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Convolutional Neural Networks to Identify Plant Nutrient Deficiencies

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ABSTRACT

A brand-new image processing technique is suggested for determining nutritional shortages in plants based on their leaves. The suggested solution begins by dividing the input leaf picture into manageable chunks. Second, a group of convolutional neural networks are given each block of leaf pixels (CNNs). The CNNs are used to determine whether a block is displaying any symptoms of the related nutritional shortage. Each CNN is uniquely trained for a distinct nutrient shortfall. The results from all CNNs are then combined using a winner-take-all method to get a single response for the block. Finally, a multi-layer perceptron is used to combine all of the replies into one to create a final response for the entire leaf. On a group of black gramme (Vigna mungo) plants cultivated in nutrient-controlled conditions, the suggested method's validity was tested. Study subjects included a set of plants with full nutritional profiles as well as five different forms of deficits, including Ca, Fe, K, Mg, and N shortages. For the purpose of the experiment, 3,000 photographs of leaves were gathered as a dataset. The suggested technology is superior to trained humans in identifying nutritional deficiencies, according to experimental data. Nutrients in the soil are vital for plants to survive. In some circumstances, such as when there is a lack of nitrogen or phosphorus in the environment, the plant can transfer these nutrients from old tissue to new tissue. This study aimed to examine how various nutritional shortages affected development over a four-week period. Over the course of the experiment, it was found that deficiencies in nitrogen, phosphorus, and all other nutrients significantly affected the ability of plants to grow. Comparing the nitrogen- and phosphorus-deficient treatments with the full nutritional treatment revealed notable variations in standard chlorophyll levels as well. These findings suggested that nutrient mobility cannot entirely compensate for an environmental nutrient shortfall; rather, it can only support the plant's attempt to survive the deficiency.

Keywords: Nutrient deficiency leaf, image analysis, machine learning, CNN, ANN, DenseNet121.

I. INTRODUCTION

Food safety and plant health are strongly related. According to the Food and Agriculture Organization of the United Nations (FAO), pests and diseases threaten food security by causing the loss of 20–40% of the world's food output. Crops may be shielded against these pests and their harvests preserved by using insecticides. Their usage has contributed to the rise in food production since the 1950s, which has made it possible to satisfy the demands of an expanding population. However, using such drugs does not have a neutral impact on the ecosystem. Applying these compounds has a detrimental effect on soil, air, and water quality as well as biodiversity, which includes insect, bird, and fish populations. Understanding the phytosanitary characteristics of a crop is crucial for reducing pesticide use while safeguarding harvests. In fact, it makes it possible for farmers to follow the necessary procedures at the appropriate time and location. However, determining whether a field is healthy demands a high level of skill and is not an easy task. In fact, a disease might manifest differently depending on the type of plant or even the variety. Different issues may contribute to a certain symptom, and these issues may coexist on the same plant.

Even pests and dietary shortages can cause symptoms that resemble those of some illnesses. It takes time to evaluate how strong a story is. On vast farms, it is not possible to repeatedly check the status of each plant throughout the growing season. Prospection may also be hampered by some crops' accessibility issues. By utilizing automatic prospection or professional help tools, the automatic detection of illnesses by images has the ability to address all of these problems.

However, judging a plant's health from a photograph is an extremely challenging undertaking. Crops are, in fact, rich, complicated habitats. Their seasonal changes in leaves, flowers, and fruits demonstrate their ongoing development. Due to how their spectral response is affected by the quantity and angle of direct solar energy, they also undergo a modest shift in appearance during the day. Several strategies, whether in simulated or actual environments, have been utilised to create crop disease identification systems. These methods were based on the establishment of specific vegetation indices, the measurement of visible and near-infrared reflectance, or even pattern analysis.

A plant's growth rate, productivity, and fertilisation are only a few of the many characteristics of its life cycle that are significantly influenced by nutrition. These procedures would be greatly impacted and agriculture would suffer greatly from nutrient deficiencies of any critical nutrient. Deficits in some nutrients can also give a plant an odd look, especially on its leaves. Around a week after nutritional deficits started, eyes might detect this visual indication, which could indicate the presence of deficiencies. However, examples of symptoms brought on by different vitamin shortages are provided; In the early stages of nutrient deficit when a unique look has not yet been readily evident, nutrient deficiency diagnosis by eyes requires domain experience and is not reliable.

Five nutrient inadequacies as stated in of plant nutrient deficits are also suggested in this article. Utilized are deep neural networks, which are being used more and more in image identification applications. Convolutional neural networks (CNNs) are specifically used to determine whether a block of leaf pixels is displaying any symptoms of a nutritional deficit. An experiment's target plant is black gramme, or Vigna mungo. The following are the main contributions and aspects of this work: creating a large image dataset of nutrient deficient leaves with ground truth, assessing the performance of the image analysis approach, comparing with humans, and researching the effectiveness of CNN-based approach for nutrient deficiency detection, studying many types of nutrient deficiencies, which is more difficult than previous works.

This article's remaining sections are structured as follows: An image dataset of nutrient-deficient plants utilised in this study is explained in Section; the suggested method's specifics are provided in Section; the experimental findings are then shown and analyzed in Section; and Section concludes the article with suggestions for the future.

Animals and plants differ greatly in many respects. Animals tend to be more mobile than plants, which are sessile and rooted to one location. The method that plants and the vast majority of animals consume nutrients essential for growth is one of the most significant differences between them. This is indicated in terms of getting the nutrients, monomers, and products required for creating energy rather than in terms of heterotrophism vs autotrophism. Most animals ingest all vital substances through a certain sort of mouth in the same location. For example, humans use their mouths to ingest food, drink, and air. Although plants must obtain specific components from various sources, they do it through many distinct ingestive techniques. The majority of photosynthesis occurs on plant leaves, which are where carbon dioxide is taken from the atmosphere. However, roots draw water and nutrients from the earth. This indicates that although sugar is produced above ground through photosynthesis, it is also required for cellular respiration by the cells in the root. However, although a lot of nutrients can be absorbed by the roots, the cells above the earth still require these nutrients for their own development and other functions. It appears from this that only cells in the roots will have access to nutrients, and only cells above ground will be able to obtain sugar for respiration.

In this study, a third therapy was contrasted with the control. In one instance, the only water accessible to the roots of the plants was distilled water. While any of the aforementioned symptoms may be expected, nitrogen deficiency symptoms are more common. This is because phosphorus plays a smaller number of roles in the plant whereas nitrogen is used in a wide variety of ways. Because usual plant growth and development is hindered without nitrogen, fewer other nutrients are required, and signs of other shortages may be milder or even nonexistent. While the majority of the symptoms are nitrogen deficiency symptoms like chlorosis and decreased development, a few phosphorus deficiency symptoms like anthocyanin presence in and around leaf veins may also occur.

We anticipated that the three deficient treatments would differ in weight and standard chlorophyll content (mg chlorophyll/g of leaves), a measurement of chlorophyll density within a leaf, given the symptoms seen in previous experiments. We predicted that the weight and standard chlorophyll content of each treatment (-N, -P, and distilled water) would differ from those of the control trial (complete nutrient availability). No matter the treatment, our null hypothesis assumed that all weights and standard chlorophyll contents would be the same.

II. RELATED WORKS

A. Camargoa, J.S. Smith: As a result of variables including climate change and unstable climatic circumstances, plant diseases and pest outbreaks have grown increasingly frequent in recent years. The present state of the crops and an individual's vulnerability to infection determine the rate of disease transmission (Lucas et al., 1992). Colored spots or streaks that might appear on the plant's leaves, branches, or seeds are only one of the signs that plants can exhibit when they get ill. As the illness worsens, these visible indicators continually alter in colour, size, and form. a banana leaf with several stages of

Black Sigatoka (Mycosphaerella fijiensis Morelet) infestation. Stage 1 of the illness, which is also its first visible symptom, is depicted in Fig. It manifests as a little area of white or yellow colour that is similar to the early stages of the Yellow Sigatoka sickness (Mycosphaerella musicola Mulder). The only part of the leaf where these symptoms may be seen is the underside. Stage 2 symptoms include stripes that are often brown in colour and visible on the underside of the leaf, as seen in Fig. 1. (b). Stage 3 symptoms, shown in Fig. 1(c), are different from stage 2 symptoms in that the stripes are longer and broader, and under some circumstances—such as when there are weak inoculums and poor climatic conditions—they can even get as long as 20 or 30 mm. Stage 4 symptoms show up as a brown patch on the underside and a black mark on the top. The elliptical spot reaches stage 5 when it is completely black and has extended to the leaf's underside. It has a golden aura surrounding it, and the centre is starting to flatten. Stage 6 is seen in Fig. 1(d), where the spot's centre dries up, turns light grey, and is encircled by a distinct black ring that is itself encircled by a bright yellow halo. Due to the persistent ring, these markings are still discernible after the leaf has dried up (Orjeda, 1998).

Jayme Garcia Arnal Barbedo: The whitefly is a tiny insect that feeds on the sap of several plant species (Flint, 2002). More than 1500 different species of whiteflies have been recognized, according to Martin and Mound (2007). This is one of the primary pests that harm agriculture, causing harm via sap loss as well as from the spread of a number of illnesses by the whiteflies. Two types of procedures are typically utilised to lessen the damages brought on by whiteflies: 1) keeping an eye on crops to spot pests as soon as possible so that control measures may be put into place more quickly; 2) study better ways to keep an eye on crops and manage pests. Counting the quantity of insects, including nymphs and adults, is an essential step in both situations. Manually identifying and counting the insects inside a chosen area is the most accurate technique to gauge the level of whitefly infestation. Generally speaking, this strategy focuses on the exceptional human capacity to clarify ambiguous situations even in less than perfect circumstances without the use of advanced equipment. Humans, however, are prone to physiological and psychological events that might serve as significant causes of mistake: among other things, tiredness, visual illusions, and boredom. Additionally, humans often take significantly longer than robots to do simple activities like counting. In the literature, there are two primary methods for mechanically counting whiteflies: one use sticky traps, and the other uses plant leaves.

By Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton: Modern methods for object recognition mostly rely on machine learning techniques. We may gather larger datasets, develop more potent models, and employ better overfitting prevention approaches to enhance their performance. The size of tagged picture datasets was typically in the tens of thousands of images until recently (e.g., NORB,19, Caltech-101/256,8, 10, and CIFAR-10/10014). With datasets this big, simple recognition tasks may be done relatively well, especially when they are combined with label-preserving changes. For instance, the MNIST digit-recognition task's best error rate at the moment (0.3%) is comparable to human performance. However, since real-world items vary widely, it takes significantly bigger training sets to become proficient at identifying them. While it is true that tiny picture datasets have several drawbacks (see, for example, Ref. 25), it has only lately been feasible to compile tagged datasets containing millions of photos. LabelMe28, which has hundreds of thousands of completely segmented photos, and ImageNet7, which contains more than 15 million annotated high-resolution images in more than 22,000 categories, are two of the new bigger datasets. We require a model with a big learning capacity to learn about thousands of items from millions of photos. Our model should also include a tonne of previous knowledge to make up for all the data we don't have because the object recognition job is so complicated that it cannot even be defined by a dataset as large as ImageNet. Convolutional neural networks (CNNs) are a type of model that fits this description.

Tao Liu, Wen Chen, Wei Wu, Chengming Sun, Wenshan Guo, Xinkai Zhu: One of the key elements that influence crop development is pest infestation. In wheat fields, aphids are a frequent and dangerous insect that feed on the phloem sap, stunt crop growth, and spread a number of viral illnesses. Obtaining timely data on aphid density is necessary for monitoring aphid population dynamics, analysing the severity of the pest infestation, and determining the economic threshold for pest treatment. Accurate assessment of aphid density is a precondition for creating pest predictions (Zhang & Swinton, 2009). Currently, manually identifying and counting the insects is the most used technique for assessing aphid infestations. Because visual examination is labor-intensive and ineffective due to how tiny the aphids are, population counts might be inaccurate due to subjective variables. Scientists have suggested computer vision approaches to automatically identify and count agricultural pests as a result of the advancement of information technology. The digital photos that are utilised for pest identification may have been taken with or without pests present on the plants. Images of pests in plants may have either straightforward or intricate backgrounds. Sticky traps are typically used to capture pests in order to take pictures of them far away from the plants. The challenge of identifying individual pest signals that touch or overlap in a shot is a technological constraint (Xia, Chon, Ren, & Lee, 2014; Yao et al., 2013, 2012). The use of sticky trap photos provides better image segmentation and higher count accuracy when compared to other image acquisition methods, although this method necessitates the collection of pests before image acquisition. The method employed often involves focusing on and counting the number of bugs on a leaf in photos of pests found on plants with a basic backdrop (Barbedo, 2014).

2. Methodology:

Proposed system:

In purposed method we are performing the classification of either the Plant nutrient deficiency identification using Convolution Neural Network (CNN) of deep learning along with the machine learning methods. As image analysis based approaches for nutrient deficiency detection. Hence, proper classification is important for the proper nutrition that which will be possible by using our proposed method. Block diagram of proposed method is shown below.

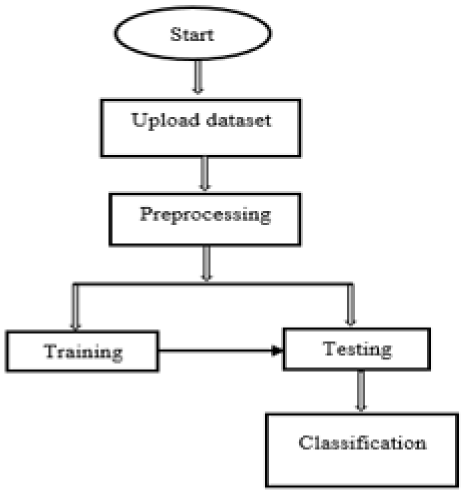


Figure 1: Block diagram

III. IMPLEMENTATION

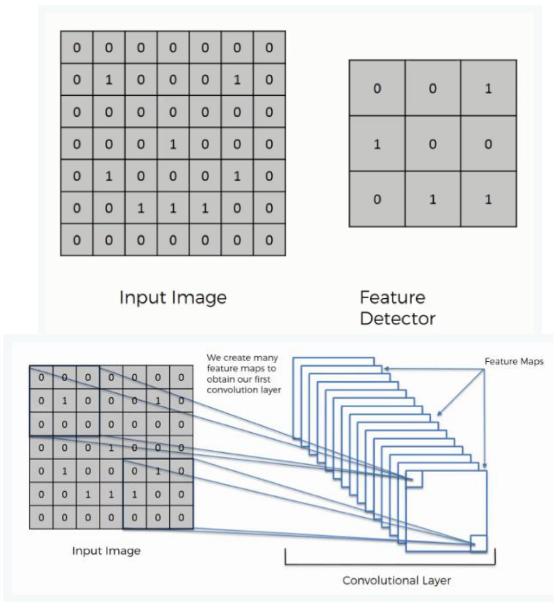
The project has implemented by using below listed algorithms.

1. Convolutional Neural Network

Step1: convolutional operation

The convolution operation is the first component of our strategy. We will discuss feature detectors in this phase since they essentially act as filters for neural networks. Additionally, we'll talk about feature maps, their parameters, how patterns are found, the detection layers, and how the results are laid out.

The Convolution Operation

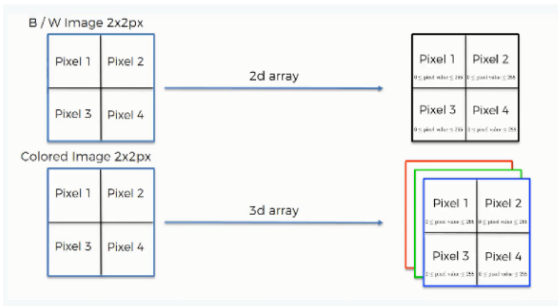


Step (1b): ReLU Layer

The Rectified Linear Unit or Relook will be used in the second portion of this process. We will discuss Relook layers and examine the role of linearity in Convolutional Neural Networks.

Although it's not required to comprehend CNN's, it wouldn't hurt to take a brief course to advance your knowledge.

Convolutional Neural Networks Scan Images



Step 2: Pooling Layer

We'll discuss pooling in this section and learn exactly how it typically operates. But max pooling will be the central concept in this situation. However, we'll discuss a variety of strategies, including mean (or total) pooling. This section will conclude with a demonstration created with a visual interactive tool that will undoubtedly clarify the entire idea for you.

Step 3: Flattening

Here's a quick explanation of the flattening procedure and how to switch between pooled and flattened layers when using convolutional neural networks.

Step 4: Full Connection

Everything we discussed in the previous section will be combined in this section. By understanding this, you'll be able to visualize Convolutional Neural Networks more clearly and understand how the "neurons" they create ultimately learn to classify pictures.

Summary

Finally, we'll put everything in perspective and provide a brief summary of the idea addressed in the section. If you think it will help you in any way (and it probably will), you should look at the additional tutorial that covers Cross-Entropy and Soft axe. Although it is not required for the course, it will benefit you greatly to be familiar with these principles since you will probably encounter them when working with convolutional neural networks.

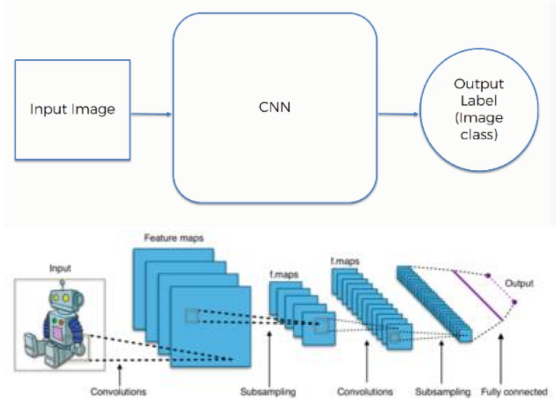
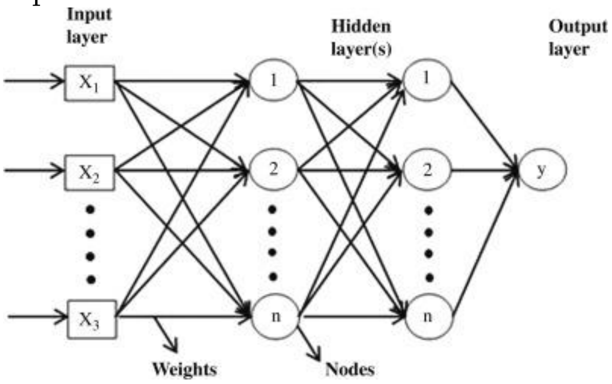


Fig. CNN Architecture

Artificial Neural Network (ANN):

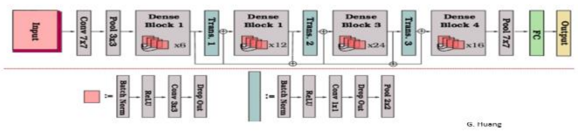
The structure and operation of the biological neural network serve as the foundation for ANN design. The neurons of ANN are organised in several layers, just like the neurons in the brain. A common type of neural network is the feed-forward neural network, which has three layers: an input layer for receiving outside data needed for pattern recognition, an output layer for providing the solution, and a hidden layer that acts as an intermediary layer between the other levels. Acyclic arcs link the neighboring neurons in the input layer to the output layer. The ANN employs a training technique to learn the datasets, and depending on the error rate between the goal and actual output, updates the neuron weights. The back propagation technique is typically used by ANN as a training procedure to learn the datasets. In the accompanying fig., the general structure of ANN is depicted.



DenseNet-121:

The first convolutional layer, which receives the input, is the only one in a traditional feed-forward convolutional neural network (CNN) that receives the output of the convolutional layer before it. This convolutional layer then creates an output feature map, which is then passed on to the subsequent convolutional layer. Consequently, there are "L" direct connections for "L" layers, one between each layer and the following layer.

However, when the CNN's layer count climbs, or as the layers go deeper, the "vanishing gradient" problem manifests. This means that when the information's travel from the input to the output layers lengthens, some information may "vanish" or "get lost," which decreases the network's capacity to learn effectively. By altering the typical CNN design and streamlining the connection between layers, DenseNets alleviate this issue. Each layer in a DenseNet design is connected to every other layer directly, giving rise to the moniker Densely Connected Convolutional Network. There are L(L+1)/2 direct connections for 'L' layers.

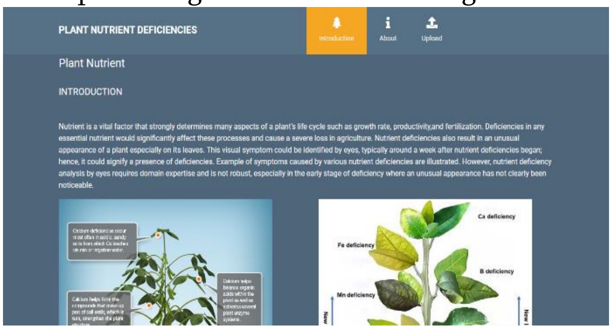


The DenseNet is separated into Dense Blocks, each of which has the same dimensions but differs in a number of filters. It is a crucial step in CNN that Transition Layer conducts batch normalization via down sampling.

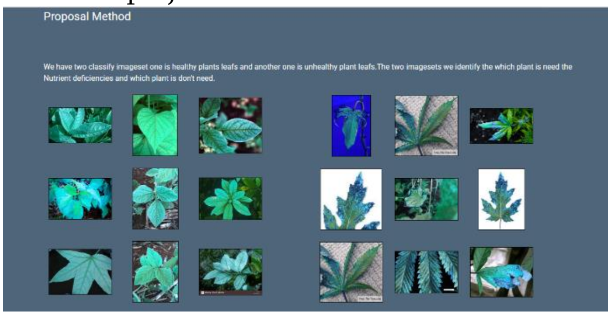
IV. Results and Discussion

The following screenshots are depicted the flow and working process of project.

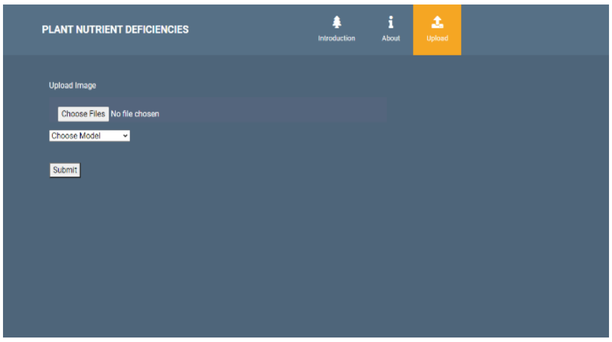
Home page: In our project, we are classifying the presence of Plant Nutrient Deficiencies, with the help of deep learning and machine learning.



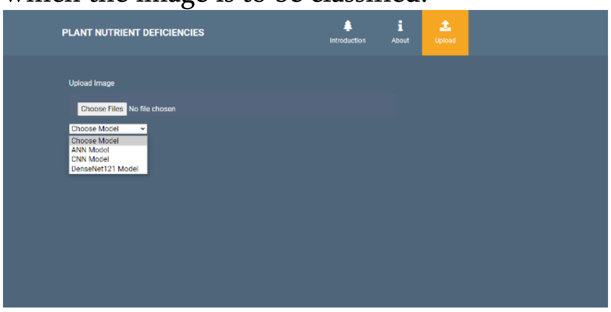
About Project: Here the user will get a breif idea about the project.



Upload Image: Here the images can be uploaded those which are to be classified.

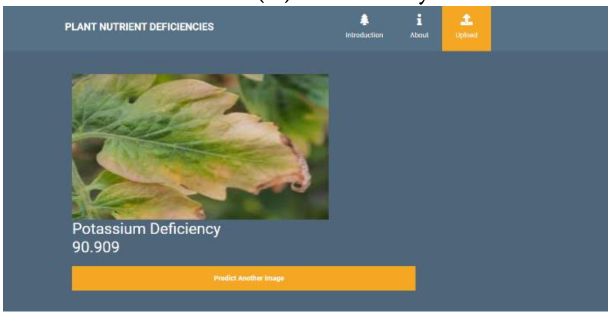


Model choosing: Here the model can be selected, by which the image is to be classified.

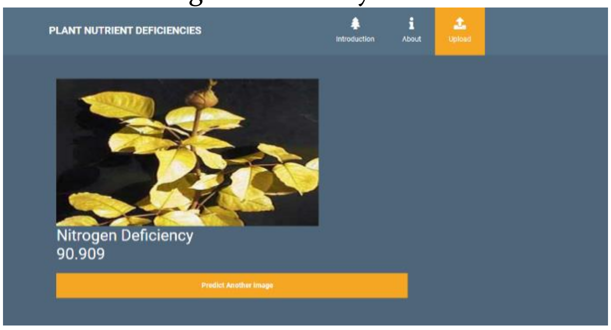


Classified output: The uploaded image is classified as the Plant Complete Nutrition.

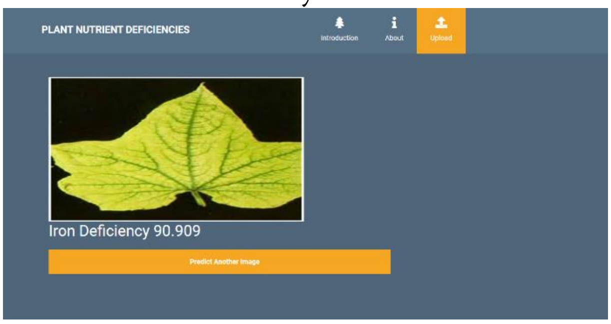
Classified output: The uploaded image is classified as Plant has Potassium (K) Deficiency.



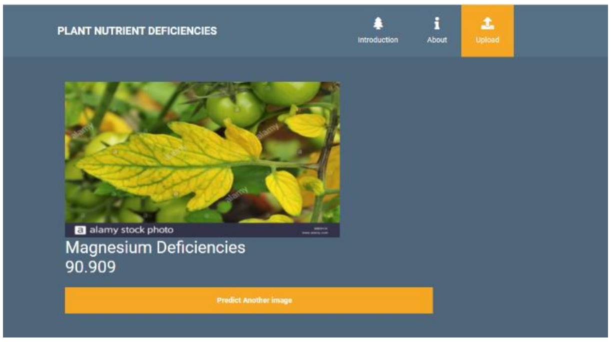
Classified output: The uploaded image is classified as Plant has Nitrogen Deficiency.



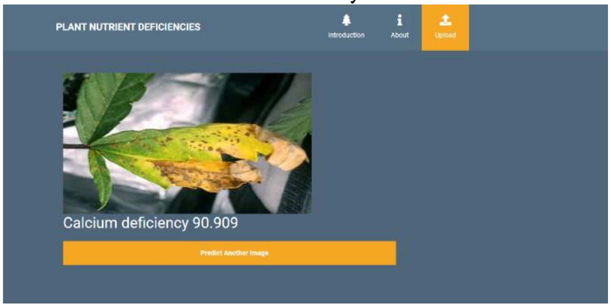
Classified output: The uploaded image is classified as Plant has Iron Deficiency.



Classified output: The uploaded image is classified as Plant has Magnesium Deficiency.



Classified output: The uploaded image is classified as Plant has Calcium Deficiency.



V. CONCLUSION

Using deep learning and machine learning, we were able to accurately categories the photos of Identification of Plant Nutrient Deficiencies as either impacted by Plant Nutrient or innutritious. Here, we have taken into account the dataset of photos of Plant Nutrient Deficiencies, which will be of various kinds of plants (healthy or unwell), and trained using CNN, ANN, coupled with some DenseNet121 transfer learning approach. After training, we put our skills to the test by submitting an image and classifying it.

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