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Thai weaving pattern classification using convolutional neural networks

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ABSTRACT

The creation of Thai weaving patterns based on reproduction of original patterns with adapted patterns inspired by designer is a way to reserve Thai textiles. Although weaving pattern designs are useful for promoting Thai textiles such as in casual attires, preserving original Thai patterns is still needed. This work aimed to classify the images of original Thai ethnic and adapted weaving patterns. In this paper, we trained 28 original Thai ethnic patterns using the convolutional neural network. We cropped and preprocessed the weaving images to a binary format. The data augmentation method was also used to increase the number of weaving patterns for training the convolutional neural network. The model was tested in the real world by using test patterns from Google images and gave the results of 0.90, 0.92, and 0.90 for precision, recall, and F1 score, respectively.

Keywords: Thai fabric; weaving pattern; classification; image processing; deep learning

1. INTRODUCTION

Thai people have known weaving since prehistoric times. By the end of the 14th century, the Lanna people were highly skilled in elaborate decorative techniques. They developed their own weaving patterns, particularly using cotton and silk (Utiswannakul, 2016). Now, local weaving in Thailand has spread to almost all regions, especially in the north and northeast. The weaving patterns may vary based on ideology, beliefs, and traditions of each ethnic region, e.g., Teen Jok weaving pattern is Thai Phuan ethnic wisdom of the Sukhothai province (Sutthiwong and Suwannawaj, 2016). In the past, clothes made of Thai fabrics is limited to senior people, and haute couture clothes made of authentic silk such as Pum Riang silk, and is only worn by Thai royalties, aristocrats, and celebrities (Dittakan and Theera-Ampornpunt, 2018). The traditional wear keeps the cutting styles and weaving patterns in a conservative way; therefore, the weaving patterns remain unchanged. Nowadays, everyone can wear Thai fabrics as everyday outfits casually or in a formal event; therefore, weaving patterns might be adapted to fit the contemporary fabric design or new designer fashions, which affects the reproduction of original weaving patterns. Figure 1 shows high fashion clothes made of silk from Sirivannavari by H.R.H Princess Sirivannavari

Nariratana Rajakanya, whose work helps local artists improve the quality of fabric and design.

In brief, the creation of textile in Asia can be traced back to ancient India. Indian textiles have been well known since the 5th millennium BC, and they played an important role in trading across continents. Archaeologists found Indian textiles in Rome, China, and Egypt (Sandhu, 2015). Indian people used homespun cotton for weaving their garments and used indigo to color their fabric. There were many known fabrics for each state, e.g., cotton fabrics are popular in Guajrat; a colorful free hand-painted or block-printed cotton called Kalamkari fabrics are famous in Andhra Pradesh; Pashmina, with the fineness of the cream-colored goat's wool, is well known in Kashmiri; a silk fabric from Southern India named Mekhala silk is famous in Assam; Phulkari, Shisa, Kanjivaram silk, and Chikankari fabrics are popular in Punjab, Rajasthan, Tamilnadu, and Uttar Pradesh, respectively (Khaire, 2011). Figure 2 shows the famous fabrics of India, which are Kalamkari, Pashmina, Chikankari, and Phulkari.

To construct the weave, the weavers may create a weaving pattern inspired by their lifestyles and way of life. Normally, the weave may be constructed by interlacing warps and wefts of dyed cotton yarn (or silk); by repeating this process, the weaver can create the fabric (Visutsak et al., 2021).

To learn the weaving patterns, many works have been investigated. Cutting-edge techniques of fabric identification using image analysis were introduced; this work surveyed all the methods from a past decade to identify weaving patterns using human observation and semi-automatic and automatic identifications (Zhang et al., 2013). Most of the earlier techniques used high-resolution and precision devices, some of which are still being used. Intelligent processing uses 2D integral projection for scanning the accurate structure of weaving pattern. Then, the method parses the feature to fuzzy C-means clustering. The classifier can detect the defects across the area of yarns by determining the gray level cooccurrence matrix. A linear discriminant analysis is also used to improve the classifier performance (Anila et al., 2018). The low-level features (binary image) of the weaving patterns have been used to compare with the gray level cooccurrence matrix. A support vector machine can be used as the classifier to detect the defects of the fabric (Ben Salem and Nasri, 2010). The color image of the dyed yarn is also used in the intelligent recognition. The $l^*a^*b^*$ color image with X-means clustering can be used to determine the weave points; however, the major drawback is the cost of preprocessing since it needed to employ Fourier transform, image segmentation, and arithmetic operations to the color image (Li et al., 2019).

More works of weaving pattern classifications based on vector quantization is also examined. An old fashion of weaving pattern inspection uses 2D wavelet transform of fabric images as training data and the learning vector quantization neural network as a classifier (Jing et al., 2011). A similar work with a complicated version of 2D wavelet was proposed. A computer vision technique called Gabor filter can be used to extract the texture features from the 2D wavelet of fabric images, and the learning probabilistic neural network can be used in the later phase to classify a low frequency of fabric images (Kang et al., 2019). Data and image mining can be also investigated. The association rule miner can be used together with image mining to extract useful information from fabric images. The gray level cooccurrence matrix is used later in the inspection process, and to determine the quality of fabric. It is recommended to inspect three defects: hole, yarn, and scratch (Mohanty and Bag, 2017).

The convolutional neural network is also used in error-prone processes to reduce human error during the inspection. The ResNet model is used, and the results were compared with a pretrained VGGNet. Unfortunately, the test results of the handicraft weaving pattern needed to be improved (Hussain et al., 2020). The recognition of Thai traditional weaving pattern in Loei province, named Tai Loei, Tai Dam, or Tai Lue is also investigated. The deep neural network is used in the application to help the tourism obtain the original Loei fabric (Boonsirisumpun and Puarungroj, 2018). An extended work of the recognition of Thai traditional weaving pattern in Loei is introduced later. Furthermore, a more sophisticated method uses three deep learning models (Inception-v3, Inception-v4, and MobileNets) to train 1,800 images of weaving patterns in the Loei province, and the classification results yielded more than 90% accuracy (Puarungroj and Boonsirisumpun, 2019). The multitask and multiscale convolutional neural network is proposed for the quality inspection for a large-scale manufacturing. By solving the drawbacks of the former image processing method, one can predict the location maps of yarns and floats and use the multitask structure to learn the relation between yarns and floats for the recognition (Meng et al., 2021).

In this paper, we proposed the classification of the original Thai ethnic weaving patterns using the convolutional neural network.

Figure 1. The haute couture clothes made of an authentic silk by Sirivannavari (http://www.sirivannavari.com)

Figure 2. Kalamkari and Pashmina (first row, from left to right), Chikankari and Phulkari (second row, from left to right) (https://medium.com/@noopurshalini/textiles-of-india-d9f5e5310dc6)

2. MATERIALS AND METHODS

2.1 Materials

The images of the original weaving patterns were gathered by investigating the information from the Royal Thai Silk Conservation Village project, the Office of Sericulture Conservation and Standard Conformity Assessment, and the Queen Sirikit Department of Sericulture, Ministry of Agriculture and Cooperatives (the Queen Sirikit Department of Sericulture, 2016). The image dataset of the original weaving patterns consisted of 28 patterns from four regions: 1) the weaving patterns of northern Thailand include Jok Mae Jam, Jok Maueng Long, Yok Mook Lab Lae, Yok Dok Lamphun silk, and Sin Maueng Nan; 2) the weaving patterns of northeastern Thailand include Hol, Hang Kra Rok, Amprom, La Buek, Sin Tiew, Saked silk, Kaab Bua, Mud Mee Chonnabot silk, Luk Kaew patterned ebony-dyed silk, Mud Mee Teen Dang, Mud Mee Kaew Mookda silk, Mud Mee Kor Naree silk, Praewa silk, Mud Mee Soi Dok Mak silk, Samor, Anloonseem, and Kid; 3) the weaving patterns of central Thailand include Thai-Yuan Yok Mook and Thai-Yuan Jok; 4) the weaving patterns of southern Thailand include Chuan Tani, Pum Riang silk, Yok Maueng Nakhon, and Na Muen Si. We used the image processing techniques for preprocessing the data and the data augmentation method to increase the number of weaving patterns for training the convolutional neural network.

2.2 Methods

Table 1 shows 28 classes of Thai weaving patterns and their sample sizes. The graphical illustration of the overall processes is shown in Figure 3. The input image contained the main pattern, and the compound pattern was reformatted to a binary image. We used gray leveling and histogram equalization to adjust the contrast of the fabric image. The binary image was then proceeded in the data augmentation process to increase the dataset. All images were used to train the convolutional neural network. The results showed the similar weaving patterns based on the testing image.

Table 1. Thai weaving patterns and the number of samples per class

Class	The original Thai weaving pattern	Number of samples per class
1	Jok Mae Jam	86
2	Jok Maueng Long	53
3	Yok Mook Lab Lae	70
4	Yok Dok Lamphun silk	78
5	Sin Maueng Nan	29
6	Hol	50
7	Hang Kra Rok	67
8	Amprom	30
9	La Buek	17
10	Sin Tiew	67
11	Saked silk	30

Table 1. (Continued)

Class	The original Thai weaving pattern	Number of samples per class
12	Kaab Bua	15
13	Mud Mee Chonnabot silk	45
14	Luk Kaew patterned ebony-dyed silk	36
15	Mud Mee Teen Dang	77
16	Mud Mee Kaew Mookda silk	89
17	Mud Mee Kor Naree silk	48
18	Praewa silk	79
19	Mud Mee Soi Dok Mak silk	54
20	Samor	14
21	Anloonseem	23
22	Kid	61
23	Thai-Yuan Yok Mook	44
24	Thai-Yuan Jok	35
25	Chuan Tani	70
26	Pum Riang silk	39
27	Yok Maueng Nakhon	45
28	Na Muen Si	37

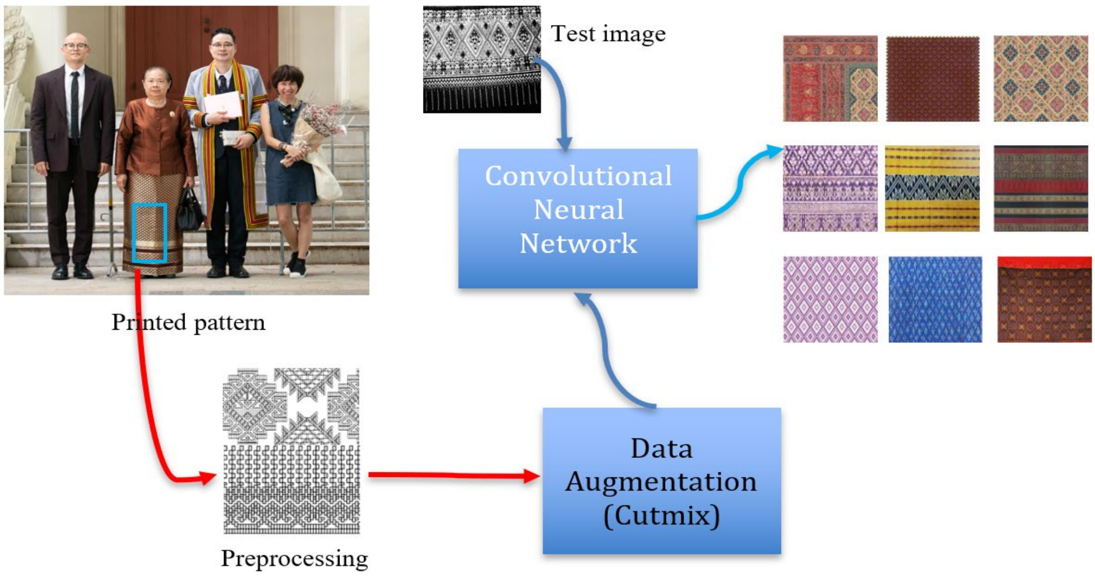

Figure 3. The system architecture of the proposed method

Figure 4 shows nine random weaving pattern images in the dataset, including Jok Mae Jam (class 1), Jok Maueng Long (class 2), Yok Dok Lamphun silk (class 4), Hol (class 6), Mud Mee Kaew Mookda silk (class 12), Praewa silk (class 18), Mud Mee Soi Dok Mak silk (class 19), Kid (class 22), and Pum Riang silk (class 26). Figure 5 shows the Pum Riang silk image after gray leveling and histogram equalization.

The original dataset was poor, as shown in Table 1. Therefore, we needed to apply the data augmentation process to increase the number of samples. Data augmentation is the image manipulation technique used to increase the amount of data by using some image processing methods such as rotation, translation, shearing, brightness adjustment, and filtering, to add the replication of modified images into the same class (Takahashi et al., 2018; Summers and Dinneen, 2019; Preechasuk et al., 2019; Zhong et al., 2020). We used the Cutmix algorithm, as shown in Figure 6, as the data augmentation for this work, using the fixed Cutmix ratio = 0.5 for both of main and compound patterns (Yun et al., 2019). Figure 7 shows the improvement of dataset distribution after applying the data augmentation process.

Figure 4. Images of class 1, 2, 4, 6, 16, 18, 19, 22, and 26

Figure 5. Pum Riang silk image after gray leveling and histogram equalization

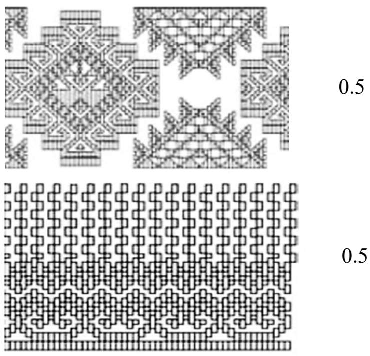

Figure 6. The Cutmix ratio for the data augmentation

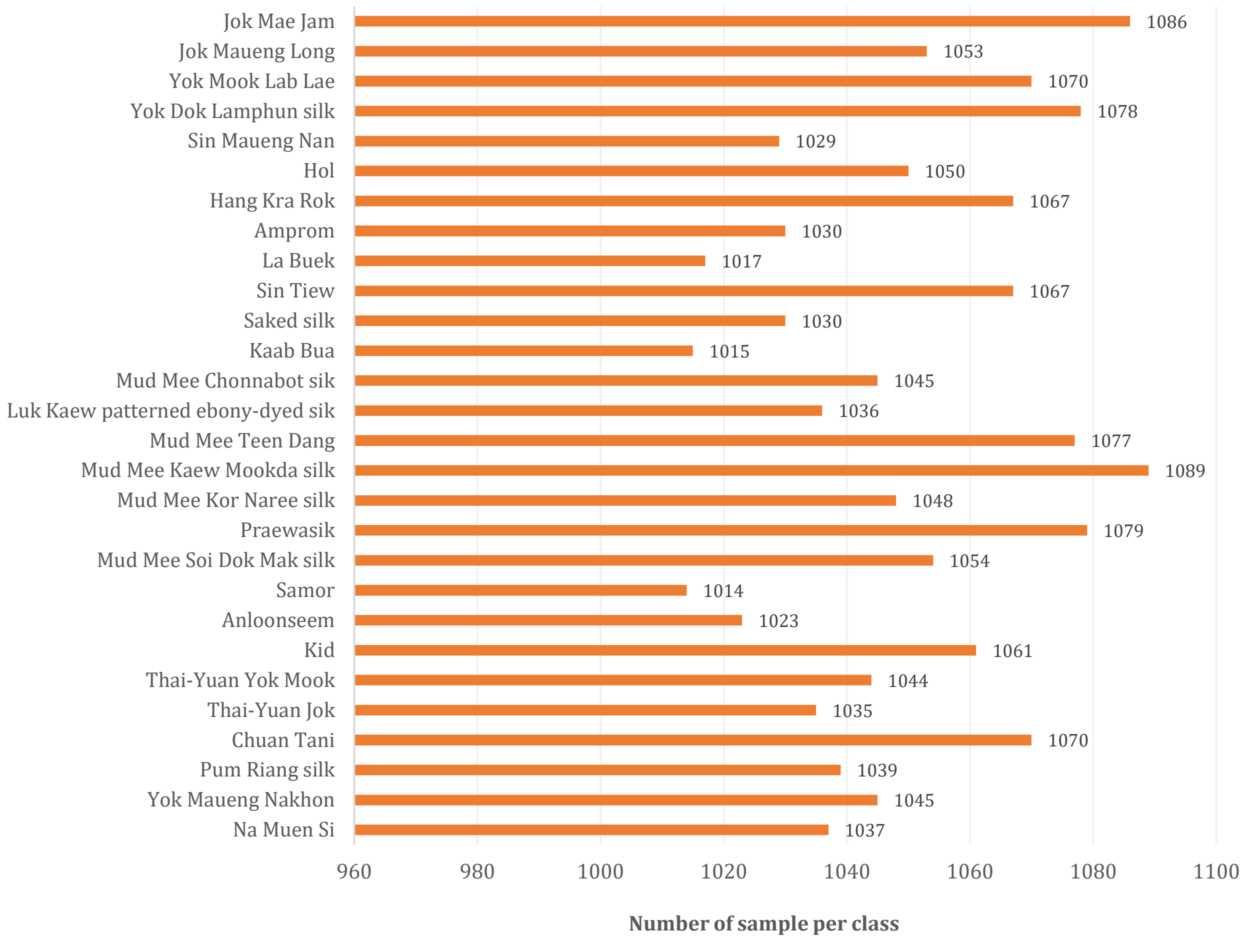

Figure 7. The data distribution of 28 classes

We modified the LeNet architecture (LeCun et al., 1998) to our work. Layer 1: the convolutional layer received the input = 32 x 32 and generated the output = 30 x 30 x 32 with the rectified linear activation function; the max pooling generated the output = 15 x 15 x 32. Layer 2: the convolutional layer received the input = 13 x 13 x 64, and the max pooling generated the output = 6 x 6 x 64. Layer 3: the convolutional layer received the input = 4 x 4 x 128, and the max pooling generated the output = 2 x 2 x 128. The convolutional neural network architecture is shown in Figure 8. The comparison between the original LeNet and our architecture is shown in Tables 2 and 3, respectively.

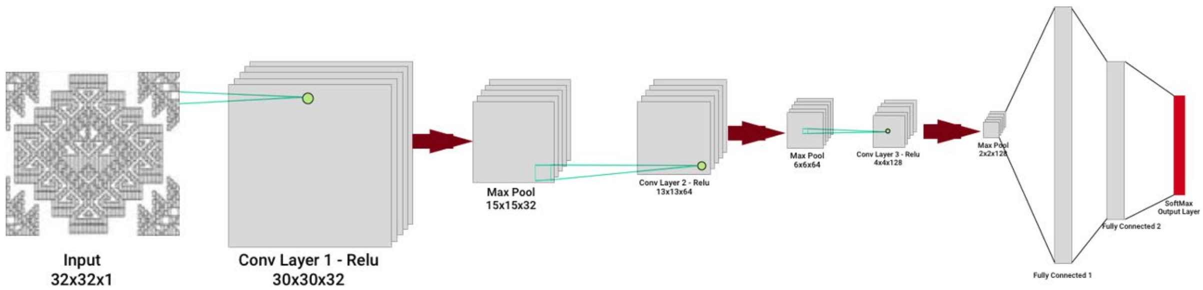

Figure 8. The convolutional neural network architecture of the proposed method

Table 2. The original LeNet

LeNet	Input	Conv. layer 1	Subsampling 1	Conv. layer 2	Subsampling 2
	32 x 32 x 1	28 x 28 x 6	14 x 14 x 6	10 x 10 x 16	5 x 5 x 16

Table 3. The proposed model

Purposed method	Input	Conv. layer 1 relu	Max pool	Conv. layer 2 relu	Max pool	Conv. layer 3 relu	Max pool
	32 x 32 x 1	30 x 30 x 32	15 x 15 x 32	13 x 13 x 64	6 x 6 x 64	4 x 4 x 128	2 x 2 x 128

3. RESULTS

Figure 9 shows the confusion matrix of the actual classes and the predicted classes. Figure 10 shows the accuracy and loss of our model; the model yielded 0.9728 accuracy at 20 epochs. Table 4 shows the classification results of the proposed model based on precision, recall, and F1.

The evaluation terms (recall, precision, and F1 score) are derived through Equations (1)-(4):

$$\text{Precision} = \frac{\text{TP}}{(\text{TP+FP})} \quad (1)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (2)$$

$$\text{Accuracy} = \frac{\text{Correct classification}}{\text{The number of entire instance set}} \quad (3)$$

$$\text{F1 score} = \frac{2*(\text{Precision}*\text{Recall})}{(\text{Precision+Recall})} \quad (4)$$

where TP (true positive) is defined as the correct classified type of activities, TN is true negative, FP is false positive, and FN is false negative.

	Mud Mee Kaew Mookda silk	Jok Mae Jam	Praewa silk	Yok Dok Lamphun silk	Mud Mee Teen Dang	Chuan Tani	Yok Mook Lab Lae	Hang Kra Rok	Sin Tiew	Kid	Mud Mee Soi Dok Mak silk	Jok Maueng Long	Hol	Mud Mee Kor Naree silk	Mud Mee Chonnabot silk	Yok Maueng Nakhon	Thai-Yuan Yok Mook	Pum Riang silk	Na Muen Si	Luk Kaew patterned ebony-dyed silk	Thai-Yuan Jok	Saked silk	Amprom	Sin Maueng Nan	Anloonseem	La Buek	Kaab Bua	Samor
Mud Mee Kaew Mookda silk	44	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Jok Mae Jam	0	40	0	0	0	0	0	0	3	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Praewa silk	1	0	47	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Yok Dok Lamphun silk	0	0	0	41	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Mud Mee Teen Dang	0	0	0	0	40	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Chuan Tani	0	0	0	0	0	44	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Yok Mook Lab Lae	0	0	1	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hang Kra Rok	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sin Tiew	1	0	0	0	0	0	0	0	41	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Kid	0	0	0	0	3	0	0	0	0	42	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Mud Mee Soi Dok Mak silk	0	0	0	0	0	0	0	0	0	0	41	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Jok Maueng Long	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hol	0	0	0	3	0	0	0	0	0	0	0	0	42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mud Mee Kor Naree silk	0	0	0	0	0	0	0	0	0	0	0	0	0	44	0	0	0	0	2	0	0	0	0	0	0	0	0	0
Mud Mee Chonnabot silk	1	0	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0
Yok Maueng Nakhon	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0
Thai-Yuan Yok Mook	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0
Pum Riang silk	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	42	1	0	0	0	0	0	0	0	0	0
Na Muen Si	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0
Luk Kaew patterned ebony-dyed silk	0	0	0	0	0	0	0	2	0	2	0	0	0	1	1	0	0	0	0	41	0	0	0	0	0	0	0	0
Thai-Yuan Jok	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0
Saked silk	1	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	47	0	0	0	0	0	0
Amprom	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	42	0	0	0	0	0
Sin Maueng Nan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	40	0	0	0	0
Anloonseem	0	2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	41	0	0	0
La Buek	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0
Kaab Bua	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	0
Samor	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	41

Figure 9. The confusion matrix of the actual and predicted classes

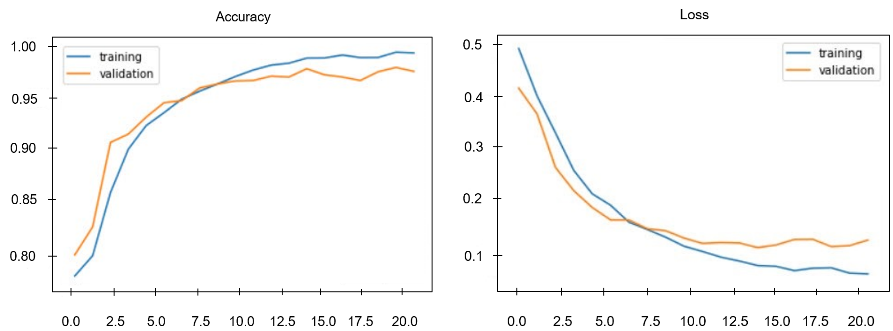

Figure 10. The accuracy and loss of the proposed model

Table 4. The classification results based on precision, recall, and F1 score

Class	Thai weaving patterns	Precision	Recall	F1 score
1	Jok Mae Jam	0.9	0.82	0.86
2	Jok Maueng Long	0.86	1	0.9
3	Yok Mook Lab Lae	1	0.83	0.91
4	Yok Dok Lamphun silk	0.86	0.82	0.84
5	Sin Maueng Nan	1	0.83	0.91
6	Hol	0.93	0.9	0.9
7	Hang Kra Rok	1	1	1
8	Amprom	0.88	1	0.9
9	La Buek	0.86	1	0.9
10	Sin Tiew	1	0.83	0.91
11	Saked silk	0.88	0.94	0.92
12	Kaab Bua	1	1	1
13	Mud Mee Chonnabot silk	0.84	1	0.9
14	Luk Kaew patterned ebony-dyed silk	0.9	0.94	0.92
15	Mud Mee Teen Dang	0.9	0.9	0.89
16	Mud Mee Kaew Mookda silk	0.85	0.92	0.88
17	Mud Mee Kor Naree silk	0.85	0.92	0.88
18	Praewa silk	0.93	0.93	0.93
19	Mud Mee Soi Dok Mak silk	0.85	0.92	0.9
20	Samor	0.86	1	0.91
21	Anloonseem	0.9	1	0.9
22	Kid	0.93	0.87	0.9
23	Thai-Yuan Yok Mook	1	0.84	0.92
24	Thai-Yuan Jok	0.86	1	0.9
25	Chuan Tani	0.92	0.92	0.92
26	Pum Riang silk	0.85	0.92	0.9
27	Yok Maueng Nakhon	0.84	1	0.9
28	Na Muen Si	1	0.83	0.92
	Average	0.9089	0.9243	0.9078

We used the QBox (https://qbox.ai) visualizations and metrics tool to generate the confusion matrix. Table 4 shows classifying results based on the proposed model. The evaluation results (precision, recall, and F1 score) were shown. The proposed model can classify all 28 classes of Thai weaving pattern images from Google. It gave an average precision of 0.90, recall of 0.92, and average F1 score of 0.90. It can be concluded that our proposed model can classify Thai weaving pattern images with high accuracy.

We also compared our model with the LeNet using the same augmented dataset. Table 5 shows that our method gave better classification results than LeNet (≈11%).

Table 5. The comparison results between the proposed method and LeNet

Model	Average		
	Precision	Recall	F1-score
The proposed model + Cutmix	0.9089	0.9242	0.9078
LeNet + Cutmix	0.8089	0.8317	0.7988

The method we used in our study provided better results in terms of precision, recall, and F1 score than LeNet. One observation for the experimental results was the appropriate amount of data generated from the Cutmix augmentation algorithm for training our model and LeNet. As shown in Table 1, the number of weaving patterns per class was our major concern for doing this experiment. The Cutmix algorithm consistently outperformed the augmentation method and helped us increase the weaving images, as shown in Figure 7.

We gathered Thai weaving patterns form Google images, as shown in Figure 11, which included the original Thai weaving patterns, the adapted weaving pattern, and the outfits made of Thai fabric. The results of 12 output images were correctly classified.

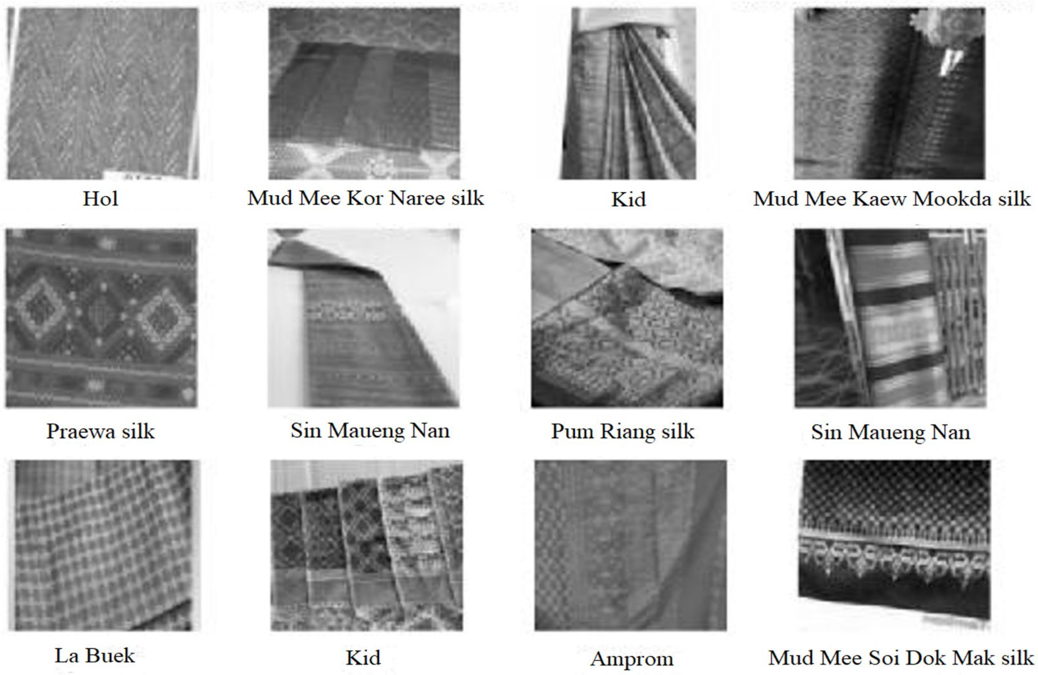

Figure 11. Classification results using Google images as the test case

4. CONCLUSION

The LeNet architecture is great for image classification problem with a well-managed distribution dataset. For a poor distribution dataset, we need the data augmentation to manage the data distribution before using the LeNet model. In this work, our fabric images are too small; therefore, we needed data augmentation to increase the number of fabric images. The next observation is the overfitting; by taking a close look at Figure 10, our model is still a little bit overfit. To solve this overfit problem, we plan to fine tune some parameters and use the justified Cutmix algorithm (we plan to adjust the Cutmix ratio for the compound pattern = 0.2 and the Cutmix ratio for the main pattern = 0.8) for data augmentation. Unlike the other augmentation techniques, the Cutmix method can define the weight of class by determining the percentage of the image of interest, which appears in the class. Therefore, this augmentation method might be suited for our dataset in which the weaving pattern can sometimes be combined with the original and adapted patterns in the same fabric image.

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