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Particle Swarm Optimization Algorithm for Hyperparameter Convolutional Neural Network and Transfer Learning VGG16 Model

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ABSTRACT

The classification process is also used in artificial intelligence (AI), which is intelligence created by a computer, so that it can mimic actions like humans in general and can capture events that occur in the surrounding environment. Seeing the very high development of the international coffee trade, it can be concluded that if there is a type of coffee that has the best quality, it will be sought after by coffee importing countries. Batik is cloth that is painted using canting and liquid wax to form motifs or patterns that have high artistic value. Batik has a variety of unique and distinctive patterns that reflect the region where the batik motif originates. One area that has batik motifs in Indonesia is batik in the North Coastal Region of Java Island. In this area, various batiks are produced according to the characteristics of the area itself. Regarding information related to the introduction of types of batik motifs, perhaps it comes from people who have batik skills and batik craftsmen who best understand batik as a whole, while the general public does not really know about batik motifs. Because batik has different motifs and batik motifs in some areas have motifs that are almost uniform but not the same. One of the technologies that can be used is deep learning. The purpose of this study is to propose a Convolutional Neural Network (CNN) and Transfer Learning (TL) model to be implemented in an intelligent system for the process of image classification of coffee bean types. The method used in this study is the PSOCNN transfer learning model VGG16 From the results of tests carried out on 2 models, namely the CNN model, the PSOCNN transfer learning model VGG16. it was found that the highest accuracy was obtained when classifying batik motives images using the PSOCNN-transfer learning model VGG16, which was 83%. The level of accuracy that is increased when compared to the usual CNN model indicates that the use of transfer learning has a good effect on the level of accuracy obtained. Although an increase of 6% is significant, but with this increase it opens up opportunities to increase even higher by using other transfer learning models.

Keywords: Batik, PSOCNN, classification, Transfer Learning.

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1. INTRODUCTION

The ability of Artificial Swarm Intelligence (SI) Algorithms, such as Genetic Algorithms(Murinto et al., 2022), Particle Swarm Optimization (PSO) (Tian & Shi, 2018), Grey Wolf Optimiser (Mirjalili et al., 2014)and Ant Colony (Dorigo et al., 2006), in optimizing real world problems is clearly visible. This is accomplished through a simple population of agents who gather guiding information from neighbors and the neighborhood and then adjust their behavior accordingly. Complex problems are often highly nonlinear and multimodal, yet SI algorithms usually perform better than traditional mathematical programming methods. The problem that arises is how to optimize the Convolutional Neural Network (CNN) hyper-parameter configuration.

Classification is a process of grouping an object into a certain class. The classification process is also used in Artificial Intelligence (AI), which is intelligence created by computers, so that it can imitate actions like humans in general and can capture events that occur in the surrounding environment. Artificial Intelligence has 2 sub-sections, namely Machine Learning (ML) and Deep Learning (DL). Deep Learning itself is a subsection of Machine Learning. In Deep Learning there are several well-known and frequently used algorithms, including: these algorithms, namely Recurrent Neural Networks (RNN)(Gill et al., 2022), Convolutional Neural Network (CNN)(Africa, 2020), (Fernandes Junior & Yen, 2019), (Kamilaris &

Prenafeta-Boldú, 2018), (Nurkhasanah & Murinto, 2022) and Deep Generative Model (DG)(Mo, 2020). CNN is a network that can describe, receive and recognize target levels from low to high. One classification is how batik is classified into several types based on its motif. Indonesian Batik has been recognized by the United Nation Educational, Social and Cultural Organization (UNESCO) as the Representative List of the Intangible Cultural Heritage of Humanity, in Abu Dhabi on October 2, 2009 as stated in the UNESCO manuscript. Batik is cloth that is painted using canting and liquid wax to form motifs or patterns that have high artistic value. Batik has a variety of unique and distinctive patterns that reflect the region where the batik motif originates. One area that has batik motifs in Indonesia is batik in the North Coastal Region of Java Island. In this area, various batiks are produced according to the characteristics of the area itself. Regarding information related to the introduction of types of batik motifs, perhaps it comes from people who have batik skills and batik craftsmen who best understand batik as a whole, while the general public does not really know about batik motifs. Because batik has different motifs and batik motifs in some areas have motifs that are almost uniform but not the same.

The TL approach is to utilize pre-trained models to train new models. The model knowledge obtained during problem solving is utilized to solve relevant problems. The properties learned by being pre-trained on large datasets can be transferred to the masonry network. TL saves time in developing and training deep learning CNN models. In this research, a Particle Swarm Optimization convolutional neural networks (CNN) model and transfer learning using machine learning techniques were built. The implementation of the resulting model is used to classify batik motifs which consist of 6 classes, namely: Buketan, Jlamprang, Liong Pekalongan, Mega Mendung, Tujuh Rupa and Singa Barong. How much research has been done to improve image classification, one of which is using deep learning CNN. CNN is a special type of multi-layer neural network inspired by the mechanism of the optical system of living things. Research conducted by Hubel and Wiesel (Hubel & Wiesel, 1962) found a cortex cell in animals that can detect light in a narrow receiving field. The CNN method has been used in image classification and recognition by several researchers. One of them is a study conducted by LeCun et al (Lecun et al., 1998). Even though CNN is proven to have quite high accuracy values, it is still wide open to improving its accuracy by optimizing its hyperparameters. One of the optimizers used is particle swarm optimization (PSO). The use of PSO is due to its good performance in overcoming optimization problems. PSO in the optimization method was developed by Eberhart and Kennedy (Bansal et al., 2011). PSO is inspired by the social behavior of animals that don't have leaders in their groups. PSO consists of a collection of particles, where the particles represent a solution. From the foregoing, this paper optimizes the CNN hyperparameter using PSO. The implementation is in the classification of batik images using the PSOCNN model and the VGG16 transfer learning model.

2. RESEARCH METHOD

In Figure 1 shows the research methodology used in this paper, where it is consisting of preparation stage, the establishment of CNN model stage, learning model stage and evaluation model stage.

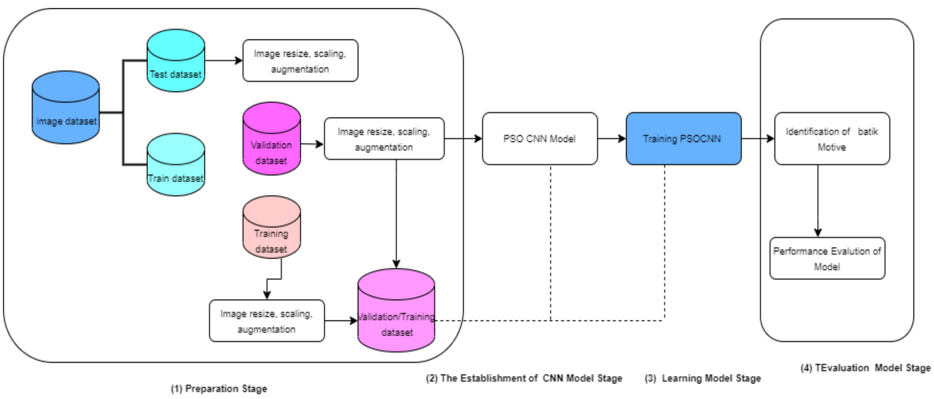


Fig. 1. Research Method

In the pre-processing process, an augmentation process is carried out, the function of which is to add new images from existing images by flipping, rotating, zooming and rescalling. Another function of augmentation is to reduce the occurrence of overfitting during the testing process. In this research, a pre-trained network is used to transfer knowledge to the existing coffee image dataset. The pre-trained network architecture used in this research is VGG16 (Rismiyati & Luthfiarta, 2021). The pre-trained weights of all architectures used in this research are from the ImageNet dataset. Here it is frozen or the weights are determined in the extraction layers when retraining and fine-tuning to adjust as needed.

A fine-tuning is involved in this step, namely dropping out some layers to reduce overfitting, changing the optimizer with Adam, changing variables (learning rate=0.001, epochs=50), using the softmax activation function as a classifier function in a fully-connected layer to get performance and the best accuracy. Experiments were carried out using CNN models, PSOCNN-transfer learning models. The PSOCNN-transfer learning model used here uses the VGG16 architecture.

Particle Swarm Optimization

Particle swarm optimization (PSO) technique, first introduced by Kennedy and Eberhart (1995)(Kennedy J, 1995), is a stochastic optimization technique that is the same as the behavior of a flock of birds or the sociological behavior of a group of humans. The basic idea of PSO is to involve a scenario where a flock of birds is searching for food sources in an area. All the birds don't know exactly where the food is, but with each iteration they will find out how far the food is to be found. The best strategy will be to follow the bird that is close to the food and also from the best position previously achieved. PSO was built with the concept of optimization through a particle swarm. The PSO algorithm is a multi-agent parallel search technique that maintains a swarm of particles and each particle represents a potential solution in the swarm. All particles fly through the multidimensional search space by adjusting their position based on their own experience and that of their neighbors.PSO algorithm was originally written in the form of velocity updated and position updated equations (Kennedy and Eberhart, 1995) as shown in equation (1) and equation (2) respectively.

$$v_{id}^{t+1} = w.v_{id}^{t} + c_1 .r_1.(p_{id}^{t} - x_{id}^{t}) + c_2 .r_2(p_{gd} - x_{id}^{t}) \quad (1)$$

$$x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t+1} \quad (2)$$

where c_1 and c_2 are positive constants, called acceleration coefficients. In this paper r_1 and r_2 are two random numbers with values in the range [0,1]. w is the inertia weight. A large value of inertia weight will facilitate a global exploration while a small inertia weight will facilitate a local exploitation. The ith particle is represented as i $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$. The best previous position of particle i is stored and represented as $P_i = (p_{i1}, p_{i2}, \dots, p_{iD})$. Position provides the best fitness value. The index of the best particle among all the particles in the population is represented by the symbol g. The rate of change of position (velocity) for particle i is represented as $V_i = (v_{i1}, v_{i2}, \dots, v_{iD})$. S During the update process, the velocity of each dimension of a particle is limited to v_{max}. D is the dimension of each search space.

Algorithm 1: ***Pseudocode*** **PSO**

Input:

S: swarms S from particles
f(x): Fitness function

Method:

1. For all particle x_i in swarm S **do**
2. Evaluation for particle fitness using function $f(x_i)$
3. Define the best particle position as pbest, posisi global best swarm sebagai gbest
4. If $f(x_i) < f(gbest) then$
5. Pbest$_i \leftarrow x_i$
6. If $f(x_i) < f(gbest) then$
7. Pbest$_i \leftarrow x_i$
8. End if
9. End If
10. End for

3. RESULTS AND DISCUSSION

3.1 Batik Dataset

The data used in this research uses image data of batik motifs originating from the North Coastal Region of Java. The results of the data collection are 6 classes of batik motifs from the North Coastal Region of Java and 1 negative class (when you do not recognize other than the six specified motifs). These motifs consist of Buketan, Singa Barong, Mega Mendung, Seven Rupa, Liong, Jlamprang and Negative class (when you don't recognize other than the six motifs above).
The total amount of data is 805 images of batik motifs. Image dataset comes from kaggle (https://www.kaggle.com/datasets/ilyamfsl/batik-pesisir-utara-jawa-with-negative-class-v2. The image data is then subjected to pre-processing, namely data augmentation including zoom, random flip, random brightness, rotation, random distortion and skew. The function of the augmentation process is to add new images from existing images. Another function of augmentation is to reduce the occurrence of overfitting during the testing process. In the end, it produced 500 images in each of the 6 batik motif classes and 700 in the Negative class. Figure 3 shows the 6 batik motifs used in this research.

Fig. 2. Batik Motives (a) Mega Mendung (b) Singa Barong (c) Liong Pekalongan (d) Jlamprang (e) Buketan (f) Tujuh Rupa

3.2 *Convolutional Neural Network* Model

The first model used is CNN. The CNN model is then used for comparison with the PSOCNN-transfer learning model in terms of accuracy. This comparison is to ascertain whether the proposed PSOCNN-Transfer learning model is better when compared to other models. The accuracy value is obtained from testing through image testing data. This CNN model has 5 layers including 3 convolution layers and 2 dense layers. The first layer in the convolution layer is also the input layer with sizes 100, 100, 3 where 100,100 is the size of the image and 3 is the RGB value for the color in the image. Each convolution layer uses max pooling with a size of 2x2 with a stride of 2 to reduce the size of the convolution in the next layer. The dense layer only accepts input in the form of a 1-dimensional vector, so the flatten layer is used before the dense layer. The dense layer has a number of neurons of 1024 and 3 respectively. The number of neurons 1024 is the number of neurons commonly used in CNN models in general, so it is used as the number of neurons in this model, while the last 3 neurons in the dense layer are used for the output of the classification. The use of the softmax activation function in the last dense layer is because the number of class categories in the dataset is more than 2. After the CNN model is obtained, the next step is training the coffee dataset to obtain model accuracy and model loss. In this research, the loss used is cross entropy loss, the optimizer used is Adam. Figure 3 shows the accuracy and loss of the model using CNN applied to the batik image dataset.

3.3 PSOCNN-Transfer Learning

In this research, transfer learning is used to prepare the base layer that we have. In this case the model used is the VGG 16 model. The reason for using this model is so that a transfer learning model can be obtained that can be used in classifying batik motifs by looking at the accuracy obtained when the model is applied. The VGG16 model is a neural network architecture that was trained on the ImageNet dataset to classify 1000 different images and the weights that have been trained in VGG16 will be used to classify coffee beans, which is the task in this research. The first step in using this model is to first import the VGG16 architecture which has been trained on the ImageNet dataset. Implementation using Python. After the VGG16 model is obtained, the next step is training on the coffee dataset to obtain model accuracy and model loss. In this research, the loss used is cross entropy loss, the optimizer used is Adam. Figure 8 shows the accuracy and loss of the model using the PSOCNN-VGG16 model applied to the batik motif image dataset.

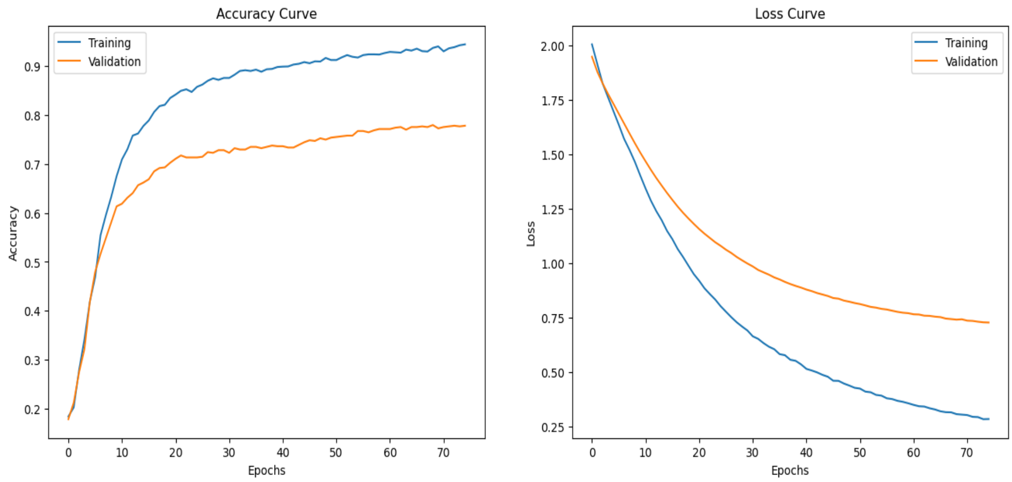


Fig. 3. Plot of model Accuracy and Loss Model of VGG16

3.4 Model CNN-transfer Testing

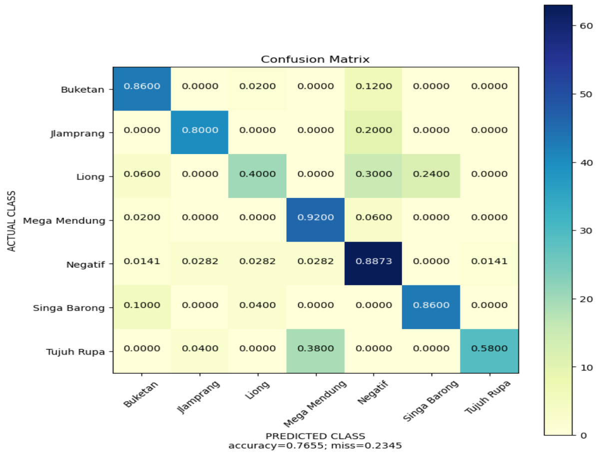
Testing was carried out using the motif image dataset as input into the VGG16 model architecture, the input parameters in the model architecture used in this study used 100 iterations, with a batch size of 28, the number of epochs was 50 and the number of classes was 6. This test data was carried out to test validation of the accuracy results obtained in Training and Validation data. Test results were obtained using a confusion matrix ("Confusion Matrix," 2012), (Wismadi et al., 2020).

3.4.1 CNN Model Testing

Table 1 shows the results of tests on the data testing the batik image dataset and the CNN model confusion matrix. The accuracy of the CNN model when used to classify batik image datasets is 77%.

Table 1. Confusion Matrix CNN Moddel

Motive	Precision	Recall	F1-Score	Support
Buketan	0.8113	0.8600	0.8350	50
Jamplang	0.9091	0.8000	0.8511	50
Liong	0.8000	0.4000	0.5333	50
Mega Mendung	0.6866	0.9200	0.7863	50
Negatif	0.6495	0.8873	0.7500	71
Singa Barong	0.7818	0.8600	0.8190	50
Tujuh Rupa	0.9667	0.5800	0.7250	50
Accuration			0.7665	371

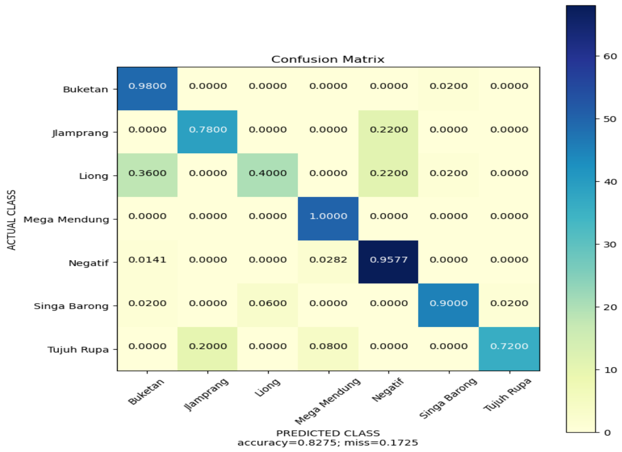


3.4.2 PSOCNN- VGG16 Testing

In Table 2, the results of testing on the coffee bean dataset testing data and the PSOCNN-VGG16 model confusion matrix are shown. The accuracy of the PSOCNN-VGG16 model when used to classify the coffee bean dataset is VGG16 at 83%.

Table 2. Confusion Matrix PSOCNN-VGG16 Moddel

Motive	Precision	Recall	F1-Score	Support
Buketan	0.7101	0.9800	0.8235	50
Jamplang	0.7959	0.7800	0.7879	50
Liong	0.8696	0.4000	0.5479	50
Mega Mendung	0.8929	1.0000	0.9434	50
Negatif	0.7556	0.9577	0.8447	71
Singa Barong	0.9574	0.9000	0.9278	50
Tujuh Rupa	0.9730	0.7200	0.8276	50
Accuration			**0.8275**	371



From the results of tests carried out on 2 models, namely the CNN model, the PSOCNN-transfer learning model VGG16, it was found that the highest accuracy was obtained when classifying batik images using the PSOCNN-transfer learning model VGG16, namely 83%. The increased level of accuracy when compared to ordinary CNN models indicates that the use of transfer learning has a good effect on the level of accuracy obtained. Although an increase of 6 % is significant, but this increase opens up opportunities to increase even higher by using other transfer learning models. It is hoped that future research will be carried out by implementing it into an application, carrying out more trials on the parameters in the PSOCNN-transfer learning model so that higher classification accuracy is obtained.

4. CONCLUSION

From the results of tests carried out on 2 models, namely the CNN model, the PSOCNN-transfer learning VGG16 model, it was found that the highest accuracy was obtained when classifying batik images using the CNN-transfer learning model VGG16, namely 83%. The increased level of accuracy when compared to ordinary CNN models indicates that the use of transfer learning has a good effect on the level of accuracy obtained. An increase of 6% is not too big, but this increase opens up opportunities to increase even higher by using other transfer learning models. It is hoped that future research will be carried out by implementing it into an application, carrying out more trials on the parameters in the PSOCNN-VGG16 transfer learning model so that higher classification accuracy is obtained.

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