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# FINE-TUNING TRANSFER LEARNING MODEL IN WOVEN FABRIC PATTERN CLASSIFICATION

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Abstract. *It is important to figure out the patterns of woven fabrics before producing woven fabric with a machine. Recognition of woven fabric pattern usually with the help of the human eye can understand the fabric pattern. However, this manual checking takes a lot of time, money, and work, which will raise the cost of making woven fabrics. This study uses the VGG16, VGG19, MobileNet, and Inception-V3 methods to classify woven fabric patterns. It also wants to see how fine-tuning method can help algorithms be more accurate at classifying images. The research was divided into four phases, including image acquisition, image preprocessing, image classification and evaluation. A total of 978 pictures of motifs included in the research dataset. There are 351 images for the cotton class, 76 images for linen, 195 images for silk, and 356 images for wool. As the result, the highest testing accuracy was in the Inception-V3 experiment (with fine-tuning) of 72.51%, and the lowest was in the VGG19 experiment (with fine-tuning) of 52.92%.*
**Keywords:** VGG16, VGG19, MobileNet, Inception-V3, Hand-woven fabric

1. **Introduction.** Research on woven fabric pattern recognition is one of the research topics in applying artificial intelligence to the fields of culture and the creative economy [1-3]. Pattern recognition on fabrics can generally help develop the woven fabric industry. In Indonesia, woven fabric is in great demand and is widely traded in traditional and modern motifs. Learning fabric patterns helps the textile industry and other areas that require it, such as developing robots or educational applications for textile knowledge, specially woven fabrics [4-6]. In addition, pattern recognition of woven fabrics needs to be done before making fabric using machines. Introducing this woven fabric pattern is usually done manually by using the human eye, which understands the fabric pattern used. However, this manual checking requires time, cost, and labor which will affect the production cost of woven fabrics. Therefore, research on pattern recognition of woven fabrics is needed to develop artificial intelligence-based applications so that quality checks of woven fabrics can be carried out automatically and according to the quality desired by the textile market [7-9].

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Artificial intelligence methods have been used to recognize patterns in various fields, for example, facial recognition [10], handwriting recognition [11], number plate recognition [12], and object recognition [7]. Many studies on weaving pattern recognition have been found in the previous literature, including [13-16]. Boonsirisumpun & Puarungroj conducted experiments using the deep neural network (DNN) method [13], Puarungroj & Boonsirisumpun conducted experiments using deep learning methods, namely the Inception-V3, Inception-V4, and MobileNets models [14], Rizki et al. conducted experiments using the convolutional neural network (CNN, or ConvNet) and Faster region-based convolutional neural networks (R-CNN) method [15] and Siregar et al. conducted an experiment using a probabilistic neural network method [16].

Based on related works above, deep neural network (DNN) can achieve 93.06% of accuracy, Inception-V3, Inception-V4, and MobileNets can obtain 91.81% until 94.19% of accuracy, Faster R-CNN can obtain 82.14% of accuracy, probabilistic neural network (PNN) can obtain 80% of accuracy. In fact, the model of transfer learning (Inception-V3, Inception-V4, and MobileNets) can obtain accuracy of 94.19% based on previous research.

Previous work has focused on machine learning, transfer learning and deep learning to improve accuracy. In this paper, we will focus on using transfer learning with fine-tuning using woven fabric pattern dataset. To prove performance of model of transfer learning, this research is attempted to use transfer learning model and conduct optimization by using fine-tuning implementation. Based on previous research, the accuracy for hand-woven fabric patterns recognition using transfer learning models is quite high using several transfer learning models, including Inception-V4 obtaining 91.81% of accuracy, Inception-V3 obtaining 92.08% of accuracy and MobileNets obtaining 94.19% of accuracy [14]. Moreover, fine-tuning implementation in transfer learning can improve accuracy, for example, accuracy of plant disease identification using deep learning can achieve 99.75% [17-19].

This paper is organized as follows. Firstly, we discuss the research background and its supported literature. In the second section, we explain related works of study to see previous research result. In the third section, we deliver the methodology of research that contains the structured phase to complete research. In the fourth section, we explain the experiment research and its justification. In the last section, we deliver conclusion of research to answer the research question.

2. **Related Works.** Boonsirisumpun & Puarungroj experimented in 2018 to determine the recognition of Loei hand-woven fabric patterns using the deep neural network (DNN) approach. By analyzing 720 images from the dataset, our research attained a 93.06 percent accuracy rate [13]. In 2019, Puarungroj & Boonsirisumpun conducted an experiment using deep learning methods, namely the Inception-V3, Inception-V4, and MobileNets models for hand-woven fabric patterns recognition. The study obtained accuracy results of 91.81% (Inception-V4), 92.08% (Inception-V3) and 94.19% (MobileNets) from the results of processing 1,800 images data [14].

In 2020, Rizki et al. conducted an experiment using the CNN and Faster R-CNN method for hand-woven fabric patterns classification. This study obtained an accuracy of 76.0% (CNN) and 82.14% (Faster R-CNN) [15]. Siregar et al. conducted an experiment using the probabilistic neural network and gray level co-occurrence matrix (GLCM) method for hand-woven fabric patterns classification named Ulos of Batak Toba. This study obtained an accuracy of 80% by processing as many as 650 images of the dataset [16]. The summary of related works is depicted in Figure 1.

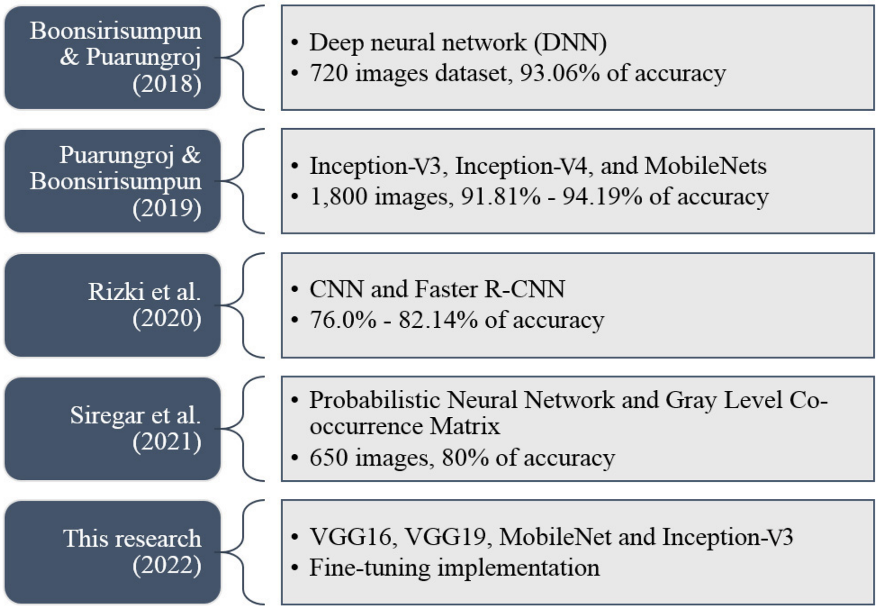


FIGURE 1. Related works

This research attempts to employ a transfer learning model and optimizes its execution through the use of the fine-tuning implementation in order to demonstrate the efficacy of a model that relies on transfer learning. The accuracy of the recognition of hand-woven fabric patterns using transfer learning models is quite high using several transfer learning models, such as Inception-V4, which obtained 91.81 percent of accuracy, Inception-V3, which obtained 92.08 percent of accuracy, and MobileNets, which obtained 94.19 percent of accuracy [13]. This information is based on previous research. Additionally, fine-tuning the implementation of transfer learning can improve accuracy.

3. **Research Methods.** The study was divided into four phases: 1) image acquisition; 2) image preprocessing; 3) image classification and 4) evaluation as depicted in Figure 2 below.

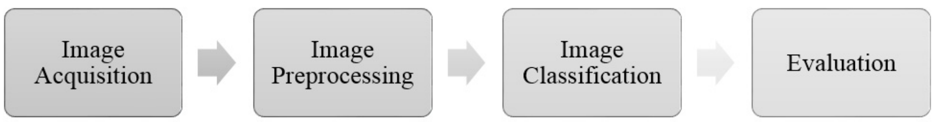


FIGURE 2. Research methods

In the image acquisition step, we collected the fabrics image dataset, a collection of images from several fabrics from the Intelligent Behavior Understanding Group (iBUG), Department of Computing, Imperial College London. This dataset consists of 26 classes with a total of 2,000 images. Using a custom-made portable photometric stereo sensor, images are taken of fabric surfaces in the field (at a clothing store) under four different lighting conditions.

We only used four classes in the image preprocessing stage, all of which were different sorts of natural materials. There were four different themes utilized in the experiment, and they were made of cotton, wool, linen, and silk. Four motifs were chosen and gathered, with numerous photos of each pattern being acquired for each theme. There was a total of 978 pictures of motifs included in the research dataset. There are 351 images for the

FIGURE 3. Example dataset

cotton class, 76 images for linen, 195 images for silk, and 356 images for wool. Figure 3 depicts four class images that are examples of their use.

The next is image classification phase. This phase involves classifying hand-woven fabric patterns using the VGG19, VGG16, MobileNet, and Inception-V3 models. The VGG19 architecture comprises 16 convolution layers and three completely connected layers in a network [20]. The VGG19 model is a transfer learning model derived from the VGG16 model by the University of Oxford Visual Geometry Group [21]. Max pool layer, fully connected, ReLU layer, Dropout layer, and Softmax layer are among the 41 layers [22]. The input layer of the VGG19 design is $224 \times 224 \times 3$, which is comparable to the VGG16 architecture. The classification layer is the final layer of VGG19 [23].

The multilayer perceptron (MLP) classifier is coupled to 16 layers of 5 convolution blocks in the VGG16 architecture. The MLP layer is coupled to the five convolution blocks. Two hidden layers and one output layer make up the MLP layer [24]. The MLP output layer is made up of nodes that directly indicate the number of classes and a softmax or sigmoid activation function (for more than two classes) (for classes less than or equal to two) [25,26].

The MobileNet architecture is based on the CNN architecture. Because it takes less computing effort than traditional CNN models, the MobileNet architecture is commonly employed for images identification. MobileNet allows data to be processed on mobile devices and computers with limited computing power. Convolution layers are included in the MobileNet architecture, a simplified network. This architecture is beneficial in terms of network size reduction and working depth. The MobileNet model's convolution layer can be used to identify details dependent on two manageable factors that effectively switch between accuracy and latency parameters [27].

The Inception-V3 model architecture is designed based on Network-In-Network consisting of three parts: the basic convolution block, the enhanced Inception module, and the classifier. The Inception-V3 model has superior performance in object recognition. Feature extraction in Inception-V3 is processed by basic convolutional blocks (convolutional with max-pooling layers) [28]. We applied those procedures with and without fine-tuning

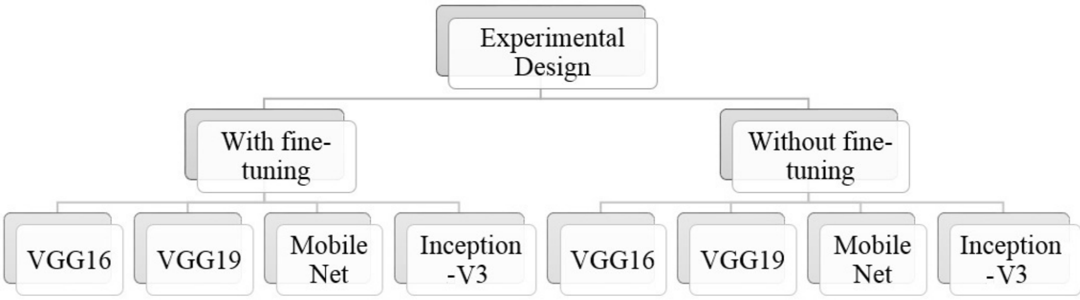


Figure 4. Experimental design

to determining the role of fine-tuning in an accuracy improvement. Figure 4 illustrates the experimental design.

The images dataset was grouped into eight folders during this evaluation phase, with each folder containing 70% of total images for training and 30% of total images for testing. This 70/30 dataset is general number to separate training and testing data [29,30]. The training was carried out with VGG16, VGG19, MobileNet, and Inception-V3 models. After training, the trained models based on VGG16, VGG19, MobileNet, and Inception-V3 models were tested with the test dataset. The accuracy of testing was calculated for each folder. Following that, the accuracy-test results were compared and analyzed. Accuracy is defined as the ratio of actual samples to total samples. The accuracy formula is presented below [4,31]:

$$Accuracy = \frac{TN + TP}{T + F} \tag{1}$$

in which $TP$ denotes the true positive rate, and $TN$ denotes the true negative rate.

4. **Main Results.** This study aims to implement the VGG16, VGG19, MobileNet, and Inception-V3 methods for woven fabric pattern classification. In addition, this study aims to see the role of fine-tuning in increasing the accuracy of algorithms in classifying. The complete experimental results, including accuracy training, accuracy validation, and accuracy testing, can be seen in the following Table 1 and Table 2.

Table 1. Model performance without fine-tuning

| **Transfer learning** | **Without fine-tuning (%)** | | |
|---|---|---|---|
| | **Training accuracy** | **Validation accuracy** | **Testing accuracy** |
| VGG16 | 80.92 | 61.11 | 54.64 |
| VGG19 | 75.42 | 60.07 | 56.70 |
| MobileNet | 91.15 | 66.32 | 63.91 |
| Inception-V3 | **97.09** | **74.23** | **71.82** |

Table 2. Model performance with fine-tuning

| **Transfer learning** | **With fine-tuning (%)** | | |
|---|---|---|---|
| | **Training accuracy** | **Validation accuracy** | **Testing accuracy** |
| VGG16 | 89.31 | 63.19 | 58.08 |
| VGG19 | 82.29 | 59.72 | 52.92 |
| MobileNet | 91.82 | 68.06 | 63.57 |
| Inception-V3 | **96.80** | **75.26** | **72.51** |

Based on Table 1, Inception-V3 obtained the highest accuracy in the experiment without fine-tuning at the training, validation and testing stages. Inception-V3 accuracy values were 97.09% (training experiment), 74.23% (validation experiment), and 71.82% (testing experiment).

Based on Table 2, Inception-V3 obtained the highest accuracy in the experiment using fine-tuning at the training, validation and testing stages. Inception-V3 accuracy values are 96.80% (training experiment), 75.26% (validation experiment), and 72.51% (testing experiment). To see how results of fine-tuning based on results of training, validation and testing, we delivered result in Figure 5 below.

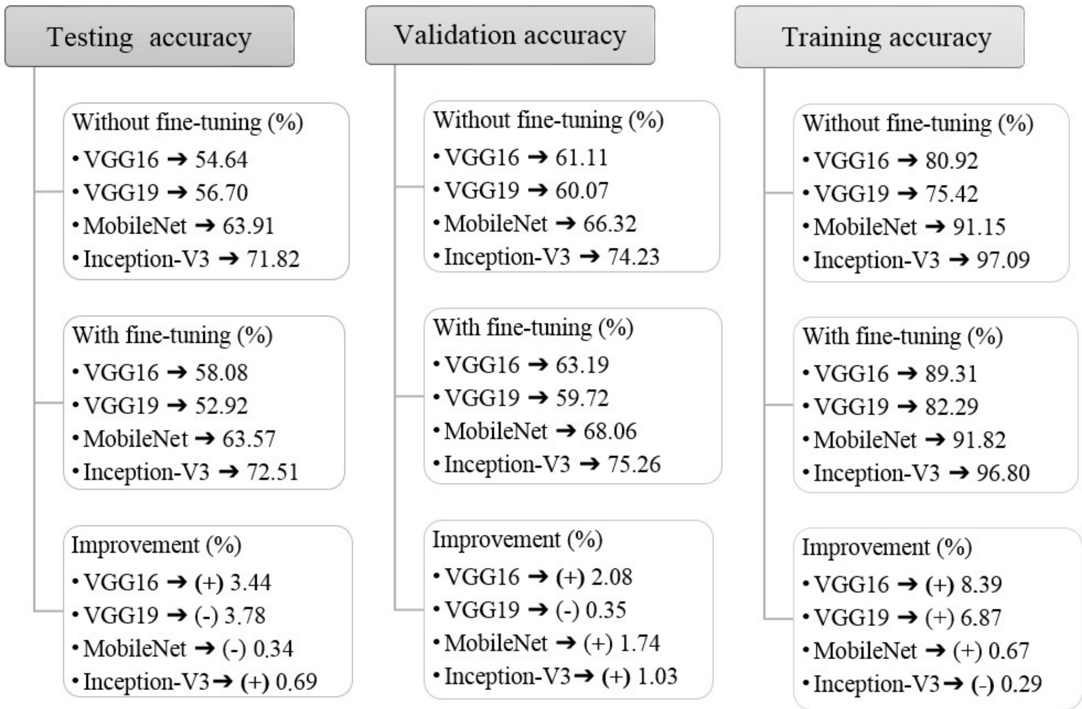


FIGURE 5. Improvement of model accuracy using fine-tuning

Based on Figure 5, the implementation of fine-tuning in testing experiment on the VGG16 and Inception-V3 models has increased accuracy by 3.44% and 0.69%, respectively, and the fine-tuning implementation in testing experiment has decreased accuracy on the VGG19 and MobileNet of 3.78% and 0.34%, respectively. In validation experiment, implementation of fine-tuning on VGG16, MobileNet and Inception-V3 has increased accuracy by 2.08%, 1.74% and 1.03%, respectively. However, the fine-tuning implementation on VGG19 models resulted in a decrease in accuracy 0.35%. In training experiment, implementation of fine-tuning on VGG16, VGG19 and MobileNet has increased accuracy by 8.39%, 6.87% and 0.67% respectively. In contrary, fine-tuning implementation on Inception-V3 models resulted in a decrease in accuracy 0.29%.

Figure 6 shows that the implementation of fine-tuning does not always impact increasing accuracy but also decreasing accuracy depending on the type of transfer learning model used. The highest positive effect is 8.39% on VGG16 in training experiment. Moreover, the highest negative effect is 3.78% on VGG19 in testing experiment.

Based on Figure 7, the highest training accuracy was in the Inception-V3 experiment (without fine-tuning) of 97.09%. The lowest was in the VGG19 experiment (without fine-tuning) of 75.42%. The highest validation accuracy was in the Inception-V3 experiment (with fine-tuning) of 75.26%. The lowest was in the VGG19 experiment (with fine-tuning)

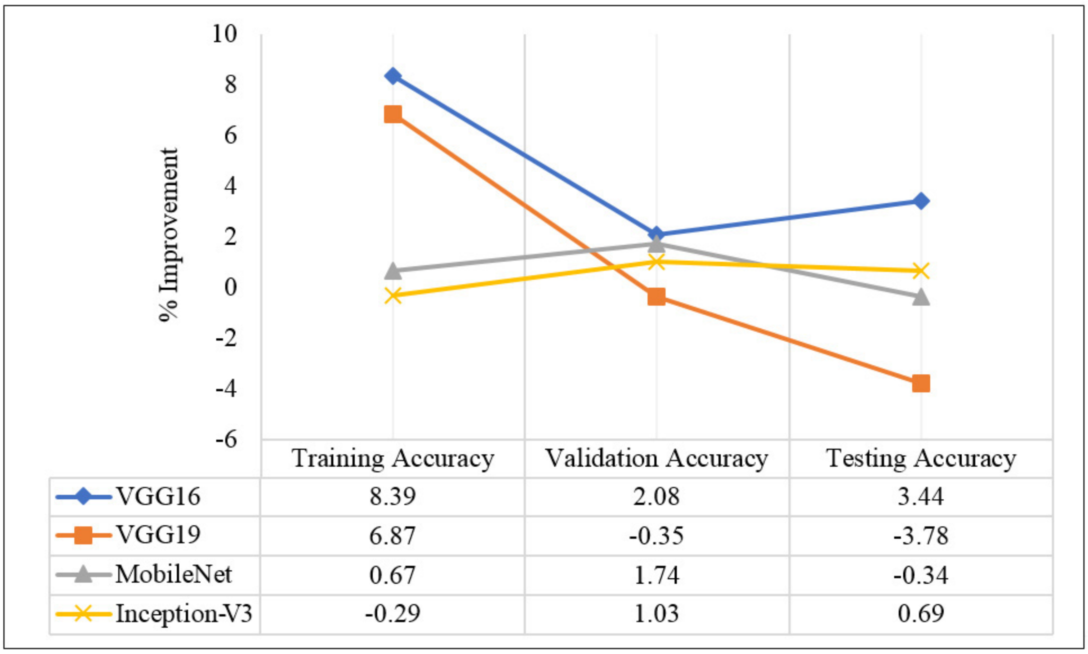


FIGURE 6. Fine-tuning effect to transfer learning model

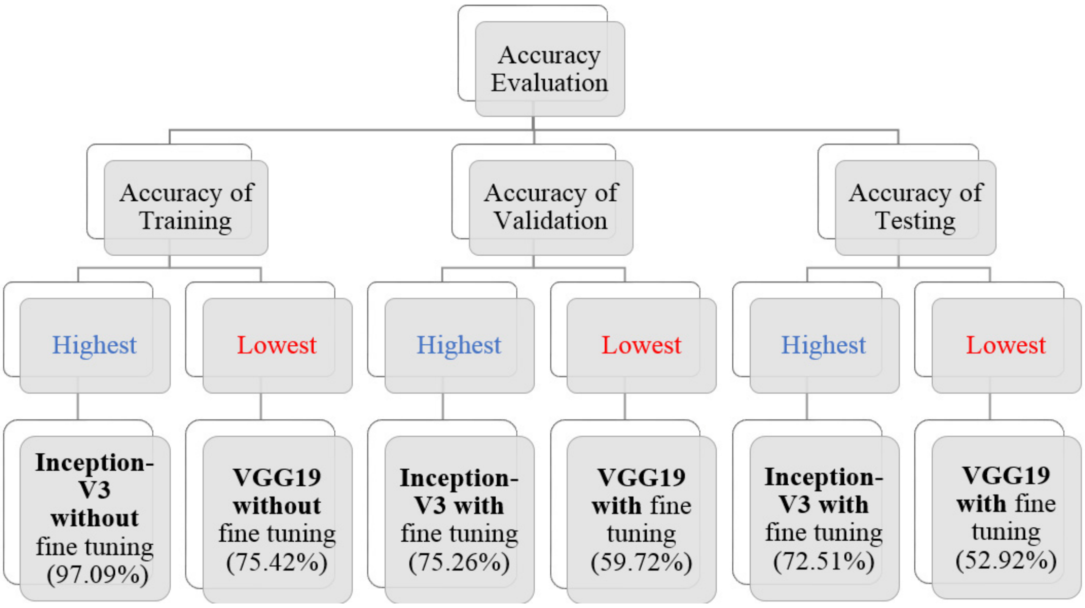


FIGURE 7. Accuracy evaluation

of 59.72%. The highest testing accuracy was in the Inception-V3 experiment (with fine-tuning) of 72.51%, and the lowest was in the VGG19 experiment (with fine-tuning) of 52.92%. The VGG19 transfer learning model is not recommended because it has low performance during training, validation, and testing experiment.

It can be concluded that the appropriate image processing for the dataset used is the transfer learning Inception-V3 model. The Inception-V3 model is widely used for transfer learning because of its advanced performance in object recognition, which benefits from the unique Inception architecture [32]. One of its uniqueness is that the $1 \times 1$ convolutional kernel is widely used to reduce the number of feature channels and accelerate the training speed [33]. In addition, the Inception-V3 model architecture uses additional classifiers so that more stable training results and better gradient convergence are obtained, and eliminating gradients and overfitting problems are reduced [28,34].

5. **Conclusions.** This paper proposed a method of woven fabrics pattern classification based on transfer learning model, and the method was compared with other methods. In particular, the method of woven fabrics pattern classification based on fine-tuning can achieve higher accuracy. Moreover, the transfer learning model based on fine-tuning transfer learning performs better in image classification on woven fabrics dataset than the model without fine-tuning implementation. In this research, VGG16 and Inception-V3 with fine-tuning models have increased accuracy by 3.44% and 0.69%, respectively. The highest testing accuracy was in the Inception-V3 experiment (with fine-tuning) of 72.51%, and the lowest was in the VGG19 experiment (with fine-tuning) of 52.92%.

This study only discusses the algorithm's performance without discussing the image processing issue. Future research will discuss the problems in image processing for woven fabric motifs, such as defects in the fabric or lighting that causes the fabric to be difficult to identify.

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