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Research paper

An Agricultural Tele-Monitoring Method in Detecting Nutrient Deficiencies of Oil Palm Leaf

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Abstract

Nutrient management in oil palm plantation is considered as one of the prominent issues especially for smallholder farmer. The nutrient contained in the tress has always been neglected and untreated and these may cause the trees to suffer from nutrient deficiencies. Therefore, in leveraging the oil yield at the maximum, a telemonitoring system is developed to assess and monitor the lack of nutrients for respective trees. This is done using image processing technique and artificial intelligence in detecting the nutritional deficiencies by analyzing the leaf. The categorization focused by classifying into four major types either as magnesium deficiencies, potassium deficiencies, nitrogen deficiencies or healthy that is based on the oil palm's leaf surface. This is achieved by extracting the features namely number of red pixels, entropy and correlations. Further, two classifiers specifically support vector machine and artificial neural network is used for classification purpose along with performance measure using accuracy(ACC), Mean Square Error (MSE), Mean Absolute Error (MAE), Sensitivity (SN), Specificity (SP), Positive Predictive Value (PPV), Negative Predictive Value (NPV) based on ten-fold cross-validation. Results attained showed that the best classifier is SVM using RBF kernel (SVM-RBF) that is capable to accurately recognize the nutrient deficiencies with 100% accuracy.

Keywords: *Oil palm; deficiencies detection; machine learning classifier; SVM (Support Vector Machine); leaf disease*.

1. Introduction

Nutrient deficiency is one of the main concerns mainly in precision agriculture. Monitoring of the nutrient deficiencies was rarely taken into account among smallholder plantation due to excessive cost of implementation and maintenance afterwards [1]. Considering the case of monitoring the nutrient deficiencies in oil palm or scientifically recognized as Elaeis Guineensis Jacq the major reasons of maintaining the nutrient level at optimum state for the respective trees could increase the yield of oil extraction. In Malaysia, it is well known that smallholder farmer contributes major revenues of the oil palm yield. However, it is observed that these farmers are prone to neglect using technology based approach in monitoring the nutrient contained inside the oil palm trees [2]. As a result, many untreated and abandoned trees remain as it is and therefore may affect the oil extraction of the respective trees. Traditionally, the inspection of nutrient deficiencies is conducted manually or based on tacit knowledge and farmers experienced. The inspection of the nutrient for the trees is observed from the leaf sample by evaluating the appearance of the pattern or colour on the leaf surface. The differentiation of this pattern is well captured and interpreted by oil palm expert and further decided the types of nutrient lacking. Further, the next action is applying the appropriate fertilizers to ensure the deficiencies are taken care. However, the primary concern of manual inspection is limited in several areas and not widely used due to excessive cost of hiring this expertise to evaluate the condition and further identify the level of nutrient of the trees. Therefore, this study proposed to automate the manual inspection by introducing an automatic tele-monitoring system for detecting the suffered deficiencies. The aims of this study are specifically addressed as follows. Firstly, is to develop a tele-monitoring detection of nutrient deficiencies using image processing and machine learning classifier. Next, is to evaluate, assess and compare the performance metric of various classifier such as ACC, MSE, MAE, SN, SP, PPV and NPV. Finally, is to validate the classifier performance using ten-fold cross-validation.

To date, several studies have demonstrated the investigations on the disease based on the crops morphology using image processing. Firstly, in a study conducted to investigate the disease of Malus Domestica (known as cucumber) which consists of Leaf miner, Downey and Powdery disorders, K-mean clustering, color and texture analysis were used [3]. The authors focused on testing different technique of identification, segmentation and classification of the spots appearances on the leaf. The results demonstrated that the qualitative leaf analysis via CCM and K-means clustering algorithms were able to differentiate the spots, but the quantitative performance measure was not reported. On the other hand, the rice disease including leaf brown spot, rice blast, sheath rot and bacterial blight was investigated as reported in [4]. Here, classification techniques for various kind of rice disease were explored. The infected region was initially segmented from the background image using fermi energy-based segmentation. Then, several features comprise of colour, shape and position were extracted followed by selection of notable features using Rough Set Theories (RST). Finally, an algorithm of rule base classifier was concluded to produce of superior performance outcome. Additionally, the analysis of common leaf disease comprises of early scorch, cottony mold, late scorch, brown spot and bacterial fungal was investigated as discussed in [5]. Authors proposed the detection technique using image processing and neural network. The leaf was acquired to be filtered using a median filter. Then, it was segmented using the k-medoid clustering technique after the images was converted from the RGB image to CIELAB color space. Further, the masking technique was applied by masking green-pixels followed by extraction of important texture features namely contrast, correlation, energy and homogeneity. Finally, neural network classification technique was implemented and with 85% accuracy. Another research highlights the detection of the pomegranate affected by Bacterial blight disease as reported in [6]. In this study, the image processing technique using color, morphology, and CCV feature vectors and clustering of the disease via K-means clustering and SVM was used to classify the image as 'infected' or 'non-infected' [6]. Evaluation showed the disease affected the pomegranate could be differentiated as high 82% of accuracy. However, the reported accuracy varies depending on the pixel capacity of the digital camera and the stages of the disease. On the other hand, a study for diagnosing wheat disease using image processing approach via converting the wheat images from RGB to HIS colour space prior to segmentation process was reported in [7]. Here, the features of texture and colour comprise of colour moment and gray level of the co-occurrence matrix was extracted and then further classified using Support Vector Machine (SVM). The results demonstrated high accuracy rate of more than 90%. Alternatively, another study discussed the detection of leaf rot disease for betel vine also known as Piper betel L using vision system of image processing [8]. Colour analysis method was conducted to identify the rotten area of the leaf. The leaf was scanned to acquire the digital image and then segmented its rotten area from normal leaf section. Several investigations of various colour models were applied specifically RGB, HVS and YCbCr. Results obtained showed that the most significant for differentiating the rotten leaf was based on hue component of HVS colour space. The identified area of rotten leaf was calculated using the number of white pixels. In summary, as reported in [8], there are evidences to indicate the ability of recognizing the disease-using image processing approach to analyze the image along with classification technique to recognize the disease. Therefore, in this research, we deemed further to investigate the nutrient deficiency in oil palm trees using suitable image processing technique, feature extraction and classification in identifying the nutrient deficiencies based on the leaf morphology and features.

2. Methodology

In this study, the database comprised of leaf images with 30 leaf for each category namely healthy, potassium deficiency, nitrogen deficiency and magnesium deficiency. Firstly, feature extraction algorithms are developed to extract features such as the texture and boundary of the leaf are extracted from all the images in the database. Next, several prominent features are extracted namely number of red pixels, entropy and correlations [14]. Further, three different types of classifier are used namely RBF, SVM-RBF and ANN using ten-fold cross-validation method. In addition, performance metrics specifically accuracy, execution time, and confusion matrix are computed too.

Fig. 1 depicted the overall methodology proposed in this study. Firstly is the capturing process of the desired leaf section. Next, the captured images are sent to the server to be processed using the feature extraction algorithms and further classified according to the four category mentioned earlier.

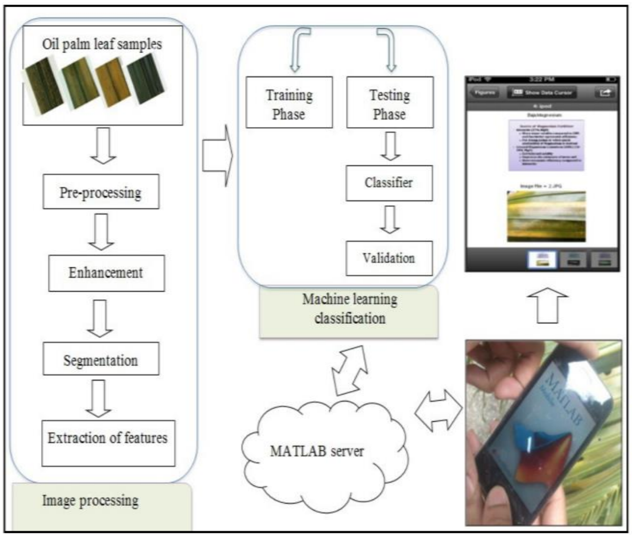

Fig. 1: Overall framework of the proposed system

Note that internet connection is crucial to establish the communication between server to output device and vice versa. Once the leaf are captured and sent to be processed, the outcomes was fed to the output display device and further the actual category or status of the leaf will be displayed. The friendly user interface in disseminating the information was to display either the leaf suffers from deficiency or healthy state as well the outcomes of deficiencies with its fertilizer recommendation. Hence, with the use of this handy portable device, the performance of the captured images acted as input to the classifier could be evaluated in the short time period.

2.1. Radial Basis Function (RBF)

The RBF classifier implements the concept of feed-forward learning of neurons that comprises of input neurons, hidden neurons and output neurons [10]. In the hidden neurons there is a network of radial basis activation function. Initially, the input neuron is constructed from feature vectors. The hidden units are formed by Gaussian function which is formulated from the input neuron, center of kernel region and spread. The output neurons can be computed by:

$$f(x) = \sum_{i=1}^{m} w_{j.}\, h_j(x) + w_{i0} \quad (1)$$

where w_j = weight of neurons and w_{i0} = the bias (threshold).

Further, the input neurons are fed to the network with four output namely that classified the leaf as nitrogen deficiency, potassium deficiency, magnesium deficiency or healthy. The architecture of RBF network is as shown in Fig. 2. During learning process, through trial and error execution, number of spreads and hidden neurons were selected at 0 and 50 respectively. Then, 25 neurons were added to hidden layer at the time repeatedly processed until the mean square error reached 0.00001. Next, testing process was conducted and evaluated to observe the outcome.

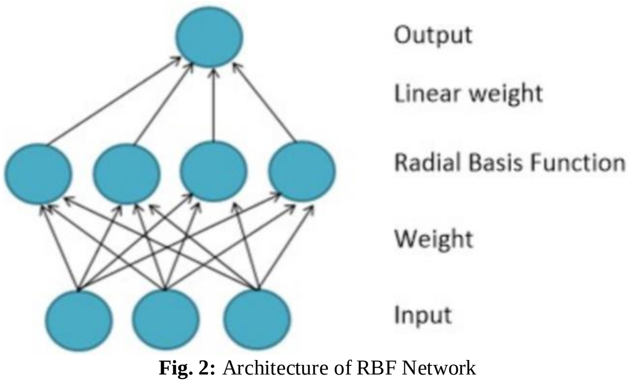

Fig. 2: Architecture of RBF Network

2.2. Support Vector Machine (SVM-RBF)

The classification using SVM classifier implements the multiclass classification of the three-class problem to distinguish between the leaves. In this study the most popular SVM multiclass classification based on RBF kernel function is utilized. By extending the basic concept of binary classification, the overall types of leaf have been decomposed into two-class discriminant function by dividing each output class into two portions of subclasses and then generating a discriminant function or known as a hyperplane [11]. In this study that involved categorizing four types of leaf, three hyperplanes were formed namely h1, h2, and h3. For instance, separating between nitrogen and non-nitrogen, detection of nitrogen was assigned as $y = 1$ whilst non-nitrogen was labeled of $y = -1$. Next procedure proceeds with h2 construction, followed by h3 and h4 whereas the process continues until all types of deficiency were successfully identified. Fig. 3 illustrated the SVM classifier used in this study.

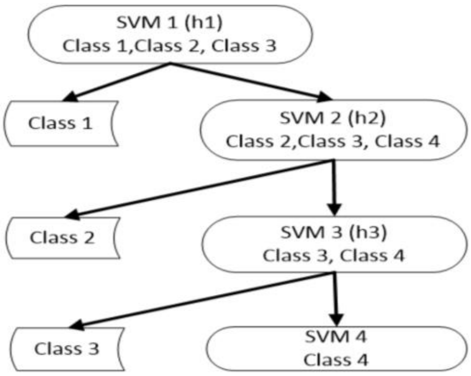

Fig. 3: BTSVM Multiclass Classification

2.3. Artificial Neural Network (ANN)

The artificial network based on neuron concept is inspired from single perceptron model of the input neuron, output neuron and intermediate layer in between, called as hidden layer. Using the MLP network in ANN is beneficial for discriminating multiple classes and non-linearly separable problems [12]. This research utilized 3 input neurons, 3 hidden neurons and 4 output neurons have been implemented with each node and layer is mutually interconnected as illustrated in Fig. 4. The datasets were divided into training, testing and validation phase. The learning process starts from the input neurons towards the output neurons and as the input are passed along to be connected, the weighting is applied and the signal was processed through activation function [13]. Then, once the signal has reached the output layer, the results are compared with the desired value and results in error generation. The errors are then propagated back to the neuron input for adjusting the weight value until the error is very small in smaller error. This learning technique of propagating error backwards through the network is called back-propagation.

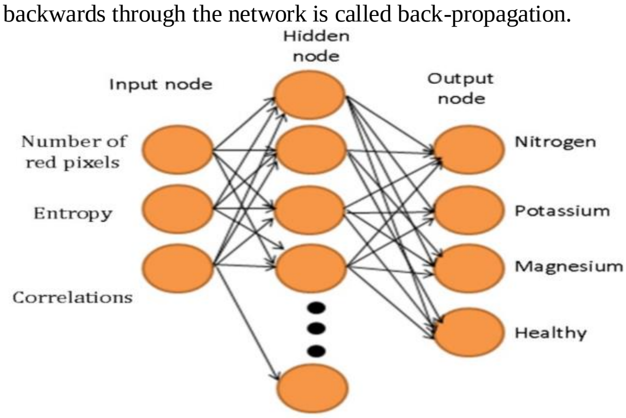

Fig. 4: Architecture of ANN network

3. Results and Discussion

This section elaborated in detail the results attained and elaborated the feature extraction, image analysis and machine learning classification in classifying the nutrient deficiency of oil palm trees based on the palm tree leaf images.

3.1. Image Processing

The resultant images produced were shown as in Fig. 5a-d. Here, the figures demonstrated HSV color conversion that could be used to identify the necessary area to be removed. The pre processing and morphological process includes enhancing the leaf characteristics such as background, vein and dried leaf. Next, enhancement of each leaf is done via decorrelation stretch in order to enhance the color differences in the leaf image. This is observed through high percentage of red pixels with low occurrence of green pixels. Next, the Wiener filter is used to remove unwanted pixels without interrupting the shape of the deficient leaf. In addition, this filter has been selected due to its capability of reducing additive noise and at the same reduced blurring effect. The comparison in terms of visual quality initially showed that the outcomes of the processed images has successfully identified the necessary features possessed by each deficiency, Next, in recognizing the nutrient deficiency, the leaf section were tested over different types of deficiencies. Further analysis was computed to measure the efficiency and effectiveness of classification technique.

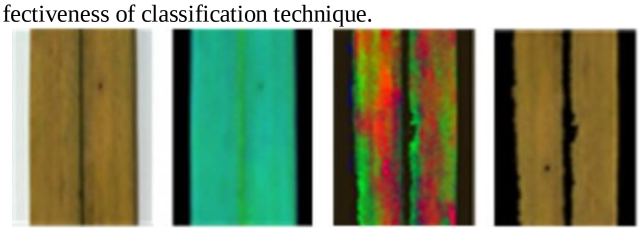

Fig. 5a: The resultant image processing of nitrogen deficiency

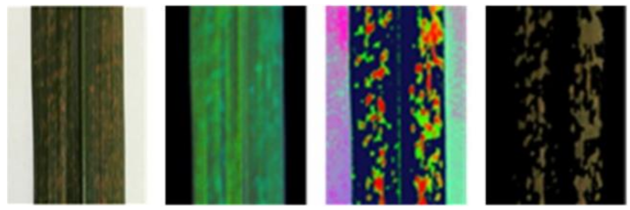

Fig. 5b: The resultant image processing of potassium deficiency

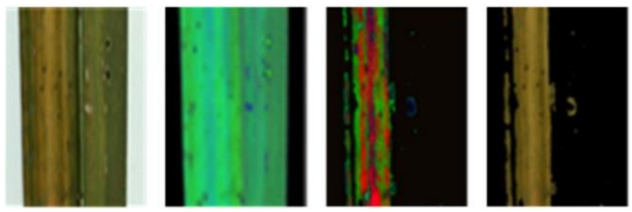

Fig. 5c: The resultant image processing of magnesium deficiency

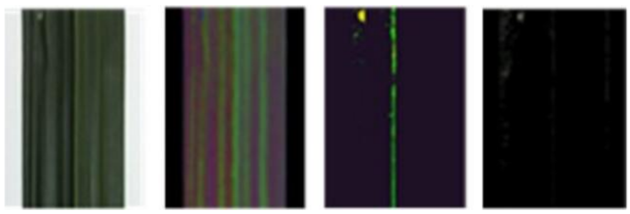

Fig. 5d: The resultant image processing of healthy deficiency

3.2. Classifier Performance Measure

Further evaluation of the classification of the deficiency leaf was conducted based on the measurement of sensitivity (SN), specificity (SP), Positive Predictive Value (PPV), and Negative Predictive Value (NPV). Referring to both Fig. 6 and Table 1, these parameters are compared and further analyzed based on accuracy (ACC), mean squared error (MSE) and mean average error (MAE). The features are classified using ten-fold cross-validation technique to examine the classifier performance. Results attained showed that both RBF and ANN obtained accuracy of 97.92% as compared to SVM-RBF attained perfect classification namely 100%. The SN scores of nitrogen deficiency for RBF and ANN classifiers are 91.67% and 92.86% respectively. Furthermore, NPV for nitrogen deficiency are 97.3% for RBF whilst for ANN is 97.14%. On the other hand, for magnesium deficiency using RBF classifier yielded 97.22% for SP and 92.31% for PPV. Similarly, healthy leaf classification results showed 97.14% and 92.86% respectively for SP and PPV. These showed that SVM-RBF showed good performances for all types of deficiencies detection. The results also revealed the SVM-RBF is less computationally complex, but fastest and produced similar results. Fig. 7 demonstrated the result of BTSVM for SVM-RBF classification. The hyperplane showed the deficiencies are successfully grouped into the three different types of deficiencies. Initially the first hyperplane, h1 divided the nitrogen deficiency and non-nitrogen deficiency followed by h2 to separate between potassium deficiency and lastly h3 distributed between magnesium deficiency and healthy leaf.

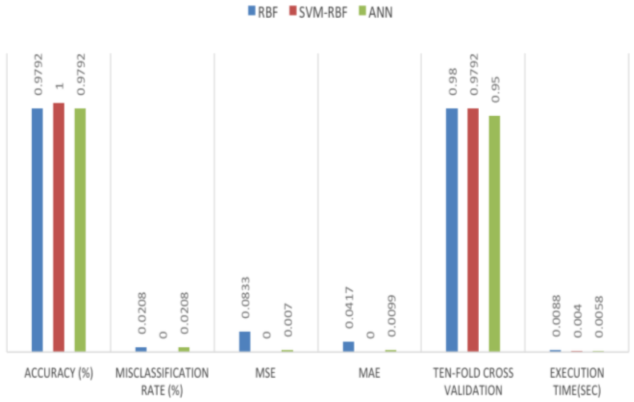

Fig. 6: Measure of performances for each classifier

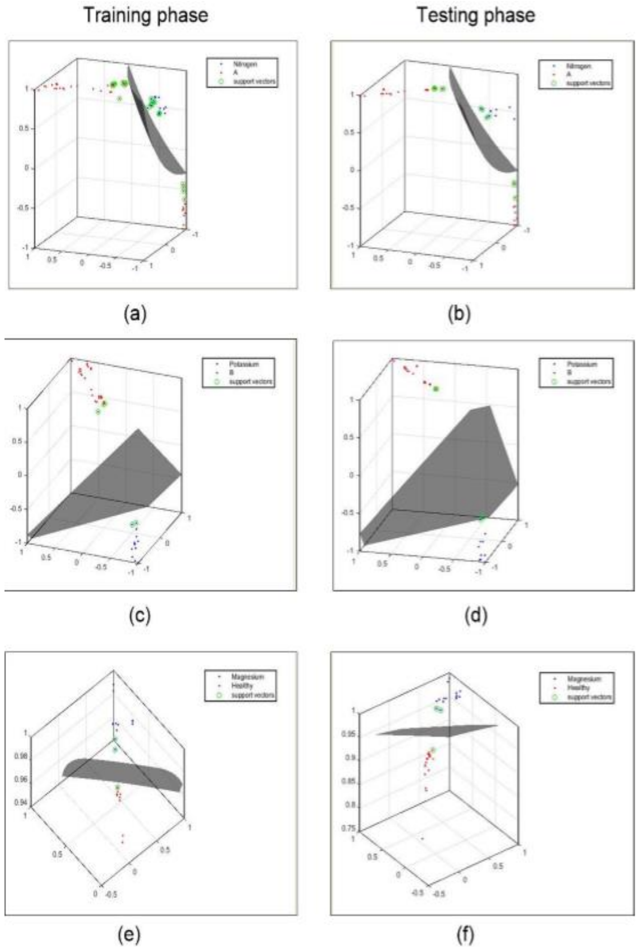

Fig. 7: The output of SVM-RBF classification

4. Conclusion

In conclusion, the framework and tele-monitoring technique specifically in recognizing the nutrient deficiencies of oil palm based on the leaf image is discussed. Several performance measures namely sensitivity (SN), specificity (SP), Positive Predictive Value (PPV), and Negative Predictive Value (NPV) showed that the proposed method is indeed suitable and capable for detection of three types of nutrient deficiency for oil palm trees. Results attained showed that classification based on SVM-RBF offers superior performance as compared to other techniques at all validity measures. Future work include evaluating the proposed method in real time scenario in oil palm plantation.

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