Int. J. Nonlinear Anal. Appl. 12 (2021) No. 2, 1175–1186
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/IJNAA.2021.5194

Detection of plant leaf nutrients using convolutional neural network based internet of things data acquisition

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(Communicated by Madjid Eshaghi Gordji)

Abstract

In this paper, the study detects the nutritional deficiencies from these leaves using Internet of Thing (IoT) based image acquisition and nutrition analyser devices. The former captures the color of the leaf and the latter helps in finding the nutrients in each zone based on the image captured by the device. The study uses an improved convolutional neural network to detect automatically the nutrients present in a leaf. The type of leaf is considered from the plants including coriander, tomato, pepper, chili, etc. The Convolutional Neural Network (CNN) is used to extract the patterns of leaf images from the data capturing IoT devices and nutrition analyser device. The system stores and process the data in cloud, where the CNN integrated in Virtual Machines enables the process of input data and process it and sends the report to the authority. A total of 3000 images are collected out of various disorders in five different plants. A 5 fold cross-validation is conducted on training and testing dataset. The system is tested in terms of accuracy, sensitivity, specificity, f-measure, geometric mean and percentage error. The comparison made with existing models shows an improved detection accuracy by CNN than other deep learning models.

Keywords: Plant Leaf Nutrients, Detection, Convolutional Neural Network, Internet of Things

1. Introduction

Nutrients are crucial to several parts of the life cycle of a plant, such as the rate of growth, productivity and fertilisation. A lack of any critical nutrients would severely disrupt these processes,

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Received: March 2021 *Accepted:* June 2021

resulting in a significant loss of agriculture. Nutrient deficiencies can also cause a plant leaves to have an unusual appearance [?]. This visual symptom can also be recognised by the eyes, usually approximately one week after the nutrient deficits start. Examples of symptoms produced by various nutrient shortcomings are shown in Figure ??.

(a) Potassium Deficiency (b) Nitrogen Deficiency (c) Magnesium deficiency

(d) Calcium Deficiency (e) Iron Deficiency (f) Healthy Leaf

Figure 1: Samples of nutrient deficiencies in plant leaves

Plants need to develop and generate nutrients well. Seventeen essential plant growth nutrients are available. Basic or essential plant nutrients are classified into micronutrients and macronutrients [?]. The macro nutrients required in vast amounts, such as copper, boron, chlorine, iron, nickel, manganese, zinc and molybdenum are in small amounts [?], [?]. Nitrogen, oxygen, carbon, sulphur, hydrogen, magnesium, phosphate, calcium, etc. are macro-alimental [?]. For the growth of a plant and its development, the right balance of nutrients is needed. If a basic component is lacking, seedlings cannot end their breeding or vegetative cycles, and will thus display symptoms of shortage.

Insufficiencies and visual symptoms will occur in the absence of any vital plant complement [?].To resolve the problem, it is essential to correctly analyse the deficiency. The first signs are generally obvious, either in young or older leaves, due to a lack of nutrition. The initial leaves show nutrient defects due to immobility, such as iron, zinc, copper, boron, manganese, nickel, sulphur, calcium and chlorine. Deficiencies in nutrients that move, such as nitrogen, potassium, phosphorus and magnesium appear first in the older leaves. Initially, inadequate molybdenum indicators appeared between a fresh and an aged leaves [?] in plants.

Plants may be hazardous due to the abundance of any nutrient. Many fertilisers can produce the effects of salt burning. This involves slight browning or leaf redness, which is segregated by a thin yellow brilliance from the green leaf tissue. The manifestation begins at the end and extends down the edges at the leaf base.

There are various aspects that can analyse the nutritional inadequacies of plants [?] [?] – [?]. Damage caused by excess sales, the dry season, pesticide damage, nematodes, plague, or any other situation is unfavorable for root development in the case of top development beyond the root framework. However, visual examination for nutrient deficiency is time-consuming and ineffective, especially during the initial stages of insufficiency when a distinct appearance is not present.

The Convolutional Neural Network (CNN) is used to extract the patterns of leaf images from the data capturing IoT devices and nutrition analyser device. The system stores and process the data in cloud, where the CNN integrated in Virtual Machines enables the process of input data and process it and sends the report to the authority. A total of 3000 images are collected out of various disorders in five different plants.

2. Related works

The author in [?] developed a model based on the creation and application of the Ion Electrodes nutrient management technique as well as computer-regulated fertiliser pumps. The volumes of individual solutions to be delivered are dependent on the calculation of tank concentrations and are calculated by a nutrient dose algorithm. In the five spiking tests, the system demonstrated a 1:1 ratio, formulating calcium and nitrous oxide values similar to the goal concentrations. But its concentration has been increased by 40% more than the aim due to low potassium value.

The author in [?] builds on the evaluation of computer based ion selective electrode for direct hydroponic macronutrient measurement. Ion electrodes are evaluated for calcium, potassium and nitrogen directed measurement for paprika hydroponic with a PVC-based membrane combined with a controlled computer system. Using contemporary gauge adaptation and two-point standardisation procedures, ion selective electrode evaluated potassium and nitrogen fixations have been detected to be closely linked to the decisions made using standard research facilities. In all cases, because of poor selectiveness and low sensitivity, the proven calcium cathode did not produce satisfactory results. A two-point standardisation strategy can be employed in automated detection of supplements in kindergartens using this methodology used in the examination, which uses a base combination in both washing terminals and baseline and two blends.

The author in [?] developed the design of an autonomous robotic vehicle, which only takes a photo of plant leaves to see the deficiency of plant nutrients. The image is then processed through the use of CNN. The strategy uses the picture taken and processes it in comparison to the data set. When the image of the information is coordinated or partially coordinated with one of the images in the dataset, it will result, as far as the rate is, in a shortage of plants.

The authors in [?] studied the nutrient deficiency in coffee plants influences growth and is hence notable in the early stages. Boron, Calcium, Iron and Potassium are detected automatically by using the form and surface characteristics of coffee leaf photographs in this article. Subsequently, they are then allowed to undergo segmentation using Otsu method by securing images containing coffee tree leaves. The Gray-Level Cooccurrence Matrix (GLCM) descriptors will next be applied to the images in order to identify our shape and surface characteristics. Finally, in order to finalise the kind of deficiencies introduced in each image, the acquired image will be used in building neural network classifiers by using the features extracted. The findings of the test reveal that the method created is good and has higher results in differentiating and iron and Boron deficits.

The author in [?] detected calcium deficits in stable and live tissue of plants by use of micro-spectroscopy. For plant-based investigations, spectrum information is dissimulated because of water absorption in fingerprint locations, in particular in active tissue. This investigation examined the ability of such a method to detect both live and fixed tissue CA deficiencies to decide how accurately they can be solved before the presence of a supplement has no side effects.

The author in [?] deals with the development of an Ion selection Electrodes, the nutrient deficiency location check frame for the sensors that can be adjusted and the particles concentration is calculated. This helps gardeners to properly manage nutrients by promptly identifying every form of imbalance that happens in recycled setups. The performance was evaluated via hydroponic setups in nurseries designed to cultivate paprika.

The author in [?] offers a machine-based learning and the discovery of abnormalities due to the lack of fruit nutrients. Two classifications are easily calculated: healthy and faulty. The faulty group thus consists of 3 subclasses. K-nearest neighbor and support vector machine uses various natural fruits, such as apples, Litchi, pears, etc. and the result is displayed alongside the stage of malformation. The SVM technique has been seen in relation to the position and phase predictions of the deformity for fruit classification.

The authors in [?] involved an automatic, reliable response to nutritional deficit detection. The data set is created using extraction, texture detection and so on for aged and healthy leaves. The supervised AI uses this dataset as a training data set for nutritional insufficiency and preventive interventions to increase yields in healthy plants.

The authors in [?] developed an IoT-based system comprises a new sensor. For the monitoring of soil nutrients, the colorimetric rule is employed. NPK sensor data is uploaded from different fields to the cloud for fast data recovery. For identification of nutritional shortages, the Fuzzy logic is applied to sensed data. During the fuzzification procedure, the exact value of each sensed data was divorced into five fluctuating values which ranged from extremely low.

The authors in [?] detected a lack of tomato leaves successfully in order to protect them from illness. The technique of image processing is utilised to determine tomato leaf deficits. The plant develops well when its vital supplements, such as potassium, phosphorus, nitrogen, etc., are available. Tomato plant leaf failure analysis will help detect diseases in the later stages. The segmentation and expectancy procedure for accurate detection is used and the highlights are derived from segmented images. The infection event due to further deficiency is presented after recognition of the outcome. Therefore, a disease is detected on leaf image by an effective analysis of the deficit. This work prevents the loss of tomato production and so increases its sales.

3. Proposed Method

The Convolutional Neural Network (CNN) is used to extract the patterns of leaf images from the data capturing IoT devices and nutrition analyser device. The CNN uses the recurrent layers at its hidden layer to improve the quality of obtaining the results with reduced errors. The CNN enables high quality results of nutritional deficiencies present in the leaves and in case if a leaf or a plant lacks from its basic nutrients. The system will automatically report the local agricultural authority regarding the deficiency of the plant and helps the authority to provide sufficient supplements. The system stores and process the data in cloud, where the CNN integrated in Virtual Machines enables the process of input data and process it and sends the report to the authority.

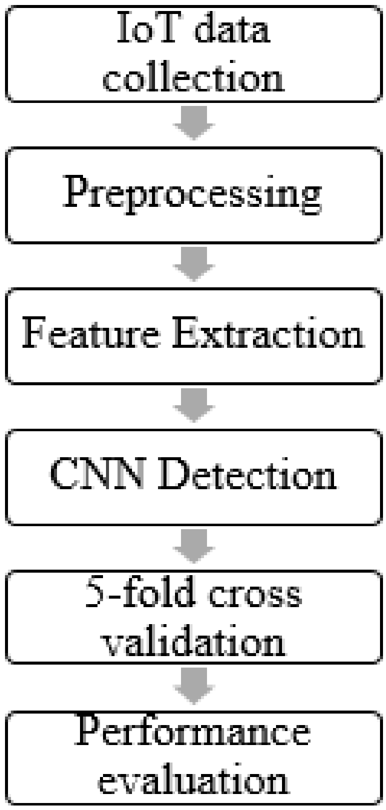

Figure 2: Architecture of Plant Leaf Nutrient Detection

Preprocessing

Due to the huge amount of input images from many IoT data acquisition cameras, various problems are reported that includes: loss of pixels, mislabeling, noise, imbalance and large size. This research is based on the preprocessing task using Symmetric Minority Over Sampling Technique or SMOTE. This enhances the accuracy of the CNN classifiers. The formula for the creation of the balanced dataset is given below

$$(A'_{new_1}, A'_{new_2}) = (A_{11}, A_{12}) + rand(0-1) * (A_{new_1}, A_{new_2}) \tag{1}$$

where
$A_{new_1} = A_{21} - A_{11}$
$A_{new_2} = A_{22} - A_{12}$
$A_{11}-$ first instance first attribute,
$A_{21}-$ second instance first attribute,
$A_{12}-$ first instance second attribute and
$A_{22}-$ second instance second attribute.
$rand(0-1)-$random number.

Feature Extraction

Shannon Entropy is used to estimate the degree complexity of input images. The entropy-weighted approach uses methods to derive the fitness weights of the relevant features. In the following steps shows the process of feature extraction:

Step 1 : Create a decision matrix using weighted score.

Step 2 : Normalize the value of decision matrix in order of data pre-processing.

Step 3 : Use the value of decision matrix to generate weighted score matrix.

Step 4 : Optimize weights via weighted entropy method.

Step 5 : Validate and Compare the weighted score from step 3 and 4.

Step 6 : Rank the weighted score in order to obtain optimal attribute.

The first stage is to change a new dataset utilising the provided technique by keeping the attribute details with the ideal characteristics chosen for the decision-making process. Next, entropy produces the expert weight. The same classification subset achieved is considered to be the best alternative for individual values. The results are calculated on the basis of the current comparison system.

First, the weighted values of the score should be combined with the weighted average score operator. Secondly, the scoring functions are computed for any alternative collective total data subset. Thirdly, the alternative is selected based on the score values. Finally, the score values may be calculated and the ranking data can be produced. With the different approaches, different order positions are reached, but the differences are subtle. The results are rational and the proposed strategy is more adaptable than the methodology proposed in the study. The comparative results confirmed that the prediction of medical disorders within the decision-making phase of the healthcare system is an accurate and realistic strategy.

Classification

Although CNN models have been demonstrated in various image processing contexts, particularly in the interpretation of medical images, Inspired by this, we offered an approach based on CNN for cervical cancer identification and categorization. Massive volumes of medical picture data are necessary to train CNN-based systems correctly. A large library of medical images is very tough to gather. Therefore, it is more common to apply fine-tuning when the database size is modest. It has a vast amount of information to train a deep CNN model. After training, the model can be used as a pre-trained model. The model parameters (pretrained) are finalised with a selected database training set to achieve the requisite accuracy. This is a perfectly tuned model for testing.

Valid experiments are conducted with the CNN and tests are undertaken with low architecture and two experiments are undertaken with deep architecture. An RGB image is used as input with size 224x224 pixels. In the first convolutional layer, there are 64 different 5 to 5 filters, and in the second convolutional layer, 128 distinct 5 to 5 filters. The stride of the filter is 2 pixels and its mask size is given as 2x2. The very best. The linear unit is used to activate the nonlinear unit. The features are then minimize reduced to a single value after the maximum pooling layer and it is fed into a fully linked layer. The two fully connected layers are connected to the bottom and the softmax layer at the top. Once the training has been finished, a separate training sub-set from the target database is completed to refine the database. For training the model with Stochastic Gradient Descent (SGD), a smaller selection of training data is used to optimise the model parameters.

- Learning rate is 0.01,
- Batch size is 20 and
- Epoch size is 50.

The study uses various pre-trained model of CNN and these models have been trained on a large number of images and have obtains more accuracy than other deep learning algorithms. We have proposed the use of an EM classifier to supplement the ELM-based classifier. The ELM is a low-lying network that offers various advantages, including simple convergence, fast learning, and less randomization. The system contains two end-to-end ELMs at the end of the CNN model's final fully linked layer. As an initial step, ELM classifies the healthy and deficient leaf and gives it as an output. In the second ELM, the result is set to offer normal and abnormal instances of categories. After completion of the first ELM training, the output will be discarded and the concealed layer as the entrance to the second ELM will be employed. The total hidden neurons used is 2048 to estimate the dense representation, so that this ELM refers to a sparse depiction. The weights are finally optimized in ELM using SGD approach.

4. Results and Discussions

In this section, we validate the efficacy of the proposed method with various other methods and the details are given below:

The simulation is conducted in Python3.8, where the CNN is modelled in TensorFlow2.2. The simulations are conducted on high end computing engine with 16 cores and 32 threads CPU, 16GB of primary memory and a graphics acceleration unit: GTX 1060.

Dataset:

The investigation was conducted using black gram crops cultivated under fertiliser control. In the beginning, black gram seeds were cultivated for two weeks in sand. The seedlings were then selected as a healthy black at roughly the same height. They were all put into a nutrient-controlled solution container, and then cultivated for 28 days. Every week, solutions are adjusted to maintain nutritional levels. Each day, photographs of black grams were taken in regulated light; one or two image per plant.

An IoT input data acquisition camera and a nutrient sensor is used as an input image acquisition tool. The simulations are conducted on 3000 input image with 70% of the data are chosen for training and 30% for training. Each image has a resolution of about 1296 × 864 pixels.

Metrics for validation:

The evaluation is conducted on various performance metrics that includes accuracy, sensitivity, specificity and F-measure.

$$Accyracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

$$Specificity = \frac{TN}{TN + FP} \tag{4}$$

$$F - Score = 2 * \frac{(Recall * Precision)}{(Recall + Precision)} \tag{5}$$

The characteristics of the pre-trained CNN model via GAP layer provides an average of all characteristics and optimised vectors. A dense layer with 512 features is employed after the GAP layer and then a dropout is used with a value of 0.25 and this eliminate the problem of overlap by eliminating the neurons which compel the layer to be represented in some other way. A sigmoid dense activation function finally forecast whether the image has deficiency or not.

In terms of the model size, the number of parameters and the number of convolution layers, data on previously trained models is presented in Table **??**.

Table 1: Comparison of various CNN models for plant nutrient detection

Pre-trained CNN Models	**Convolutional Layers**	**Model Size**	**Parameters**
VGG16	16	528MB	138,357,544
VGG19	19	549MB	143,667,240
ResNet50	50	98MB	25,636,712
DenseNet121	121	33MB	8,062,504
DenseNet169	169	57MB	14,307,880
DenseNet201	201	80MB	20,242,984

This data set was used to screen forged photos with different transformations and post-processing. This data set comprises both copying and moving and splicing photos. We have split up the data set for training and testing, in which 70% of the images were utilised to form the model. For validation and testing of the model, the remaining 30% of the images are used. The model takes approximately 20 minutes for each epoch, which can be decreased with a better system setup. After some early experimentation with the dataset, the hyper-parameters were selected. In Adam Optimizer, the study utilised binary cross-entropy as a loss function and for the first learning rate, the study utilized $1e^{-4}$. In order to reduce the learning rate when losses stop and improve, the study used the callback function. All images were resized to $256x256$ and the model was trained in a 16^{th} batch.

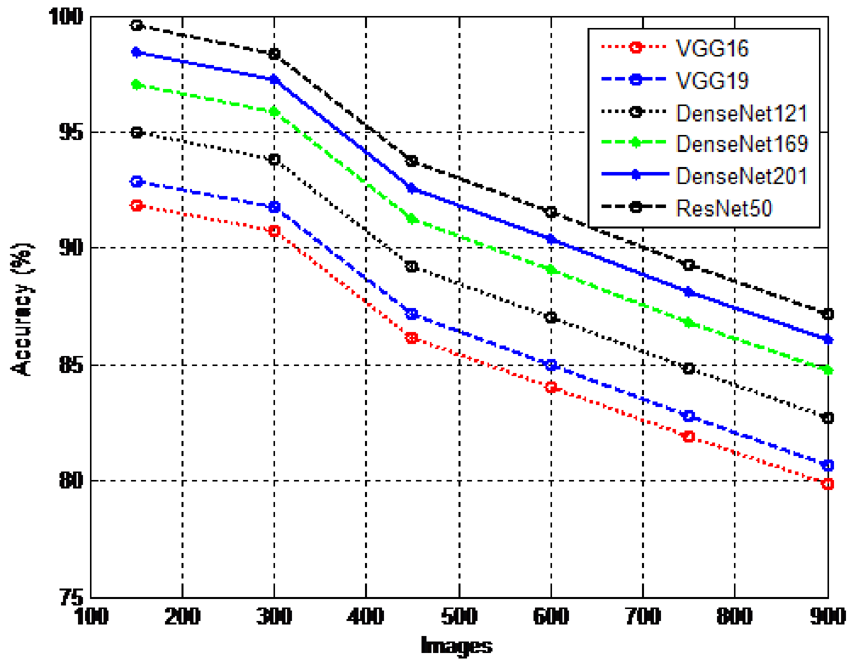

Figure 3: Accuracy

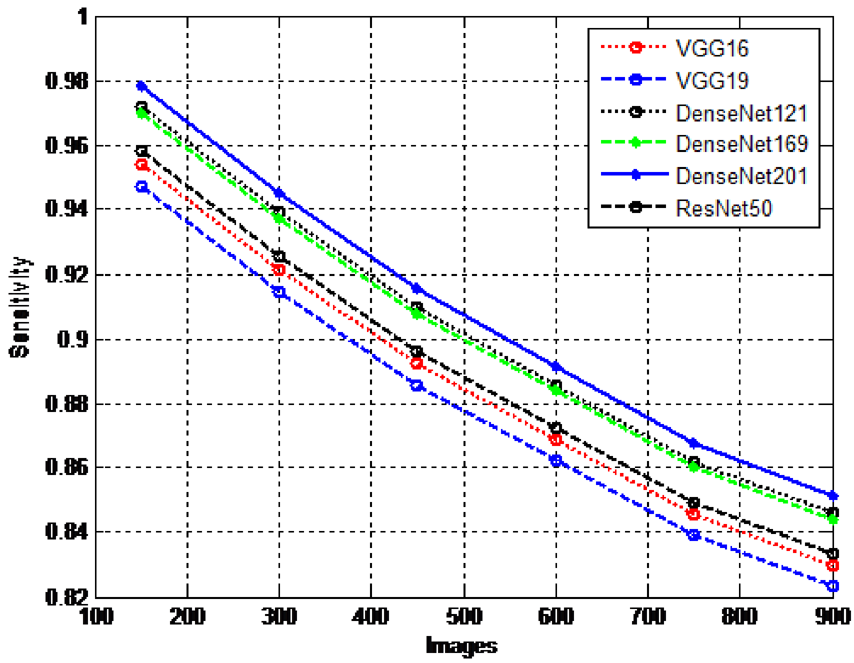

Figure 4: Sensitivity

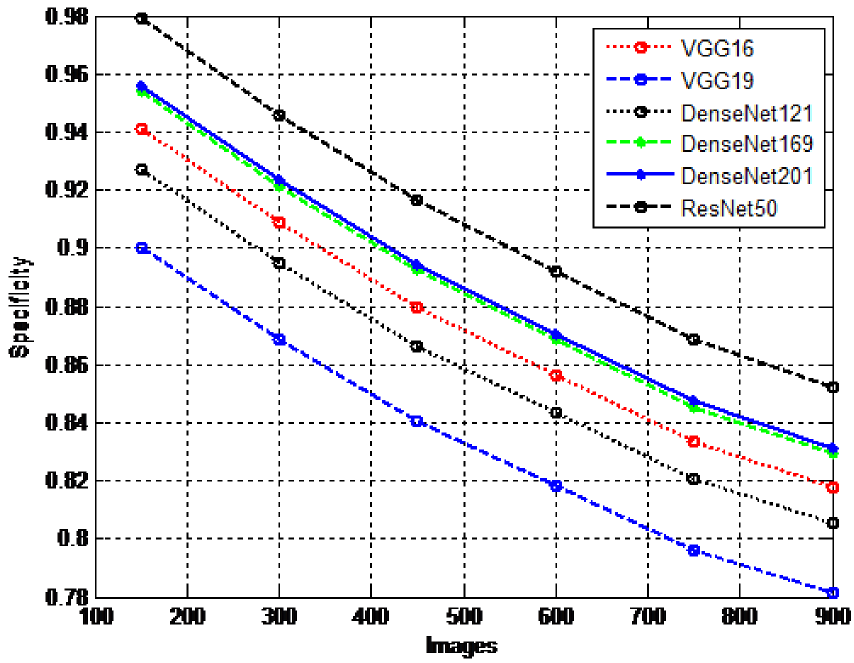

Figure 5: Specificity

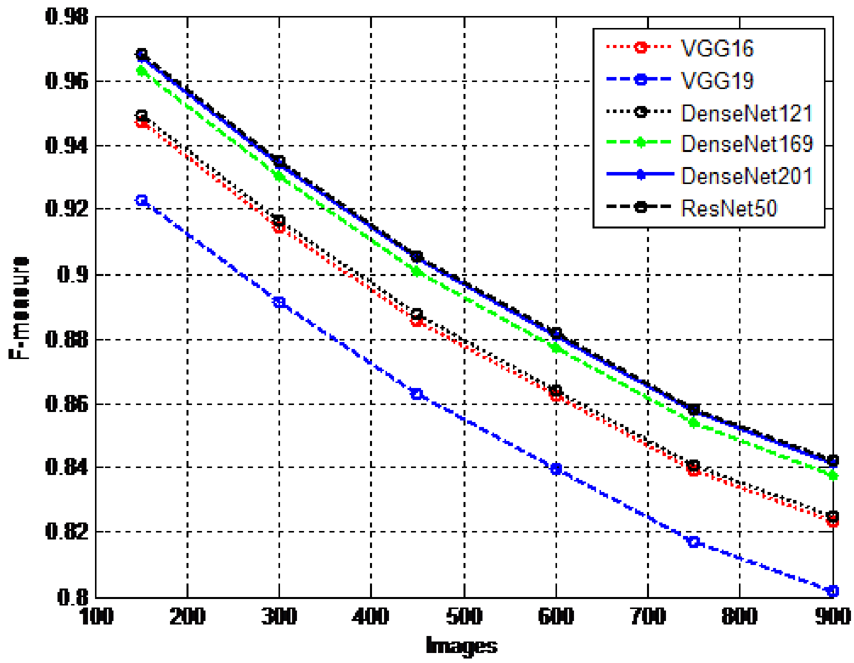

Figure 6: F-measure

The approach provided could produce a highly accurate classification (Figure ??-Figure ??) performance, which was significantly better than for a trained human being. Furthermore, the results show that the identifying task was extremely challenging even for human eyes, taking into account several kinds of vitamin deficits. The issues may be explained by a number of explanations. For starters, the symptoms of a lack of the same nutrients, i.e. changes in internal classes, are severe.

Based on our observation, the symptoms become visibly obvious in approximately 6-10 days. Therefore, it is quite difficult to discern between a nutrient-deficient leaf and a healthy one during this period. The symptoms for shortage in nutrients may be identical in one stage to the symptoms of another. These interclass similarities produce considerable complexity for the approach proposed and even for experts. Certain symptoms, such as tip burns, are established locally. These symptoms are difficult to identify, especially when they begin to develop. They are small. Moreover, some other regions of the leaf with no apparent symptoms would still not be distinct from a healthy leaf.

5. Conclusions

In this paper, CNN detects the nutritional deficiencies from the leaves of coriander, tomato, pepper, chili using input IoT image acquisition device and nutrition analyser device. The capturing of leaf color and nutrients across each zone is captured by these IoT devices effectively in remote environment. The collected input image data is sent to the data analytics unit that initially removes noises and extracts relevant features from the captured leaves. Finally, the nutrients are extracted using CNN, where it detects the possible nutrients from the plants. The entire analyses are conducted in hybrid cloud environment, where CNN module acts as a center controller that helps in classification of nutrients. Simulation on 5000 images of different plants show that the proposed modified CNN model obtains improved training and testing classification accuracy than other methods. Here, the results of simulation shows that the modified CNN has reduced percentage error than other deep learning models.

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