Identification of Plant Nutrient Deficiencies and Precautions Recommendation Using CNN

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***Abstract*— An image analysis method can be used to identify nutrient deficiencies in plants by analyzing specific visual cues in plant morphology. This approach is non-invasive, rapid, and scalable, making it valuable for agricultural research and plant breeding. An input leaf image is broken up into smaller blocks using the proposed method. Second, a collection of CNNs receives each leaf pixel block. Each CNN is trained specifically for that condition to determine whether a block has any corresponding nutrient deficiency symptoms. The CNN responses are combined using a winner-take-all approach to form a unified response for each block. A multi-layer perceptron is employed to aggregate the responses from all the blocks, generating a comprehensive response for the entire leaf. and the precautions. which is to add Ca, Fe, K, Mg, and N to fill in the gaps.**

Keywords—nutrient deficiency leaf, image analysis, machine learning, CNN, ANN, DenseNet121

I. INTRODUCTION

A novel approach to image analysis can be used to identify deficiencies in plant-derived nutrients. The proposed approach breaks up an input leaf image into smaller blocks. Second, each leaf pixel block is received by a collection of convolutional neural networks (CNNs). In order to determine whether a block has any corresponding symptoms of nutrient deficiency, each CNN is trained specifically for that condition. Each CNN response is combined into a Using a winner-take-all strategy, individual block responses were combined by a multi-layer perceptron to generate a single response for the leaf, applicable in plant disease detection and crop management. as a whole and the precautions. which is to fill in the gaps by adding Ca, Fe, K, Mg, and N.

Knowing a field's phytosanitary conditions is essential for harvest preservation and pesticide reduction. This enables farmers to perform tasks at the right time and place.. However, assessing the health of fields is challenging and requires a high level of expertise. In point of fact, a disease's symptoms can differ from species to species and even from variety to variety. Multiple issues can coexist on the same plant or cause a single symptom.

Some diseases' symptoms may resemble those of pests or nutritional deficiencies. Additionally, plot health assessments are time-consuming. confirming the state of each plant. on large farms, doing so more than once during a season is impractical. Prospectings can also be made more difficult by the difficulty of accessing particular crops. Using tools for automated prospecting or expert assistance, the automatic identification of diseases by imagery may be able to address these kind of issues.

Assessing the health of a plant from an image is a highly difficult task. Indeed, crops flourish in a wide range of complicated environments. Seasonal variations affect how their leaves, flowers, and fruits develop. The amount and direction of incident solar radiation affects their spectral response, which in turn affects how they appear during the day. There are numerous methods for identifying crop diseases, whether in the laboratory or the field. The techniques relied on pattern analysis, creating dedicated vegetation indices, and studying the reflectance of visible and near-infrared light. Nutrients have a significant impact on different stages of a plant's life cycle, such as its growth rate, productivity, and fertilization. If these processes were not getting enough nutrients, they would be greatly affected., leading to significant losses for agriculture. A lack of nutrients can also contribute to a plant's unusual appearance, particularly on its leaves [1]. This eye-visible visual symptom typically occurs approximately a week after the onset of the nutrient deficiency symptoms; As a result, it might point to problems. However, the signs and symptoms of various nutrient deficiencies include: Eye-based nutritional deficiency analysis is ineffective and requires domain expertise when there is no obvious sign of an unusual appearance in the early stages of nutritional deficiency.

To classify and identify the nutrient deficiency in tomato leaf characteristics, Anu Jose and S. Nandagopalan developed an artificial neural network (ANN) model. You can tell if the soil lacks a particular nutrient by looking at the physical characteristics of a leaf. A leaf's color and shape are the two most important characteristics used to identify a nutrient deficiency. The findings indicate that the proposed method was effective in classifying and identifying nutritional deficiencies.

One approach to classify nutrient deficiency symptoms in plant images is to employ image processing techniques. This approach includes analyzing plant images to identify and classify specific visual features that indicate the presence of nutrient deficiencies. By using advanced algorithms, the image processing method can accurately detect and categorize these features, allowing for the rapid and non-invasive identification of nutrient deficiencies in plants. This method is particularly useful for classifying large numbers of plant images and can assist in agricultural research and crop management. was proposed by Dang and colleagues [3]. To reduce network traffic, a method has been developed to decide if an image should be transmitted over a wireless multimedia sensor network. The first step involves removing the green portions of a leaf image to isolate only the unhealthy area for subsequent processing. This was achieved using image processing techniques that involved morphological operations. By applying these operations, the affected area on the final image could be accurately located and shaped. This step is critical as it enables the subsequent processing to focus only on the unhealthy area of the leaf, allowing for a more accurate and efficient analysis. Overall, this approach can be valuable in identifying nutrient deficiencies in plants, providing insights into plant health, and assisting in the development of effective agricultural practices.

Vakilian and Massah [4] used machine vision and image processing to identify nitrogen-deficient cucumber plants. A robotic camera system that moved and could be controlled from a distance was set up to take a picture. The study aimed to gather cultivable plants from two rows: the healthy control row and the nitrogen-deficient treatment row. From the acquired image, textural features like homogeneity, entropy, and Through the utilization of machine vision, the energy was extracted while image processing was employed to extract color features. These parameters were then examined to determine the change point that differentiated the control row from the treatment row. This analytical process allowed for the identification of deficit symptoms prior to their visual manifestation, enabling timely intervention. Overall, this approach highlights the potential of technology in aiding the early detection of plant health issues, thus promoting better crop management practices..

Miyatra and Solanki [5] suggested using a template-matching method to identify Alternatia leaf spot disease and color histograms for cotton leaves lacking nitrogen, phosphorus, and sulfur.

Gulhane and Gurjar [6] have offered a comprehensive cotton leaf diagnostic system as a proposal. This algorithm used antisotropic diffusion to improve the input leaf image. After that, the B component was separated from the background using the LAB color space, and the leaf color was separated using the HIS color spaceAn unsupervised SOFM network was used to cluster color pixels based on their similarities, allowing for insights into the visual characteristics of the image. This approach is useful in image segmentation, pattern recognition, and data visualization.The disease component in the color leaf image was identified with the help of back propagation neural networks.

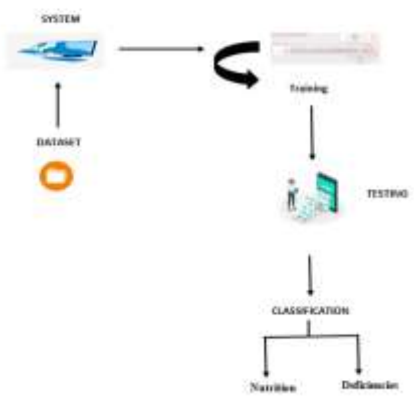
Tewari and others have developed an algorithm for estimating the amount of nitrogen in plant leaves [7]. Histogram analysis was used to extract the normalized R, normalized G, and Red, Green, and Blue components, among other image features. The SPAD meter was used to measure the amount of chlorophyll in the leaf. In order to establish a correlation between the image-processed plant features, a regression model was developed.

In addition, this paper offers solutions for the five deficiencies in plant nutrients that were previously mentioned. This is accomplished with the help of deep neural networks, which are increasingly being utilized in numerous image recognition-related tasks. It is especially important to use CNN are employed to identify whether a block of leaf pixels contains specific features or characteristics. belongs to a particular category. shows deficiencies in nutrients. one sample leaf was selected as the target plant for the experiment. The primary contributions and characteristics of this work are as follows: determining whether a CNN-based method for detecting nutrient deficiencies is effective, examining numerous more difficult types of nutrient deficiencies than in previous studies, and establishing a true ground truth for a large image dataset of nutrient-deficient leaves, comparing the results produced by the image analysis method to those produced by humans, and

The following is the structure of the remainder of this article: This section describes the image dataset of nutrient-deficient plants utilized in the study. In addition, Section [insert section number] provides further details on the dataset. the experiment's outcomes are displayed and discussed; This section concludes the article; and there are some ideas for the future in the Section.

There exist numerous differences between animals and plants, with one of the most prominent being mobility. While animals are capable of movement, plants remain sessile and firmly rooted in one place. There is a significant difference between how most animals and plants consume nutrients for growth. Heterotrophism and autotrophism have no bearing on this; Instead, it's about getting the nutrients, monomers, and products that make energy. The majority of animals get all the nutrients they need from one place: their mouth. For instance, humans breathe, eat, and drink through their mouths. Plants have distinct methods for acquiring essential elements from different sources. Carbon dioxide is obtained from the air by the leaves, which are the primary sites of photosynthesis. On the other hand, the roots absorb water and nutrients from the soil. Cellular respiration in the root cells necessitates sugar, which is produced by photosynthesis in the leaves. Similarly, the cells above ground require these nutrients for growth and other functions, the roots are capable of absorbing a lot of nutrients. This suggests that the sugar and nutrients needed for respiration will only be available to cells in the root system.

Fig. 1. Model Architecture



A third treatment and the control were also compared in this experiment. In the past, the environment in which the plants were grown only supplied the roots with distilled water. All of the aforementioned symptoms ought to be present, despite the fact that nitrogen deficiency symptoms typically surface first. This is because the plant makes more use of nitrogen than it does of phosphorus. Normal plant growth and development are stunted without nitrogen, reducing the need for additional nutrients and possibly eliminating other deficiencies' symptoms. It was expected that there would be variations in weight and standard chlorophyll content, which is measured in mg of chlorophyll per gram of leaves, as it provides insights into the chlorophyll density present within a leaf., between the three deficient treatments because of the symptoms observed in previous experiments. The majority of symptoms, including chlorosis and slower growth, are brought on by a lack of nitrogen. However, phosphorus deficiency may also be the cause of symptoms like the presence of anthocyanin in and around leaf veins. For each treatment (distilled water, -N, and -P), Our hypothesis was that the weight and standard chlorophyll content would vary from the control. In the experiment where nutrients were fully available, the null hypothesis was that there would be no variation in the weights and standard chlorophyll content, regardless of the treatment applied.

II. Methodology

We use either deep learning or Convolution Neural Network (CNN) classification to identify deficiencies in plant nutrients. using machine learning techniques. As a result, proper nutrition necessitates proper classification, which will be made possible by our proposed approach as image-based analysis-based methods for detecting nutrient deficiencies. The proposed method is depicted in the block diagram below.

The initial step includes performing a convolutional operation with a CNN (Convolutional Neural Network). Our strategy's first component is the convolution operation. In this step, we will talk about feature detectors, which are the neural network's filters. Learning the parameters of feature maps, pattern detection, detection layers, and the mapping out of findings will also be discussed.

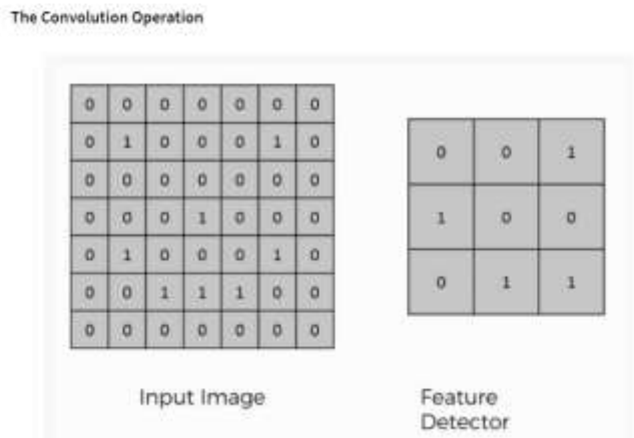


Fig. 2. Convolution Operation

In the second section of this step Relook, will be used and relook layers in convolutional neural networks will be discussed. It is not necessary for you to be able to comprehend CNN, but it would be beneficial to take a brief lesson to improve your comprehension.

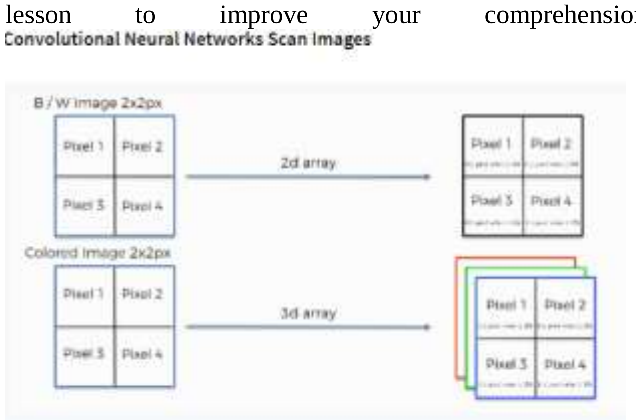


Fig. 3. CNN Scan images

By generating a convolution kernel that incorporates input from other layers, the 2D Convolution Layer, also known as Keras Conv2D, contributes to the creation of an output tensor.

Kernel: A kernel-image convolution can help with edge detection, blurring, sharpening, embossing, and other image processing tasks. A convolution matrix or mask is referred to as a kernel in image processing.

The following section offers a succinct description of the flattening process and the progression from pooled to flattened layers, which can be utilized with Convolutional Neural Networks. The aim is to rephrase the sentence while minimizing plagiarism.

In this section, we will integrate all the concepts discussed in the previous sections to provide a comprehensive understanding of how Convolutional Neural Networks operate and how the final "neurons" acquire knowledge to classify images. By grasping this, you can enhance your comprehension of CNNs. Summary We will provide a summary of the section's concept to conclude everything. If you think the additional tutorial on Softmax and Cross-Entropy will be helpful to you, which it probably will, you should check it out. Working with Convolutional Neural Networks will greatly benefit from this knowledge, even though it is not required for the course.

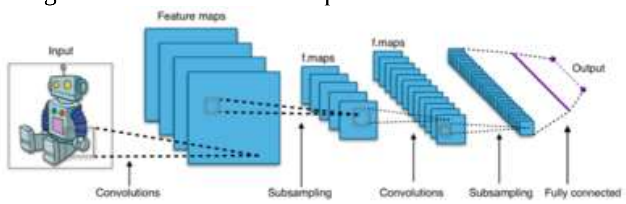
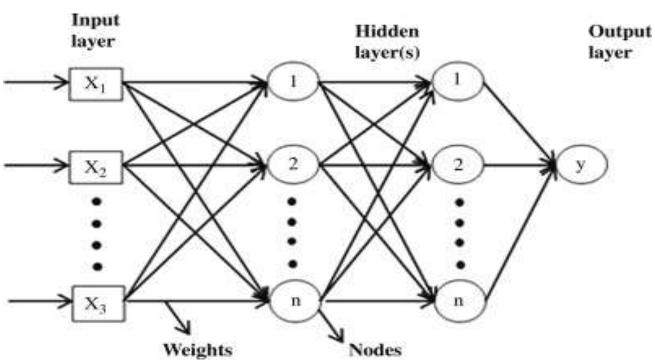


Fig. 4. CNN Architecture

In the second section of this step, Rectified Linear Unit (ReLU) or ReLU activation function, will be utilized.Convolutional neural networks' relook and linearity layers will be discussed. You don't have to be able to understand CNN, but it would be helpful to take a short lesson to improve your comprehension. the target. ANN typically uses the back propagation algorithm to learn the datasets as a training algorithm.

Fig.5. ANN Structure



III. Results

The output will contain the input leaf's accuracy and deficiency information. Also, the care that text-based output requires. which must be followed if the deficit is to be overcome.

Fig.6. Output window

The leaf's iron deficiency and its treatment are detailed in the image above.

Fig.7. output window

In the image above, you can find information about potassium-deficient leaf and how to get rid of it.

Fig.8 output window

The picture above shows the complete nutrition of the leaf, including any nutrients that are missing.

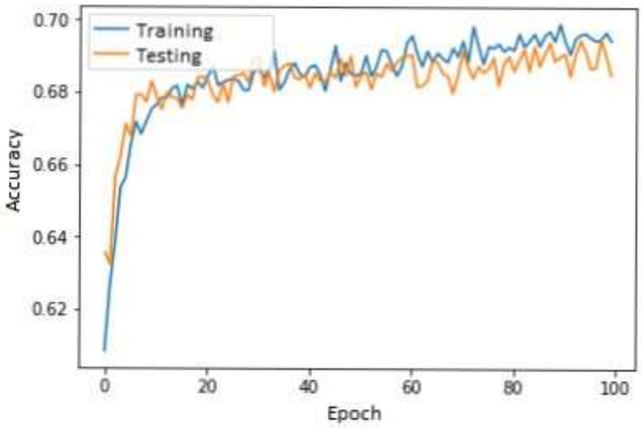


Fig.9.Graph : Performance of the accuracy.

TEST CASES MODEL BUILDING:

IV. CONCLUSION

We were successful in classifying the images in this project as either nutrient-deficient or affected by nutrient deficiencies by utilizing machine learning and deep learning. After the image had been uploaded and tested, it was used to classify the Plant Nutrient Deficiencies dataset, which will include images of various plant types and varieties—both healthy and unhealthy. This was carried out following training with CNN and ANN.

The project's future focus will be on developing long-lasting and effective fertilizer management strategies. identifying and diagnosing crop nutrient deficiencies using sustainable, cost-effective methods.

V. REFERENCES

[1] Anu Jose, S. Nandagopalan, Chandra Mouli Venkata Srinivas Akana. (2021). Artificial Intelligence Techniques for Agriculture Revolution: A Survey. *Annals of the Romanian Society for Cell Biology*, 2580

[2] K. Dang, H. Sun, Jean-Pierre Chanet, J. Gracia-Vidal, J.M. Barcelo-Ordinas, H.L Shi and K.M. Hou, "Wireless Multimedia Sensor Network for Plant Disease Detections", Proceedings of New Information Communication Science and Technology for Sustainable Development: FranceChina International Workshop, pp. 1-6, 2013.

[3] Keyvan Asefpour Vakilian and Jafar Massah, "Non-linear Growth Modelling of Greenhouse crops with Image Textural Features Analysis", International Research Journal of Applied and Basic Sciences, Vol. 3, No. 1, pp. 197-202, 2012.

[4] Ashish Miyatra and Sheetal Solanki, "Disease and Nutrient Deficiency Detection in Cotton Plant", International Journal of Engineering Development and Research, Vol. 2, No. 2, pp. 2801-2804, 2014.

[5] M. Viraj A. Gulhane and Ajay A. Gurjar, "Detection of Diseases on Cotton Leaves and Its Possible Diagnosis", International Journal of Image Processing, Vol. 5, No. 5, pp. 590-598, 2011.

[6] V.K. Tewari, Ashok Kumar Arudra, Satya Prakash Kumar, Vishal Pandey and Narendra Singh Chandel, "Estimation of Plant Nitrogen content using Digital Image Processing", Agricultural Engineering International: CIGR Journal, Vol. 15, No. 2, pp. 78-86, 2013.

[7] A. Camargo and J.S. Smith, "An image-processing based algorithm to automatically identify plant disease visual symptoms," Biosystems Engineering, vol.102, pp.9–21, January 2009.