Research Article

Buddhist Amulet Recognition by Using ResNet50

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ABSTRACT

The objective of this research is to develop a computer system which can recognize Buddhist amulet images. The system is called "Buddhist amulet recognition system (BARS)". BARS consists of four main modules, namely: 1) dataset training, 2) image acquisition, 3) ResNet50 classification and 4) result presentation. The system dataset consists of 3,248 images belonging to 203 amulet types, with 16 images per type. The system analyzed both metal & clay amulets, which consisted of 146 metal amulets and 57 clay ones. BARS employed the pre-training convolutional neural network (CNN) called "ResNet50" in MATLAB for recognizing Buddhist amulets. The accuracy, sensitivity, specificity and precision rates for the training dataset of BARS are 0.9998, 0.9879, 0.9999 and 0.9879, respectively. The system also conducted cross-validation on an untrained dataset, which has accuracy, sensitivity, specificity and precision rates of 0.9999, 0.9541, 0.9999 and 0.9541, respectively. The average training time is 3,183.2 seconds and the average access time is 1.34 second per image. Finally, this research compares the accuracy of ResNet18, ResNet50 and ResNet101, with the same amulet dataset.

eywords: Buddhist Amulet, Image Recognition, Convolutional Neural Network, Deep Learning, ResNet50

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Introduction

Approximately 93.40 percent of Thai people are Buddhists. They worship Buddha statues at home and wear small Buddhist amulets around their necks while traveling for adornment and protection [1]. Normally, Thai Buddhist amulets are made by monks in temples. Amulets are made of various types of materials, namely: metal, clay, stone, parts of animal bodies, parts of plants, etc. [2]. There are plenty of amulets today, which have different material, shape and texture. Therefore, the motivation of this research is to help people identify Buddhist amulets correctly. The research experiments were conducted on metal and clay amulets because both types of materials are the major materials used for making amulets, and both of them are easily photographed. A sample of metal amulets is shown in Figure 1 (a) – (d) and clay amulets are shown in Figure 1 (e) – (h).

Figure 1 A sample of some Buddhist amulets in this research, namely: (a) Luuang-por Sot, (b) Krom-luunag Chum-pon-ket-udom-sak (c) Pra-taat Pa-nom, (d) Luuang-por Koon, (e) Pra Som-dej, (f) Pra-pong Por-bpor-ror, (g) Ja-dtu-kaam-raam-tep and (h) Pra Kun-paen

Many scientists and researchers employ many techniques to recognize Buddhist amulet images, which have the following brief details.

Euclidean distance technique

A Euclidean distance is the length of a line segment between two points. It can be calculated from the Cartesian coordinates of the points to measure the similarity between various objects. Thumwarin et al. [3] illustrated robust amulet recognition by the rotation invariance technique and Euclidean distance technique. The experiment was conducted on a United States 25 cent coin and a Thai five-baht coin, with the error rates of 7.14 and 7.89 percent, respectively. Pornpanomchai et al. [4] employed the Euclidean distance technique to recognize 52 Buddhist amulets, with a total of 318 images. The precision of the system was 80 percent.

K-nearest neighbor algorithm

The k-nearest neighbors (KNN) algorithm is a simple, supervised machine learning algorithm that can be used to solve both classification and regression problems. Fugthong and Meesad [5] showed how to retrieve Buddhist amulet images by k-nearest neighbors on 1,400 images with 44 kinds of amulets. The precision rate of the system was 98.97 percent. Kompreyarat and Bunnam [6] developed Thai Buddhist amulet recognition by k-nearest neighbors on 240 images of 80 classes, with the precision rate of 89.35 percent.

Neural network method

A neural network is a series of algorithms which mimics how the human brain operates to recognize the relationships between a set of objects. Kitiyanan and Pornpanomchai [7] applied a neural network to recognize 1,000 Buddhist amulet images of 10 classes. The precision rate of the system was 97.67 percent. Laongkum and Kumeechai [8] implemented the Buddhist amulet classification with a wavelet transform and neural network on 40 types of amulets, with a total of 1,400 images. The system precision rate was 90.80 percent. Mookdarsanit [9] checked the originality of a Buddhist amulet by using a convolutional neural network, with the accuracy rate of 90.00 percent. Butploy and Boonying [10] employed a convolutional neural network to recognize 5 classes of Buddhist amulets called "Ben-ja-paa-kee", with a total of 500 images. The precision rate of the system was 88.88 percent.

Convolutional neural network

A convolutional neural network (CNN) architecture consists of 4 components, which are an input-layer component, convolutional-layer component, full connection-layer component and output-image component, as shown in Figure 2 [11]. The input-layer component feeds an input image to the CNN. The convolutional-layer component combines local connections, weight sharing and pooling operations together. The full connection-layer component extracts various input-image features and applies a full connection neural network to classify a recognition result. Finally, the output-image component shows the output result.

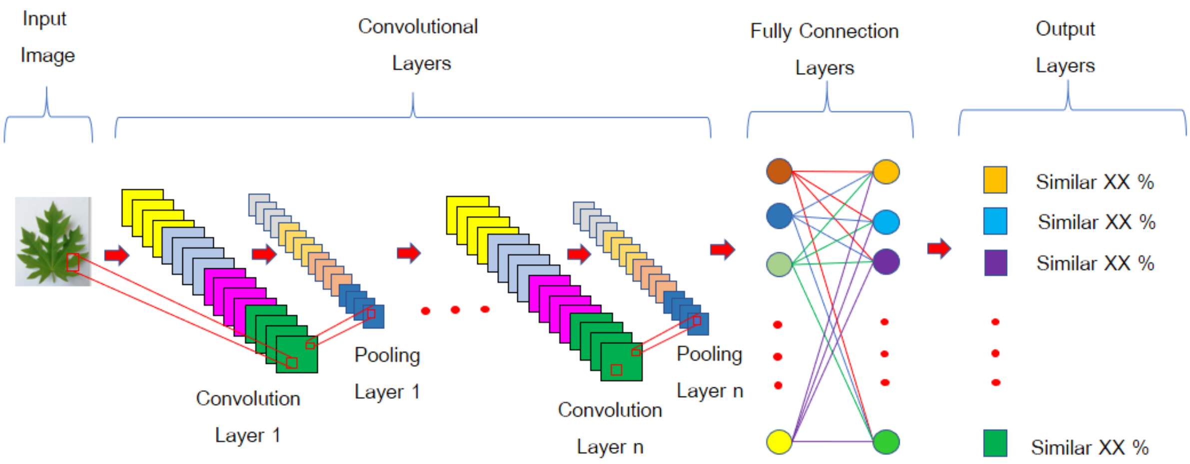

Figure 2 The convolutional neural network architecture

ResNet50 is a convolutional neural network, which consists of 50-layer depth. It works by using residual blocks to stack over previous residual blocks to increase the network's accuracy. Moreover, the ResNet50 can skip some unnecessary residual blocks to save the processing time but VGG16, MobileNet, and Inception do not have this process [12]. Deshpande [13] used GoogleNet, AlexNet, VGG16, ResNet50 and Inception V.3 to classify 2,900 brain tumor images. The accuracy rate of the training dataset for each CNN model is shown in Table 1 and the ResNet50 is shown to have the highest accuracy.

Table 1 CNN accuracy comparison

CNN Model	**accuracy rate (%)**
GoogleNet	81.67
AlexNet	91.84
VGG16	93.06
ResNet50	**98.14**
Inception V.3	90.79

Based on the previous research works, the Euclidean distance is unsupervised learning techniques, but the K-nearest neighbors, the neural network and convolutional neural network are supervised learning techniques. A supervised learning method has a procedure to learn the objects before recognizing them but an unsupervised learning method does not have the learning procedure. The unsupervised method just extracts such Buddhist amulet features~~,~~ as color, shape, texture, etc., and then recognizes the amulet by comparing the similarity between the features. The convolutional neural network technique can recognize a Buddhist amulet with higher precision rates than the Euclidean distance or K-nearest neighbor techniques. Therefore, this research adopts the ResNet50 of the convolutional neural network (CNN), which is a powerful technique to recognize Buddhist amulets. The BARS conducted the experiment with a bigger dataset than the previous research, aimed at making concrete experimental results. Moreover, this research compares the accuracy of ResNet18, ResNet50 and ResNet101, with the same amulet dataset. The details of system design and implementation are presented as follows:

Materials and Methods

BARS was developed on the following computer hardware and software. The Intel(R) Core(TM) i5-11400HQ CPU @ 2.60GHz was used as the central processing unit and Windows 10 was the software system. MATLAB R2020b with license number 40598465 was the developing software. The digital cameras used in this research were Huawei Y9.

Conceptual diagram

The BARS conceptual diagram starts with a user capturing a Buddhist amulet image by using a simple mobile phone camera. Then the amulet image is submitted to the computer system for recognition. The BARS identifies an unknown Buddhist amulet by matching it with the Buddhist amulet training dataset, using a deep learning technique. Finally, the system displays the recognition results, as shown in Figure 3.

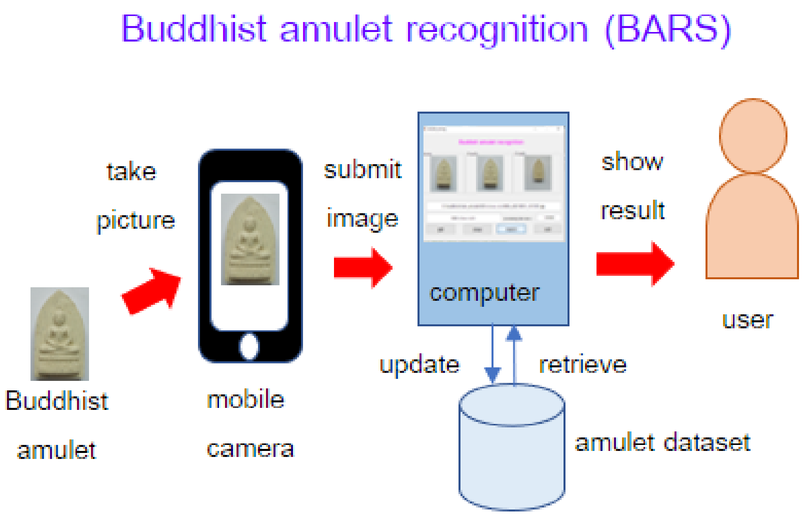

Figure 3 The BARS conceptual diagram

System structure chart

The BARS structure chart consists of four main modules, namely: 1) training dataset module, 2) image acquisition module, 3) ResNet50 classification module and 4) result presentation module, as shown in Figure 4. The ResNet50 classification module contains five submodules, which are 1) input image submodule, 2) convolution submodule, 3) pooling submodule 4) ~~fully~~ connection submodule and 5) evaluation result submodule. The details of each module are revealed as the following:

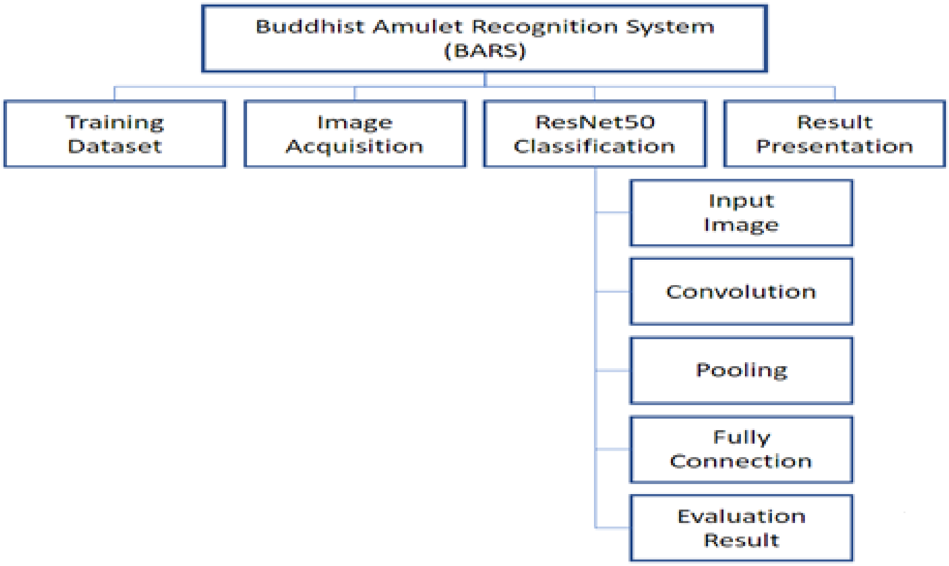

Figure 4 The BARS structure chart

Training dataset module

Regarding our BARS, ResNet50 is trained using our Buddhist amulet dataset. The CNN is famous and commonly used to implement image recognition without human supervision [14]. This research separates the training-dataset into two parts, which are the training part and the testing part. The training part consists of 80% of the dataset randomly selected while the remaining 20% of the dataset is the testing part. The structure of ResNet50 contains five components, namely: 1) input component, 2) convolutional component, 3) pooling component, 4) fully connected component and 5) classification result [15]. The average training-dataset time is 3,183.2 Seconds or 53 Minutes and 8.2 Seconds. The dataset consists of 3,248 images, which are 203 Buddhist amulet categories containing 16 images each.

Image acquisition module

The Buddhist amulets in this research were captured by a normal mobile phone camera under an uncontrolled environment. The distance between the camera and amulets was 15 centimeters. The system dataset consisted of both metal & clay amulets, broken down into 146 metal amulets and 57 clay ones. The photos of both front and rear sides of each Buddhist amulet were taken. The top of both sides points towards 8 directions, namely: 1) north, 2) north-east, 3) east, 4) south-east, 5) south, 6) south-west, 7) west and 8) north-west (as shown in Figure 5 (a) – 5 (p), respectively). The format of the input image should be a .JPG file. The size of the input image is 4,160 x 3,120 X 3 (pixels X pixels X planes).

Figure 5 The Buddhist amulet taken in 8 directions of both the front and rear of the amulet.

ResNet50 classification module

The ResNet50 is a convolutional neural network (CNN) model, which is modified from a visual geometry group (VGG) network. It is an effective tool for image classification tasks. The architecture of the ResNet50 consists of five components, which are 1) input image component, 2) convolutional component, 3) pooling component, 4) fully connection-network component and 5) classification output component, as shown in Figure 6. Each component has the following details.

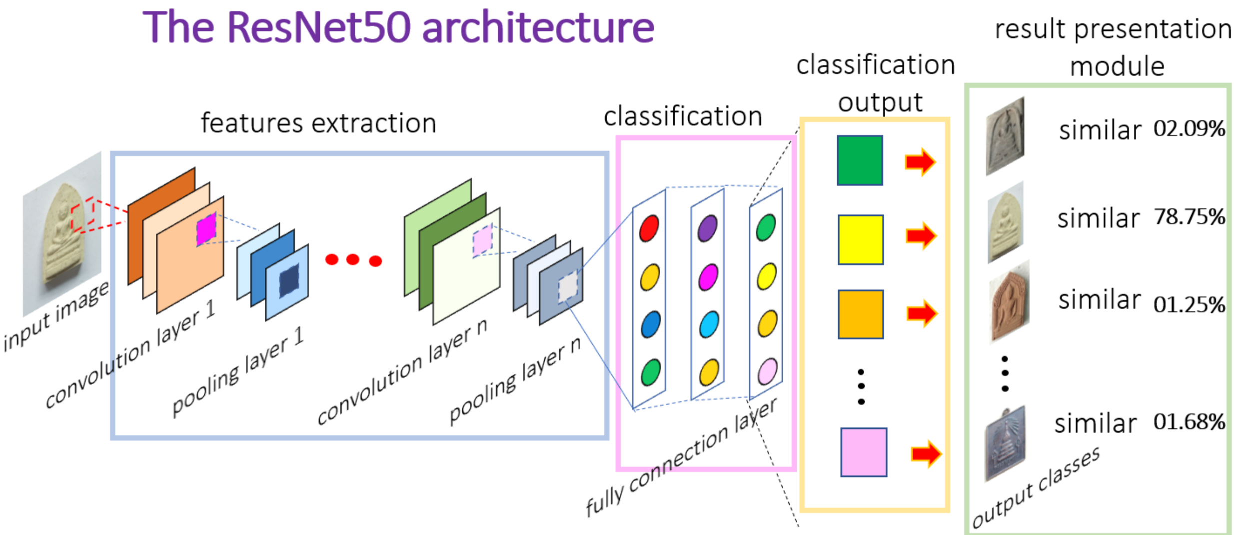

Figure 6 The architecture of ResNet50 in this research

Result presentation module

This module shows the Buddhist amulet recognition results. The BARS graphic user interface (GUI) is composed of three display-graphic windows, three display-text boxes and four push buttons, as shown in Figure 7.

The three display-graphic windows have the following details:

1) In the label 1 of Figure 7, the display-graphic window for showing the amulet input image.

2) In the label 2 of Figure 7, the display-graphic window for showing the front image of recognizing the result.
3) In the label 3 of Figure 7, the display-graphic window for showing the rear image of recognizing the result.

The three display text boxes have the following details:

1) In the label 4 of Figure 7, the display of the input path and filename box.
2) In the label 5 of Figure 7, the display of the recognition amulet-name box.
3) In the label 6 of Figure 7, the display of the average access time box.

The four push buttons have the following details:

1) In the label 7 of Figure 7, the get image button for getting the Buddhist amulet image.
2) In the label 8 of Figure 7, the clear button for clearing all the BARS system values.
3) In the label 9 of Figure 7, the recognition button for recognizing the Buddhist amulet.
4) In the label 10 of Figure 7, the exit button for exiting the system

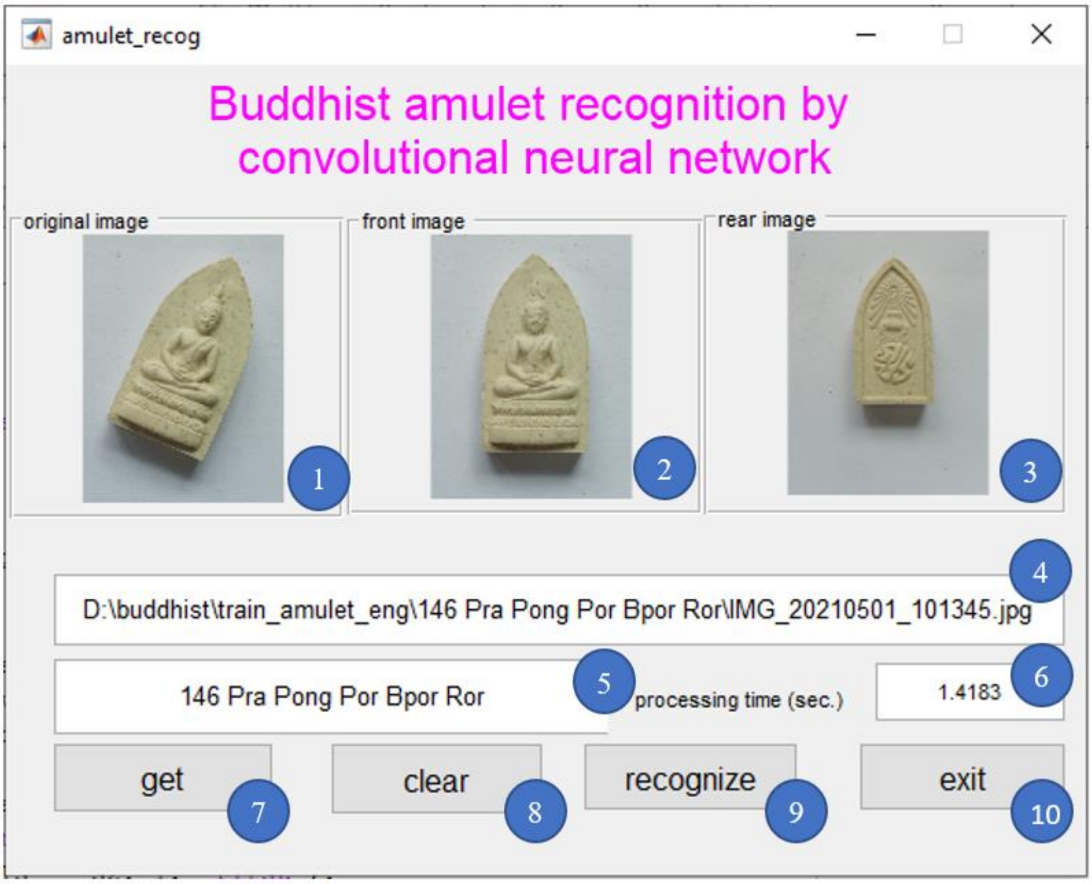

Figure 7 The GUI of the BARS system

Results and Discussion

Experimental results

There are two categories of Buddhist amulets processed on the BARS system as follows: 1) metal amulets, containing 146 amulet types and 2) clay amulets, containing 57 amulet types. 16 pictures in 8 directions of both the front and the rear were taken of both the metal and clay amulets, as shown in Figure 5. The total number of the Buddhist amulet images in the BARS dataset is 3,248 (146 X 16 + 57 X16) images, which are stored in 203 folders. The system employed the MATLAB convolutional neural network, called "ResNet50", to recognize the Buddhist amulet dataset. The system randomly selected 80 percent of the dataset for training and 20 percent for testing the CNN. After that, the BARS system applied the MATLAB function called "confusion.getMatrix" to calculate statistical values for measuring the system performance. There are three calculation procedures, namely, convert multi-class confusion matrix, calculate the statistical values, and find an average of the statistical values [16]. Each procedure has the following details.

3.1.1 Convert the multi-class confusion matrix output to a true positive (TP), false positive (FP), false negative (FN) and true negative (TN), as shown in Table 2

Table 2 The confusion matrix of the training dataset

		True class	
		positive	negative
Prediction class	positive	3,209 (TP)	39 (FP)
	negative	39 (FN)	656,057 (TN)

Remarks: TP = true positive; FP = false positive; FN = false negative; TN = true negative

3.1.2 Calculate the statistical values, namely: accuracy, sensitivity, specificity and precision of the Buddhist amulet types. Each statistical value has the following details.

3.1.2.1 Accuracy is one of the most common measurements of recognition performance and it is defined as the ratio between the correct object recognition and the total number of objects, as shown in Equation 1.

$$\text{accuracy} = (TP + TN) / (TP + FP + FN + TN) \quad (1)$$

3.1.2.2 Sensitivit y (true positive rate, hit rate or recall) represents the ratio of the positive correct object recognition to the total number of positive objects, and it is estimated according to Equation 2.

$$\text{sensitivity} = TP / (TP + FN) \quad (2)$$

3.1.2.3 Specificity (true negative rate or inverse recall) is expressed as the ratio of the correctly recognize negative objects to the total number of negative objects, as shown in Equation 3.

$$\text{specificity} = TN / (FN + TN) \quad (3)$$

3.1.2.4 Precision is a measure of how well a recognition performs with a specific object, as shown in Equation 4.

$$\text{precision} = TP / (TP + FN) \quad (4)$$

3.1.3 Find an average value of accuracy, sensitivity, specificity and precision from 203 Buddhist amulet types. These are the results:

accuracy:	0.9998
sensitivity:	0.9879
specificity:	0.9999
precision:	0.9879

The average access time of BARS is 1.3468 s/image. The learning curve of the BARS system shows both precision and loss curves with maximum 16 epochs, one iteration per epoch and learning rate 0.01, as shown in Figure 8.

Figure 8 The learning curve of the BARS training dataset

Cross-validation

BARS employed 15 untrained Buddhist amulet types, with 16 images per each type (15 X 16 = 240 images) for the cross-validation process. The confusion-matrix for cross-validation is shown in Table 3. Then the accuracy, sensitivity, specificity and precision of the validation dataset listed in Equations 1 to 4 were calculated as the following values.

accuracy:	0.9999
sensitivity:	0.9541
specificity:	0.9999
precision:	0.9541

Table 3 The confusion matrix of the cross-validation dataset

		True class	
		positive	negative
Prediction class	positive	229 (TP)	11 (FP)
	negative	11 (FN)	656,085 (TN)

Remarks: TP = true positive; FP = false positive; FN = false negative; TN = true negative

Some of the mismatched amulet images are shown as Figure 9 (a) and (b), the Pra Pong Pra Put Ta So Ton in pink (Figure 9 (a), Label 1) mismatches to the front of Pra Phong Pra Put Ta So Ton in light purple (Figure 9 (a), Label 2) and the rear of Pra Phong Pra Put Ta So Ton in light purple (Figure 9 (a), Label 3). Also, the Pra Pong Pa Put Ta Chin Na Rat (Figure 9 (b), Label 4) mismatched with the front of Pra Pong Som Dej Pat Ta Ra Ma Ha Rat (Figure 9 (b), Label 5) and the rear of Pra Pong Som Dej Pat Ta Ra Ma Ha Rat (Figure 9 (b), Label 6)

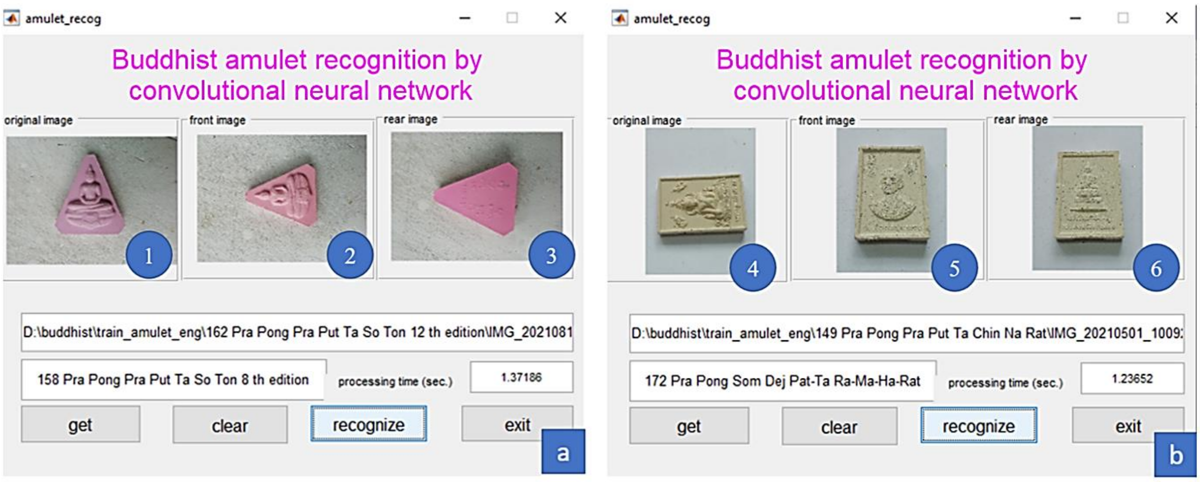

Figure 9 Some examples of mis-recognition in this research (a) Pra Pong Pra Put Ta So Ton in different colors but the same shape and size (b) Pra Pong Pa Put Ta Chin Na Rat with the same color, shape and size with Pra Pong Som Dej Pat Ta Ra Ma Ha Rat

ResNet comparison

This research was conducted on 3 different ResNet versions, namely: ResNet18, ResNet50 and ResNet101, with the same Buddhist amulet dataset. These 3-ResNet versions are supported by the MATLAB 2020b version. The comparison of accuracy, sensitivity, specificity, precision and training times is shown in Table 4. The ResNet18, ResNet50 and ResNet101 have network architectures of 18-layer, 50-layer and 101-layer depth, respectively. ResNet18 gives the shortest training time, with the lowest precision rate, and ResNet101 gives the longest training time, with the middle precision rate. ResNet50 generates the highest precision rate, with medium training time. Therefore, ResNet50 was selected to conduct the experiment because it gave the highest precision rate.

Table 4 Performance and training time comparison.

ResNet architecture	Accuracy	Sensitivity	Specificity	Precision	Training time (sec.)
ResNet18	0.9625	0.9625	0.9997	0.9759	1961.8
ResNet50	0.9998	0.9879	0.9999	0.9879	3183.2
ResNet101	0.9721	0.9721	0.9998	0.9806	4361.3

Discussion

Many researchers applied different image processing techniques to identify Thai Buddhist amulets, as shown in Table 5. There is no consensus as to which recognition techniques are the best to recognize a Buddhist amulet. Most of the researches in Table 5 have precision rates of around 90.00 percent. However, all of the researches conducted experiments with a small dataset size, compared with the total number of Buddhist amulets in Thailand. This research tried to capture more images and create a bigger amulet dataset, aimed at making concrete experimental results.

Table 5 Comparison of dataset sizes among previous Thai Buddhist amulet recognition researches.

Researcher name (year)		Techniques	Dataset size (images)	Precision rate
Pornpanomchai, (2010)	[4]	Euclidean distance	318	80.00%
Fugthong, (2013)	[5]	k-nearest neighbors (KNN)	1,400	98.97%
Kitiyanan, (2014)	[7]	artificial neural network (ANN)	1,000	97.67%
Kompreyarat, (2015)	[6]	k-nearest neighbors	240	89.35%
Mookdarsanit, (2019)	[9]	convolutional neural network (CNN)	n/a	90.00%
Laongkum, (2020)	[8]	wavelet transform / ANN	1,400	90.80%
Butploy, (2020)	[10]	convolutional neural network	500	88.88%
This research (2021)		convolutional neural network	3,248	98.79%

There are two difficult problems found in developing a Buddhist amulet recognition system. First is an unlimited Buddhist amulet dataset, with the history of Buddhist amulets starting more than 780 years ago (Sukhothai era) and new Buddhist amulets being made every year. Even in Thailand, no one can give an exact number of Buddhist amulets. Therefore, it is impossible for researchers to create a complete amulet dataset. Secondly, some Buddhist amulets are old, rare and very expensive. For example, Som Dej Wat Rakhang Kositaram (1788 – 1872) is made from clay in a small size of about 2.2 X 3.5 X 0.4 centimeters, but it is worth around 24-million-baht or 720,000 USD [17]. Consequently, a lot of fake amulets have appeared in every part of Thailand. Only an expert, not the ordinary person, can identify real or fake Buddhist amulets. Many people have asked for researchers to establish an expert system which can identify real or fake Buddhist amulets. Therefore, many scientists and researchers have tried to solve both challenging tasks in a Buddhist amulet recognition system. Won-in et al.

employed non-destructive analysis called "particle induced x-ray emission (PIXE)" to investigate many substances, namely: Al, Si, K, Ca, Ti, Mn, Fe, Cu and Zn in the Som Dej Wat Rakhang Kositaram amulet [18]. Moreover, an image processing technique is also a non-destructive analysis method, which is used for the investigation of real Buddhist amulets.

Conclusion

The BARS system fulfills the objective of this research, which is to develop a computer system recognizing Thai Buddhist amulets. The system processed 3,248 Buddhist amulet images, belonging to 203 types. BARS employed the MATLAB convolutional neural network called "ResNet50" to recognize the Buddhist amulet images. Moreover, the system used the MATLAB confusion matrix routine called "confusion.getMatrix" to analyze the experimental results. The precision rate of the system was 98.79 percent, with ~~an~~ average access time of 1.3468 s/image.

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