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Palembang *songket* fabric *motif* image detection with data augmentation based on ResNet using dropout

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ABSTRACT

A good way to spread knowledge about Palembang *songket* woven cloth patterns is to use information technology, especially artificial intelligence technology. This study's main goal is to develop a ResNet model with dropout regularization methods and find out how dropout regularization affects the ResNet model for detecting Palembang *songket* fabric *motif* with more data. Data was collected in places like *tujuh saudara songket*, Zainal *songket*, *songket* PaSH, AMS *songket*, and *batik*, Ernawati *songket*, Nabilah collections, Ilham *songket*, and Marissa *songket*. We used eight class of data for this research. A dataset of 7,680 data for training, 960 data for validation, and 960 data for testing is a dataset that has been prepared to be implemented in experiments. In the final results, the experimental results for DResNet demonstrated that accuracy at the training stage was 92.16%, accuracy at the validation stage was 78.60%, and accuracy at the submission stage was 80.3%. The experimental results also show that dropouts are able to increase the accuracy of the ResNet model by adding +1.10% accuracy in the training process, adding +1.80% accuracy in the validation process, and adding +0.40% accuracy in the testing process.

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1. INTRODUCTION

Traditional woven fabrics not only represent the culture of the Indonesian people but also their identity and values [1]. One of Indonesia's national priorities is the preservation of traditional woven fabrics. In collaboration with the center for environmental standardization and forestry, the ministry of environment and forestry, the SWITCH Asia program on sustainable consumption and production of traditional weaving, supports this initiative. The preservation and re-promotion of woven fabrics within the community is one of the measures taken to preserve cultural values so they can be passed on to future generations. In addition, this action can enhance the popularity of woven fabrics, thereby encouraging the local and international growth of the woven fabric industry [2]–[4].

Indonesia is renowned for producing numerous *songket* woven fabrics, including Palembang *songket* woven cloth. Typically woven with gold and silver strands, *songket* fabric from Palembang features an assortment of *motif* and hues [5]–[7]. Plant *motif* (particularly the distillation form of flowers), geometric *motif*, and combined plant and geometric *motif* make up the majority of Palembang *songket motif*. The dragon *besaung motif* (*nago besaung*), rose *motif* (*bungo mawar*) and Chinese floral *motif* (*bungo cino*) are quite well-known and have existed for a very long time as traditional *motif* of Palembang *songket* woven cloth [8].

The woven fabric of Palembang *songket* features a variety of patterns or designs. The regular and irregular arrangement of fundamental *motif* forms the pattern of woven fabric. The conventional method for identifying *motif* on Palembang *songket* woven fabric focuses on the shape and arrangement of *motif* elements. However, only a few Palembang people are familiar with the patterns on Palembang *songket* woven fabric. This is due to a dearth of learning knowledge and the absence of Palembang *songket* woven fabric *motif* recognition applications that could assist individuals in identifying the *motif*'s name [9]–[12].

Utilizing information technology, particularly artificial intelligence technology is a viable option for re-promoting *motif* knowledge on Palembang *songket* woven fabric. Pattern recognition is one of the artificial intelligence technologies supporting this program [13]–[15]. This technology can be incorporated into applications to aid in recognizing woven fabric *motif* without consulting a cultural expert [16]–[25].

The advancement of research in the field of pattern recognition facilitates the advancement of research in the field of *motif* recognition in woven fabrics. For example, model deep neural network (DNN) was utilized by Boonsirisumpun and Puarungroj [26] for the recognition of woven fabrics in their research. This investigation utilized 720 fabric image data with four classes. This study's accuracy attained 93.06%. They also used the mobile nets model for woven fabric recognition. The data used in this study was fabric image data as much as 4,500 data. The accuracy of this study reached 98.22%.

Research by Puarungroj and Boonsirisumpun [27], using the inception-v3 method to detect phasin-woven fabric. The accuracy of this study was 92.08%. The study employed a dataset containing 1,800 data divided into 10 data classes. Moreover, investigation on the detection of Malay woven fabrics utilized the faster R-CNN method. This study did not optimize Faster R-CNN, so this method's performance was only 82.14% [28].

Research by Hussain *et al*. [29] used ResNet-50 for fabric recognition of woven fabric patterns. The accuracy of this study reached 99.3%. The dataset used in the study amounted to 3,540 data. To detect *ulos* woven fabrics, Siregar and Mauritsius [30] employ the convolutional neural network (CNN) technique. The accuracy of this study was 87.27%.

Based on previous research, the ResNet model performs better than other methods. However, in the case of fabric pattern recognition using transfer learning models, there are often cases of overfitting. This is due to a very deep and complex network model [31]. Overfitting cases will cause too good motive recognition results during training but not optimally during testing. If a model is overfitting, then the model cannot generalize well. This causes testing using different data to reduce the accuracy results [32].

However, these cases of overfitting can be reduced by using the dropout technique. In some other cases, dropout techniques are widely used to reduce overfitting cases [29], [33]–[36]. The dropout regularization technique can be implemented avoiding overfitting by stopping hidden units from depending on a particular unit from the previous layer [37]. Based on the background above, the main objective of this study is to propose a ResNet model with dropout regularization techniques and find out the effect of dropout regularization on the ResNet model for Palembang *songket* fabric *motif* image detection with data augmentation.

2. METHOD

The experimental phase of this research is structured and well-planned so that the research can be conducted properly following the research objectives: propose a ResNet model with dropout regularization techniques to detect Palembang *songket motif*. Data collection was carried out in various locations of Palembang *songket* woven fabric centers, including *lain tujuh saudara songket*, Zainal *songket*, *songket* PASH, AMS *songket* and *batik*, Ernawati *songket*, Nabilah collections, Ilham *songket*, and Marissa *songket*.

The process of acquiring images of Palembang *songket* fabric *motif* is carried out by photographing fabric *motif* with different positions and light levels. After the shooting is complete, crop the image using the help of the adobe photoshop CS3 application as needed. Cropping techniques are performed to change the pixel size of the image with a size of 512x512 pixels for each image. In the meantime, the research phases are depicted in Figure 1.

We used eight class of *motif* for this research. The class of *motif* used is a traditional *motif* typical of Palembang *songket* woven fabric, not derivative *motif* and creation *motif*. The types of woven fabric *motif* tested are *bintang melati*, *bunga bintang*, *bunga mawar*, *kucing tidur*, *naga besaung*, *pucuk rebung balai anak*, *pucuk rebung penuh* and *tampuk manggis* as seen in Figures 2(a) to (h).

Data preprocessing involves the application of data augmentation using six techniques. We used image horizontal shift, image vertical shift, image magnification, image rotation, image shear, and image flipping for data augmentation. The datasets are distributed with a proportion of 90% train-validation data and 10% test data. Complete data is divided into multiple containers for the labelling procedure, with the following information in Table 1.

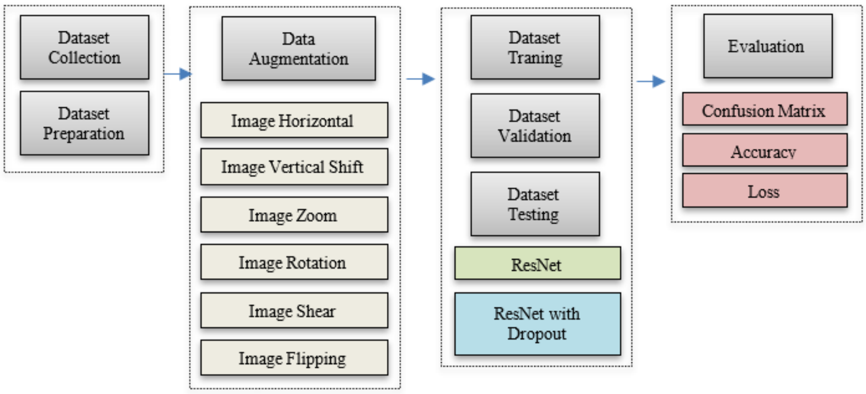


Figure 1. Research method

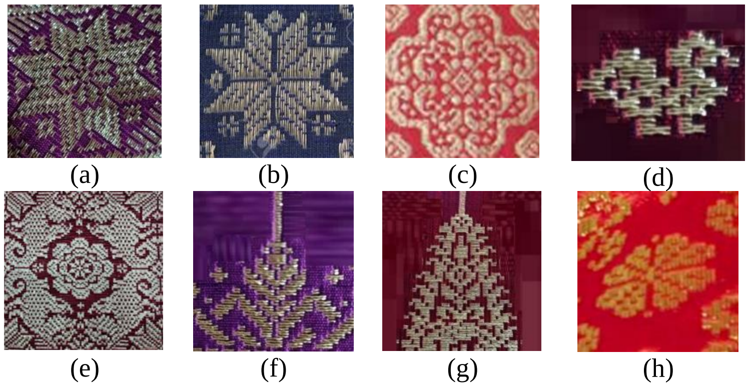


Figure 2. Dataset example, *motif* example of; (a) *bintang melati*, (b) *bunga bintang*, (c) *bunga mawar*, (d) *kucing tidur*, (e) *naga besaung*, (f) *pucuk rebung balai anak*, (g) *pucuk rebung penuh*, and (h) *tampuk manggis*

Table 1. Detail of research dataset

Dataset	Original data (x)	Number of class (N)	Augmentation technique (a)	Number of final data $\mu = a \, x \, 4 \, N$
Train	40	8	6	7,680
Validate	5	8	6	960
Test	5	8	6	960
Total	50	8	6	9,600

The next stage is an experiment using the ResNet model and ResNet with dropout (DResNet). Based on previous research, the Resnet model produces better performance than other methods. However, pattern recognition using transfer learning models often cases of overfitting. This is due to the very deep and complex network model. Overfitting cases will cause too good motive recognition results during the training process, but not optimally during the testing process. If a model is overfitting, then the model cannot generalize well. These overfitting cases can be reduced by using the dropout technique. In some other cases, dropout techniques are widely used to reduce cases of overfitting dropout regularization techniques can be implemented to avoid overfitting by stopping hidden units from depending on a particular unit from the previous layer [29], [34]–[37].

This study used confusion matrix, accuracy, and loss evaluation methods. The confusion matrix is one of the accuracy calculation methods widely used in deep learning models. This method is a matrix of predictions that will be tested in estimating true and false objects to calculate the accuracy, precision, and recall value. The confusion matrix represents the predictions and actual conditions of the data generated by ResNet and DResNet at the time of the experiment. Next is the accuracy model, which describes how accurately the model can classify correctly. In other words, accuracy is the degree of proximity of the predicted value to the actual value. The accuracy value can be obtained by (1):

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \times 100\% \quad (1)$$

Furthermore, the evaluation method used is the loss model. This model measures values that represent the sum of errors in ResNet at the time of the experiment. The loss model measures how well (or badly) the ResNet and DResNet models detect Palembang *songket* woven fabric *motif*. The lower the loss value, the better the ResNet and DResNet models work.

3. RESULTS AND DISCUSSION

The implementation of the ResNet and ResNet algorithms with dropout or namely DResNet is intended to be able to determine the accuracy results in the detection of Palembang woven fabric *motif*. Through the analysis of experimental results, it can be known about the role of dropouts in improving ResNet accuracy results. Experiments on the ResNet algorithm will be carried out in two stages. The first stage of the experiment is an experiment on the ResNet algorithm without the application of dropout regularization and the second experiment is an experiment on the ResNet algorithm with the application of dropout regularization (DResNet). The results of this study will be analyzed and discussed based on the evaluation results of the confusion matrix model, accuracy model, and loss model.

At this stage, what is done is to analyze the experimental results, namely testing the model using an accuracy model against ResNet without dropouts and ResNet with dropouts. A dataset of 7,680 data for training, 960 data for validation and 960 data for testing is a dataset that has been prepared to be implemented in experiments. A graph of the results of the accuracy per epoch evaluation for ResNet can be seen in the Figure 3(a) and accuracy for DResNet can be seen in Figure 3(b).

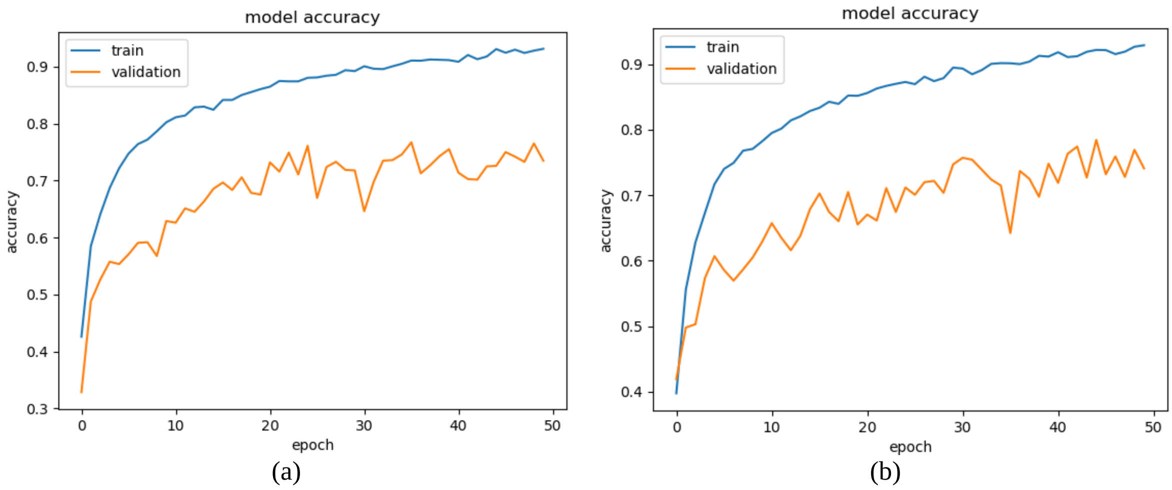
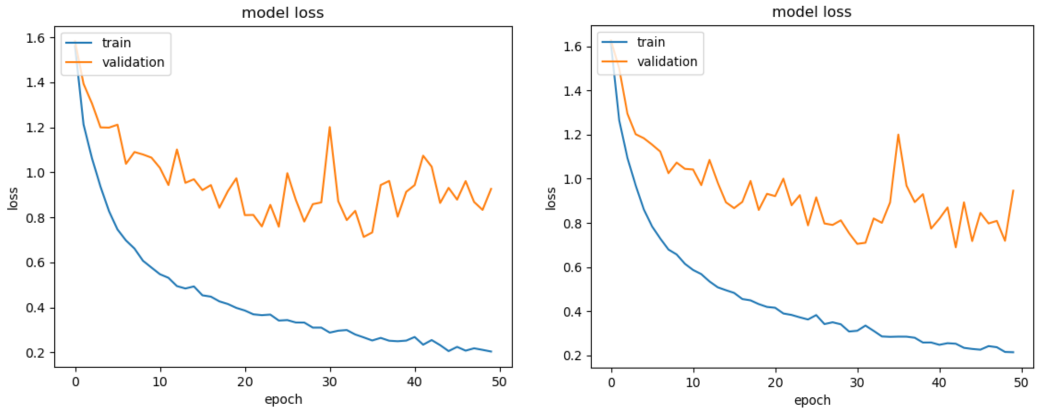


Figure 3. Model accuracy of; (a) ResNet and (b) DResNet

The next step is to analyze the results of the experimental evaluation using a loss model against ResNet without dropouts and ResNet with dropouts. The dataset was 7,680 data for training, 960 data for validation and 960 data to find out how the loss results trend in the ResNet and DResNet models for each epoch. From the experimental results, the loss value in both the ResNet and DResNet models showed that the results decreased at each epoch. The ResNet and DResNet models detect Palembang *songket* woven fabric *motif* well. The results of the loss value trend chart for ResNet can be seen in the Figure 4(a) and loss value chart for DResNet can be seen in the Figure 4(b).

The next step is to analyze the results of the confusion matrix for the ResNet model. From the experimental results for the ResNet model, the *bintang melati motif* got an accuracy of 73%, the *bunga bintang motif* got an accuracy of 94%, the *bunga mawar motif* got an accuracy of 70%, the *kucing tidur motif* got an accuracy of 98%, the *naga besaung motif* got an accuracy of 62%, the *pucuk rebung balai anak motif* got an accuracy of 72%, the *pucuk rebung penuh* got an accuracy of 86%, and the *tampuk manggis motif* gets an accuracy of 84%. For details of the results of the confusion matrix of the ResNet model, see Table 2.



(a) (b)

Figure 4. Model loss of; (a) ResNet and (b) DResNet

Table 2. Confusion matrix of ResNet model

	Bintang melati	*Bunga bintang*	*Bunga mawar*	*Kucing tidur*	*Naga besaung*	*Pucuk rebung balai anak*	*Pucuk rebung penuh*	*Tampuk manggis*
Bintang melati	**91**	8	6	3	13	1	2	1
Bunga bintang	0	**118**	0	0	2	0	0	5
Bunga mawar	17	1	**88**	3	5	11	0	0
Kucing tidur	3	0	0	**122**	0	0	0	0
Naga besaung	15	17	1	8	**77**	0	7	0
Pucuk rebung balai anak	22	0	1	4	0	**90**	8	0
Pucuk rebung penuh	3	2	3	4	1	4	**108**	0
Tampuk manggis	3	15	0	2	0	0	0	**105**

The next step is to analyze the results of the confusion matrix for the DResNet model. From the experimental results for the DResNet model, the *bintang melati motif* got an accuracy of 61%, the *bunga bintang motif* got an accuracy of 87%, the *bunga mawar motif* got an accuracy of 66%, the *kucing tidur motif* got an accuracy of 100%, the *naga besaung motif* got an accuracy of 61%, the *pucuk rebung balai anak motif* got an accuracy of 82%, the *pucuk rebung penuh* got an accuracy of 95%, and the *tampuk manggis motif* gets an accuracy of 90%. For details of the results of the confusion matrix of the ResNet model, see Table 3.

Table 3. Confusion matrix of DResNet model

	Bintang melati	*Bunga bintang*	*Bunga mawar*	*Kucing tidur*	*Naga besaung*	*Pucuk rebung balai anak*	*Pucuk rebung penuh*	*Tampuk manggis*
Bintang melati	**76**	1	9	4	24	5	5	1
Bunga bintang	0	**109**	0	2	6	3	0	5
Bunga mawar	1	0	**82**	7	5	28	2	0
Kucing tidur	0	0	0	**125**	0	0	0	0
Naga besaung	8	6	9	15	**76**	2	9	0
Pucuk rebung balai anak	5	0	0	4	1	**103**	12	0
Pucuk rebung penuh	0	0	0	3	0	3	**119**	0
Tampuk manggis	3	7	0	2	0	0	0	**113**

The test accuracy can be calculated based on the confusion matrix results from the testing phase. The accuracy calculation describes how well the ResNet and DResNet models can correctly classify or describe the proportion of correct predictions (positive and negative) relative to the entire data set. In other terms, precision is the degree to which the predicted value closely matches the actual value. In the testing phase, ResNet, and DResNet effectively predicted the true, and false values in the Table 4.

Based on experiments, the results of ResNet and DResNet show an increasing trend of accuracy at each epoch. However, as a final result, ResNet obtained accuracy results of 91.06% at the training stage, 76.80% at the validation stage and 79.90% at the testing stage. For DResNet, the experimental results showed that accuracy at the training stage got results of 92.16%, accuracy at the validation stage was 78.60% and accuracy at the submission stage got results of 80.30% as depicted in Figure 5.

Table 4. The percentage of true value based on *motif* class

No	Class name	ResNet			DResNet		
		True	False	True (%)	True	False	True (%)
1	*Bintang melati motif*	91	34	73	76	49	61
2	*Bunga bintang motif*	118	7	94	109	16	87
3	*Bunga mawar motif*	88	37	70	82	43	66
4	*Kucing tidur motif*	122	3	98	125	0	100
5	*Naga besaung motif*	77	48	62	76	49	61
6	*Pucuk rebung balai anak motif*	90	35	72	103	22	82
7	*Pucuk rebung penuh motif*	108	17	86	119	6	95
8	*Tampuk manggis motif*	105	20	84	113	12	90

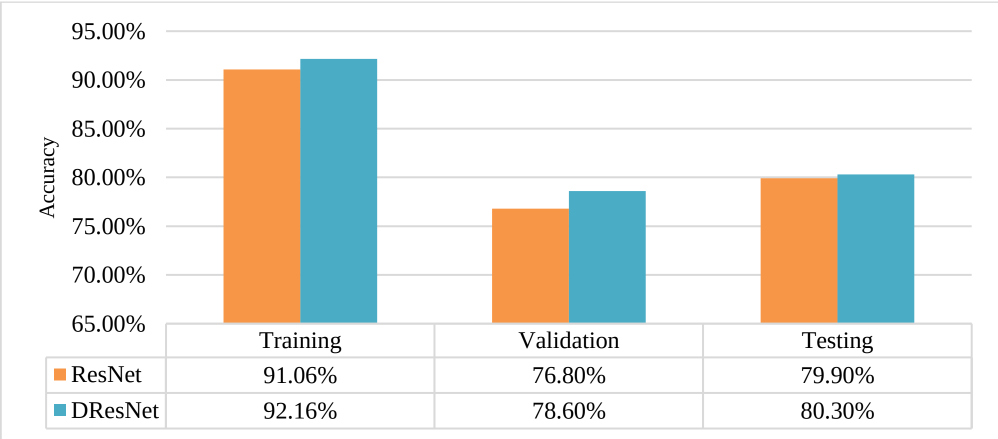


Figure 5. Experiment result of accuracy

Based on the experiment result, ResNet with dropout or namely DResNet (dropout rate less than a certain small value), accuracy will gradually increase, and loss will gradually decrease. The model can no longer be correctly fitted when dropout exceeds a certain threshold. The experimental results also show that dropouts are able to increase the accuracy of the ResNet model by adding +1.10% accuracy in the training process, adding +1.80% accuracy in the validation process, and adding +0.40% accuracy in the testing process as shown in Figure 6.

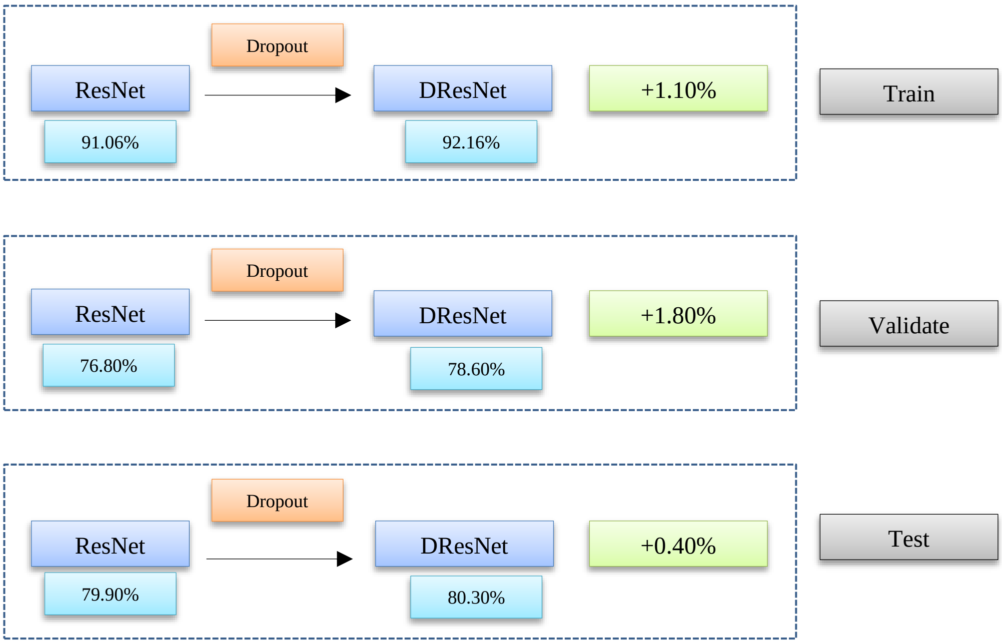


Figure 6. Effect dropout to model ResNet based on accuracy

The experimental results obtained are based on the results using the DResNet model with several parameter value settings. The basic DResNet model is ResNet50 with the addition of a global average pooling layer, flatten layer, dense layer and dropout layer. The details of the layers and parameters used can be seen in Figure 7.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 resnet50 (Functional)       (None, 7, 7, 2048)        23587712

 global_average_pooling2d (G  (None, 2048)             0
 lobalAveragePooling2D)

 flatten (Flatten)           (None, 2048)              0

 dense (Dense)               (None, 4096)              8392704

 dense_1 (Dense)             (None, 1072)              4391984

 dropout (Dropout)           (None, 1072)              0

 dense_2 (Dense)             (None, 8)                 8584

=================================================================
Total params: 36,380,984
Trainable params: 12,793,272
Non-trainable params: 23,587,712
```

Figure 7. Parameter of model DResNet

4. CONCLUSION

The primary objective of this study is to construct a ResNet model with dropout regularization techniques and determine how dropout regularization affects the ResNet model's ability to detect Palembang *songket* fabric *motif* with more data. A dataset consisting of 7,680 data for training, 960 data for validation, and 960 data for testing is prepared for use in experiments. ResNet achieved 91.06% accuracy during the training phase, 76.60% during the validation phase, and 79.90% during the testing phase. In addition, the experimental results for DResNet showed that accuracy at the training stage was 92.16%, accuracy at the validation stage was 78.5% and accuracy at the submission stage was 80.3%. The experimental results also indicate that dropouts can enhance the accuracy of the ResNet model by +1.10 percentage points in the training process, 1.80% points in the validation process, and 0.40% points in the testing process.

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