Identification of Plant Nutrient Deficiencies Using Convolutional Neural Networks

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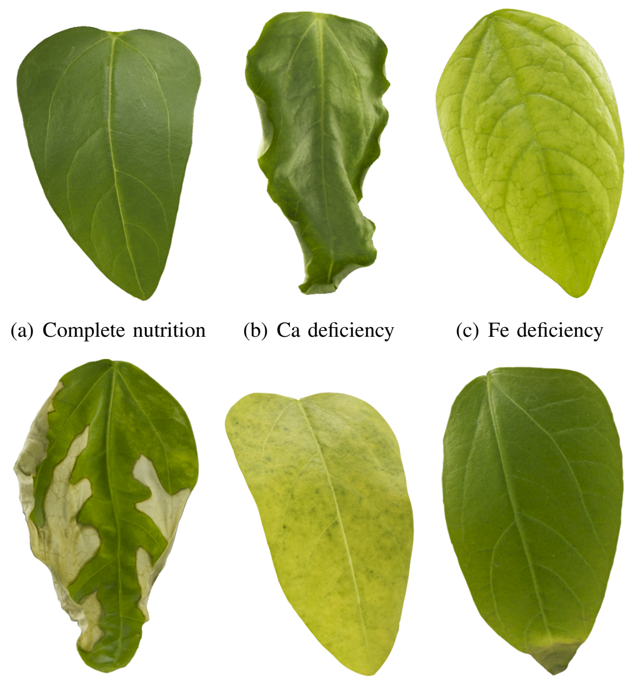
***Abstract*—A novel image analysis method for identifying nutrient deficiencies in plant based on its leaf is proposed. First, the proposed method divides an input leaf image into small blocks. Second, each block of leaf pixels is fed to a set of convolutional neural networks (CNNs). Each CNN is specifically trained for a nutrient deficiency and is utilized to decide if a block is presenting any symptom of the corresponding nutrient deficiency. Next, the responses from all CNNs are integrated to produce a single response for the block using a winner-take-all strategy. Finally, the responses from all blocks are integrated into one using a multi-layer perceptron to produce a final response for the whole leaf. Validation of the proposed method was performed on a set of black gram (*Vigna mungo*) plants grown under nutrient-controlled environments. Five types of deficiencies, i.e., Ca, Fe, K, Mg, and N deficiencies, and a group of plants with complete nutrients were studied. A dataset consisting of 3,000 leaf images was collected and used for experimentation. Experimental results indicate the superiority of the proposed method over trained humans in nutrient deficiency identification.**

Keywords*—*nutrient deficiency; leaf; image analysis; machine learning; convolutional neural network

I. Introduction

Nutrient is a vital factor that strongly determines many aspects of a plant's life cycle such as growth rate, productivity, and fertilization. Deficiencies in any essential nutrient would significantly affect these processes and cause a severe loss in agriculture. Nutrient deficiencies also result in an unusual appearance of a plant especially on its leaves [9]. This visual symptom could be identified by eyes, typically around a week after nutrient deficiencies began; hence, it could signify a presence of deficiencies. Example of symptoms caused by various nutrient deficiencies are illustrated in Fig. 1. However, nutrient deficiency analysis by eyes requires domain expertise and is not robust, especially in the early stage of deficiency where an unusual appearance has not clearly been noticeable.

Image analysis techniques have been applied to automate various tasks in the field of agriculture; for example, automated fruit localization and harvesting [4], [10], [15], insect detection and counting [3], [11], selective weed control [6], [18], [19], plant species identification [2], or plant disease detection [1], [14]. Recently, image analysis based approaches for nutrient deficiency detection have also been investigated. Wang et al. [17] studied techniques used to estimate nitrogen status in rice plants using color information. Story et al. [16] proposed an image analysis method for detecting calcium deficiency in lettuce. Ji-Yong et al. [7] investigated the use of a chlorophyll distribution map of cucumber leaves to diagnose nitrogen deficiency. Xu et al. [20] developed an image analysis method based on color information to detect nitrogen and potassium deficiencies in tomato plants. Romualdo et al. [13] utilized texture-based features to analyze nitrogen status in maize plants from scanned leaves. Although several of these research attempts could achieve an accurate performance, they studied only on one or two types of nutrient deficiencies, resulting in less practicality in real situations.



(a) Complete nutrition (b) Ca deficiency (c) Fe deficiency
(d) Mg deficiency (e) N deficiency (f) K deficiency

Fig. 1. Example of black gram leaves with nutrient deficiencies

In this article, five nutrient deficiencies as listed in Table I are considered. An image analysis method for identification

TABLE I. KEY SYMPTOMS OF SELECTED NUTRIENT DEFICIENCIES

Type of deficiencies	Key symptoms
Calcium-deficient (-Ca)	Curling, irregularly shaped leaves
Iron-deficient (-Fe)	Interveinal chlorosis (turning yellow between veins)
Magnesium-deficient (-Mg)	Necrosis (cell injury), interveinal chlorosis
Nitrogen-deficient (-N)	Stunted growth, uniformly yellowish leaves
Potassium-deficient (-K)	Brown scorching, curling leaf tip

TABLE II. THE NUMBER OF LEAF IMAGES IN THE DATASET

Type of solutions	The number of plants	The number of images
Complete nutrients (CPLT)	10	519
Calcium-deficient (-Ca)	11	412
Iron-deficient (-Fe)	10	496
Magnesium-deficient (-Mg)	12	594
Nitrogen-deficient (-N)	10	490
Potassium-deficient (-K)	10	489
Total	63	3,000

of plant nutrient deficiencies is also proposed. Deep neural networks [5], which have been increasingly adopted in many image recognition tasks, are exploited. Specifically, convolutional neural networks (CNNs) [8] are utilized to decide if a block of leaf pixels is presenting any symptom of a nutrient deficiency. Black gram (*Vigna mungo*) is chosen as a target plant for experimentation. The key contributions and features of this work are as follows: 1) investigating the effectiveness of CNN-based approach for nutrient deficiency detection, 2) studying many types of nutrient deficiencies which is more challenging than previous works, 3) constructing a large image dataset of nutrient deficient leaves with ground truth, and 4) evaluating the performance of the image analysis approach and comparing with humans.

The remaining of this article is organized as follows: an image dataset of nutrient deficient plants used in this research is described in Section II; the detail of the proposed method is given in Section III; experimental results are presented and discussed in Section IV; finally, the article is concluded and suggestion for future is given in Section V.

II. Image Dataset

Black gram plants grown under nutrient control were used in this research. At first, black gram seeds had been planted in sand and grown for two weeks. Then healthy black gram seedlings with approximately the same height were chosen. Each had been moved to a bottle of nutrient-controlled solution (soilless growing), and was then grown for 28 days. Six different types of solution were used in the experiments: 1) complete nutrients (denoted as CPLT), 2) calcium-deficient (-Ca), 3) iron-deficient (-Fe), 4) magnesium-deficient (-Mg), 5) nitrogen-deficient (-N), and 6) potassium-deficient (-K) solutions. The solutions were changed every week to maintain the amount of nutrients. For each type of solution, 10–12 black gram plants were grown; 8–10 plants were used for training and 2 plants for testing. The images of black gram leaves were taken everyday (except day 20 due to a problem) under a controlled light condition; one or two images (older and younger leaves) per plant. A DSLR camera, i.e., Canon EOS 550D with 18–55 mm and f/3.5-5.6 lens, was used in image acquisition. In total, the dataset consists of 3,000 leaf images with a resolution of 1,296×864 pixels. Each image contains a target leaf, which was manually segmented by human (as shown in Fig. 1). The distribution of leaf images is shown in Table II.

III. Proposed Method

An overview of the proposed method is diagrammed in Fig. 2. An input leaf image is first divided into blocks of size $S \times S$ pixels, in this work $S = 64$. Blocks that contain only leaf pixels are then selected as inputs for the next step, whereas blocks with background pixels are ignored. The reason for using blocks instead of the whole image is that some symptoms of nutrient deficiencies may not uniformly appear throughout the leaf but locally develop especially in the early stage.

Next, a set of CNNs is utilized to predict the probability that the symptoms of a deficiency present in a selected block. In particular, each is trained in a one-versus-all manner to focus only on one type of solution. For example, a CNN for calcium deficiency class is trained with two different labels: calcium deficiency and not calcium deficiency. Totally, six CNNs are generated; one CNN is specifically trained for deciding if a leaf is grown under a complete nutrient condition and each of the remaining for each type of deficiency. Each CNN consists of three convolutional layers (with filters of size 11×11, 5×5, and 3×3, respectively), two pooling layers (filters of size 3×3), and two fully connected layers (each with 2,048 neurons). The responses from all six CNNs are then integrated into a single response for the block using a winner-take-all strategy, that is, the type of nutrient deficiency corresponding to the CNN producing the highest response is chosen to be the answer of the block-level decision.

Finally, the prediction responses from all selected blocks in the input leaf image are then combined. The proportion for each type of response is computed and fed to a multi-layer perceptron with one hidden layer to produce a final response for the leaf-level decision.

It is worth noting that in the training step of CNNs, all leaf blocks from the complete nutrient class are incorporated; however, for a nutrient deficiency class, only blocks that appear abnormally are chosen and used to train CNNs. Examples of normal and abnormal blocks are demonstrated in Fig. 3. The reason is that symptoms of nutrient deficiency are not always uniformly presented throughout the whole leaf; some regions without symptoms which are closely similar to those from the complete nutrient class should be excluded to avoid confusion. A technique based on histogram analysis previously proposed by the authors is adopted here to separate abnormal regions in an input leaf image [12].

IV. Experimental Results

To assess the performance of nutrient deficiency identification, the proposed method was compared with trained humans. Two humans trained for distinguishing these six types of nutrient deficiency treatments were asked to predict the type of nutrient deficiency for each presented black gram leaf image. The prediction results were collected and their average prediction performance was calculated. Precision, recall, and F-measure were used as performance measures:

$$\begin{aligned} Precision &= \frac{t_p}{t_p + f_p}, \\ Recall &= \frac{t_p}{t_p + f_n}, \\ F\text{-}measure &= 2 \times \frac{Precision \times Recall}{Precision + Recall}, \end{aligned} \tag{1}$$

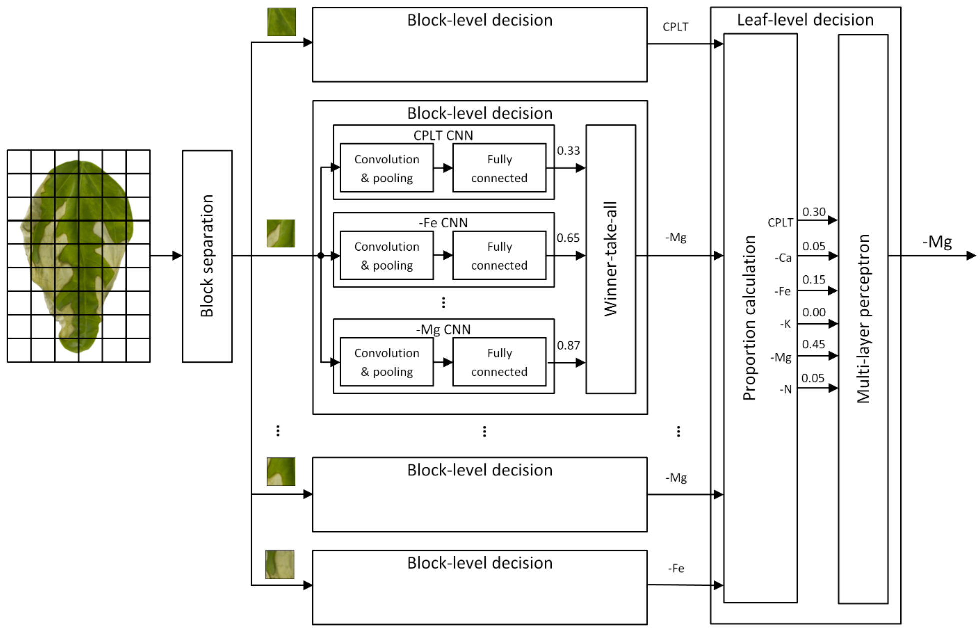


Fig. 2. The overview of the proposed method

Fig. 3. Example of extracted blocks from normal (top) and abnormal (bottom) regions

where t_p, f_p, f_n are true positive, false positive, and false negative, respectively.

Experimental results are reported in Table III. Although the proposed method could not achieve a very accurate identification performance, it was notably more successful than the trained humans overall. The results also reveal that when considering many types of nutrient deficiencies, the identification task turned out to be highly problematic even for human eyes. There are several reasons that could explain the difficulties. First, there are great variations of symptoms caused by a deficiency of the same nutrient, i.e., within-class variations. Figure 4 demonstrates a progressive development of symptoms caused by magnesium deficiency. The appearance of symptoms became slightly noticeable on day 11 after stress, and greatly developed since then. Necrosis regions (brown regions on the left and right borders) obviously appeared on day 13 and turned into white on day 19. Additionally, the other green regions of the leaf became yellowish on day 25. Second, the symptoms are not obvious in the early stage after nutrient control. Based upon our observation, it took around 6-10 days until the symptoms had become visually noticeable. Consequently, during this stage, it would be very difficult to distinguish a nutrient deficient leaf from a healthy one. As an example shown in Fig. 4(a), a magnesium-deficient leaf on day 6 after stress was still very similar to a normal one. Thirdly, the symptoms of a nutrient deficiency at a stage might be similar to those of another deficiency. For example, a magnesium-deficient leaf in Fig. 4(c) became irregularly shaped which is a key symptom of calcium deficiency (Fig. 1(b)). These between-class similarities considerably create confusion for the proposed method and even for the trained humans. Fourthly, some symptoms such as necrosis or tip burn are locally developed. These symptoms are hard to detect because they are small in size especially when they start to develop. Furthermore, some other parts of the leaf where symptoms have not yet appeared would be indistinguishable from a healthy leaf.

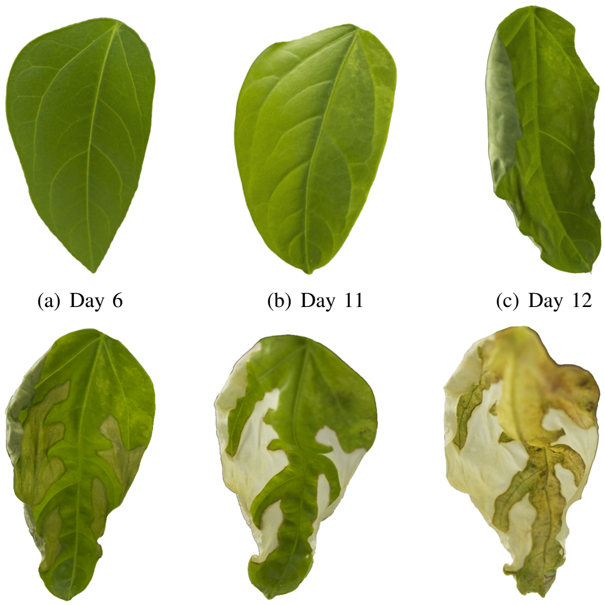
V. Conclusion and Future Works

Experimental results present the feasibility of using CNNs to identify nutrient deficiencies in black gram plants based on their leaves, and indicate its superiority over humans in performance comparison. On the other hand, the results also suggest that there is room for further improvement. Considering many types of nutrient deficiencies in the identification process apparently became, even for humans, much more difficult than the case of identifying only one or two types of deficiencies due to within-class variations, between-class similarities, and other issues.

Our next steps include but not limit to further analysis on the time factor, i.e., date after nutrient deficiency stress. Research questions such as how soon the deficiencies could reasonably be identified in the early stage will be studied. Other factors including nutrient mobility and leaf age, e.g.,

TABLE III. COMPARISON OF CLASSIFICATION PERFORMANCE BETWEEN THE PROPOSED METHOD AND HUMANS

Deficiency type	**Proposed method**			**Humans**		
	Precision (%)	**Recall (%)**	**F-measure (%)**	**Precision (%)**	**Recall (%)**	**F-measure (%)**
Complete (CPLT)	83.76	92.45	87.89	15.03	61.70	24.00
Calcium (-Ca)	36.36	13.33	19.51	24.75	24.01	23.24
Iron (-Fe)	63.79	59.68	61.67	66.27	20.38	27.52
Magnesium (-Mg)	23.29	56.67	33.01	26.68	21.94	23.18
Nitrogen (-N)	29.41	11.90	16.95	18.70	15.01	15.68
Potassium (-K)	34.48	28.57	31.25	13.94	10.93	11.84
Overall	**43.02**	**52.13**	**47.14**	**27.37**	**26.46**	**20.85**



(a) Day 6 (b) Day 11 (c) Day 12

(d) Day 13 (e) Day 19 (f) Day 25

Fig. 4. Development of magnesium deficiency symptoms

younger or older leaves, which can affect the symptoms would also be considered to improve the reliability of the identification. Aiming at being more practical in real situations, multi-nutrient deficiency, i.e., lacking of two or more nutrients, should be further investigated in the future.

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