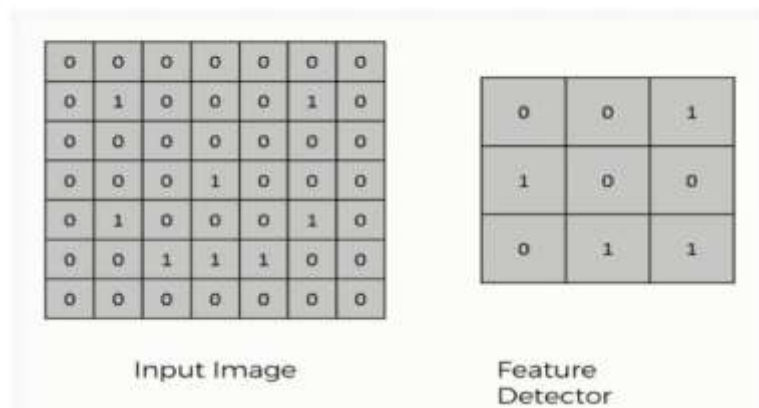


Figure : Feature Detection

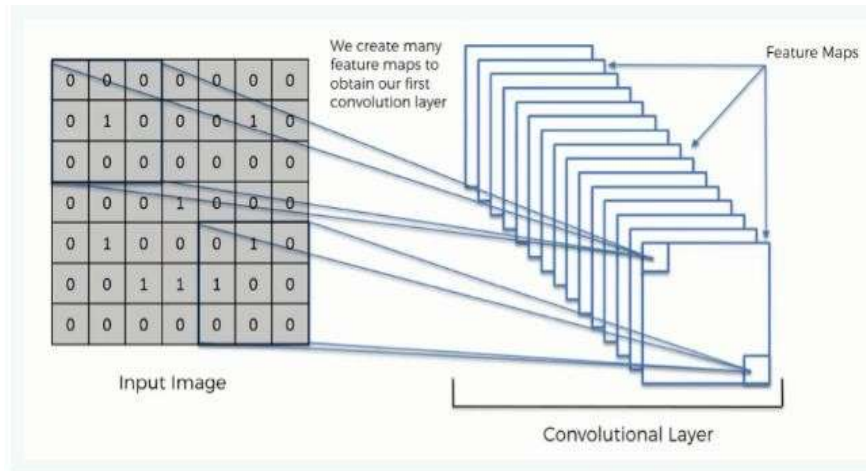


Figure : Feature Extraction

Step (1b): ReLU Layer:

The second part of this step will involve the Rectified Linear Unit or ReLU. We will cover

ReLU layers and explore how linearity functions in the context of Convolutional Neural Networks.

Convolutional Neural Networks Scan Images

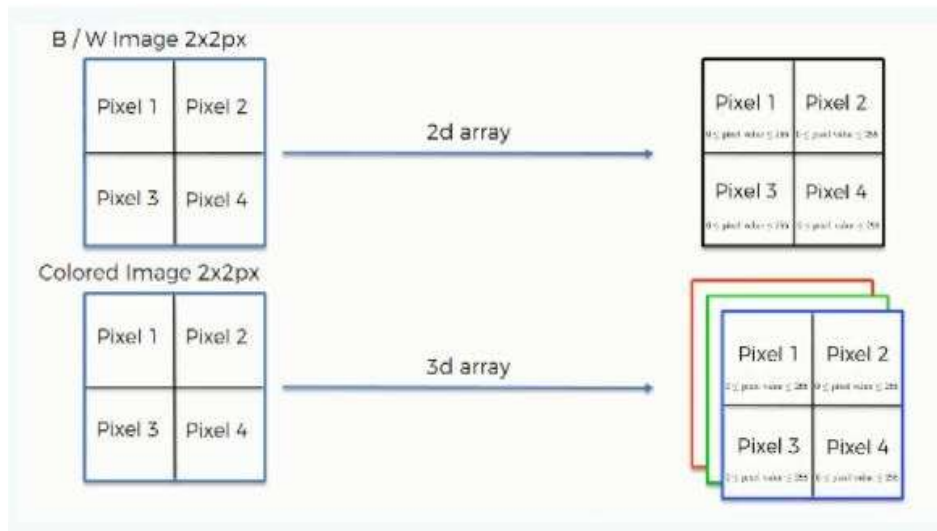


Figure: CNNs Scan Images

Step 2: Conv2D:

Keras Conv2D is 2D Convolution Layer; this layer creates a convolution kernel that is wind with layers input which helps produce a tensor of outputs.

Kernel: In image processing kernel is a convolution matrix or masks which can be used for blurring, sharpening, embossing, edge detection, and more by doing a convolution between a kernel and an image.

This will be a brief breakdown of the flattening process and how we move from pooled to flattened layers when working with Convolutional Neural Networks.

Step 3: Flattening:

Step 4: Full Connection:

The input to this layer is the output from the final Pooling or Convolutional Layer, which is flattened and then fed into the fully connected layer. In this

layer, everything that we covered throughout the section will be merged together.

WORKING OF CNN ALGORITHM

First we divide the input leaf image into blocks of size $S \times S$ pixels, in this work $S = 64$. Blocks that contain only leaf pixels is selected as input for the next step, where as blocks with background pixels are ignored. Here, we are using the blocks rather than whole-leaf image because some nutrient deficiency symptoms may not manifest locally, especially in the early stages. Next, a set of CNNs are utilized to predict, the symptoms of a deficiency present in a selected block or not. Here, each CNN is trained in a one-versus-all manner which focus only on one type of solution. For example, a CNN block for iron deficiency class is trained with two different labels: iron deficiency and not iron deficiency. Totally, six CNNs are generated, one CNN is specifically

trained for deciding if a leaf is grown under a complete nutrient condition or not and remaining for each type of deficiency like Ca, Fe, Mg, N, K. Each CNN consists of three convolutional layers (with filters of size 11×11 , 5×5 , an 3×3 respectively), two pooling layers (filters of size 3×3), and two fully connected layers. Then responses from all the CNNs are then integrated into a single response of block using a winner-take-all strategy, that is, the type of nutrient deficiency corresponding to the CNN which gives the highest response is chosen to be the answer of the block-level decision. Finally, the prediction responses from all selected blocks are combined. The proportion of each type of response is computed and fed to a multi-layer perception with one hidden layer to produce a final response for the leaf-level decision, and the user can upload the image and can view the result.

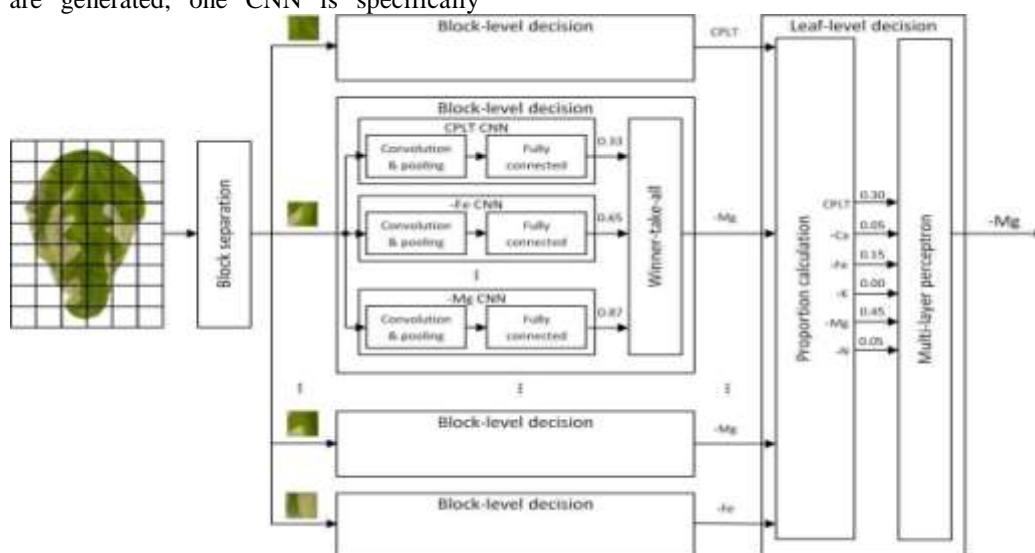


Figure 3.1.1.4. Block Diagram

3.1.2 ARTIFICIAL NEURAL NETWORK (ANN)

ANN architecture is based on the structure and function of the biological neural network. Similar to neurons in the brain, ANN also consists of neurons which are arranged in various layers. Feed forward neural network is a popular neural network which consists of an input layer to receive the external data to perform pattern recognition, an output layer which gives the problem solution, and

a hidden layer is an intermediate layer which separates the other layers. The adjacent neurons from the input layer to output layer are connected through acyclic arcs. The ANN uses a training algorithm to learn the datasets which modifies the neuron weights depending on the error rate between target and actual output. In general, ANN uses the back propagation algorithm as a training algorithm to learn the datasets. The general structure of ANN

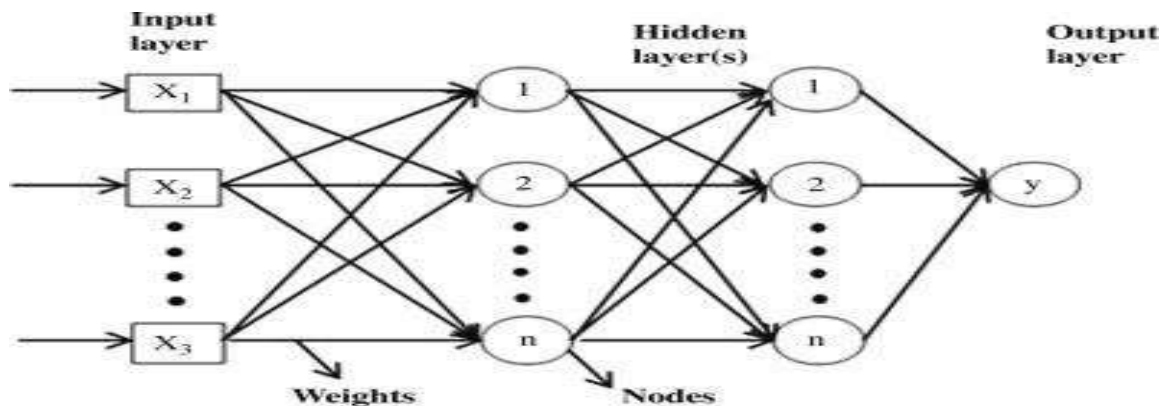


Figure 3.1.2 Block Diagram (ANN)

IV. SYSTEM TESTING

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub-assemblies, assemblies and/or a finished product. It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of tests. Each test type addresses a specific testing requirement. System testing ensures that the entire integrated software system meets requirements. It tests a configuration to ensure known and predictable results. After the development of the system are already complete. This system will be test using two techniques of software testing which are black box testing and white box testing in order to examine the functionality of the system. Black box testing module involve login, manage user, manage budget, manage income, and manage report. In white box testing it involve generate the report.

4.1 TESTING STRATEGIES

Unit testing

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application. It is done after the completion of an individual unit before integration. This is a structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to

the documented specifications and contains clearly defined inputs and expected results.

Integration testing

Integration tests are designed to test integrated software components to determine if they actually run as one program. Testing is event driven and is more concerned with the basic outcome of screens or fields. Integration tests demonstrate that although the components were individually satisfaction, as shown by successfully unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

Functional test

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals. Organization and preparation of functional tests is focused on requirements, key functions, or special test cases. In addition, systematic coverage pertaining to identify Business process flows; data fields, predefined processes, and successive processes must be considered for testing. Before functional testing is complete, additional tests are identified and the effective value of current tests are determined.

White Box Testing

White Box Testing is a testing in which in which the software tester has knowledge of the inner workings, structure and language of the software, or at least its purpose. It is purpose. It is used to test areas that cannot be reached from a black box level.

Black Box Testing

Black Box Testing is testing the software without any knowledge of the inner workings,

structure or language of the module being tested. Black box tests, as most other kinds of tests, must be written from a definitive source document, such as specification or requirements document, such as specification or requirements document. It is a testing in which the software under test is treated, as a black box. you cannot “see” into it. The test provides inputs and responds to outputs without considering how the software works.

4.2 TEST CASES

A test case is a set of condition or variables under which a tester will determine whether a system works correctly or under test satisfies requirement. Process of developing test case may help to find problem in the requirement or design of an application. Below shows the cases for several process in the Expenses Tracker System.

Tested By:	K Hemanth
Test Type	Black Box Testing
Test Case Number	TC001
Test Name	Register
Test Description	User can enter valid username password
Item(s) to be tested	
1	Email id to be tested
2	Password to be tested
Specifications	
Input	Expected Result
User can enter valid email id and password	Register successfully.
Procedural Steps	
1	Go to Login page

2	Enter the user email and Password Email: Hemanthkatari6@gmail.com Password: 1234
3	Click 'Register' button.

Table-4.2.1: Test Case for Register

Tested By:	K Hemanth
Test Type	Black Box Testing
Test Case Number	TC002
Test Name	Login
Test Description	User can enter valid username and password to login
Item(s) to be tested	
1	Email login to be tested
Specifications	
Input	Expected Result

User can enter valid email-id and password	Register Successfully
Procedural Steps	
1	Go to login page
2	Enter the user email and password Email:shabanakomala132000@gmail.com Password:123
3	Click on “Login” button





Table-4.2.2: Test Case for Login Page




Tested By:	K Hemanth
Test Type	Black Box Testing
Test Case Number	TC003
Test Name	Upload Image
Test Description	User Can Upload the image
Item(s) to be tested	
1	Image Uploaded

Specifications	
Input	Expected Result
Admin can download the file	File Uploaded
Procedural Steps	
1	Predict the Results

Table-4.2.3: Test Case for Uploading Image

V. REPORTS

S.NO	User Name	Uploaded Image	Algorithm Used	Algorithm Accuracy	Nutrient Deficiency	Type Nutrient Deficiency
1	Shabana		CNN	90.90	YES	Calcium
2	Vineetha		CNN	90.99	NO	--
3	Vishnu Priya		CNN	90.09	YES	Iron
4	Sonu nehal		ANN	84.76	YES	Magnesium

5	Keerthana		CNN	90.09	YES	Nitrogen
6	Vamsi		ANN	84.89	YES	Potassium
7	Akhila		CNN	90.98	NO	--

Report-5.1: Reports

VI. CONCLUSION

In this project we have successfully classified the images of Identification of Plant Nutrient Deficiencies, are either affected with the Plant Nutrient or innutritious using the deep learning and machine learning. Here, we have considered the dataset of Plant Nutrient Deficiencies images which will be of different types and different plants (healthy or unhealthy) and trained using CNN and ANN algorithms. After the training we have tested by uploading the image and classified it .

6.1 LIMITATIONS

Every system needs some limitation to ensure it performs as it supposed. There are also a few problems and limitations that occur throughout the development of these project which are, In this project internet must be required, if internet connection not there we can't perform any operation.

6.2 FUTURE WORK

This can be utilized in future to classify the types of different Deficiencies easily that which can tend to easy to Predicated the Nutrient for plant in early stages and can take the initial curing of plants and take measures to not affect other plants.

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