Intelligent Precision Nitrogen Fertilizer Application Based on Speaking Plant Approach for Environmental Sustainability

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Abstract. In vegetable farming, one of important issues is determining the right dose application of nitrogen fertilizer. The advantages and disadvantages of nitrogen fertilizer in spinach (Amaranthus sp.) will have an adverse effect on its productivity. The total nitrogen measurement by chemical analysis is too expensive, inefficient, and cannot be applied directly. The use of digital image analysis and intelligent modelling such as artificial neural network (ANN) can provide a real-time and accurate solution to predict the content of nitrogen in spinach leaf. This study aims to model the relationship between texture parameter based on colour co-occurrence matrix (CCM) and nitrogen content in spinach leaves. The texture analysis consists of 40 CCM textural features derived from RGB and grey colour. From the 40 CCM textural features, some of the best CCM textural features are selected to be used as ANN inputs in predicting nitrogen content. The best parameter selection method applying two approaches are the filter method including: (1) correlation-based feature selection; (2) correlation attribute evaluation; (3) linear regression; and (4) relief attribute evaluation and the wrapper method which is neural-genetic algorithm (N-GA). The best parameter selection result in the filter method based on the validation result is correlation-based feature selection (using 10 CCM textural features, training MSE = 0.0028; validation MSE = 0.00016; testing accuracy R2 = 0.96). However, when compared to all filter methods, the wrapper method using N-GA still demonstrates better results (using 8 CCM textural features, training MSE = 0.00039; validation MSE = 0.000038; testing accuracy R2 = 0.993). From CCM textural features which have been selected, it can be used as input ANN to predict the nitrogen content of spinach leaves accurately. The best ANN structure has been built by using 1 input layer (8 inputs), 1 hidden layer (20 nodes), and 1 output layer (1 node).

Keywords: ANN, spinach leaves, CCM textural features, nitrogen content

1. Introduction
Nitrogen content in plants is considered as a very important factor which affects the process of photosynthesis and agricultural productivity both quantitatively and qualitatively. Excessive use of nitrogen fertilizers unfortunately contributes to underground and surface water pollution leading to environmental damage. It is needed to develop an application to use the right fertilizer to maintain environmental sustainability. Conventional nitrogen content measurements (destructive-sensing) can
only be applied to limited land, with a low degree of accuracy. The development of non-destructive measurements may include broader, more effective, and real-time application on farmland. Several methods which can be applied for non-destructive measurements of nitrogen contents in plant include: (1) spectrometric measurement by using normalized vegetation differential index (NDVI) [1] and (2) visible light digital camera, where leaf colour is analysed by using image analysis algorithms [2].

The use of image analysis in machine vision in precision farming has been extensively studied to model and to detect nitrogen stress in plants. Jia [3] and Pagola [4] have successfully modelled nitrogen content in winter wheat and barley plants by using conventional digital cameras. Baresel [5] carried out research applying conventional digital cameras to detect nitrogen content through measurements on non-destructive green areas of plants. The advantages of image analysis using conventional digital cameras include: its non-destructive measurement, portability, cheaper price, easier application, and its ability to create special algorithms to distinguish leaf objects with other biomass objects. Non-invasive measurements usually include colour, shape, or surface texture. Red (R), green (G), and blue (B) (RGB) colour with the intensity of each colour ranging from 0 to 255 can be used to analyse images based on colour, shape and texture of the surface. In recent studies, the results show the superiority of texture analysis to measure biological objects compared to other image parameters. Meanwhile, research in the field of texture analysis is still dominated by the use of grey colour [6]. Hendrawan and Murase [7] have proven that the colour co-occurrence matrix (CCM) texture analysis algorithm can also be used for measuring the surface biological object texture besides using only grey colour co-occurrence matrix (GLCM) texture analysis.

The measurement of nitrogen content in plant leaves is a non-linear problem with an irregular pattern that will be difficult to model with conventional statistical modelling. Compared to statistical methods, artificial neural networks (ANNs) have better capabilities in analysing data, especially for complex modelling problems with nonlinear data that have an irregular pattern of data distribution [8]. Moghaddam [2] presents a study to model the nitrogen content of sugar beet leaves by using colour-image-based analysis. The ANN model and the linear regression model were used to predict the nitrogen content of sugar beets using RGB. The result shows that ANN model have better performance than linear regression model in predicting nitrogen content in sugar beet leaves. Many studies have proven performance improvement from ANN modeling after using feature selection method [9~12]. Merging feature selection method with ANN modeling can be said as hybrid-ANN. The objectives of this study are: (1) to test CCM textural features of RGB and grey colour as non-destructive measurement method to predict total nitrogen content of spinach leaves (Amaranthus sp.); (2) to choose the best combination of CCM textural features using filter and wrapper methods to be input into ANN modeling; and (3) to develop ANN structures which can be applied in real-time to predict nitrogen content of spinach leaves based on machine vision and texture analysis.

2. Materials and Methods

A total of 300 samples of spinach leaves were randomly selected from spinach plants cultivated with a wide variety of nitrogen content. To manipulate the physiological conditions of spinach, spinach cultivation was carried out in polybags which were divided into various levels of nitrogen content (20%, 40%, 60%, 80%, and 100%) from urea as the only source of fertilization. Spinach leaf images were taken by using a conventional digital camera (Nikon Coolpix A10, 16 megapixels, Japan) and were placed in a dark box, white background surface, with illumination from stable fluorescent light which were placed just below the camera as presented in Figure 1.

Research stages include: (1) image acquisition; (2) CCM textural features extraction; (3) feature selection; and (4) ANN modelling. Nitrogen content analysis was performed by using Kjeldahl method [13]. The learning method to obtain ANN model was conducted by using supervised Back Propagation Neural Network (BPNN). The feature selection stage in this research involved the filter and the wrapper method [14; 15]. The filter methods [16] used in this study include: (1) hybrid ANN and correlation-based feature selection [17]; (2) hybrid ANN and correlation attribute evaluation described by Mark [16]; (3) hybrid ANN and linear regression [15]; and (4) hybrid ANN and relief attribute evaluation [17].
Meanwhile, the wrapper method [9] applied in this research which was neural-genetic algorithm (N-GA). Measurement error value (error) in the training process and validation are calculated based on mean square error (MSE).

Texture analysis can be considered as a method to measure the surface of biological objects [12; 18]. The CCM algorithm-making procedure consists of three mathematical processes [19], which are: (1) RGB color space conversion to gray by using the formulas developed by Rotterman and Porat [20]; (2) the development of spatial gray-level dependence matrices (SGDMs) by using methods developed by Pydipati [21], which produce CCM for each colour space (RGB and gray); and (3) the calculation of ten equations of Haralick textural features by using CCM normalization data. CCM textural features are analysed by 40 features consisting of CCM textural features for each R, G, B, and grey.

3. Results and Discussion

Figure 2 shows some examples of leaves of spinach leaves with varying nitrogen content. If it is viewed at a glance by using the colour parameters, then each leaf image of the spinach will be difficult to distinguish. Another approach method is required to measure the nitrogen content through the use of CCM texture analysis. The next problem is to select the best features of 40 CCM textural features.

Figure 2. Spinach leaf with various nitrogen content: (a) 3.39%; (b) 4.41%; (c) 4.45%.

3.1. Correlation-Based Feature Selection

Correlation-based feature selection identifies relevant features when moderate feature dependencies exist. It evaluates the value of attributes of subset by considering the individual predictive ability of each feature along with the degree of redundancy between them [16]. Figure 3a shows the best results of the correlation-based feature selection method obtained from sensitivity analysis through preliminary research. Figure 3a illustrates the relationship between the number of features (ten best CCM textural features) as input BPNN and MSE value in training as well as data validation. Models with the most optimal solutions are achieved when using ten CCM textural features: red sum mean, green entropy, grey entropy, red entropy, blue entropy, grey IDM, green IDM, red IDM, blue IDM, and grey homogeneity. The performance results achieved by the best selected features show the value of MSE training-set data of 0.0028 and the validation-set data of 0.00016. Moreover, the ANN model performance results which have been formed on 30 test-set data (figure 3b) and the relationship between the actual data and the predicted data with the value $R^2 = 0.96$. 
3.2. Correlation Attribute Evaluation

Correlation attribute evaluation evaluates the worth of an attribute by measuring the correlation (Pearson's) in between and the class [16]. Figure 4a shows the best result of selecting ten CCM textural features with the top ranking by using the correlation attribute evaluation feature selection method. The value of the MSE data validation-set is at the lowest position when using seven CCM textural features as BPNN input in the order as recommended by the correlation attribute evaluation method. The best model performance based on the lowest MSE data validation-set value consists of seven CCM textural features, which are grey cluster tendency, grey variance, grey correlation, red contrast, red correlation, green correlation, and green entropy. The model of the selected subset feature with the correlation attribute evaluation method achieved the lowest MSE value in the training-set data of 0.016 and in the validation-set data of 0.0048. Figure 4b describes the model test. The test results show the comparison between the actual value and predicted value is good enough with $R^2$ value of 0.76.

3.3. Linear Regression

Linear regression evaluates the line that best predicts Y from X [15]. Figure 5a shows that the best results selected by linear regression is based on the smallest MSE value of the training-set and validation-set data through the sensitivity analysis process. The best results based on the smallest MSE values in the validation-set data are shown when using eight CCM textural features which are: red sum mean, grey maximum probability, grey sum mean, green sum mean, grey cluster tendency, grey variance, blue maximum probability, and red maximum probability. The selected subset features have performance with the smallest MSE value in the training-set data of 0.0076 and the smallest MSE value
in the validation-set data of 0.0044. Furthermore, figure 5b presents the comparison between the actual and the predicted data with the value of $R^2$ of 0.89.

![Image of Figure 5](image1)

**Figure 5.** (a) MSE Value in data training-set and validation-set from selected ten (10) CCM textural using linear regression method; (b) validation data between actual and predicted.

### 3.4. Relief Attribute Evaluation

Relief attribute evaluation evaluates the value of the same attributes and different classes [16]. Figure 6a shows the top ten best selected CCM textural features by using the relief attribute evaluation feature selection method based on the sensitivity analysis which has been conducted in the preliminary study. MSE values in the lowest validation-set data are achieved when using eight CCM textural features in the recommended order of relief attribute evaluation methods. The best results of the model produced by the relief attribute evaluation include eight CCM textural features such as blue entropy, blue energy, red sum mean, grey maximum probability, red contrast, green variance, green cluster tendency, and grey sum mean. The selected CCM model textural features by using relief attribute evaluation are able to achieve the lowest MSE value in the training-set data of 0.0051 and in the validation-set data of 0.0026. Figure 6b illustrates the results of the testing-testing data set and the comparison between the actual value and the predicted value resulting in $R^2$ of 0.93.

![Image of Figure 6](image2)

**Figure 6.** (a) MSE value of data training-set and validation-set based on ten (10) CCM textural features as a result of relief attribute evaluation method; (b) validation data between actual and predicted.

### 3.5. Neural-Genetic Algorithms

N-GA is one of the feature selection methods that is a hybrid of ANN for modelling and genetic algorithms (GA) for optimization [9]. The best results generated by N-GA are shown when using eight CCM textural features of: blue contrast, green maximum probability, red sum mean, grey correlation, grey contrast, red IDM, blue sum mean, and grey cluster tendency. The subset feature selected by N-GA gives the smallest MSE value result in the training-set data of 0.00039 and the validation-set of 0.000038. The learning process which has been accomplished by BPNN shows effective performance as long as the value of MSE in the training-set data decreases with the increasing number of iterations. The results show that the performance of N-GA (wrapper method) has better accuracy than all feature
selection methods in the filter method, with $R^2$ of 0.993. Based on the results of feature selection by using several filter and wrapper methods, the best results are achieved by N-GA. The subset features generated by N-GA can then be reversed to construct ANN model structures that can connect among eight CCM textural features to the predicted nitrogen content of spinach leaves. The result of ANN structure is shown in figure 7.

![ANN structure made to predict nitrogen content of spinach leaf.](image)

The application by using an artificial intelligence approach are necessary to model the CCM textural features to accurately predict the nitrogen content of spinach leaves. The performance of the BPNN model has been effectively tested to describe the relationship between CCM textural features and the nitrogen content of spinach leaves. This indicates that CCM textural features can be an alternative parameter to accurately predict the nitrogen content of spinach leaves. The estimation model of nitrogen content can later be used for the application of the right fertilizer so that it does not damage the environment to support the environmental sustainability.

4. Conclusions
This study was conducted to evaluate the effectiveness of using CCM textural features as a non-invasive measurement method to predict the nitrogen content of spinach leaves. In this research, CCM textural features are developed by using RGB and grey colour space. Back-Propagation Neural Network (BPNN) has been tested very effectively to describe the relationship between CCM textural features and nitrogen content of spinach leaves. Neural-Genetic Algorithm (N-GA) performs better than four filter methods with performance outcomes of: 10 CCM textural features; training MSE = 0.000094; validation MSE = 0.0000083; and testing accuracy $R^2 = 0.99$. The estimation model of nitrogen content can later be used for the application of the right fertilizer so that it does not damage the environment.

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