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Toward Adaptive Manufacturing Development: Implementation of NasNet for Identifying Leather Defects

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ABSTRACT

Artificial intelligence was the powerful approach that was proven to be impactful for solving several problems. In the leather inspection cases, artificial intelligence also contributed some research works that effected for leather inspection process. In this research, we employed NasNet architecture conducted by using fine-tunning transfer learning method to distinguish the types of leather defects. We used 3600 images that was distributed into six classes which are folding marks, grain off, growth marks, loose grains, pinhole and non-defective. Our proposed solution successfully achieved accuracy for training data is 0.9788 with loss of 0.0198. While the maximum accuracy in validation data is 0.8059 with loss of 0.2126. In the testing data, our experiment obtained accuracy of 0.8603 with loss of 0.1603. These results indicated that our proposed solution was suitable to recognize the characteristics of leather defects and suitable to distinguish them.

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1. INTRODUCTION

Hides (refers to large animals' skin, such as cows) and skins (refers to the small animals' skin, such as sheep) are mostly produced in slaughterhouses [1]. Those materials are then processed chemically to produce leathers. In the leather factory, leather is denatured by three major processes, i.e., sorting, chemical processing and physical processing [2]. Those three steps are strongly important and have to conducted thoroughly due to the production of high-quality leather since their quality may give significant impact to the price. Hence, factory workers have to ensure that the leather denaturing process is well carried out before it is used for creating products such as clothes, shoes, bags, etc. Considering to the leather quality, it is not only affected by the denaturation process. The natural defect (such as scars, spots, wrinkles, holes and uneven color created from the animal fur (see in Figure 1) in the leather surface also become the hurdle for creating the good quality of leathers [2]. In the leather factory, workers conduct an inspection of leather defects and conduct monitoring consistently. However, since the inspection proses is conducted manually, it leads to the subjective evaluation and may cause the high false defect recognition due to the human mistake and mis-interpretation. Furthermore, the quantity of professional leather inspector is quite small due to the qualification process. The qualified inspectors have to accomplish a series of inspector professional training to be certified as a high quality of leather defect inspector [2].

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(a) (b) (c)

Figure 1. Example of several leather defects: (a) black line; (b) wrinkle, and (c) insect bite [2]

Regarding to the aforementioned problem, artificial intelligence (AI) offers a significant contribution in the leather defect detection process. Several research communities and academy have been done in the development of intelligent system for detecting leather defect by applying artificial intelligent. Jawahar et.al., [3] proposed a combination of wavelet (refers to feature extraction method) and support vector machine as classifier which was evaluated in 700 data with resolution of 256 by 256 pixels. The dataset was comprised into two classes which are 500 data containing of leather defect and 200 normal images. 70% of those data were performed as the training data and 30% of the total data were performed as testing data. This research work successfully achieved accuracy of 95%. Bong et.al., [4] evaluated 2500 images containing of four classes such as scar, pinhole, scratch and normal leather. This study successfully obtained accuracy of more that 98%. Liong et.al., [5] performed canny edge detection combined with artificial neural network for evaluating 2378 images and achieved accuracy of 84%. Another research performed segmentation technique for recognizing the location and area of leather defect. Liong et.al., [1] successfully utilized Mask R-CNN for evaluating 584 images and achieved accuracy of 91.5%.

Regardless to the excellent performance resulted from the previous research works, developing intelligent inspection method for detecting leather defect still remained some hurdles. Almost previous studies were carried out by utilizing traditional method in which it was not suitable enough for the complex dataset. It also required more time for executing the method. Hence, an alternative method that was suitable with complex dataset was needed. To address those problems, we proposed deep learning approach for identifying the type of leather defect by developing deep learning architecture that was suitable for recognizing five types of leather defects.

2. RESEARCH METHOD

The defect identification process was occurred by conducting several processes as depicted in the Figure 2. Generally, the defect identification process was done by employing deep learning classification network. NasNet was considered to be classification network in this research work since its outstanding performance in distinguishing the feature patterns of small objects. Before we began those processes, we conducted the data acquisition by creating an xml file of data and ground truth since it was required for the deep learning training process.

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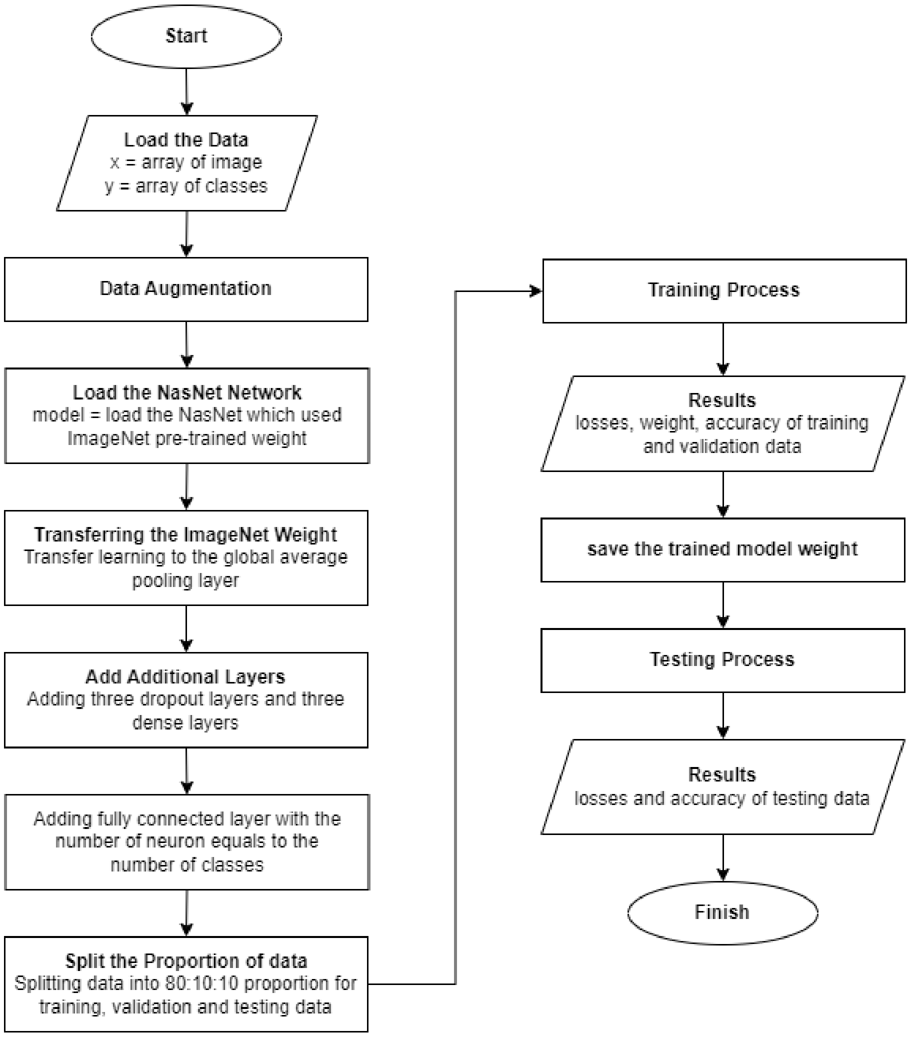
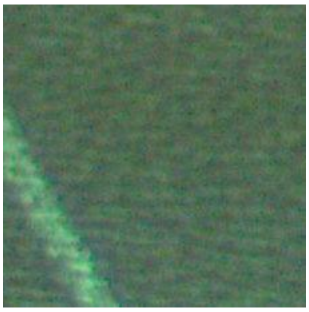


Figure 2. Flowchart of the proposed solution

2.1. Dataset

This research work used leather public dataset comprising of 3600 images. The dataset consisted of six classes which are folding marks, grain off, growth marks, loose grains, pinhole and non-defective. The dataset was completed with classification ground truth. An example of dataset is depicted in Figure 3. Therefore, the detail information of dataset is illustrated in Table 1.


(a)


(b)


(c)

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(d) (e) (f)

Figure 3. Example of data : (a) folding marks, (b) grain off, (c) growth marks, (d) loose grains, (e) pinhole and (f) non-defective

Table 1. The Detail Information of Dataset

Component	Detail Information
Type of image	Leather defect images
Dimension	227 x 227
Ground truth	Classification which contained of six classes (folding marks, grain off, growth marks, loose grains, pinhole and non-defective).
Number of data	The dataset consisted of 3600 images divided in the following proportion: a. folding marks : 600 images b. grain off : 600 images c. growth marks : 600 images d. loose grains : 600 images e. pinhole : 600 images f. non-defective : 600 images
Source of data	The used dataset was secondary dataset from previous research work conducted by Vasagam et.al [6]

2.2. Experimental Design

Our experiment was divided into three major processes. In the first processes, we divided the data into three part of data which are training data, validation data and testing data with proportion of 80:10:10. We used training data and validation data as an input of training process. Whereas, the testing data was used in the testing process. In this study, we employed NasNet architecture [7] by conducting transfer learning method to distinguishing the types of leather defect. Transfer learning was a practical deep learning approach that transferred knowledge from the trained model. It worked by extracting certain data to produce a weight representing the data. The weight was then called as a pre-trained model. To utilize the pre-trained model, we can used two approach which were using the pre-trained model as feature extractor [8][9] and using it as fine-tuning [10]. Using the pre-trained model for extracting the feature was like we employing this method to extract all important information from the data and then fit those results to the classifiers. While, fine-tunning allowed us to re-create a new model considering the weight of the existing model which it was powerful to handle overfitting and underfitting problem. It also can improve the performance of model [11]–[14].

In this research work, we employed fine-tunning method by utilizing the weight from ImageNet [15]. Its architecture is illustrated in Figure 4. This weight was then fit to the architecture of NasNet. NasNet was considered to be implemented in this study since it performed outstanding result comparing other architecture [16]. The architecture of NasNet is illustrated in Table 2.

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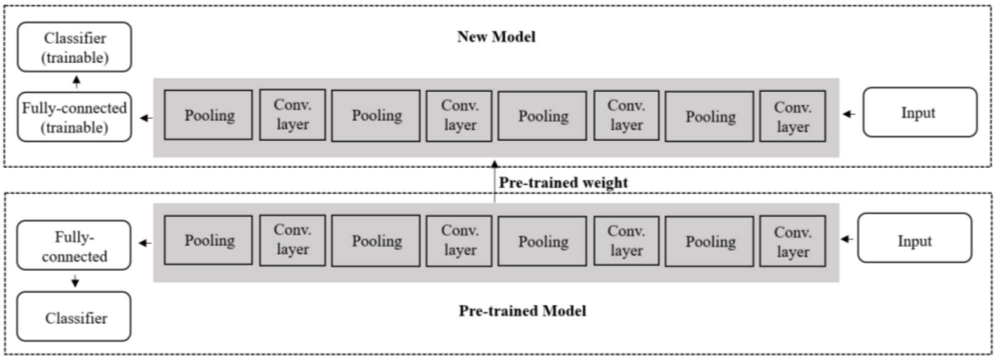


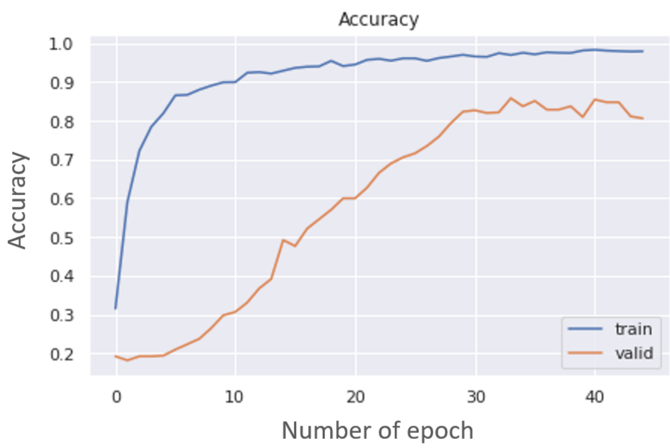
Figure 4. Architecture of fine-tuning pre-trained model

Table 2. The architecture of NasNet

Layer (type)	Output shape	Parameters
NasNet (functional)	(None, 11, 11, 4032)	84916818
global_average_ pooling2d	(None, 4032)	0
dropout (Dropout)	(None, 4032)	0
dense (Dense)	(None, 16)	64528
dropout_1 (Dropout)	(None, 16)	0
dense_1 (Dense)	(None, 8)	136
dropout_2 (Dropout)	(None, 8)	0
dense_2 (Dense)	(None, 2)	18

3. RESULTS AND ANALYSIS

In this research, we performed NasNet architecture by using fine-tunning transfer learning method. Before conducting training process, we divided the data into three part which are training data, validation data and testing data with proportion of 80:10:10. Result of training process is illustrated in Figure 5. Figure 5(a) illustrates the accuracy during training process, while Figure 5(b) illustrates the loss during training process. In both figure, blue line illustrates the result in every epoch for training data. Whereas the orange line illustrates the result in every epoch for validation data. According Figure 5, we can conclude that maximum accuracy for training data is 0.9788 with loss of 0.0198. While the maximum accuracy in validation data is 0.8059 with loss of 0.2126. In the testing data, our experiment obtained accuracy of 0.8603 with loss of 0.1603. The detail result of our experiment can be seen in Table 3.



(a)

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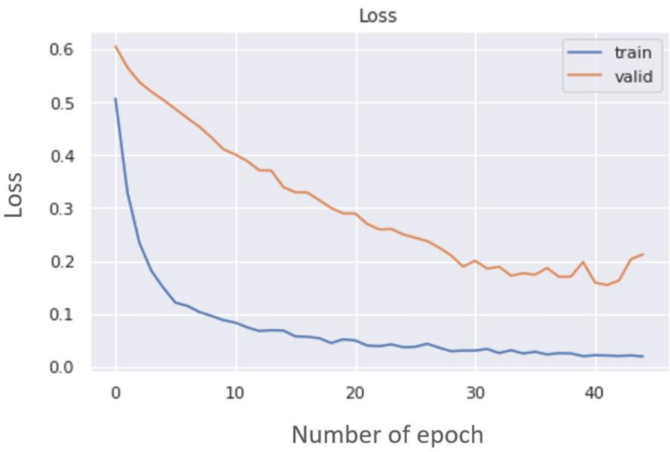

(b)

Figure 5. Result of training process: (a) accuracy of training process and (b) loss of training process

Table 3. Summary of Results

Component		Description/Results
Size of input data		227x227
Proportion of data		80:10:10
Augmentation		Online
Number of epochs		45
Number of parameters		84,916,818
Accuracy	Training	0.9788
	Validation	0.8059
	Testing	0.8603
Loss	Training	0.0198
	Validation	0.2126
	Testing	0.1603

According to Table 3, it can be concluded that the NasNet was suitable for distinguishing the leather defects with the accuracy of more than 80% in training data, validation data and testing data. Actually, the dataset has been employed by the previous research work and has achieved an accuracy of 94.25%. However, it only used a part of data which was consisted of two classes of defect. The researcher also used several image processing techniques that was more suitable for the proposed cases. Comparing to our proposed solution results, that previous research was seemingly much better. Despite of its consideration, our proposed solution was employed six type of leather defects that was much difficult to be distinguished. Hence, in the future, we can combine our proposed solution with additional pre-treatment processes to increase the results.

4. CONCLUSION

This study focused to create a deep learning model for distinguishing the types leather defects. We introduced the proposed solution that was divided into three main processes which are data acquisition, training process and testing process. We performed our proposed solution in 3600 images that was distributed in five classes of defect. Our proposed solution successfully achieved accuracy for training data is 0.9788 with loss of 0.0198. While the maximum accuracy in validation data is 0.8059 with loss of 0.2126. In the testing data, our experiment obtained accuracy of 0.8603 with loss of 0.1603. The used data has actually been utilized by the previous research work and has achieved an accuracy of more than

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90% in which it seemingly much better than our findings. Despite of its consideration, our proposed solution was conducted by performing six types of defects. While, the previous research only used two types of defects. Hence, for further research, we can employe additional processes that supporting in achieving an outstanding performance.

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