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Using Deep Learning to Identify Iron Chlorosis in Plant

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ABSTRACT: To ensure the higher quality of the input data, ratings should be performed by several experts and/or several times by one expert. Testing with a large number of soybean cultivars for IDC measurement with replications providing a sufficiently large number of images will improve the performance of the selected machine learning as well as other advanced methods, such as convolutional neural network, and deep learning. As the most effective way to avoid IDC is to use tolerant cultivars, which have the lowest visual ratings, the image-based objective technique of the study will be of great use in soybean cultivar selection. This developed plot-scale image processing technique could be extended with suitable modification to field-scale operations through aerial imaging platforms (unmanned aerial vehicles, UAV) as well as mobile application development.

I.INTRODUCTION

The US is the second largest exporter of soybean and its product in the world with a crop value of over $39 billion in 2018, and the Midwest is one of the biggest production regions. However, soybean production in general and in the Midwest specifically can be declined by iron deficiency chlorosis (IDC). IDC is characterized by a reduction in the chlorophyll of the leaves, which makes the leaves turn from green to yellowish that in consequence interferes with photosynthesis, causing reduced plant height and leaf area, which negatively affect the production. For efficient management of soybean IDC, measurement and assessment of the extent of the damage is the key step. The most common and current method employed IDC assessment is the manual visual scoring system by the field experts, where a higher score means increased incidence. This method, however, is laborious, expensive, and time-consuming, as well as subjective. Furthermore, it is impractical to use this method on larger scales. Therefore, a modern method of image processing from the actual field images was proposed, tested, and compared with manual rating in this study.

As an alternative to manual visual rating, digital image processing can be used for efficient IDC assessment in field conditions. Digital image processing captures the reflection of light similar to human eyes and is much more objective and expected to be consistent compared to visual rating. These images were used for phenotyping of different crops by extracting different color vegetation indices (CVI) from them. Yellow and green disks, components of the standard color board, of known DGCI values, were used to compensate for different lighting conditions and the effect of different sensitivity to colors among various cameras on corn. A close relationship between the amount of nitrogen in corn leaf and DGCI value was reported from that study. Image processing was demonstrated to estimate chlorophyll from soybean leaf images using the DGCI.

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

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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.

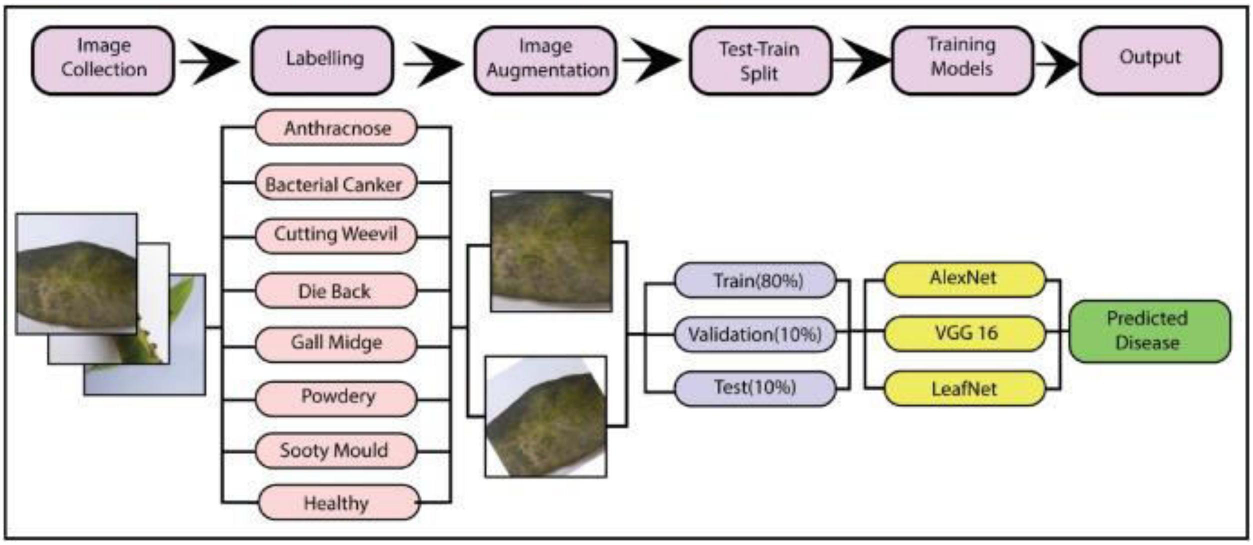

Fig 1: A proficient convolutional neural network

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.

BACKGROUND OF WORK

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 noninvasive 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

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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.

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.

METHODS

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 imagebased 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.

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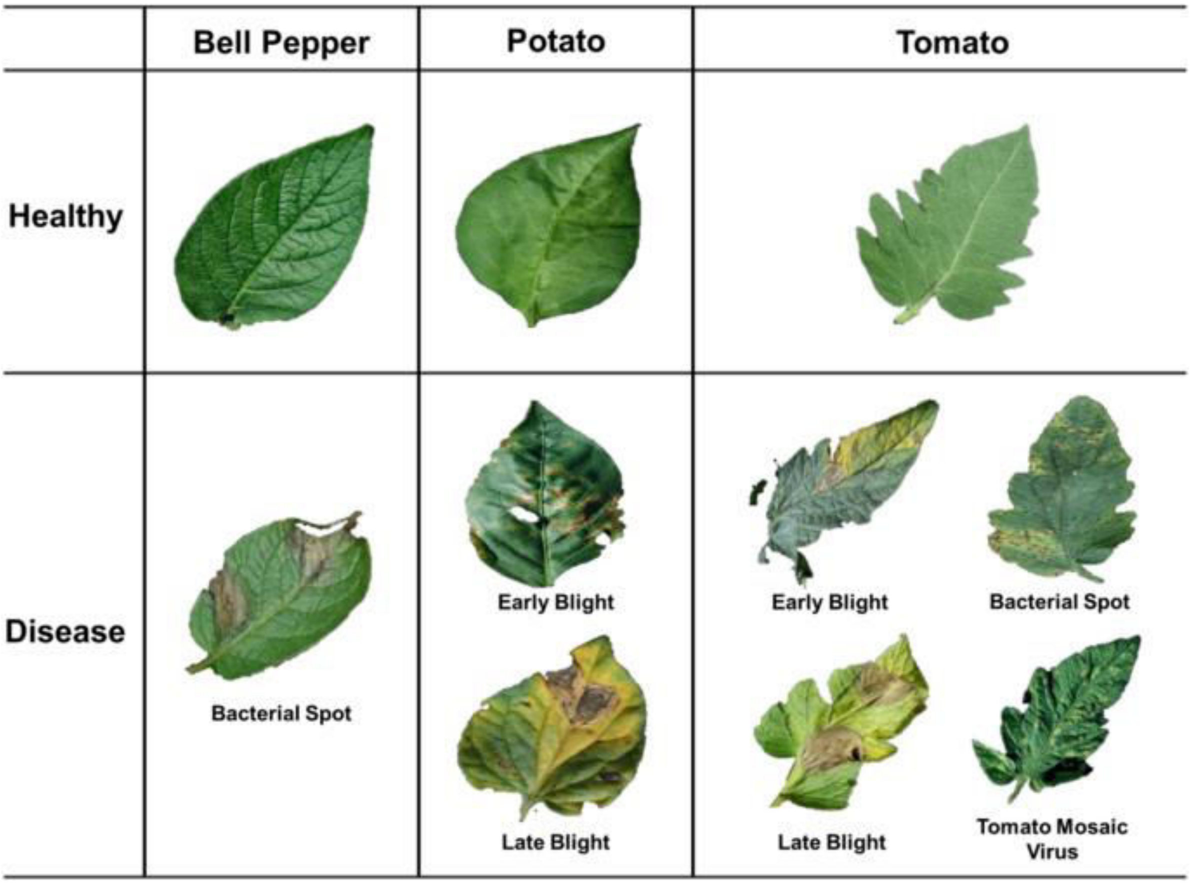

Fig 2: analysis

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.

RESULT ANALYSIS

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.

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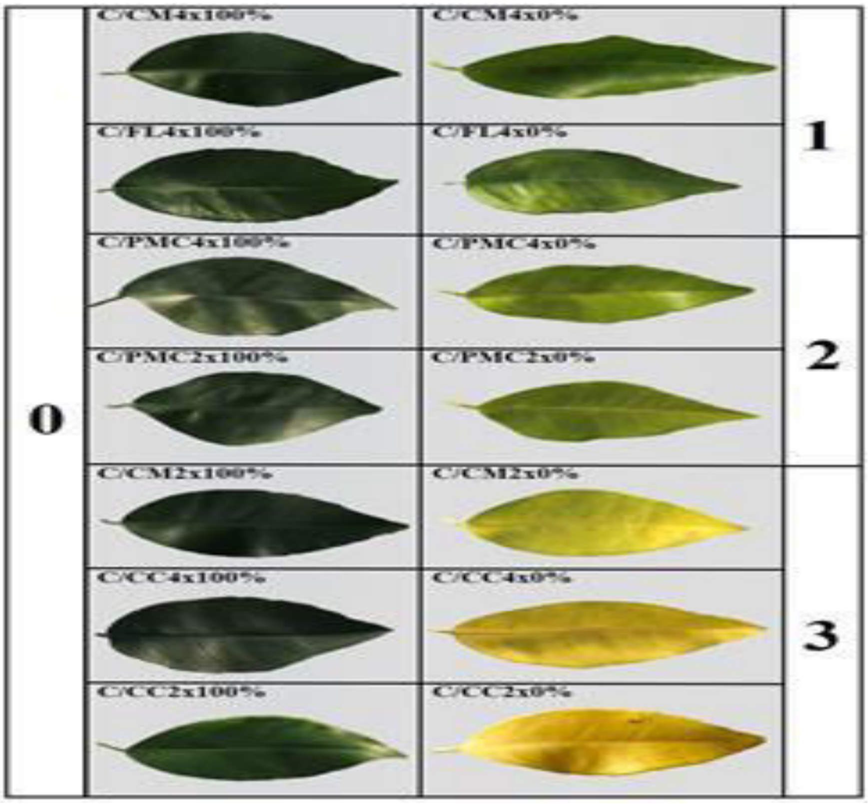

Fig 3: nutrient deficiency - List of Frontiers

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 CrossEntropy 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.

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.

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