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Recognition Of Nutrients Deficiency In Plant Leaves Using Machine Learning

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ABSTRACT

Agriculture is the primary method used to cultivate various plant species to produce food and a variety of other desired items as well as to raise domestic animals. Because there is no nutritional shortfall in plants, farmers are unable to identify which nutrient is declining. Early farmers used conventional ways to detect nutrient deficiencies in crop output, but it was difficult to do so, which posed a serious dilemma for farmers. This paper played a key part in the development of an automation that aids farmers by showing them the results of nutrient deficiency in plants with just one click of an image. Using a traditional neural network, the leaf's picture is processed (CNN). This method uses picture capture and CNN image processing. It will compare the image to the already existing set, show the actual result on the screen, and suggest how to correct the deficit using the fertilizers we foresee. It needs to be applied according to the percentage we've specified after measuring the amount of agricultural production harm that has been done to plants. It will assist contemporary farmers in recognize and easing their burden.

Keywords: ***Nutrient deficiency, Detection, Prediction, Automation, CNN, Fertilizer*.**

1. INTRODUCTION

All areas of the developing world are greatly impacted by technology. Agriculture is primarily necessary for human existence. In our agricultural practices, we continue to use the conventional ways. Farmers still have a tough time identifying nutrient deficiencies in their crops. It will require more time, effort, and money to identify nutrient deficiencies in crops using antiquated methods. Time, money, and product output tend to suffer from incorrect identification.

In general, agricultural labs and knowledgeable people are used to detect this kind of nutrient deficiencies (farmers).The forecasts for nutritional deficits following to a number of environmental factors, manually, could go wrong. Crops that are lacking in nutrients may show it in their leaves, stems, blossoms, fruits, etc. In order to detect nutrient deficiencies in vegetables, we use the leaf.

For effective development, a plant should require nearly twelve nutrients. They are nitrogen, phosphorus, potassium, magnesium, calcium, iron, Sulphur, molybdenum, zinc, boron, copper, and chloride.

Micronutrients and macronutrients are two categories for these nutrients. They are Molybdenum, Zinc, Boron, Chloride, Copper, and Iron. The macronutrients are calcium, magnesium, phosphorus, potassium, Sulphur, nitrogen, and potassium. Numerous crop illnesses will be brought on by the lack of these nutrients. This will have a secondary impact on yield rate. Typically, signs such as reduced leaf size, distorted leaf edges, necrosis, black spots, etc. are used to detect nutrient deficiencies in agricultural plants' leaves. To determine which nutrients are deficient, the farmer must uproot the entire plant and test it in the proper laboratory.

2. LITERATURE SURVEY

(2015) (Jung et al.) [8] This article is founded on the development of a nutrient management technique using computer-controlled fertilizer pumps and ion selective electrodes (ISEs). The volumes of each individual solution to be given are calculated using a nutrient dose up algorithm based on calculations of the current concentrations in a tank.In five spiking tests, it creates five Ca and NO3 concentrations that are similar to the goal concentrations. However, because of the low K values, its concentration was helpful in reducing signal drifts that arise from in-line ion concentration measurement. In a greenhouse, lettuce is grown using this automated technology. In order to achieve the goal, the concentrations of three ions were controlled at 140 mg NO3, Ca and K ions respectively

2013 (Kim et al) [9] The evaluation and development of a computer-controlled ISEs-based system for directly measuring macronutrients in hydroponic solution served as the foundation for this paper. The directed measurement of NO3-N, Ca, and K for hydroponically grown paprika is evaluated using an ISE array with a PVC-based membrane and a computer-controlled system. ISE-estimated K and NO3-N fixations in diluted/spiked hydroponic tests were found to be highly correlated with those determined using standard research facility instruments using recently developed gauge adjustment and two-point standardization methods. In any event, the hydroponic setup's poor selectivity and decreased sensitivity meant that the calcium cathode experiment didn't produce satisfactory results. This technique of analysis, which uses a base mixture for both washing the terminals and referencing the baseline automated detecting of hydroponic supplement in nurseries.

2020 (Amirtha ET AL) [10] This article is founded on the creation of an automated robotic machine that can identify nutrient deficiencies in plants simply by taking a photo of the plant's leaves. The captured image is then processed using convolutional neural networks (CNN). The method makes use of a captured image and processes it by comparing it to a data collection. The information picture will reveal the rate-based effects of nutrient deficiency in plants at the point where it is coordinated or at least somewhat coordinated with any of the current pictures in the data collection. The LCD will display the name of the illness associated with inadequate supplements and the appropriate amount of compost. This lessens the labour force problems.

(2017) Vassallo-Barco et al. [11]
Nutrient deficiencies in coffee plants affect their development, and as a result, they are

It's important to be acknowledged early. The focus of this article is on using shape and surface descriptors in images of coffee tree leaves to automatically identify deficiencies in calcium (Ca), boron (B), potassium (K), and iron (Fe). These leaves are then subjected to a division procedure using Otsu's strategy. Following that, they used the descriptors Gray-Level Co-occurrence Matrix (GLCM) and Blurred Shape Model (BSM) for the following images to determine our shape and surface properties. Finally, the acquired image is used to create Neural Network, Naive Bayes, and KNN classifiers using the extracted characteristics in order to determine the type of deficiency. introduced in each investigated picture.
The test results show that the created strategy has a good accuracy, with the better more outcomes in distinguishing deficiencies of Boron (B) and Iron (Fe)

[12] Butler ET AL, 2017 This study uses synchronic radiation-based Fourier-transform infrared (FTIR) micro spectroscopy to identify Ca deficiency in stationary and living Camelina communes plant tissues. As a result of water absorption in fingerprint regions, particularly in live tissues, spectrum information is hidden, making this technology's application for plant-based studies comparatively underdeveloped. This study investigated the ability of such a method to handle Ca deficiency in both living and fixed tissue, in order to determine how exactly this could be resolved prior to the presence of supplement deficiency side effects. It demonstrates how SR-FTIR can accurately determine the Ca status of C. communes leaf tests produced at a scope before harvest. of Ca accessibility. This type of procedure would not exclusively be exceptionally good

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for more
extensive nutrient screening applications, yet in addition for distinguishing other abiotic stresses, for example, biotic stress and ozone harm etc.
(Cho et al 2018) [13] This paper covers developing the on- location ion checking framework dependent on Ion specific electrodes (ISEs) those could adjust the sensors and also calculate the concentration of individual particles ($Ca2+$, $K+$ and $NO3−$,) in hydroponic solutions. This empowers growers in adequately managing the nutrients in recycled arrangements by quickly distinguishing any kind of imbalance that occurs. Performance was assessed utilizing hydroponic arrangements arranged for developing paprika crops in nurseries. To examine the feasibility of utilizing the created system for the automated estimation of three macro nutrients ($Ca2+$, $NO3−$, and $K+$) in a genuine greenhouse, an application test was made. The outcomes demonstrated that the created framework had the capability of measuring $NO3−$ concentrations, demonstrating a practically 1:1 connection with standard instrument, i.e., ion chromatography. In spite of the fact that this system underestimated and over-estimated the $Ca2+$ and $K+$ with slope of 0.75 and 1.17 individually.

Yogesh et al. 2019, p [14] It suggests using machine vision to look for defects caused by a shortage of nutrients in fruits. By including two classifications—healthy and defective— the computation is made simple. The primary stage, thesecond stage, and the last stage are the next 3 sub-classes that make up the defective class. With various natural fruits like litchi, apple, pomegranate, and pears, Google Net, SVM, and KNN are used to observe the output along with the stage of deformity. According to observations, the SVM method is superior for classifying fruits in terms of the location of defects and the prediction of their stage. The limitation of the suggested structure is that a trained system of various fruit deficiencies is not accessible. Without astructure in place, one must create a database.

(2018) Shah, Gupta, and Ajgar [15] This study focuses on providing accurate, automated responses for nutrient deficiency monitoring. The data collection was created using image processing techniques for deficient as well as healthy leaves' RGB highlight extraction, edge recognition, texture detection, and other functions. These created files are used as a training data set for supervised AI to find nutrient deficiency and identify preventative actions to increase the output in healthy plants.

2019's Lavanya, Rani, and Ganesh Kumar [16] It incorporates an Internet of Things (IoT) based device by designing a novel NPK sensor with LDR and LED. The colorimetric concept is employed for soil nutrient monitoring and analysis.
To enable quick information retrieval, sensed data from the NPK sensor are uploaded to a Google cloud database. Applications of fuzzy logic are used to observed data to identify nutrient deficiencies. During the fuzzification process, the very value of each detected data was divided into 5 fuzzy values ranging from very low to very high. On the premise of each chemical solution of potassium (K), phosphorus (P), and nitrogen (N), a set of if-then rules are developed (N). There is a Mamdani inference setup. deriving the inference about Nitrogen (N), Phosphorous (P) and Potassium (K) deficiency in the soil chosen for testing and thus as a result an alert message to farmer is being sent regarding the quantity of fertilizer to be used at regularintervals.

Tewari et al. 2013, 17 4 tyre A manually operated test trolley was created to take colour photographs of plants and crops outdoors in low light in order to forecast how much nitrogen the crop will contain. A camera is used to take pictures of the crop or plant, a laptop is used for data processing, and four lights are used to regulate the lighting. After transplantation, the aforementioned setup was carefully examined for four observations of the rice plant every fifteen days. The crop's chlorophyll content, which was assessed using a SPAD meter, was then compared. The color plant image processing software used is called MATLAB 7.0. For both processes, various features including R, G, B, normalized 'r' and normalized 'g' were investigated. Then Models for regression were created. Models were developed and evaluated among different image feature a& crop's nitrogen content and thus it has been observed that, the minimum accuracy was 65% with an average of 75% (Standard Deviation ±1.9), real and predicted values of nitrogen percent were linearly interrelated with R2 value (0.948), this depicts that the plant nitrogen content can be successfully projected by its leaf color image feature.

(Mohana Priya & Sivagami 2019) [18] The main goal of this research is to effectively detect deficiencies in tomato leaf tissue in order to protect it from disease. To find deficiencies in tomato leaves, image analysis techniques are used. When plants are given their necessary nutrients, such as potassium, nitrogen, phosphorus, etc., they grow well. Analysis of tomato plant leaf deficiency will aid in predicting the occurrence of disease in later phases. The use of segmentation and expectation processes maximizes detection accuracy, and highlights from segmented pictures have been extracted. To determine whether it is a normal leaf or an escaped leaf, categorization is carried out based on the highlights that were extracted. Following recognition of the outcome, the infection event caused by a supplement deficit is demonstrated.

A. *Maintaining the Integrity of the Specifications*

Which had a success rate of up to 99.4%. The accuracy of the trained model was significantly reduced to 31.4% when other labelled images taken under various circumstances were used, but it was still significantly better than that based on random selection (2.6%). Because of this, the deep learning model was very precise but not reliable. With images collected in a similar context using a regularized process, the Plant Village dataset based on expert knowledge might include some noise through variations in different experts' manual labelling, which could account for the difficulty in creating a robust model. The dataset should be as big as it can be because visible signs are tissue- and time-dependent. Following up research by Mohanty et al. revealed that diversifying the images would improve crop disease detection

3. PROBLEM STATEMENT

The problem statement is to develop a machine learning model that can accurately recognize nutrient deficiencies in plant leaves. Nutrient deficiencies can lead to stunted growth, decreased crop yield, and even plant death. Early detection and identification of nutrient deficiencies can help farmers take appropriate action to rectify the situation and avoid crop losses.

The model would be trained on a dataset of images of plant leaves with different nutrient deficiencies, along with labels indicating the type of deficiency. The images would be pre-processed to extract relevant features that can be used as inputs to the machine learning model.
Once trained, the model could be used to classify new images of plant leaves and identify any nutrient deficiencies.The output of the model could then be used to alert farmers or crop managers to the presence of a nutrient deficiency, and suggest appropriate actions to rectify the issue.
Overall, the goal of this problem statement is to develop a machine learning solution that can help farmers and crop managers quickly and accurately identify nutrient deficiencies in plant leaves, and take proactive measures to address the issue.

4. EXISTING SYSTEM

The current method utilizes A quick way to determine the soil's macronutrient content is to use a soil test kit. It uses a calorimeter to measure the quality of three main macronutrients (nitrogen, phosphorus, and potassium), as well as the pH level of the soil, which identifies the soil's acidity, neutrality, or basicity. The test results will serve as the foundation for recommendations on how much fertilizer the soil needs to produce a specific crop. Rapid Soil Test Kit (RST), a new soil test kit produced by BSWM, measures the secondary macronutrients (zinc, calcium, and magnesium), which are also necessary for plant development. It also provides information on the recommended dosage of a particular fertilizer. The traditional technique of soil preparation, which uses a soil test kit, is not widely used by farmers. The most frequent reasons why farmers do not use STK and

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RST are a lack of knowledge about their existence, the proper usage of soil test kits, and how to interpret the results in order to make the required fertilizer recommendations.

5. PROPOSED SYSTEM

A prevalent issue in agriculture, nutrient deficiency in plant leaves can lead to decreased crop yield and unhealthy plants. In the past, finding nutrient deficiencies in plants required costly and time-consuming laboratory analysis of plant tissue samples or visual inspection by knowledgeable staff. However, improvements in computer vision and machine learning have created new opportunities for automating the process of identifying nutrient deficiencies in vegetation. Automated nutrient deficiency detection is possible thanks to machine learning algorithms' capacity to identify patterns and characteristics in plant images that indicate nutrient deficiencies. System Design in ProposalFarmers can photograph a leaf that exhibits certain signs. Farmers can submit leaf images suspected of having nutrient deficiencies to nearby servers. The image processing engine retrieves the uploaded images from the server and processes them. The system will use a classification algorithm based on(artificial neural network) ANN. The procedure entails gathering and preprocessing a dataset of plant picture data, extracting pertinent features from the images, and building a machine learning model on the extracted features to categorize the images (healthy leaves, leaves with nutrient deficiencies, etc.).

The color, texture, shape, and size of leaves, as well as the presence of obvious signs of nutrient deficiency like chlorosis, necrosis, and stunted growth, are some typical characteristics that can be extracted from plant images to identify nutrient deficiencies. Support Vector Machines (SVMs), Random Forests, and Neural Networks are a few examples of machine learning algorithms that can be used for classification. The complete block diagram representation:

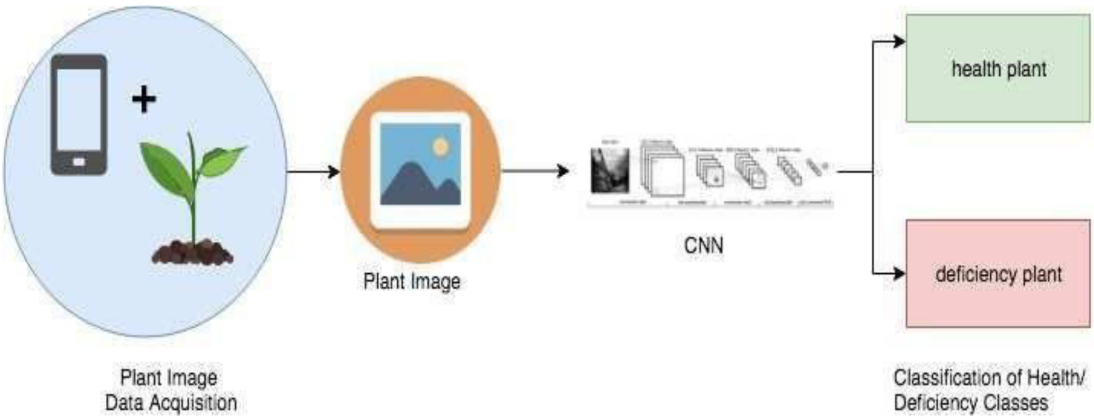

Figure 1: Overall block diagram of proposed system

Farmers and gardeners can swiftly and reliably find nutrient deficiencies in their crops by using machine learning to detect nutrient deficiencies in plant leaves. This enables them to take the necessary corrective actions, like applying fertilizer or adjusting the pH of the soil. This may contribute to increased crop output and improved plant health and yield. It can identify nutrient deficiencies; the picture's extracted features can be used to compare the image to the trained dataset and determine whether the plant is nutrient-deficient or healthy. If the test image is a nutrient deficient image, it will output the name of the deficiency along with the appropriate quantity of fertilizer.

6. METHODOLOGIES

The methodologies used to determine whether crops arelacking in nutrients include:

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- Image pre-processing
- Image segmentation
- Convolutional neural network
- Post processing image enhancement
- Future extraction (comparing techniques)

An image's qualities are its most crucial attributes. Edges,Corners, Ridges, Blobs, etc. are among the characteristics. The following stages make up the proposed system for identifying nutrient deficiency in plant leaves using machinelearning:

Data collection: Images of nutrient-deficient plant leaves are used to create a dataset. Several sources, including onlinedatabases, plant nurseries, and agricultural research facilities,can be used to acquire this dataset.

Data preprocessing: To extract pertinent characteristics like texture, color, and shape from the images in the dataset, preprocessing is performed. This process serves to make the dataset less dimensional and increases the machine learning model's precision.

Feature extraction: The pertinent features are taken out ofthe preprocessed images in this phase. Techniques like Principal Component Analysis (PCA), Local Binary Patterns (LBP), and Histogram of Directed Gradients can be used forthis (HOG).

Model training: A machine learning model is trained using the extracted characteristics. Convolutional neural networks (CNN), Random Forest, and support vectormachines (SVM) are a few examples of models that can be used for this. In order to understand the patterns of nutrient deficiency in plant leaves, the model is trained on the labelled dataset.

Model validation: Using a different collection of plant leaf images with nutrient deficiencies, the learned model is put to the test. This aids in evaluating the model's accuracy and locating any possible problems that require attention.

When processing images, the edges and corners are primarily used to distinguish one picture from another. To start, the trained dataset's picture features areextracted in order to determine the sample threshold values. These characteristics are used to teach the system to recognize different nutrient deficiencies. The differentthreshold numbers represent the severity of different nutrient deficiencies. A local picture patch can be extracted around the feature once it has been identified. The feature description is the extraction's output. Starting with the collection of measured values, feature extraction creates the derives values that are indented to be informative.

Following the extraction of features, characteristics are learned. There are two varieties of this: monitored and unsupervised. The learning of features from labelled data is the supervised approach. As a result, the algorithm was able to calculate the error degree required for failure and use that information as feedback to improve the learning process. Thebest illustration of this kind is neural networks. Learning features from unlabeled data is what is referredto as the unsupervised approach. Finding the low- dimensional structures that support the high-dimensional structures is made easier by doing this.

7. IMAGE DATA SET

The images used to teach the vehicle are gathered from various plants in various locations. Two sets—the test dataset and the train dataset—were created from the gathered leaf pictures. The images gathered across all regions are includedin the trained dataset.

These pictures show both nutrient-rich and nutrient-poor foliage.

The vehicle is taught to recognize images of nearly all nutrient deficiencies as well as images of healthy leaves. Theinput pictures from the vehicle's camera are included in the test dataset. The trained picture is then compared to the inputimages to determine the percentage of the deficiency.

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Experimental results

a) Positioning images: If so, the system will identifywhich major nutrients are lacking and display this information on the display. A graph showing the connection between different nutrient deficiency threshold levels is tabulated. The threshold values for various nutrient deficiencies are identified from that graph, and the severity of the deficiency impacted is determined.

S.No.	Deficiency type	Count
1	Potassium	383
2	Nitrogen	440
3	Phosphorous	333
4	Healthy	374

Table-1: Collection of images by their deficiency

Figure 2: Image classification and it's bar graph

8. RESULTS

Using a different collection of plant leaf images with nutrientdeficiencies, the learned model is put to the test. This aids in evaluating the model's accuracy and locating any possible problems that require attention. When processing images, the edges and corners are primarily used to distinguish one picture from another. The results are:

Figure 3: K_Deficiency and its recommended fertilizer

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Figure 4: P_Deficiency and its recommended fertilizer

Figure 5: N_Deficiency and its recommended fertilizer

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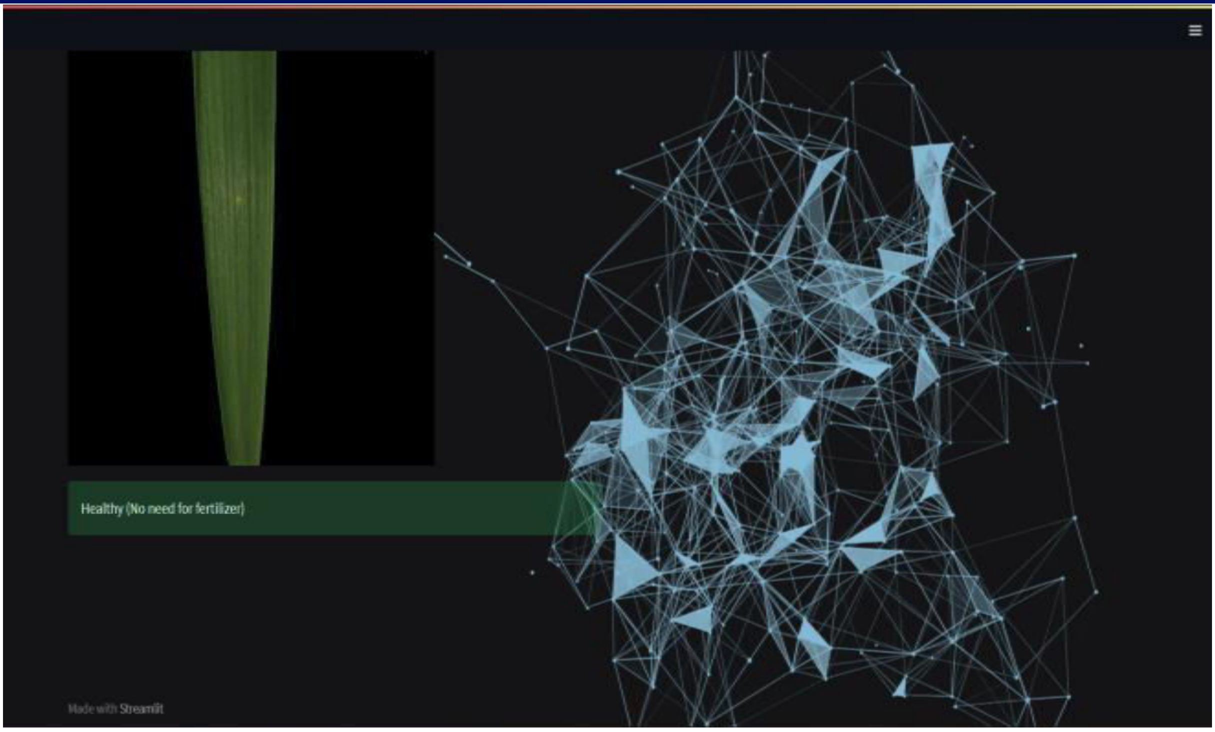

Figure 6: Healthy Leave output

CONCLUSION

In conclusion, by automating the process of nutrient deficiency detection in plants, plant nutrient deficiency detection using machine learning has tremendous potential to revolutionize agriculture. Farmers and gardeners can quickly and accurately identify nutrient deficiencies in their crops by using machine learning algorithms to analyze plant images and find patterns and features that are suggestive of nutrient deficiencies. This enables them to take the necessary corrective actions to improve plant health and productivity.

The convolutional neural network program detects nutritional deficiencies and displays them in the system. Additionally, the quantity of fertilizer needed to make up the corresponding nutrient deficiency is shown (in terms of percentage). Future development will involve an automatic system for applying fertilizer to the field. The collection and preprocessing of a dataset of plant images, the extraction of pertinent features from the images, and the training of a machine learning model on the extracted features are the steps in the process of nutrient deficiency detection using machine learning.

The automated fertilizer dressing is done using a variety of methods. For calculating the amount of fertilizer, the input from different sensors, such as soil moisture, humidity, temperature, and pH, is taken into account. If there are weeds, they can be removed using the weed remover connected to the system. This weeds eater has customizable settings. As a result, the complete agricultural process can be incorporated into one system.

Overall, applying machine learning to agriculture has the potential to increase crop yields, decrease waste, and increase the sustainability of food production. The future of farming and food output can be greatly improved by applying machine learning to agriculture in a variety of ways, one of which is the detection of nutrient deficiencies in plants.

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