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Research article

Using Deep Learning for the Image Recognition of Motifs on the Center of Sukhothai Ceramics

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Abstract

Keywords

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machine learning;

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ancient Thailand ceramics recognition;

ancient ceramics analysis;

image classification

The motifs on the center of Sukhothai ceramics are essential elements for determining the age of the ceramics. Sukhothai ceramics in each kiln were made with different pattern production techniques, and thus one specific pattern appears only in a particular kiln. Thus, archaeologists can determine which ceramic was produced from which particular kiln site by investigating its motif. Motif identification requires a well-experienced expert to identify the tracery of the pattern on the center of a ceramic. Thus, identifying such archaeological evidence is complex even for general archaeologists. The aim of this research was to study the use of deep convolutional neural networks for classifying seven motif patterns on the center of Sukhothai ceramics (i.e. Chrysanthemum bouquet, Classic scroll, Conch shell, Fish pattern, Flower head pattern, Printed Chrysanthemum head, and Tibetan Buddhist vajra). We collected a new dataset, including 557 images of ceramics, from two kiln sites. Each ceramic's motif was labeled by Thai ceramic experts. The collection of the motifs on the center of the Sukhothai ceramic dataset was called CMC Sukhothai Ceramic Dataset. The efficiency of the motif identification on the center of Sukhothai ceramics was evaluated by comparing five pretrained convolutional neural network models: DenseNet121, InceptionV3, VGG16, GoogLeNet, and AlexNet. Then, the models that were efficient for our dataset were selected and trained by fine tuning. Results showed that the motif recognition of VGG16 + our classification layers generated the best efficiency at 500 epochs of training and 86.54% of accuracy in the test dataset.

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1. Introduction

Ancient ceramics are considered historical and cultural heritage. They are also essential cultural evidence that reflects the economic and trade relationships between countries. They demonstrate the evolution of ceramic manufacturing technology, which indicates the prosperity of arts, culture, wisdom, the influence of neighboring countries, and the history of each era. Thus, determining the age of ancient ceramics is essential for historians and archaeologists because it helps identify the era of artifacts, and better understand the links between historical data.

To determine the age of ceramics, many elements such as soil, glaze, shape, motif, and manufacturing technology, must be considered [1]. Of all the elements, motif is the most crucial element in determining the era of production of each ceramic. Thailand has many kiln sites scattered in various areas. Thailand's kiln sites are categorized into three major groups: Lanna Kingdom, Sukhothai Kingdom, and Ayutthaya Kingdom sites [2]. Of the three groups, Sukhothai ceramic sites are more well acknowledged than the other sites because they contain a range of ceramic types that have attracted the interest of and were studied by many scholars from different fields. Sukhothai has of two essential kiln sites: the Old Sukhothai City site and the Si Satchanalai site [2]. Sukhothai ceramics from each kiln site demonstrate different motif production techniques. Some motifs are found only in one kiln. Hence, motifs help identify the age of ceramics and the kiln site in which they were produced. However, motif identification requires well-experienced experts.

Archaeological excavations in different areas of Thailand have revealed various types of ceramics from many different periods. Such excavations offer proof that Thailand traded ceramics with China and other neighboring countries. The ceramics found in Thailand can be divided into two major groups according to their places of manufacture: domestic and foreign-made ceramics [3]. It was because of trade that both groups of ceramics spread from production sites to different areas in Thailand. Information from surveys and interviews with archaeologists demonstrates that if ancient artifacts are found in an archaeological excavation site, archaeologists attempt to describe and classify the artifacts into different categories based on their characteristics. The motif found on the center of many ceramics, is one characteristic that can indicate the age of antiquities. Moreover, it can specify kiln site, and especially in the case of Sukhothai ceramics. This motif can also help archaeologists narrow down the possible years of production. However, presently, archaeological interpretation only specifies the origins of archaeological evidence and broadly determines their original years. Such interpretation does not focus on the motifs found on the center of Sukhothai ceramics.

In general, the motif patterns at the center of ceramics are found in complete and incomplete conditions in archaeological excavations. If archaeologists excavate in an excavation site where the same motif or pattern has been found and identified before (e.g., lotus patterns, peony patterns, fish patterns, and conch shells), archaeologists can comprehend the antiquities' motifs before sending them to an expert for verification. Nevertheless, exploration and excavation in archaeological sites might discover a small number of ceramics with central motifs that are more difficult to place. Some motifs may have never been identified, whilst others may have been identified at other sites or at an earlier time, but in any case, archaeologists do not know about the earlier identification. These problems happen because an updated central database of the motifs on the center of ceramics is lacking. When some sites discover ceramic motifs or some new motifs have been identified, the discovery and all related knowledge are not distributed to other archaeologists. Therefore, the motifs of the discovered ceramics are difficult to analyze. In addition, not all archaeologists are experts in the central motifs of Sukhothai ceramics. Each person's studies and skills are not the same; thus, some of them can only initially or superficially identify the discovered ceramics and then they have to send them to a specialist for a more accurate examination.

Furthermore, this field only has a few specialists, and most of them are occupied by their workload. Therefore, analyzing various data can take a long time before answers are found.

For the above reasons, we consider Sukhothai ceramics to be valuable historical and cultural heritage items, which are important and limited. Presently, the study of motifs on the center of ceramics can be performed using networks that simulate human neural networks, i.e. convolutional neural networks (CNNs). Given the advantages of CNN's features, extraction and classification, they can be used to train computer systems to self-learn the provided data. Therefore, we use CNNs to recognize the motifs on the center of Sukhothai ceramics. This study contributes to the development of the knowledge of central motifs of Sukhothai ceramics; one that will be useful for future generations of archaeologists.

At present, artificial intelligence is used to replicate the human mind's ability to analyze data, and it finds applications in various fields and industries. It is used in medicine to diagnose diseases from images [4-6], and in agriculture to recognize and identify plant diseases [7-9]. In archaeology, researchers have been developing information and knowledge to improve historical and cultural values by using various computer technology techniques, including the classification of ancient paintings, characters, coins, and other kinds of antiquities. In recent years, Chen *et al*. [10] studied the chronological classification of ancient paintings using multiview feature combination. Their work was based on the premise that drawing style could indicate the age of ancient paintings. They developed a new method of calculating local color properties and simulating multiple perspectives from drawings. Then, they used feature histograms for each image, shown in the form of bag-of-visual words, and used supervised learning to train classifiers. They used two datasets: Flying-Apsaras 660 images and Painting-91. Painting-91 is a painting dataset created by Khan *et al*. [11], and it contains 4,266 paintings from 91 different artists. Each painting has a tag that demonstrates artistic styles and relevant artists. The researchers used Painting-91 to evaluate the performance of artist and style classification. They tested their artist classification method using the Painting-91 dataset. The painting style was used to identify the structures of the painted lines and color, and it was proven to be a sufficient basis for determining the age of paintings [12]. The style of painting, created in Dunhuang, China, also strongly related to the era. Later on, Can *et al*. [13] studied three CNN architectures: Sketch-a-Net, VGG-16, and ResNet-50. Their study compared the efficiency of Mayan hieroglyphics classification from the Maya Codice dataset [14]. The dataset included complex mark and symbol images, which were divided into 150 classes. They used gradient backpropagation and Grad-CAM methods to distinguish hieroglyph symbols from the images. The distinguished images were used as the simulated training dataset. Overall, the results showed that Sketch-a-Net was more accurate and profound than ResNet-50. Moreover, a remarkable potential was found when using the Grad-CAM method, which can accurately classify hieroglyphics according to experts' explanations.

Ancient Roman coins are other interesting artifacts that are commonly classified by machine learning because the patterns on the coins can illustrate many historical stories. Schlag and Arandjelovic [15] used deep convolutional networks to identify the emperor's face on ancient Roman coins for classification. A total of 83 different styles were found. They used three newly compiled datasets: RIC-Hq images of 29,807 coins, RPC-Scan images of 19,164 coins, and RIC-Cond images of 600 coins. Each dataset was divided into three equal-sized subsets: training, test, and validation. They also used a dedicated data domain, which had never been used in any previous research, making their research the most extensive coin collecting dataset and the most effective and complete in the literature. Aslan *et al*. [16] furthered the research by analyzing two sides of the coins using semisupervized learning methods. They created a new dataset based on the original dataset, resulting in a more effective classification accuracy.

Cooper and Arandjelović [17] applied AlexNet to identify five patterns of Roman coins: "horse," "patera," "cornucopia," "eagle," and "shield." They used the pictures of 100,000 ancient Roman coins from an auction lot and split the data into three data set: 70% for the training dataset, 15% for the test dataset, and 15% for the validation dataset. Their method applied image learning by linking artificial neural networks to the semantic analysis of the coins. Thus, this research was better than any previous studies. However, color, which is another important element of coins, was overlooked. Ma and Arandjelović [18] focused on color, which is an essential feature of analysis of ancient coins. They classified ancient coins into four classes: ases, sestertii, dupondii, and denarii. They created a new dataset of 400 coins, which were divided into 100 coins per set. They effectively used decision trees and random forest classifiers in conjunction with color properties. Antique art, especially motifs and styles, can indicate much about history as can Motifs on wares.

Motif is a component that can indicate an artifact's age. Previously, researchers used machine learning algorithms to classify pottery from soil and glaze chemical compositions. Cui *et al.* [19] and Yang [20] studied the classification of ancient Chinese ceramics by chemical composition in conjunction with support vector machine. Yu and Yan [21] studied the relationship of porcelain chemical composition from two kiln sites using gray relational analysis. Afterwards, Sun *et al*. [22] used four machine learning algorithms (random forest, SVM, AdaBoost, KNN) together with soil and glaze composition to compare the efficiency of the algorithms for Chinese ancient celadon classification for samples from eight kiln sites. The results showed that random forest was the most suitable algorithm for celadon chemical composition classification with the highest average accuracy of 96.41%.

Previous research on ceramic classification overlooked ceramic motifs, but recently Bickler [23] used libraries and machine learning algorithms to analyze and identify patterns found on ancient ceramics from archaeological sites in New Zealand. It was found that the accuracy was not as good as it could have been due to the small number of ceramic pictures contained in each motif pattern. Moreover, the tools used were not specially designed for archaeological datasets. Therefore, special algorithms for classifying patterns on ancient ceramics needed to be developed. Chetouani *et al.* [24] used a CNN to identify ceramic fragments derived from Saran (France). The repetitive patterns of ceramics were made with a carved wooden wheel. When they were classified, they illustrated a proliferation of ceramic production. The research dataset used for training and testing was the ceramic fragments obtained by scanning with a 3D scanner (NextEngine) to reveal the depth of the patterns. The patterns' aspects from a total of 888 images were classified into four classes identified by archaeologists: 211 images of diamond aspect, 259 images of stick aspect, 274 images of square aspect, and 144 images of chevron aspect. Of all the approaches, the most effective and productive method was the use of ResNet18 in conjunction with SVM. It resulted in an accuracy of 87.94% [24]. Afterwards, Chetouani *et al*. [25] developed the research by combining a feature vector with a learned CNN model. Then, they applied, refined, and compared deep learning methods until 95.23% accuracy was achieved by using CBP (VGG19, ResNet50) + FC. Later, Alby *et al*. [26] created a specific training dataset for each type of artifact. They used data from excavation reports containing meanings and images obtained from video recording of 3D artifacts in conjunction with CNN for recognizing archaeological objects. If a database is large, it contributes to a more complete automatic identification of antiquities at excavation sites. Mu *et al*. [27] extracted three key elements to identify ancient Chinese ceramics: shape, inscription, and ornamentation. Previous studies had demonstrated the possibility of using machine learning to identify ancient Chinese ceramics.

The aforementioned researchers applied deep learning to classify ancient paintings, ancient characters, ancient coins, and other kinds of antiques. Previous research on wares utilized chemical composition to separate types of ancient antiquities with machine learning. However, the researchers overlooked the motifs on those ancient artifacts. Moreover, no research has specifically focused on central motifs found on Sukhothai ceramics; motifs that can indicate much about the era of production. The present study explored CNNs and compared the efficiencies of five pretrained CNN models to find the most suitable models for the dataset. The five pretrained CNN models were: DenseNet121, InceptionV3, VGG16, GoogLeNet, and AlexNet. Then, the most suitable and effective models were selected and trained by fine tuning. The dataset was newly created as a dataset including seven motifs found at the center of Sukhothai ceramics. The motifs had been identified by Thai pottery experts. The newly created dataset was used to recognize the motifs on the center of Sukhothai ceramics using a deep learning technique.

2. Materials and methods

2.1 Process overview

In overview, this article is concerned with the development and testing of a model for the study of motifs found on the center of Sukhothai ceramics by using a deep convolutional neural network. Three main processes were performed, as shown in Figure 1: image preparation, data augmentation, and model training. For this research, 577 images were divided into two subsets; 90% for training, and 10% for testing. Data augmentation techniques were used to increase the number of images to 1,540. To find the most beneficial baseline CNN model, we compared the performance of five CNN architectures including DenseNet121, InceptionV3, VGG16, GoogLeNet, and AlexNet, and utilized them in transfer learning.

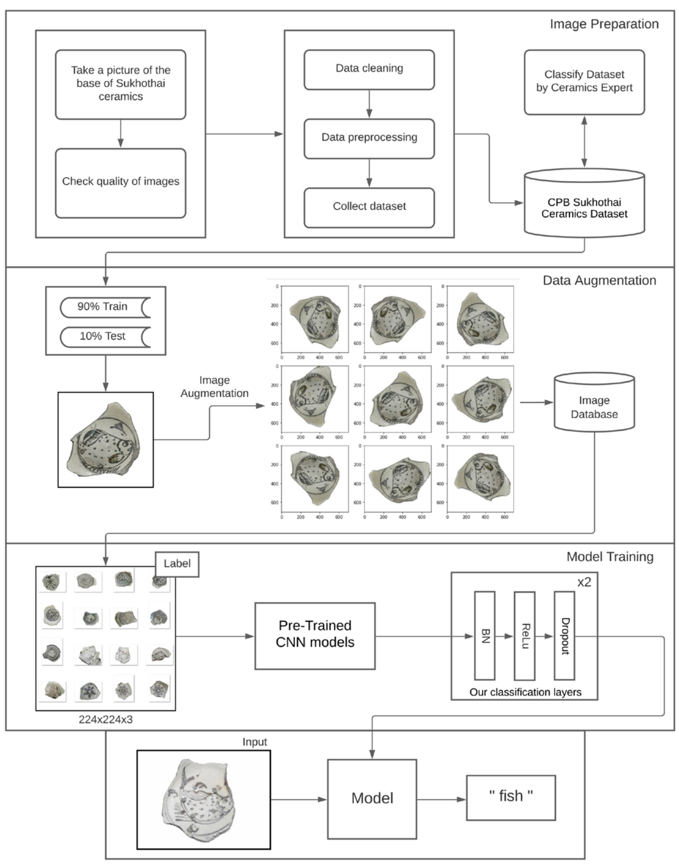

Figure 1. System architecture

2.2 Image preparation

Currently, no dataset collection of the motifs on the center of Sukhothai ceramics is available. These motifs are essential for determining the era of each piece of ceramic. Thus, the researchers created the Collection of the Motifs on the Center of Sukhothai Ceramics Dataset, or the CMC Sukhothai Ceramics Dataset, which is a learning dataset for recognizing the motifs on the center of Sukhothai ceramics by using a deep convolutional neural network. The CMC Sukhothai Ceramics Dataset represents a new collection of the motifs that appear on the center of Sukhothai ceramics. The images in the dataset were obtained by photographing the antiquities of Sukhothai kilns displayed in many private museums. A total of 557 images of different pieces that featured seven types of motifs were collected, and the motifs were: Chrysanthemum bouquet, Classic scroll, Conch shell, Fish pattern, Flower head pattern, Printed Chrysanthemum head, and Tibetan Buddhist Vajra. All the motifs' names were defined by Dr. Pariwat Thammapreechakorn, a ceramic art expert in Thailand and an honorary curator for Bencharong, Chinese trade ware and Southeast Asian ceramics. The seven types of motifs are shown in Table 1. Examples of the motifs on the center of Sukhothai ceramics are shown in Figure 2.

The dataset only included motifs found on the center of Sukhothai ceramics that had been produced from Sukhothai kilns. In the first step, the researchers took photos of the ceramics. Afterwards, the researchers cleaned the data by extracting blurry and extraneous pictures. Then, the pictures underwent data preprocessing calculation, background and noise removal, and resizing before importing to the database. Lastly, an expert classified the dataset pictures.

2.3 Data augmentation

The CMC Sukhothai Ceramics Dataset was a small dataset consisting of 557 motif images, all of which were classified by an expert. Although many Sukhothai artifacts were available, they were scattered around various locations, making it difficult to collect them and form a large database. The deep learning method for recognizing the motifs required substantial data. Furthermore, the data in the various classes needed to be balanced because unbalanced data sets would worsen the efficiency of the motif identification on the center of Sukhothai ceramics.

In fact, the images in each class of the CMC Sukhothai Ceramics Dataset were not balanced. Thus, we added data by using oversampling to increase the images in the minor class, randomly. Data augmentation was implemented by image processing. The processes included rotation, width shift, and zoom. After the processing had been completed, the images in the CMC Sukhothai Ceramics Dataset increased in number from 557 to 1,540.

Table 1. Types of motifs on the center of Sukhothai ceramics

Class No.	Name
1	Chrysanthemum bouquet
2	Classic scroll
3	Conch shell
4	Fish pattern
5	Flower head pattern
6	Printed Chrysanthemum head
7	Tibetan Buddhist vajra

Figure 2. Images showing different motifs from the CMC Sukhothai Ceramics Dataset

2.4 Model training

This research used 1,540 images from the CMC Sukhothai Ceramics Dataset that were adjusted to 224 × 224 pixels in image size. We divided the dataset into 90% for training and 10% for testing. Then, the training dataset was subdivided into 75% for training and 25% for validation. To establish the most suitable and effective model for identifying the motifs on the center of Sukhothai ceramics, we used five pretrained CNN models: DenseNet121 [28], InceptionV3 [29], VGG16 [30], GoogLeNet [31], and AlexNet [32]. Transfer learning [33] helps reduce learning time. Therefore, we used transfer learning with the pretrained CNN models. We experimented with five pretrained CNN models and used the (weight) initialization of ImageNet to train the CMC Sukhothai Ceramics Dataset. We used 200 epochs for each model. We also used GlobalAveragePooling2D to summarize the information from ImageNet's CNN layer. Afterwards, we selected the two most effective pretrained models and trained them by fine tuning. We removed the original image classifications and used the (weight) initialization of ImageNet from the pretrained CNN models. Afterwards, we added our seven neurons of image classification layer in the output layer to classify all the motifs of the seven classes. Then, we added our classification layers to the pretrained CNN models. "Our classification layers" were derived from adding a batch normalization layer before ReLU and a dropout layer after ReLU. We trained the networks by using the Adam optimizer with an initial learning rate of 0.00001. Training was performed for 200 epochs for each model and for 500 epochs for some models on NVIDIA GeForce GTX 1080Ti with 8 GB RAM.

3. Results and Discussion

The comparison of the CNN performance showed that the VGG16 together with our classification layers yielded the best results with accuracy of 0.847. It was also suitable for the CMC Sukhothai Ceramics Dataset, which consisted of seven types of motifs and 557 images of motifs at the center of Sukhothai ceramics. To achieve the most effective motif recognition, we compared five CNN models: DenseNet121, InceptionV3, VGG16, GoogLeNet, and AlexNet. We evaluated the pretrained CNN models by using the CMC Sukhothai Ceramics Dataset, which had been earlier identified by the expert. For the statistical test, we evaluated accuracy and loss of test dataset. The evaluations used in this research included average accuracy, average loss, and standard deviation. The results are shown in Table 2. Figure 3 illustrates the graphs of accuracy and loss for the training and validation sets (at 200 epochs, 0.00001 learning rate) of architecture: DenseNet121, InceptionV3, VGG16, GoogLeNet, AlexNet, DenseNet121, DenseNet121 + our classification layers, and VGG16 + our classification layers.

As shown in Table 2 and Figure 3, AlexNet had the lowest marginal performance from our experiment possibly because it was not suitable for our dataset. The AlexNet structure proceeded with three max pooling layers. Max pooling may reduce the efficiency of the motif detail learning on Sukhothai ceramics. Moreover, AlexNet consisted of five convolutional layers and three fully connected layers. The DenseNet121 and VGG16 architectures had more convolutional layers and higher degree of nonlinearity than AlexNet. Therefore, DenseNet121 and VGG16 were capable of more complicated performance.

From the five architectures, after training the dataset by 200 epochs at a learning rate of 0.00001, DenseNet121 and VGG16 performed similarly; however, when our classification layers were added, the accuracies were 84.29% and 84.71%, respectively. Hence, we increased the number of epochs on both architectures and our classification layers to 500 epochs with a learning rate of 0.00001 to find the most suitable architecture for our dataset. The results are shown in Figure 4.

Table 2. Comparison of the performance of the seven methods

Methods	**Loss**	**Accuracy**
DenseNet121	0.5803±0.0026	0.8186±0.0064
InceptionV3	0.9238±0.0039	0.6943±0.0032
VGG16	0.6875±0.0093	0.7600±0.0064
GoogLeNet	1.8061±0.0302	0.5314±0.0165
AlexNet	1.9340±0.0954	0.3200±0.0228
DenseNet121 + our classification layers	0.4672±0.0000	0.8429±0.0000
VGG16 + our classification layers	0.4528±0.0188	0.8471±0.0109

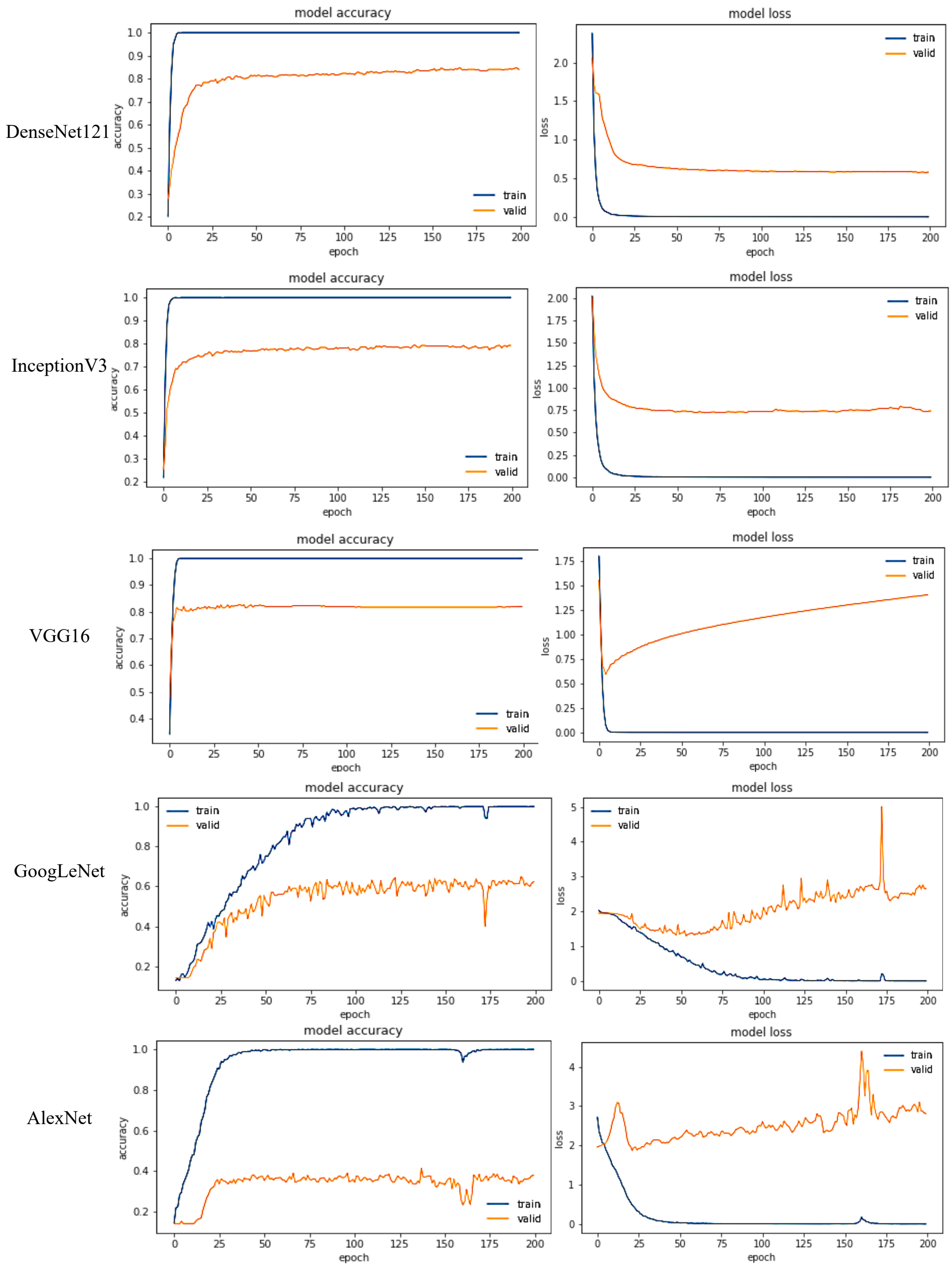

Figure 3. Graphs of accuracy and loss of the training and validation sets of architecture for 200 epochs in the CMC Sukhothai Ceramics Dataset

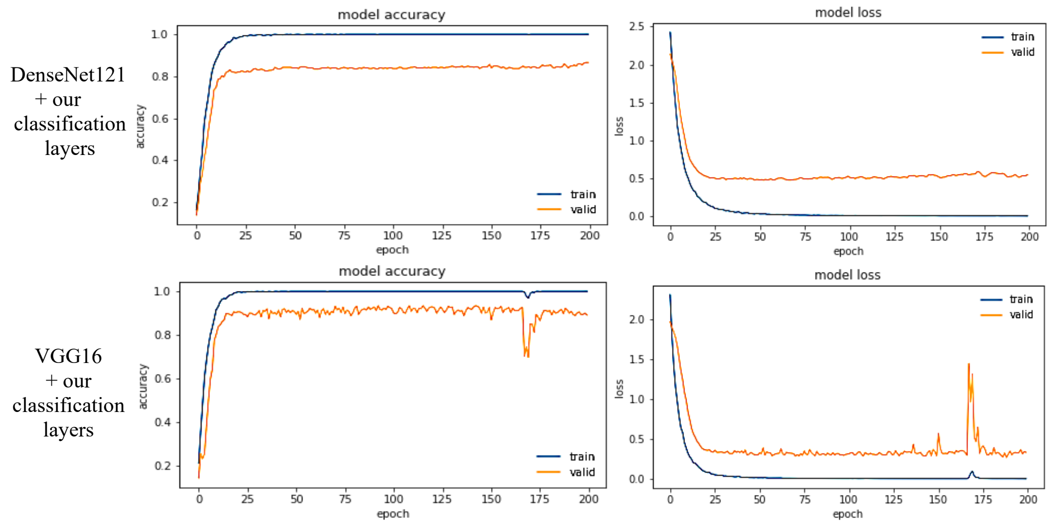

Figure 3. (continued) Graphs of accuracy and loss on the training and validation sets of architecture for 200 epochs in the CMC Sukhothai Ceramics Dataset

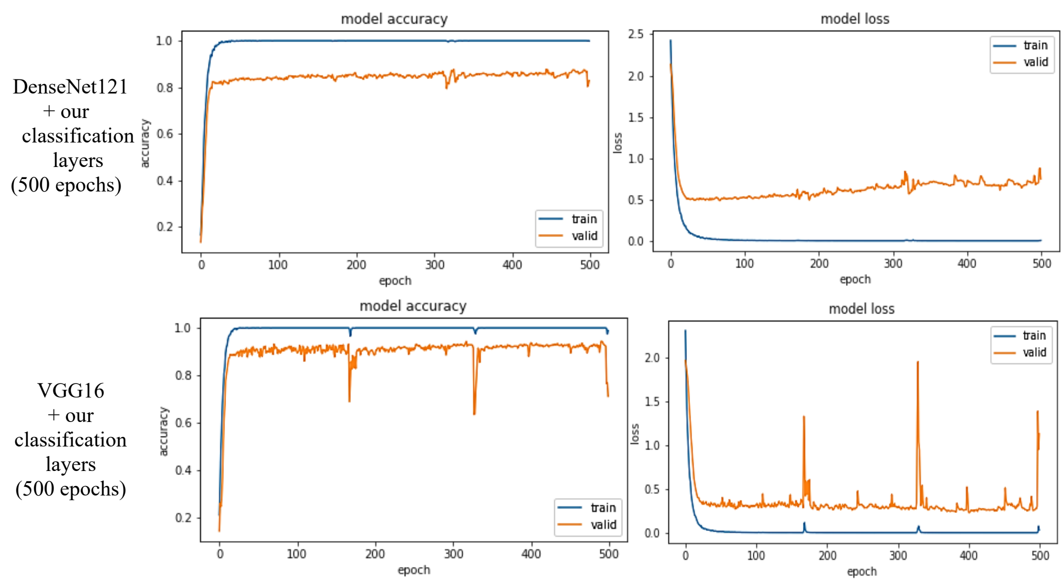

Figure 4. Graphs of accuracy and loss of the training and validation sets of DenseNet121 + our method and VGG16 + our method for 500 epochs in the CMC Sukhothai Ceramics Dataset

We trained the models using DenseNet121 + our classification layers and VGG16 + our classification layers for 500 epochs with a learning rate of 0.00001 in the CMC Sukhothai Ceramics dataset. The accuracy of VGG16 + our classification layers was 87.86%, which was more than that of DenseNet121 + our classification layers (84.29%) (Table 3). Figure 4 illustrates the accuracy and loss of the training and validation sets of DenseNet121 + our classification layers and VGG16 + our classification layers.

Table 3. Performance of DenseNet121 + our classification layers and VGG16 + our classification layers for 500 epochs

Methods	Loss	Accuracy
DenseNet121 + our classification layers	0.4712± 0.0088	0.8427± 0.0005
VGG16 + our classification layers	0.4342± 0.0152	0.8654± 0.0124

From the results of the comparison of deep CNNs with different structures, we concluded that using VGG16 + our classification layers for 500 epochs was the most effective method, and the combination provided 86.54% accuracy rate. This method was the most suitable for identifying the motifs on the center of Sukhothai ceramics. Figure 5 illustrates the confusion matrix of VGG16 + our classification layers for 500 epochs in the CMC Sukhothai Ceramics Dataset, and Figure 6 shows the Precision/Recall/F1-score values of VGG16 + our classification layers for 500 epochs in the CMC Sukhothai Ceramics Dataset.

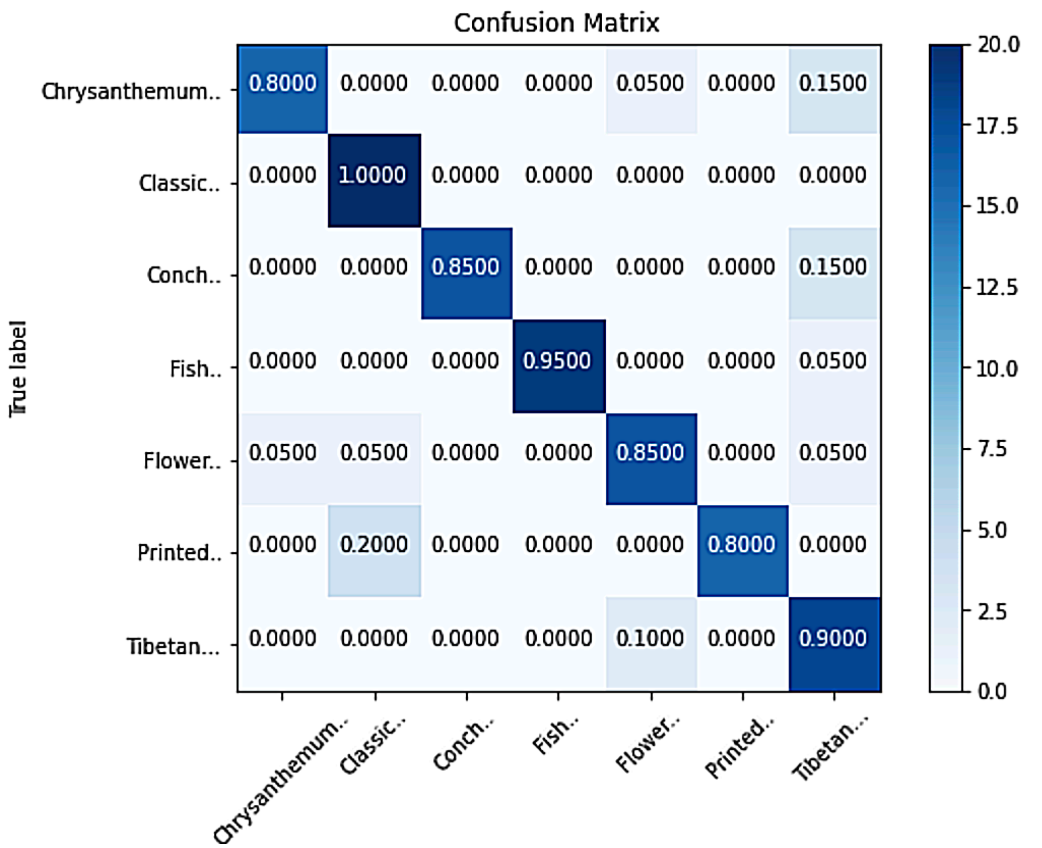

Figure 5. Sample of a confusion matrix of VGG16 + our classification layers for the CMC Sukhothai Ceramics Dataset

	precision	recall	f1-score	support
chrysanthemum_bouquet	0.9412	0.8000	0.8649	20
classic_scroll	0.8000	1.0000	0.8889	20
conch_shell	1.0000	0.8500	0.9189	20
fish	1.0000	0.9500	0.9744	20
flower_head	0.8500	0.8500	0.8500	20
printed_chrysanthemum_head	1.0000	0.8000	0.8889	20
tibet_amulet	0.6923	0.9000	0.7826	20
accuracy			0.8786	140
macro avg	0.8976	0.8786	0.8812	140
weighted avg	0.8976	0.8786	0.8812	140

Figure 6. Picture of Precision/Recall/F1-score of VGG16 + our classification layers for 500 epochs in the CMC Sukhothai Ceramics Dataset

However, the confusion matrix in Figure 5 indicates the prediction of the test set data. We found that the models incorrectly predicted the data from class no. 6 (printed_chrysanthemum_head image class) the most, as class no.6 was mistaken for class no.2 (classic_scroll image class).

The images of the two classes from the CMC Sukhothai Ceramics Dataset in Figure 7 are similar and thus may cause the models to predict incorrectly. Another possible reason is that the number of images collected for model training is insufficient to allow the model to classify the characteristics of each type of image class clearly.

classic_scroll printed_chrysanthemum_head

Figure 7. Images of classic_scroll class and printed_chrysanthemum_head class in the CMC Sukhothai Ceramics Dataset

4. Conclusions

This research presents the application of deep learning techniques through the use of CNNs, including DenseNet121, InceptionV3, VGG16, GoogLeNet, and AlexNet. These models were trained by a small database (i.e. CMC Sukhothai Ceramics Dataset) and used for recognizing the images of the motifs found on the center of Sukhothai ceramics.

From the experiment results, we conclude that VGG16 + our classification layers has the highest experimental results with a learning rate of 0.00001 and a learning cycle of 500 epochs. Therefore, CNN using VGG16 architecture is the most suitable for recognizing the motifs on the center of Sukhothai ceramics because it provides the highest accuracy rate, which is 86.54%.

In the future, we have planned to collect more motif's pattern in order to increase the number of image dataset. Although the performance of the models may decrease due to the increased dataset, we will be able to classify more diverse patterns. The ability to identify more motifs will lead to better links in the archaeological knowledge, which should help indicate the origins of kiln sites and the ages of Sukhothai ceramics.

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References

[1] Thammapreechakorn, P., 2004. *Using Dated Chinese and Vietnamese Ceramics for Studying Thai Archaeological Works and Art Styles: A Case Study on the 14th-18th Centuries Stucco Decorations of Ancient Monuments in Thailand.* MA. Silpakorn University, Thailand.

[2] Thammaprichakọn, P., Phinsi, K. and Nguanphianphak, U., 1992. *Sukhothai Ceramics: Explication of Thai Ceramics.* Bangkok: Bọrisat Osotsapha.

[3] Thammapreechakorn, S. and Chantawit, N., 1987. In S. Intaralip, ed. *The Ceramics of South-East Asia from the 10th to 16th Centuries A.D.* Bangkok: Bọrisat Osotsapha, p. 14.

[4] Zhang, J., Xie, Y., Wu, Q. and Xia, Y., 2019. Medical image classification using synergic deep learning. *Medical Image Analysis*, 54, 10-19.

[5] Saba, L., Biswas, M., Kuppili, V., Godia, E.C., Suri, H.S., Edla, D.R., Omerzu, T., Laird, J.R., Khanna, N.N., Mavrogeni, S. and Protogerou, A., 2019. The present and future of deep learning in radiology. *European Journal of Radiology*, 114, 14-24.

[6] Hoang, D.T. and Kang, H.J., 2019. A survey on deep learning based bearing fault diagnosis. *Neurocomputing*, 335, 327-335.

[7] Sun, Y., Liu, Y., Wang, G. and Zhang, H., 2017. Deep learning for plant identification in natural environment. *Computational Intelligence and Neuroscience*, 2017, https://doi.org/10.1155/ 2017/7361042

[8] Coulibaly, S., Kamsu-Foguem, B., Kamissoko, D. and Traore, D., 2019. Deep neural networks with transfer learning in millet crop images. *Computers in Industry*, 108, 115-120.

[9] Lateef, F. and Ruichek, Y., 2019. Survey on semantic segmentation using deep learning techniques. *Neurocomputing*, 338, 321-348.

[10] Chen, L., Chen, J., Zou, Q., Huang, K. and Li, Q., 2017. Multi-view feature combination for ancient paintings chronological classification. *Journal on Computing and Cultural Heritage*, 10(2), 1-15.

[11] Khan, F.S., Beigpour, S., Van de Weijer, J. and Felsberg, M., 2014. Painting-91: a large scale database for computational painting categorization. *Machine Vision and Applications*, 25(6), 1385-1397.

[12] Zou, Q., Cao, Y., Li, Q., Huang, C. and Wang, S., 2014. Chronological classification of ancient paintings using appearance and shape features. *Pattern Recognition Letters*, 49, 146-154.

[13] Can, G., Odobez, J.M. and Gatica-Perez, D., 2018. How to tell ancient signs apart? Recognizing and visualizing Maya glyphs with CNNs. *Journal on Computing and Cultural Heritage*, 11(4), 1-25.

[14] Can, G., Odobez, J.M. and Gatica-Perez, D., 2017. Maya codical glyph segmentation: A crowdsourcing approach. *IEEE Transactions on Multimedia*, 20(3), 711-725.

[15] Schlag, I. and Arandjelovic, O., 2017. Ancient Roman coin recognition in the wild using deep learning based recognition of artistically depicted face profiles. *Proceedings of the IEEE International Conference on Computer Vision Workshops*, Venice, Italy, October 22-29, 2017, pp. 2898-2906.

[16] Aslan, S., Vascon, S. and Pelillo, M., 2020. Two sides of the same coin: Improved ancient coin classification using graph transduction games. *Pattern Recognition Letters*, 131, 158-165.

[17] Cooper, J. and Arandjelović, O., 2020. Understanding ancient coin images. In L. Oneto, N. Navarin, A. Sperduti and D. Anguita, eds. *Recent Advances in Big Data and Deep Learning*, pp. 330-340. Cham: Springer.

[18] Ma, Y. and Arandjelović, O., 2020. Classification of ancient roman coins by denomination using colour, a forgotten feature in automatic ancient coin analysis. *Sci*, 2(2), 37, https://doi.org/10.3390/sci2020037.

[19] Cui, P.F., Ji, Y., Li, G.X., Zhao, W.J., Li, R.W., Sun, H.W., Zhao, Q.Y., Sun, X.M., Zhao, W.J., Xie, J.Z. and Guo, M., 2009. Study on ancient famous porcelains classification based on support vector machine. *Journal of Henan Normal University (Natural Science),* 37(2), 78-81. (in Chinese)

[20] Yang, L.-H., 2015. Study about ancient ceramics classification based on support vector machine. *Proceedings of the 2015 Sixth International Conference on Digital Manufacturing and Automation*, Changsha, China, January 17-18, 2015, pp. 349-353.

[21] Yu, W.Z. and Yan, L.J., 2011. Ancient ceramics classification based on grey-relation theory. *Journal of Henan Normal University* (Natural Science), 39(5), 59-62. (in Chinese)

[22] Sun, H., Liu, M., Li, L., Yan, L., Zhou, Y. and Feng, X., 2020. A new classification method of ancient Chinese ceramics based on machine learning and component analysis. *Ceramics International*, 46(6), 8104-8110.

[23] Bickler, S.H., 2018. Machine learning identification and classification of historic ceramics. *Archaeology in New Zealand*, 2018, 20-32.

[24] Chetouani, A., Debroutelle, T., Treuillet, S., Exbrayat, M. and Jesset, S., 2018, October. Classification of ceramic shards based on convolutional neural network. *25th IEEE International Conference on Image Processing (ICIP)*, Athens, Greece, October 7-10, 2018, pp. 1038-1042.

[25] Chetouani, A., Treuillet, S., Exbrayat, M. and Jesset, S., 2020. Classification of engraved pottery sherds mixing deep-learning features by compact bilinear pooling. *Pattern Recognition Letters*, 131, 1-7.

[26] Alby, E., Desbiolles, V. and Lecocq, M., 2020. Automatic identification of archaeological artifacts on the excavation site. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 43, 1347-1353.

[27] Mu, T., Wang, F., Wang, X. and Luo, H., 2019. Research on ancient ceramic identification by artificial intelligence. *Ceramics International*, 45(14), 18140-18146.

[28] Huang, G., Liu, Z., Van Der Maaten, L. and Weinberger, K.Q., 2017. Densely connected convolutional networks. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Honolulu, USA, July 21-26, 2017, pp. 4700-4708.

[29] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J. and Wojna, Z., 2016. Rethinking the inception architecture for computer vision. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Las Vegas, USA, June 27-30, 2016, pp. 2818-2826.

[30] Simonyan, K. and Zisserman, A., 2014. *Very Deep Convolutional Networks for Large-scale Image Recognition*. [online] Available at: http://arxiv.org/abs/1409.1556.

[31] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V. and Rabinovich, A., 2015. Going deeper with convolutions. *Proceedings of the IEEE*

Conference on Computer Vision and Pattern Recognition, Boston, USA, June 7-12, 2015, pp. 1-9.

[32] Krizhevsky, A., Sutskever, I. and Hinton, G., 2017. ImageNet classification with deep convolutional neural networks. *Communications of the ACM*, 60(6), 84-90.

[33] Beikmohammadi, A. and Faez, K., 2018. Leaf classification for plant recognition with deep transfer learning. *4th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS)*, Tehran, Iran, December 25, 2018, pp. 21-26