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APPLICATION OF SIAMESE NETWORK TO CLASSIFY SMALL DATASET OF THE MOTIFS ON THE CENTER OF SUKHOTHAI CERAMICS

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Abstract. *This study proposes a novel system for identifying central motifs on Sukhothai ceramics using a Siamese neural network. Traditional motif recognition techniques face challenges due to limited information and incomplete patterns. The Siamese network identifies similarities between images, making it well-suited for comparing unknown motifs to a database of known motifs. The proposed system utilizes a deep convolutional neural network (CNN) for feature extraction. Data augmentation techniques are employed to enrich the dataset and address limitations caused by the small number of available motif images. The Siamese network architecture is trained to compute similarity between image pairs, enabling the system to effectively categorize unknown motifs based on their resemblance to known examples. Experimental results demonstrate that the CNN with a dropout layer 0.3 achieves the highest test accuracy (0.82), indicating its effectiveness in motif identification. This research has potential applications in ceramic conservation, research, and data retrieval, aiding archaeologists, and the public in studying and cataloging Sukhothai ceramic motifs. This approach offers a promising solution for identifying patterns on Sukhothai ceramics, despite data limitations.*
Keywords: Siamese network, Ancient ceramics identification, Ancient Thailand ceramics recognition, Ancient ceramics analysis

1. **Introduction.** The motifs on the center of Sukhothai ceramics are crucial for identifying the ceramics' origin and date. Each kiln produces ceramics with unique pattern manufacturing techniques, so specific patterns are associated with individual kilns. By analyzing these motifs, archaeologists can trace each ceramic piece to its respective kiln site. However, motif identification requires skilled specialists, and a major challenge in historical research in Thailand is the limited information available. This lack of data makes it difficult to build effective learning models for classification, grouping, and retrieval.

In our previous research, we addressed this challenge by applying deep learning techniques, specifically CNN models, to classifying and recognizing motifs on the center of Sukhothai ceramics [1]. Despite the potential of deep learning, limitations such as the incompleteness of some patterns and the availability of only one or two fragments of certain motifs complicate the development of high-performance models.

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FIGURE 1. Example of complete and fragmented motifs ceramics [2]

Artificial intelligence (AI) has revolutionized archaeological research, particularly through advanced image classification techniques. Researchers are increasingly using AI to analyze archaeological objects like ceramics, paintings, and coins [3,4]. For example, Kuntitan and Chaowalit [1] employed CNNs to classify motifs on the center of Sukhothai ceramics, achieving an accuracy of 86.54% with the VGG16 model. This demonstrates the potential of deep learning for motif identification, a crucial aspect of Sukhothai ceramic studies. Other studies, such as those by Smith et al. [5] and Debroutelle et al. [6], have explored various techniques, including texture and color descriptors, to analyze ceramic fragments. Huang and Guan [7] developed a non-destructive identification method for ceramics, further demonstrating the role of AI in archaeological analysis.

A common challenge in archaeological image classification is the scarcity of data, as artifacts are often limited in number, making it difficult to build large training datasets. To overcome this issue, several techniques have been proposed. Koulali et al. [8] demonstrated the effectiveness of transfer learning combined with data augmentation and fine-tuning using the VGG16 network. Kolář et al. [9] introduced a semi-supervised self-training method to improve classification accuracy, while Mishra et al. [10] focused on dynamically tuning the learning rate for better performance. Zhu et al. [11] proposed an image-text dual network to improve classification with small datasets. These methods highlight the potential of overcoming data limitations in image classification tasks.

Siamese networks present a promising solution to the problem of limited data. These networks excel at comparing data points, making them ideal for tasks with small datasets. Liu et al. [12] and Jia et al. [13] demonstrated improved performance using Siamese networks in various domains, including motif identification. Li et al. [14], Pan et al. [15] and Anggriawan et al. [16] also proposed variations of Siamese networks for stereo estimation and target classification, further showcasing their potential in diverse applications. In this study, we explore the use of Siamese networks for the motifs on the center of Sukhothai ceramic identification, despite the challenges of limited data.

Conventional image classification methods typically require a large amount of training data, which is often unavailable in archaeological studies. While traditional image classification methods face challenges due to limited data, techniques like Siamese networks, along with transfer learning and data augmentation, offer promising solutions. These methods can help overcome data scarcity and improve motif identification in archaeological studies. This research addresses the issue of limited datasets in identifying archaeological ceramic motifs. To overcome this limitation, we propose utilizing a Siamese neural network [17] for image feature comparison. Siamese networks excel at detecting similarities between two inputs, making them particularly well-suited for tasks with limited data. Our proposed system will compare an unknown motif image to a database of known motifs, establishing relationships between them and potentially achieving accurate motif identification. In this study, we aim to apply a Siamese network to classifying a small dataset of motifs on the center of Sukhothai ceramics.

2. Material and Method.

2.1. **Process overview.** This study focuses on developing and validating a deep convolutional neural network model for analyzing motifs on the center of Sukhothai ceramics.

The proposed system consists of three main components, outlined in Figure 2: data preprocessing, data auagmentaion and Siamese neural network architecture. This research used an image dataset from the Silpakorn Collection of the Motifs of Sukhothai Ceramic Dataset (Silpa CMC Dataset) [1], in which image dataset was classified by ceramics expert. We selected one image for each class, resulting in a total of 64 images. These were divided into two distinct subsets: 32 images were allocated for training, while the remaining 32 were designated for testing.

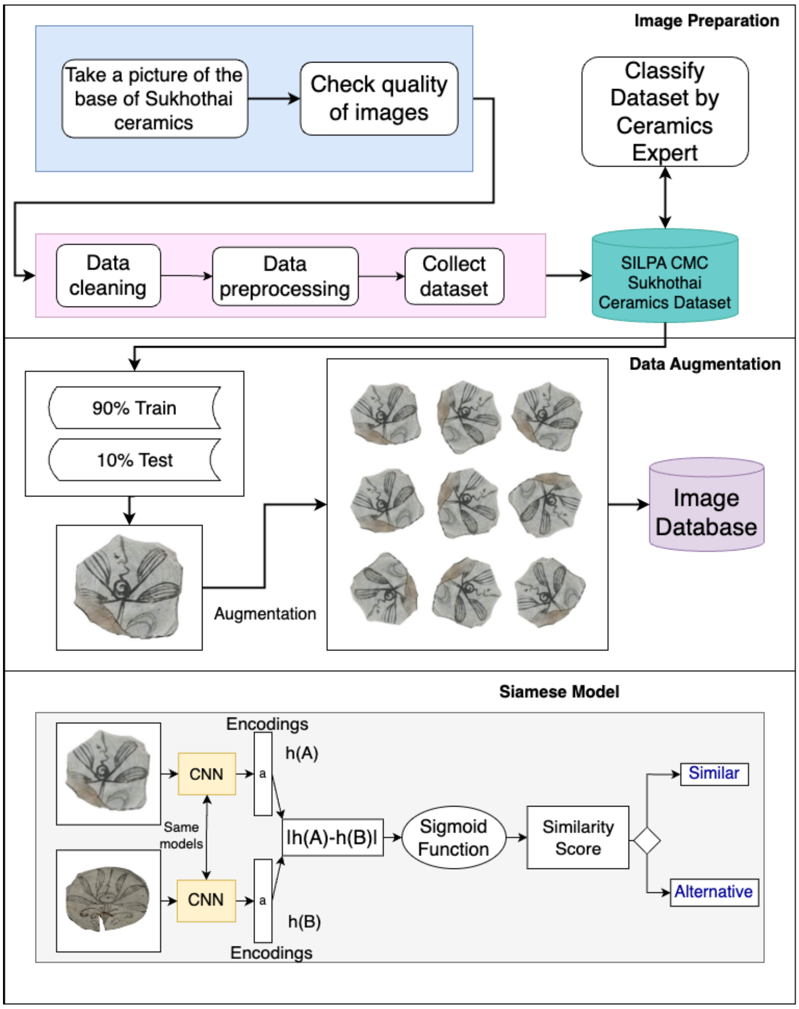


Figure 2. System architecture and the Siamese neural network architecture

2.2. **Data preparation and augmentation.** Following the selection of representative motif images (one per class across 32 distinct categories), we employed data augmentation techniques to enrich the dataset. Oversampling techniques, such as rotations, flips, and zooms, were applied to each image, generating ten variations per class. This process resulted in a significantly larger dataset of 320 images (10 variations per image $\times$ 32 classes).

We constructed image pairs (tuples) along with corresponding labels. These labels indicated a similar relationship between the paired images. They were categorized as either "similar" (motifs from the same class) or "dissimilar" (motifs from different classes or unknown motifs). Figure 3 visually depicts this process, where the labels represent the similarity or dissimilarity between the image pairs.

FIGURE 3. Example of pair input dataset

2.3. **Model training and evaluation.** We employed a Siamese neural network architecture for motif identification. This architecture features the input images from the previous section. The extracted features are then fed into a fully connected layer that computes the similarity between the two images. The images were entered into a subnetwork of the Siamese neural network. Both subnetworks of the Siamese network use CNN structure to extract important characteristics and content of images. After doing feature extraction, the outputs from the Siamese twins were combined using a merged layer, which calculated the similarity, using similarity Euclidean distance ($|h(A) - h(B)|$). That is called contrastive learning which predicts the similarity of two images. The results are arranged in a format that illustrates the degree of similarity between the two images. Figure 4 shows an example of the similar output image.

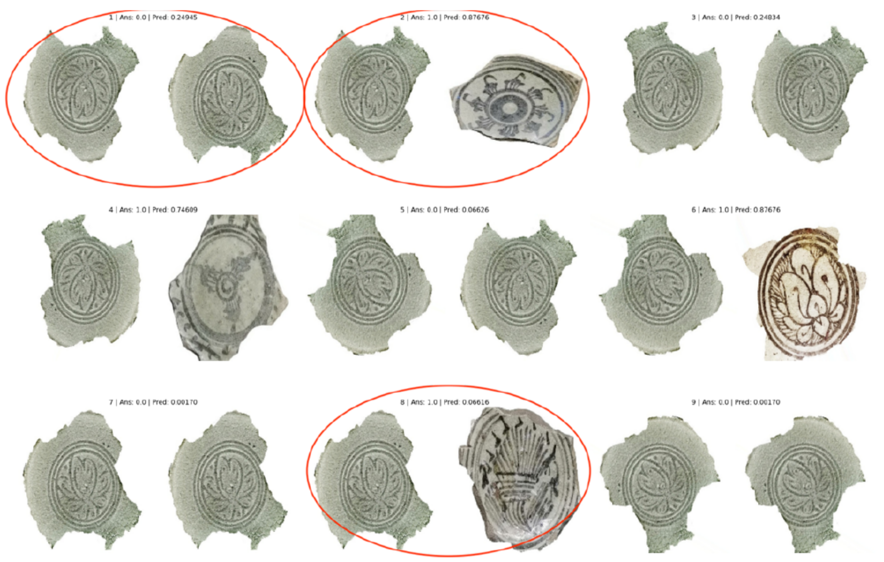


FIGURE 4. Example of output

In Figure 4, Ans mean result: 0.0 (similar), 1.0 (different), and Pred. is similarity value. If it is nearly zero that means very similar and 1 is very different. For the first pair of images, the answer (Ans.) is 0.0, which means they are from the same class, and the prediction (Pred.) is 0.24945, indicating a high degree of similarity. For the second pair, the answer is 1.0, meaning they are not from the same class, and the prediction is 0.89676, indicating low similarity. In the experiment, the similarity level was set at 0.5. That means the result in numbers 1, and 2 image pairs are correct. However, for the number 8 pair of images, the answer (Ans.) is 1.0, which means they are from different classes, while the prediction (Pred.) is 0.06616. That is the wrong answer. So, an application retrieval program should show a list of image order similarities and more than one similar image.

3. **Results and Discussion.** The CNN model consists of an input layer, a convolutional layer that extracts features using filters, an activation layer that introduces non-linearity, a pooling layer that reduces dimensionality, and a fully connected layer that classifies the data based on the extracted features.

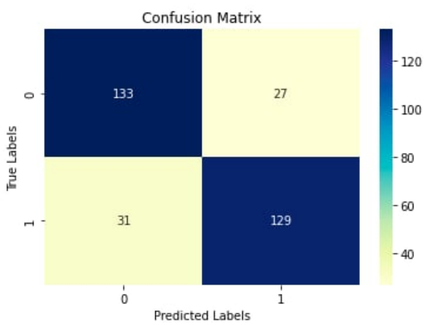
We have created a comparison model as CNN base model, CNN with dropout 0.3, and CNN with dropout 0.5. The experimental result is shown in Table 1.

TABLE 1. Experimental result

Model	Test loss	Test accuracy
CNN base model	0.141	0.79
CNN with dropout layer 0.3	**0.141**	**0.82**
CNN with dropout layer 0.5	0.177	0.77

Table 1 shows the result that information is explained in the model, test loss, and test accuracy columns. The model column identifies the three different models used in the experiment. The first model is a baseline CNN, which likely refers to a convolutional neural network without any dropout layers. The other two models are CNNs with dropout layers 0.3 and 0.5, respectively. Dropout is a technique used to prevent overfitting in neural networks. The next column is test loss. This column shows the test loss for each model. The test loss is a measure of how well a model performs on unseen data. Lower test loss indicates better performance. All three models have relatively low test loss values, and they all generalize well to unseen data. The last column is test accuracy. This column shows the test accuracy for each model. Test accuracy is the proportion of images that the model correctly classified on the unseen test data. Higher test accuracy indicates better performance. The CNN with a dropout layer 0.3 has the highest test accuracy (0.82), followed by the baseline CNN (0.79) and the CNN with a dropout layer 0.5 (0.77). The CNN with dropout layer 0.3 achieved the best overall performance based on test accuracy. This research dropout has helped improve the performance of the baseline CNN. However, using a dropout rate 0.5 might have led to underfitting, as evidenced by the lower test accuracy than the 0.3 dropout model. From the experiment, model CNN with dropout layer 0.3 gives the best results, which can be seen from the accuracy and loss values in Figure 5.

In conclusion, the table suggests that using a CNN with a dropout layer 0.3 can improve test accuracy compared to a baseline CNN model for this specific image classification task.



	precision	recall	f1-score	support
0.0	0.8061	0.8313	0.8185	160
1.0	0.8258	0.8000	0.8127	160
accuracy			0.8156	320
macro avg	0.8159	0.8156	0.8156	320
weighted avg	0.8159	0.8156	0.8156	320

FIGURE 5. Summary result

From the experimental results, we can see that this research will be used in the conservation and research of ceramics in Thailand. It will be utilized for data searching, enabling the general public who are interested in studying, and assisting researchers in data collection. Besides serving as a source of knowledge, it will help in cataloging patterns, such as those found on the center of ceramics, discovered in various locations. This will determine whether the patterns have been previously identified, estimate their age, and identify which kiln they originated from. It can also add new pattern information or correct existing data to make it more complete and accurate.

4. **Conclusions.** Due to the lack dataset of the motifs on the central in Sukhothai ceramics, clustering using powerful deep learning techniques such as VGG16, ResNet, DenseNet, or transfer learning techniques cannot be good accuracy. Therefore, applying the Siamese neuron network and improving the feature extraction to suit the data domain will be the appropriate solution. In this research, CNN was used to find image features and added a dropout layer to reduce the model data memorization. The experiment result is 0.8156. However, if the dropout number is higher, the accuracy will be poor as well. In this research, CNN is the most suitable for the data, with a dropout layer 0.3. Future research directions include investigating the application of the proposed system to other types of ceramics and exploring advanced deep learning techniques to further improve motif identification accuracy. Additionally, incorporating additional data sources, such as historical records and archaeological findings, could enhance the system's knowledge base and broaden its applicability.

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