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Research article

Image Based Papaya (*Carica Papaya* Linn.) seed germination evaluation by ResNet50

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Abstract: The researchers developed a papaya seed germination evaluation system (PSGES) using ResNet50, a convolutional neural network, to evaluate papaya seed germination potential from single seed images. Using a comprehensive dataset of 12,600 papaya seed images, they allocated 11,600 images for training (with an 80/20 training-testing split) and 1,000 images for validation. The system achieved impressive performance metrics, with an overall accuracy of 99.58% and an average processing time of 1.4705 seconds per image. The training dataset demonstrated exceptional performance with 0.9958 accuracy, 0.9980 precision, 0.9972 recall, and 0.9976 F1-score. When compared to existing seed evaluation methods in the literature, PSGES showed superior precision at 99.59%, significantly outperforming Rice (ANN) at 92.80%, Beet (NIR) at 89.00%, and Chili (ANN) at 71.71%. The study revealed a papaya seed germination rate of 84.92%, calculated from (10,000 + 20 + 677 + 3) ÷ 12,600 × 100. Notably, ResNet50 demonstrated superior performance compared to six other CNN architectures tested, including AlexNet, GoogLeNet, Inceptionv3, ResNet18, ResNet101, and VGG16, in both training and validation performance metrics.

Keywords: Convolutional neural network; Papaya; Pattern recognition; ResNet50; Seed germination evaluation.

1. Introduction

Papaya (*Carica papaya* Linn) is one of the most popular fruits cultivated in tropical areas worldwide. It was initially from Central America [1]. Papaya fruit has various nutrients and many unique properties. Papayas contain carbohydrates, proteins, lipids, dietary fiber, beta-carotene, sodium, potassium, iron, calcium, zinc, phosphorus, copper, manganese, and magnesium [2]. Additionally, papayas have antioxidant, anti-cancer, anti-dengue, anti-malarial, anti-infertility, anti-diabetes, insecticidal, and anti-AIDS activities [3]. People consume papaya in both the mature and unripe stages. They eat mature papaya as a fresh fruit and unripe papaya in vegetable salads. Som Tum is one of the most famous Thai foods, and it is made from unripe papaya [4]. Papaya, like other fruits, is propagated from its seeds. All fruit seeds should be collected from mature, healthy, pest-free, and disease-free fruits [5]. Typically, papaya seeds take more than ten days to germinate, with germination rates of less than 80% [5].

Researchers applied various techniques to produce several seed germination measurements, as shown in Table 1. Lanjhiyana and Sahu [5] showed that the germination rates of rangpur lime (*Citrus limonia*) seeds and papaya (*Caricvera papaya* Linn) seeds are 93.33% and 66.17%, respectively. Marchi and Cicero (2017) employed Seed Vigor Imaging System (SVIS) software to evaluate carrot (*Daucus carota* L. Brasilia) seed vigor with germination rates of 87.00% [6]. Yang et al. [7] used hyperspectral image processing technology to realize the germination prediction of sugar beets (*Beta vulgaris*) seeds with carrot germination rates of 33.33% and a system precision of 95.50%. Pang et al. [8] employed a convolutional neural network (CNN) to identify and predict corn (*Zea mays* L.) seed germination with a system precision rate of 99.96% and a seed germination rate of 62.00%. Severiano et al. [9] used X-ray and Seed Vigor Image System (SVIS) software to analyze Formosa papaya seed germination and found germination rates of 74.5%. Zhou et al. [10] made beet seed germination predictions using near-infrared hyperspectral images of 3072 seeds. The experiments showed germination rates of 50.00% with precision rates of 89.00%. Genze et al. [11] employed convolutional neural networks (CNN) for germination prediction of three species of seeds, maize (*Zea mays*), rye (*Secale cereal*), and pearl millet (*Pennisetum glaucum*), with precision rates of 97.90%, 94.20%, and 94.30%, respectively. Using image processing, Lurstwut and Pornpanomchai [12] evaluated rice (Oryza sativa L.) seed germination. The experiments showed a precision of 73.49% and rice seed germination rates of 74.59%, with an average access time of 8.31 seconds per image. Pornpanomchai et al. [13] evaluated chili (*Capsicum frutescence*) seed germination using Euclidean distance and neural network techniques with precision rates of 59.71% and 71.71%, respectively. The experiments had chili seed germination rates of 75.40% with an average access time of 0.74 seconds per image.

Table 1. Comparison of seed types and germination rates from previous research.

Researchers	Seed type	Germination Rates (%)
Lanjhiyana *et al*. [5]	rangpur lime (*Citrus limonia*)	93.33
	papaya (*Caricvera papaya* Linn)	66.17
Marchi and Cicero [6]	carrot (*Daucus carota* L. Brasilia)	87.00
Yang *et al.* [7]	sugar beet (*Beta vulgaris*)	33.33
Pang *et al.* [8]	corn (*Zea mays* L.)	62.00
Severiano *et al.* [9]	papaya (*Carica papaya* L. var. Formosa)	74.50
Zhou *et al*. [10]	beet (*Beta maritima*)	50.00
Lurstwut and Pornpanomchai [12]	rice (*Oryza sativa* L.)	74.59
Pornpanomchai *et al.* [13]	chili (*Capsicum frutescence*)	75.40

2. Materials and Methods

2.1 System hardware and software specifications

The PSGES (Papaya Seed Germination Evaluation System) was developed using computer hardware and software. The central processing unit used an AMD Ryzen Pro 7 5850U with Radeon graphics at 1.90 GHz with 16 GB of RAM. The operating system was Windows 11. MATLAB R2020b (license number 40598465) was used for software development. A Xiaomi Redmi Note 8 mobile phone was used for papaya imagery. To avoid copyright issues, the researchers created their papaya seed dataset called the "Papaya dataset." The system design used in this research is as follows.

2.2 Papaya seed sampling

All papayas in this research were purchased from a local market in Bangkok, Thailand, from September to December 2023. Figures 1 (a) and (b) show the Holland papaya and papaya seeds. A papaya seed image before germination is shown in Figure 1 (c), and after germination in Figure 1 (d).

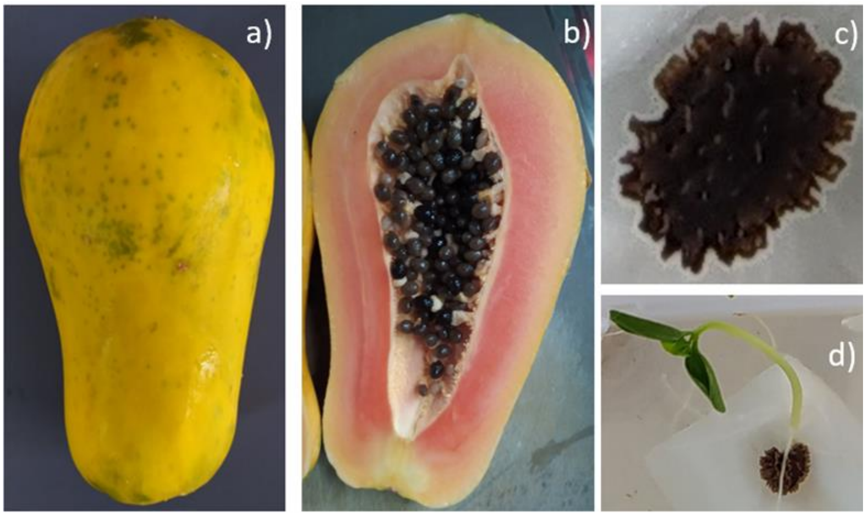

Figure 1. Sample of papaya imagery in this research (a) a whole papaya fruit, (b) bisection of papaya with a group of seeds, (c) a papaya seed before germination, and (d) a papaya seed after germination for 20 days.

2.3 Convolutional neural network

This research employed ResNet50 to evaluate papaya seed images. ResNet50 is a convolutional neural network (CNN) in the MATLAB toolbox. CNNs are some of the most potent recognition methods to identify unknown images in a dataset [14]. ResNet50 has three main components: feature extraction, classification, and output classification functions, as depicted in Figure 2. The operation of ResNet50 is done as follows. First, an input image is acquired. Then, feature extraction is repeatedly done in the convolution and pooling layer until it extracts all input image features. Next, the full connection component uses all neural network input layer features and classifies an input image to show to an output layer. Finally, the output classification component displays the most similar image between the input and dataset images [15].

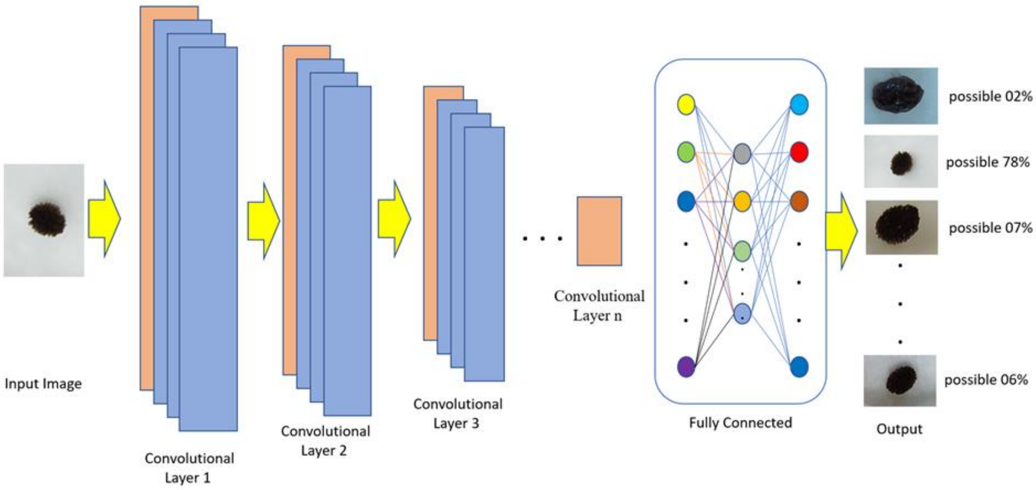

Figure 2. Convolutional neural network architecture

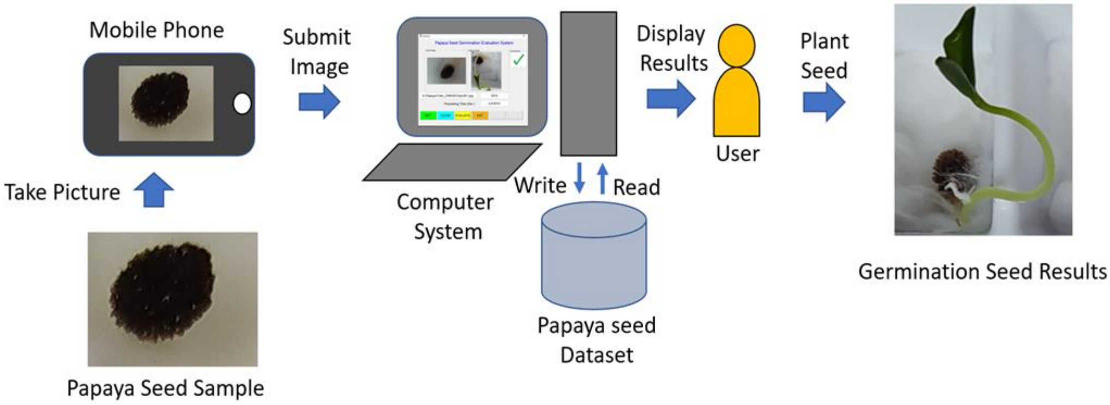

Figure 3. PSGES conceptual diagram

2.4 PSGES conceptual diagram

The PSGES conceptual diagram has three steps, as shown in Figure 3. The first step is to capture a papaya seed image using a mobile phone camera. Then, the seed image is transferred to the computer system to evaluate the seed's germination potential. Finally, based on the image, the system shows the results to the user.

2.5 PSGES flowchart

The PSGES flowchart depicts three main processes: image-making, training, and evaluation (as shown in Figure 4). The imagery process has two main routines and one decision sub-process, which are 1) the papaya image collecting process, 2) the papaya imaging process, and 3) the training process or evaluation sub-process. The training process consists of two routines and one sub-process, which are 1) training the ResNet50 routine, 2) planting and validating the germination seeds process, and 3) making decisions to train the sub-process further. Finally, the evaluation process has a main routine and two sub-processes, which are 1) image recognition by ResNet50, 2) display of evaluation results sub-process, and 3) decision to evaluate more papaya images sub-process. Each process has the following details.

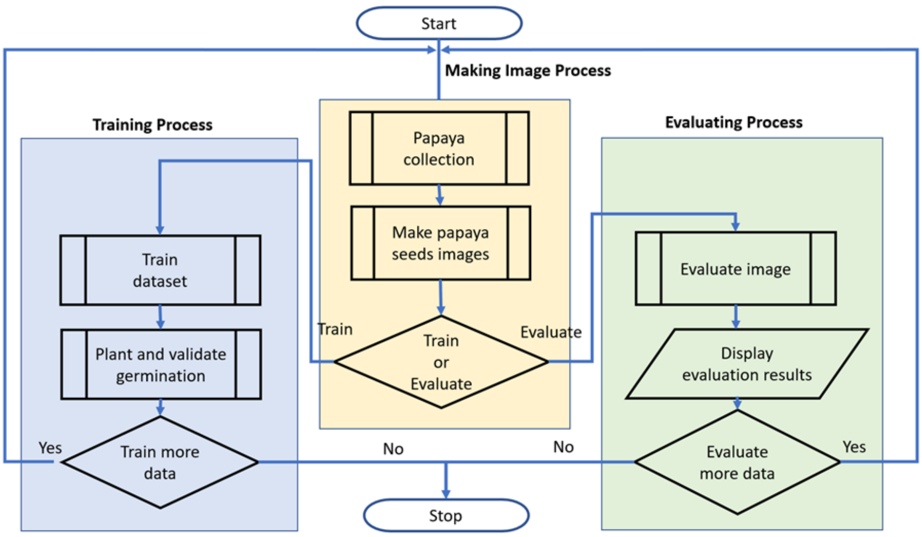

Figure 4. PSGES flowchart

2.5.1 image making process

The image-making process consists of two main routines: the papaya collection routine and the make papaya seeds images routine. Details of these processes are as follows.

2.5.1.1 Papaya collection routine

This research used seven papaya fruits after their bisection. Researchers needed to remove the sarcotesta from the seeds for good germination results. The papaya sarcotesta is an outer and usually soft fleshy jelly covering around the seeds. This research employed 1,260 papaya seeds, which have sizes of 0.5-0.6 cm x 0.3-0.4 cm (length x width), as shown in Figure 1 (c).

2.5.1.2 Make papaya seed images routine

This research planted papaya seeds in a clear 35 cm x 22 cm x 2.5 cm (width x length x height) plastic box with a cover, as shown in Figure 5 (a). The plastic box is separated into 40 small 4.0 cm x 4.0 cm x 2.5 cm (width x length x height) compartments, and each compartment contains a papaya seed on a piece of cotton, as shown in Figure 5 (b). This research used a simple mobile phone camera to make papaya seed JPG format images in each compartment that were 3,000 pixels x 4,000 pixels with a resolution of 72 dpi. Finally, we cropped each papaya seed image into a JPG file format of 300 pixels x 300 pixels x 3 planes with a resolution of 72 dpi, as shown in Figure 5 (c). Each cropped papaya seed image is assigned a unique ID number for referencing.

2.5.1.3 Make decisions in training or evaluate processes

After making papaya seed images, the next step is to decide to do a training or evaluation process according to the following details.

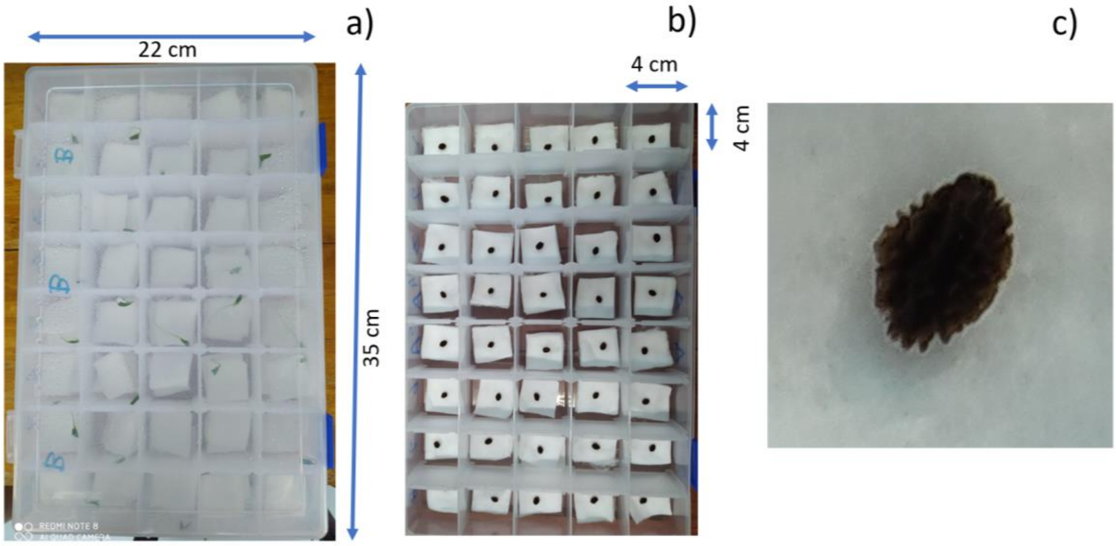

Figure 5. (a) plastic box for planting papaya seeds, (b) papaya seeds on pieces of cotton in compartments, and (c) cropped image of a papaya seed.

2.5.2 Training process

The training process consists of two main routines and one sub-process. They are 1) train dataset routine, 2) plant and validate germination routine, and 3) decision to further train. Each routine has the following details.

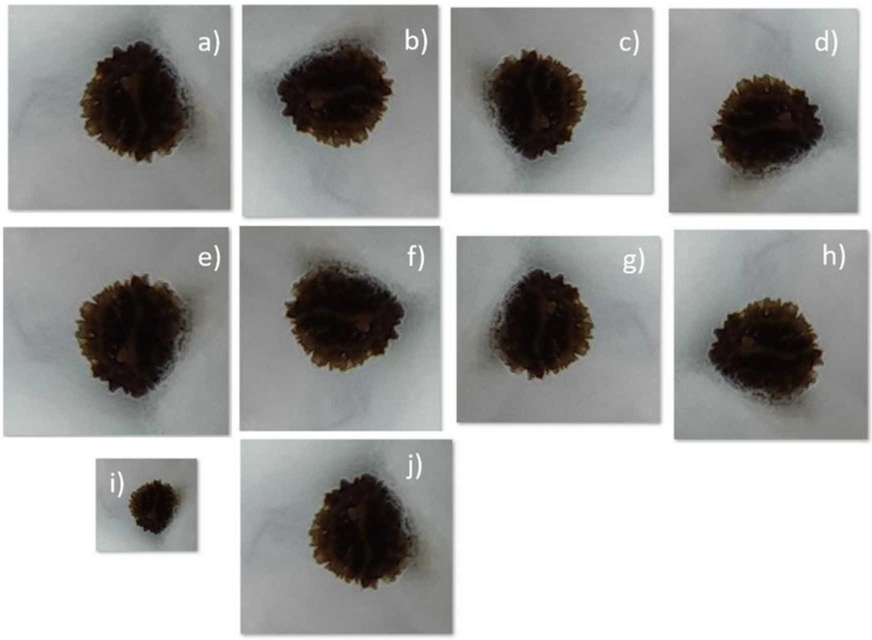

Figure 6. PSGES augmented images (a) original image, (b) original image rotated 90◎, (c) original image rotated 180◎, (d) original image rotated 270◎, (e) original image flipped, (f) flipped image rotated 90◎, (g) flipped image rotated 180◎, (h) flipped image rotated 270◎, (i) resized original image with ratio 1:0.5, and (j) resized original image with ratio 1:2.5

2.5.2.1 Train dataset routine

PSGES employed a powerful CNN called "ResNet50", available in the MATLAB toolbox, to train the system on the papaya dataset. ResNet50 resized all papaya seed images to 224 pixels x 224 pixels x 3 planes before including them in the system training dataset. PSGES employed 11,600 papaya seed images in the training dataset, from which 80% of the images were randomly selected for the training dataset, and 20% were for the testing dataset. The system used 1,000 papaya images to validate its performance. This research also employed a data augmentation technique to increase the number of papaya seed images in the dataset. The augmentation method rotated the original papaya images (as shown in Figure 6 (a)) into 90◎, 180◎ , and 270◎ images, as shown in Figures 6 (b), 6 (c) and 6 (d), respectively. After that, the augmentation method flipped the original papaya images (Figure 6 (e)). Then, it rotated the flipped image into 90◎, 180◎ , and 270◎ images, as shown in Figures 6 (f), 6 (g) and 6 (h), respectively. Finally, the augmentation method resized an original image with the ratio of 1:0.5 and 1:2.5, as shown in Figures 6 (i) and 6 (j), respectively. The papaya dataset contained 12,600 images (1,260 x 10) for training.

2.5.2.2 Plant and validate germination routine

PSGES used images of 1,260 planted papaya seeds to validate every seed for germination. The system directly mapped all papaya seed images before germination with all papaya seed images after germination, as shown in Figures 7 (a) and (b).

2.5.2.3 Decide to train further using more data

The last step of the dataset training process is to further train using more data from the system dataset or stop the PSGES program.

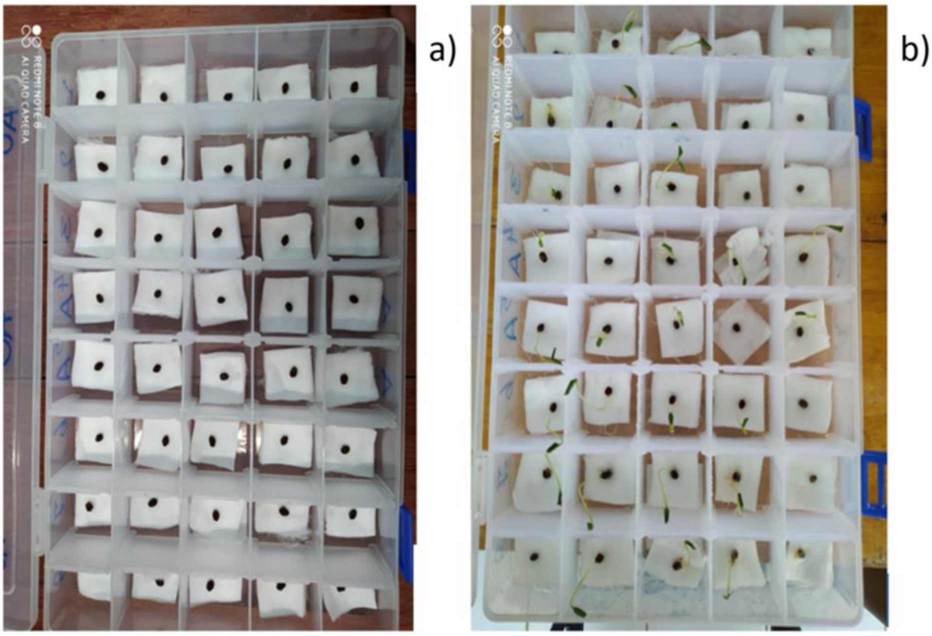

Figure 7 Papaya seeds image (a) before germination and (b) after germination

2.5.3 Evaluation process

The evaluation process consists of a main routine and two sub-processes. These are 1) the image evaluation routine, 2) the display evaluation results sub-process, and 3) the decision to evaluate more papaya images sub-process. Each routine and sub-process are detailed as follows.

2.5.3.1 Evaluate image routine

PSGES employed ResNet50 to train a papaya seed dataset and to evaluate papaya seeds by matching input papaya seed images with all images in the training dataset. Finally, the PSGES illustrated the best image matching to the PSGES graphical user interface (GUI).

2.5.3.2 Results illustration sub-process

PSGES shows papaya seed germination evaluation results via a graphical user interface. The GUI has three components: a graphics window, text boxes, and push buttons, as shown in Figure 8. Each component is described as follows.

The four graphical windows are 1) a graphics window showing the papaya seed input image, 2) a graphics window showing an actual papaya seed germination, 3) a graphics window showing an evaluation of papaya seed germination, and 4) a graphics-window check-box showing an evaluation result, respectively labeled 1 to 4 in Figure 8. A check-box ☑ symbol) represents a correct papaya seed evaluation, while an x-box ☒ represents an incorrect evaluation.

Three text boxes are 1) the input path and filename, 2) the matching folder name, and 3) the average processing time. These are, respectively, labeled 5 to 7 in Figure 8.
The five push-buttons are 1) the get image button to retrieve the input papaya seed image, 2) the clear button for deleting all GUI values, 3) the evaluate button to match a papaya seed image with all papaya images in the dataset, 4) actual papaya seed germination or failure to germinate, and 5) an exit button to stop the PSGES. These are shown as labels 8 to 12 in Figure 8, respectively.

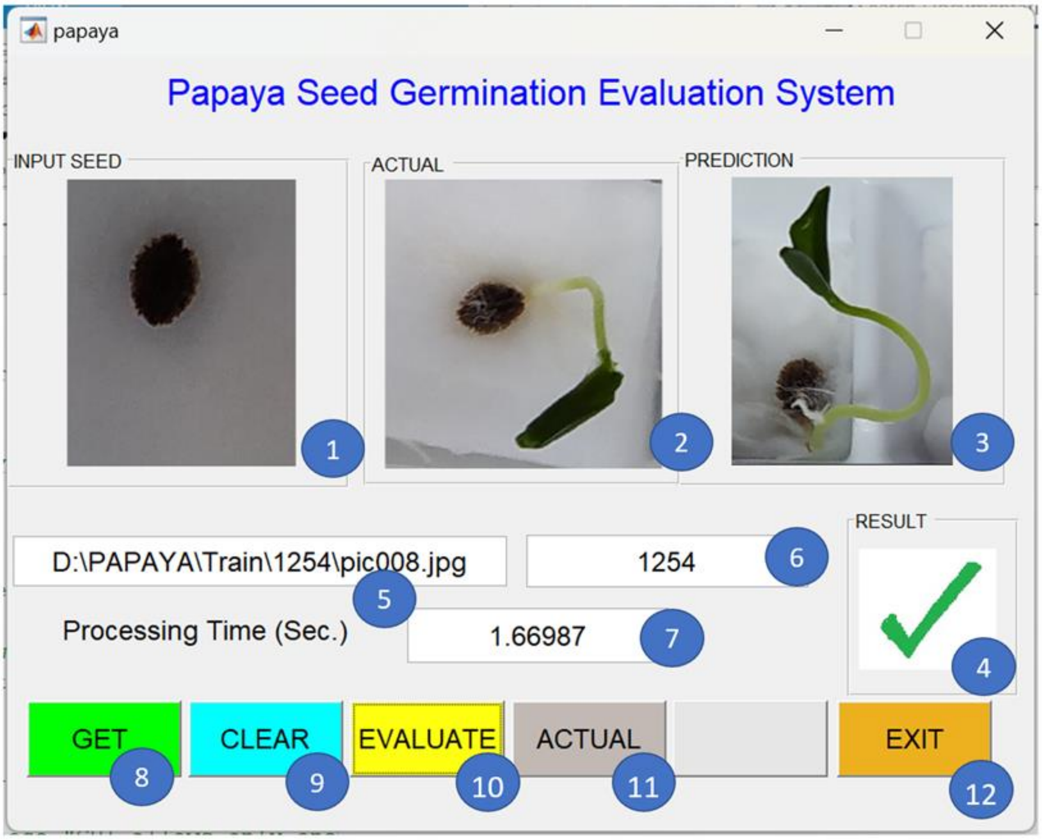

Figure 8. PSGES graphic user interface

2.5.3.3 Decide to evaluate more seed images

The last sub-process of evaluation is to decide between evaluating more papaya seed images or stopping the PSGES program.

2.6 Statistical values

Accuracy, precision, recall, and F1-scores were used to compare the performance of seven CNN structures: AlexNet, GoogLeNet, Inceptionv3, ResNet18, ResNet50, ResNet101, and VGG16. The accuracy, precision, recall, and F1-score equations are as follows.

2.6.1 Accuracy statistical value

The accuracy value, defined in Equation (1), is the ratio of images matching the correct value and the total number of images.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

2.6.2 Precision statistical value

The precision value is the number of true positives divided by the number of true positives plus the number of false positives, as shown in Equation (2).

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

2.6.3 Recall statistical value

A recall value is the capability of the system to associate an image with other relevant images within a dataset. The recall value is the number of true positives divided by the number of true positives plus the number of false negatives, as shown in Equation (3).

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

2.6.4 F1-score statistical value

The F-score is a harmonic mean of precision and recall. It can be interpreted as a weighted average of precision and recall. This parameter is shown in Equation (4).

$$F1 - Score = \frac{2\ X\ Precision\ X\ Recall}{Precision+Recall} \tag{4}$$

3. Results

This research was conducted using seven different convolutional neural networks: 1) Alex Net, 2) GoogLeNet, 3) Inceptionv3, 4) ResNet18, 5) ResNet50, 6) ResNet101, and 7) VGG16, all using the same PSGES dataset. The MATLAB 2020b version supports these seven different convolutional neural network types. Comparisons of accuracy, precision, recall, and F1 score follow Equations 1– 4.

The PSGES employed 12,600 papaya images in these experiments, separated into 11,600 images (1,160 seeds x 10 images) to train the dataset and 1,000 images (100 seeds x 10 images) to validate the system. The system randomly selected 80% of 11,600 images to train the system dataset and 20% to test the system dataset. The germination rate of papaya seeds for the training dataset is 86.37% (10,020 ⊚ 11,600 x 100), and the germination rate of papaya seeds for validating the dataset is 68.00% (680 ⊚ 1,000 x 100). The confusion matrix comparison of the different CNN models for the training and validation datasets are shown in Tables 2 and 3, respectively.

Table 2. Comparison of the different CNN models for the training dataset

CNN Model	True Positive	False Positive	False Negative	True Negative
1. AlexNet	9,187	833	852	728
2. GoogLeNet	9,973	47	52	1,528
3. Inceptionv3	9,998	22	29	1,551
4. ResNet18	9,991	29	26	1,554
5. ResNet50	10,000	20	28	1,552
6. ResNet101	9,925	95	1,275	305
7. VGG16	9,997	23	35	1,545

Table 3. Comparison of the different CNN models for the validation dataset

CNN Model	True Positive	False Positive	False Negative	True Negative
1. AlexNet	598	82	296	24
2. GoogLeNet	614	66	295	25
3. Inceptionv3	597	83	274	46
4. ResNet18	582	98	283	37
5. ResNet50	677	3	317	3
6. ResNet101	609	71	288	32
7. VGG16	615	65	297	23

Moreover, the PSGES employed four statistical values for checking the system performance: 1) accuracy, 2) precision, 3) recall, and 4) F1-score, as shown in Equations (1)– (4). All statistical values were calculated from the confusion matrix to determine 1) true positive (TP), 2) false positive (FP), 3) true negative (TN), and 4) false negative (FN) values.

The PSGES also employed these four statistical values to evaluate the seven CNN model training dataset performance levels, as shown in Table 4. Inceptionv3 has the shortest training dataset time for the training dataset, while GoogLeNet has the longest training dataset time, 761.20 and 1,678.90 seconds, respectively. ResNet50 has the highest accuracy, performance, and F1-score, 0.9958, 0.9980, and 0.9976, respectively. AlexNet has the lowest performance, precision, recall, and F1-score, 0.8637, 0.9168, 0.9151, and 0.9159, respectively.

ResNet50 generates the highest performance, precision, recall, and F1-score for the validation dataset, 0.6800, 0.9956, 0.6811, and 0.8080, respectively. ResNet18 gives the lowest accuracy, performance, and F1-score, 0.6190, 0.8559, and 0.7524, respectively.

Based on the experimental results, ResNet50 was chosen for the PSGES to train and evaluate papaya seed germination owing to its highest accuracy in training and validating datasets, 0.9958 for the training dataset and 0.6800 for validating the system. A comparison of the accuracy, precision, recall, and F1 scores of different CNN models for training and validation is shown in Tables 4 and 5, respectively. The germination rates of papaya seeds in this research are 84.92% ((10,000 + 20 + 677 +3) ÷ 12,600 x 100).

Table 4. Performance comparison among the different CNN models for the training dataset

CNN Model	Accuracy	Precision	Recall	F1-score	Training Time (sec)
1. AlexNet	0.8637	0.9168	0.9151	0.9159	1,643.50
2. GoogLeNet	0.9915	0.9953	0.9948	0.9951	1,678.90
3.Inceptionv3	0.9956	0.9978	0.9971	0.9974	761.20
4. ResNet18	0.9952	0.9971	0.9974	0.9972	1,080.10
5. ResNet50	0.9958	0.9980	0.9972	0.9976	785.02
6. ResNet101	0.8818	0.9905	0.8861	0.9354	1,259.30
7. VGG16	0.9950	0.9977	0.9965	0.9971	1,145.40

Table 5 Comparison performance among the different CNN models for the validation dataset

CNN Model	Accuracy	Precision	Recall	F1-score	Training Time (sec)
1. AlexNet	0.6220	0.8794	0.6689	0.7598	220.34
2. GoogLeNet	0.6390	0.9029	0.6755	0.7728	1,643.50
3. Inceptionv3	0.6430	0.8779	0.6854	0.7698	685.58
4. ResNet18	0.6190	0.8559	0.6728	0.7534	1,080.10
5. ResNet50	0.6800	0.9956	0.6811	0.8080	721.38
6. ResNet101	0.6410	0.8956	0.6789	0.7724	1,259.30
7. VGG16	0.6380	0.9044	0.6743	0.7726	1,145.40

Accuracy and loss graphs for training ResNet50 are shown in Figures 9 (a) and 9 (b), respectively. Setting parameters for training ResNet50 have one epoch per iteration, a 0.01 learning rate, and a maximum of 16 epochs.

Papaya seed germination sample evaluations are shown in Figure 10. Figure 10 (a) shows an accurate positive evaluation in which the evaluated and planted seeds germinated. Figure 10 (b) shows a false positive evaluation, in which the evaluated seed germinated, but the planted seed was un-germinated. In Figure 10 (c), a false negative evaluation is presented, where the evaluated seed was un-germinated, but the planted seed germinated. Finally, Figure 10 (d) shows a true negative evaluation, where both the evaluated and planted seeds were ungerminated.

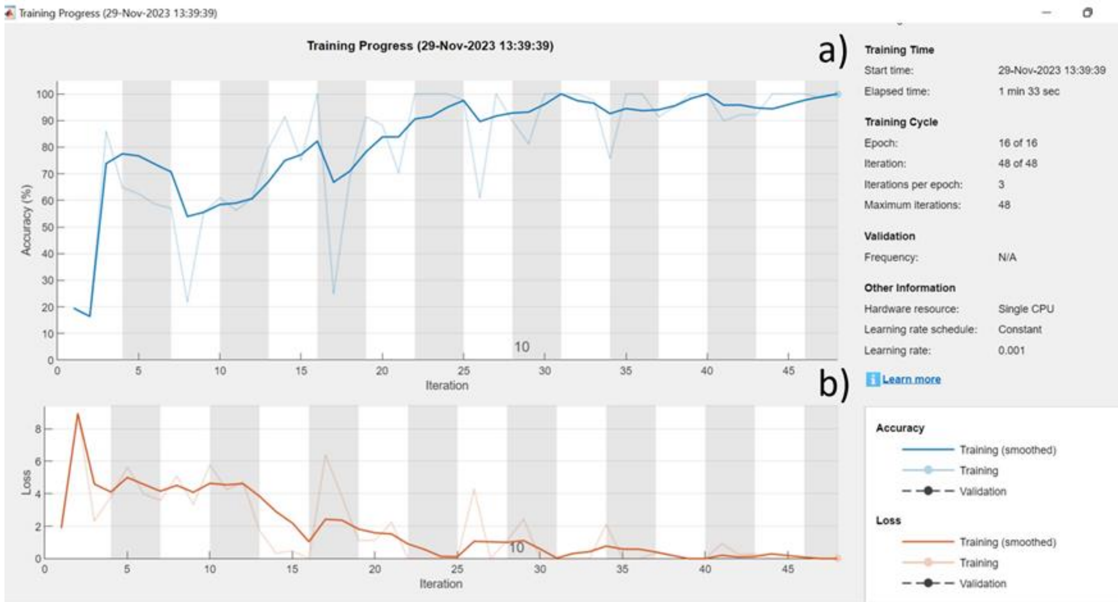

Figure 9. Accuracy and loss curves for training ResNet50 in the PSGES

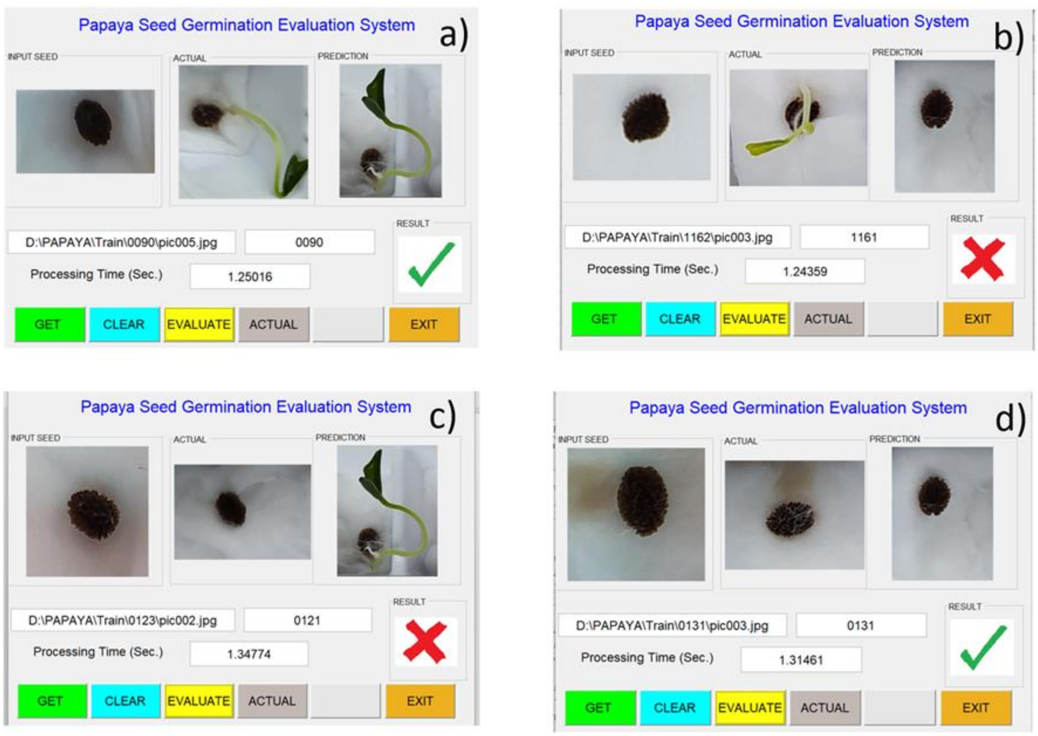

Figure 10. PSGES GUI sample screens, (a) true positive, and (b) true negative, (c) false negative, and (d) false positive

4. Discussion

Evaluating plant seed germination is a very challenging task for many researchers. Previously, researchers evaluated seed germination by physiological, biochemical, and stress tolerance tests [6], all destructive methods. Currently, researchers are attempting to apply non-destructive methods, using X-rays [9], infrared radiation [10], and image processing [12, 13]. There is no consensus about which method is best. Both X-ray and infrared methods require sophisticated equipment to evaluate seed germination. However, image processing is not only non-destructive but also uses simple equipment. Farmers can use a mobile phone camera and computer to evaluate seed germination. A comparison among various kinds of plant seeds is shown in Table 6. Lurstwut and Pornpanomchai (2017) employed an artificial neural network (ANN) to evaluate the germination of 34,835 rice seeds using their color, shape, and texture attributes. They used only a single rice seed image to evaluate seed germination with a precision rate of 92.80%. Marchi and Cicero (2017) used a seed vigor imaging system (SVIS) to evaluate carrot seed germination. Zhou et al. (2020) evaluated the germination of 3,072 beet seeds using near-infrared hyperspectral images with an 89.00% accuracy. Pornpanomchai et al. (2020) used chili seed attributes, shape, color, and texture to evaluate their germination. The experiments were conducted using an ANN with a precision rate of 71.71%. The current research used ResNet50, a convolutional neural network (CNN) available in the MATLAB toolbox. The PSGES employed only a single papaya seed image to evaluate its germination with a precision rate of 99.59%.

Table 6 Comparison of various kinds of seeds for germination evaluation

Researcher (Year)	Seed Type	Dataset Size	Technique	Precision (%)
Lurstwut (2017) [12]	rice	34,835	ANN	92.80
Marchi and Cicero (2017) [6]	carrot	350	SVIS	n/a
Zhou (2020) [10]	beet	3,072	NIR	89.00
Pornpanomchai *et al*. (2020) [13]	chili	2,820	ANN	71.71
This Research (2024)	papaya	12,600	CNN	99.59

5. Conclusions

The PSGES fulfills the objective of this research, which is to develop a computer system for evaluating papaya seed germination using only a single image. Its dataset consists of 12,600 papaya seed images, 11,600 images for a training dataset, and the remaining 1,000 images for a validation dataset. The average precision rates of the system are 0.9980 for training the dataset and 0.9959 for the system validation. The average access time of the system is 1.4705 sec/image. The PSGES is also compared for its performance against that of various kinds of CNNs. Experimental results show a state-of-the-art image-based papaya seed germination evaluation. Papaya is a fruit planted from seeds, and its seeds have a very low germination rate. Therefore, this research can help farmers reduce costs and time spent planting papaya because they can select seeds that will be more likely to germinate. Researchers can apply techniques in this research to evaluate the germination of other kinds of fruit seeds, such as oranges, longan, mango, and durian. A mobile phone application based on this research can be developed.

The limitations of this research are the low germination rates and the long time required to plant papaya seeds in order to conduct the experiments. The researchers need a large number of papaya seeds for a training dataset and more time to build a larger dataset. Normally, large datasets have higher precision than smaller ones. Moreover, farmers will have more confidence in a larger papaya seed dataset.

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Author: Contributions: Conceptualization, experimental design, carrying out experiment, data acquisition, writing and editing, C.P.

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Conflicts of Interest: The authors declare no conflict of interest.

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