LeafCheckIT: A Banana Leaf Analyzer for Identifying Macronutrient Deficiency

Jonilyn A. Tejada
University of the Immaculate Conception
Fr. Selga St., Davao City,
Philippines
+63 998 5322 061
jonilyn.tejada@gmail.com

Glenn Paul P. Gara
University of the Immaculate Conception
Fr. Selga St., Davao City,
Philippines
+63 917 1491 091
ggara@uic.edu.ph

ABSTRACT
Nutrient deficiency affects the production of banana fruits. Plant malnutrition may visually reflect on their leaves, however, identifying deficiency symptoms could be a difficult task and often requires laboratory tests such as leaf and soil analysis. This paper introduces the LeafCheckIT, a web and mobile application that uses Random Forest machine learning algorithm to identify Nitrogen (N), Phosphorus (P), and Potassium (K) collectively known as macronutrients deficiency symptoms on banana leaves. Based on the training set evaluation and 10-fold cross validation test conducted on WEKA data mining software, the technique used in the application resulted in 100 and 91.64 percent accuracy rate respectively.

CCS Concepts
• **Computing methodologies~Supervised learning by classification** • *Computing methodologies~Classification and regression trees*.

Keywords
Leaf classification; nutrient deficiency analyzer; random forest; machine learning; image analysis.

1. INTRODUCTION
Climate change poses threats in securing enough food for the society. Abrupt weather changes such as heavy rains, drought and flood may result to a decrease in agricultural production and an increase in the distribution of pest and diseases [1]. To mitigate and adapt to the said changes, farmers nowadays are shifting from traditional farming to precision farming.

Precision farming, also known as Precision Agriculture (PA) is a farm management approach that uses modern information and communication technologies to aid in decision-making [2] by providing farmers automated solutions such as water analysis, fertilizer recommendations, drainage evaluation, yield data interpretation and leaf sampling [3]. Technologies used in PA includes but not limited to GPS services, sensors, robotic drones and data analysis techniques such data mining and machine learning [4].

ICCIP'17, November 24-26, 2017, Tokyo, Japan.

ACM ISBN 978-1-4503-5365-6/17/11…$15.00
DOI: https://doi.org/10.1145/3162957.3163035

In Uganda, the machine learning technique called extremely randomized trees was successfully used to diagnose Banana Bacterial Wilt (BBW) and Black Sigatoka (BBS) disease. A 12-megapixel digital camera was used to capture sample images and served as an input to Python with OpenCV and Scikit-learn libraries. The 10-fold validation test of the classifier used in the program resulted in Area Under Curve (AUC) of 0.96 for detecting BBW and 0.91 for BBS [5].

One of the popular precision farming applications that uses machine learning techniques in the Philippines was the classification of rice grains to automatically assess the quality of rice produced by farmers. The neural networks were used to automatically classify 52 varieties of rice grains according to size, shape and varietal type. The author used 110 samples per variety type and used image processing technique to extract grain features from the images. The project resulted in 98.76% accuracy in classifying grains according to size, 96.67% based on shape, 85.81% in classifying lowland irrigated, 94.58% for lowland rainfed, 96.16% for saline prone and 97.39% for upland rice variety. The overall performance of the classification was about 70 % for group classification [6].

The Davao Region is the top producer of banana in the Philippines [7] and one of the top exporters of the fruit worldwide. To cope with the banana fruit demands all over the globe, most of the Filipino farmers use fertilizers to increase production yield.

Based on the interview conducted by the researchers on banana growers in Sto. Tomas, Davao del Norte, some farmers apply fertilizer either based on the instructions given by the fertilizer manufacturer or by just a rough estimation. Some farmers estimate the volume of fertilizers to be applied to farms based on either soil or leaf analysis of the crop from government-accredited environmental laboratories.

Only 51 government recognized environmental laboratories that operate in the Philippines as of 2016. Only three of the said laboratories are located in Davao Region, all of which are located in Davao City [8]. Farmers from nearby provinces have to travel several miles to submit samples to the laboratories. The most accurate test to determine crop nutrition is leaf testing by using plant tissue analysis. The analysis rate differs to the type of nutrient to be analyzed in the sample banana tissue. The complete nutrient analysis for each sample would cost 1,800.00 Philippine Peso (PHP) (35.41 USD) and 500.00 PHP (9.84 USD) for only macronutrient analysis in all government-owned laboratories while private laboratories offer services at a higher price. The analysis would also require a month of preparation to soften the sample tissue for analysis. The cheaper alternative to tissue analysis is the soil analysis. The cost per sample also varies to the nutrient to be analyzed. A complete soil analysis for banana would cost 1,300.00 PHP (25.57 USD) and 150.00 PHP (29.51 USD) for macronutrient analysis. The soil sample to be analyzed should be air-dried for typically 1-2 weeks, depending on the moisture of the sample provided. The test results are typically released in 2-3 weeks in government-owned laboratories. As an alternative, soil test kits are also available online for DIY testing which offers cheaper but with lesser accuracy. Each kit costs around 953.22 PHP (18.75 USD) excluding the shipping fee.

As a solution, the researchers came up with a project, the LEAFCHECKIT: A CAVENDISH LEAF ANALYZER FOR IDENTIFYING MACRONUTRIENT DEFICIENCY. The LeafCheckIT is an application that can accept banana leaf images from the user and analyze it to determine whether the crop has Nitrogen (N), Phosphorus (P) or Potassium (K) deficiency, the elements needed in large quantities by plants, also known as macronutrients to fully grow and produce fruit. The following are the objectives of this project:

1. Extract image features needed in classifying leaf images.
2. Train a classifier to categorize the user uploaded leaf image into healthy, nitrogen (N), phosphorus (P) and potassium (K) deficient and non-banana leaf.
3. Develop a web and mobile application that can be used as user-interface in diagnosing banana leaf deficiency.

2. REVIEW OF RELATED LITERATURE

2.1 Nutrient Deficiency Symptoms on Banana Leaves

Just like human beings, plants need nutrients to survive and grow properly. These nutrients are divided into two categories: macronutrient and micronutrient [9].

A macronutrient is a group of elements needed in large amount and is classified into primary and secondary nutrients. The primary nutrients are nitrogen, phosphorus, and potassium and the most frequently required in a crop fertilization program [10]. The secondary nutrients are calcium, magnesium, and sulfur. Usually, enough of these nutrients can be found naturally in soil and not always need in fertilization [11]. Micronutrients are known as trace elements for they are used in very small amounts. Nutrients under this classification are boron, chlorine, copper, iron, manganese, molybdenum and zinc [9]. Each type of plant is unique and has a minimum and optimum nutrient level. Excessive nutrient uptake can cause toxicity and causes poor growth [12]. Conversely, if one of the nutrients from the soil is not present, the plant develops deficiency symptoms [9].

Nutrient deficiency symptoms may vary according to the type of plant to be tested. For bananas, nutrient deficiency and toxicity can be a difficult task. Other plant stressors such as salinity, pathogens and air pollution can also induce visual symptoms to leaves which sometimes resembles to nutrient deficiency [13]. Laboratory tests are sometimes needed to confirm the characterized symptom is a nutrient deficiency symptom [11]. Such tests include soil testing, plant analysis, and visual observations [13]. Both soil and plant analysis are quantitative tests comparing soil and plant concentrations to the sufficiency range for a particular crop [11].Visual observation is a qualitative assessment of noticeable changes on crop appearance such as stunted growth or discoloration of leaves as a result of nutrient stress [11]. The general signs of macronutrient deficiency are as follow [9]:

Nitrogen (N) deficiency symptoms include yellow discoloration of leaves from tip backward and older leaves become brown. The lower leaves may die prematurely while the top of the plant remains green. Fig. 1 shows nitrogen deficiency symptoms [12].

Figure 1. Banana with nitrogen deficiency

Figure 2. Severe Phosphorus Deficiency

Figure 3. Mild Phosphorus Deficiency

Phosphorus (P) deficiency shows dark bluish green, purpling and browning from the tip backward of the banana leaves. Fig. 2 and 3 shows sample banana leaf images with phosphorus deficiency symptoms [14].

Potassium (K) deficiency has several stages and each stage has different manifestations on banana leaves. The first stage of the deficiency starts with leaves turning to yellowish orange color [15] (Fig. 4). The stage 2 of the deficiency is considered as the moderate stage and as the right time to apply K fertilizer to the plant [14] [15]. During this stage, necrosis starts to appear at the leaf margin of the plant. On the third stage of the deficiency, the necrosis at the leaf edges thickens and will reach up to the leaf midrib (Fig. 5). Almost the entire banana leaf will wither and starts to curl in the fourth stage of the deficiency and is considered as the extreme condition [15] [16] (Fig. 6). The last stage of the deficiency, stage 5 is the lethal stage. The stage will show a total necrosis on the leaf which starts to bend, pointing towards the base of the plant. Fig. 7 shows the lethal stage of K deficiency.

Figure 4. Mild Potassium Deficiency Symptom

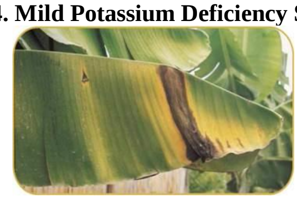

Figure 5. Severe Potassium Deficiency

Figure 6. Extreme Potassium Deficiency

Figure 7. Lethal Potassium Deficiency

2.2 Machine Learning Algorithms Used for Image Classification

Data mining and ML algorithms are proven to be effective in recognizing and forecasting possible trends and patterns in various fields [16], [17] and even agriculture [5][6].

For instance, ML techniques were utilized to automate the diagnosis of the banana diseases Bacterial Wilt and Black Sigatoka Disease [18]. A standard digital camera was used to collect sample images of disease infected and healthy banana leaves. The images were processed using image processing techniques and machine learning algorithms Nearest Neighbors, Decision Tree, Random Forest, Naïve Bayes and Support Vector Machine classifier were trained to classify healthy and disease-infected leaves. The result of test indicated that the extremely randomized trees is the most optimized algorithm in this case.

Machine learning algorithm was also used to classify defective from good quality apple [19]. The images used for machine learning were taken from a high-resolution digital camera with a fixed distance and were saved in a database. The 210 sample images include defected and non-defected stem and calyx. Included in the samples of the defect types were fungi attack, bruise, and punch. The preprocessing technique used for the images include dark, uniform colored with a black background and was converted into HSV (Hue, Saturation, and Value) plane images and was converted into 25 non-overlapping equal parts. A feature extraction technique was used extract sensible features for classification. Then the nearest neighbor algorithm was used to classify defected and non-defected apple. The classifier performed around 92% accurate recognition and was implemented under Matlab 7.2 R2006a environment.

3. METHODOLOGY

3.1 Requirements Specification

To determine the necessary details about banana leaf deficiency symptoms and the validation techniques, a literature review was conducted. According to the review, nutrient deficiency can be diagnosed based on visual observation. Noticeable changes in crop appearance such as stunted growth or discoloration of leaves appear in most crops with unsatisfied nutrient requirements [20]. Table 1 shows the summary of visual symptoms on leaves.

Table 1. Leaf visual symptom based on leaf classification

Classification	Visual Symptoms on Leaves
Healthy	Green Leaves
Nitrogen Deficiency	Light green to yellow leaves; Reddish pink to reddish brown petiole and midrib
Phosphorus Deficiency	Yellowish white (chlorosis) on some parts; Purple brown necrosis surrounding the chlorosis
Potassium Deficiency Stage 1	Yellowish orange of some leaf parts
Potassium Deficiency Stage 2	Yellowish orange of some leaf parts; Brown on leaf margin (necrosis)
Potassium Deficiency Stage 3	Yellowish orange on some parts; Brown on leaf margin; Dark brown thick and long stripes from leaf margin to midrib
Potassium Deficiency Stage 4	Yellow orange on most parts; Dark brown on some parts
Potassium Deficiency Stage 5	Dark brown on most parts; Yellow orange on some parts

The images used as datasets for training the algorithm were captured through the camera of an iPhone 5 mobile phone. Samples gathered were captured from selected areas in Davao del Norte and Compostela Valley Province. Soil test kit and soil analysis through Regional Soils Laboratory of the Department of Agriculture were conducted in order to verify the validity of the images used for sampling [21].

For accuracy purposes, the images were cropped to retain only the leaf sample and were not graphically enhanced. To standardize the sampling, a technique close to the standard sampling procedure for extracting leaf for plant tissue analysis was applied to the datasets. All images used as training datasets were taken from the midrib up to the margin of the third leaf of the banana plant [22]. The Fig. 8 shows the sample captured leaf images with Phosphorus deficiency symptom.

Figure 8. Sample leaf image with Phosphorus deficiency

3.2 Analysis

The purpose of the application is to give faster and seamless alternative solution to laboratory tests, the researchers decided to provide a cross-platform application to the users. Hence, the researchers decided to use Python programming language to achieve the cross-platform compatibility.

The OpenCV framework was also used to simplify the feature extraction and machine learning process of the application. The DenseSIFT technique used by Joshi in OpenCV with Python by Example, was used to extract the texture of the images. The said technique uses the Dense algorithm to divide the image into equal overlapping parts, afterwards the features were extracted by using SIFT algorithm [23].

Several experiments were conducted to determine the suitable color feature to be used in the application. Different color spaces were explored such as RGB, HSV, YCbCr, and CIE Lab. The researchers agreed to use the Linear SVM classifier as an initial classifier in testing the appropriateness of the datasets to be used since most of the successful image classification literature uses the algorithm [18][19]. The initial training sets includes 705 images which consists of 50 healthy banana leaf images, 255 leaf images nitrogen deficient, 155 phosphorus deficient cases, 90 potassium deficient cases and 160 non-banana leaf images.

The experiments were conducted using a laptop with an Intel I3 processor and a 2 GB RAM. The researchers employed WEKA data mining software to analyze the appropriateness of the datasets and machine learning algorithm to be used in the application.

4. RESULTS

4.1 Leaf Classification through Image Features Extraction

Based on the conducted tests, the researchers found out that the most appropriate data set for the application is the combination of DenseSIFT extracted texture feature and the mean and standard deviation of the RGB, CIELab, YCrCb color representation of the sample image. The table 2 summarizes the result of the said test.

Table 2. Summary of the feature datasets to be used in the leafcheckit app using linear svm classifier

Color Feature (Mean, Standard Deviation)	Texture	Accuracy (Training Set Validation)
RGB	DenseSIFT	90.96
YCbCr	DenseSIFT	92.05
CIELab	DenseSIFT	91.59
HSV	DenseSIFT	89.72
RGB, CIELab, YCrCb	DenseSIFT	93.61
RGB, HSV, YCrCb	DenseSIFT	92.83

4.2 Training a Classifier to Classify Leaf Images

The researchers utilized the extracted features from the previous test to assess and finally decide which among the available classifiers would produce best results for the classification. Among the evaluated classifiers are the Linear SVM, Artificial Neural Network (ANN), Naïve Bayes and Random Forest. The table 3 shows the results of the validation test conducted in order to determine the accuracy of the classifier used for the LeafCheckIT application.

The validation test shows that the most appropriate classifier to be used in the LeafCheckIT application is the Random Forest algorithm which resulted in 100% accuracy during training set evaluation and 91.64% during 10-fold validation test. The table 4 presents the detailed accuracy report by class of the Random Forest classifier during the 10-fold validation test.

Table 3. Summary of the Validation Tests Results of the Classifier used in LeafCheckIT project

Classifier	Training set evaluation	10 fold Validation test
SVM	93.61	87.53
ANN	99.29	87.67
Naïve Bayes	86.64	85.83
Random Forest	100	91.64

Table 4. Detailed Accuracy Report of the Random Forest Classifier 10-Fold Validation Test

Class	TP Rate	FP Rate	Precision	ROC
Healthy	0.662	0.016	0.818	0.98
Nitrogen Deficiency	0.952	0.053	0.898	0.993
Phosphorus Deficiency	0.986	0.009	0.966	0.998
Potassium Deficiency	0.918	0.29	0.856	0.987
Non-leaf Objects	0.908	0.004	0.986	0.996

4.3 Banana Leaf Deficiency Diagnostic Cross-Platform Application

The LeafCheckIT application consists of three types of application. The first application is the backend machine learning module. The backend module was written using Python language with OpenCV framework. The module is used to detect and extract color and texture image feature, train random forest classifier. It can be also used in classifying images once the SVM is already trained.

The second module of the application is the web application. The application was developed using Python language and Django web framework. The module provides the web interface for both user and administrator of the application. The web module also serves as the server that caters all the leaf classification requests from both web and mobile users. The Django-REST framework was then used to create an API to interface the web version of the system to the mobile application. The API handles all user requests from the mobile application such as creating an account, account authentication, uploading an image, predicting leaf deficiency and viewing of tests requests. Figure 9 shows the conceptual framework of the LeafCheckIT application.

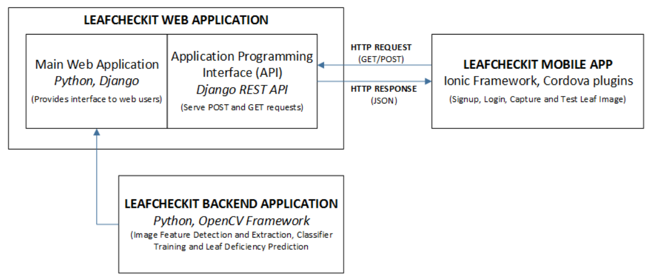

Figure 9. LeafCheckIT app conceptual framework

The web application offers features that can allow users to create an account, access information about the nutrient deficiency symptoms on banana leaves, upload banana leaf images and use the application to test the sample of nutrient deficiency symptoms and view the previously conducted tests. The fig. 10 shows a sample screenshot of the web application.

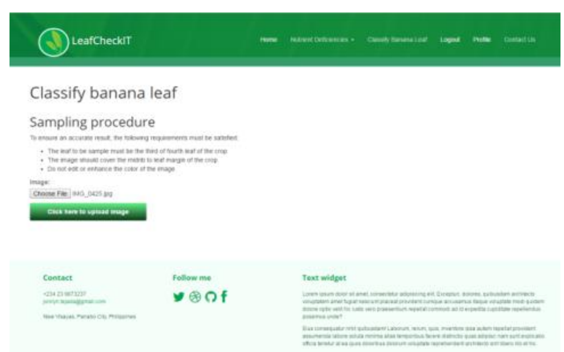

Figure 10. Screenshot showing the LeafCheckIT web app

The LeafCheckIT mobile application offers the same functionality of the web version. The user can also create an account, access information about nutrient deficiency symptoms on banana leaves, upload banana leaf images and use the application to test the sample of nutrient deficiency symptoms and view the previously conducted tests. The fig. 11 shows a sample screenshot of the LeafCheckIT mobile version.

Figure 11. Screenshot of LeafCheckIT mobile app

5. CONCLUSION

The project "LeafCheckIT: A Cavendish Leaf Analyzer for Identifying Macronutrient Deficiency" aimed to provide a tool that can diagnose macronutrient deficiency symptoms based on user-uploaded images. To create the tool, the researchers have to discover ways to extract feature data from images, train a machine learning algorithm to predict leaf deficiency and deploy the trained algorithm to platforms accessible to farmers.

The researchers used a combination of color and texture feature from images which consist of the mean and standard deviation of the RGB, YCbCr, and CIELab color spaces and texture feature sets were extracted using the DENSE SIFT feature extraction technique. The Random Forest classifier was also used to predict the occurrence of macro deficiency symptoms in the leaves. Based on the validation test conducted using 705 leaf images consisting of healthy, nitrogen, phosphorus, and potassium leaf deficiency and non-leaf images through WEKA data mining software, the feature extraction technique garnered an accuracy of 100% using training set validation and 91.64% using 10-fold validation test. Thus, the technique being utilized as feature extraction method is effective in predicting leaf macro deficiency symptoms. The classifier was also deployed on a web application to cater both web and mobile requests from the user.

The LeafCheckIT web application was developed using Python Django web framework. The app has two types of interfaces, the client and administration page. The client page serves as the user's interface to the web app for leaf testing while the administration page is the administrator's interface to train the machine learning classifier. The LeafCheckIT mobile version is an application developed by using the Ionic framework. The application offers leaf analysis for authenticated users by allowing them to sign in to the system's web server and connecting them to the trained classifier deployed in the web app through an API.

Though the application was successfully launched online for use, its efficiency and performance are not yet measured. The user evaluation should be conducted to assess the user satisfaction on the application.

6. REFERENCES

[1] Ganpat, Wayne G. *Impacts of Climate Change on Food Security in Small Island Developing States*. 30 Sep 2014. IGI Global

[2] Pierce, F. J., & Nowak, P. (1999). Aspects of Precision Agriculture. Advances in Agronomy Advances in Agronomy Volume 67, 1-85. doi:10.1016/s0065-2113(08)60513-1

[3] Auernhammer, H. (2001). Precision farming — the environmental challenge. *Computers and Electronics in Agriculture*, 30(1-3), 31-43. doi:10.1016/s0168-1699(00)00153-8

[4] Blackmore, S. (1994). *Precision Farming: An Introduction. Outlook on Agriculture*, 23(4), 275-280. doi:10.1177/003072709402300407

[5] Owomugisha, G, Quinn, J, Mwebaze, E, and Lwasa, J. Automated Vision-Based Diagnosis of Banana Bacterial Wilt Disease and Black Sigatoka Disease. In *International Conference on the Use of Mobile ICT in Africa* (Stellenbosh, Africa 2014).

[6] Guzman, J and Peralta, E. Classification of Philippine Rice Grains using Machine Vision and Artificial Neural Networks. In *World Conference on Agricultural Information and IT* (2008).

[7] National Economic and Development Authority. (2011). *Davao Regional Development Plan 2011-2016*. Retrieved from http://www.neda.gov.ph/wp-content/uploads/2013/10/RegXI_RDP_2011-2016.pdf

[8] Department of Environment and Natural Resources. *DENR Recognized Environmental Laboratories*. (2016). Retrieved from http://119.92.161.2/embgovph/Portals/22/DENR%20Recognized%20Environmental%20Laboratories%202016.pdf

[9] International fertilizer industry association. *Fertilizers and their use: A pocket guide for extension officers 4th Edition*. Food and Agriculture Organization of the United Nations (Rome, 2000).

[10] Fageria, N. K. (2010). *The use of nutrients in crop plants*. S.l.: Taylor & Francis/CRC Press.

[11] Barker, A. V., & Pilbeam, D. J. (2010). *Handbook of plant nutrition*. S.l.: Taylor & Francis/CRC Press.

[12] Uchida, R. *Essential Nutrients for Plant Growth: Nutrient Functions and Deficiency Symptom*. Hawaii, 2000.

[13] Taiz, L., Zeiger, E., Moller, I., Murphy, A. (2015). Symptoms of Deficiency in Essential Minerals. In *Plant Physiology and Development*. Oxford University Press.

[14] Haifa. (n.d.). *Nutritional recommendations for banana*. Haifa Chemicals Ltd.

[15] Gowen, S. (1995). *Bananas and Plantains*. Dordrecht: Springer Science Business Media. doi:10.1007/978-94-011-0737-2

[16] Gara, G. P. P., & Padao, F. R. F. (2015). Mining Association Rules on Students' Profiles and Personality Types. Proceedings of the International Multiconference of Engineers and Computer Scientists.

[17] Gara, G. P. P., & Padao, F. R. F. (2016, August). Correlation Analysis of Profiles and Personality Types Using Association Rule Learning Algorithm. In *IAENG Transactions on Engineering Sciences: Special Issue for the International Association of Engineers Conferences 2015* (p. 91). World Scientific.

[18] Quinn, G and Lwasa. Automated Vision-Based Diagnosis of Banana. In *First International Conference on the Use of Mobile ICT* (Stellenbosch, South Africa 2014).

[19] Arlimatti, S. R. Window Based Method for Automatic Classification of Apple Fruit (2012). *International Journal of Engineering Research and Applications* (1010-1013).

[20] McCauley, A., Jones, C., & Jacobsen, J. (2009). Plant nutrient functions and deficiency and toxicity symptoms. *Nutrient management module*, 9, 1-16.

[21] Jackson, M. L. (1958). *Soil chemical analysis*. Prentice-Hall, Inc.; Englewood Cliffs.

[22] Memon, N, Hassan, Z, and Oad, F. Banana Nutrition Management through Plant Analysis. Pakistan: *Pakistan Journal of Applied Sciences* (2001), Vol. 1. 563-574.

[23] Joshi, Prateek. *OpenCV with Python by example*. Packt Publishing, 2015.