Corzea: Portable Maize (Zea Mays L.) Nutrient Deficiency Identifier

Von Ryan P. Marcelo, Joe G. Lagarteja

Abstract: Nutrients are vital in corn crops and its determination of nutrient deficiency is not an easy job for corn farmers with insufficient formal education or training in the field of agriculture. Traditional methods were adapted in the analysis of nutrient deficiency. This includes the processes like visual inspection, soil testing, and tissue analysis. These processes were tedious, subjective and also time consuming especially on very large farms. With the advent of computer vision and machine learning techniques, this offers new prospects in non-destructive field-based analysis for nutrient deficiency. This suggests that there is a need to revolutionized this outdated process and develop an automated system that will help corn farmers to determine what nutrient is lacking from their corn crops to sustain high corn production and of disaster risk reduction. This paper provided a new method to classify and identify nutrient deficiencies in corn through image processing. Two hundred (200) samples were used in the study for testing, and Five thousand (5000) images of corn leaves were used as a training set. The results in the study show an overall accuracy rate of 91.5%, thus provides a better and innovative way of determining nutrient deficiencies in corn.

Index Terms: Artificial Intelligence, Classification, Convolutional Neural Network, Supervised Learning

1. INTRODUCTION

Corn (Zea mays) locally known as “mais” in the Philippines is one of the most important cereal crops plant belonging to the Poaceae family (Karthik, S.K., Mahesh, T., Sumanth, B.&Tanmay, 2017). Corn is a crop having short life cycle and requires warm weather, appropriate apprehension and management (Karthik, S.K., Mahesh, T., Sumanth, B.&Tanmay, 2017). This domesticated crop originated in the Americas and is one of the most widely distributed of the world’s food crops. Corn is used as livestock feed, as human food, as biofuel, and as raw material in industry (Karthik, S.K., Mahesh, T., Sumanth, B.&Tanmay, 2017). The second most important crop in the Philippines is corn, in terms of total area planted and overall value next to rice. Yellow corn is the most important corn type in the Philippines, and is primarily used as feed especially for poultry and swine (De los Santos, Lansigan, & Hansen, 2007). The country's corn rose 4.66 percent to 2.48 million metric tons (MT) in the first quarter of 2018 from 2.37 million MT in the same period in 2017. In 2016, corn harvest nationwide weighed 1.92 million MT in the same period (Catherine Teves, n.d.), gaining some 4.2% year-on-year (Ralf Rivas, n.d.). Plants and crops require 13 essential mineral supplements to grow and survive. They obtain these supplements from the soil. Deficiency of these supplements influences the development and quality of the plant/crop. Hence, diagnosing supplement status of minerals plays a crucial part in agriculture and farming. Nutrient lack indications in plants/crops would normally be obvious in leaves. These indications incorporate interveinal chlorosis, minimal chlorosis, uniform chlorosis, necrosis, distorted edges, diminishment in measure of the leaf etc. Even though similar indication shows in old and young leaves, the deficient nutrient may differ(Jeyalakshmi & Radha, 2018). One of the vital nutrients needed for healthy corn production is potassium (K). K deficiency led to inhibit the growth of 90-21-3 and D937, more seriously in shoots than roots. The total root length and surPface area, especially the fine root, were significantly reduced under K deficiency wherein roots have great significance to nutrient absorption and play an important role in the growth and development of plants (Han et al., 2017). Determining the nutrient deficiency from corn crops is not so easy job for native farmers with insufficient to no formal education/training to agriculture. The traditional methods implemented for nutrient deficiency analysis mainly include visual inspection, soil testing, tissue analysis etc. Visual analysis of deficiency symptoms is very tedious, subjective and also time consuming especially on very large farms. The application of computer vision and machine learning techniques offers new prospects in non-destructive field-based analysis for nutrient deficiency. This implies that there is a need to revolutionized this outdated process and develop an automated system that will help our native farmers to determine what nutrient is lacking from their corn crops to sustain high corn production and of disaster risk reduction. Today, the application of computer vision and machine learning techniques offers new prospects in non-destructive field-based analysis for nutrient deficiency. Hanks, T et.al (2018) collected corn images through three different ways (handheld, boom and drone) which was valuable for furthering the development of novel computer vision approach that is specific to the target disease and insensitive to such variations. N. Leena and K. K. Saju (2018) uses different machine learning techniques like Artificial neural networks, Support Vector Machine (SVM), k Nearest Neighbour (kNN) and Deep Networks Using Autoencoders to classify the images of the corn to identify the corn’s nutrient deficiency.

Based from the works of (Abdullahi et al., 2017) “Using Convolution neural network (CNN), also known as ConvNet, a network can be trained from scratch with a large data set or fine tuning an existing model or making use of ‘’off the shelf Convolution neural network features’’. Fine tuning involves transferring weights of the first ‘n’ layers learned from a previous base network to the new network. The dataset obtained for the new network is now trained to perform specific tasks. CNN can efficiently learn generic image features and the features can be used with simple classifiers to solve most computer vision challenges.

This paper presented the implementation of image processing operations on Raspberry Pi. The Raspberry Pi is a basic embedded system and being a low cost, a single-board

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computer used to reduce the complexity of systems in real time applications. The system was developed using advanced image processing techniques for image classification, deep convolutional neural network with Googles TensorFlow, and package with Raspberry pi for its portability.

2 MATERIALS AND METHODS

2.1 Conceptual Framework

This paradigm is displayed to show the concept of the researcher in fulfilling the set objectives of this paper through realistic outline of information stream and rationale inside the framework.

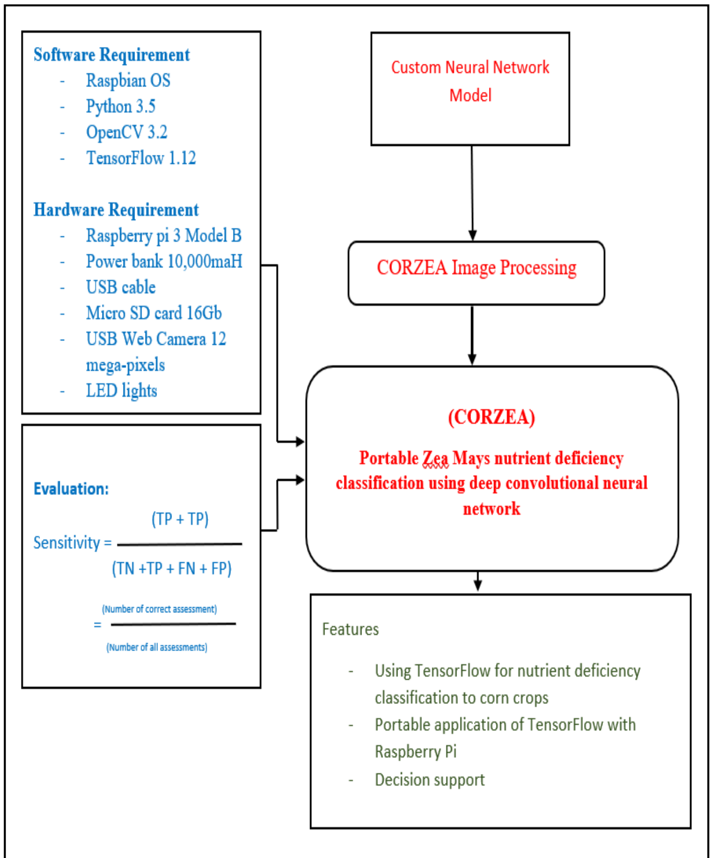

***Fig. 1**. Conceptual Framework of the study.*

As shown in Figure 1, the system starts with the training the custom classifier based from Google's SSD Mobilenet V2 COCO 2018. Wherein, images of the different corn leaves categorize per nutrient deficient will be collected via online resources (www.image-net.org) and from actual environment (corn farms from Ilagan City, Isabela). Training images will be taken from both controlled and natural environment.

Ten (10%) percent of collected images from each nutrient deficient was used as test set and the remaining Ninety (90%) percent as training set. It is vital that the test set is not part of the train set images, thus the validation result has precise representation of how accurate was the trained model. After training the custom neural model, a script written in python was required to capture 2-3 chunks of the input corn leaf and stitch those images to form single image and perform analysis. With the defined software and hardware tools as initial requirements, building the system prototype was possible. The

TABLE 3

SOFTWARE SPECIFICATION

Software	Usage
Raspbian OS (Stretch or Higher)	Operating System
OpenCV 3.2	For image processing
Python 3.5	Programming language
TensorFlow 1.12	For Deep Convolutional Neural Network
Google's SSD Mobilenet V2 COCO 2018	Pre-trained model from

TABLE 1

TRAINING SAMPLES PER NUTRIENT DEFICIENCY

Nutrient Deficient	Training Samples
Phosphorus	50
Potassium	50
Nitrogen	50
Magnesium	50

accuracy of the classifier on actual test was calculated using a simple mathematical formula adapted from the work of(Wen Zhu, Nancy Zeng, 2010). With the system design, the researchers aim to build a portable nutrient deficiency classification to corn crops with TensorFlow. This device significantly aids the local farmers to easily analyze their corn crops if there is any nutrient deficiency and if in case that there is manifestation then they can immediately apply appropriate fertilizers to sustain the high production of corn in the country.

2.2 Research Methodology

This chapter presents the methods taken in this study to develop CORZEA: Portable Zea Mays nutrient deficiency classification using deep convolutional neural network for nutrient deficiency identification. The evolutionary prototyping (breadboard prototyping) was considered by building actual functional prototypes with minimal functionality at the start. Figure 2 shows the cycle of the evolutionary prototyping method.

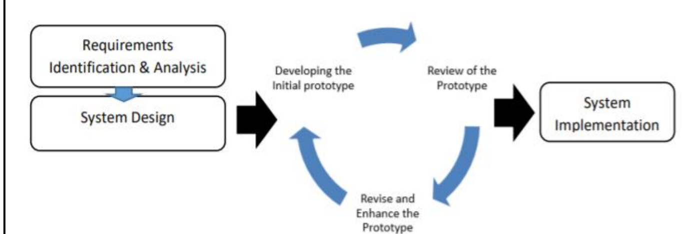

***Fig. 2**. The evolutionary prototyping method was employed in the development of the system.*

- Basic Requirement Identification
  In this phase, the different information requirements, were initially identified, importantly the actual structure was determined.
- Developing the Initial Prototype
  In this phase, the initial prototype was developed where the basis requirements were showcased and initial physical structure was provided.
- Review of the Prototype
  In this phase, the prototype developed was presented to the users. The feedback/suggestions were collected and was used for further enhancement of the system.
- Revise and Enhance the Prototype

In this phase, the feedback and the review comments were discussed and some negotiations and solutions with the users were settled. The changes accepted were again incorporated in the new prototype developed and the cycle repeats until the users' expectations where be met.

2.3 Hardware and Software Needed in Building the Prototype Device

Building the prototype involves the structuring, layout, specifications, and actual building as shown in Table 2, 3 and Figure 3.The portable Zea Mays nutrient deficiency classification using deep convolutional neural network includes Raspberry pi 3 Model B installed with 3.5 inch touch screen, 16GB SD card (class 10), and a 12 mega-pixels web camera, all powered by a 20,000mAH portable battery pack. Enclosed in a 40.5 cm x 40.5 cm cardboard box with plain white background color in the inside and installed strip LED lights on each side for better lightning when capturing images as presented in Figure 5 Foldable enclosed cardboard box with installed Raspberry Pi 3 Model B and web camera.

TABLE 2

HARDWARE SPECIFICATION

Hardware	Usage
Raspberry Pi 3 Model B	Main Processing Unit
16GB SD Card (Class 10)	Where the Raspbian OS was installed and at the same time act as storage
3.5-inch Touch Screen	Monitor
12 Mega Pixel Web Camera	Camera module, for capturing chunk images
20,000mAH Battery Pack	Portable power supply
White LED light strip (40cm long)	For better lighting condition
Foldable Cardboard Box (40.5 cm x 40.5 cm)	Enclosed box, serves as photo booth
USB Cable	Power cable supply for LED lights and main processing unit
HDMI Connector	Connector between the Raspberry Pi and the Touch Screen Panel

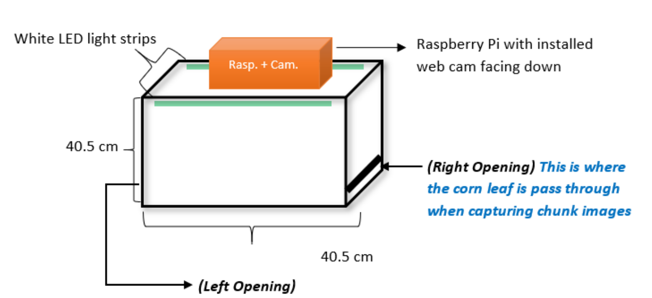

***Fig. 3**. Foldable enclosed cardboard box with installed Raspberry Pi 3 Model B and web camera.*

The web camera was installed on the upper center section of the enclosed box facing down. An opening located at the bottom left and right side of the box, this was where the corn leaf will pass through when taking chunk images of the leaf. CORZEA image processing was divided into 3 sub processes which include image acquisition, image preparation & training process, and finally the classification and output.

2.4 System Development

The pre-trained base model that was used in this study was Google's SSD Mobilenet V2 COCO 2018 from TensorFlow models, for its remarkable performance with micro processing units. Cloud computing was also an option and was efficient as it may sound but it requires high speed and stable internet connectivity between the back-end and front-end application which was a pressing concern to most rural areas in the country. Internet speeds provided to Philippine consumers are among the worst in the world, while prices for such services remain high(A. Senft et al., 2017). Initially, the researcher visited the municipal agriculture office located at Ilagan City, Isabela to get better understanding about nutrient deficiency to corn crops and also to collect sample data(images) that were used as basis in collecting images for training dataset. Later on, with the assistance of an agricultural technologist, the researcher colletcted samples from the corn fields located in Ilagan City Isabela. Samples collected were carefully examined and analyzed that it falls with the correct category based on visual symptoms from its leaves.

2.5 CORZEA Image Processing

To address the objective of the study, the researcher came up with a self-made image processing procedure patterned from the Google's TensorFlow model using Mobilenet V2 coco 2018 and is called CORZEA image processing as presented in Figure 4.

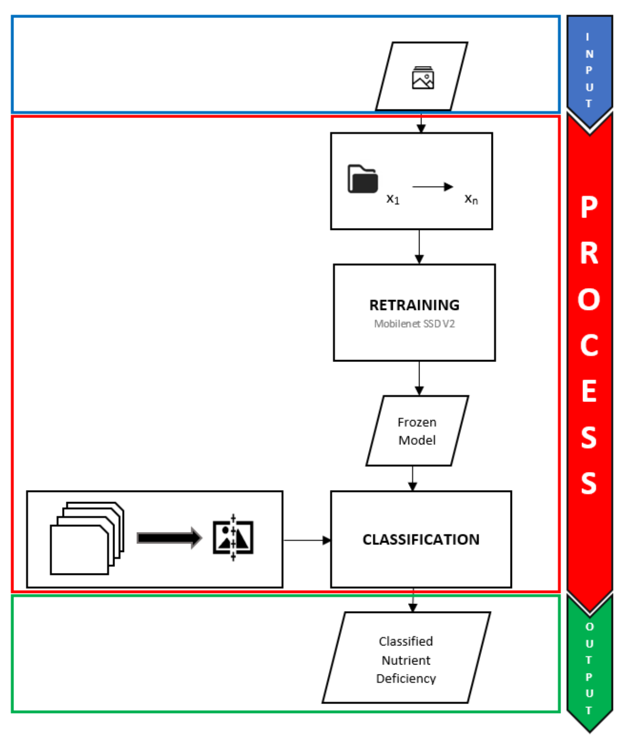

***Fig. 4**. CORZEA image processing procedure.*

CORZEA image processing was divided into 3 sub processes which include image acquisition, image preparation & training process, and finally the classification and output.

2.6 Image Acquisition

Image acquisition involves collecting image sample(s) of the identified nutrient deficient corn leaves per category as shown in Figure 4. Sample images of nutrient deficient corn leaf.

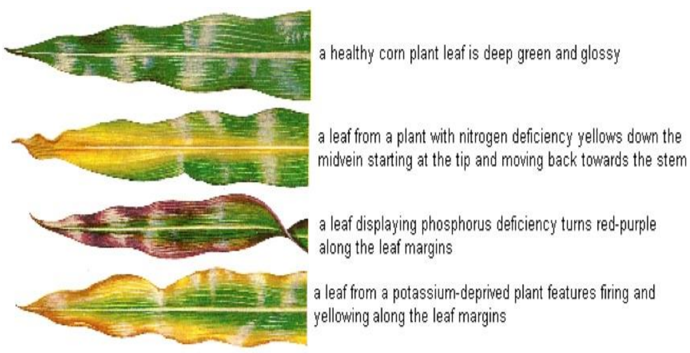

***Fig. 6**. Sample images of nutrient deficient corn leaf.*

The same camera quality as with the one installed at the top of the enclosed box was used in capturing training dataset to maintain consistency of images for the training dataset and the actual data to be inputted during the implementation period.

2.7 Training Custom TensorFlow Model Using Google's SSD Mobilenet V2 COCO 2018

The Tensorflow Object Detection API uses protobuf files to configure the training and evaluation process. The schema for the training pipeline can be found in object_detection/protos/pipeline.proto. At a high level, the config file is split into 5 parts (https://github.com/tensorflow):

1. The model configuration. This defines what type of model will be trained (ie. meta-architecture, feature extractor).
2. The train_config, which decides what parameters should be used to train model parameters (ie. SGD parameters, input preprocessing and feature extractor initialization values).
3. The eval_config, which determines what set of metrics will be reported for evaluation.
4. The train_input_config, which defines what dataset the model should be trained on.
5. The eval_input_config, which defines what dataset the model will be evaluated on. Typically, this should be different than the training input dataset.

For the training, the researcher will be using the pre-trained model SSD Mobilenet V2 COCO 2018 which was trained internally at Google. The pre-trained model will be re-trained at 100,000 steps with a training batch size of 500, 0.01 learning rate and, validation batch size of 200. To use the trained classifier with the propose system, it requires to capture 2-3 inter1related images from a single corn leaf. The images will be taken from a custom designed enclosed box with controlled illumination using LED lights wherein the system is embedded. This method is applied to capture the whole image of a corn leaf while limiting the physical size of the device, given the fact that the length of corn leaves grows more than 2 feet. These 2-3 chunks of images will be stitched together to form a single image of a corn leaf, output image will pass through the frozen model for classification.

2.8 Evaluation of Classification's Accuracy

Results of the test were calculated using a simple mathematical formula adapted from the work of Zhu [20] wherein:

$$Accuracy = \frac{(TN + TP)}{(TN + TP + FN + FP)} = \frac{NUMBER\ OF\ CORRECT\ ASSESSMENT}{NUMBER\ OF\ ALL\ ASSESSMENTS}$$

WHERE: TP – True Positive, TN – True Negative, FN – False Negative, FP – False Positive

For example, we have,

- Class 1: Positive
- Class 2: Negative

Positive (P): Observation is positive.
Negative (N): Observation is not positive.
True Positive (TP): Observation is positive, and is predicted to be positive.
False Negative (FN): Observation is positive, but is predicted negative.
True Negative (TN): Observation is negative, and is predicted to be negative.
False Positive (FP): Observation is negative, but is predicted positive.
However, there are problems with accuracy. It assumes equal costs for both kinds of errors. A 99% accuracy can be excellent, good, mediocre, poor or terrible depending upon the problem.

3 RESULTS AND DISCUSSIONS

Corn leaf samples were taken up for the detection and classification of nutrient deficiencies in corn.

TABLE 4

CLASSIFICATION RESULTS

Nutrient Deficient	Corn Leaf Samples	TP	TN	FP	FN	Accuracy
Phosphorus	50	47	0	6	0	94%
Potassium	50	47	0	10	0	94%
Nitrogen	50	42	0	12	0	84%
Magnesium	50	47	0	11	0	94%

Table 4 shows that forty-seven (47) out of fifty (50) Phosphorous deficient were classified correctly, forty- seven (47) out of fifty (50) Potassium deficient, forty-two (42) out of 50 Nitrogen deficient, and forty-seven (47) out of fifty (50) Magnesium deficient respectively. This points to an overall accuracy rate of 91.5%. Confusion and misclassifications were attributed to lighting condition; this is also the case in the study of (Tan & Triggs, 2010).

4 CONCLUSION

The procedure in identifying the nutrient deficiencies in corn was studied and with the information obtained, the study was conducted. The training of the neural network took 28 minutes to accomplish. Based on the results, the accuracy of the system in classifying corn nutrient deficiencies based on image has an overall accuracy rate of 91.5%. Such high accuracy together with the system developed may provide an important tool for corn farmers in the Philippines.

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