ICIC Express Letters
Volume **17**, Number **2**, February **2023**

ICIC International ©2023 ISSN 1881-803X
pp. 143–152

QUALITY GRADING OF CROWN FLOWERS USING CONVOLUTIONAL NEURAL NETWORK

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Received May 2022; accepted July 2022

Abstract. *This article presents an image classification for quality grading of crown flowers using convolutional neural network and transfer learning. It consists of 1) image acquisition, 2) pre-process, and 3) data classification. Using data of 1,500 white crown flowers, they are divided into five classes as follows: 1) flowers with the base of the petals close together, 2) flower with mold, 3) flowers with more than one bad trait, 4) flowers with unequal petal length, and 5) complete flower. The experiment divided the data into two parts, including 80% of training data and 20% of testing data. This article experiments with four models, including Convolutional Neural Network (CNN), Xception, VGG16, and InceptionV3. The experiment results show that accuracies of convolutional neural networks and InceptionV3 Networks were 85%; moreover, those of Xception and VGG16 were 83% and 81%, respectively. Finally, the performance measurements of the CNN model show the highest average of all precision, recall, and F1-score equations. Accordingly, the CNN model is the deep learning of the characteristics of the image, which gets to more efficiently and accurately than other models. It can be applied to classifying the quality of crown flowers, which supports the gardeners in grading flowers more efficiently.*

Keywords: Deep learning, Transfer learning, Convolutional neural network, Image classification

1. **Introduction.** Thailand has many economic flowers. Calotropis gigantea, or the crown flower [1,2], is widely used in religious activities which are commonly used in garlands and artificial flowers. Therefore, it is in demand year-round and is grown as a flower of community economics. The crown flower is a flower that is very resistant to environmental conditions. It is common in every province of Thailand and blooms in bunches, and each bouquet contains many small flowers. It has a crown-like flower with five petals; each is oval with a pointed tip, about 0.5 to 0.8 cm wide and 1 to 1.5 cm long. In Thailand, the crown flower has two colors: white and purple. Nowadays, farmers in many provinces are

DOI: 10.24507/icicel.17.02.143

increasingly turning to plant the crown flower, such as Phichit and Saraburi, as supplementary occupations while waiting for second-field farming. The selling price is 10 to 300 baht per kilogram. Usually, these crown flowers are sold wholesale to merchant middlemen. Farmers do not classify the quality of each flower, which causes them to sell them at low prices. However, if the farmers can classify, they can get a high price. Low-quality crown flowers have many characteristics, such as moldy flowers, unequal lengths of petals, and the flower is not yet fully grown. Usually, most farmers do not grade quality crown flowers because they require significant expertise. It needs to require high accuracy and works for a long time. Therefore, if we can use technologies to help solve this problem, it will benefit Thai flower farmers.

Image processing can be applied to supporting image classification, which has several techniques. It can be used to help identify the quality of the image analyses. Image classification requires image analysis, in which image data must be imported and characterized by Artificial Intelligence (AI), which has two forms. The first is to analyze the distinctive feature itself and send it to machine learning. The second is to allow machine learning to identify features automatically. The first method has been used in research: size classification of mangoes [3], mango classification [4,5], fruit classification [6], and rice classification [7]. The model's advantages are that it uses essential machine learning, fast processing, and does not consume many machine resources. However, if data is to be classified with a large amount of segmentation, it is necessary to use a wide range of knowledge for feature analysis to classify it correctly. When the data is large, the accuracy rate of the results increases slightly. The second method is examining and counting tomatoes in greenhouses [8], ripening classification of mangosteen [9], and flower selection [10-12]. Convolutional Neural Network (CNN) and Deep Convolutional Neural Network (DCNN) use machine learning and deep learning to analyze specifically. It has the advantage of being able to use images as input directly. Moreover, it tends to provide higher accuracy with the large data quantity.

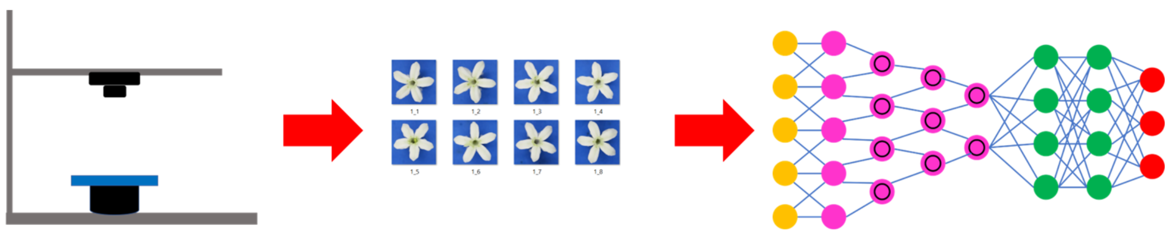
The advantage of machine learning is the automatic identification of critical features in flower classification. We found some research that used this technique for classification. The first article identified 200 classes of flowers using 9,500 flower images for accurate flower image recognition. The recognition rate required was 97.78% [13]. In addition, the research identified roses using 3,670 flower images and numbered five classes in which the accuracy was 90.58% [14]. Moreover, this article was to examine flower species in an extensive database with 102 classes. The model gave an accuracy of 86.66% [15]. Furthermore, the research used flower and leaf knowledge for plant identification. It is a plant identifier rather than a flower or uses both flowers and leaves with an accuracy of 98% [16]. In addition, this research presented identifying natural flowers by CNN technique [17] with a large dataset that used 79 categories of flowers. The accuracy was 76.54 percent, tested on an Oxford dataset of 102 flower datasets and got an accuracy of 84.02 percent. In addition, the research was to present the flower classification, which consists of 2 steps: 1) automatic flower segmentation and 2) using CNN to classify flowers. This method is durable, accurate, and can recognize flowers in real time with an accuracy of 97 percent [18]. Moreover, this research presents orchid classification using the Deep CNN method [19]. Therefore, CNN can be used to identify flowers and have high accuracy. It is interesting to classify crown flowers for agricultural industry promotion. It consists of 2 parts: 1) improvement of feature map by Spatial Transformer Network (STN) and 2) using DCNN technique which uses 3,559 images of 52 class datasets which the result is 93.32%.

Therefore, it is interesting to use CNN to assist classification. Significantly, deep learning can improve the efficiency of image classification better. This article will present an algorithm for classifying the image of crown flowers using convolutional neural network techniques. However, the experiment of this article will classify the image using several classification methods to present the efficiency of each method. The crown flower will be set into five groups, divided into one group of complete flowers and four groups of defective flowers. The group of defective flowers consists of the base of the petals adjacent to each other, fungi on flower, flowers with more than one trait, and flowers with unequal petal lengths. Deep learning techniques are applied to simplifying the finding of the features themselves, and crown flowers can be classified according to the facts of the flowers. This research is expected to increase farmers' income because crown flowers can be classified accurately.

2. **Background.** The Convolutional Neural Network (CNN) [20,21] is one of the most popular terms of Deep Neural Network (DNN) [22]. It takes this name from a linear mathematical operation between matrixes called convolutional. A convolutional neural network is a type of multi-layered neural network. Information passes from the first layer and flows in the same direction to the last layer, known as the feedforward neural network. The images are divided into pixels for analysis in matrix form. CNN is divided into three parts. 1) The input part is responsible for importing the image. 2) The feature learning part extracts the image's distinctive features. 3) The classification part, which is used to classify objects in the image, is determined by the characteristics.

After a literature review, we would like to investigate classifying the images of crown flowers to compare efficiency on four models, including CNN, Xception, VGG16, and InceptionV3, which have several feature parameters and are reliable and widely-used models. Finally, in the conclusion section, we will discuss which model can achieve high accuracy.

3. **Research Methodology.** In this research, the operation steps of image classification consist of 3 parts: 1) Image acquisition is the device determination, environment determination, and imaging methods for this research; 2) Pre-processing involves manipulating image files obtained from shooting into the same format for use in the next step; 3) Classification is a machine learning process of classifying crown flower images, as shown in Figure 1.

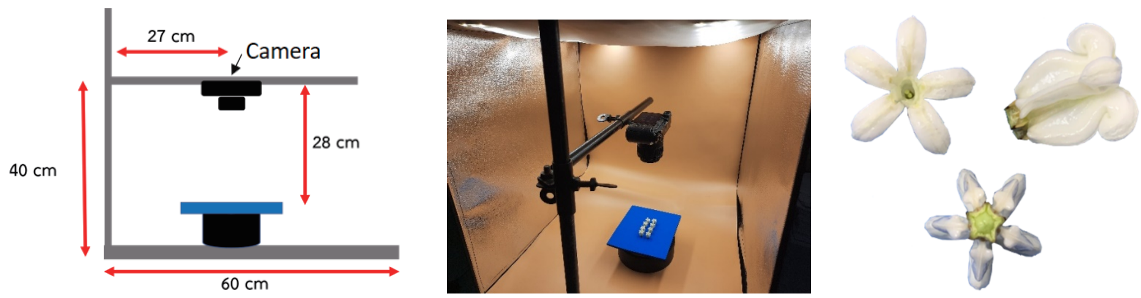


1) Image acquisition 2) Pre-processing 3) Classification

Figure 1. Overview of research methodology in image classification

3.1. **Image acquisition.** This step details how to collect the crown flower data. It consists of three parts: 1) photographic equipment and settings, 2) determining the environment of taking a photo, and 3) flower arrangement pattern for photography.

Photographic equipment and settings: A mirrorless digital camera was used in this research. The camera's brand is Panasonic model DMC-GX85, and uses a macro lens Leica model H-ES045E – setting the parameters shooting as follows: aperture value F2.8, ISO sensitivity 400, shutter speed 1/400. A shooting base of the camera is built to help hold the camera steady, which is a steel structure with 60×60 centimeters, a 60-centimeter-high pole attaching a steel axis to keep a digital camera stationary. Also, the axis will move up and down to adjust the height. In addition, the camera will face down at the



(a) (b) (c)

FIGURE 2. (a) Shooting base of the camera, (b) a studio for photography, and (c) crown flower arrangement

base, in which the camera's height from the floor is 40 centimeters, and away from the pole is 27 centimeters, as shown in Figure 2(a).

Determining the environment of taking a photo: The photography uses a studio with a width, length, and height of 60 centimeters and has 120 LED lights inside, 1690 lumens, 5500K of color temperature, and 60 watts of power. Reflection of light makes objects clearly visible in 360 degrees, as shown in Figure 2(b).

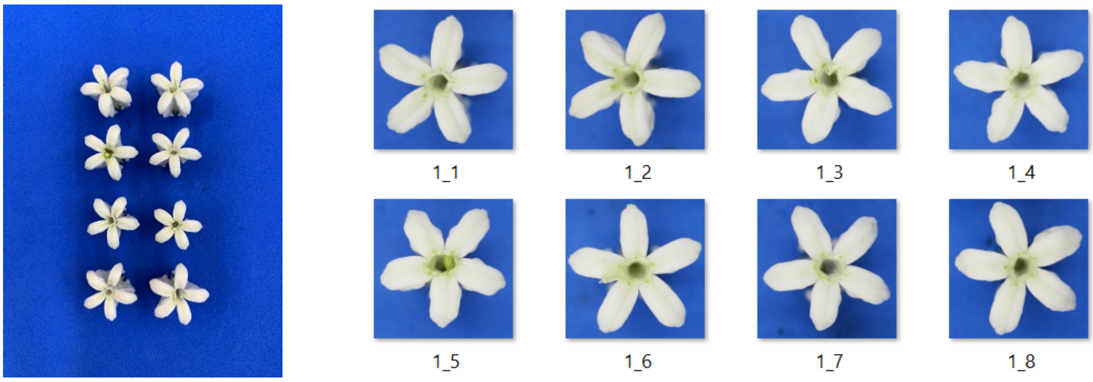
Flower arrangement pattern for photography: the flower arrangement can be arranged in 3 views: the top of the flower, the side of the chest, and the bottom of the flower, as shown in Figure 2(c). Each view can be used to classify the crown flowers differently.

In addition to placing the flowers in different scenes, it is necessary to determine the complete flower with precision to consider its features and the completeness of the crown flower. This research was designed to consider the integrity of crown flowers into six characteristics: fungi, petal length, thalamus, the slenderness of the petals, flower aging, and having more than one trait to be classified as shown in Table 1.

TABLE 1. Flower features for classification

Views of flower arrangement	**Determining features of completeness**					
	Fungi	**Petal length**	**Thalamus**	**Slenderness of the petals**	**Flower aging**	**More than one trait**
The top of the flower	√	√	√	√	√	√
The side of the chest	√				√	
The bottom of the flower	√					√

3.2. **Pre-processing.** In this section, all images are prepared before the classifying process. Each image file from the image acquisition steps has a width of 4,592 pixels, a height of 3,064 pixels, and a resolution of 180DPI in a JPG type. These photos contain eight flowers arranged in two rows and four columns, as shown in Figure 3. This process crops up to one flower per image by detecting the area of interest and cropping the image for the following procedure. For the cropping technique, this paper uses a histogram technique to perform the thresholding, separates the background from the flower image, and then fills hole to improve the crown flower area without gaps in the petals. Finally, the Region of Interest (ROI) is used to find the flower position and crop each image.



(a) (b)

FIGURE 3. (a) Original file, and (b) image after the pre-processing

3.3. **Data classification.** This section classified the image with the classification method into their respective categories. Data classification proposes the neural network methods, CNN technique, and three learning transfer techniques: Xception, VGG16, and InceptionV3. They can be classified as creating a model consisting of 2 parts: model training and model testing. In training, 80% of the total data will be used, divided into ten groups based on the principle of 10-fold cross validation to train the resulting model from this part, the flower classification model in the test section. Another 20 percent of the data will be used, and the model's effectiveness was measured in all four techniques (CNN, Xception, VGG16, and InceptionV3). All images are processed for the four models to determine the complete flower's best performance. The results of each model are discussed, and a conclusion is drawn.

4. Experiment.

4.1. **Dataset.** We used all datasets of flower images; we used the crown flower breed named "Rak Kaew", which has white petals. Usually, they are used to make garlands or perform religious ceremonies. However, the experiment will determine the results more accurately. Therefore, they are divided into five groups, detailed in Table 2, classified by experts. The images used in each group consist of 300 flowers, including 1,500 flowers. The image file has a width and height of 256 pixels, resolution of 96 DPI.

4.2. **Evaluation.** The performance measurement model [23] is used for finding performance in data using a confusion matrix determined from the model results and actual results. True Positive or TP is a positive predictive value, True Negative or TN is a correct negative prediction, and False Positive or FP is a positive predictive error. Moreover, False Negative or FN is a negative predictive error value and all equations are used for performance measurement as shown in this equation, i.e., Precision $= TP/(TP + FP)$, Recall $= TP/(TP + FN)$, F1-score $= 2 \times (Precision \times Recall)/(Precision + Recall)$ and Accuracy $= (TP + TN)/(TP + FP + FN + TN)$.

5. **Experimental Results.** The experiment uses 1,500 images in which each image has only one crown flower. Image width and height are 256 pixels; the resolution is 96 DPI. They are set to be five classes of 300 images each, as follows: crown flowers at the base adjacent to each other (Class 0), flowers with mold (Class 1), damaged flowers with more than one trait (Class 2), damaged flower with unequal petal length (Class 3) and complete flower (Class 4). Next, they are divided into training model data on 80% or 1,200 images and testing model 20% of data or 300 images using a convolutional neural network model and a transfer learning model.

TABLE 2. Characteristics of each group of crown flowers

Image	Flower	Characteristics	Class
	Flowers with the base of the petals close together	The base of the petals is slightly spaced or adjacent bases.	0
	Flower with mold	Petals are black or contaminated brown.	1
	Flowers with more than one bad trait	Petals with more than 1 trait in 2-6.	2
	Flowers with unequal petal length	Petals are not the same length from base to tip.	3
	Complete flower	The white petals are approximately the same length. The base of the petals is not closely spaced together.	4

5.1. **Parameter configuration.** Parameter of convolutional neural networks in all four layers uses an epoch of 100 and a learning rate of 0.001. Furthermore, the input data and classification parameter are shown in Table 3.

TABLE 3. Parameters of 4 models

Input	Feature learning	Classification
Input shape (256×256)	Activation = ReLU Pooling = Maxpooling (2×2) Dropout = 0.4	Dense unit = 512 Activation = ReLU Dense units = 6 Activation = softmax

In the convolutional neural network model, feature learning created three internal layers: kernel type 3×3, the first layer using feature map size of 64 pixels, the second layer using size of 128 pixels, and the third layer using of 256 pixels. ReLU (Rectified Linear Unit) [24] is the classification function in a deep neural network used as an activation function for converting a feature map to a nonlinear form that solves the gradient vanishing problem. It replaces the negative pixel values with 0. The result after ReLU is only positive, which makes training the model faster.

5.2. **Performance measurement.** Performance measurement is applied to the model training and testing of the four models. The performance was measured using a confusion matrix and the validity values, with the neural networks providing the highest accuracy, convolutional neural networks, and InceptionV3. Convolutional neural networks can use fewer parameters with 85% accuracy, in which CNN uses parameters to classify the crown flower less than Inception V3 is 6,865,632 or 16.82%. Moreover, VGG16 has 83% accuracy, and Xception has 81% accuracy, respectively. CNN can improve the number of convolutional layers flexibly. It provides feature learning that is more suitable for flower image classification, causing accuracy and precision to be higher than other models, as shown in Table 4.

Table 5 exposes the precision of each class calculated according to precision. The CNN had the highest average precision, and the Xception had the lowest mean precision. All classes of CNN have a precision of over 80%. However, some Xception, VGG16, and

Table 4. Parameter and accuracy values of 4 models

Models	Accuracy	Parameter
CNN	**85.00%**	33,946,438
Xception	81.00%	54,550,830
VGG16	83.00%	23,238,214
InceptionV3	**85.00%**	40,812,070

Table 5. Precision values of 4 models

Class	CNN	Xception	VGG16	InceptionV3
0	0.81	0.86	0.75	0.76
1	0.86	0.85	1.0	0.92
2	0.81	0.74	0.73	0.80
3	0.95	0.75	0.82	0.84
4	0.87	0.79	0.87	0.94
Average	**0.86**	0.80	0.83	0.85

InceptionV3 classes have less than 80% precision. However, CNN is a model that can get the experiment's highest precision average. Nevertheless, all models can precisely recognize the mold on flowers with greater than 80% in Class 1. Moreover, Class 3 is a flower with unequal petal length class by defining a 3×3 convolution grid; many small details can be captured, resulting in a highly accurate feature that distinguishes this class. In summary, the performance measurement of CNN with precision can be suitably used for all classes. Only Class 1 uses precision for all models to accurately detect mold on flowers in this class.

Figure 4 illustrates the performance measurement of the model in each class, calculated according to recall. The CNN had the highest average recall at 85%, while Xception had the lowest average recall at 80%. The figure presents that CNN and Xception have two classes with a recall value greater than 90%, of which one class in VGG16 and InceptionV3 recall value is more excellent than 90%. Furthermore, Class 2 of the Xception model had the lowest, only 55%. Overall, performance measurement with recall equation is not

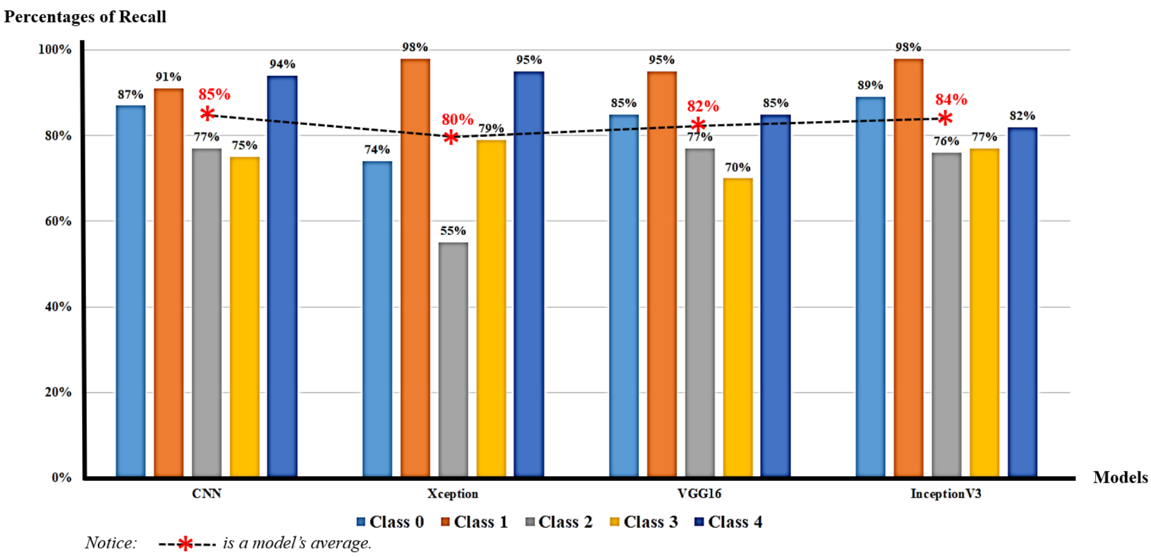


Figure 4. Comparison of Recall among four models

suitable for both Class 2 and Class 3 because they are less than average recall on every model. To sum up, CNN and InceptionV3 are suitable for using recall equations because they calculate high accuracy of 85% and 84%, respectively, especially Class 0, Class 1, and Class 4.

From Figure 5, it is apparent of the performance measurement of the model in each class, calculated according to the F1-score. CNN and InceptionV3 had the highest average F1-score values at 85%; however, Xception has the lowest average F1-score at 79%. Therefore, the F1-score is not helpful for performance measurement in the Xception model.

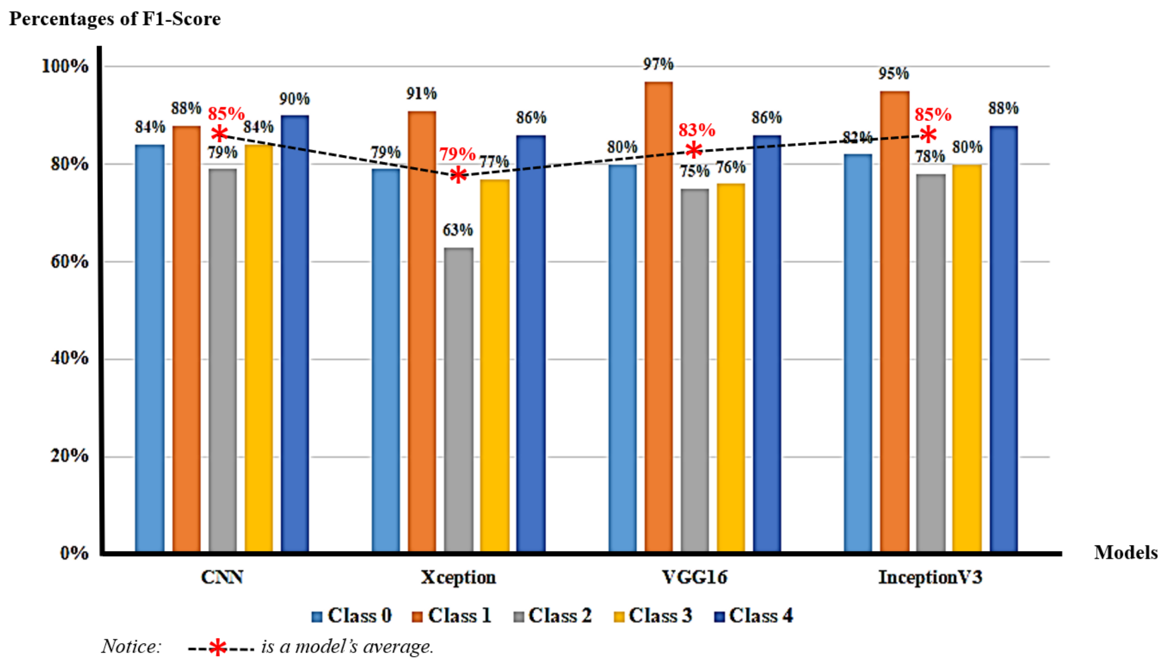


FIGURE 5. Comparison of F1-score among four models

After the experiment, for the performance measurements of all four models, we found that Class 1 or the flower with mold had the high accuracy in every model with precision, recall, and F1-score equations, because mold on a white crown flower may be simple to classify by image classification technique. Moreover, the CNN model achieved the highest precision, recall, and F1-score. In contrast, other models have less accuracy than CNN, including InceptionV3, VGG16, and Xception. Therefore, CNN would be the best choice for grading the quality of the crown flowers with the image classification technique.

6. **Conclusion.** This article investigates the image classification of the crown flower. We apply convolutional neural network and transfer learning for comparative performance in classifying. CNN and transfer learning models including Xception, VGG16, and InceptionV3 were used in this research. The experiment was designed to analyze the image classification by grading the flower quality. Firstly, all datasets were collected with 1,500 images divided into five classes. Next, the performance measurement is adapted to find models' accuracy and precision, including precision, recall, and F1-score. In the experimental results, the convolutional neural network achieved the highest accuracy in image classification. It provides 85% accuracy, 86% precision, 85% recall, and 85% F1-score, better than Xception, VGG16, and InceptionV3. However, in terms of precision, CNN is the highest of two classes, the first is one with more than one fault, and the next class is one with unequal length. Furthermore, in recall, CNN has a maximum of one class, a flower class with more than one lousy characteristic. Nevertheless, considering each neural

network capability class, CNN had the highest value in classifying the four classes except the flower with mold or Class 1. Accordingly, the experimental results revealed that the CNN could determine pattern recognition and digital image processing, especially classifying crown flower quality, to support gardeners grading flowers more efficiently. To sum up, CNN can get a great overall result because CNN uses a particular type of layer called the convolutional layer, which extracts parts of an image, such as the borders of objects. Consequently, the model can learn the characteristics of the image more efficiently and accurately than other models in this article. Therefore, CNN would be the most suitable model for developing the application to solve the problems for grading the quality of the crown flowers.

In future work, we will increase the crown flower class. Alternatively, the number of images should improve for a guideline for further classification. Moreover, the purple crown flowers would be applied to the experiment.

Acknowledgment. This research was supported by the Computer Science Program, Faculty of Science and Technology, Pibulsongkram Rajabhat University, and Center of Excellence (CoE), Faculty of Science, Naresuan University for supporting the facility and equipment for this research.

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