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Image analysis on color and texture for chili (*Capsicum frutescence*) seed germination

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ABSTRACT

The objective of this research was to develop a computer system for evaluating the germination of a chili seed. The system called "chili seed germination analysis or (CSGA)", evaluated the bird's eye chili (*Capsicum frutescence*) seed and long fed pepper (*Capsicum annuum* var. *acuminatum* Fingerh.) seed germination by using an image processing technique. The chili seed images were taken by a mobile phone camera with 60 × microscope. The CSGA consisted of six main modules, namely 1) image acquisition, 2) seed image segmentation, 3) feature extraction, 4) germination evaluation, 5) result presentation and 6) germination verification. The CSGA employed color and texture features of chili-seed images to evaluate the germination. The system applied the Euclidean distance and a neural network technique to perform the system evaluation. The system precision rates were 59.71% and 71.71% for Euclidean distance and a neural network technique, respectively. The average access time was 0.74 seconds/image for the Euclidean distance and 3.54 seconds/image for the neural network technique.

Keywords: bird's eye chili seed; color feature; long fed pepper seed; seed germination evaluation; texture feature

1. INTRODUCTION

There are many conditions for the growth of plants from seeds, namely minerals (Montri et al., 2009), temperature, humidity (Olaniyi and Ojetayo 2010), harmful insects (Ishak et al., 2011) and seed diseases (Schreinemachers et al., 2015). Many researchers have applied an image processing technique to evaluate seed quality and detect non-germination seeds for two important reasons. First, a digital camera and mobile phone camera are easy to manage and are reasonably priced for farmers. Second, the image processing technique is non-destructive and does not change the structure of the plant seeds. Based on these two reasons, researchers are inclined to employ an image processing method for the plant seeds application because there are no negative side effect to the seeds from this method (Lurstwut and Pornpanomchai, 2017). There are many non-destructive techniques for evaluating the germination of seeds. Rahman and Cho (2016) presented machine vision, spectroscope, hyperspectral image, X-ray imaging, thermal imaging and electronic noses for assessing the quality of agriculture seeds. Zhou and Ji (2019) applied hue-intensity-saturation (HIS) and a support

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vector machine-radial basis function (SVM-RBF) to predict the germination of sugar beet seeds. Skrubej et al. (2015) used an artificial neural network (ANN) to predict the germination of tomato seeds. Masry et al. (2019a) applied linear discriminated analysis (LDA) to evaluate cowpea (*Vigna unguiculate*) seeds germination.

Chili pepper is an important vegetable cultivated around the world. People widely use the chili pepper not only for cooking food but also for treating health problems (Christopher and Yusoff, 2011). Therefore, many researchers have conducted research using non-destructive methods to evaluate the chili pepper quality and germination rate. Dell' Aquila (2007) employed X-ray and image processing analysis to analyze pepper seed germination. Ke-ling et al. (2018) applied color, shape and weight features to select high quality pepper seeds. Mo et al. (2014) used an RGB LED hyperspectral reflection image with a partial least squares discriminant analysis (PLS-DA) to classify pepper seeds. The objective of this research was to develop a computer system that can help farmers to evaluate chili seeds germination.

2. MATERIALS AND METHODS

The chili seed germination analysis (CSGA) was developed on the following computer hardware and software. The Intel(R) Core (™) i7-7700HQ CPU @ 2.80GHz (Intel's headquarters in Santa Clara, CA, USA) was used as the central processing unit, and Windows 10 (Microsoft Corp.; Redmond, WA, USA) was the software system. The MATLAB R2017a (The Math Works Inc.; Natick, Massachusetts, USA) with license number 40598465 was the developing software. The digital cameras used in this research were the iPhone SE, iPhone XR (Apple Computer, Inc., Cupertino, CA, USA), Huawei P20 Pro (Huawei Technologies Co., Ltd., Shenzhen, China) and Vivo V3Max (Vivo Communication Technology Co. Ltd.. Guangdong, China). All mobile phones are outfitted with a 9882W universal clip 60 × cellphone microscope (FastTech's main warehouse, Guangdong, China), as shown in Figure 1. The mobile phone microscope has dimensions of 20 mm depth, 37 mm height and 40 mm width, and weighs 19 g with a clip. The microscope is shown in Figure 1(a) and a mobile phone with the clipped on 60 × microscope is shown in Figure 1(b).

(a)

(b)

Figure 1 Mobile phone 60 × microscope: (a) a microscope with led lamp and clip, (b) a mobile phone with clipped on 60 × microscope

2.1 Conceptual diagram

The CSGA conceptual diagram started with a user taking a chili seed image by using a simple mobile phone with a 60 × microscope clipped to it. Then, the chili seed image was submitted to a computer system for evaluating the germination. After that, the system compared the chili image with all chili images in the system database. Finally, the CSGA displayed the evaluation results, as shown in Figure 2. Farmers can verify the evaluation result by planting and checking the germination of seeds.

2.2 System structure chart

The system structure chart of the CSGA program was composed of six main modules, namely image acquisition, image segmentation, feature extraction, germination evaluation, result presentation, and germination verification (as shown in Figure 3). Each module had the following details.

2.2.1 Image acquisition

This module captured a chili seed image using a camera and microscope. Normally, a chili seed has a round shape with a diameter of around 2-4 mm. A chili seed has quite a small shape compared with some plant seeds, for example, rice seed, sweet beet, peanut, etc. Therefore, this research captured only one chili seed per image so that the whole chili surface can be seen (as shown in Figure 4 (a)). It is suggested that the user took the chili seed image with a 60 × microscope, while zooming in and focusing on the seed as much as possible (as shown in Figure 4 (b)). The format of the input image should be a BMP or JPG file.

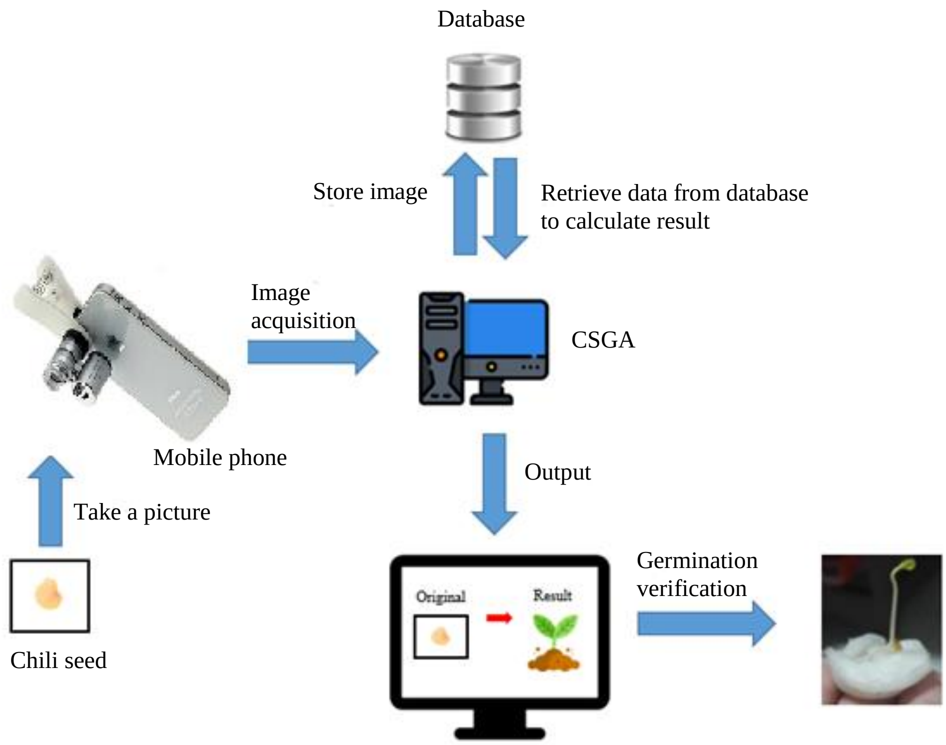


Figure 2 The CSGA conceptual diagram

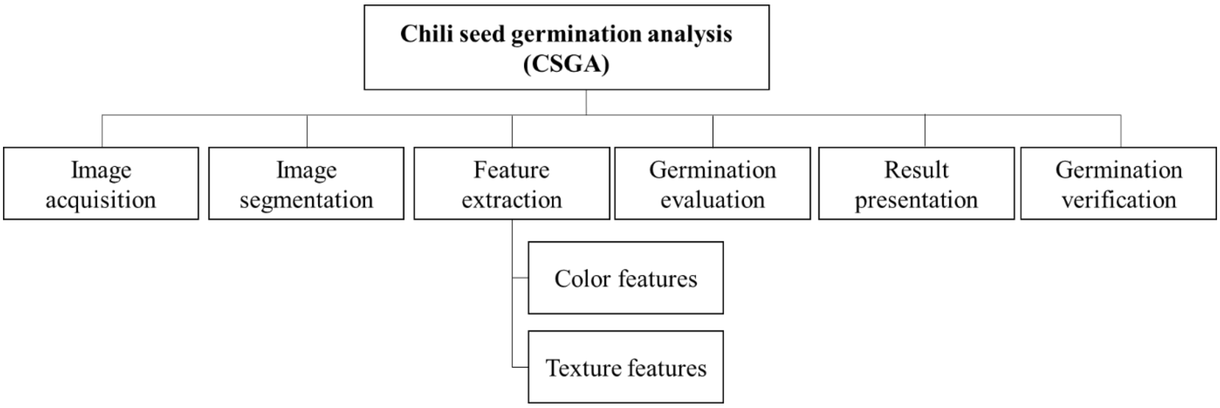


Figure 3 The CSGA system structure chart

(a) (b)

Figure 4 The photos showing how to take chili seed image; (a) chili seed photo (b) mobile phone with 60 × microscope

2.2.2 Image segmentation

This module consisted of three submodules, which had the following details.

2.2.2.1 Image resizing

This submodule resized the chili image from the image acquisition module into the size of 1000 × 1000 pixels. The resized image should include both the chili seed and the white background.

2.2.2.2 Marking cropping starting-point

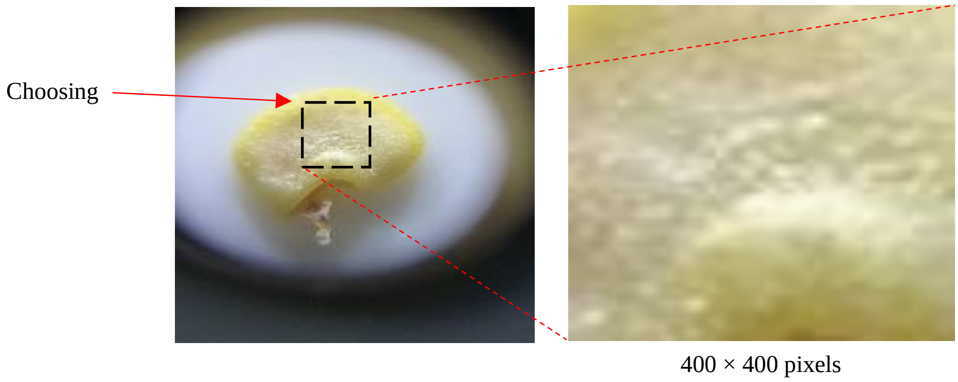
This submodule allowed the user to choose a starting-point for cropping at the top-left of the chili seed (as shown in Figure 5 (a)). A good starting-point for cropping should be a point located at the top-left corner of a rectangle size of 400 × 400 pixels, which covered only the chili seed excluding any white background.

2.2.2.3 Cropping image

After the user selected the cropping starting-point, the CSGA system performed automatic segmentation on only the chili seed texture based on the choice of cropping point with a size of 400 × 400 pixels (as shown in Figure 5 (b)). The user can repeat the image segmentation module again if the cropped image contains interference from some white backgrounds.

2.2.3 Feature extraction

The CSGA system employed two main chili seed features, which are color and texture features. The color feature contained four values, namely, 1) mean of red color, 2) mean of green color, 3) mean of blue color and 4) mean of gray color. The gray-level co-occurrence matrix (GLCM) in this research applies four texture features: 1) entropy, 2) energy, 3) correlation, and 4) homogeneity. Each texture feature was calculated based on Equations as shown in Table 1 (Zareiforoush et al., 2015). The segment of MATLAB code for finding color and GLCM texture features is shown in Figure 6.



(a) (b)

Figure 5 Cropping chili seed images; (a) choosing the starting-point before cropping (b) close-up of chili seed after segmentation

Table 1 The GLCM statistics and explanation

Statistic	Short description	Formula
Entropy	Measures the disorder of an image and it achieves its largest value when all elements in P matrix are equal.	$\sum_{i,j}^{N} P_{(i,j)} * \log_2 P_{(i,j)}$
Energy	Measures the uniformity of the texture that pixel pairs represent.	$\sum_{i,j=0}^{N-1} (P_{i,j})^2$
Correlation	Measures the linear dependency of gray levels on those of neighboring pixels.	$\sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2}$
Homogeneity	Measures the smoothness of the gray level distribution of the image.	$\sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2}$

Note: All the GLCM textural values are defined in Table 1 using terms where $P_{(i, j)}$ is the entry in a normalized gray-tone spatial-dependence matrix and N is the number of distinct gray levels in the quantized image. The μ_i, μ_j, σ_i and σ_j represent the mean and standard deviations of $P_{(i, j)}$

```
% pic is a chili seed image
meanr   = mean(mean(pic(:,:,1)));
meang   = mean(mean(pic(:,:,2)));
meanb   = mean(mean(pic(:,:,3)));
gray    = rgb2gray(pic);
imggray = mean(mean(gray));
glcm    = graycomatrix(gray,'O', [0,1]);
A       = graycoprops(glcm);
Energy  = A.Energy;
corre   = A.Correlation;
homo    = A.Homogeneity;
rngfil  = rangefilt(pic);
entro   = entropy(rngfil);
```

Figure 6 The segment of MATLAB code to find the GLCM and their statistic values

2.2.4 Germination evaluation

The chili seed dataset was divided into 2 datasets, which were a training dataset and a testing dataset. The testing dataset was compared with the training dataset, which consisted of all chili seeds features and included germination and non-germination results. The CSGA employed two techniques to evaluate the chili seed germination, which were the Euclidean distance technique and the neural network technique. Each technique had the following details.

2.2.4.1 The Euclidean distance method

The Euclidean distance was used to measure the similarity distance between the value of all features from an input image and images in the database. The CSGA system will apply Euclidean distance and find which image had the minimum distance with an input image. Minimum distance can identify that both images were similar to each other. The Euclidean distance was calculated in Equation 1:

$$ED = \sqrt{\sum_{i=1}^{n}\left(a_i^2 - b_i^2\right)} \quad (1)$$

where ED = Euclidean distance value between 2 images

n = number of features

a_i = the value of feature i in the database

b_i = the value of feature i from an input image

2.2.4.2 The neural network technique

The neural network was used to find the greatest similarity between the value of all features from an input image and images in the database. Although it is similar to Euclidean distance, it can operate with more accuracy. The result of the neural network will be between 0 and 1, where 0 means non-germinate seed and 1 means germinate seed.

The structure of the neural network that the researchers have chosen to use consisted of 8 input nodes representing 1) mean of red, 2) mean of green, 3) mean of blue, 4) mean of gray, 5) energy, 6) entropy, 7) correlation and 8) homogeneity. Another 6 hidden nodes were chosen by using the principle for the selection of the number of hidden nodes according to the following three rules: the number of hidden neurons should be between the size of the input layer and the size of the output layer, the number of hidden neurons should be 2/3 the size of the input layer, plus the size of the output layer, and the number of hidden neurons should be less than twice the size of the input layer. There is one additional node as the output node which showed the results of whether the seeds can germinate or not (as shown in Figure 7). The parameters for the training network are shown in a part of MATLAB code as seen in Figure 8.

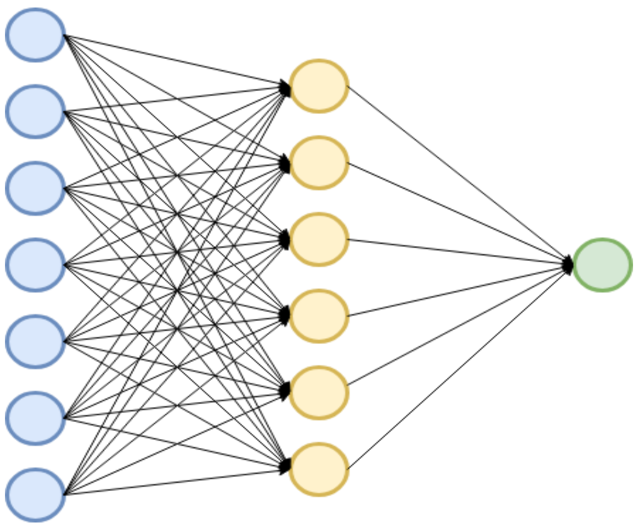


Figure 7 The structure of the neural network in this research

```
x  =input';                  % 8 input nodes
t  =output';                 % 1 output node
trainFcn  ='trainbr';
hiddenLayerSize  =6;         % 6 hidden nodes
net=fitnet(hiddenLayerSize,trainFcn);
net.divideParam.trainRatio=80/100;
net.divideParam.valRatio=10/100;
net.divideParam.testRatio=10/100;
net.trainParam.showWindow  =false;
net  =train(net,x,t);
```

Figure 8 A part of MATLAB code showing training neural network parameters

2.2.5 Result presentation

This section showed chili seed germination evaluation results. The CSGA graphic user interface (GUI) consisted of eleven display text boxes and four push buttons, as shown in Figure 9. The CSGA GUI had the following details.

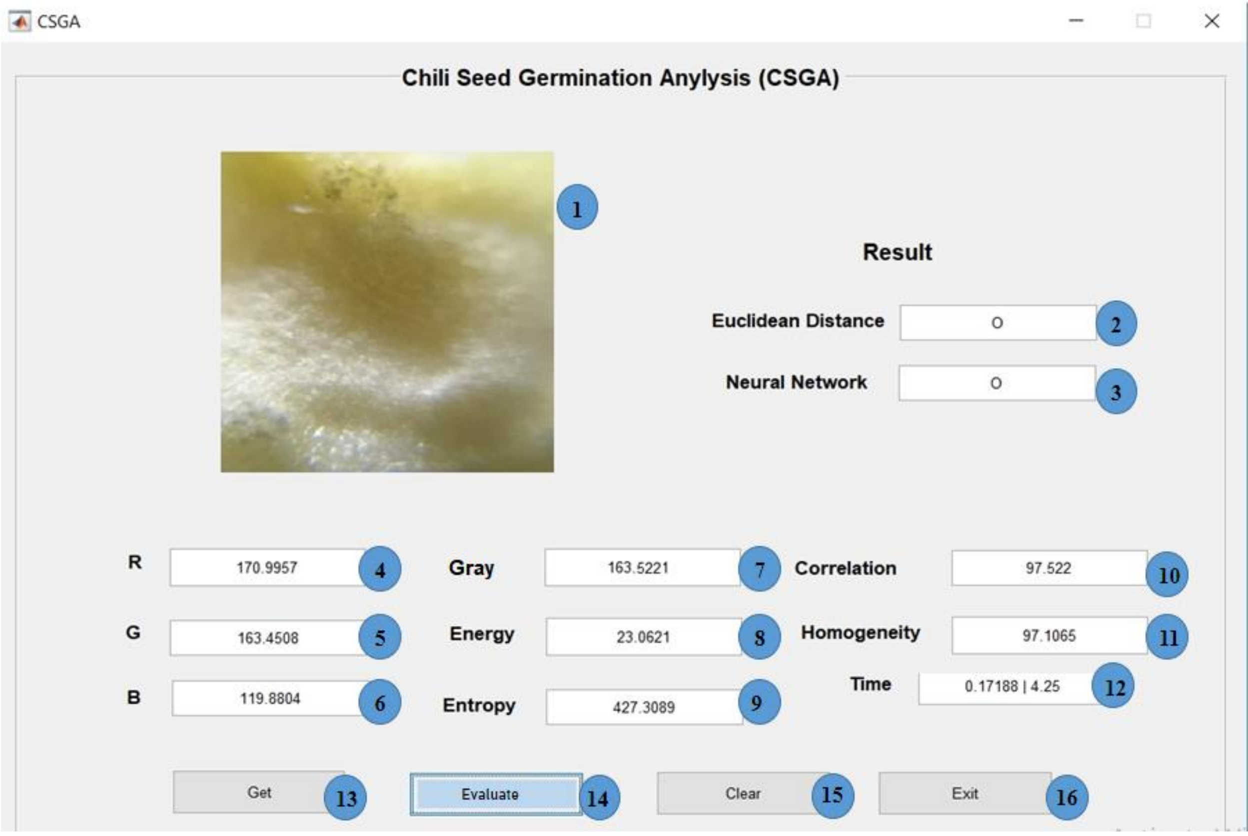


Figure 9 The GUI of the CSGA system

Note: Close-up of a chili seed image (label 1), Euclidean distance result box (label 2), neural network result box (label 3), mean of red value (label 4), mean of green value (label 5), mean of blue value (label 6), mean of gray value (label 7), energy texture value (label 8), entropy texture value (label 9), correlation texture value (label 10), homogeneity texture value (label 11), average access time of both Euclidean distance and neural network methods (label 12), the get image button for getting a chili seed image (label 13), the evaluation button for analyzing the chili seed for germination (label 14), the clear button for clearing all CSGA system values (label 15) and the exit button for exiting the system (label 16)

2.2.6 Germination verification

The germination verification module tested the chili seed germination results by growing the testing seeds and checking the germination results. The CSGA can record the new chili seed germination results in the system database.

3. RESULTS AND DISCUSSION

3.1 Experimental results

There were two types of datasets used for testing the experiment results as follows: 1) a training dataset, which contained 2,470 bird's eye chili seeds in the database and 2) a testing dataset, which contained 350 bird's eye chili (*Capsicum frutescence)* seeds and 150 long fed pepper (*Capsicum annuum* var. *acuminatum* Fingerh.) seeds. The CSGA employed two matching techniques, which were the Euclidean distance technique and a neural network technique. The experimental results of the Euclidean distance technique are shown in Table 2, and the neural network technique is shown in Table 3.

Based on the experimental results of the Euclidean distance technique in Table 2, the CSGA system evaluated the bird's eye chili with 158 (131+27) chili seeds for germination and 192 (114+78) chili seeds for non-germination and the long fed pepper with 66 (47+19) chili seeds for germination and 84 (53+31) chili seeds for non-germination. For the neural network method, the CSGA system evaluated the bird's eye chili with 304 (225+79) chili seeds for germination and 46 (20+26) chili seeds for non-germination and the long fed pepper with 148 (99+49) chili seeds for germination and 2(1+1) chili seeds for non-germination, as shown in Table 3. The experiment showed the false accept rate of 25.99% (79÷304×100) and the false reject rate of 43.47% (20÷46×100) for bird's eye chili and the false accept rate of 33.11% (49÷148×100) and the false reject rate of 50.00% (1÷2×100) for long fed pepper. The CSGA evaluated the bird's eye chili with the precision rate of 59.71% ((131+78)÷350×100) for the Euclidean distance technique and the precision rate of 71.71% ((225+26)÷350×100) for the neural network technique. Moreover, the CSGA evaluated the long fed pepper with the precision rate of 52.00% ((47+31)÷150×100) and 66.67% ((99+1)÷150×100) for the Euclidean distance and neural network techniques, respectively, as shown in Table 4. Using the same dataset, the neural network technique evaluated germination seed with greater accuracy than the Euclidean distance technique because the neural network evaluated all seed image features in many iterations, but the Euclidean distance technique compared all features in the dataset and selected the highest similar image in an iteration. Due to the difference in the number of iterations used by each technique, the neural network method needed more processing time than the Euclidean distance technique.

Table 2 The experimental results of the Euclidean distance technique (350 chili seeds and 150 long fed pepper)

Species	Evaluated germination (seeds)		Evaluated non-germination (seeds)	
	Germination	**Non-germination**	**Germination**	**Non-germination**
Chili	131	27	114	78
Long fed pepper	47	19	53	31
Total	178	46	132	144

Table 3 The experimental results of the neural network technique (350 chili seeds and 150 long fed pepper)

Species	Evaluated germination (seeds)		Evaluated non-germination (seeds)	
	Germination	**Non-germination**	**Germination**	**Non-germination**
Chili	225	79	20	26
Long fed pepper	99	49	1	1
Total	356	96	21	27

Table 4 The precision rate and average access time of the CSGA system

Species	Euclidean distance technique	Neural network technique	Average access time seconds/image
Chili	59.71%	71.71%	0.74
Long fed pepper	52.00%	66.67%	3.54

The CSGA used two main chili seed features, which were color and texture features. The color feature consisted of four sub-features, which were mean of red, mean of green, mean of blue and mean of gray color. The texture feature also consisted of four sub-features, which were energy, entropy, correlation and homogeneity. The color-feature and texture-feature values for germination and non-germination seed are shown in Table 5. All feature intervals of germination and non-germination seed-images were overlapped because both germination and non-germination seed-images had the similar round-shape, yellow-color and coarse-texture. Therefore, a farmer cannot distinguish a germination and non-germination chili-seed by using the naked eye.

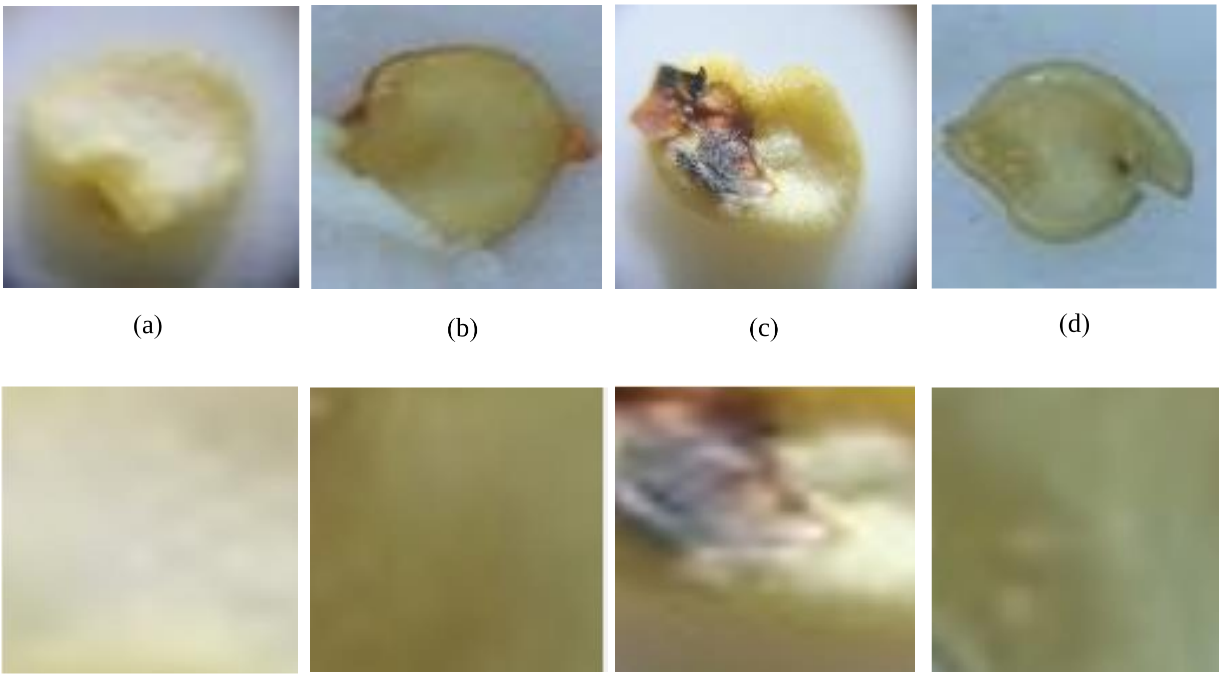
Table 5 Summary of color and texture feature values for chili seed germination and non-germination

Feature	Germination	Non-germination
Red	105.3255-237.4049	55.0069-234.9275
Green	95.2468-217.9569	52.4567-228.7616
Blue	58.5650-217.9539	45.7447-209.9264
Gray	96.7941-228.7952	52.4544-227.2822
Energy	0.1321-0.8102	0.1398-0.7952
Entropy	2.5554-5.9665	2.7727-5.7574
Correlation	0.6011-0.9938	0.6977-0.9918
Homogeneity	0.8653-0.9983	0.8883-0.9871

The germination seed images are shown in Figure 10 (a) and (b) and non-germination seed images are shown in Figure 10 (c) and (d). The cropped images of germination seed are shown in Figure 10 (e) to (f) and non-germination seeds are shown in Figure 10 (g) to (h), respectively. The comparison of all features between germination and non-germination chili seeds images is illustrated in Table 6.

3.2 Discussion

This research employed color and texture features to evaluate chili seed germination because the color features can detect chili seed aging and insect pest contamination and the texture features can detect cracked chili seed and seed contaminated with fungus (Masry et al., 2019b). Based on the germination and non-germination chili seeds comparison, as shown in Figure 10 and Table 6, the color (RGB) of both germination and non-germination chili seeds were very similar because all of the seed images in this research were taken from fresh chili seeds. The non-germination seed image in Figure 10 (c) was contaminated with the dark-brown fungus and Figure 10 (d) had a white color in the middle of the seed. The textural differences between the cropped germination images in Figure 10 (e) and (f) with the non-germination cropped images in Figure 10 (g) and (h) are described as follows.



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure 10 The images of germination and non-germination chili seeds and their cropped images

Table 6 The comparison features between germination and non-germination chili seeds

Features	Germination seed		Non-germination seed	
	Fig. 10 (a) & (e)	Fig. 10 (b) & (f)	Fig. 10 (c) & (g)	Fig. 10 (d) & (h)
Mean red	210.5526	134.4806	169.7550	136.7659
Mean green	207.7330	124.7025	159.5296	140.4457
Mean blue	182.7783	73.8152	123.7697	99.2539
Mean gray	205.7065	121.8510	158.5112	134.6630
Energy	0.8151	0.6229	0.2124	0.5933
Entropy	2.5599	2.6727	3.4722	2.8098
Correlation	0.9933	0.9922	0.9844	0.9770
Homogeneity	0.9939	0.9985	0.9804	0.9963

First, the energy values of Figure 10 (e), (f), (g) and (h) were 0.8151, 0.6229, 0.2124 and 0.5933, respectively. The cropped images in Figure 10 (e) and (f) had a higher energy value than the cropped images in Figure 10 (g) and (h). The energy texture measured the different information between the pixels in an image, and the more similar all pixels in an image were, the closer the energy value will equal to one. The energy values showed that all pixels of germination seeds had more similarity than the pixels of non-germination seeds.

Second, the entropy values of Figure 10 (e), (f), (g) and (h) were to 2.5599, 2.6727, 3.4722 and 2.8098, respectively. The cropped images in Figure 10 (e) and (f) had lower entropy value than the cropped images in Figure 10 (g) and (h). The entropy texture measured the details inside an image. If all pixels around a considered pixel had the same gray color values as the considered pixel, then the entropy value will equal to zero. The results in Table 6 showed that the images of non-germination seeds had more details than the images of germination seeds.

Third, the correlation values of Figure 10 (e), (f), (g) and (h) were 0.9933, 0.9922, 0.9844 and 0.9770, respectively. The cropped images in Figure 10 (e) and (f) had a higher correlation value than the cropped images in Figure 10 (g) and (h). The correlation feature was the measure of the mean and standard deviation of all pixels in an image surface, and the correlation value will have a NaN (not a number) if all pixels in an image had the same values. The correlation values in Table 6 suggested that the pixels of non-germination seeds images had a more distributed value than the images of germination seeds.

Finally, the homogeneity values of Figure 10 (e), (f), (g) and (h) were 0.9939, 0.9985, 0.9804 and 0.9963, respectively. The cropped image in Figure 10 (g) had the lowest homogeneity value, and Figure 10 (e) had a lower homogeneity value than the cropped images in Figure 10 (f) and (h). The homogeneity measured the similarity between a pixel and the nearby pixels, and the homogeneity value will equal to one if all pixels and their nearby pixels have the same values of gray color. The results in Table 6 revealed that the pixels of a non-germination seed had more different gray values than the germination seeds. All germination and non-germination chili seed images had an overlap of feature values, and it is very difficult to identify the germination or non-germination seed. Therefore, the CSGA combined both the color and texture features with a neural network technique to evaluate a complex chili seed germination problem.

Many researchers have illustrated how to apply a digital image processing method to analyze the plant seed with a focus on three main objectives, which are seed species classification, seed quality control and seed germination evaluation.

3.2.1 Seed species classification

Olaes et al. (2020) classified bell pepper and chili pepper using a fuzzy logic technique with a precision rate of 85.00%. Lurstwut and Pornpanomchai (2011) classified fifteen species of fruit seeds, namely cantaloupe, corn, legume, lemon, longan, orange, papaya, sapodilla, tamarind, watermelon, cucumber, grape, kaffir lime, rice and star gooseberry. The system employed shape, size, color and texture features with the Euclidean distance technique to recognize fifteen plant seeds with the precision of around 95.10%. Ouiza et al. (2007) used seed size, form and texture features to recognize four kinds of seeds, which are oats, corn, lentil and barley. The system applied the Euclidean distance technique, with the precision rate of 78%. Zhong-Zhi and You-gang (2009) developed a peanut seed recognition system. The system extracted peanut texture and color with an artificial neural network to recognize the peanut seeds, with the precision of 93.0%. Some plant seeds, for example, orange, lemon, kaffir lime and pomelo seeds have a similar shape, size, color and texture, which make these seeds very difficult to identify. Therefore, a computer system can help farmers to identify the plant seed species before cultivation.

3.2.2 Seed quality control

Many researchers have applied non-destructive techniques to evaluate seed quality control. Musaev et al. (2019) applied X-ray imaging as a quality control evaluation for 25 types of vegetable seed. Desai and Rao (2017) illustrated the use of an artificial neural network for grading rice seeds. Masry et al. (2019b) reviewed an image processing technique for quality control of many kinds of seed, such as spinach, tomato, wheat, rice, maize, triticale, sunflower, castor, hazelnut, chili pepper, soybean pea and barley. Tanwar et al. (2018) showed a number of standard image-processing procedures for seed quality evaluation. The standard image-processing procedures included seed shape measurement, seed color evaluation and seed morphological extraction.

3.2.3 Seed germination evaluation

Many researchers have illustrated how to evaluate germination of many seeds by using image processing techniques, as shown in Table 7. Dell' Aquila (2007) applied X-rays and a mean germination time equation to 50 pepper seeds for germination evaluation with the precision rate of 87.00%. Skrubej et al. (2015) evaluated tomato seeds germination by texture and shape features with the precision of 95.44%. Lurstwut and Pornpanomchai (2017) evaluated rice seed germination by using color, texture and shape of rice seed with the precision rate of 92.80%. Zhou and Ji (2019) employed an SVM-RBF technique to evaluate sweet beet seeds with the precision rate of 87.30%. Masry et al. (2019b) illustrated how to use a multispectral image with the LDA method to classify and evaluate cowpea seeds with the precision of 81.80%. Finally, this research applied the artificial neural network technique to predict chili seeds germination by using their color and texture features with the precision rate of 71.71%. Nevertheless, all researchers in Table 7 have evaluated germination of different types of seeds with an image processing technique. Moreover, based on previous research, the color, texture, shape and size are common features to classify plant seed species and evaluate their cultivation.

An image processing method with a simple mobile phone camera is easy, and it has a reasonable cost for farmers to operate in their farm. There are additional non-destructive methods for evaluating cultivated plant seed, such as electronic smell (E-nose) (Cheng et al., 2017), X-ray based (Brugginkt and Duijn 2017) and near infrared spectroscopy (Lohumi et al., 2013), but the necessary equipment is very difficult to operate and CSGA system gives an acceptable precision rate. To increase the system precision rate, two improvements need to be performed in the CSGA, which are an increase in the training dataset size and extract more chili features.

Table 7 Comparison of seeds germination evaluation

Researcher (year)	Seed type	Number of testing (seeds)	Extraction features	Technique	Precision rate
Dell' Aquila (2007)	pepper	50	X-ray & shape	MTG	87.00%
Skrubej (2015)	tomato	700	texture, shape	ANN	95.44%
Lurstwut (2017)	rice	34,835	color, texture, shape	ANN	92.80%
Zhou (2019)	sugar beet	3,072	color	SVM-RBF	87.30%
Masry (2019b)	cowpea	501	multispectral image	LDA	81.80%
Pornpanomchai (this research)	chili	2,820	color, texture	ANN	71.71%

4. CONCLUSION

The CSGA system fulfills the objective of this research, which is to develop a computer system to evaluate the chili seed germination. The CSGA system employed both the Euclidean distance and neural network methods to evaluate chili seed germination with the precision rate of 59.71% and 71.71%, respectively. The system was implemented with un-trained chili seed (long fed pepper) with the precision rate of 52.00% for the Euclidean distance technique and 66.67% for the neural network technique. The average access time for the Euclidean distance is 0.74 seconds/image and for the neural network technique is 3.54 seconds/image. The neural network gives a higher precision rate than the Euclidean distance method, but the Euclidean distance method evaluates faster than the neural network method. The CSGA system is a non-destructive method for helping farmers to not only store viable seeds for planting but also to reduce both time and labor by planting only seeds suitable for cultivation.

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