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THAI BUDDHA AMULET CLASSIFICATION USING DISCRETE WAVELET TRANSFORM AND TRANSFER LEARNING

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Abstract. *Most of Thai people believe that wearing the amulets endows wearers with the holy's faith and supernatural power. Traditionally, Thai Buddhist amulets are made by using the Buddha image and the famous Thai monks. These days, the Buddhist amulets go beyond the doctrine belief to the big business in Thailand. In the collectibles market, the authentic amulets made and blessed by the famous monks a hundred years ago can be sold for 10 million baths upwards. Therefore, fraudulent people made counterfeit Buddhist amulets to sell in the market. These fake amulets never chanted consecrated by monks under the right ceremony in the temple to make them holy, but they were made massively by fake moulds and materials. This paper aims to classify the Benjapakee Buddha amulets (Phra Somdej Toh, Phra Nangphya, Phra Phong Suphan, Phra Rod, and Phra Sumko) by using the transfer learning technique with discrete wavelet transform as the feature extraction. Our proposed model was tested in the real world by using the retrieved images of Buddha amulets from Google and obtained the results of 0.9367, 0.9379, and 0.9373 for precision, recall, and F1 score, respectively. We also compared our work with the GoogleNet. The deployment of the model, discussions and further remarks are also provided in this paper. This work was implemented using MATLAB R2021a.*
Keywords: Thai Buddha amulets, Benjapakee Buddha amulets, Discrete wavelet transform, Transfer learning, Classification, Feature extraction

1. **Introduction.** Thai Buddhist amulets are being worn in Thailand from centuries. Thai Buddhist amulets are also known as a good luck charm and Thai Buddhist people always wear at least one amulet to repel disease, witchcraft, and misfortune by wearing on a cord of chain around the neck [1]. In the past, Thai Buddhist monks gave amulets to their disciples in a special occasion. Amulets are made using the Buddha image and the famous Thai monks, and amulets can be made various in size, shape, and materials such as plaster, bone, wood, or metal [2,3]. Figure 1(a) shows Thai man wearing the collection of amulets in chain around his neck. When an artist made the amulets, to make them powerful to repel bad luck, an artist will ask a monk or a group of monks to chant, pray, and bless the amulets by setting the spiritual environment in the temple to get close to the holy Buddha. Sometimes this process can be taken a week to a month to accomplish. Figure 1(b) shows the setting of ceremony and the group of monks are blessing the amulets in the temple. As times goes by like a half of century or a century, the amulet prices (the amulet which is blessed by the famous monk) can be increased in the collectibles market (depends on the ages of amulet and the master monk who blessed the amulet) [4].

These days, Thai Buddhist amulets are not only the spiritual holy item, but they are also the valuable item in the collectible's world. The rare precious amulets, e.g., the

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(a) (b)

Figure 1. Thai Buddhist man wears amulets on a cord of chain around his neck, and some of amulets were made using the famous Thai monk images (a); the monks are blessing the amulets (b) [4]

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

Figure 2. Some of the most expensive Thai Buddhist amulets: The Benjapakee Buddha amulets (a), Luang Puu Kai amulet (b), Phra Kring Pawareth (c), Phra Khun Phaen (d), and Phra Pid Tra (e) [5]

Benjapakee Buddha amulets, Luang Puu Kai amulet from Cherng Lane temple, Phra Kring Pawareth (Ringing amulet), Phra Khun Phaen, and Phra Pid Tra (Figure 2), can cost hundreds of thousands of dollars [5].

In this paper, we proposed the transfer learning technique with discrete wavelet transform (DWT) as the feature extraction to classify the Benjapakee Buddha amulets (one of the most expensive amulets in Thailand). We gathered the images of Benjapakee Buddha amulets from Google images and used image processing techniques, e.g., gray level imaging, rescaling, binarizing, and masking for preprocessing our dataset. The feature extraction and classification model were applied in the later steps, and this work was implemented using MATLAB R2021a. This paper is organized as follows. Section 2 describes the problem statement and literature reviews. The implementation is shown in Section 3. Section 4 describes the experimental results and discussions. The conclusions are mentioned in Section 5.

2. **Problem Statement and Preliminaries.** As the spiritual holy item turns to the business, fraudulent people made counterfeit Buddhist amulets to sell in the market by using fake moulds and materials in a scam business. The main contribution of this work is the classification of the Benjapakee Buddha amulets (Benja means five and Pakee means participant), which is the collection of Phra Somdej Toh, Phra Nangphya, Phra Phong Suphan, Phra Rod and Phra Sumko; a collection of the most expensive Thai Buddhist amulets. We collected the images of the Benjapakee Buddha amulets from Google images and used DWT as the feature extraction. We used transfer learning or pre-trained network for generating our classification model. The objective of this work is to classify the Benjapakee Buddha amulets from the other Buddhist amulets which might be fraudulent or similar to the Benjapakee collection.

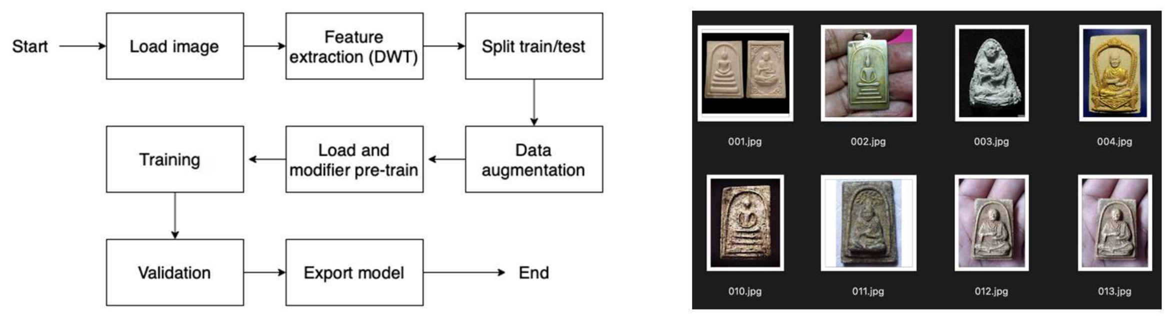
To extract the low dimensional feature in image processing, Haar wavelet or DWT is the practical tool for image analysis applications (recognition and classification tasks).

There are two types of DWTs, 1-dimensional wavelet transform (1D), and 2-dimensional wavelet transform (2D). DWT is a powerful method for describing signals both in time and frequency domain simultaneously [6]. Until this day, DWT has been applied in many applications such as [7,8]. In [7], DWT was used in transient signal analysis in electric power systems. The good property of DWT for capturing the multi-resolution signal is the best practice for critical analysis in electrical power plants because the system must deal with the dynamic factors which are changing all the times. In [8], DWT was also applied in digital signal processing to removing noise in measurement process. The external electrical noise is often induced in the electrochemical electrode scanning process which causes an error in signal measurement. To remove the external noise, DWT was used to carry electrical noise with signal to noise ratio (SNR). By setting the appropriate SNR threshold, the noise can be removed; therefore, it increases the accuracy of digital measurement.

To identify the Buddha amulets by using simple local correlation features in texture map introduced by [9], the paper claimed that the method could deal with the variety of materials composed in amulets. The work generated a plain background color and computed the difference of intensity between each pixel to find the local correlation. The work used the K-nearest neighbors as classification technique; the model gained the recognition rate about 89.35%. The shortage of the work is that the texture map itself cannot be used as the important feature to describe the properties of image, e.g., image couture and boundary. The classification of the Buddha amulets using deep learning technique was proposed by [10]. The paper used the applied convolutional neural network (CNN) system model to classify the Benjapakee Buddha amulets. The modified model used 3-layer CNN. Without any use of image processing technique and data augmentation method, the major drawback of the work is the unbalanced dataset and poor of the number of training data. The results of classification were claimed that the model could identify Phra Somdej Toh, Phra NangPhya, Phra Rod and Phra Somko with the accuracy of 0.8 and Phra Phong Suphan images with the accuracy of 0.7. The online validation of genuine Buddhist amulets was proposed by [11]. The concept of the system is simple as the middleman where the system manages the amulet experts and the collectors into the same place. The system was trained by the amulet experts using deep learning with 75% of accuracy. The system also acts as the quality assurance agency to the collectors in online market. By the way, the major shortage of the work is the dependence of amulet experts (without any attempt of applying machine learning or computer visions technique). The difficulties to identify the ancient murals usually are the damage caused by natural factors, the low resolution of image, and the similarities in content of murals. The classification in artworks and crafts using deep learning and transfer learning was also included in [12-14]. The emerging issue of ancient murals classification was introduced in [12]. The paper proposed CNN for mural image classification with computer vision technique to deal with multiple low-level features extraction, e.g., color and texture in mural image. Pre-trained VGGNet was used to generate mural image classification model. The experiment gave the results of 80.64%, 78.06% and 78.63%, for precision, recall, and F1 score, respectively, over the constructed mural dataset. In [13], the paper compared all models including transfer learning model for classifying the artworks in the digital format into 3 classes: genres, styles, and artists. The evaluation of 7 different models was done in the art gallery and museum. The pre-trained models included ResNet and its variants (e.g., RegNet, ResNeXt, Res2Net, ResNeSt, and EfficientNet) and CNN. The implementation of the work was done using 3 different datasets (Painting-91, WikiArt-WikiPaintings, and MultitaskPainting100k). In [14], the classification of the authentic Thai weaving patterns and applied Thai weaving patterns using CNN was investigated. The work trained 28 classes of the authentic Thai weaving pattern with adjusted CNN; the work also used the CutMix algorithm as data augmentation process to increase the number of weaving patterns. More works of deep learning in the classification of ancient objects were also investigated in [15-17]. In [15], the paper proposed a transfer learning-fused Inception-v3 model for dynasty-based classification. The model gave the results of 88.4%, 88.36%, and 88.32%, for precision, recall, and F1 score, respectively, on a constructed small dataset. In [16], the work used CNN to classify various image and photo of an ancient temple. The model gained an accuracy of 98.99% on the training set and accuracy of 85.57% on the test set, and there was not any additional image processing technique implemented in this work. The CNN for estimating the ages of bone in the archaeological record was proposed in [17], and the work used CNN to estimate the probability of multiple structures to identify similar and dissimilar marks on bones. The work used the model to estimate the ages of 3 types of mark (cut, tooth, and trampling marks) with the accuracy of 92%.

3. **Methods.** Our proposed method used the combination of DWT and transfer learning, which greatly improve accuracy and computational cost. The implementation of both DWT and transfer learning in this work was done using MATLAB R2021a (9.10.0.166983 1). We also used the image processing commands in MATLAB for preprocessing the images such as image resizing and image transform (color image to gray scale image). Data augmentation process requires the image processing toolbox to run the MATLAB commands for generating more images from the original one, e.g., rotation, reflection, filtering (masking), shearing, and cropping. DWT was used as feature extraction for decreasing feature vector size. We used transfer learning (ResNet-50) to generate our classification model. The block diagram of the proposed method is presented in Figure 3(a). The explanation of the block diagram will be described later throughout in this section.

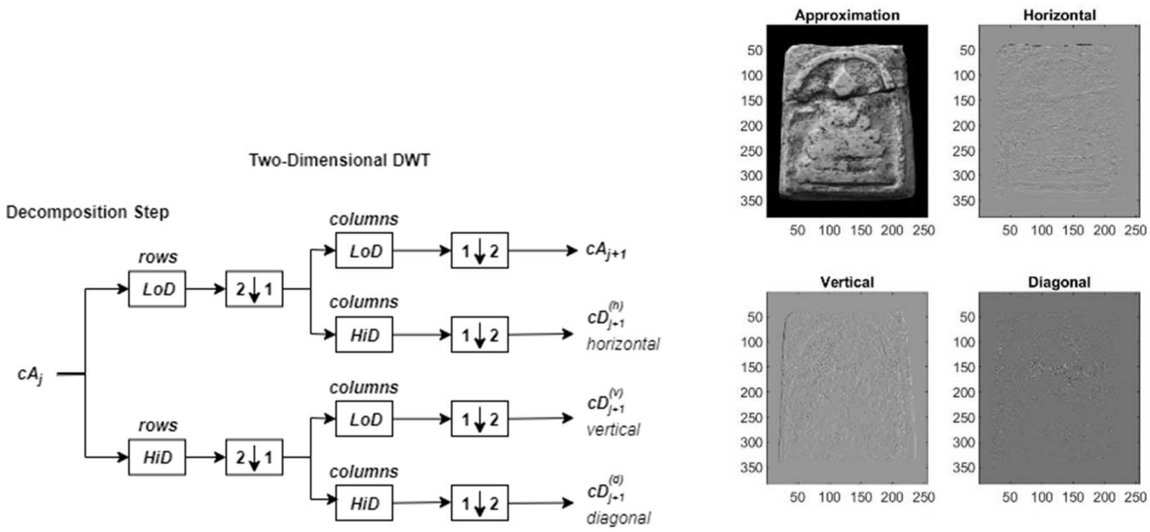
We gathered dataset by saving images from Google image by using the Google custom image search and the Javascript console in Chrome, and we retrieved the bunch of Thai Buddha amulet image URLs in a CSV file. In this case, our dataset has 5 classes, consisting of Phra Somdej Toh, Phra Nangphya, Phra Phong Suphan, Phra Rod, and Phra Sumko. Each class contains 100 images. The examples of Thai Buddha amulet dataset are also shown in Figure 3(b).



(a) (b)

Figure 3. The block diagram of the proposed method (a); the examples of Thai Buddha amulet dataset (b)

In DWT process, an input image is read for feature extraction, it will be extracted into four new images. Those new ones are reduced to 1/4 of the original size. Thus, four components: LL, LH, HL, and HH corresponding to the approximation, horizontal, vertical, and diagonal values of the respective properties are generated at each branching level. New images are named after a filter (low-pass or high-pass), which is applied to the original image horizontally and vertically. Figure 4(a) describes the basic decomposition steps for images and Figure 4(b) shows the results of DWT for Thai Buddha amulet image.



(a) (b)

Figure 4. The decomposition step of 2D DWT, the input image will be divided into 4 sub-images corresponding to its rows and columns (a); the DWT of an input image (b)

We split the dataset into train dataset and test dataset by using the MATLAB function "splitEachLabel()". This function allows us to split the dataset by setting the split ratio; in this work, we set the split ratio to 0.9. Therefore, train dataset will be 90% of the dataset and test dataset will be 10% of the dataset. We augmented the dataset to match our preferences. Due to a lack of data, we needed data augmentation to increase the number of Thai Buddha amulet images enough for training the model. In this case, we used 2 image processing techniques (rotation and reflection) in data augmentation process. We augmented data for both of train and test dataset to improve the accuracy of the model (we did the same command for the test dataset as well).

Transfer learning is a technique used to reduce the computational cost for training a brand-new deep learning model but applying some parts of existing pre-trained model which already generated to solve the new problem. The well-known pre-trained models with the accuracy (Keras applications) such as Xception (Top-5 accuracy = 0.790), InceptionV3 (Top-5 accuracy = 0.937), and ResNet152V2 (Top-5 accuracy = 0.942). ResNet or Residual Network uses the rest of the learning instead of trying to learn some features. The rest can be simply understood as removing the properties learned from that layer's input [18]. There are some variations of ResNet, in addition to ResNet-50. Normally, the ResNet consists of 34 layers; instead of training all of 34 layers, the main idea of ResNet is to offer shortcut or bypass connections which allows to cross one or more layers. In our work, we selected ResNet-50 with weight from ImageNet. Once the network was loaded, we used MATLAB "deepNetworkDesigner" to modify the network by changing the number of classes corresponding to our works. We trained the new network by replacing the last layer with the new one. We replaced some layers of networks and exported the modified network back; the important parameters were setting up for training our model such as the optimization algorithm = "Adam", the execution environment = "parallel", the minibatch size = 128, and the learning rate = 0.0003. We set the output size = 5 according to the 5 classes of Thai Buddha amulet images. When all settings were already set, we trained our model by using augmented training data and modified pre-trained model as we described. Our final model is shown in Figure 5.

The modified ResNet-50 consisting of the convolutional layer received the input = $224 \times 224 \times 3$ and generated the output = $7 \times 7 \times 64$; the bypass layer 1: the convolutional

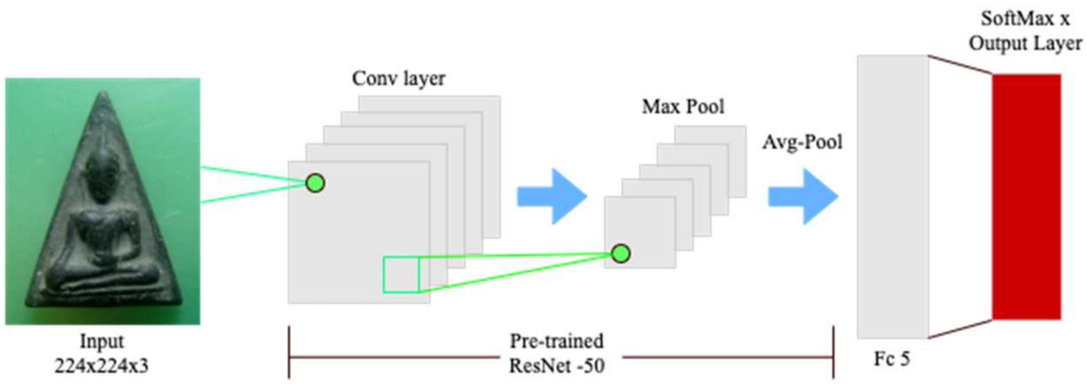


FIGURE 5. The proposed model

layer received the input $= 1 \times 1 \times 64$, and generated the output $= 1 \times 1 \times 256$; the bypass layer 2: the convolutional layer received the input $= 1 \times 1 \times 128$, and generated the output $= 1 \times 1 \times 512$; the bypass layer 3: the convolutional layer received the input $= 1 \times 1 \times 256$, and generated the output $= 1 \times 1 \times 1024$; the bypass layer 4: the convolutional layer received the input $= 1 \times 1 \times 512$, and generated the output $= 1 \times 1 \times 2048$; the average pooling will pass the output to the fully connected (5 layers); the output layer used the SoftMax activation function.

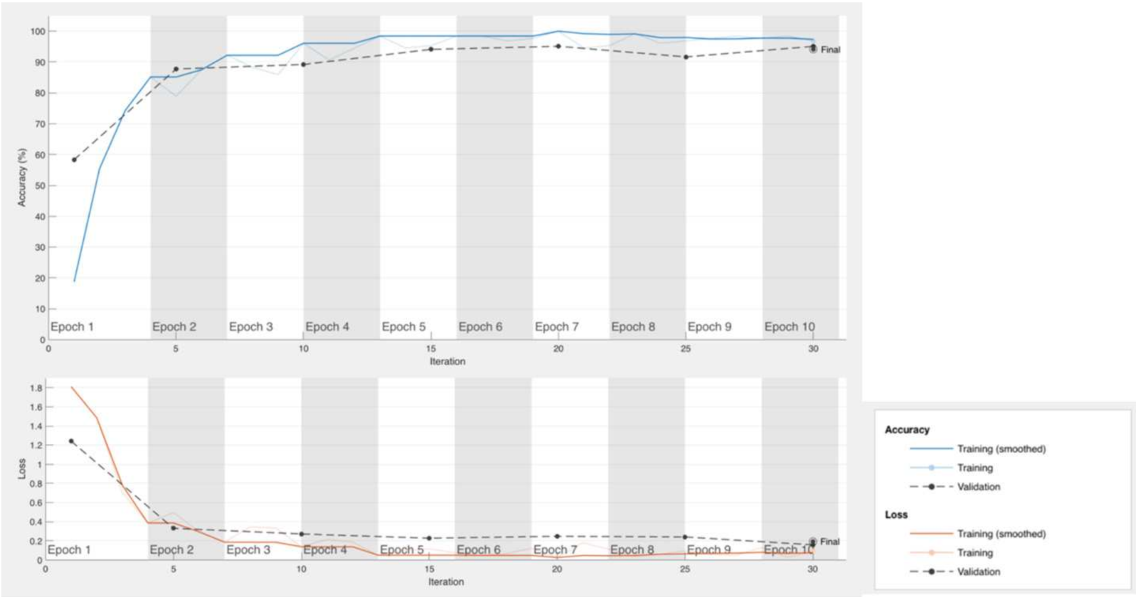
4. **Results and Discussions.** The experimental results are shown in this section and we also show how to deploy our model via web-based application. The results of the training process are shown in Table 1 and the accuracy and loss of our model are also shown in Figure 6(a). The model yielded 94.12% of accuracy at 30 epochs. We estimated the accuracy of this network by testing the image dataset that we separated earlier (the MATLAB generated the predicted scores as shown in Figure 6(b)). For an example of the result in row no.4, the proposed model gave the true prediction = 99.98% (a true label is Phra Nangpyha, and the model predicted that it was Phra Nangpyha with the scores = 0.9998; whereas the model predicted that it was Phra Phong Suphan with the scores = 0.0002). The rest of true prediction in Figure 6(b) shows that our proposed model can classify the true label (Phra Nangpyha) correctly.

TABLE 1. Training process and parameters

Epoch	**Iteration**	**Time elapsed (hh:mm:ss)**	**Mini batch accuracy (%)**	**Validation accuracy (%)**	**Mini batch loss**	**Validation loss**	**Base learning rate**
1	1	00:01:53	18.75	58.33	1.8108	1.2415	0.0003
2	5	00:06:47	78.91	87.75	0.4956	0.3318	0.0003
4	10	00:12:18	96.09	89.22	0.1393	0.2726	0.0003
5	15	00:17:19	95.31	94.12	0.1172	0.2281	0.0003
7	20	00:22:13	100.00	95.10	0.0267	0.2484	0.0003
9	25	00:26:45	96.88	91.67	0.0968	0.2411	0.0003
10	30	00:31:23	96.88	95.10	0.0937	0.1594	0.0003

The confusion chart in Figure 7 is also provided to show the categories which network was not able to classify accurately; therefore, we can check our data and retrain the network with improved data to see whether it rectifies the issue.

We evaluated our model by using precision, recall, accuracy, and F1 score. We compared our approach to GoogleNet. The criteria used for comparison are precision, recall,



(a)

```
[predicted,scores] = classify(MonkNet,valset);
tableofscores = [table(predicted) array2table(scores,"VariableNames",categories(valset.response))]
```

tableofscores = 204×6 table

	predicted	Pha Nangphya	Pha Phong Suphan	Pha Rod	Pha Somdej Toh	Pha Sumko
1	Pha Nangphya	0.9886	0.0113	7.3655e-05	1.5803e-05	6.0555e-07
2	Pha Nangphya	0.9702	0.0298	7.0271e-10	8.1221e-08	7.5123e-11
3	Pha Nangphya	0.9765	0.0226	4.9330e-06	8.7776e-04	6.9879e-07
4	Pha Nangphya	0.9998	0.0002	1.5067e-07	4.4604e-08	1.0148e-08
5	Pha Nangphya	0.9032	0.0961	6.5279e-04	6.3139e-05	6.3149e-07
6	Pha Nangphya	1	0	1.0457e-13	6.4879e-14	4.1017e-14
7	Pha Nangphya	0.9180	0.0820	7.1358e-06	3.9802e-07	2.9007e-07
8	Pha Nangphya	1	0	6.4889e-12	1.5884e-11	4.9844e-13
9	Pha Nangphya	0.9997	0.0003	2.8860e-07	2.2387e-08	2.0001e-09

(b)

FIGURE 6. The accuracy and loss of the proposed model (a); the evaluation of the model (b)

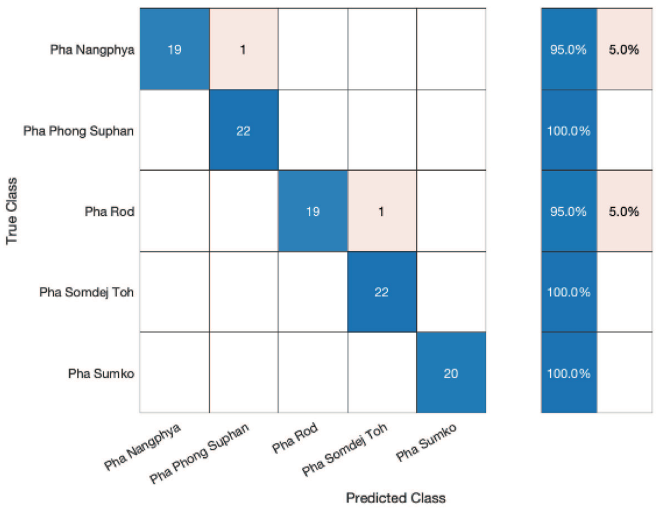


FIGURE 7. The confusion chart of misclassification

Table 2. The comparison of precision, recall, F1 score, training duration and accuracy between the proposed model and GoogleNet

Model/Criteria	**Precision**	**Recall**	**F1 score**	**Training duration (minute)**	**Accuracy (%)**
The proposed method	0.9367	0.9379	0.9373	29.14	94.12
GoogleNet	0.9076	0.9097	0.9087	14.7	89.71

F1 score, training duration, and accuracy. The comparison of the criteria between our proposed model and GoogleNet is shown in Table 2.

The proposed model which we used in this study provided better results in all criteria than GoogleNet (precision, recall, F1 score, training duration, and accuracy) as shown in Table 2. MATLAB also provided the deployment of model. We deployed our model to the web application. MATLAB GUI of this work is shown in Figure 8, Thai Buddha amulet image will be loaded on the left side of the GUI and the results of classification will be shown on the right side of the GUI which are true label, ResNet predicted label, confident scores of ResNet prediction, GoogleNet predicted label, and confident scores of GoogleNet prediction. Figure 8 shows the results of the classification, Thai Buddha amulet image will be browsed and loaded into the panel, and the results of the classification will be shown. The screen captured shows that Thai Buddha amulet is Phra Somdej Toh (true label); ResNet predicted label = Phra Somdej Toh, with the confident scores of ResNet prediction = 100%; GoogleNet predicted label = Phra Somdej Toh, with the confident scores of GoogleNet prediction = 89.9%.

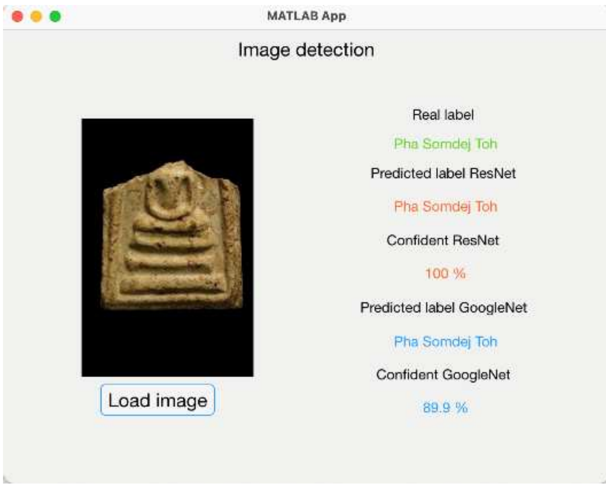


Figure 8. The screen captured of the application

Most of the pre-trained models were trained from a very large-scale image dataset called ImageNet: ImageNet Large-Scale Visual Recognition Challenge (ILSVRC). ImageNet contains more than 1 million images in 1000 categories of image; the pre-trained models can be used in many applications, e.g., feature extraction, classification, and transfer learning. Figure 9 shows the comparisons of accuracy (%) and relative prediction time in GPU of the well-known pre-trained models [19]; the diameters of each scatter plot refer to the penalty cost related to the performance of given model. Focusing on ResNet-50 and GoogleNet which we used in this work, by trading off the prediction running time of GPU and the accuracy we will gain from each model, ResNet-50 is somewhere between ResNet-101 and ResNet-10. If we choose ResNet-10 in our work, this will spend less GPU time but it will give us only 70% of accuracy whereas if we put more efforts on ResNet-101, the accuracy result seems not to be more interesting for the greater GPU running

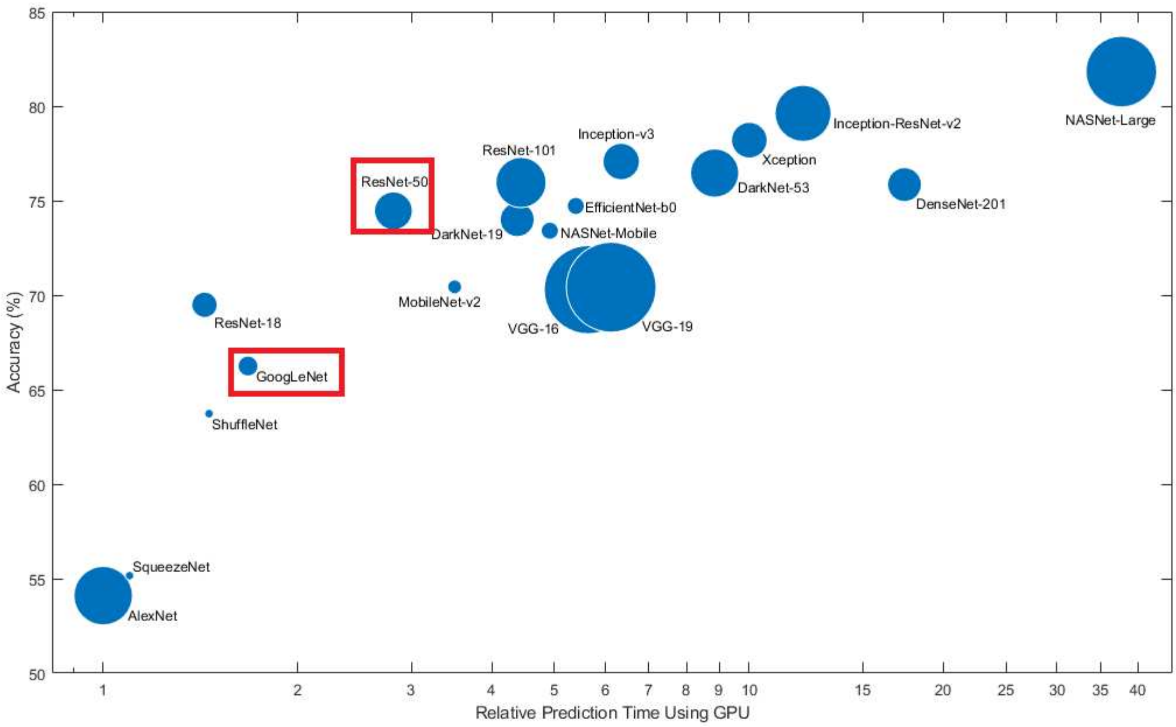


Figure 9. The comparison of accuracy (%) and GPU running time of the well-known pre-trained model [19]

time. This is a reason why we choose ResNet-50 for our work. GoogleNet is very popular pre-trained model for using as benchmark because its compact size and the GPU running time are quite good with a reasonable accuracy.

5. **Conclusions.** The contribution of this work is to classify the Benjapakee Buddha amulets which is the one of the most expensive amulets in Thailand by using the transfer learning technique with DWT as the feature extraction. We took the benefits of DWT in terms of the reducing of the vector size (the output image of DWT can be reduced to 1/4 of the original image) and the meaningful features extracted from DWT (this can be done through low-pass and high-pass filtering in MATLAB DWT). We traded off many well-known pretrained model and we chose ResNet-50 determined by the computational cost. We also compared our work to GoogleNet and the results show that our method outperforms in all criteria (precision, recall, F1 score, training duration, and accuracy). One observation for our model is the overfitting; by taking a close look at Figure 6(a), our model is still a little bit overfit. We will fine tune some parameters to solve this problem, e.g., the learning rate schedule, the maximum iterations, and the iterations per epoch. The major problem of this work is that our Thai Buddha amulets dataset is too small, although we can increase the number of datasets by using data augmentation; therefore, we need transfer learning for this work. We recommend using the sophisticated CutMix algorithm [20] for data augmentation which seems to be appropriate for the work which has a small size of dataset. We already proved that the CutMix algorithm was quite good in practice for gaining more data in our previous work [14]. Another choice to overcome the unbalanced or poor dataset is oversampling and undersampling techniques. The oversampling technique will be applied in the minority class, by selecting some images for duplication and augmentation. Whereas, apply the undersampling technique to reducing images contained in the majority class [21]. One more choice for our future work is the snapshot ensemble CNNs. The snapshot can be referred as the best weight model generated in each cycle during in a cyclic learning rate schedule [22]. The main idea of snapshot

ensemble CNNs with a cyclic learning rate schedule is to find the different local minimum costs instead of discovering only the global minimum cost as in a standard learning rate schedule.

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