Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 4, 1483-1495
2024
Publisher: Learning Gate
DOI: 10.55214/25768484.v8i4.1522

CNN driven nutrient deficiency detection in plants using real-world leaf images

Anish Sathyan[1*], Palanisamy P[2]
[1]CIG, CDAC, Trivandrum, Kerala, India; satyan@cdac.in (A.S.)
[2]ECE Department, NIT Trichy, India; palan@nitt.edu (P.P.)

Abstract: In agriculture, our farmers currently lack efficient methods to classify and identify plant nutrient deficiencies or diseases, leading to ineffective remedial measures. However, the potential for early detection of plant nutrient deficiencies using colour gradients or leaf patterns, coupled with the advancements in Image Processing, Deep Learning (DL), and Artificial Intelligence (AI), offers a promising future. This paper presents deep learning-based methods to segregate nutrient deficiencies using leaf images, a potential game-changer for the industry. Our research has the potential to revolutionize plant nutrition management, inspiring a new wave of efficient and effective practices in agriculture. We analyzed the International Plant Nutrition Institute (IPNI) dataset and applied an image augmentation mechanism to enhance the training process with the available dataset. By utilizing Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and learning algorithms, we minimised loss and improved accuracy. The model, incorporating over 1.5 million parameters, has shown promising results in predicting deficiencies accurately. We propose an SGD-based training mechanism to balance localization and classification tasks, a step towards a more efficient and effective approach to plant nutrition management.
Keywords: *ANN, Classification, CNN, Deep learning, Nutrient deficiency, Plant leaf, Prediction,*

1. Introduction

Nutrient deficiency adversely affects the plant's uptake and yield; the crop's metabolic activities change, resulting in a reduced life span. In this scenario, real-time plant nutrient assessment at a regular interval of the plant's life cycle and timely applications of fertilizers to optimize growth and yield are highly imperative.

In reIn recent years, we have seen an ever-growing demand for automation in agriculture. The latest practice adopted worldwide is precision farming. Conventional soil sampling & chemical analysis are costly and time-consuming as they require complex processes for pre-treatment and expensive instruments for samples to be quantitatively analyzed. The high cost and long delays of such methods have limited their use in variable-rate fertility management systems. With the help of a proper decision support system, the plants can be cultivated in an ideal condition, ensuring the plant never suffers from over nutrients or deficiency, thus enhancing quality, optimum growth, and high yield. Nutrients are essential in correct proportion for the ideal growth and uptake of the plant as well as to ensure optimum yield. The necessary nutrients for the plants could be classified into two groups viz macro nutrients and micro nutrients. Nitrogen, Phosphorous, Potassium, Calcium and Magnesium come under macronutrients. Whereas micro nutrients consist of Boron, Molybdenum, Copper, Sulfur, Chloride and Zin. Chlorosis of the intermediary leaves is the typical nitrogen deficiency symptom which generates visible patterns in plant leaves. In case of severe nitrogen deficiency, the older leaves become yellow in colour due to stronger chlorosis. The most important thing in agriculture cultivation are early detection

* Correspondence: satyan@cdac.in

and timely action. The deficiencies of Nitrogen, Potassium and Calcium will get established early in plant leaves and fruits. These nutrients directly affect the growth of the plant and the quality of the fruit.

An inadequate supply of nutrients adversely affects the normal growth and development of the plant, which results in metabolic disorders and reduced yield. In this scenario, the plant nutrient deficiency assessment is highly imperative for sustainable growth and high yield. Visual pattern and colour analysis are the most commonly adopted practice in crop cultivation. The occurrence of nitrogen deficiency is characterised by slight loss of green hue of intermediary leaves in the main stem [1]. The typical nitrogen deficiency symptom is the chlorosis of the intermediary leaves. After the process of nutrient redistribution [2] in plants, initiates the chlorosis in old leaves and become visible. To meet the requirements of newly formed tissues, nutrients shaped into amino acids will be released. This is due to the process of proteolysis of the Rubisco enzyme and other proteins [3]. With unadorned deficiency of Nitrogen, the chlorosis in intermediary leaves become stronger and the older leaves shows a yellowing. The spread of technology-based precision agriculture, and inclusion of modern advanced technologies like Artificial Intelligence and Deep Learning supports the farmers to categorize nutrient deficiency at a very early stage itself which ensures judicious use of fertilizers and pesticides.

Early detection and timely action are the most important things in agriculture cultivation. The spread of technology-based precision agriculture and the inclusion of modern advanced technologies like Artificial Intelligence and Deep Learning support farmers to categorize nutrient deficiencies at a very early stage, ensuring judicious use of fertilizers and pesticides. This paper is based on research work carried out over the IPNI dataset of Nitrogen-deficient plant leaf images [**4**]. To strengthen the dataset for the training of leaf images, image augmentation algorithms were developed and implemented. This work proposes a system that identifies nitrogen deficiency using a machine learning technique. Image segmentation, clustering, Convolutional Neural Network (CNN), and Pooling algorithms are developed as part of the learning model. Transfer learning techniques, along with CNN, are used to reduce training time. Thus, the developed sophisticated system delivers an accuracy of 95.57% or higher with a loss value of 1.48%.

2. Related Works

The latest advancements in Image Processing, Artificial Intelligence (AI) and Deep Learning (DL) has multifaceted use cases in various fields like industry, surveillance, agriculture, medicine etc. Human like intelligence could be established for machines using DL & AL algorithms, using which the devices could replicate human vision paradigm to detect, identify and recognize patterns from visual images. For the processing of images, speech and video, the usage of deep convolutional nets could be employed for better and optimum results as described by LeCun et al. [6]. A detailed study of more than 40 DL models was carried out by Kamilaris et al. for various agriculture applications the Long Short-Term Memory (LSTM) model, the widely used CNN architecture, Scalable Vector Machines (VSM), the Differential Recurrent Neural Network (DRNN) model, and the like [7]. Deep Learning models will play major role in leaf classification, plant identification, crop management, farming infrastructure management etc. as explained in [8]. Recent research on agricultural image processing advances in the areas like plant disease prediction and nutrient deficiency identification using Artificial Intelligence and convolutional Neural Network [9].

The pathological analysis of plants can also be carried out using neural networks and deeplearning techniques. In order to identify leaf diseases, Ferentinos carried out research with several CNN-based models. For his research work, a database of 87,848 images were used from 29 crops he achieved a success rate of 94.50%, as mentioned in [10]. Another research paper proposed an advanced and reliable mechanism to identify diseases and pest attacks in plants of tomato. Alvaro Fuentes et al. [11] used a combination of three different detectors. They used Region-based Fully Convolutional Network (R-FCN), Faster Region-based Convolutional Neural Network (Faster R-CNN) and Single Shot Multibox Detector (SSD). Visual Geometry Group (VGG-16), ResNet-152 and ResNet-50 are the different models used for comparing and validating the results. The usage of ANN algorithms for plant leaf image analysis is explained in Izabela A. Samborska et al. [12]. A Convolutional Neural Network was developed for the purpose of analyzing 22 species of crops and weeds with 10,413 images by Mads Dyrmann et al [13]. An accuracy of 86.2% was achieved with the above images by applying CNN. Barbedo[14] suggested different factors for the identification and detection of plant diseases, based on the visual images and patterns. Plant nitrogen status during side-dressing operations was estimated by Noh et al. [15]. The reflections of Maize leaf canopy in different color regions was evaluated for identifying the maize leaf nitrogen deficiency using ANN model. They have considered the convention of Near Infrared (NIR) range, green and red colors patterns in the resulted images. The images captured by mobile devices are used by Artzai Picon et al. [16], to identify and classify the plant diseases using Neural Network (NN) model.

Estimation of nitrogen status for crops under controlled cultivation was done by Anna Chlingaryan et al. [17]. Various Machine Learning algorithms were utilized to complete the study. LSTM with Gaussian Processes, back-propagation Neural Network, Complex CNN architecture, Least Squares Vector Machine and M5-Prime Regression Trees were used to compare the performance analysis. R. K. Gautam et al. [18], used ANN and aerial images to predict and analyse the corn plant leaf nitrogen deficiency in natural scenario without causing destruction to the plant. a root mean square error of prediction (RMSEP) of 6.6% and 88.8% minimum prediction accuracy (MPA) were achieved in their study. Color normalization and image segmentation methods to fuse the deep learning multilayer perceptron (DL-MLP) was introduced by S. B. Sulistyo et al. [19]. Genetic Algorithms were used to format and normalize the color images to evaluate the nitrogen deficiency. In-order to extract and analyze the RGB color layers they have used number of standard Multi-Layer Perceptrons. This infact ensures a stable and robust prediction model for predicting the nitrogen deficiency. Bayes' theorem based model for estimating leaf nitrogen content using multi spectral imaging was attempted by C.D. Jones et al. [20]. This method was claiming a coefficient of determination of 0.82 and root mean square difference (RMSD) nearing to 4.9%. A model developed by Srdjan Sladojevic et al. [21] could differentiate and identify 13 different plant diseases. He used a DL based Convolution Neural Network model called Caffe for the research purpose and claims precision of between 91% and 98% for different group of plant diseases.

Another method recommended by S. B. Sulistyo et al. in [22] to identify the nutrient deficiency in wheat leaves is using advanced vision sensing mechanism using Artificial Intelligence. The colour variation dute to varying sunlight intensity was nullified by using Genetic Algorithms(GA) and Deep Spare Extreme Learning Machines (DSELM) . The above methods results very lower Mean Absolute Percentage Error (MAPE). Another Genetic algorithm based method proposed by Guili Xu et al. [23] was used to identify the potassium and nitrogen deficiency in tomatoes. The color and texture features of tomato leaves were extracted to get an accuracy of 82.5%. To estimate the leaf area of tomato growths using ANN based model was proposed in Z. Hanxu et al. in [24]. This helps to analyse the plant growth in different climatic conditions and with varying external parameters. Support Vector Machine (SVM) along with near-infrared spectrogram helps to develop an improved classifier to differentiate Normal Tomatoes from anti-nematode tomatoes [25].

A low cost, accurate and simple method for identifying the nitrogen deficiency was introduced by S. B. Sulistyo et al. [26]. The input images are evaluated for twelve RGB color features using committee machines along with a Neural Network (NN) algorithm. Their main interest was to distinguish wheat leaves from the group using NN techniques. In wheat leaves, the nitrogen deficiency was identified by using Genetic Algorithms (GA) along with committee machines. In another study by the above authors, they used different NN methods to extract the basic colors to identify the nitrogen deficiency. They also compared several methods for performance evaluation [27]. They achieved better results with committee machines with MSE of 0.016 and a MAPE of 3.15%.

In the above mentioned papers, serious effort was put forth by different researches world around to identify, analyse and predict different plant diseases and deficiency of nutrients from leaf textures and

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 4: 1483-1495, 2024
DOI: 10.55214/25768484.v8i4.1522

leaf color images. Most of the studies are based on images taken under ideal conditions. Little effort is made to capture and analyse the real-world leaf images. Also, it was found that deep neural network models are used less to extract leaf features. This paper mainly concentrates on the application of a Deep Neural network along with CNN to extract different leaf parameters from real-world images in a non-intrusive manner. Here, we are using the nutrient-deficient dataset provided by the International Plant Nutrition Institute (IPNI). Developed Image augmentation mechanisms to increase the number of training and test data set. Also paid attention to evaluate the performance criteria of the study, so that it could give more accurate and robust results.

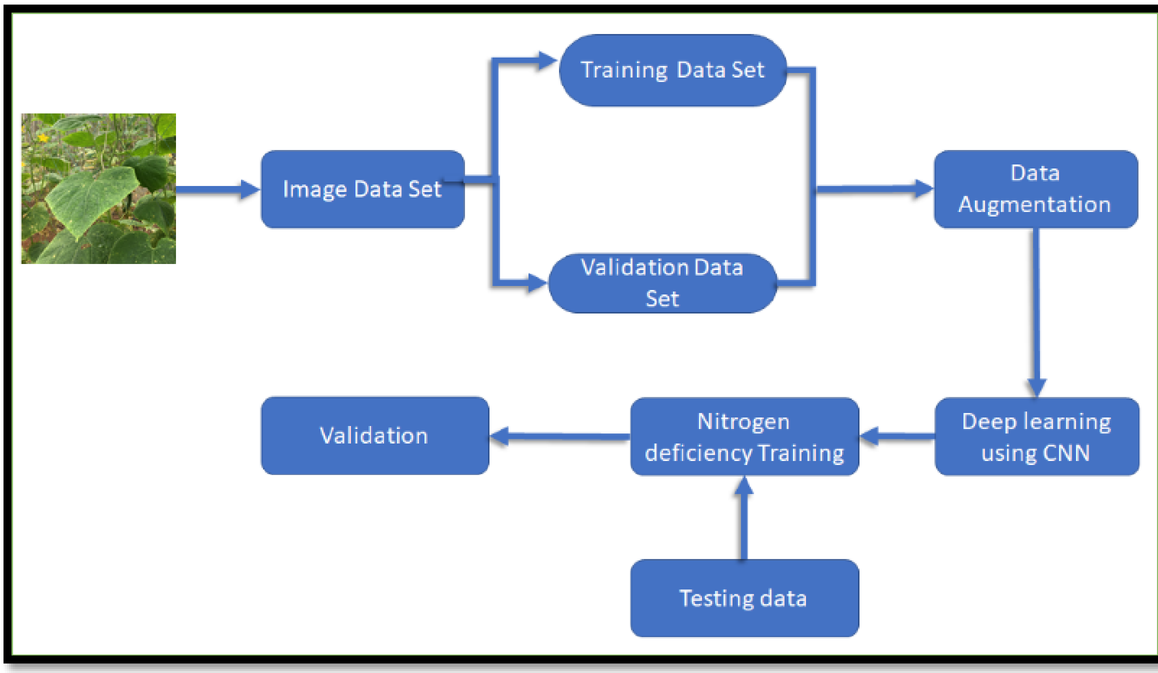

Figure 1.
CNN prediction methodology.

The training activity was carried out with Autoencoder and Inception-ResNet v2 to progress further in the research, promising better identification, analysis, and prediction. The CNN layered structure was designed to provide better and increased accuracy of background extraction, faster region of interest identification, and sophisticated prediction results using AI mechanisms. The methodology is described in Fig.1. Unlike previous papers and studies, nondestructive mechanisms are used to capture and analyze leaf images. So, any farmer with a camera could capture and utilize the services to identify and classify nutrient deficiencies in the simplest way. This helps farmers avail themselves of timely help at different stages of plant growth without consulting any experienced plant pathologists. An improved version of Autoencoder and Inception-ResNet v2 was developed to enhance the efficiency of image identification and prediction mechanisms. The results were discussed in detail in this paper's results & discussion section. This method of predicting nutrient deficiency could improve farming practices and promote the judicious use of fertilizers and pesticides, thereby saving our planet.

Worldwide lot of research is going on in the field of agriculture. Attempts are made to identify and classify various diseases affecting the plant leaves using digital image processing. An image-processing-based algorithm to automatically identify plant disease visual symptoms, by Camargoa, & J.S. Smith b [5], static image capturing, and no attempt was made to classify the disease accordingly are the limitations. A Colour Transform Based Approach for Disease Spot Detection on Plant Leaf By Piyush

Chaudhary et.al [28]. An algorithm for disease spot segmentation using image processing techniques in plant leaf is implemented. This method uses the Otsu threshold for disease spot detection, and unnecessary spots are removed using a median filter. Overview of image processing approach for nutrient deficiencies detection in Elaeis Guineensis By Muhammed Ashraf and Shah Rizam [29]. Oil palm leaves are used for the study using static images of the leaves are taken from a fixed distance. Symptoms of Nutrient Deficiencies on Cucumbers By V. V.Carmona, L. C. Costa and A. B. Cecílio Filho[1]. Their study aimed to describe and photograph the initial symptoms and the development of nutritional deficiencies in cucumbers and determine the concentration of the omitted macronutrient in leaves, on which symptoms of deficiency were observed.

In India, plant leaf image analysis is a hot research topic. However, most of the works focus on image identification, plant classification, and common disease identification through leaf analysis. The following are some of the works carried out in India in this regard: Classification of diseased plant leaves using neural network algorithms by K. Muthukannan et al. [30]. I attempted the classification of diseased plant leaves using Feed Forward Neural Network (FFNN), Learning Vector Quantization (LVQ), and Radial Basis Function Networks (RBF) by processing the shape and texture features from the affected leaf image. A Study of Image Processing in Agriculture for Detecting Plant Diseases [31] by Prof. Rekha Chahar et al. This paper compares various image classification algorithms like ANN, the Clustering method, and the Support Vector Machine method. Image recognition-based crop disease identification system: a survey by Nitin S. Tijare et al. sl[32]. A comparative literature review was done on detecting disease by extracting color features, detecting disease by extracting shape features, and detecting disease by extracting texture features.

3. Proposed Method

The Deep Learning algorithm developed for identifying nitrogen-deficient leaf images from normal images consists of the following steps, as depicted in Figure 2.

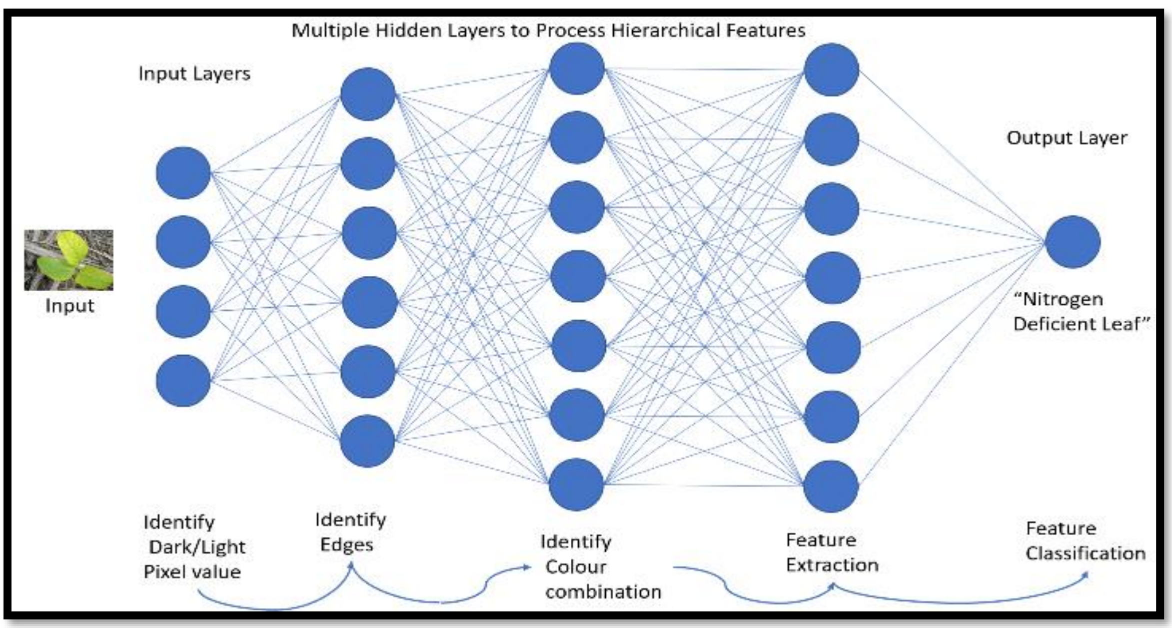

Figure 2.
Proposed system flow diagram.

ISSN: 2576-8484
Vol. 8, No. 4: 1483-1495, 2024
DOI: 10.55214/25768484.v8i4.1522

To make the model testing and training faster and realistic, resizing and make the picture size uniform is performed. This resizing will preserve the information content in the image. Convolution Neural Network (CNN) have weights, biases and outputs through a non-linear activation. The system design flow diagram is depicts in Figure 3 & Figure 4.

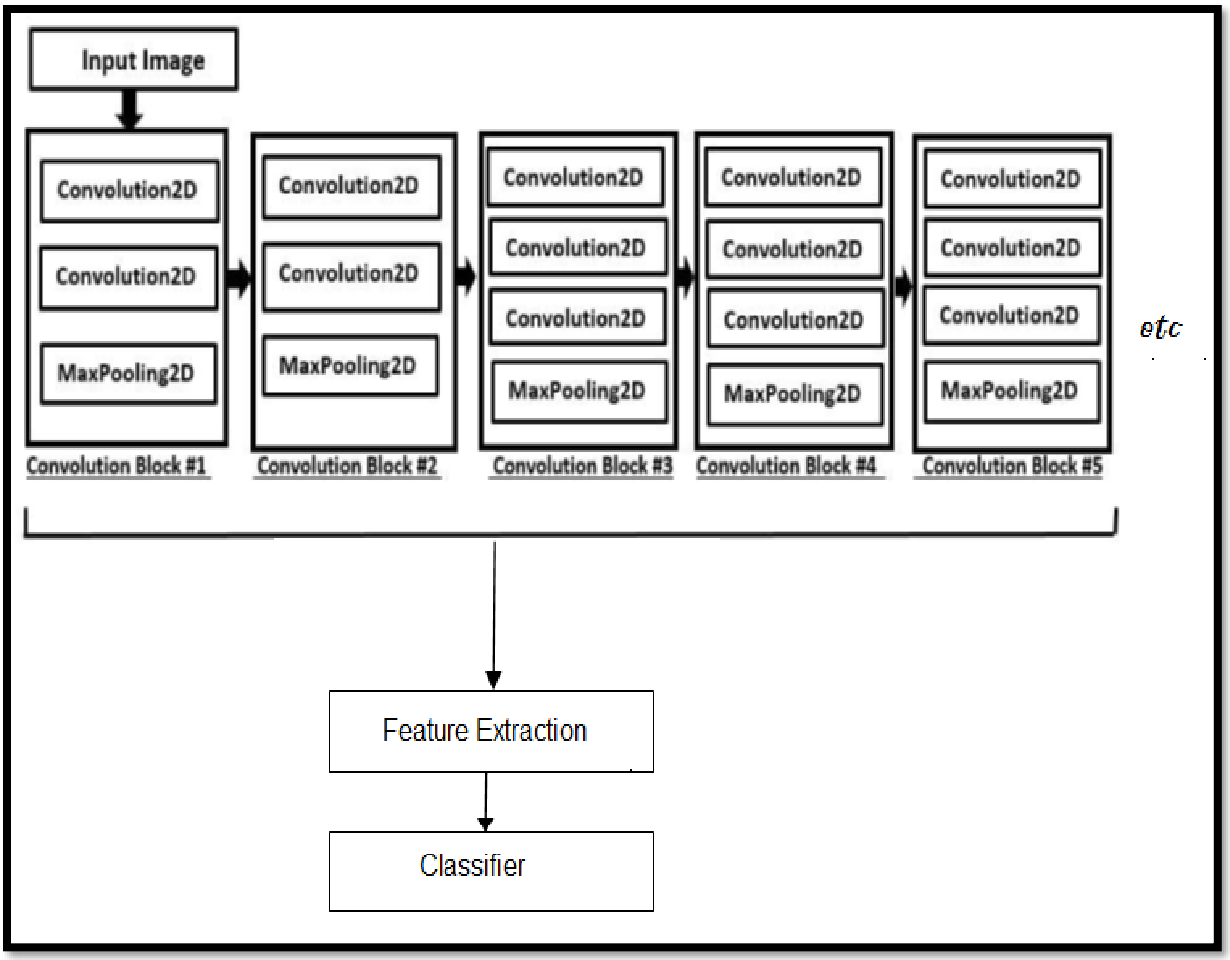

Figure 3.
Proposed system flow diagram.

For image analysis, the number of layers will be huge if we use normal neural networks in the place of CNN[11]. For processing, an image will be considered as a volume with height, width and depth. The neurons in CNN will be arranged in volumetric fashion. Max pooling layers are placed between the convolution layers. The size of the image across layers will get reduced by sampling. The maximum value will be selected to perform the sampling. The regularisation in pooling also helps to avoid overfitting.

ISSN: 2576-8484
Vol. 8, No. 4: 1483-1495, 2024
DOI: 10.55214/25768484.v8i4.1522

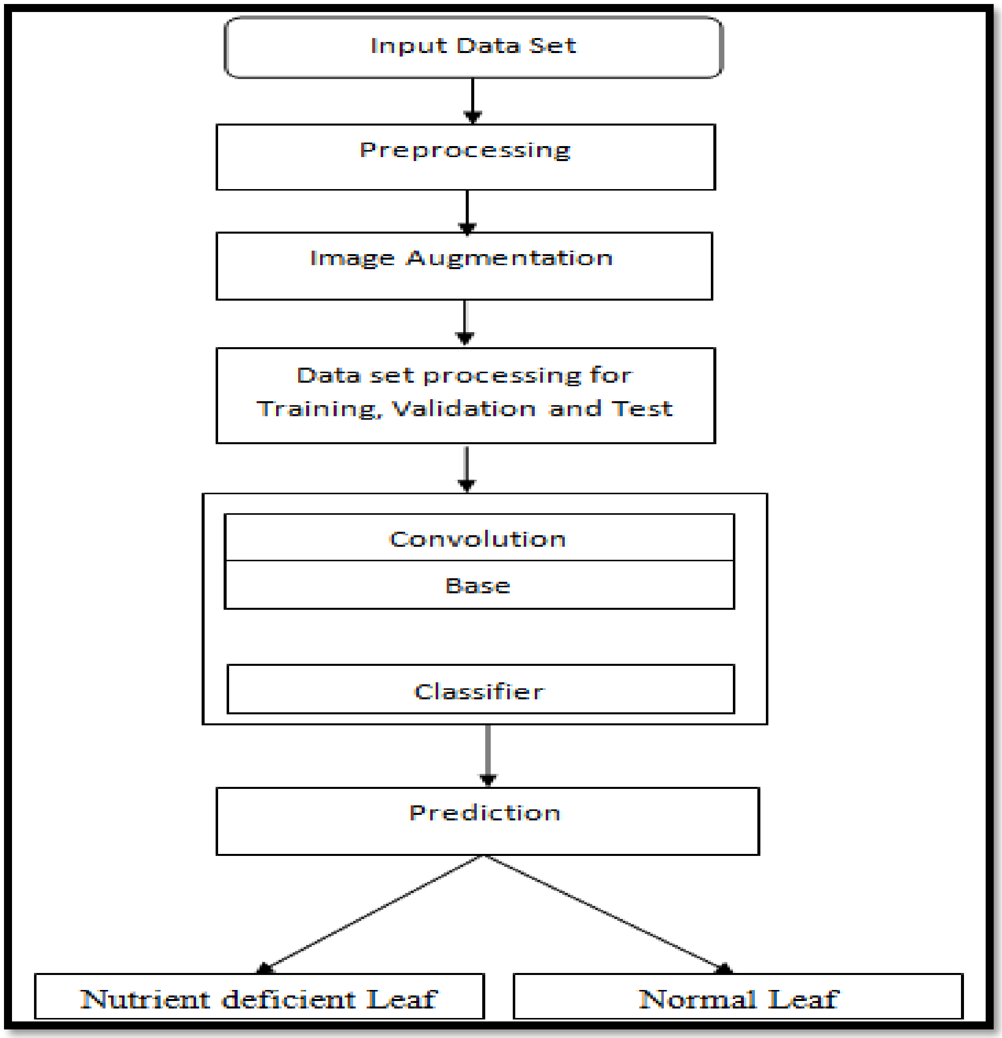

Figure 4.
Proposed system flow diagram.

Hyper parameters are determined outside the learning algorithm. Binary cross entropy as loss function calculates the performance of the classification model using the below equation.

$$Loss = -\frac{1}{Output\ Size} \sum_{i=1}^{output\ size} yi \, . \, log\, yi' + (1 - yi) \, . \, log(1 - yi')$$

Where, the ith scalar model value is represented by y_i' and ith target value by y_i.

The model could be realised with a direct acrylic graph, describing how the functions are composed together. The output function will be a weighted sum of the different layer outputs. Conventional CNN algorithm entails of three layers: Convolutional Layer, Pooling Layer and Connected layer. The computation intensive layer is convolutional layer, whereas the pooling layer reduces the size of data between the convolution layers without loading the information content. The connected layer is the last layer, which predicts the labels of input data. The applied convolution function, transfers the data from one layer to the other through multiple channels called tensor.

4. Model & Methods

The complete practice for the development of an ideal model for the analysis and classification of the nitrogen-deficient leaf images from the rest of the images is using a deep Convolutional Neural Network (CNN). An authentic dataset is the primary thing required for training and further for evaluation. For the analysis purpose, collected the dataset from IPNI, USA. They have formulated this database from the images collected through various agencies, world-wide. For distinguishing the healthy leaves from the Nitrogen-deficient leaves, a separate folder structure was followed. Image augmentation was used to enrich the available dataset. As the dataset is big enough in number of images, the model get trained easily to distinguish the nitrogen deficient leaves from the normal leaves. The Fig. 5 shows the learning curve after a sequence of continues training.

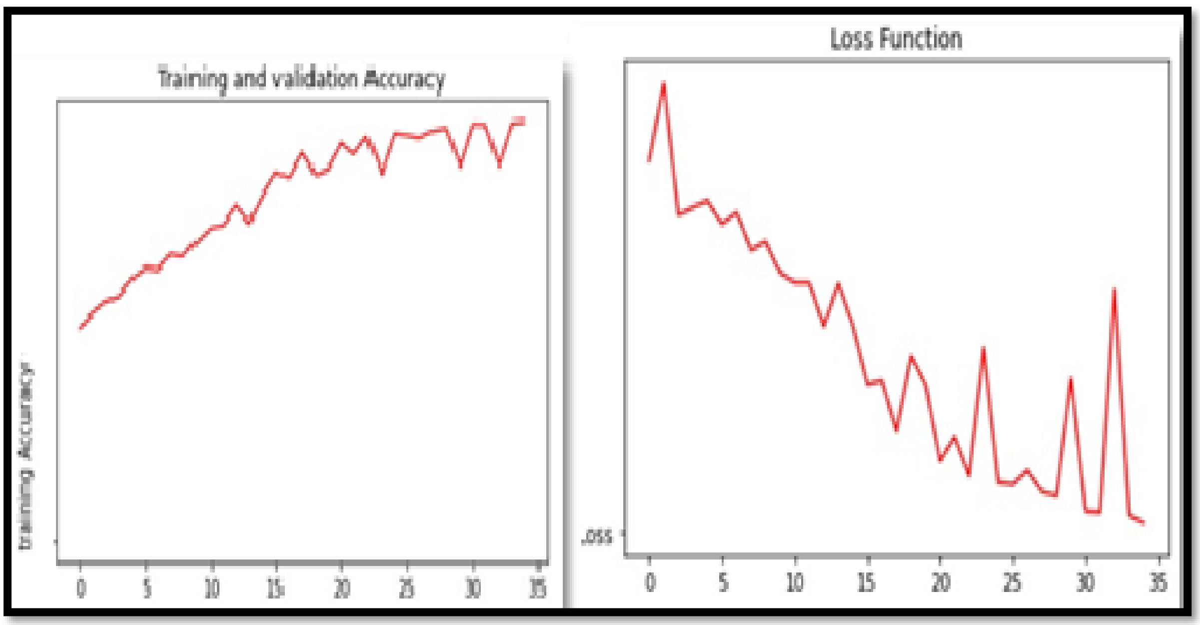

Figure 5.
Training accuracy & loss curve.

As the training get strengthens epoch after epoch, the loss function value starts declining to minimum. The feed forward neural network for the identification of nitrogen deficiency in plant leaves approximates some function f*. For a classifier, *y= f*(x;€)* and learns the value of the parameters € that results in the best function approximation. During the neural network training, we drive f(x) to match *f*(x)*. At different training points, the training data provides noisy, approximate examples of *f*(x)* evaluated at different training points. For each input value accompanied by a label *y = f*(x)*. After each iteration with the input value x, it produces an output value close to y.

For realizing an effective and accurate image classification algorithm, deep Convolutional Neural Network based model was developed. There exist various libraries available for this purpose. For the development and deployment of deep learning algorithm, an open source library so-called Tensor Flow was used. Tensor Flow uses computational graphs for numerical calculations and for data flow. The graph had nodes that represents numerical computations and the graph edges represents multidimensional data arrays.

The image data path needs to be set for the first time. After setting the path for the nitrogen deficient images and for the normal images, a group of 16 images will be plotted using plot.*show()* on random basis. Fig6. Depicts a random selection of the dataset used for training.

Figure 6.
Training image dataset.

Deep learning model is realised with the *keras* framework. The user-friendly APIs in *keras* helps to prototype the deep-learning models.. The summary of the model used in the classification approach is represented by Fig7.

The developed deep learning engine is powered by Stochastic Gradient Descent (SGD) which is an extension of the Gradient Descent Algorithm. The gradient is an expectation in SGD. Using small set of samples, this expectation could be approximately estimated. On each step of the algorithm, samples a small batch of examples.

B={*x(1)*, *x(2)*, ... *x(m)*}

drawn uniformly from the training set. Where m : represents the size of the batch. The estimation of the gradient is formed as

$$g = \frac{1}{m'} \nabla_\theta \sum_{i_-}^{m'} L\left(x^{(1)}, y^{(1)}, \theta\right)$$

Image data generator is used for generating and auto-labelling the available images both in training and validation datasets. Before applying the data generators, the images are transformed or normalized. Here, we have followed the simple rescaling method. For the data generator, flow_from_directory() is used. The same is the case with the validation data generator. As seen in Fig.4, here we used a five-stage Convolution2D operation followed by the max pooling. The number of filters is designed to give optimum performance. Here, we have increased the number of filters as the image size reduces. In the first layer, the fed images shall be reshaped to 300 x 300 x 3 to match the data generator's data size. Sigmoid activation is used at the output layer to select between Nitrogen-deficient leaves and healthy leaves.

```
model.summary()

Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 298, 298, 16)      448
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 149, 149, 16)      0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 147, 147, 32)      4640
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 73, 73, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 71, 71, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 35, 35, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 33, 33, 64)        36928
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 16, 16, 64)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 14, 14, 64)        36928
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 7, 7, 64)          0
_________________________________________________________________
flatten (Flatten)            (None, 3136)              0
_________________________________________________________________
dense (Dense)                (None, 512)               1606144
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 513
=================================================================
Total params: 1,704,097
Trainable params: 801,521
Non-trainable params: 0
_________________________________________________________________
```

Figure 7.
Deep neural network model.

Since we use binary cross-entropy loss, we need binary labels class_mode='binary'. After creating the test data generator and train data generator, we tried to fit the model with the train data generator.

5. Result & Discussion

This network has learned around 2 million parameters to execute a prediction. Similarly, around 1 million parameters are used for training. After the convolution and max pooling, there will be 512 hidden layers. Here, the callback function is incorporated to achieve maximum accuracy, automatically stopping the iteration once the desired accuracy is achieved. In our case, 96.8% accuracy was the criterion for discontinuing the execution. Table 1 and Fig.8 show the results of the proposed innovative non-destructive leaf image analysis method for nitrogen deficiency.

Table1.
Comparison average performance measures of Nitrogen deficient leaf detection.

S. no.	Method	Accuracy
1	Deep neural networks	94.5
2	Nitrogen deficient leaf detection using ANN	95.2
3	Nitrogen deficient leaf detection using CNN	96.8

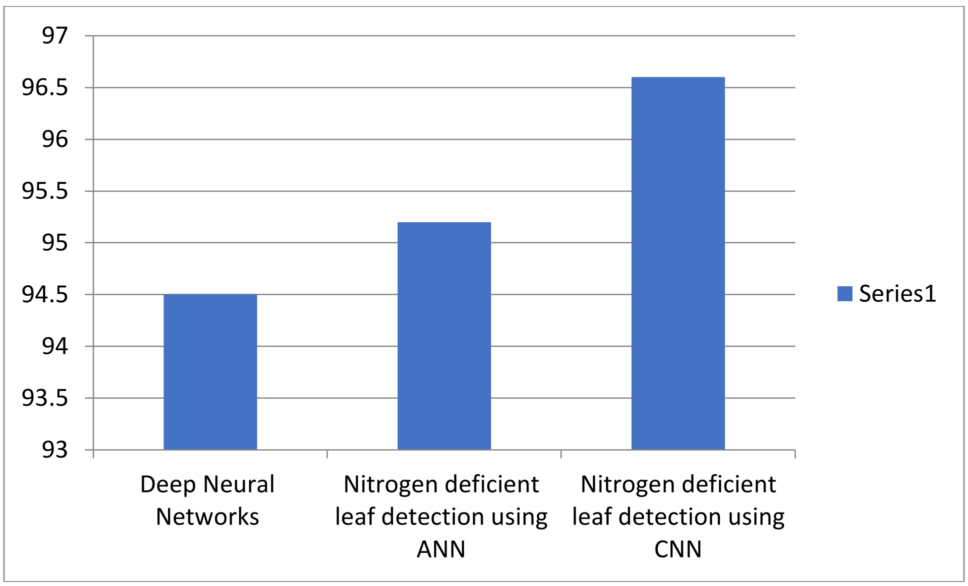

Figure 8.
Deep neural network model.

One way of measuring the performance of the model is to compute the mean squared error of the model on the test set. If $\hat{y}^{(\text{test})}$ gives the predictions of the model on the test set, then the mean squared error is given by

$$\text{MSE}_{\text{test}} = \frac{1}{m}\Sigma(\hat{y}^{(\text{test})} - y^{(\text{test})})^2{}_i$$

6. Conclusion

The deep convolution neural net was used to classify and identify the nutrient deficient leaves from the normal leaves. the colour features are fed to the model to distinguish it from the normal leaves. Once this could be identified at an early stage of development, appropriate remedial measures could be implemented to restore the normal uptake of the plant and there by improves yield and profit to the farmers. Test data generator and training data generator were formulated to train and test the formulated model. Image augmentation techniques was also implemented to strengthen the dataset available. Further, there are chances of occurrence of multiple deficiencies in a leaf image. In future, this area has to be improved to identify multiple nutrient deficiency symptoms from a single leaf image.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 8, No. 4: 1483-1495, 2024
DOI: 10.55214/25768484.v8i4.1522

References

[1] V V Carmona, L C Costa & A B Cecilio Filho. "Symptoms of Nutrient Deficiencies on cucumber". International Journal of Plant & Soil Science 8(6): 1-11, 2015 Article No.IJPSS.20243 By

[2] Feller U, Anders I, Mae T. Rubiscolytics: fate of Rubisco after its enzymatic function in a cell is terminated. J. Exp. Bot. 2008;59:1615-1624.

[3] Feller U, Anders I, Demirevska K. "Degradation of rubisco and other chloroplast proteins under abiotic stress". Gen. Appl. Plant Physiol. 2008;34:5-18.

[4] IPNI is a global organization with initiatives for the world's growing need for food. www.ipni.net.

[5] Camargo, J.S. Smith, "An Image-processing Based Algorithm to Automatically Identify Plant Disease Visual Symptoms," Biosystems Engineering, vol. 102, no. 1, pp. 9-21, January 2009. ISSN 1537-5110. doi: 10.1016/j.biosystemseng.2008.09.030.

[6] LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* 2015, *521*, 436–444.

[7] Kamilaris, A.; Prenafeta-Boldú, F.X. Deep learning in agriculture: A survey. *Comput. Electron. Agric.* 2018, *147*, 70–90.

[8] Liakos, K.G.; Busato, P.; Moshuo, D.; Pearson, S.; Bochtis, D. Machine learning in agriculture: A review. *Sensors* 2018, *18*, 2674.

[9] Jeyalakshmi, S.; Radha, R. A review on diagnosis of nutrient deficiency symptoms in plant leaf image using digital image processing. *ICTACT J. Image Video Process.* 2017, *7*, 1515–1524.

[10] Ferentinos, K.P. Deep learning models for plant disease detection and diagnosis. *Comput. Electron. Agric.* 2018, *145*, 311–318.

[11] Fuentes, A.; Yoon, S.; Kim, S.C.; Park, D.S. A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. *Sensors* 2017, *17*, 2022.

[12] Samborska, I.A.; Alexandrov, V.; Sieczko, L.; Kornatowska, B.; Goltsev, V.; Cetner, M.D.; Kalaji, H.M. Aritificial neural networks and their application in biological and agricultural research. *J. NanoPhotoBioSciences* 2014, *2*, 14–30.

[13] Dyrmann, M.; Karstoft, H.; Midtiby, H.S. Plant species classification using deep convolutional neural network. *Biosyst. Eng.* 2016, *151*, 72–80.

[14] Barbedo, J.C.A. A review on the main challenges in automatic plant disease identification based on visible range images. *Biosyst. Eng.* 2016, *144*, 52–60.

[15] Noh, H.; Zhang, Q.; Shin, B.; Han, S.; Feng, L. A neural network model of maize crop nitrogen stress assessment for a multi-spectral imaging sensor. *Biosyst. Eng.* 2006, *94*, 477–485.

[16] Picon, A.; Alvarez-Gila, A.; Seitz, M.; Ortiz-Barredo, A.; Echazarra, J.; Johannes, A. Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. *Comput. Electron. Agric.* 2018.

[17] Chlingaryan, A.; Sukkarieh, S.; Whelan, B. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Comput. Electron. Agric.* 2018, *151*, 61–69.

[18] Gautam, R.K.; Panigrahi, S. Leaf nitrogen determination of corn plant using aerial images and artificial neural networks. *Can. Biosyst. Eng.* 2007, *49*, 71–79.

[19] Sulistyo, S.B.; Wu, D.; Woo, W.L.; Dlay, S.S.; Gao, B. Computational Deep Intelligence Vision Sensing for Nutrient Content Estimation in Agricultural Automation. *IEEE Trans. Autom. Sci. Eng.* 2018, *15*, 1243–1257.

[20] Jones, C.D.; Jones, J.B.; Lee, W.S. Diagnosis of bacterial spot of tomato using spectral signatures. *Comput. Electron. Agric.* 2010, *74*, 329–335.

[21] Sladojevic, S.; Arsenovic, M.; Anderla, A.; Culibrk, D.; Stefanovic, D. Deep neural network based recognition of plant diseases by leaf image classification. *Comput. Intell. Neurosci.* 2016.

[22] Sulistyo, S.B.; Woo, W.L.; Delay, S.S. Regularized Neural Networks Fusion and Genetic Algorithm based On-Field Nitrogen Status Estimation of Wheat Plants. *IEEE Trans. Ind. Inform.* 2016, *13*, 103–114.

[23] Xu, G.; Zhang, F.; Shah, S.G.; Ye, Y.; Mao, H. Use of leaf color images to identify nitrogen and potassium deficient tomatos. *Pattern Recognit. Lett.* 2011, *32*, 1584–1590.

[24] Zhang, H.; Liu, G. Dichotomous research on near infrared spectrogram of tomato leaf based on SVM algorithm. In Proceedings of the 2013 International Conference on Mechatronic Sciences, Electric Engineering and Computer (MEC), Shengyang, China, 20–22 December 2013.

[25] Vazquez-Cruz, M.A.; Luna-Rubio, R.; Contreras-Medina, L.M.; Torres-Pacheco, I.; Guevara-Gonzalez, R.G. Estimating the response of tomato (Solanum lycopersicum) leaf area to changes in climate and salicylic acid applications by means of artificial neural networks. *Biosyst. Eng.* 2012, *112*, 319–327.

[26] Sulistyo, S.B.; Woo, W.L.; Dlay, S.S.; Gao, B. Building A Globally Optimized Computational Intelligence Image Processing Algorithm for On-Site Nitrogen Status Analysis in Plants. *IEEE Intell. Syst.* 2018, *33*, 15–26.

[27] Sulistyo, S.B.; Woo, W.L.; Delay, S.S. Ensemble Neural Networks and Image Analysis for On-Site Estimation of Nitrogen Contents in Plants. In Proceedings of the SAI Intelligent Systems Conference (IntelliSys 2016), London, UK, 21–22 September 2016.

[28] Piyush Chaudhary, Anand K. Chaudhari, Dr. A. N. Cheeran "Color Transform Based Approach for Disease Spot Detection on Plant Leaf" At International Journal of Computer Science and Telecommunications [Volume3,Issue6,June 2012]

[29] Muhammed Ashraf & Shah Rizam UniversitiTeknologi MARA, Malaysia "Overview of image processing approach for nutrient deficiencies detection in Elaeis Guineensis" At 2011 Internation conference on System engineering & Technology.

[30] K. Muthukannan, P. Latha, R. Pon Selvi Einstein "Classification of diseased plant leaves using neural Network algorithms" At ARPN Journal of Engineering and Applied Sciences VOL. 10, NO. 4, MARCH 2015

[31] Prof. Rekha Chahar & Priyanka Soni "A Study of Image Processing in Agriculture for Detect the Plant Diseases" At International Journal of Computer Science and Mobile Computing IJCSMC, Vol. 4, Issue. 7, July 2015, pg.581 – 587

[32] Nitin S. Tijare, Prof. Sagar S. Badnerkar G. H. "Image recognition-based crop disease identification system" At International Journal of Computer Science and Mobile Computing IJCSMC, Vol. 3, Issue. 4, April 2014