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DETECTION OF MICRO AND MACRO NUTRIENT DEFICIENCY IN OKRA (ABELMOSCHUS ESCULENTUS L) PLANT LEAVES USING MACHINE LEARNING APPROACH

Dipankar Das [1*], Dr. Uzzal Sharma [2]

[1] Research Scholar, Department of Computer Science, Assam Don Bosco University, Assam, India; dpnkrcrazy@gmail.com
[2] Associate Professor, Department of Computer Science, Birangana Sati Sadhani Rajyik Viswavidyalaya University, Assam, India

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ABSTRACT

This work proposes a unique technique for the identification of micro and macro nutrient deficits in the leaves of the Okra (Abelmoschus esculentus L) plant. The approach utilises machine learning to accomplish this detection. The purpose is to create a system that is both efficient and accurate for identifying nutrient shortages, which is essential for maximising crop output and quality. The procedure entails the gathering of photographs of leaves, the extraction of features, and the categorization of the images via the use of machine learning algorithms. **Method:** The suggested method starts with the collection of high-resolution photographs of the leaves of the okra plant that are displaying indications of nutritional shortages. Techniques from the field of image processing are used in order to improve contrast, eliminate noise, and separate respective leaf sections. An operation known as feature extraction is carried out in order to get pertinent information about the morphology, colour, and texture of the leaf. These features are then used as input to machine learning techniques such as support vector machines (SVM), random forests, or convolutional neural networks (CNNs). **Result:** In the process of identifying micro and macro nutritional deficits in the leaves of the okra plant, the machine learning technique that was created exhibits promising positive outcomes. The identification of nutrient deficiency symptoms displays good levels of accuracy, sensitivity, and specificity, according to the results of an evaluation conducted on a heterogeneous dataset consisting of leaf pictures with ground truth labels. In terms of both accuracy and efficiency, the approach shows superior performance compared to the conventional visual inspection methods. In addition to this, the method demonstrates excellent resistance to changes in the lighting conditions and the orientation of the leaves. **Conclusion:** In conclusion, the machine learning technique that was provided offers a dependable and automated solution for the identification of micro and macro nutritional deficits in the leaves of the okra plant. Because of its precision and effectiveness, the technology is appropriate for incorporation into agricultural operations. There is a possibility that its applicability in real-world settings might be improved by further validation on bigger datasets and field tests, which would make sustainable agricultural production and food security easier to achieve.

INTRODUCTION

The presence of proper amounts of water, sunshine, and nutrients in a plant is essential to the functioning of the agricultural system. Each plant has a unique need for a certain quantity of nutrients, which may be broken down into two categories: macronutrients and micronutrients. The term "macronutrient" refers to nutrients that are present in greater quantities than micronutrients. This is due to the fact that their presence is essential for the growth of plant cells and tissues. Micronutrients include ferrum (Fe), zinc (Zn), copper (Cu), and manganese (Mn), whereas macronutrients include nitrogen (N), phosporus (P), potassium (K), calcium (Ca), sulphur (S), and magnesium (Mg). Magnesium (Mg) is known as the most abundant mineral in the world. Deficiency in macronutrients has an effect on the development of leaves, which in turn creates disruptions in the creation of food particles. One of the factors that contributes to growth disorders, such as dwarf plans, poor blooming and fruiting, is an inadequate amount of food created. The symptoms of nutrient inadequacy, which manifest themselves immediately on the colour of the leaves and the development of the foliage, are detailed in Table 1, which may be found here.

Table 1: Macronutrients deficiency symptomps

Macronutrients	Symptoms
Nitrogen (N)	Light green of upper leaves and yellow of lower leaves
Pottasium (K)	Yellow and purple leaves with brown at leaves edge and poor flower and fruit.
Phosporus (P)	Slow growth and yellow folliage.
Magnesium (Mg)	Yellow between the leaf veins with red brown tints and early leaves fall.

During this whole period, deficiency monitoring has been carried out by the use of manual observation. Growers do routine checks on the state of the plants to see whether or not the plant's nutritional requirements are being met. Nevertheless, if the agricultural area is relatively vast, this strategy presents a challenge that must be overcome. In order to see the whole field in depth, further work is required. There have been a number of different methods developed by previous academics in order to automatically monitor and adjust the soil nutrients of crops. Calcium shortage in lettuce may be identified in greenhouses by the application of a machine vision technology that takes into account changes in the plants' morphology, colour, and temporal variations. By using this technology, calcium deficiency was successfully identified at an earlier stage in comparison to human eyesight. Optical sensor data may be used to make predictions about the production of potatoes and the presence of a sulphur deficit in other kinds of crops. Principal Component Analysis (PCA) was the method that Hengl et al. used in order to make predictions about macronutrients and micronutrients in Sub-Saharan Africa (SSA) using geographical data information.

There is no new development in the world of agriculture when it comes to machine learning; in fact, numerous different methods to machine learning have already been deployed to assist agricultural processes, control tasks, or monitoring activities. The use of deep learning, which is a subfield of machine learning, is widespread. One example is the segmentation of maize colour images for three-dimensional reconstruction. It is helpful to assess the impact on growth using the three-dimensional reconstruction. The camera is used to photograph the maize plant from six distinct angles, with each angle of view around 30 degrees apart, as well as from a top-view perspective. The identification of leaf vein patterns for three different legume species namely, white bean, red bean, and soy bean is accomplished with the use of deep learning in further research. When it comes to the construction of extensive catalogues of plant species, this identification has been helpful in reducing the amount of time spent on categorization and the involvement of human experts.

Additionally, deep learning is used extensively for the diagnosis of plant diseases, in addition to its usage in the recognition of leaf patterns. UtilizingConvolution Neural Networks (CNN) allows for the efficient identification of diseases that affect maize plants, such as Northern Leaf Blight (NLB), which is a sign of sickness. The results of the experiment shown that CNN is capable of identifying 1796 photos with an accuracy of 96.7%.

These images include 1028 images that were infected with NLB and 768 images that were not infected. With the use of a 54,306 picture dataset, Mohanty et al. were able to identify 14 crop species and 26 diseases with an accuracy rate of 99.35% on the basis of their application of Alex Net and Google Net architecture to the identification of disease or healthy state from plant leaves. Despite the fact that Hanson et al. used deep learning, CNN was utilised in this particular instance to detect leaf disease that is caused by pests. There is a 95% level of accuracy achieved by this study as the performance assessment. Ferentinos made a significant advancement in the identification of plant diseases using their expertise. A CNN technique was used in order to identify the 87,848 photos that included data covering 25 distinct plant species and 58 categories of disease and health categories. Alex Net, AlexNetOWTBn, Google Net, Overfeat, and VGG were the five CNN approaches that were considered for comparison by the researcher. According to the findings, the accuracy of VGG is the greatest, coming in at 99.48%, followed by AlexNetOWTBn with 99.44%, AlexNet with 99.06%, Overfeat with 98.96%, and Google Net with 97.27%.

Previous studies have provided a basic overview of the use of technology to identify diseases and automatically monitor the state of plants (automatic monitoring). On the other hand, monitoring for macronutrient deficiencies is constantly overlooked, despite the fact that it has a significant influence on the quality of their plants. As a result, the purpose of this study is to present a method that is based on deep learning and can identify macronutrient deficiencies in plants by using picture input data. An strategy based on deep learning is used to identify the gradation colour of leaves as a result of nutrient insufficiency. This observation serves as a monitoring procedure to prevent severe conditions.

This paper is organized in the following manner. The data collecting and analysis processes are carried out in Section 2, with the end goal of providing input for the deficiency detection algorithm, which is discussed in Section 2.2. In the third and fourth sections, respectively, the results of the experiment and the conclusion will be provided.

REVIEW OF LITERATURE

U.B.Angadi (2019) After moisture stress, one of the most important limiting factors for crop productivity is nutrient stress. The crop yield losses are estimated to an extent of 10-20% with or without-visual symptoms ("Hidden hunger"). Of the several nutrients, P, Fe, Zn, B & Mg are reported to be in short supply for plant growth and productivity globally. Especially the low level of Fe and Zn has a bearing on human nutrition also. Diagnosis and remedies are critical components of crop productivity. In view of this; we propose a web-based expert system for diagnosis of plant macro and micronutrients disorders in crops. This system aims to provide a guide to identify deficiency of nutrients in crops, i.e., disorders in leaves, stems and roots of a plant. To avoid diseases caused by deficiency, and to solve the problems, expert system is developed using the virtual diagnosis framework. Mineral Information System is a knowledge based information system, which gives detailed information on characteristics of minerals, availability in soil, role and deficiency symptoms in plant growth, prevention and management to correct the nutrition deficiency, and sources and cost of minerals. This system would be of much use to extension workers, scientists and researchers involved in mineral aspects of research. The development methodology adopted and the current status of the system for diagnosis of deficiency in crops is discussed in this paper. The expert system infers the knowledge on diagnosis of nutritional deficiency diseases in crops, which are specific to each nutrient element. The roles, management, symptoms, quantification, critical limits etc. are parameters which will be used to identify the micronutrient deficiencies in the diseased crops. This will help the ultimate user to find remedies to correct the deficient plants by exerting a control on specific parameters. The experience acquired in the development of this expert system as well as its future research potential is also presented.

REVIEW OF LITERATURE

Anu Jose (2021) The agriculture industry is the most important source of revenue for the Indian economy. According to the most current collected statistics, it is responsible for 17.9% of the gross domestic product in this sector. Technology improvements in the agricultural sector have made it possible to produce a greater quantity of agricultural commodities while simultaneously reducing the amount of time, money, and labour that is wasted. It is essential to recognise the significance of nutrients in the growth of plants. Plant development and agricultural production are both negatively impacted when there is a lack of nutrients in the soil. Through the examination of the characteristics of tomato leaves, we want to build a model of an artificial neural network to identify and classify nutritional deficiencies. Farmers will find this beneficial for controlling the amount of nutrients that are supplied to the plant. It is possible to determine whether or not a certain nutrient is lacking in the soil by observing the appearance of a leaf. Taking a glance at the leaves of a plant is one of the most popular techniques to determine whether or not the plant is deficient in a certain plant nutrient. By making comparisons between the various segmentation techniques, such as hue-based and threshold-based schemes, we are able to see how the performance of the recommended system is affected by these strategies.The impact that a number of different activation functions have on the ANN is another aspect that is investigated in this work. The data make it abundantly evident that the technique that was presented was effective in identifying and categorising situations with nutritional deficiencies.

ArieQurania (2020) An inquiry is being conducted with the purpose of determining whether or not there is a scarcity of two nutrients at the same time. In this particular instance, the elements in issue are nitrogen (N) and phosphorus (P), as well as potassium (K) and phosphorus (P). In the context of this discussion, we are referring to a deficiency in the nutrients nitrogen and phosphorus, in addition to potassium and phosphorus. In order to create a method for identifying nutritional differential in cucumbers, researchers make use of RGB colour features, Sobel edge detection for leaf shape recognition, and Artificial Neural Networks (ANN) for identification. Within the dataset of plant pictures, there are 450 photographs that are used for training, and there are 150 photographs that are utilised for testing. There are three tests that are carried out in order to assess whether or not backpropagation neural networks are effective in identifying deficiencies in plant nutrients. The researchers begin by demonstrating that they are able to achieve an accuracy of 65.36 percent by employing RGB colour extraction and Sobel edge detection. When using RGB colour extraction, its accuracy is 70.25 percent, which brings us to our second point. 59.52% is the accuracy rate that is achieved when it comes to the detection of Sobel edges.

WilfriedDibi (2018) There are still technical and budgetary obstacles to overcome before proximal in-field sensing of the bulk of agricultural nutrients can be achieved. The Okra plant is the subject of this investigation, which makes use of effective multi-excitation fluorescence and reflectance wavelengths in order to achieve this objective. For the purpose of collecting data on visible-near infrared (400 - 1000 nm) reflectance and multi-fluorescence at the leaf size in a chemically fertilised field, an Arduino-based LED driver clip and a USB spectrometer were used. To determine the levels of nitrogen, phosphorus, potassium, and calcium in the leaf samples, tested methodologies were used. The IRIV-PLS regression method was used once the spectrum pretreatments were completed in order to calibrate the average pod yield as well as the macronutrient composition of the leaves. Single informative wavelength bands in reflectance, red, and far-red fluorescences were used in the construction of models for crop production and the content of macronutrients.

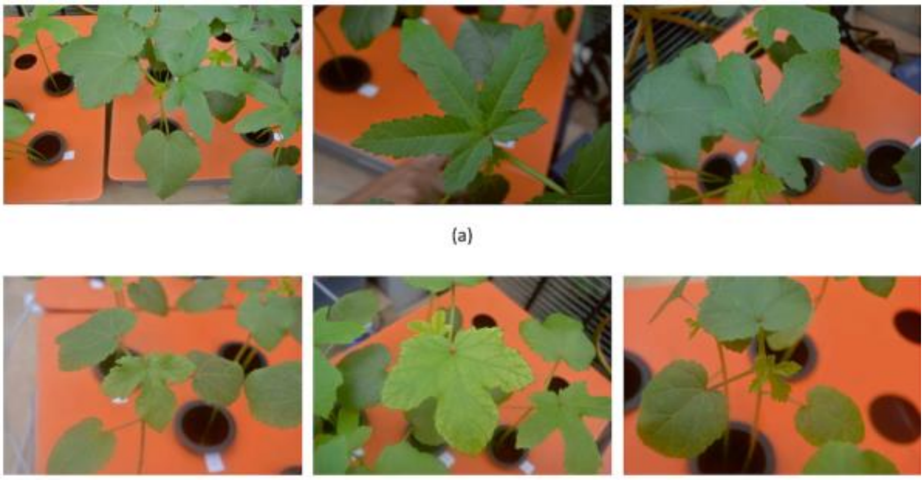
Majeeduddin Solangi (2022) According to one point of view, okra is a vegetable crop that is very vulnerable to problems such as nutritional inadequacies and excessive fertilisation. On the other hand, there is a dearth of studies about the ways in which essential nutrients may influence okra. In 2009 and 2010, researchers were able to effectively investigate the impact of micronutrients and macronutrients being combined on the physiological characteristics of okra. The researchers used three distinct types of okra, namely Bemisal, SabzPari, and Reshum. Additionally, they utilised seven distinct levels of nitrogen, phosphorus, and potassium (NPK) (0-0, 25-25-25, 50-25-25, 75-37-37, 100-50-50, 125-62-62, and 150-75-75 kg ha-1) and six distinct levels of zinc (Zn-B) (0-0, 10-1.5, 10-2.0, 15-1.5, 15-2.0, 20-1.5, and 20-2.0 kg ha-1). For the purpose of the experiment, a Randomised Complete Block Design (Factorial) was used, and there were three individual replications.

OBJECTIVES

1. To study micro and macro nutrient deficiency detection
2. To study machine learning for okra (*Abelmoschus Esculentus L*) leaf micro and macro nutrient deficiency detection

MATERIALS AND METHODS

Plant image data: The data that was used for this paper was okra, which is referred to as (*Abelmoschus Esculentus)* in the scientific community. Okra, which is considered to be one of the medicinal herbs, may be beneficial to patients who suffer from diabetes or excessive cholesterol. Okra that is in excellent health has leaves that are dark green and around 10 centimetres wide, while okra that is in bad health has leaves that are approximately 3 centimetres wide and have an appearance that is similar to a light yellowish green (See Figure 1). It is not simple to visually differentiate the early stages of leaf colour modification, which makes early detection and treatment extremely problematic. This is one of the challenges that arises when attempting to diagnose deficiencies.



(a)

(b)

Figure 1: Images of a healthy plant (a) and a sick plant (b) as a sample

The plantation laboratory makes use of standard-spec phone cameras with a resolution of 12 megapixels in order to conduct data collection on plants. In order to artificially expand the size of the dataset via manipulations, image augmentation is used once the picture data has been reduced to a resolution of 299 × 299 pixels. In order to do photo augmentation, we make use of the picture Data Generator class that is given by Keras. The transformations that are performed include rotation, shifts in height and width, shear, zooming, and horizontal flipping. This picture data is used as inputs for the convolutional neural network approach for processing images.

Nutrient deficit detection using a convolutional neural network

The Convolutional Neural Network (CNN) is a technology that is used in deep learning for the purpose of extracting spatial information from photographs. Previous researchers have attempted to increase CNN's effectiveness in image identification by including a variety of designs into the network throughout its development. The Inception Resnet method was used in this work for the purpose of determining whether or not plant photographs included any nutritional deficits. Data is collected by utilising the camera on a smartphone to snap pictures of plants, both healthy and ill, and then using those pictures as input. For the purpose of determining whether plants are healthy or unwell depending on the data that is supplied, the CNN method is used (see Figure 2).

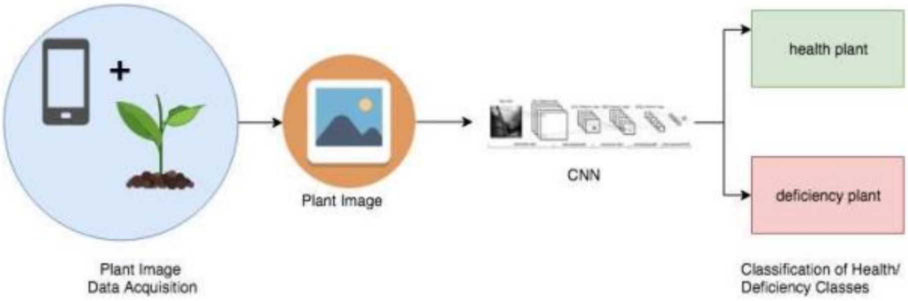


Figure 2: Research methodology

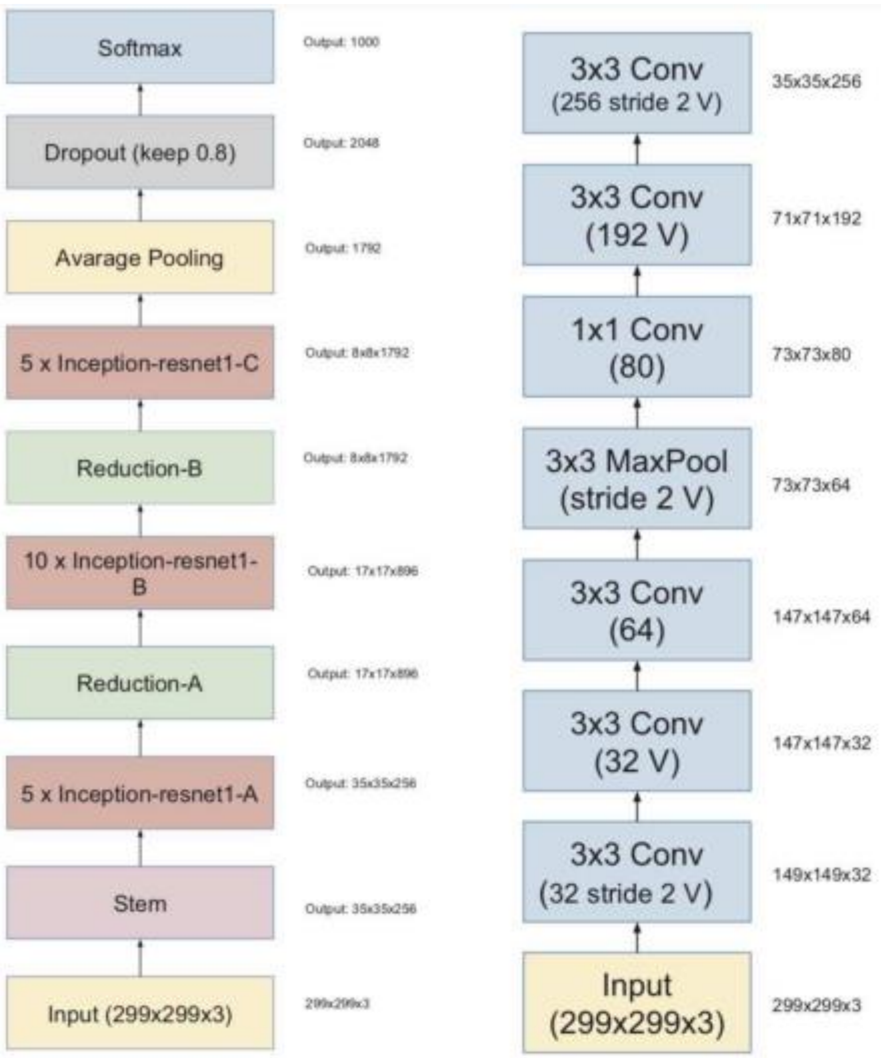


Figure 3: Inception ResNet-v2 architecture

This work makes use of Inception ResNet-v2, which contains stem, Inception Resnet1, reduction, and fully linked classes. Figure 3 depicts the architecture of these classes. The classifications are deficient and normal respectively. ResNet-v2 is an upgraded version of Inception-v4, with the objective of lowering the amount of computing that is required by the use of 1 x 1 convolutions that does not include an activation function.

RESULT

There are two distinct phases that make up the training process: the transfer learning phase and the fine tuning phase for the training. Transfer learning is something that can be implemented by using our very own image-class-based softmax layer in conjunction with weights that we have learned from the ImageNet dataset. Following the completion of the first 249 levels, the network will be able to undergo training without any interruptions. If both approaches are used, the training will eventually attain a condition that is stable and constant. The lack of a frozen layer, which may potentially destroy the learned weights in the convolutional base, results in large gradient updates being generated by randomly initialised weights throughout the process.

One hundred and forty-seven pieces of testing data and 184 pieces of training data are available. There are a total of 231 bits of data. The first training setup, which makes use of the Adam optimizer and a learning rate of 0.0001 over a period of one hundred epochs, produces decent results (with an accuracy of more than 95%). However, when it comes to testing, the accuracy is all over the place, with scores ranging from 56% to 63% at an absolute maximum. In the subsequent iteration, we will make an effort to reduce the number of epochs while concurrently increasing the learning rate from 0.0001 to 0.001. The result is just as unexpected, with the accuracy of the training ranging from 83 percent to one hundred percent, but the accuracy of the testing only reaches somewhere between 56 and twelve percent.

In conclusion, we make an effort to implement a two-stage training procedure, with each stage utilising fifty epochs. The first stage involves training the network's final layers that are completely connected, with a learning rate of 0.001. The second stage involves fine-tuning the network by freezing its first 249 layers and training the remaining layers. This approach not only produces outcomes that are much better but also provide results that are more constant and stable. Following the completion of the first training phase, the accuracy is close to 96% after five trials, although the accuracy during testing is about equivalent to 86%. The comparative performance is shown in Figure 4, which is based on the parameter information that are presented in Table 2.

Figure 4: Evaluation of the fine-tuning method and transfer learning in terms of training and testing

Table 2: Experimental process parameter

Experiment	Method	Learning rate	Epoch
Exp 1	Transfer Learning	0.0001	100
Exp 2	Transfer Learning	0.001	50
Exp 3	Fine Tuning	0.001	50

Leaf chlorophyll content SPAD values

Taking a glance at the chlorophyll concentration in the leaves of a plant may provide insight into the proliferation of chloroplasts, the amount of nitrogen present, and the overall health of the plant. For the purpose of evaluating the chlorophyll content of plants, the soil-plant analytical development (SPAD) metre is an instrument that is simple, rapid, and does not cause any damage whatsoever. When the SPAD value is greater, it shows that the plant is healthy and has high leaf nitrogen content. The readings for the SPAD are three-digit (unitless). We started collecting SPAD data four weeks after planting the crop, which was when the leaves of the crop had reached the point where they were mature enough to yield SPAD readings that were accurate. In order to ascertain the quantity of chlorophyll present in the okra leaves, SPAD measurements were made on a weekly basis after that (up to week 7), and those measurements were repeated after harvest (Figure 5). In spite of the fact that SPAD levels were subject to significant fluctuations during the course of the study, there were discernible differences in treatment at five and six weeks after sowing. A substantial increase in plant vigour and leaf chlorophyll content was seen in the plants that were grown in the TS and TB pots when compared to the control pots. This was shown by the considerably higher average SPAD values, which were 1.29 and 1.33 times higher, respectively, with a p-value of less than 0.05. Similar findings were reported by Romanowska-Duda et al., who demonstrated that the use of cyanobacteria for biofertilization increased the quantity of chlorophyll present in the leaves, as well as the productivity of photosynthetic processes and the production of enzymes that are necessary for the growth of plants.

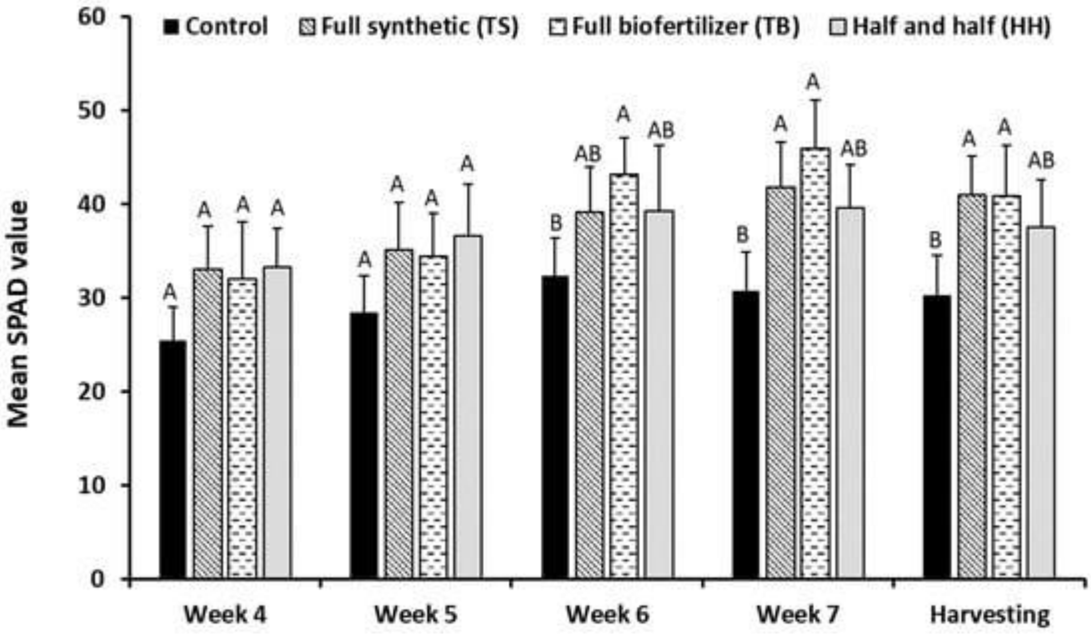


Figure 5: SPAD values of okra varied during its developmental phases. Similar capital letters do not signify a significant difference at a significance level of $p < 0.10$.

CONCLUSION

Through the use of transfer learning, we established the Inception ResNet-v2 network. A dataset known as ImageNet was used in order to train the network. After that, the model is educated once again with the help of photographs of okra plants. The learning rate and the number of epochs are two examples of hyper parameters that may be altered in order to perform certain tests. In the beginning, the performance of the training does not provide favourable results. We have reason to believe that this is due to the fact that the data from ImageNet and the okra dataset are quite unlike to one another. For the purpose of achieving a more favourable outcome, some early layers are frozen during the fine-tuning process. It has been determined that the best results for training are 96%, while the best results for testing are 86%. Three different training regimens have been explored. The approach of fine adjustment produced the best outcomes. The use of more straightforward architectures, such as Mobilenet, which makes it simple to deploy on the Mobile platform, contributes to the improvement of this work.

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