

Coffee Arabica Nutrient Deficiency Detection System Using Image Processing Techniques

Firezer Tenaye

Jimma University

Chala Diriba (✉ chala.diriba@ju.edu.et)

Jimma University <https://orcid.org/0000-0003-1573-2928>

Muktar Bedaso

Jimma University

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Abstract

This study mainly focused on the detection of Coffee Arabica nutrient deficiency by using image processing techniques. Coffee nutrition deficiency techniques are very traditional and time taking which means the agronomists simply detect deficiencies by observing the leaves of the coffee and decide by guessing. The study employed experimental research design which involves dataset preparation, designing classification model and evaluation. In addition, Python programming languages were used. The researcher has 422 total nutritional deficient Coffee plant leaves image data set, from this data first the researcher split 20 percent for testing which is 84 images and 338 training image data, and further from the remaining training data, the researcher again split 20 percent validation data which is 10 images. The three pre-trained deep learning models were used to evaluate the experiments. The evaluation of the system indicated the performance of Mobile Net (0.9882), VGG16 Net (0.6471) and Inception_V3 (0.8095). Therefore, testing and training value of Mobile Net model was more accurate than the rest of two models. Finally, the prototype for detection of Coffee nutrient deficiency developed by using Mobile Net deep learning model. For the future the researchers suggest doing more researches by using others CNN architectures and more datasets.

I. Introduction

Coffee is a beverage obtained from cherry or the fruit of coffee plant. It is widely used as a beverage but nowadays it is also used as input in some food processing industries like for a flavoring to various pastries, ice-creams, chocolate. Among different types of coffee, the major economic species are coffee Arabica and coffee Robusta. Coffee Arabica and Robusta accounts for 80%, 19.5% respectively of the world coffee trade, while coffee Liberica and Excelsa together supply less than 1% (Nation, 2018).

Agriculture has always been an important component of the economy of many countries across the world. For instance, agriculture is the main source of the Ethiopian economy. It is a wild crop that grows in the forests especially south-western parts of Ethiopia Jimma and Wollega and Ilu Abbaa Bori Zones. Currently, coffee production and marketing is the common occupation for Ethiopian farmers. Coffee production in Ethiopia is a longstanding which dates back to dozens of centuries. Ethiopia is where coffee Arabica the coffee plant originates. As Amamo (2014) stated twenty seven percent (27%) of foreign income comes from coffee and twenty five (25) million of the population relying on coffee production for their livelihood.

A plant disease is any abnormal condition that alters the appearance or function of a plant. It is a physiological process that affects some or all plant functions. This could emerge because of various reasons: it could be due to deficiency of nutrients, drought/deficiency of water and/or due to pathologic microorganisms.

Among all, this paper focuses on the image processing of the plant disease caused by nutrient deficiency. Nutrient deficiency reduces amount and quality of harvested products. Nutrient deficiency is a gradual

process or a change that occurs over time. It does not occur instantly like injury. Therefore, plants nutrient deficiency usually takes the attention of several researchers, in order to prevent and mitigate the negative effect of diseases in crops.

Several efforts have been focused on exploiting digital image processing techniques and supervised classification approaches for detecting plants diseases through the analysis of several parts such as roots, fruits, stems, and leaves (Mahlein, 2016). Image processing would be implemented through the science of computer vision that develops the theoretical and algorithmic by extracting and analyzing useful information can be automatically from an observed image using computation made by computers. Thus, the aim objective of this study was to design a prototype for coffee Nutrient deficiency detection by using digital image processing techniques.

II. Material And Method

Regarding the necessity of identifying nutritional deficiencies in images of coffee leaves using a deep learning approach, here it is proposed the development of a frame work that is based on the usual architecture employed in approaches focused on images recognition through unsupervised classification.

A. Image acquisition

The data acquisition technique in this research is crucial concern to generate clear, unbiased and simplified digital coffee leaf sample database for further analysis and processing. For acquiring images of coffee plant canon EOS600 camera was used. The images were taken by fixing camera on a stand which reduces the movement of hand and capturing images in uniform ways. It has used three varieties of distance 110mm, 130 mm and 155 mm from the coffee leaf. Finally, the images were collected at the distance of 130mm from the coffee leaf. In addition, to obtain uniform lightning or balanced illumination 100Wlamp were used. The images captured using a digital camera are transferred into a computer, displayed on a screen and stored on the hard disk in PNG format as digital color images. All the captured images were in PNG file format. PNG image file format is selected because of its lossless behavior for preserving image data.

During image acquisition from the environment, experts can use different resolution pixels. Images can be acquired at 1200 x 1200, 1456 x 1544, 696x514 and others. For instance Gonzalez (2020) used 1240x800 for better resolution. Thus, the researcher used 1240 x 800 resolutions to collect image's dataset. The coffee tree leaves used in this research were recollected in coffee plantations located at Jimma and Limmu coffee farms. After wards, the nutritional deficiencies were identified by agricultural experts from Jimma agriculture research center and Limmu Coffee farm.

Table 1
Number of Coffee leaves
image used

Nutrients	No. of Image
Boron	80
Iron	111
Calcium	110
Potassium	121
Total	422
Total	422

B. Image Preprocessing

Mean and median were used for the coffee leaves image filtering purpose. Smoothing quality enhancer technique was also employed for enhancing the quality of images for better understanding. Collected images were normalized and converted in black-white space for further processing and analysis. Dynamic range expansion in the image is usually to bring the image into a range that is more familiar or normal to the senses. These used for reducing noises from the acquired image data.

C. Image classification

Classifier is a program that takes input feature vectors and assigns it to one of a set of designated classes. Python is used for developing model by using three classifiers. The researcher used the Convolutional Neural Network (CNN) architectures Mobile-Net, VGG16 and InceptionV3 pre-trained model.

D. Implementation tools

Google Co-lab is a project from Google Research, a free, Jupyter notebook based environment that allows us to create Jupyter notebooks to write and execute Python (machine learning frameworks such as Tensorflow, Keras, OpenCV).

F. System Evaluation

The system performance is evaluated by measuring Accuracy, Precision, Recall and F1 Score.

iii. Experiment And Results

In this section the experiment performed and result achieved were discussed as follows.

CNN mainly consist of three type of layers, where a kernel (or filter) of weights is convolved in order to extract features; Nonlinear layers, which apply an activation function on feature maps in order to enable

the modeling of non-linear functions by the network; and pooling layers, which replace a small neighborhood of a feature map with some statistical information about the neighborhood and reduce spatial resolution. Advantage of CNNs is that all the receptive fields in a layer share weights, resulting in a significantly smaller number of parameters than fully-connected neural networks.

E. Training and Testing datasets

In this study the researcher split the data 80 by 20 as a result the researcher can get training 60 percent, evaluation 20 percent, and testing data 20 percent. The researcher has 422 total nutritional deficient Coffee plant leaves image data set, from this data first the researcher split 20 percent for testing which is 84 images and 338 training image data, and further from the remaining training data, the researcher again split 20 percent validation data which is 10 images. So split our data 50 for training, 40 for testing (unseen data during training), and 10 for evaluation.

Table 2
Accuracy and loss of training and testing of the three models

	Mobile Net	VGG-Net 16	Inception-Net-V3
Training Accuracy	0.9911	0.6677	0.9643
Training Loss	0.0157	0.4853	0.0889
Testing Accuracy	0.9882	0.6471	0.8095
Testing Loss	0.0761	0.5028	0.3820

A. Mobile-Net classifier

Mobile-Net is one of CNN architectures that used for image classification and mobile vision. Mobile-net classifier uses depth wise separable convolutions. It significantly reduces the number of parameters when compared to the network with regular convolutions; this is why the research used mobile net.

B. VGG 16

VGG 16 is also one of CNN architectures. It is considered to be one of the excellent visions types of CNN architectures. In VGG16 approach instead of having a large number of hyper-parameter they focused on having convolution layers of 3x3 filter with a stride 1 and always used same padding and max pool layer of 2x2 filter of stride 2. Model architecture Iron = 0.336% Potassium = 0.256% Calcium = 0.226% Boron = 0.184%.

C. Inception V3

Inception V3 is a CNN for assisting in image analysis and objects detection. It is the modification of a Google-net. Third edition of Google's Inception CNN, Inception V3 is a widely-used in image recognition model. It has been shown to attain greater than 78.1% accuracy on the Image-Net dataset. The model

itself is made up of symmetric and asymmetric building blocks, including convolutions, average pooling, max pooling, con-cats, dropouts, and fully connected layers. In this experiment potassium, calcium, iron, boron 0.289% 0.47%, 0.206 and 0.154% respectively.

Iv. Classification Performance

The researcher evaluated the performance of nutritional deficiency model via Accuracy, Precision, Recall and F1 Score metrics. Finally the researcher get good accuracy when we compare the above three architecture the Mobile-net models have good accuracy.

Table 3
Classification performance

Mobile -Net				
	precision	Recall	f1-score	support
Potassium	1.00	1.00	1.00	32
Calcium	1.00	0.94	0.97	17
Boron	1.00	1.00	1.00	19
Iron	0.94	1.00	0.97	17
accuracy			0.99	85
macro-avg	0.99	0.99	0.99	85
weighted-avg	0.99	0.99	0.99	85
VGG 16				
	precision	Recall	f1-score	support
Potassium	0.38	1.00	1.00	32
Calcium	0.57	0.94	0.97	17
Boron	0.00	1.00	1.00	19
Iron	0.57	1.00	0.97	17
accuracy			0.48	42
macro-avg	0.38	0.49	0.40	42
weighted-avg	0.40	0.48	0.40	42
Inception V3				
	precision	Recall	f1-score	support
Potassium	0.58	0.88	0.70	8
Calcium	0.85	1.00	0.92	11
Boron	1.00	0.30	0.46	10
Iron	0.93	1.00	0.96	13
accuracy			0.81	42
macro-avg	0.84	0.79	0.76	42
weighted-avg	0.86	0.81	0.78	42

V. Discussion

As it's possible to understand from the above results better results were got for detection of Iron (Fe) and Boron (B) nutritional deficiencies. These results could be related to the fact that the symptoms associated to the Boron and Iron deficiencies are more remarkable than those associated to the other nutrients; therefore they could be identified in an easier way. Specifically, the best results associated to the Mobile-Net descriptor were notably obtained in the identification of deficiencies, with a large difference in relation to other pre-trained models which means VGG16 and inception v3.

Finally, a direct comparison between the three classification approaches concludes that using the information associated descriptor, for all the deficiencies the classifier with best accuracy results was the Mobile-Net (98.82%). However, for the descriptor the results do not evidence the superiority of some classifier over the remaining two. In contrast, the best results associated to each nutritional deficiency, were shared across the three classifiers. In related to this study as Setiawan, W., Syarief, M., & Prastiti, N. (2019) depicted in their study on the title of Maize leaf disease image classification using bag of features by using 200 images using VGG 16, VGG19, GoogleNet, Inception-V3. After experimentation they got results accuracy, sensitivity, specificity of 93.5%, 95.08%, and 93%, respectively. In addition, Zhang et al., (2018), conducted the study entitle Identification of maize leaf diseases using improved deep convolutional neural networks achieves performance evaluation of an average accuracy of 98.8%. Moreover, as Rajbongshi et al., (2020) stated in their study on the title of rose diseases recognition using Mobile-net they got model performance evaluation result 95.63% accuracy.

Vi. Conclusion

The focus of this research was to detect coffee Arabica nutrient deficiencies especially iron, potassium, calcium and boron using image processing techniques. CNN architecture were applied and mobile net score best performance.

Declarations

I declare that this manuscript is my original work and it has not been published on any journal yet and on this topic. All the material sources used in this work are duly acknowledged.

COI: I declare that this manuscript is our original work and it has not been published on any journal yet. The authors declare that there is no conflict of interest. All the material sources used in this work are duly acknowledged.

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Figures

Figure 1

Normalization confusion matrix of Mobile-Net

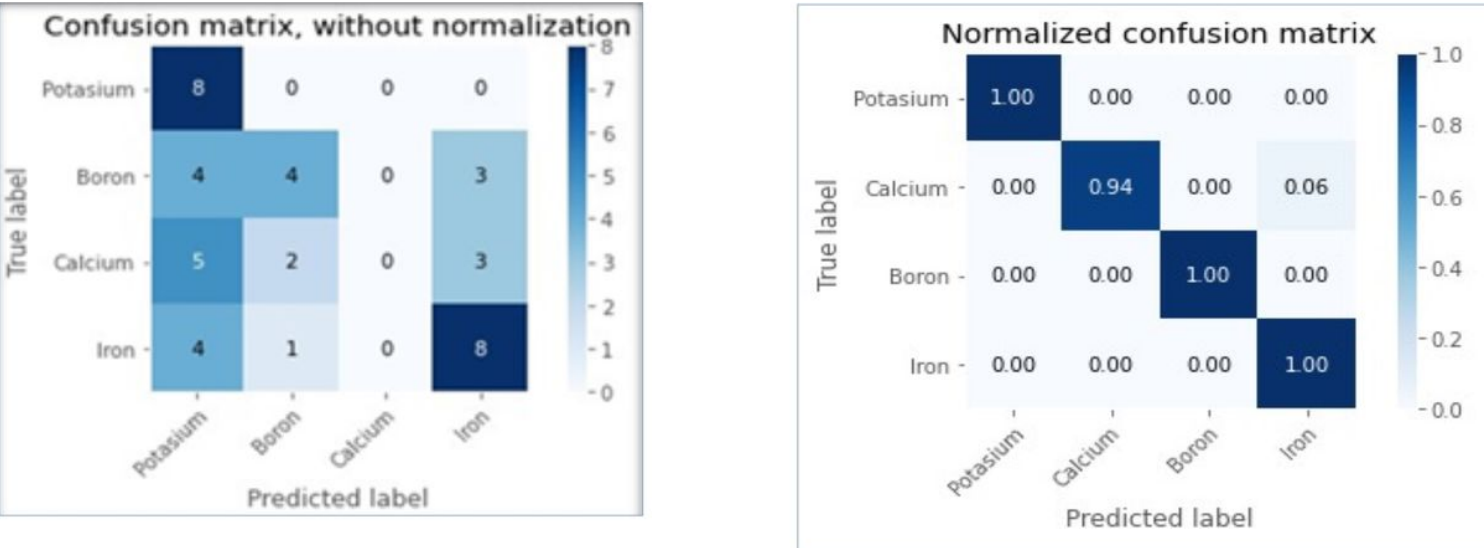


Figure 2

Normalization confusion matrix of VGG16

Figure 3

Normalization confusion matrix of Inception V3

