Journal of Theoretical and Applied Information Technology
31st March 2022. Vol.100. No 6

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

AN OVERVIEW OF IDENTIFICATION AND ESTIMATION NUTRIENT ON PLANT LEAVES IMAGE USING MACHINE LEARNING

[1]DEFFA RAHADIYAN, *[2]SRI HARTATI, [3]WAHYONO, [4]ANDRI PRIMA NUGROHO

[1,2,3]Department of Computer Science and Electronics, Universitas Gadjah Mada, Yogyakarta, Indonesia
[4]Department of Agricultural and Biosystems Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia
E-mail: [1]deffa.rahadiyan@mail.ugm.ac.id, *[2]shartati@ugm.ac.id, [3]wahyo@ugm.ac.id, [4]andrew@ugm.ac.id

ABSTRACT

Lack of nutrients affects plant growth and causes plant damage. Deficiency of macronutrient such as nitrogen, potassium, calcium, and phosphorus are big problem for agriculture and its prevention will be very useful for agro-industry. The destructive methods for identifying nutrient deficiencies are soil analysis, plant tissue analysis which requires expert knowledge and laboratory testing, but the test results are not necessarily accurate due to human error. Non-destructive methods such as computer vision can help digital farmer who lack knowledge of botany to identify macronutrient deficiencies. Identification and estimation of macronutrient deficiencies using computer vision consists of several stages, namely data acquisition, preprocessing, segmentation, feature extraction, to identification and estimation method. Image data in the form of RGB, NIR, etc. Several researchers have conducted studies to identify and estimate macronutrient deficiencies using different method. These methods are traditional methods such as rule based to K-Nearest Neighbor (KNN), Linear Regression, Artificial Neural Networks (ANN), Deep Learning with various architectures, and others. Several studies have their respective results and limitations, therefore this paper focuses on reviewing current research developments and providing an overview of the work and challenges in the future. The result of the comparative study is that Deep Learning such as CNN is a promising method because most studies can identify macronutrient deficiencies with an accuracy of more than 80%. However, there are still some challenges such as overcoming overlapping images with complex backgrounds, identification of multi-deficiencies, and estimation of the content of each macronutrient in RGB images.

Keywords: *Deep Learning, Classifier, Feature Extraction, Macronutrient Deficiency, Image Processing.*

1. INTRODUCTION

Nutrients has important role for plant growth and development [1],[2]. Nutrients contain macronutrients and micronutrients. Some of macronutrients such as N, P, K, Ca, Mg, S elements are required in large quantities (>1000 mg/kg dry matter). Otherwise, micronutrient such as Iron, Mn, Zn, Cu, Cl, B and Mo are required in small amounts (<100 mg/kg dry matter) [1],[3],[4]. If the nutrients are not in accordance with the needs of the plant, it affects the plant growth and can cause plant damage[5],[6]. Leaves are one of the plant parts that show visual symptoms due to nutrient deficiency

Plant that are lack of nutrient shows obvious symptoms in the colour, shape and leaf texture [4],[7]. Each leaf on a particular part of the plant represents a specific deficiency trait. For example, Ir or Ca deficiency shows a visual effect on young leaves [8], [9]. For K, visual characteristics can be observed on leaves in the middle part of plant [10],[11], and for Mg , N, or Mn deficiency on leaves in the bottom plant [1],[12]. These characteristics shows on Figure 1 and in Table 1.

Table 1: Key Symptoms of Nutrient Deficiencies [11]

Nutrient	Key symptoms
Ca	Irregularly shaped leaves, curling
Ir	Interveinal chlorosis (turning yellow between veins)
Mg	Interveinal chlorosis, necrosis (cell injury),
N	Stunted growth, uniformly yellowish leaves
P	Curling leaf tip, brown scorching,

Identification of macronutrient deficiencies can use two methods such as destructive and non-destructive method[13]. The destructive is usually

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

carried out by soil analysis, plant tissue analysis which requires expert knowledge and laboratory testing, but the test results are not necessarily accurate due to human error[1],[14]. Therefore, identification using non-destructive methods such as computer vision can help digital age farmers who lack knowledge of botany to identify macronutrient deficiencies relatively easily [2], [15], [16]. Some steps to identify nutrient deficiencies are plant recognition, plant segmentation, feature extraction, classification and even estimation of nutrient content [16]–[18].

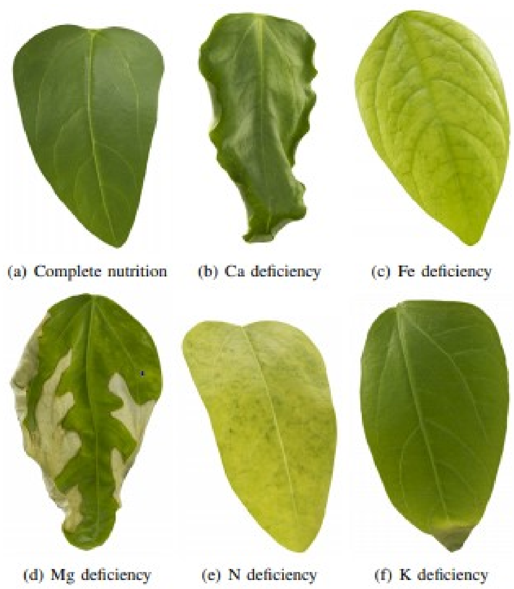

Figure 1: The Different Visual Characteristics of Black Gram Leaves Under Macronutrient Deficiencies [11]

Many studies have tried to reduce and solve problems related to the identification process of macronutrient deficiencies in plants. They have applied a combination of several types of image processing, pattern recognition and classification tools [7], [19], [20]. However, their research still opens gaps so that there are many new challenges that must be completed. Some of them are identification of complex backgrounds in real time, estimation of the percentage of deficiencies to support precision agriculture, and others. Therefore, this paper attempts to organize and present each study in a meaningful and useful way so that the challenges are clearly identified. The sections of this paper are structured as follows: Part II describes the theory and stages of image processing. Section III describes a comparative study for case classification and estimation, then discusses the results. Sections IV and V describe the discussion, challenges, and conclusions of the paper.

2. IMAGE PROCESSING METHOD

There are several steps to do image processing. The first step is image acquisition where an image must be captured by a certain camera type. There are several types of image such as hyperspectral image [21], [22], [23], RGB image [9], [18], [24], and etc. The next step is preprocessing, segmentation, and feature extraction. Image feature extraction is useful for pattern analysis of each type of nutrient deficiency [25]. Some estimation methods are used to estimate certain level of deficiency. Figure 2 shown the processes in digital image processing.

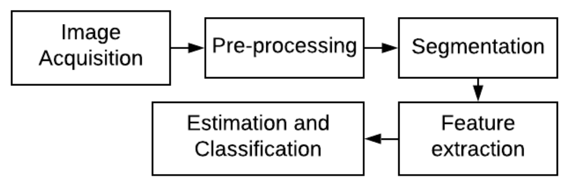

Figure 2: Steps for Estimation and Identification nutrient deficiency leaves image

2.1 Pre-processing

The image pre-processing is the initial step. The purpose of preprocessing is to enhances important image features for further processing [26]. Several categories of image pre-processing methods are pixel brightness and geometric transformations, a local neighborhood of the processed pixel, and image restoration [18],[27]. Pixel Brightness Transformation modify pixel brightness and methods such as grayscale, histogram equalization, and brightness correction [15], [28]. Geometric transform is often approximated by the bilinear transformation[27]. A local neighborhood of the pixel are Nearest Neighbor and Brightness Interpolation. Last, Image restoration methods are min, max, mean, and median [28], [29].

2.2 Segmentation

Segmentation plays an important role in image processing [8], [30]. Segmentation step has important role to detect specific object and separate object from background [31]. In that process, image will be partitioned into various subgroups of pixels. Image segmentation usually partitions objects from the background based on certain features such as pixel intensity, colors, textures, and etc. [9], [17].

2.3 Feature Extraction

Feature extraction is the next step after segmentation phase. The purpose of feature extraction is to get the required information from the object in a lower dimensional space [32]. But, there are several methods that has their automatic feature extraction such as CNN, and etc [7], [10], [33].

2.4 Classification and Estimation

Classification is the process of categorizing and labeling groups of pixels or vectors within an image based on specific rules [34]–[36]. Two general methods of classification are supervised and unsupervised [10], [37]. Supervised method is the process of visually selecting samples (training data) within the image and assigning them to pre-selected categories to create statistical measures to be applied to the entire image [5], [8]. Unsupervised method is a fully automated process without the use of training data such as clustering and pattern recognition [10].

Estimation has attracted significant research effort[38]. Estimation is not always about doing calculations, it is important for system to be able to estimate how many things system can see, or how long something is or how big something is [36]. But, in precision agricultural system nutrient content is important so nutrient solution will be given precisely. Several common methods for estimation are regression, neural networks, and etc. [7], [39].

3. LITERATURE REVIEW

Nutrient deficiency symptoms in plants usually visible in leaves [32]. The symptoms are interveinal chlorosis, uniform chlorosis, marginal chlorosis, distorted edges, etc. [16]. Based on the symptoms, nutrient deficiency is difficult to detect subjectively [26]. Therefore, this paper discusses objective recognition using digital image processing.

3.1 Data Acquisition dan Augmentation

Some research collects plant data using different camera type such as RGB, red edge, infrared, and others [40], [41]. Red edge and infrared camera are usually work to capture big area as like tea [21], Oil palm [42], and etc [40]. The other camera type is near infrared that usually use to capture wheat plants [43], and others [3], [22], [40]. But, camera type that common used for capture image in hydroponics environment is RGB. RGB has been used to many plants such as pomegranate [18], tomatoes [34], [40], pepper[44], paddy[24], [45], [46] and etc [47], [48]. Characteristics of each camera type are shown on the Figure 3.

Leaf hyperspectral reflectance can be used to estimate nutrient concentrations in plants in a narrow band of the electromagnetic spectrum for tea and wheat plants [14], [21], [49], [50]. In addition, a multispectral image has also been developed for the estimation of N in sandalwood leaves based on the changes of reflectance in different bands [50]. Not only crop, hyperspectral has also captured a single cucumber leaf image for N and P content estimation [23], [51].

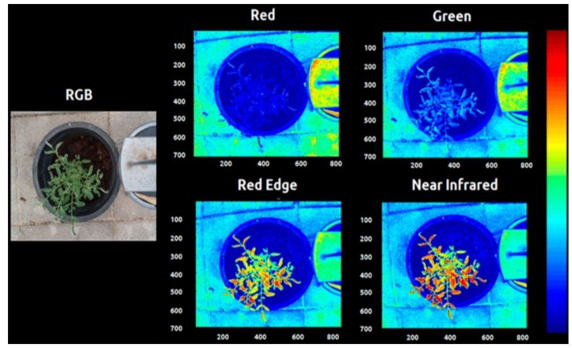

Figure 3: Types of Images Produced by the Sensor after Shifting and Clipping the Area of Interest [40]

Near infrared camera contributes to many studies to evaluate plant health [22]. The visible and near infrared cameras can produce an index, namely the Normalized Difference Vegetation Index (NDVI) which is the best index for evaluating plant health based on the green vegetation [22], [52]. But, the image result characteristics is different with human view as shown on Figure 3. where RGB image camera works like the human eye which is sensitive to RGB light bands [34]. Due to the high price of near infrared cameras, RGB can be an alternative to measure plant health. RGB cameras have similar index with NDVI, namely the Visible Atmospherically Resistant Index (VARI) [53], [54].

Some cameras are useful for generating RGB image datasets [24], [55]. Dataset consists different number of images and categories. More than 500 images of tomatoes plant in 4 categories of deficiencies [34], [56], [57] has been collected, 270 datasets in 4 categories [58], even more than 4000 images of Vigna mungo plants [8]. Most of the image are leaves or plants in complex background [56], [58]. Combination of 1000 images of coffee young and old leaves with deficiencies in Boron, Ca, Fe, N, P, K, Mg, and Zn has been used [59]. They found that the combine image supports more useful information than a single image[60].

Augmentation is the process of modifying an image [25], [61]. Several studies used augmentation to enrich datasets, especially for learning methods to avoid an overfitting [62],[45]. Then, duplicate a number of image until each class has the same amount of data boosts the accuracy until 5% [61].

3.2 Preprocessing

Journal of Theoretical and Applied Information Technology
31st March 2022. Vol.100. No 6

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The preprocessing phase aims to improve image quality. But, some research that use deep learning method such as CNN[11] and RCNN [58] did not used preprocessing. Image data need to reduce some noise, adjusts the image ratio and brightness correction [62], [63]. In identification macronutrient issue, some common preprocessing methods are brightness correction and image resizing [15]. Resizing is useful to reduce processing time [64]. Maize leaf image and the other data are resized from 3024x4032 to 28x28 pixels to make an equal dimensions [55], [65][55]. Resizing image can be done manually [12], [66], [67] or using methods such as Gabor filter such as in maize plant images[68].

In digital image processing, datasets can be represented to different color models. There are several color models such as RGB, YUV, HE, CIELAB, YCbCr, HSV and others. [25]. Color model conversion aims to limit the size and type of color space[69]. RGB image converted to HIS and HSV for multi-plant [68], [70], [55], [71]. It's not only HSV and HIS model, converting the images into binary values and grayscale for threshold and segmentation has been done [59], [72] as shown on Figure 4.

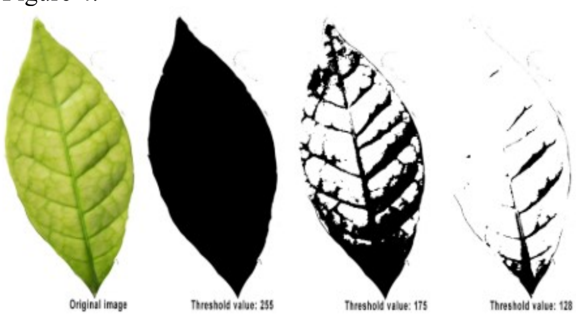

Figure 4: Coffee Leaves in Different Threshold Value [59]

The images need to enhances such noise reduction and discarded low contrast before go through to the next process[73]. The median filter is noise reduction method that adopts a non-linear digital filtering technique [59], [62], [64]. Furthermore, other research applied contrast enhancement to RGB images to emphasize the leaf color using gamma transformation[6]. Increase and decrease the contrast affects the information contain in the image [15]. RGB image convert to CIE L*a*b and, Each component subjects to a contrast enhancement using histogram equalization to highlight the ROI [27], [74]. The result shows on Figure 5.

Enhanced RGB images are useful for next process. For example, the image that uses thresholds to obtain Hu and Fourier descriptor [27]. Then, the combination of deep sparse extreme learning machine (DSELM) and GA fusion can reduce color variability due to variations in light intensity [48]. Then, image adjustment before segmentation were applied using Otsu and K-means clustering [55].

Figure 5: A Leaf Before and After Noise Elimination [27]

There are several pre-processing procedures for hyperspectral image [14]. The suturing process and median filter also apply in multispectral images [50]. Another preprocessing method is Sliding window smoothing (SWS) that integrated with Multiplicative Scattering Correction (MSC) or Standard Normal Variable transformation (SNV) for wheat reflectance spectrum images. Spectroscopic samples of visible and near infrared light at a wavelength of 450,900 nm were processed using SWS, MSC and SNV. The experimental results show that use of SWS and SNV achieve the most accurate estimation [43].

3.3 Segmentation

Segmentation is a crucial part in digital image processing, especially to detect object in complex background. Machine learning with image segmentation shows better result than without segmentation [72]. Sometimes, not all of the researches use segmentation [7], [75]. Several segmentation method are analyzing pixel, morphology, the ROI (Region of Interests) [76], edge detection (Sobel, Prewitt, Robert method) and K-means clustering method [68], [69].

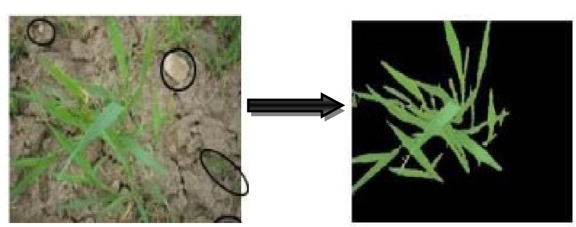

Figure 6: Original and Segmented Image using DSELM and GA [48].

One of the segmentation based on pixel values is using mean and binary conversion lab image[39,64], hue based and histogram based Otsu for tomato and coffee leaves [26], [75], [78]. But, several methods above are applied to single leaf images with an uncomplex background. To do segmentation leaf image in complex backgrounds as like Figure 6, a combination of several approach is required [17].

Based on Figure 6, there are several step to do segmentation in complex background using DSELM and GA[48]. Segmentation step divided into two parts such as masking green pixels and extract useful segments [48][71]. They process images using digital image processing technology to eliminate background noise and interference [18]. Besides GA, other methods such as CNN-DeepLabV3 architecture can segment rice leaf images [46].

3.4 Feature Extraction

Extraction feature is useful for retrieving information from images. Feature extraction retrieves information such as color, texture, shape, geometry, and others [32], [42], [79]. Some studies only analyze one feature, but other studies combine them [7].

Leaf color is usually useful as feature for estimate nutrient content and assessing plant health [80]. Paddy leaves color plays important role to identify nutrient deficiencies, especially for Nitrogen component [12]. Leaf color is used as a feature analyze three RGB channels [34], [70], [81]. RGB color has been used to detect brown spot disease on Paddy leaf [45], [82]. HSV is other color model that can be used to extract information based on H,S,V statistical value[12], [26]. Healthy leaves are dominant in green color, whereas unhealthy leaves are not dominant in green and it can be extracted using Fuzzy C-mean and NN [24], [55], [83]. Therefore, leaves color distribution such as variance, mean, kurtosis, and skewness are extracted and utilized as predictors [48], [76], [84].

GLCM is a method that extracts color information. GLCM is used for feature extraction with 4 different angles to obtain 4 GLCM Color features of both healthy [26], [64]. But, not only for color feature, GLCM is useful for considering texture features such as contrast, entropy, etc. [9], [64],[57]. GLCM extracts the texture features from ventral, dorsal and a combination of them sides of leaf images [85]. Combination of dorsal-ventral shown better result. Statistical values such as mean have also been used for texture in multispectral images[50]. Positive and negative correlations between different texture features can produce Texture Average Value Index (TMVI) and increase linear correlation [50].

Several research has used combine feature [24] [27][86]. Color, shape, and texture features are important parameters in feature extraction [59,61]. A combination GLCM, hue and color histogram has been used for analyze maize plant [64]. The extracted features are RGB values and texture value of the leaves[10]. And then, the other research applied the descriptors Blurred Shape Model (BSM) and GLCM for extract the characteristics of shape and texture in coffee leaves images [9]. The characteristics of RGB color and Sobel edge detection for leaf shape detection has been used [87], [88]. The use of different features affects the result. First, combination of RGB color and Sobel edge detection produces 65.36% of accuracy. Second, RGB color extraction produces 70.25% of accuracy. Last, Sobel edge detection produces 59.52% of accuracy [89]. The combination of features in most studies can not always improve the results for both identification and estimation tasks.

Several studies have separate feature extraction methods with identification systems, but others combine them so that the feature extraction process occurs automatically[46], [56]. Most of them was using CNN [84], [90], [61], [91]. A research automatically extracts and computes leaf color similarity with the reference colors[38]. They accomplished the feature extraction process automatically using ResNet50 deep pre-trained model [60]. Then, Stacked Sparse Autoencoder (SSAE) network is useful for studying the intrinsic features of leaf RGB images automatically through so that compact feature data is obtained [18].

3.5 Identification of Nutrient Deficiency

Image processing methods have their own characteristics. To do learning, the number of dataset effects the result model. More training data will get a better modeling result and the lack of data makes the training less so that affects its accuracy[92].

There are two methods to identify nutrients in plants, they are supervised and unsupervised machine learning [10], [37]. Supervised learning algorithms rely on labeled input data to learn the relationship between data and labels. Unsupervised is an opposed to supervised learning [10]. Supervised learning are usually used to solve simple task such classification or regression problems [38] So, it is quite difficult to perform complex tasks. Unsupervised learning is useful to solve complex tasks such as clustering even though they require high costs [10].

Several of the methods without learning are rule based method, pattern analysis, and etc.

Detection of brown spot disease on paddy leaf has been done using Horsfall and Heuberger method [76]. Then, statistics information are useful to determine unhealthy leaves based on the number of blobs, if the number of blobs are more than 90 so the object is unhealthy [76]. The pattern range and color properties of defective leaves are computed and stored in database. The database is useful for rule based [12], [59]. Rule based classify a test image as healthy or unhealthy and cannot fix high dimensional data [12]. One of the methods that can overcome for high dimensional data is Random forest technique with 78.35% of accuracy [64].

Combination of machine learning with image processing techniques can handle high dimensional data for identification nutrient deficiency [68], [93]. K-NN could be a method for classification study when there is little or no prior knowledge about the distribution data [71]. KNN has been compared with other method such as J48, Naïve Bayes, Partial Least Square (PLS), Classification and Regression Tree (CART), Classification Tree(CT). Highest accuracy is 86,52% to analyze dorsal-ventral combine with statistical feature using KNN method [85]. Then, the results of the image representation are used to train the KNN, Naïve Bayes and Neural Network classifiers using the extracted features. It was taken into consideration the use of K = 1 nearest neighbors and neural network was a 3-layer perceptron trained using the backpropagation algorithm[9]. Other studies uses logistic regression, SVM, and MLP to identify nutrient deficiency of black gram plants. The MLP models achieved superior performance [60].

Each deficiency effects the performance of the model. ANN has been used and the research result shows 93% accuracy for magnesium deficiency and 68% accuracy for Sulfur [26]. Other methods that common uses for identification is SVM [22]. The goal of SVM is to outline the features based on GLCP parameter into higher dimensional feature space. The number of iterations also affects accuracy. For example, SVM classifier achieve accuracy using up to 500 iterations [69]. Then, the other proposed work is to identify individual N,P,K and combination of NP, PK and NPK deficiencies in a leaf at a same time. These features of multi plants image are combined and fed to the SVM classifier 85%[24].

One of the methods that needs learning is Learning Vector Quantization (LVQ) [34], [94]. LVQ is a method in Artificial Neural Networks for learning supervised layers. Pattern classification method with each unit-output representing a particular class or category. Training and testing are using the LVQ algorithm by processing a total of 500 feature vectors obtained from the original image with 86 of accuracy average [34]. Different filters or convolution sizes affect the recognition rate in the classification.

A Convolutional Neural Network (CNN) is a Deep Learning algorithm which extracting the features from input image automatically and adaptively from low to high level features [79], [82], [95]. Then, it requires a minimum preprocessing compared to other classifier method [4], [7], [96]. CNN has been compared with ANN, MLP, and SVM shown best result because the convolutional layer learn multi color or texture images[45]. CNN provides the predicted nutritional deficiencies in the coffee plants through classification and detection [65], [75]. Otherwise, CNN has been used to determine nitrogen fertilizer recommendation [46]. The Stochastic Gradient Descent with Momentum (SDGM) algorithm for training can generate a suitable trained CNN model (2 hyperparameters) [6]. CNN to identification nutrient deficiency of black gram plant used different specification such as three convolutional layers (of size 11x11, 5x5, and 3x3 pixels), two max-pooling layers, and two Fully-connected layers (each with 2,048 nodes). An example of CNN architecture shown on Figure 7. Prediction results are integrated together using a winner-takes-all strategy. Finally, the multilayer perceptron combines the predicted results from all leaf blocks into one so that the type of nutrient deficiency is known [11]. However, the CNN method uses an automatic feature extraction feature so it is difficult to analyze the effect of features combination on the results obtained [59], [97], [98]. An example of CNN architecture shown on Figure 7.

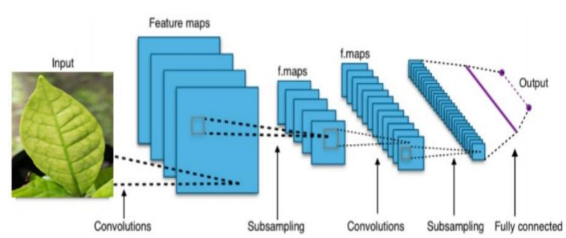

Figure 7: CNN Architecture [59].

There are several deep CNN model thas has been created [95]. They investigated the following deep CNN models: AlexNet, GoogLeNet, Inception-v3, Xception, ResNet50, MobileNet, MobileNetV2, and IncResNetV2 [62], [67], [73], [75]. This study shows that CNN with Densenet-121 architecture is the best deep CNN model with an accuracy around 97% [61]. In addition, VGG16, VGG19, ResNet101, DenseNet121, DenseNet169, DenseNet201 has been compared [61], [75], [78]. Inception-ResNet v2 based CNN is applied to distinguish mineral nutrients (i.e. Ca and K) with the captured images of tomato plant [33]. Based on several studies using same data, Inception-V3 requires low cost, but the accuracy is also the lowest. The longest computation time is VGG19 and the highest accuracy is VGG16.

Besides CNN, DCNNs have been tested and it obtained accuracies for over 90% and outperformed two traditional machine learning methods, color feature with SVM and HOG with SVM [75]. CNN collaborates with other methods and produces good results like CNN+SVM [72]. CNN combine with Artificial Hydrocarbon Network (AHN) as dense layer has been used with an accuracy of 95.57% and F1-score of 95.75% [56]. CNN and Generative Adversarial Networks (GANs) combination results 98% of accuracy on the number of real-time images[90]. Transfer learning and Fine tuning can be used to do pattern recognition after training VGG16 Neural Network[87]. In several cases, deep learning did not gave promising results because of data complexity, so the computer detects multi detection [58]. Table 2 and Table 3 present a summary of the identification research using the Machine Learning and Deep Learning methods.

Table 2: Research Summary of Nutrient Deficiency Identification Issue using Machine Learning

Plant	Preprocessing	Feature Extraction	Classifier	Result and Gaps	Reference
Paddy	Manual resize to be 256x256 and Median Filter	RGB feature (0-255)	Rule based	improving the database and refining the rules can improve the accuracy. But this work can be used for high dimension data.	[99]
Paddy	RGB to HSV	HSV color model	Rule based	The use of HSV color model increase 86% of accuracy. However, rule-based methods cannot cope with complex data.	[12]
Coffee	Segmentation using Otsu method	BSM and GLCM to extract Shape and Texture	KNN, Naïve bayes, NN	the best results associated with the GLCM for Iron. But, result model are not robust for all nutrients	[9]
Maize	RGB to HSV, Gabor filter for resizing and noise filtering, K-Means for segmentation.	Shape, texture, and Histogram based feature	Autoencoders, ANN, SVM, KNN	Histogram based feature show best performance than shape and texture. Feture combinations are not used.	[68]
Mango	Gaussian Filters	Texture RGB (0-255)	K-Means Clustering	Provide better accuracy for unlabeled data. unable to overcome nutrient deficiency with non-coloured symptoms	[10]
Black gram	There is no pre-processing	ResNet-50	logistic regression, SVM, and MLP	MLP model performs the best result with 88.33 of % accuracy. Research has not yet detected the percentage of deficiency.	[60]
Cucumber	RGB value	characteristics of RGB and Sobel edge detection for leaf shape	Artificial Neural Networks	Combination of RGB color extraction and sobel edge detection did not show a highest accuracy.	[89]
Tomato	Noise removal, RGB to HSV, and segmentation using hue and histogram-based Otsu	GLCM and LOG	Artificial Neural Networks	Highest accuracy are 93% for Magnesium and the lowest is 68% for detecting Sulphur.	[26]
Tomato	Resizing, filtering using salt and pepper method, grayscale, then contrast enhancement	Statistical feature such as mean, variance, skewness, and SD, GLCM	ANFIS	Cannot detect nutrient deficiency for deficiency traits in only one leaf	[57]
Coffee	Contrast improvement using SIFT, Thresholding to obtain Hu and Fourier descriptors	Fourier, Hu, and SURF descriptor.	Neural Network	The model does not recognize Calcium well because almost all leaves are Calcium deficiency	[27]
Olive tree	RGB to HSV colorspace, masking	YGB , percentage of RGB value	ML, decision tree and Naïve Bayes models	machine learning model showed the best results with 97% of accuracy. But, they only used color information.	[70]
Multi Plant	Thresholding to get ROI	Statistical analysis such as Mean, SD, etc.	BP-NN, Random Forest, Naive Bayes and SVM	The lowest result was obtained for the earliest measured stage of plant.	[37]

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 2: Research Summary of Nutrient Deficiency Identification Issue using Machine Learning (Continue)

Plant	Preprocessing	Feature Extraction	Classifier	Result and Gaps	Reference
Maize	Resizing image and Median filter	GLCM, Hue-Histogram, Color Histogram	Random Forest Technique	Several nutrients have the same characteristics, so it is difficult to identify it.	[64]
Cucumber	Reduce image dimensions and ROI	Feature extraction by PCA and ICA	KNN, BP-ANN	BP-ANN shows best accuracy (97.5%). The research only considers one type of deficiency	[23]

Table 3: Research Summary of Nutrient Deficiency Identification Issue using Deep Learning

Plant	Preprocessing	Feature Extraction	Classifier	Result and Gaps	Reference
Chili	There is no pre-processing	Automated FE	3 RCNN topologies	inception v2 mask model produces the lowest total loss and the fastest time. RCNN Mask method has not been able to classify in as much detail as desired by experts	[58]
Tomato	Contrast enhancement and image resize	Automated FE	CNN model has three degrees of depth	It does not consider the light conditions and the effect of the contrast enhancement.	[6]
Black gram	Divide into small blocks.	Automated FE	CNN (winner take all strategy is used)	the proposed method cannot achieve highly accurate identification	[11]
Tomato	There is no pre-processing	Automated FE	Inception-ResNet v2 based CNN	The overall result of test accuracy reaches approximately 92% but the system has not been implemented in the real system	[33]
Black gram	There is no pre-processing	Automated FE	Various Deep CNN	ResNet50 with data augmentation achieved the best performance (65.44%) but the accuracy is still low.	[8]
Tomato	RGB	Automated FE	CNN and LVQ	the leaves with different diseases are very similar to each other so the accuracy is around 86%.	[34]
Multi Plant	There is no pre-processing	Automated FE	CNN	the model only searches for colours in the leaf images	[95]
Banana	Data augmentation, RGB convert to YUV, HE, CIELAB, YCbCr and HSV.	Automated FE	Neural Network. VGG16 model.	The model has very high accuracy and minimal error by data augmentation. Other features need to be considered.	[25]
Multi Plant	preprocessing task using SMOTE	CNN is used to extract the patterns of leaf images	ELM-based classfiier.	proposed modifed CNN model obtains improved training and testing classication accuracy but it is only at the simulation stage	[96]
Coffee	Grayscale, Binary values for thresholding and segmentation	Automated FE	CNN	Detection rates depend on size and threshold value. It has not been implemented	[59]
Rice Plant	There is no pre-processing	Automated FE for DCNN and color feature for SVM	DCNN, SVM, HOG SVM	that the learning rate of 0.00001 was most suitable for the model to run 50 epochs for training. DCNN shows best accuracy than SVM and HOG SVM. Features combination will be considered	[75]
Okra Plant	Resizing image to 299 x 299 and data augmentation using ImageDataGenerator	Automated FE	Inception ResNet-v2 CNN	the amount of data for several deficiency only produces 2 classes	[87]
Rice	Segmentation using Mean Shift image. Then, RGB image is convert to grayscale, YCbCr and HSI	Color using Ybr and HSI value, shape using traditional shape feature such as area, roundness, shape complexity	CNN, Deep learning CNN + SVM, AlexNet, VGG	CNN with image segmentation shows better result than without segmentation. But, CNN +SVM best result. Other feature such as texture needs to be considered	[72]
Rice	Otsu segmentation, median filter, and size is decrease	Pre-trained ResNet50 model to extract the functionality	CNN denseNet-BC	DenseNet-BC adopts a non-linear transformation (96% of accuracy). region based object detection can be utilized to extract the deficient regions	[78]

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 3: Research Summary of Nutrient Deficiency Identification Issue using Deep Learning (Continue)

Plant	Preprocessing	Feature Extraction	Classifier	Result and Gaps	Reference
Rice	Add background to solve different image size, rescaled image to 500x500 and 224x224. RL for augmentation until each class has 500 data	Automated FE	CNN model Self-Design, GoogleNet, ResNet, DenseNet121,	CNN Densenet-121 is the best accuracy around 97% and duplicated a number of image until each class has 500 data boosts the accuracy by 5%. Their CNN model self-design produces the lowest of accuracy	[61]

3.6 Estimation of Nutrient Deficiency

Several classification methods above only determine the type of nutrient deficiency. Even though the level of nutrient deficiency affects the nutrient solution that will be given [50]. To support precision farming systems, the system can also analyze the percentage of macronutrient deficiencies. One of the ways that can be used to determine the percentage of nutrient deficiency is to estimate the nutrient levels. Several studies has been done for estimate nutrient content based on leaves plant images and will be discussed in this paper.

Macronutrient such as Nitrogen and chlorophyll content has been estimated. There are several ways to estimate chlorophyll content such as using SPAD and Computer Vision [7], [18]. A prediction model between RGB leaf image features and its SPAD (arbitrary units) value was established to predict the chlorophyll content in the paddy leaf [38], [46]. The results show that the deep neural network in this study resulted in higher accuracy and automation of detecting chlorophyll content than traditional machine learning methods. [18]. SVM as a classifier is trained and tested using several kernel functions such as RBG, MLP, and Polynomial kernel[55]. Then, estimate nutrient content in wheat leaves has been done by analyze color features of the leaf images. The leaves captured on field with various lighting conditions. To estimate nitrogen content in wheat leaves, a number of DSELMs and committee machine had combined and optimize using the GA[48]. Therefore, there was low cost Chlorophyll estimator using Field Programmable Gate Array (FPGA). It shows that nonlinear terms provides best fit than estimated terms multivariate regression model [80].

Other studies have determined the nutritional content of rice plants [75]. They used digital numbers (DN) from smartphones that were reliable to predict the nitrogen (N), phosphorus (P), and potassium (K) content in rice. The best formula is N = 0.0035 * DN + 0.8192 (*R*2 0.84), N = 0.0035 * DN + 0.8192 (*R*2 0.84), and P = 0.0049 * DN – 0.2042 (*R*2 0.70) [82].

In addition to determining the percentage, estimation can take place by determining the level of deficiency. Olive tree estimation has 5 deficiency levels. Machine learning models, decision trees and naive bayes were compared to analyze RGB image data. The result is that the machine learning model obtains the highest accuracy, which is 97% . Another study compared the PCA, KNN, BP-ANN methods for the estimation of macronutrient deficiency. The result is that the BP-ANN model yields the best model with possible evidence to diagnose whether the plant was in a P-deficient state 21 days earlier [23].

Other image type to estimate leaf nutrient concentrations is leaf hyperspectral reflectance [22], [37]. One of the studies identified and estimated using PCA and Multi Linear Regression methods on cucumbers. The 95% identification results and the MLR model have succeeded in modeling the relationship between color bands and chlorophyll concentration as shown in Figure 8 [51].

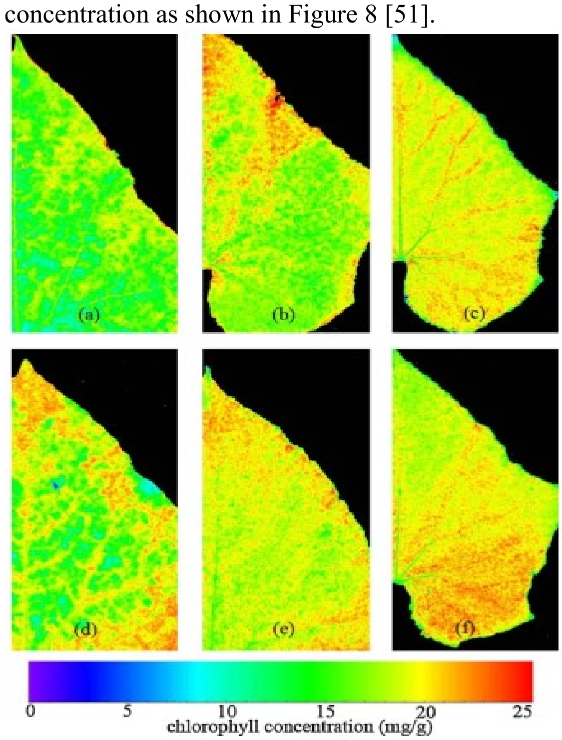

Figure 8: Chlorophyll distribution map on cucumber leaf based on near infrared hyperspectral image [51].

Another study analyzed leaf hyperspectral leaf image using the Partial Least Squares Regression

(PLSR) method [40]. The first derivative was more accurate for predicting N, P, and S. The estimates for concentrations of Ca, Mg, and K were using the logarithm transformation and for iron concentrations were using the smoothed reflectance. Br and Mn were more accurate using the first derivative, while Zn using the second derivative[14]. Nonlinear mixed-effects model with dummy variables improved the fitting degree and estimation accuracy compared with results of SVR and BPNN and exponential shown the best result. Then, the relationship between the relative chlorophyll content of leaves and the reflectance spectrum resulted in a specific model using partial least squares (PLS) and back-propagation neural networks [43].

Wheat chlorophyll content has been estimated using different method such as BP-ANN, KNN, and Stepwise-Based Ridge Regression (SBRR). SBBR is a method to do multiple regression with adding or remove predictor variable. The comparisons and verification show that SBRR approach achieve better experimental results and can be considered a reliable and low-cost alternative for estimating the chlorophyll content of wheat leaves in field[7]. Other studies found that Regression nonlinear terms provides best fit between estimated terms. That's because the residuals are near in baseline and the adjusted coefficient of determination is very significant[80]. Table 4 present a research summary of the nutrient deficiency estimation Issue.

Table 4: Research Summary of Nutrient Deficiency Estimation Issue

Plant	Preprocessing	Feature Extraction	Method	Result and Gaps	Reference
Multi-plant	Grayscale and resize image using Otsu, K-Means, RGB to HIS	Color using HIS value, texture using GLCM	Analyze the feature of image	the model cannot handle data under the different light conditions	[55]
Wheat	Calculate varians and standard deviation of RGB image	Statistical feature from RGB color	Multivariate linear regression	only estimates the amount of chlorophyll present in plant leaves is sufficient or not	[80]
Wheat	Segmentation using DSELM and GA	Color	a number of DSELMs and committee with GA	single color features and their combinations are not suitable to estimate nitrogen	[48]
Multi-plant	Segmentation using Thresholding, noise processing, and background separation	Color feature using Stacked Sparse Autoencoder (SSAE)	Deep Neural Network	The model is still in design stage.	[18]
Eucalyptus	First and second Derivative, Leaf reflectance logarithmic transformation	Color feature	PLSR	each nutrient has high performance in different methods	[14]
Wheat	Sliding Window Smoothing (SWS) and Standard Normal Variable Transformation (SNV)	-	PLSR	the combination of multiple preprocessing is an effective way to improve the accuracy	[43]
Wheat	Iterative Threshold Segmentation, Multiple color spaces Calculation	Statistical feature from RGB and La*b* Color space	stepwise-based ridge regression (SBRR), BP-ANN, KNN	Mean feature b* value from the La*b* are correlated with chlorophyll content. But, the resulting accuracy is still low which is less than 80%.	[100]
Tomato	596 images of 3024 x 4032 px size were stored in the dataset	a set of convolutional layers as the feature extraction part,	CNN+AHN+ PCA layer	CNN+AHN+PCA produces 95.57% of accuracy. Then, data acquisition is still done manually	[56]
Cucumber	the average spectra obtained from the ROI in leaf hyperspectral images were extracted	Using statistic value such as Min, Mean, Max, SD from each pixel	PCA and Multi Linear Regression (MLR)	MLR produce correlation between chlorophyll concentration and color of image.	[51]
Rice	Rectification	Visible light, RGB Digital Number (DN)	Linear Regression	It reliable to predict the NPK content in rice. the model is not designed to be robust against different lighting	[82]
Olive	RGB to HSV colorspace, masking	YGB value percentage	ML model, Decision Tree and Naïve Bayes	Best result is using Machine Learning model	[70]

4. FUTURE WORK AND DISCUSSION

Identification of nutrient deficiency in plants using image processing is a challenge in recent times. Many studies have contributed to resolving several challenges. Based on the analyses, it is proved that the image processing technology can

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

support the development of farming automation to accomplish the advantages of low price, high efficiency, and high accuracy. Since the development of monitoring technology in smart farming systems, the challenges are getting bigger. This paper presents a discussion of new challenges that can be solved in the future.

4.1 How to separate object in complex background and fix the overlapping object

There are two types of data, namely field data and individual plant data. Field data is usually acquired by a camera at a certain height [47], [48], [100], while individual crop data is captured at close range [11]. Therefore, it is not surprising that usually field data can be processed using color characteristics without any segmentation process. individual data can be captured under certain conditions with a set environment. But in real monitoring systems, usually there are not only plants in one location. Data usually capture on complex background conditions[48]. Preprocessing such as image segmentation with several methods can be applied to complex backgrounds [17], [101]. However, usually there are overlapping objects in the form of leaves or fruit that are found, making it difficult to extract features in the form of shapes. Methods to overcome overlapping objects in the real environment can be a challenge for future research.

4.2 Identification nutrient deficiency in different light intensity

There are several types of agriculture, such as systems in controlled and uncontrolled environments [47]. A system in a controlled environment is a system that has no impact on changes in weather until the season[48]. It means that the system is arranged in such a way, but what about the system in an uncertain environment. One of the things that is always change in real environment is light condition[7], [21]. Different light conditions affect the result of the task for both identification and estimation. Several identification studies have been carried out [21], [55], [80], but they have not been able to solve the problem of lighting differences in the acquired image.

4.3 Identification of multi nutrient deficiency

In real systems, it found that plants often lack more than one type of nutrient. Some of them are NP, NK, PK, NPK, MgS and so on [12], [24]. Several systems have been established for the identification of certain multi-nutrients, but the plant environment is a specific environment. So, how to identify multi nutrient deficiencies in real systems with an uncertain environment?

4.4 Estimation percentage of Nutrient deficiency

To build a precision farming system, the system doesn't just identify but the system have to calculate and provide an optimal solutions[14], [36], [50]. In the nutrient supply system, to find out how much nutrient supply is optimal, the system has to know the amount of nutrients that plants need first. Therefore, we need a system that can estimate plant nutrients, not only one type of nutrient but many nutrients. So, nutrient that given are based on plant needs. Most studies have tried to estimate macronutrient deficiencies [56], but they are still limited to NIR images and cannot be applied to monitoring systems [50]. In addition, most studies have not been able to estimate several types of macronutrients [47], [50].

4.5 Smart Farming

The current era is the digital era. The challenge is how to engage technology to help and facilitate work that is difficult for humans to do. One of them is to monitor the health condition of plants and determine the solution. Most of the research is still doing image data acquisition manually [96], whereas data acquisition can be done automatically with IoT [9]. After data acquisition, the image processing process can also run automatically until the condition of plants that lack macronutrients is known and the percentage of deficiency is known. The system is also expected to be able to perform calculations automatically so that the number of solutions and actions that must be given are carried out automatically by the system

5. CONCLUSION

Plant health is influenced by several things such as pests, diseases, environmental factors, and nutrient deficiencies. Unhealthy plants usually have observable visual features such as discoloration, abnormal number of leaves, etc. Digital image processing is a suitable method for processing visual data from leaves. Several studies of digital image processing with various methods to diagnose deficiency symptoms in plants are presented in this paper. The use of leaf characteristics such as color, texture, and shape affects the accuracy of the results. Some studies that combine features can produce higher accuracy, some do not. However, the use of the same amount of data for each class has proven to be successful in increasing the accuracy of the model. Several non-destructive methods such as traditional rule-based methods to deep learning have been applied. Deep Learning CNN with various architectures is proven to be able to recognize nutrient deficiencies based on leaf image data. However, there are several new challenges, such as how to overcome overlaps in leaf segmentation to how to estimate the content of each nutrient in plants.

ACKNOWLEDGMENT

This study was funded by Directorate of Research and Community Service, Deputy for Strengthening Research and Development, Ministry of Research, Technology/National Research and Innovation Agency of the Republic of Indonesia in the PMDSU program.

REFRENCES:

[1] V. Aleksandrov, "Identification of nutrient deficiency in bean plants by prompt chlorophyll fluorescence measurements and Artificial Neural Networks," *bioRxiv*, no. June, p. 664235, 2019, doi: 10.1101/664235.

[2] R. Perwiratama, Y. K. Setiadi, and Suyoto, "Smart hydroponic farming with IoT-based climate and nutrient manipulation system," *Proceeding - 2019 Int. Conf. Artif. Intell. Inf. Technol. ICAIIT 2019*, pp. 129–132, 2019, doi: 10.1109/ICAIIT.2019.8834533.

[3] H. J. Butler, S. Adams, M. R. McAinsh, and F. L. Martin, "Detecting nutrient deficiency in plant systems using synchrotron Fourier-transform infrared microspectroscopy," *Vib. Spectrosc.*, vol. 90, pp. 46–55, 2017, doi: 10.1016/j.vibspec.2017.03.004.

[4] T. T. Tran, J. W. Choi, T. T. H. Le, and J. W. Kim, "A comparative study of deep CNN in forecasting and classifying the macronutrient deficiencies on development of tomato plant," *Appl. Sci.*, vol. 9, no. 8, 2019, doi: 10.3390/app9081601.

[5] A. Shah, P. Gupta, and Y. M. Ajgar, "Macro-Nutrient Deficiency Identification in Plants Using Image Processing and Machine Learning," *2018 3rd Int. Conf. Converg. Technol. I2CT 2018*, pp. 1–4, 2018, doi: 10.1109/I2CT.2018.8529789.

[6] C. Cevallos, H. Ponce, E. Moya-Albor, and J. Brieva, "Vision-Based Analysis on Leaves of Tomato Crops for Classifying Nutrient Deficiency using Convolutional Neural Networks," pp. 1–7, 2020, doi: 10.1109/ijcnn48605.2020.9207615.

[7] Y. Song, G. Teng, Y. Yuan, T. Liu, and Z. Sun, "Assessment of wheat chlorophyll content by the multiple linear regression of leaf image features," *Inf. Process. Agric.*, 2020, doi: 10.1016/j.inpa.2020.05.002.

[8] K. A. M. Han and U. Watchareeruetai, "Classification of nutrient deficiency in black gram using deep convolutional neural networks," *JCSSE 2019 - 16th Int. Jt. Conf. Comput. Sci. Softw. Eng. Knowl. Evol. Towar. Singul. Man-Machine Intell.*, pp. 277–282, 2019, doi: 10.1109/JCSSE.2019.8864224.

[9] M. Vassallo-Barco, L. Vives-Garnique, V. Tuesta-Monteza, H. I. Mejía-Cabrera, and R. Y. Toledo, "Automatic detection of nutritional deficiencies in coffee tree leaves through shape and texture descriptors," *J. Digit. Inf. Manag.*, vol. 15, no. 1, pp. 7–18, 2017.

[10] M. Merchant, V. Paradkar, M. Khanna, and S. Gokhale, "Mango Leaf Deficiency Detection Using Digital Image Processing and Machine Learning," *2018 3rd Int. Conf. Converg. Technol. I2CT 2018*, pp. 1–3, 2018, doi: 10.1109/I2CT.2018.8529755.

[11] U. Watchareeruetai, P. Noinongyao, C. Wattanapaiboonsuk, P. Khantiviriya, and S. Duangsrisai, "Identification of Plant Nutrient Deficiencies Using Convolutional Neural Networks," *iEECON 2018 - 6th Int. Electr. Eng. Congr.*, pp. 2018–2021, 2018, doi: 10.1109/IEECON.2018.8712217.

[12] M. V. Latte, S. Shidnal, and B. S. Anami, "Rule Based Approach to Determine Nutrient Deficiency in Paddy Leaf Images," *Int. J. Agric. Technol.*, vol. 13, no. 2, pp. 227–245, 2017.

[13] V. R. P. Marcelo and J. G. Lagarteja, "Corzea: Portable maize (Zea Mays L.) nutrient deficiency identifier," *Int. J. Sci. Technol. Res.*, vol. 9, no. 2, pp. 1049–1053, 2020.

[14] L. F. R. Oliveira and R. C. Santana, "Estimation of Leaf Nutrient Contrentation from Hyperspectral Reflectance in Eucalyptus using Partial Least Squares Regression," *Sci. Agric.*, pp. 1–10, 2020, doi: http://dx.doi.org/10.1590/1678-992X-2018-0409.

[15] D. Story and M. Kacira, "Design and implementation of a computer vision-guided greenhouse crop diagnostics system," *Mach. Vis. Appl.*, vol. 26, no. 4, pp. 495–506, 2015, doi: 10.1007/s00138-015-0670-5.

[16] S. Jeyalakshmi and R. Radha, "a Review on Diagnosis of Nutrient Deficiency Symptoms in Plant Leaf Image Using Digital Image

Processing," *ICTACT J. Image Video Process.*, vol. 7, no. 4, pp. 1515–1524, 2017, doi: 10.21917/ijivp.2017.0216.

[17] I. Kiruba Rajia and K. K. Thyagharajan, "An analysis of segmentation techniques to identify herbal leaves from complex background," *Procedia Comput. Sci.*, vol. 48, no. C, pp. 589–599, 2015, doi: 10.1016/j.procs.2015.04.140.

[18] Y. Peng and Y. Wang, "Prediction of the chlorophyll content in pomegranate leaves based on digital image processing technology and stacked sparse autoencoder," *Int. J. Food Prop.*, vol. 22, no. 1, pp. 1720–1732, 2019, doi: 10.1080/10942912.2019.1675692.

[19] H. Tian, T. Wang, Y. Liu, X. Qiao, and Y. Li, "Computer vision technology in agricultural automation —A review," *Inf. Process. Agric.*, vol. 7, no. 1, pp. 1–19, 2020, doi: 10.1016/j.inpa.2019.09.006.

[20] D. Andújar, J. Dorado, C. Fernández-Quintanilla, and A. Ribeiro, "An approach to the use of depth cameras for weed volume estimation," *Sensors (Switzerland)*, vol. 16, no. 7, pp. 1–11, 2016, doi: 10.3390/s16070972.

[21] R. Sonobe, Y. Hirono, and A. Oi, "Non-destructive detection of tea leaf chlorophyll content using hyperspectral reflectance and machine learning algorithms," *Plants*, vol. 9, no. 3, 2020, doi: 10.3390/plants9030368.

[22] S. Debnath *et al.*, "Identifying individual nutrient deficiencies of grapevine leaves using hyperspectral imaging," *Remote Sens.*, vol. 13, no. 16, pp. 1–21, 2021, doi: 10.3390/rs13163317.

[23] J. Shi, Y. Wang, Z. Li, X. Huang, T. Shen, and X. Zou, "Characterization of invisible symptoms caused by early phosphorus deficiency in cucumber plants using near-infrared hyperspectral imaging technology," *Spectrochim. Acta Part A Mol. Biomol. Spectrosc.*, no. xxxx, p. 120540, 2021, doi: 10.1016/j.saa.2021.120540.

[24] S. G. Brahmini and K. J. Rani, "NPK deficiency detection in paddy leaf images," *Int. J. Futur. Revolut. Comput. Sci. Commun. Eng.*, vol. 3, no. 9, pp. 102–107, 2017.

[25] R. Guerrero, B. Renteros, R. Castaneda, A. Villanueva, and I. Belupu, "Detection of nutrient deficiencies in banana plants using deep learning," pp. 1–7, 2021, doi: 10.1109/icaacca51523.2021.9465311.

[26] A. Jose, S. Nandagopalan, V. Ubalanka, and D. Viswanath, "Detection and classification of nutrient deficiencies in plants using machine learning," *J. Phys. Conf. Ser.*, vol. 1850, no. 1, p. 012050, 2021, doi: 10.1088/1742-6596/1850/1/012050.

[27] J. Sosa, J. Ramírez, L. Vives, and G. Kemper, "An Algorithm for Detection of Nutritional Deficiencies from Digital Images of Coffee Leaves Based on Descriptors and Neural Networks," *2019 22nd Symp. Image, Signal Process. Artif. Vision, STSIVA 2019 - Conf. Proc.*, pp. 3–7, 2019, doi: 10.1109/STSIVA.2019.8730286.

[28] Z. Chen, C. Ying, C. Lin, S. Liu, and W. Li, "Multi-View Vehicle Type Recognition with Feedback-Enhancement Multi-Branch CNNs," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 29, no. 9, pp. 2590–2599, 2019, doi: 10.1109/TCSVT.2017.2737460.

[29] S. Perumal and T. Velmurugan, "Preprocessing by Contrast Enhancement Techniques for Medical Images," *Int. J. Pure Appl. Math.*, vol. 118, no. 18, pp. 3681–3688, 2018.

[30] M. P. Rico-Fernández, R. Rios-Cabrera, M. Castelán, H. I. Guerrero-Reyes, and A. Juarez-Maldonado, "A contextualized approach for segmentation of foliage in different crop species," *Comput. Electron. Agric.*, vol. 156, no. December 2018, pp. 378–386, 2019, doi: 10.1016/j.compag.2018.11.033.

[31] V. Singh and A. K. Misra, "Detection of plant leaf diseases using image segmentation and soft computing techniques," *Inf. Process. Agric.*, vol. 4, no. 1, pp. 41–49, 2017, doi: 10.1016/j.inpa.2016.10.005.

[32] L. Kamelia, T. K. B. A. Rahman, H. Saragih, and R. Haerani, "The comprehensive review on detection of macro nutrients deficiency in plants based on the image processing technique," *Proc. - 2020 6th Int. Conf. Wirel. Telemat. ICWT 2020*, pp. 0–3, 2020, doi: 10.1109/ICWT50448.2020.9243623.

[33] C. Jae-Won, T. T. Trung, T. Le Huynh Thien, P. Geon-Soo, C. Van Dang, and K. Jong-Wook, "A nutrient deficiency prediction method using deep learning on development of tomato fruits," *iFUZZY 2018 - 2018 Int. Conf. Fuzzy Theory Its Appl.*, pp. 338–341, 2018, doi: 10.1109/iFUZZY.2018.8751688.

[34] M. Sardogan, A. Tuncer, and Y. Ozen, "Plant Leaf Disease Detection and Classification Based on CNN with LVQ Algorithm," *UBMK 2018 - 3rd Int. Conf. Comput. Sci. Eng.*, pp. 382–385, 2018, doi: 10.1109/UBMK.2018.8566635.

[35] P. Tm, A. Pranathi, K. Saiashritha, N. B. Chittaragi, and S. G. Koolagudi, "Tomato Leaf Disease Detection Using Convolutional Neural

Networks," *2018 11th Int. Conf. Contemp. Comput. IC3 2018*, 2018, doi: 10.1109/IC3.2018.8530532.

[36] X. Wang, Y. Chen, F. Liu, R. Zhao, X. Quan, and C. Wang, "Nutrient resorption estimation compromised by leaf mass loss and area shrinkage: Variations and solutions," *For. Ecol. Manage.*, vol. 472, no. March, p. 118232, 2020, doi: 10.1016/j.foreco.2020.118232.

[37] A. Siedliska, P. Baranowski, J. Pastuszka-Woźniak, M. Zubik, and J. Krzyszczak, "Identification of plant leaf phosphorus content at different growth stages based on hyperspectral reflectance," *BMC Plant Biol.*, vol. 21, no. 1, pp. 1–17, 2021, doi: 10.1186/s12870-020-02807-4.

[38] T. Haider *et al.*, "A Computer-Vision-Based Approach for Nitrogen Content Estimation in Plant Leaves," pp. 1–19, 2021.

[39] M. D. Fariñas, D. Jimenez-Carretero, D. Sancho-Knapik, J. J. Peguero-Pina, E. Gil-Pelegrín, and T. Gómez Álvarez-Arenas, "Instantaneous and non-destructive relative water content estimation from deep learning applied to resonant ultrasonic spectra of plant leaves," *Plant Methods*, vol. 15, no. 1, pp. 1–10, 2019, doi: 10.1186/s13007-019-0511-z.

[40] M. C. F. Lima, A. Krus, C. Valero, A. Barrientos, J. Del Cerro, and J. J. Roldán-Gómez, "Monitoring plant status and fertilization strategy through multispectral images," *Sensors (Switzerland)*, vol. 20, no. 2, 2020, doi: 10.3390/s20020435.

[41] S. Kolhar and J. Jagtap, "Plant trait estimation and classification studies in plant phenotyping using machine vision – A review," *Inf. Process. Agric.*, no. xxxx, 2021, doi: 10.1016/j.inpa.2021.02.006.

[42] M. Rendana, S. Abdul Rahim, T. Lihan, W. Mohd Razi Idris, and Z. Ali Rahman, "A Review of Methods for Detecting Nutrient Stress of Oil Palm in Malaysia," *J. Appl. Environ. Biol. Sci. J. Appl. Environ. Biol. Sci.*, vol. 5, no. 6, pp. 60–64, 2015, [Online]. Available: www.textroad.com.

[43] J. Zhang, W. Han, L. Huang, Z. Zhang, Y. Ma, and Y. Hu, "Leaf chlorophyll content estimation of winter wheat based on visible and near-infrared sensors," *Sensors (Switzerland)*, vol. 16, no. 4, pp. 1–11, 2016, doi: 10.3390/s16040437.

[44] M. P. S. da Silva, M. S. Mendonça Freitas, P. Cesar Santos, A. J. C. de Carvalho, and T. S. Jorge, "Capsicum annuum var. annuum under macronutrients and boron deficiencies: Leaf content and visual symptoms," *J. Plant Nutr.*, vol. 42, no. 5, pp. 417–427, 2019, doi: 10.1080/01904167.2018.1544255.

[45] N. Senan, M. Aamir, R. Ibrahim, N. S. A. M. Taujuddin, and W. H. N. W. Muda, "An efficient convolutional neural network for paddy leaf disease and pest classification," *Int. J. Adv. Comput. Sci. Appl.*, vol. 11, no. 7, pp. 116–122, 2020, doi: 10.14569/IJACSA.2020.0110716.

[46] T. Islam, R. U. B. Rizan, Y. A. Tusher, M. Shafiuzzaman, M. A. Hossain, and S. Galib, "Nitrogen fertilizer recommendation for paddies through automating the Leaf Color Chart (LCC)," *Int. J. Adv. Comput. Sci. Appl.*, vol. 11, no. 8, pp. 745–752, 2020, doi: 10.14569/IJACSA.2020.0110891.

[47] S. B. Sulistyo, W. L. Woo, and S. S. Dlay, "Regularized Neural Networks Fusion and Genetic Algorithm Based On-Field Nitrogen Status Estimation of Wheat Plants," *IEEE Trans. Ind. Informatics*, vol. 13, no. 1, pp. 103–114, 2017, doi: 10.1109/TII.2016.2628439.

[48] S. B. Sulistyo, D. Wu, W. L. Woo, S. S. Dlay, and B. Gao, "Computational Deep Intelligence Vision Sensing for Nutrient Content Estimation in Agricultural Automation," *IEEE Trans. Autom. Sci. Eng.*, vol. 15, no. 3, pp. 1243–1257, 2018, doi: 10.1109/TASE.2017.2770170.

[49] R. Sonobe, H. Yamashita, H. Mihara, A. Morita, and T. Ikka, "Estimation of leaf chlorophyll a, b and carotenoid contents and their ratios using hyperspectral reflectance," *Remote Sens.*, vol. 12, no. 19, pp. 1–19, 2020, doi: 10.3390/rs12193265.

[50] Z. Chen and X. Wang, "Model for estimation of total nitrogen content in sandalwood leaves based on nonlinear mixed effects and dummy variables using multispectral images," *Chemom. Intell. Lab. Syst.*, vol. 195, no. July, p. 103874, 2019, doi: 10.1016/j.chemolab.2019.103874.

[51] S. Ji-Yong *et al.*, "Nondestructive diagnostics of nitrogen deficiency by cucumber leaf chlorophyll distribution map based on near infrared hyperspectral imaging," *Sci. Hortic. (Amsterdam).*, vol. 138, pp. 190–197, 2012, doi: 10.1016/j.scienta.2012.02.024.

[52] L. Han, G. Yang, H. Yang, B. Xu, Z. Li, and X. Yang, "Clustering field-based maize phenotyping of plant-height growth and canopy spectral dynamics using a UAV remote-sensing approach," *Front. Plant Sci.*, vol. 871, no. November, pp. 1–18, 2018, doi: 10.3389/fpls.2018.01638.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[53] L. Kamelia, T. K. B. A. Rahman, H. Saragih, and R. Haerani, "The comprehensive review on detection of macro nutrients deficiency in plants based on the image processing technique," *Proc. - 2020 6th Int. Conf. Wirel. Telemat. ICWT 2020*, pp. 7–10, 2020, doi: 10.1109/ICWT50448.2020.9243623.

[54] L. S. Eng, R. Ismail, W. Hashim, and A. Baharum, "The Use Of VARI, GLI, and VIGREEN Formulas In Detecting Vegetation In Aerial Images," *Anal. Standar Pelayanan Minimal Pada Instal. Rawat Jalan di RSUD Kota Semarang*, vol. 3, no. 7, pp. 103–111, 2015, doi: https://dx.doi.org/10.14716/ijtech.v10i7.3275.

[55] S. Sahurkar, P. B. J. Chilke, and S. M. Tech, "Assessment of Chlorophyll and Nitrogen Contents of Leaves Using Image Processing Technique," *Int. Res. J. Eng. Technol.*, vol. 04, no. 07, pp. 2243–2247, 2017.

[56] H. Ponce, C. Cevallos, R. Espinosa, and S. Guti´errez, "Estimation of Low Nutrients in Tomato Crops Through the Analysis of Leaf Images Using Machine Learning," *J. Artif. Intell. Technol.*, vol. 1, no. 2, 2021, doi: 10.37965/jait.2021.0006.

[57] S. Sivagami and S. Mohanapriya, "Automatic detection of tomato leaf deficiency and its result of disease occurrence through image processing," *Int. J. Innov. Technol. Explor. Eng.*, vol. 8, no. 11, pp. 4165–4172, 2019, doi: 10.35940/ijitee.K1539.0981119.

[58] A. R. Bahtiar, Pranowo, A. J. Santoso, and J. Juhariah, "Deep Learning Detected Nutrient Deficiency in Chili Plant," *2020 8th Int. Conf. Inf. Commun. Technol. ICoICT 2020*, 2020, doi: 10.1109/ICoICT49345.2020.9166224.

[59] K. P. Lewis and J. D. Espineli, "Classification and detection of nutritional deficiencies in coffee plants using image processing and convolutional neural network (Cnn)," *Int. J. Sci. Technol. Res.*, vol. 9, no. 4, pp. 2076–2081, 2020.

[60] K. A. Myo Han and U. Watchareeruetai, "Black Gram Plant Nutrient Deficiency Classification in Combined Images Using Convolutional Neural Network," *2020 8th Int. Electr. Eng. Congr. iEECON 2020*, 2020, doi: 10.1109/iEECON48109.2020.229562.

[61] C. Wang, Y. Ye, Y. Tian, and Z. Yu, "Classification of nutrient deficiency in rice based on CNN model with Reinforcement Learning augmentation," *Proc. - 2021 Int. Symp. Artif. Intell. its Appl. Media, ISAIAM 2021*, pp. 107–111, 2021, doi: 10.1109/ISAIAM53259.2021.00029.

[62] M. A. Zaki, S. Narejo, M. Ahsan, S. Zai, M. R. Anjum, and N. U. Din, "Image-based Onion Disease (Purple Blotch) Detection using Deep Convolutional Neural Network," *Int. J. Adv. Comput. Sci. Appl.*, vol. 12, no. 5, pp. 448–458, 2021, doi: 10.14569/IJACSA.2021.0120556.

[63] D. Kuznichov, A. Zvirin, Y. Honen, and R. Kimmel, "Data augmentation for leaf segmentation and counting tasks in rosette plants," *arXiv*, 2019.

[64] N. Sabri, N. S. Kassim, S. Ibrahim, R. Roslan, N. N. A. Mangshor, and Z. Ibrahim, "Nutrient deficiency detection in maize (Zea mays L.) leaves using image processing," *IAES Int. J. Artif. Intell.*, vol. 9, no. 2, pp. 304–309, 2020, doi: 10.11591/ijai.v9.i2.pp304-309.

[65] C. Cevallos, H. Ponce, E. Moya-Albor, and J. Brieva, "Vision-Based Analysis on Leaves of Tomato Crops for Classifying Nutrient Deficiency using Convolutional Neural Networks," *Proc. Int. Jt. Conf. Neural Networks*, 2020, doi: 10.1109/IJCNN48605.2020.9207615.

[66] A. J. Rau, J. Sankar, A. R. Mohan, D. Das Krishna, and J. Mathew, "IoT based smart irrigation system and nutrient detection with disease analysis," *TENSYMP 2017 - IEEE Int. Symp. Technol. Smart Cities*, pp. 3–6, 2017, doi: 10.1109/TENCONSpring.2017.8070100.

[67] M. A. Islam, N. Rahman Shuvo, M. Shamsojjaman, S. Hasan, S. Hossain, and T. Khatun, "An Automated Convolutional Neural Network Based Approach for Paddy Leaf Disease Detection," *Int. J. Adv. Comput. Sci. Appl.*, vol. 12, no. 1, pp. 280–288, 2021, doi: 10.14569/IJACSA.2021.0120134.

[68] L. N and K. K. Saju, "Classification of Macronutrient Deficiencies in Maize Plant Using Machine Learning," *Int. J. Electr. Comput. Eng.*, vol. 8, no. 6, pp. 4197–4203, 2018, doi: 10.11591/ijece.v8i6.pp4197-4203.

[69] T. Makkar and Yogesh, "A computer vision based comparative analysis of dual nutrients (boron, calcium) deficiency detection system for apple fruit," *2018 4th Int. Conf. Comput. Commun. Autom. ICCCA 2018*, pp. 1–6, 2018, doi: 10.1109/CCAA.2018.8777678.

[70] J. Drdsh, D. Eleyan, and A. Eleyan, "A Prediction Olive Diseases Using Machine Learning Models, Decision Tree and Naïve Bayes Models," *J. Theor. Appl. Inf. Technol.*, vol. 99, no. 18, pp. 4231–4240, 2021.

[71] N. Minni and N. Rehna, "Detection of Nutrient Deficiencies in Plant Leaves using Image

Processing," *Int. J. Comput. Algorithm*, vol. 5, no. 2, pp. 84–87, 2016, doi: 10.20894/ijcoa.101.005.002.004.

[72] F. Jiang, Y. Lu, Y. Chen, D. Cai, and G. Li, "Image recognition of four rice leaf diseases based on deep learning and support vector machine," *Comput. Electron. Agric.*, vol. 179, no. April, p. 105824, 2020, doi: 10.1016/j.compag.2020.105824.

[73] S. Lathuiliere, P. Mesejo, X. Alameda-Pineda, and R. Horaud, "A Comprehensive Analysis of Deep Regression," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 42, no. 9, pp. 2065–2081, 2020, doi: 10.1109/TPAMI.2019.2910523.

[74] A. Sinha and R. S. Shekhawat, "Olive Spot Disease Detection and Classification using Analysis of Leaf Image Textures," *Procedia Comput. Sci.*, vol. 167, no. 2019, pp. 2328–2336, 2020, doi: 10.1016/j.procs.2020.03.285.

[75] Z. Xu *et al.*, "Using deep convolutional neural networks for image-based diagnosis of nutrient deficiencies in rice," *Comput. Intell. Neurosci.*, vol. 2020, 2020, doi: 10.1155/2020/7307252.

[76] N. S. A. M. Taujuddin *et al.*, "Detection of plant disease on leaves using blobs detection and statistical analysis," *Int. J. Adv. Comput. Sci. Appl.*, vol. 11, no. 8, pp. 407–411, 2020, doi: 10.14569/IJACSA.2020.0110852.

[77] A. K. Ghorai *et al.*, "Image Processing Based Detection of Diseases and Nutrient Deficiencies in Plants," no. March, 2021.

[78] R. Sathyavani, K. JaganMohan, and B. Kalaavathi, "Classification of nutrient deficiencies in rice crop using denseNet-BC," *Mater. Today Proc.*, no. xxxx, 2021, doi: 10.1016/j.matpr.2021.10.466.

[79] T. Amirtha, T. Gokulalakshmi, P. Umamaheswari, and T. R. M. Tech, "Machine Learning Based Nutrient Deficiency Detection in Crops," *Int. J. Recent Technol. Eng.*, vol. 8, no. 6, pp. 5330–5333, 2020, doi: 10.35940/ijrte.f9322.038620.

[80] V. Mande, "Estimation of chlorophyll based on FPGA and Matlab," *2017 Int. Conf. Nascent Technol. Eng. ICNTE 2017 - Proc.*, pp. 1–5, 2017, doi: 10.1109/ICNTE.2017.7947986.

[81] D. P. Putra, P. Bimantio, T. Suparyanto, and B. Pardamean, "Expert system for oil palm leaves deficiency to support precision agriculture," *Proc. 2021 Int. Conf. Inf. Manag. Technol. ICIMTech 2021*, no. August, pp. 33–36, 2021, doi: 10.1109/ICIMTech53080.2021.9535083.

[82] A. N. Putra, A. F. Sitorus, Q. L. Hakim, M. Adelyanti, I. Nita, and Sudarto, "Rapid Identification of Rice Macronutrient Content in Saline Soils Using Smartphone Camera," *Agriculture*, vol. 67, no. 2, pp. 61–75, 2021, doi: 10.2478/agri-2021-0006.

[83] A. T. Alisaraei and N. Resources, "Using image processing technique to detect nutrient deficiency and toxicity in pistachio tree leaves," no. May, 2016.

[84] H. Alaa, K. Waleed, M. Samir, M. Tarek, H. Sobeah, and M. A. Salam, "An intelligent approach for detecting palm trees diseases using image processing and machine learning," *Int. J. Adv. Comput. Sci. Appl.*, vol. 11, no. 7, pp. 434–441, 2020, doi: 10.14569/IJACSA.2020.0110757.

[85] A. Kumar, V. Patidar, D. Khazanachi, and P. Saini, "An Approach to Improve Classification Accuracy of Leaf Images using Dorsal and Ventral Features," *Int. J. Adv. Comput. Sci. Appl.*, vol. 6, no. 9, 2015, doi: 10.14569/ijacsa.2015.060917.

[86] S. S. Lomte and A. P. Janwale, "Plant Leaves Image Segmentation Techniques: A Review," *Artic. Int. J. Comput. Sci. Eng.*, vol. 5, no. 5, pp. 147–150, 2017, [Online]. Available: www.ijcseonline.org.

[87] L. A. Wulandhari *et al.*, "Plant nutrient deficiency detection using deep convolutional neural network," *ICIC Express Lett.*, vol. 13, no. 10, pp. 971–977, 2019, doi: 10.24507/icicel.13.10.971.

[88] Q. Wang, X. Mao, X. Jiang, D. Pei, and X. Shao, "Digital image processing technology under backpropagation neural network and KMeans Clustering algorithm on nitrogen utilization rate of Chinese cabbages," *PLoS One*, vol. 16, no. 3 March 2021, pp. 1–24, 2021, doi: 10.1371/journal.pone.0248923.

[89] A. Qur'ania, P. Harsani, T. Triastinurmiatiningsih, L. A. Wulandhari, and A. A. S. Gunawan, "Color Extraction and Edge Detection of Nutrient Deficiencies in Cucumber Leaves Using Artificial Neural Networks," *CommIT (Communication Inf. Technol. J.*, vol. 14, no. 1, p. 23, 2020, doi: 10.21512/commit.v14i1.5952.

[90] A. A. Gomaa and Y. M. A. El-Latif, "Early Prediction of Plant Diseases using CNN and GANs," *Int. J. Adv. Comput. Sci. Appl.*, vol. 12, no. 5, pp. 514–519, 2021, doi: 10.14569/IJACSA.2021.0120563.

[91] S. Singh Manhas, R. Randive, S. Sawant, P. Chimurkar, and G. Haldankar, "Nutrient Deficiency Detection in Leaves using Deep Learning," pp. 1–6, 2021, doi: 10.1109/iccict50803.2021.9510093.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[92] Z. Wang, M. Hu, and G. Zhai, "Application of deep learning architectures for accurate and rapid detection of internal mechanical damage of blueberry using hyperspectral transmittance data," *Sensors (Switzerland)*, vol. 18, no. 4, pp. 1–14, 2018, doi: 10.3390/s18041126.

[93] D. Zermas, H. J. Nelson, P. Stanitsas, V. Morellas, D. J. Mulla, and N. Papanikolopoulos, "A Methodology for the Detection of Nitrogen Deficiency in Corn Fields Using High-Resolution RGB Imagery," *IEEE Trans. Autom. Sci. Eng.*, vol. 18, no. 4, pp. 1879–1891, 2021, doi: 10.1109/TASE.2020.3022868.

[94] J. Johnson, R. Barron, and L. Barron, "Identification of trace mineral and nutrient deficiencies as an adjunct to treatment of eating disorders," *J. Eat. Disord.*, vol. 1, no. Suppl 1, p. P10, 2013, doi: 10.1186/2050-2974-1-s1-p10.

[95] S. S. Manhas, "Nutrient Deficiency Detection in Leaves using Deep Learning," 2021.

[96] R. Sathyavani, K. Jaganmohan, and B. Kalaavathi, "Detection of plant leaf nutrients using convolutional neural network based internet of things data acquisition," *Int. J. Nonlinear Anal. Appl.*, vol. 12, no. 2, pp. 1175–1186, 2021, doi: 10.22075/ijnaa.2021.5194.

[97] M. Buzzy, V. Thesma, M. Davoodi, and J. M. Velni, "Real-time plant leaf counting using deep object detection networks," *Sensors (Switzerland)*, vol. 20, no. 23, pp. 1–14, 2020, doi: 10.3390/s20236896.

[98] C. Y. Khew, "Evaluation of Deep Learning for Image-based Black Pepper Disease and Nutrient Deficiency Classification," pp. 1–6, 2021.

[99] M. V. Latte and S. Shidnal, "Multiple nutrient deficiency detection in paddy leaf images using color and pattern analysis," *Int. Conf. Commun. Signal Process. ICCSP 2016*, pp. 1247–1250, 2016, doi: 10.1109/ICCSP.2016.7754352.

[100] Y. Song, G. Teng, Y. Yuan, T. Liu, and Z. Sun, "Assessment of wheat chlorophyll content by the multiple linear regression of leaf image features," *Inf. Process. Agric.*, no. xxxx, 2020, doi: 10.1016/j.inpa.2020.05.002.

[101] A. Jose, S. Nandagopalan, V. Ubalanka, and D. Viswanath, "Detection and classification of nutrient deficiencies in plants using machine learning," *J. Phys. Conf. Ser.*, vol. 1850, no. 1, 2021, doi: 10.1088/1742-6596/1850/1/012050.