The Comprehensive Review on Detection of Macro Nutrients Deficiency in Plants Based on The Image Processing Technique

Lia Kamelia
Department of Electrical Engineering
UIN Sunan Gunung Djati
Bandung, Indonesia
lia.kamelia@uinsgd.ac.id

Titik Khawa Binti Abdul Rahman
Department of Information Communication Technology
Asia e-University
Selangor, Malaysia
titik.khawa@aeu.edu.my

Hoga Saragih
Faculty of Engineering and Computer Science
Bakrie University
Jakarta, Indonesia
hoga.saragih@bakrie.ac.id

Reni Haerani
Department of Informatics Management
Politeknik PGRI Banten
Cilegon, Indonesia
renihaerani@politeknikpgribanten.ac.id

***Abstract*—Images are a significant source of data and information in agricultural technologies. The use of image processing techniques had important implications for the analysis of smart farm. The analytical system using digital image processing would classify the nutrient deficiency symptoms much prior than a human could identify. This will enable the farmers to adopt appropriate corrective action in time. The paper discusses various methods used in the detection of nutrient deficiencies in plants based on visual images. The image processing techniques have several stages to get the best results in nutrient deficiency detection, namely image acquisition, image enhancement, image segmentation, and feature extraction. Based on the analyses, it is proved that the image processing technology can support the development of farming automation to accomplish the advantages of low price, high efficiency, and high accuracy. Through analysis and discussion, the paper proposed a new technique in every phase of image processing for the detection of nutrient deficiency as the basis of the implementation in future research. Consequently, the research will support the growth of agricultural automation equipment and systems in more smart approaches.**

Keywords—image processing; nutrient deficiency; smart farm

I. Introduction

Research on identifying nutrient deficiencies in plants using image processing techniques in Indonesia has not been done much because the majority of research focuses on identifying plant diseases. Indonesia as an agrarian country is demanded to develop the latest technology in agriculture. Nutrient deficiency in plants can result in decreased crop yields. Research on nutrient deficiencies has been done by Munir and Purnama, but the research conducted only has an accuracy of 59% because it only classifies leaves based on texture. Several other studies recommend a system that is equipped with an automatic identification system on plants[1]. Steps to deal with nutrient deficiencies in plants must be carried out. Thus, losses at harvest can be minimized and extreme application of fungicides can be avoided. Many supporting technologies have been established to automate data and facts based on image processing. The design and implementation of this technology will greatly support in limiting the use of chemical fertilizers, reducing charges, and increase production. There are a large number of tasks when applying image processing technology and learning algorithms for plant nutrition recognition. The proposed algorithms should be very accurate and the margin of error should be very slight since incorrect detection could be very destructive to agricultural production.

Deficiency analysis can be done in 3 ways, namely Soil analysis, plant analysis, and visual observation[2]. Soil analysis and plant analysis can be carried out by laboratory testing. Nutrient deficiency symptoms in plants usually visible in leaves and fruits. The symptoms in leaves include marginal chlorosis, interveinal chlorosis, uniform chlorosis, distorted edges, reduction in the size of the leaf, necrosis, etc. Even though similar symptoms present in old and new leaves, the deficient nutrient may vary defends on other factors. Deficiency symptoms are most widely used to find the nutrient responsiveness at leaves [3]. Visual analysis is a qualitative analysis that is carried out directly by looking at plant growing, the color of the leaves, and textures of leaves, fruit, stems, or other parts of the tree. However, this training method required special skills and equipment, requires actions that damage plants to obtain the samples, require high costs, and must be repeated regularly. The test results will be known after days or weeks, even though the condition of the plant will get worse and even cause death. To overcome losses and recover costs, nutrient deficiencies must be detected as early as possible so farmers can take proper corrective treatment.

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The need for accurate selection, sorting of fruits and food or agricultural products arises because of increasing expectations of consumer standards for food quality and safety. Computer vision and image processing are safe methods, accurate, and reliable to pursue fast selection targets. The use of image processing technology mostly detects disease in fruit yields [4]–[6], automatically sorting fruit [7], [8], and detecting the type and diversity of fruit or plants [9]. These observations must be supported by sophisticated and accurate detection systems so that the combination of visual observation and image processing technology is a suitable method in early detection of nutrient deficiencies.

Research on the detection of nutrient deficiencies with image processing is still rare. Nutrient deficiencies are an early symptom of disease in plants. Detection of symptoms of nutrient deficiency earlier will facilitate the handling and treatment of the disease. Diagnostic methods using digital imaging based on the morphological leaf (color and texture) can produce qualitative and quantitative information that can be used to automatically identify the nutritional status of plants [10].

II. METHODOLOGY

Many applications that use machine vision technology have been developed in the agricultural sector, such as precision agriculture, land and air-based remote sensing for the assessment of natural resources, quality detection and safety of post-harvest products, automatic processes and classification and sorting. this is because the machine vision system not only distinguishes the shape, size, texture, and colour of the object but also provides the numerical attributes of the object or scene imaged [11]. Digital Image Processing is a part of signal technology that deals with changes in digital images to perfect their features and characteristics. Operations on images are carried out using efficient algorithms specifically designed for image processing purposes. Input is the picture taken and the output is also an image or feature that has been extracted. There are many techniques for image processing that are applied to digital images to extract various information from the image under study.The fundamental steps in image procesing as shown at Fig.1 consist of 3 main steps : Pre-processing , image segmentation and feature extraction.

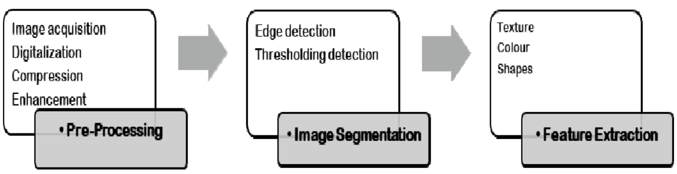

Fig 1. Fundamental steps in image processing.

A. Pre-Processing Technique

The first step in image Processing is image capture. The processing of photos or scientific images can be done quite effectively using scanned images or data from digital cameras. Most of the methods using the Camera and scanner to collect the image. Some researchers used the CCD camera because it is low-cost, easy to find, and captured the image in high resolution[1][2][14]. The use of a scanner is effective for a 2D image such as for the identification leaves [10], [15]. The essential to detect nutrient deficiencies is needed by farmers to determine the condition of their crops as early as possible. The non-destructive testing method is becoming more important due to its advantages. some researchers have researched measuring the nutritional levels of the leaves that are portable [16]. but the use of this tool will make it difficult for farmers because it requires a high understanding to operate it, so it is necessary to build a system that allows farmers to take pictures of leaves/trees. The use of a camera on a smartphone is the best solution to make it easy for farmers to take pictures on farms and send data to the nutrient deficiency detection system automatically.

B. Image Segmentation

After pre-processing, image segmentation is required and is the first step in image analysis. Segmentation means partitioning of an image into various parts of the same features or having some similarity. In image processing, segmentation falls into the category of extracting different image attributes of an original image[17]. Image segmentation techniques aim to partition an image into meaningful parts that are used for further analysis. The segmentation process is typically driven by both the underlying data and a prior on the solution space, where the latter is useful in cases where the images are corrupted or contain artifacts due to limitations in the image acquisition[18].

The method of converting RGB to HSV color space for color detection/thresholding is proposed because HSV is more resistant to changes in lighting from the outside. This means that in the case of small changes in external lighting, such as pale shadows, the Hue value varies relatively lower than the RGB value. The threshold system is the simplest way of segmentation. The threshold technique area can be classified based on base range values, which are set on the image pixel intensity value. Thresholding is the conversion from input to binary segmented output images[19]. The edge detection technique is used to find discontinuities in grey-level images. There are some edge detection problems, namely false edge detection, actual edge loss, edge localization, problems due to noise and long processing times, etc. Therefore, the purpose of segmentation at this stage is to compare various detection edges and thresholds and then analyze the performance of the various techniques. The proposed research will perform Canny edge detection and Sauvola's methods for the detection process. The advantage of Canny edge detection is the ability to reduce noise before performing edge detection calculations. Sauvola's method is one of the threshold methods that are still new that have been modified in the concept of integral image to match the computational speed of the Otsu method.

C. Feature Extraction

A feature is a number or a set of numbers derived from a digital image. The idea is that some objects belong to groups based on each of these measurements. The key issue of leaf image retrieval, the same as that of plant recognition, is whether extracted features are stable and can distinguish individual leaves. Many techniques have been used to extract features from images. Some of the commonly used methods are spatial features, transform features, edge and boundary features, color features, shape features, and texture features [20].

Most research in agriculture on plant recognition or plant disease detection considers the nature of colors and textures for categorization. Color and texture are the best features for early detection of nutrient deficiencies in leaves because what distinguishes less nutritious leaves from normal leaves lies in their color. while what distinguishes the type of nutrients needed is seen in the texture of the leaves.

Feature extraction is a method of processing images or images used to take the characteristics of an image so that it can be distinguished before it is classified. So that each picture is easier to distinguish from the features that have been taken. The feature itself is stated by the arrangement of numbers that can be used to identify objects. This research proposes the use of GLCM texture characteristics combined with the global color histogram methods for the extraction of color features [21]. This study applies GLCM to extract the texture feature value of an image and integrate the weight factor entered by the direction scope to obtain the final texture feature of an image. GLCM is widely applied in texture description, and the results from the co-occurrence matrix are better than other texture discrimination methods. However, this method has disadvantages in terms of high computational complexity and lack of global information, making it difficult to study the relationship between pixels at the texture scale. Calculations using local color histograms are easier and resistant to small variations in the image, so indexing and retrieval of the image database are very important[22].

III. Discussion

The processing carried out is divided into two phases. The first processing phase is the offline phase or training phase. In this initial phase, a set of leaf images consisting of leaves with anomalies and normal leaves is inserted into the processor and processed by an image analyzer and certain color and texture features are extracted. Then these features are provided as input to the classification system, so information is obtained about whether the leaf image is anomalous or normal. The overall proposed framework is shown in Fig.2.

Mean Square Error (MSE), Root Mean Squared Error (RMSE), and Peak Signal-to-Noise Ratio (PSNR) are examples of parameters that are commonly used as indicators to measure the similarity of two images. These parameters are often used to compare the results of image processing with the initial image or the original image[23]. MSE is the average error value between the original image and the manipulated image. In an image reconstruction development and implementation, a comparison between the reconstructed image and the original image is required. A common measure used for this purpose is the Peak Signal to Noise Ratio (PSNR). A higher PSNR value implies a closer resemblance between the reconstructed results and the original image. PSNR can be calculated using the MSE value[23]. After the analysis of phase 1 is conducted, the next phase is the image segmentation.

The first phase in the research is the initial sample treatment. This phase aims to get samples that match the expected conditions. the next stage is the stage of shooting using a smartphone camera. This stage is carried out by photographing the leaves on different parameters namely at different nutritional conditions and weeks after treatment. The segmentation stage is the main process in image processing. The process is the conversion of the RGB image to HSV color, then the segmentation process based on thresholding and edges. The color extraction process is done as the initial process of image recognition before classification. The extraction of images is based on differences in color and texture.

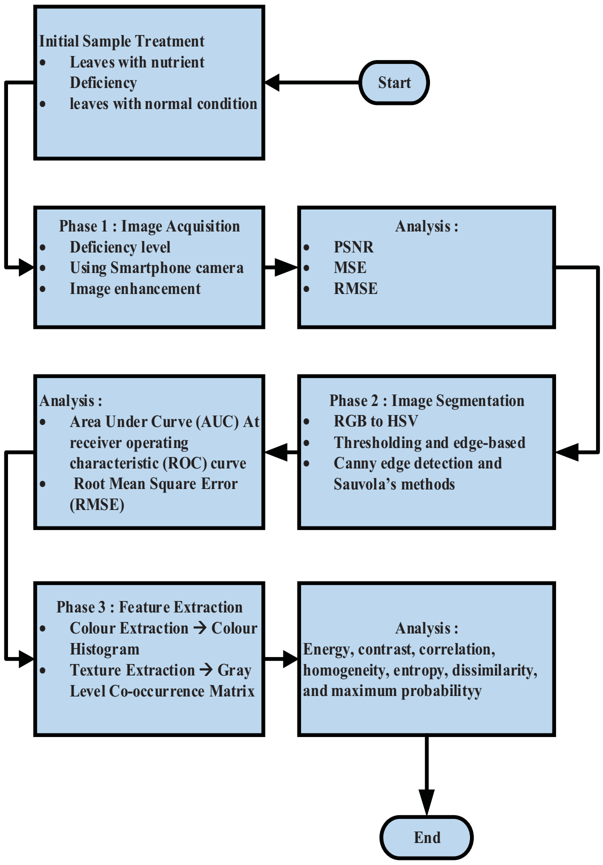

Fig.2. Proposed design.

The analysis for image segmentation is to calculate the AUC at the Receiver Operating Characteristics (ROC) curve. ROC is a kind of performance measurement tool for classification problems in determining the threshold of a model. AUC makes it easy to compare models with one another. The AUC is the area under the ROC curve or the integral of the ROC function. This research proposes the use of GLCM texture characteristics combined with the global color histogram methods for the extraction of color features. The color feature is the most sensitive and easily understood feature of an image. Various techniques are available to show color information. One of them is a color histogram. Colour histograms are fast and not sensitive to image changes such as rotation, translation, and so on [24]. There are 7 features of GLCM used in this research, namely energy, contrast, correlation, homogeneity, entropy, dissimilarity, and maximum probability.

. In contrast, the attribute shows the size of the spread (moment of inertia) of the image matrix elements. Energy is a feature for measuring the concentration of intensity pairs on the co-occurrence matrix. Entropy represents a measure of the randomness of the intensity distribution. Homogeneity aims to measure the homogeneity of variations in an image. Correlation is used to measure the degree of linear dependence of the degree of the grayness of neighboring pixels. Dissimilarity shows the size that defines the variation in the intensity level of the pixel pairs in the image.

Based on the analyses, it is proved that the image processing technology can support the development of farming automation to accomplish the advantages of low price, high efficiency, and high accuracy. Through analysis and discussion, the paper proposed a new technique in every phase of image processing for the detection of nutrient deficiency as the basis of the implementation in future research. Consequently, the research will support the growth of agricultural automation equipment and systems in more smart approaches.

IV. Conclusion

The new methods for identifying and classifying the level of nutrient deficiency for macronutrients have been proposed. Every step at image processing has the novel methods used based on the literature review process. The image acquisition will use the smartphone camera to facilitate the farmers identifying the nutrient deficiency symptoms. The segmentation process is based on the threshold and edge-based. The extraction process using texture and color features for identifying the images. In the future, the application of the proposed methods and also a classification for the applications of nutrient deficiencies detection will be researched

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