



## A DECISION SUPPORT SYSTEM FOR AUTOMATIC FERTILIZER APPLICATION TO TOMATO PLANTS USING ARTIFICIAL NEURAL NETWORK



Olatayo M. Olaniyan\*, Mutiu A. Adegboye, Bolaji Omodunbi, Badmus T and Ibraheem A. Mutolib

Department of Computer Engineering, Federal University Oye-Ekiti, Ekiti State, Nigeria

\*Corresponding author: [olatayo.olaniyan@fuoye.edu.ng](mailto:olatayo.olaniyan@fuoye.edu.ng)

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**Abstract:** One of the sectors that contribute to the country's economy is agriculture which needs the improvement of science and technology from time to time such as in its fertigation system. The manual applications of fertilizer that are commonly used are very stressful and consume enormous time especially when cultivating a large area of land and also do not ensure efficient management of fertilizer. This paper presents a Decision Support System (DSS) for automatic application of fertilizer and water to tomato plants using artificial neural network. The system is capable of dispensing required fertilizer to tomato plants; at the developmental stages based on nitrogen, phosphorous, and potassium contents of the soil. The tomato plant images at every stages of its growth were acquired using digital camera, in addition to NPK sensor used to measures the available fertilizer at every stages of the tomato plants. The acquired images were preprocessed using Contrast enhancement, RGB to Grayscale conversion and Median filter. The feature extraction techniques such as number, perimeter, area, minor axis and major axis length of the connected regions were used for the purposed of differentiating the stages of tomato. The combination of information from the images and data obtained using NPK sensor was used to determine whether fertilizer should be applied or not. For twelve experiments that were taken, an accuracy of 91.67% was achieved. The experimental results promise that the system will fulfil the needs for efficient management of fertilizer.

**Keywords:** Artificial neural network, decision support system, Fertigation

### Introduction

Tomato (*Lycopersicon esculentum* Mill.) is one of the most widely cultivated crops in the world and it is an important source of minerals, vitamins, dietary fibers and essential amino acids (Shankara *et al.*, 2005). Tomato requires high and accurate input of fertilizer and irrigation in other to ensure its maximum yield (Matt & Bussan, 2007). Whereas, lack of fertile land for tomato cultivation remain one of the major challenges famers are facing (Adegboye *et al.*, 2017). Owing to this challenge, farmers have been finding it difficult to achieve its maximum productivity which in turn affecting the price and availability of the tomato in the market. For this reason, automatic systems are needed for applying fertilizer to the crop in order to reduce farmer's stress as well as increasing the productivities.

A lot of challenges are being faced by farmers with large plantation of the crop during manual application of fertilizer. Manual application of fertilizer can be strenuous and time consuming for these farmers and this may serve as a source of discouragement to others who are willing to cultivate the crop in large quantity. Subsequently, the nutritive value of tomato in diet cannot be over-emphasized, so its cultivation in large quantity is required in order to increase their availability at cheaper and more affordable prices in markets. Therefore, there is need for development of intelligent systems that can automatically handles the application of fertilizer to tomato plants without needing the consent of the farmers

A prerequisite of decision support system has brought Artificial Neural Network (ANN) to become a new technology which provides assorted solution for the complex problems in agriculture researches (Kriesel, 2005). Since it can solve many problems that linear systems are incapable to resolve, ANN becomes crucial especially in innovating and developing better products for society (Kriesel, 2005). Though there are many types of ANN, this paper only presents the most commonly used type of ANN, which is the feed-forward back propagation network. After a thorough background work, some of the most valuable recent papers are; Mohd Salih *et al.* (2012) designed a solar powered automated fertigation control system for melon (*Cucumis melo*) cultivation in green house. The system was powered with a

solar system and tested on its effectiveness to control the nutrient mixing process and injecting nutrient solutions according to plants growth rate and also monitor all key parameters in fertigation system at the same time.

Odilio *et al.* (2015) developed an artificial neural network to serve as an alternative to volumetric water balance in drip irrigation management in watermelon crop. The volumetric water balance was taken as the standard for comparing the management carried out with the implementation of ANN. Multilayer Perceptron (MLP) network was used, the network had an input layer, a hidden layer and an output layer. At the input layer of the network, values for soil moisture obtained with capacitive sensors in land cultivated with irrigated watermelon were used.

Yin and Zhang (2015) proposed a Fertigation control system based on embedded platform and self-adaptive control strategy. The system was made of open-tank mixing equipment with automatic control system based on embedded platform. The open-tank mixing equipment consisted of different tanks in which different fertilizers needed were stored and mixed with water appropriately. Ghorban and Yaser (2016) developed an artificial neural network model for the prediction of milk price for five months' time horizon in Iran. The model was developed along with an Auto-regressive integrated moving average (ARIMA) model; Data from February 2006 to March 2013 were collected from Bureau of Animal Husbandry and Agriculture Support of Iran for the development of the model.

In this paper, we are presenting a decision support system for fertilizer application to tomato plant. The system is able to make decision on whether to apply fertilizer to tomato plant or not, using the soil parameters (Nitrogen, phosphorous and potassium contents) measured from sensors and the current growth stage of the plant.

### Materials and Methods

#### Data acquisition

The data acquired for the development of the system was in two places. The first data which was image data for the different growth stages of the tomato plants were obtained using digital camera. Fig. 1 shows experimental set up of the

data acquisition system. The camera was used for capturing the growth of the tomato plants, while the NPK sensor is measuring the fertilizer requirement for every growth stages. The stages considered are: (a) Planting stage (b) Vegetative stage (c) Flowering stage (d) Fruit set stage (e) Fruit growth

stage (f) First harvest stage (g) Second harvest stage (h) Third harvest stage and (i) Last harvest stage. The samples of the dataset are presented in Appendix A.

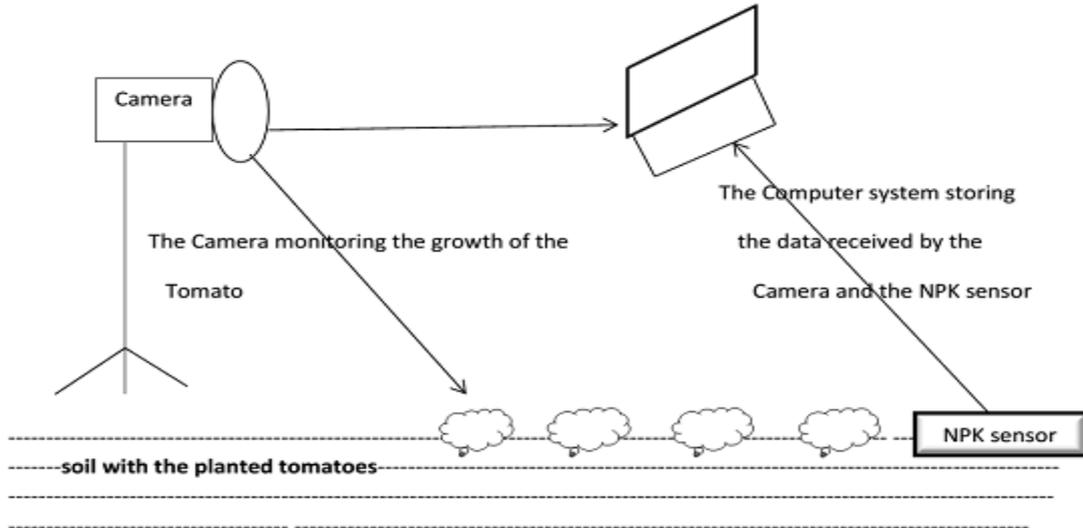


Fig. 1: Experimental set up data acquisition system

The second data acquired was the dataset that was used for the development of the proposed system. For this paper, the dataset used for the development of the model was formulated based on fertilizer requirement of tomato plants at every stages of their growth obtained from study of Haifa (2005). Table 1 presents the NPK contents requirement for the tomato plants.

Table 1: NPK contents requirement for the tomato plants (Haifa, 2005)

S/N	Tomato growth Stages	Days from Sowing/ planting	Soil Parameters (Kg/ha)		
			N	P	K
1	Planting	1	1	0	1
2	vegetative	2-15	8	2	13
3	Flowering	16-30	9	2	4
4	Fruit Set	31-40	6	2	9
5	Fruit growth	41-60	24	6	38
6	1 <sup>st</sup> harvest	61-65	6	2	9
7	2 <sup>nd</sup> harvest	66-120	1	1	4
8	3 <sup>rd</sup> harvest	121-170	2	0	1
9	Last harvest	171-210	2	1	3

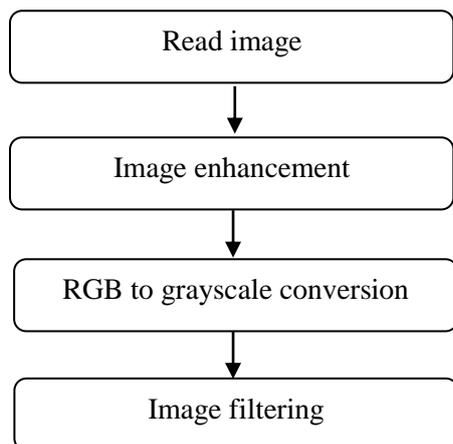


Fig. 2: Image preprocessing stages

**Image preprocessing**

Image preprocessing process generates an improved image that are more suitable in processing the tomato images. The image preprocessing techniques such as contrast enhancement, RGB to Grey Scale Conversion and median filter. Fig. 2 describes the preprocessing stages that were carried out in this study.

**Image enhancement**

Image enhancement is an important process to enhance the visual appearance of image in order to obtain more accurate extraction features from the images. There are variety of image enhancement algorithm. These include contrast enhancement, histogram equalization, gamma correction and image sharpening. In this study, contrast enhancement was adopted to adjust the intensity contrast value of images to a better view. Fig. 3 (a) and (b) shows original image and image after enhancement.

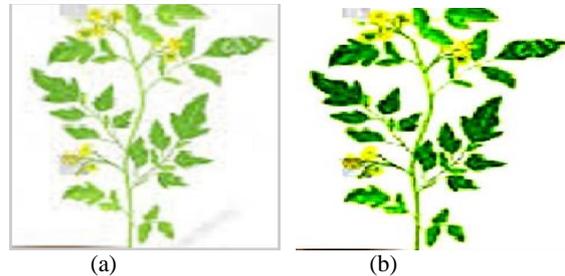


Fig. 3:(a) Original image and (b) image after enhancement

**RGB to grayscale conversion**

The second preprocessing stage involves conversion of resulting image with it primary color to the gray scale image. The image acquired using digital camera appears in its primary spectral components namely; Red (R), Green (G) and Blue (B) characterized by their space corresponding intensities. Storing of RGB image in the database for the computation is not adequate based on the fact that it required considerable amount of space to RGB image as well as very computationally intensive. Therefore, it is necessary to process the three different channels in order to obtain efficient results. In this study, grayscale technique is adopted using

mathematical model in (1) to convert the RGB image to the grayscale image (Aliyu et al., 2017). The converted RGB image to grayscale image is shown in Fig. 4.

$$I(x, y) = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B \quad (1)$$

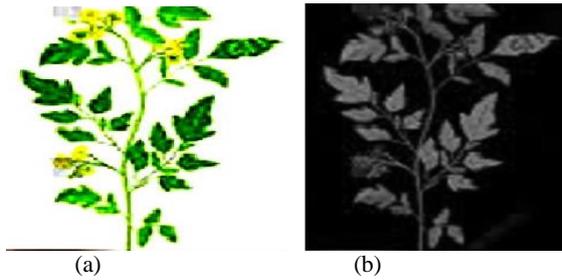


Fig. 4: (a) RGB image (b) Grayscale image

**Image filtering**

The third stage involve the application of filtering to the grayscale images. This is done to remove unwanted noise caused due to different lighting conditions. In digital image processing, it is required to carry out filtering processing to obtain usable and effective result. There are different image filtering techniques, the choice of selection depends on area of application. In this study, median filtering technique is applied. The choice of selection is based on the fact that median filter looks at its nearby neighbor’s pixel values to decide whether or not it is representative of its surrounding pixels and replace with the median of those values. Fig. 5 (a) and 5 (b) shows grayscale filtered image.

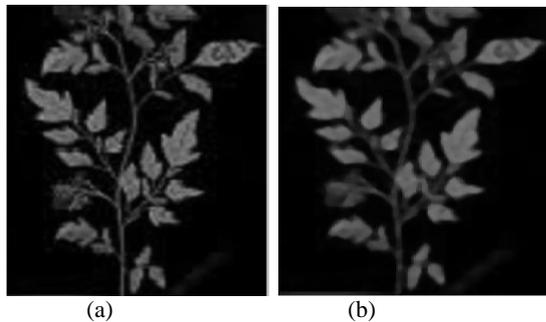


Fig. 4: (a) Greyscale image (b) Filtered image

**Feature extraction**

After the preprocessing of the acquired images, feature extraction process was performed on the images in order to obtain feature suitable for the system to differentiate tomato growth stages. The number of connected regions in the images includes Area (A), Perimeter (P), Minor Axis Length (Mails)

and Major Axis Length (MjAL) was determined. The mean values of the feature extracted are presented in Table 2. These serve as input to the developed system.

**Table 2: Extracted image feature values of some sample dataset**

Tomato growth stages	Days from planting	Mean A	Mean P	Mean MiAL	Mean MjAL
Planting	1	918	138.1445	35.7321	26.6207
vegetative	2-15	4157	441.3690	99.5434	72.2392
Flowering	16-30	5.4067e+03	214.8757	47.1202	30.9415
Fruit Set	31-40	3.7727e+03	148.4619	36.0364	22.7619
Fruit growth	41-60	16125	488.1415	133.7536	83.7441
1 <sup>st</sup> harvest	61-65	7.9385e+03	174.2033	63.0926	51.6553
2 <sup>nd</sup> harvest	66-120	13939	628.4080	157.3839	121.3396
3 <sup>rd</sup> harvest	121-170	5.3063e+03	217.7000	55.6484	32.7885
Last harvest	171-210	2.4372e+03	95.5554	28.6572	17.4129

**System design**

The developed system was designed and trained to dispensing required fertilizer to tomato plants; at the developmental stages based on input parameters. The Multilayer Perceptron (MLP) neural network was used since it follows feed-forward architecture and supervised training. The perceptron network that was developed has a layer of input, output and hidden layers in between. The input layer consists of raw data which include planting stage, nitrogen, potassium, and phosphorous contents of the soil. In addition, the hidden layers have weights and generate output layer. The MLP uses back propagation as its training algorithm. This algorithm repeats presentation of the input data to the neural network. In each iteration, the output data is compared with the desired one, error is computed and fed back (back propagated) to the network. This feedback is used to modify the weights of neurons. Finally, the desired output was generated based on iterations. The diagram of the developed ANN network is described in the Fig. 5.

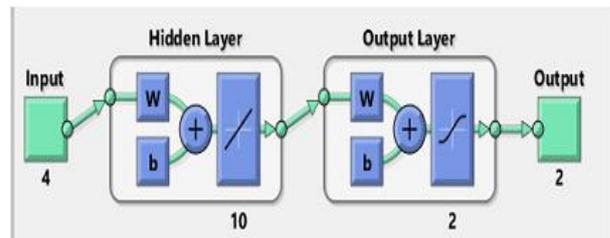


Fig. 5: The developed ANN system

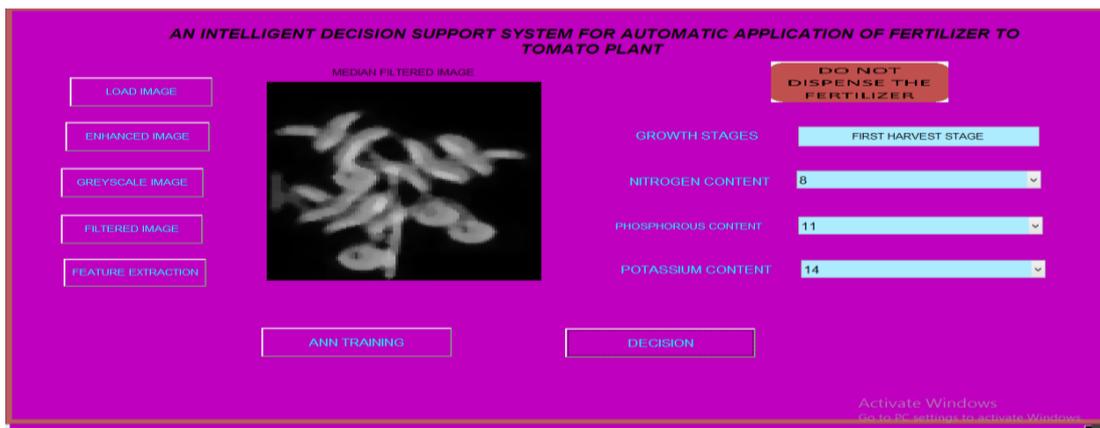


Fig. 6: SIFP design for the second harvest stage of the tomato plant

**System interactive front panel (SIFP) development**

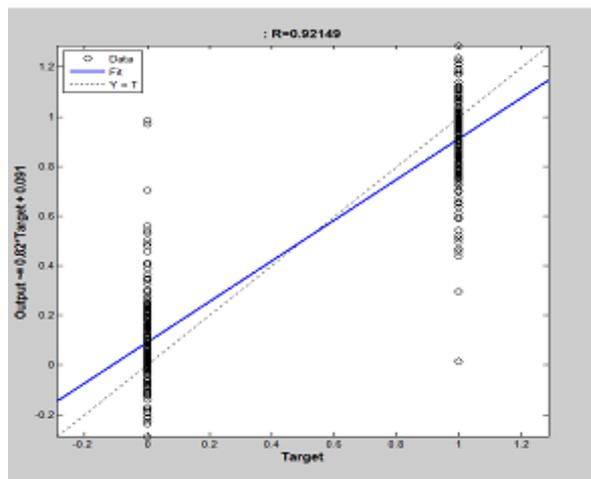
The SIFP developed comprises of two sections. The first section is handling the image processing aspect of the system, while the second section is handling the mineral contents of the soil. In the first section, the panel is used to load images automatically, execute preprocessing task and feature extraction on the preprocessed images. The images acquired are for each stage in the growth of the tomato plant. After the preprocessing of these images, the system was able to determine the stage for every input image. The second section of the SIFP is for the selection of the nitrogen, phosphorous and potassium contents of the soil. The system was developed in a way that after it identifies the stage tomato growth from the input image, and the nitrogen, potassium and phosphorous contents are determine, it can automatically determine whether to dispense the fertilizer or not to. The SIFP was designed from the GUI workspace in MATLAB. Fig. 6 shows SIFP design for the second harvest stage of the tomato plant.

**Results and Discussions**

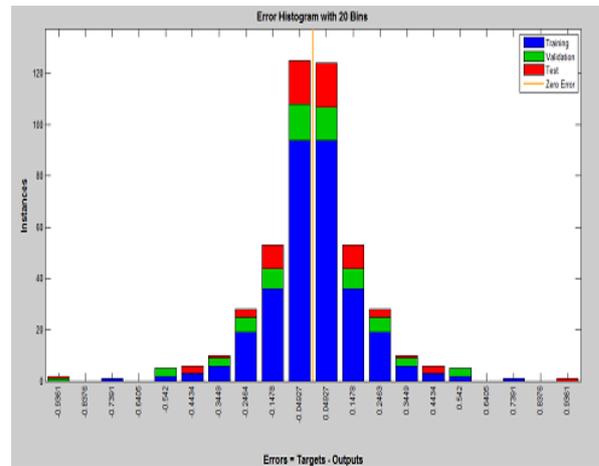
The network was trained with a data split of 70% for training, 15% for validation and 15% for the evaluation of the system performance. The input layer used 4 neurons, the output layer had 2 neurons and the hidden layer was set by trial and error. It was found that the network performed best with 10 neurons in the hidden layer. Table 3 shows obtained results for the different number of selected hidden neurons, while Figs. 7 and 8 show regression plot and error histogram for the best result at 10 neurons in the hidden layer.

**Table 2: System accuracy Vs. hidden layers**

Number of hidden layers	Accuracy (%)
1	48.13
2	63.22
3	71.49
4	79.90
5	83.12
6	83.89
7	85.69
8	87.83
9	90.08
10	91.90
11	87.63
12	86.99



**Fig. 7: Regression plot**



**Fig. 8: Error histogram**

Some instances were taken from the result of the SIFP implementation of the system, and they were verified with the dataset used in training the ANN. From the dataset, the stages in the growth of tomato plant that requires application of fertilizer are nine (planting stage, vegetative stage, flowering stage, fruit set stage, fruit growth stage, first harvest stage, second harvest stage, third harvest stage, last harvest stage), the fertilizer nutrient considered are three (Nitrogen, Phosphorous and Potassium) and the output are “dispense” and “no dispense”. After the development of the system, some samples were taken from the dataset and tested with system. The first sample taken was when the growth stage of the tomato was planting stage, and the nitrogen, phosphorous and potassium content of the soil was 1, 0, 1 (Kg/ha) respectively, the decision made by the system was to dispense fertilizer. The second sample taken was when the growth stage of the tomato was vegetative stage, and the nitrogen, phosphorous and potassium content of the soil were 8, 2, 13, respectively; the decision made by the system was “not to dispense fertilizer”. The third sample taken was when the growth stage of the tomato was flowering stage, and the nitrogen, phosphorous and potassium content of the soil was 9, 2, 4 respectively, the decision made by the system was not to dispense fertilizer. The fourth sample taken was when the growth stage of the tomato was fruit set stage, and the nitrogen, phosphorous and potassium content of the soil was 6, 2, 9 respectively, the decision made by the system was not to dispense fertilizer. The fifth sample taken was when the growth stage of the tomato was fruit growth stage, and the nitrogen, phosphorous and potassium content of the soil was 24, 6, 38 respectively, the decision made by the system was not to dispense fertilizer. The sixth sample taken was when the growth stage of the tomato was first harvest stage, and the nitrogen, phosphorous and potassium content of the soil was 6, 2, 9 respectively, the decision made by the system was not to dispense fertilizer. The seventh sample taken was when the growth stage of the tomato was second harvest stage, and the nitrogen, phosphorous and potassium content of the soil was 1, 1, 4 respectively, the decision made by the system was to dispense fertilizer. The rest of the samples taken and their correctness with the dataset used for the training are illustrated in table 2. However, from the twelve test samples taken, the accuracy of the designed system can be calculated as 10/12 which is equal to 91.67%.

**Conclusion and Recommendations**

In this paper, a decision support system for automatic application of fertilizer and water to tomato plants using artificial neural network is presented. The system was

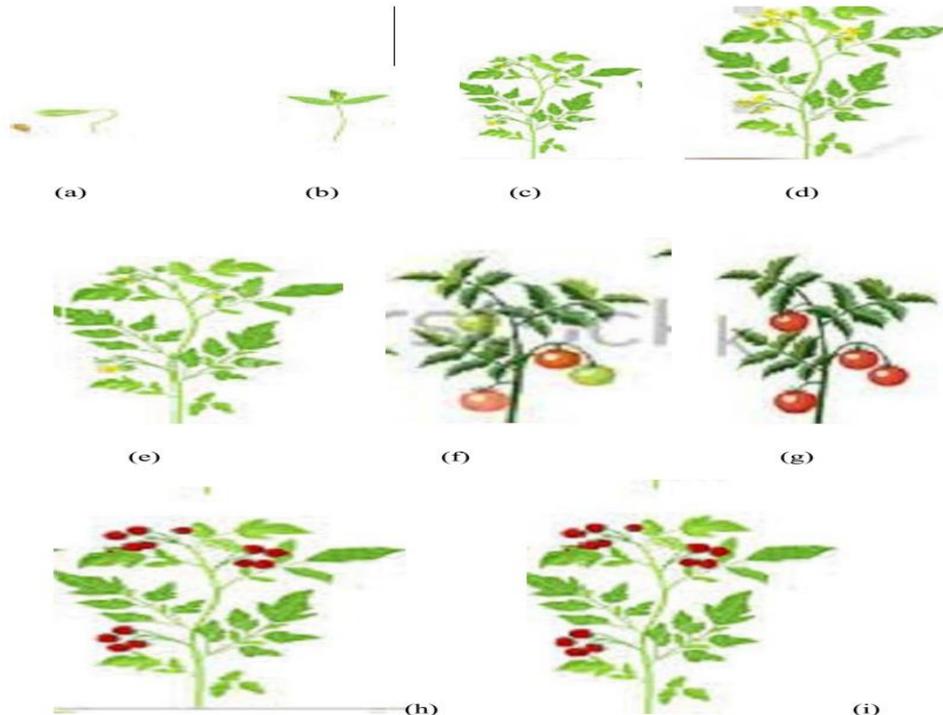
designed to dispense required fertilizer to tomato plants based on nitrogen, phosphorous, and potassium contents of the soil at the different developmental stages. The input and output neurons for the input and output layers were 4 and 2 neurons, respectively; while the number of neurons in the hidden layer was set by trial and error with the best performance of 91.67% accuracy at 10 neurons for the hidden layer. The MATLAB GUI tools was used to develop a SIFP through which the user can select any image corresponding to the current growth stage of the tomato plant together with the nitrogen, phosphorous and potassium contents of the soil. With the 91.67% accuracy of the system, the decision of the system can be said to be accurate. Future works directions are suggested to be towards developing decision support systems for other cash crops and other crops that require high and timed application of fertilizer in order achieve their maximum productivity. Also, hardware implantations of these systems are suggested in other future works.

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**Appendix A: Set of images for the different growth stages of the tomato plant**



(a) planting stage (b) vegetative stage (c) flowering stage (d) fruit set stage (e) fruit growth stage (f) 1<sup>st</sup> harvest stage (g) 2<sup>nd</sup> harvest stage (h) 3<sup>rd</sup> harvest stage (i) Last harvest stage