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Results	Query	Domains (original links)
Unique	Bulletin of Electrical Engineering and Informatics Vol	-
Unique	1430~1437 ISSN: 2302-9285, DOI: 10.11591/eei	-
Unique	Corresponding Author: Mohammad Arif Rasyidi, Department of Informatics, Universitas Internasional Semen Indonesia, Jl	-
Unique	Veteran, Gresik, Jawa Timur 61122, Indonesia	-
Unique	One of the most well-known Indonesian arts in the world is Batik	-
Unique	In Indonesia, batik has a variety of different patterns in each region	-
Unique	These patterns can be divided into two main categories, namely geometric and non-geometric patterns	-
Unique	Some examples of geometric patterns include Ceplok, Banji, Parang, Kawung, and Mega Mendung patterns	-
Unique	In batik, the pattern functions as a characteristic that identifies the type of batik	-
Unique	However, often this information is difficult to find	-
Unique	Furthermore, the system can also be integrated with other systems	-
Unique	For example, as a component for automatically classifying batik in an online store	-
Unique	The classification of batik patterns was also carried out by Alkaff et al	-
Unique	using scale invariant feature transform and support vector machine [5]	-
Unique	The study resulted in an accuracy of 95% for the four predicted patterns	-
Unique	However, the training data used in these studies were very limited	-
Unique	CNN is a state-of-the-art method that has been widely used for image classification	-
Unique	Feature extraction on CNN is done internally in conjunction with the model development process	-

Unique	Thus, in this study, the images are used directly without first extracting their features	-
Unique	In previous studies, CNN has often been reported to deliver excellent performances	-
Unique	employed them for handwriting recognition with a character error rate of 4.7% [16]	-
Unique	In this study, we use CNN for batik pattern identification	-
Unique	Research methodology ISSN: 2302-9285 Bulletin of Electr Eng & Inf, Vol	-
Unique	4, August 2020 : 1430 – 1437 1432 2.1	-
Unique	Some examples of batik pattern images can be seen in Figure	-
Unique	Thus, the training and test sets consist of 756 and 188 images respectively	-
Unique	Some examples of batik patterns used in this study 2.2	-
Unique	Some examples of transformation in the augmentation process can be seen in Figure	-
Unique	Thus, the classification model will be faced with different training data on each iteration	-
Unique	Thus, all models produced will be evaluated using the same test data	-
Unique	The transformation parameters for image augmentation in this study are shown in Table	-
Unique	Original Image Flip Horizontal Flip Vertical Rotate Zoom Lighting Warp Figure	-
Unique	Some examples of random transformations used in image augmentation Table	-
Unique	Each model is trained for eight cycles using the 1cycle policy [25]	-
Unique	Overall, the DenseNet network architecture shows the best performance compared to other network architectures	-
Unique	Actual: Kawung Prediction: Ceplok Actual: Kawung Prediction: Banji Actual: Banji Prediction: Kawung Figure	-
Unique	Some examples of the most confused patterns	-
Unique	Therefore, one batik fabric can contain more than one pattern at a time	-
Unique	This is dangerous because the model will give users the wrong information	-
Unique	unesco.org/en/RL/indonesian-batik-00170	-
Unique	Wiryadinata, “Banten batik classification with backpropagation neural network,” MATEC Web of Conferences, vol	-
Unique	Arymurthy, “Automatic Indonesian’s Batik pattern recognition using SIFT approach,” Procedia Computer Science, vol	-
Unique	Hutkowski, “Intelligent character recognition using fully convolutional neural networks,” Pattern Recognition, vol	-
Unique	LeCun et al., “Backpropagation applied to handwritten zip code recognition,” Neural Computation, vol	-
	Krizhevsky, “One weird trick for parallelizing convolutional neural networks,”	

Unique	ArXiv-Neural and Evolutionary Computing, pp	-
Unique	Zisserman, “Very deep convolutional networks for large-scale image recognition,” ICLR 2015-Conference Track Proceedings, pp	-
Unique	Her research interests include Transportation Management, Logistics, and Optimization	-
Unique	history: Received Dec 4, 2019 Revised Mar 6, 2020 Accepted Mar 23, 2020 Batik is	-
Unique	Batik is a fabric that is painted using canting and liquid wax so that	-
Unique	In this study, we applied the convolutional neural network (CNN) to identify six batik	-
Unique	994 images from the 6 categories were collected and then divided into training and	-
Unique	Image augmentation was also done to provide variations in training data as well as	-
Unique	indicated by accuracy of 94% and top-2 accuracy of 99% which was obtained using the	-
Unique	Keywords: Batik Classification CNN Pattern recognition This is an open access article under the	-
Unique	INTRODUCTION Indonesia is an archipelago that has diverse cultures such as music, dance, and	-
Unique	Batik is a pictorial fabric that is made specifically by writing or applying wax	-
Unique	world recognition by being designated as one of the world's cultural heritage by UNESCO in	-
Unique	The word "batik" itself comes from the Javanese word "amba", which means to write	-
Unique	and fabric dyeing by using a color barrier material, called "malam" (wax) which is applied	-
Unique	There are thousands of batik patterns that have been created by craftsmen and artists	-
Unique	While the patterns that are classified as non-geometric patterns include Semen, Cuwiri, Lunglungan, and	-
Unique	These patterns are usually arranged repeatedly to illustrate the basic pattern on the fabric	-
Unique	The diversity of batik patterns in Indonesia has the potential to develop the tourism	-
Unique	Many tourists, both domestic and foreign, are interested in batik and want to find	-
Unique	What's more, not everyone knows the name of the batik pattern they want to	-
Unique	know the name of the batik pattern, both from books and online information sources, such	-
Unique	not know the name of the pattern which makes it difficult for us to find	-
Unique	Therefore, it is necessary to build a system that can facilitate he recognition of	-

Unique	The system can also be used as a learning medium for students as an	-
Unique	In designing the system, a model that is able to classify batik patterns is	-
Unique	In a previous study, Nurhaida compared several types of feature extraction methods to classify	-
Unique	The best results are given by gray level co-occurrence matrices (GLCM) with an average	-
Unique	used artificial neural networks and GLCM to classify seven batik patterns with the highest	-
Unique	From these previous studies, it can be seen that the classification methods used had	-
Unique	Nurhaida [3], for example, used training data with a total of 40 images for	-
Unique	number, namely 20 images for each pattern, while Alkaff [5] employed a total of 160	-
Unique	of the resulting model may be different if used with real-world data where images can	-
Unique	Another thing we note is that most previous studies had focused more on feature	-
Unique	Traditionally, image recognition starts with the extraction of features from the images to be	-
Unique	These features will then be used as training data for machine learning algorithms during	-
Unique	6-9], scale-invariant feature transform (SIFT) [5, 10-12], multi texton histogram (MTH) [13], Gabor and log-Gabor	-
Unique	In this study, we propose the implementation of convolutional neural network (CNN) for batik	-
Unique	In contrast to image recognition methods in general, CNN generally does not require	-
Unique	Seo and Shin, for example, used CNN to classify fashion images resulting in 93%	-
Unique	applied them to classify retinal tomographic images with more than 92% accuracy [15], while	-
Unique	In other studies, Putri and Fanany used CNN to generate photographs from sketches [17]	-
Unique	utilized them for finger vein identification [18], where good results had been reported in	-
Unique	Based on these related researches, the CNN method is deemed appropriate for this batik	-
Unique	RESEARCH METHOD Convolutional neural network is a type of deep learning commonly used to	-
Unique	Although it was introduced more than three decades ago [19], the construction of deep	-
Unique	This is supported by the development of information technology, especially hardware that is capable	-

Unique	The steps we use to employ CNN to solve this problem are illustrated in	-
Unique	Data collection At this stage, we have collected 944 images of batik patterns that	-
Unique	These images have been obtained from various sources, such as search engines, online stores,	-
Unique	There are six batik patterns used in this study, namely Banji, Ceplok, Kawung, Mega	-
Unique	These images are then divided into two datasets namely training and test sets with	-
Unique	The composition of dataset Pattern Image count Banji 87 Ceplok 114 Kawung 135 Mega	-
Unique	Image augmentation Deep learning requires a large amount of data to be able to	-
Unique	Thus, naturally, to improve the quality of the resulting model and to avoid overfitting,	-
Unique	However, this may be difficult to do because of limited costs, time, and so	-
Unique	to provide variations Bulletin of Electr Eng & Inf ISSN: 2302-9285 □ Batik pattern recognition	-
Unique	With image augmentation, during the training process, the image given to the model will	-
Unique	Transformations that can be done include rotation, reflection, magnification, lighting, and so on, as	-
Unique	In this study, random transformations for each image in the training data are performed	-
Unique	This is done to prevent overfitting so that the resulting model can be more	-
Unique	data so that the total number of images to be tested on the resulting model	-
Unique	Unlike the augmentation of training data, augmentation of the test data is only done	-
Unique	Image augmentation parameters Transformation Value Horizontal Flip True/False Vertical Flip True/False Max Rotation 45°	-
Unique	Model training In the construction of CNN models, network architecture plays a very important	-
Unique	In previous studies, many CNN architectures have been developed and tested to produce good	-
Unique	VGG (vgg16_bn and vgg19_bn) [21], ResNet (resnet18, resnet34, resnet50, resnet101, and resnet152) [22], SqueezeNet (squeezenet1_0	-
Unique	We use models that have been previously trained on the ImageNet database to speed	-
Unique	Testing Each model produced is then tested using test data that have been prepared	-
Unique	The results of this test will then be summarized in the form of	-

Unique	Based on the confusion matrix, accuracy, precision, and recall are calculated according to the	-
Unique	= False Negative FP = False Positive = Number of data Other than those metrics,	-
Unique	FP 6/FN 5 C6 FP 1/FN 6 FP 2/FN 6 FP 3/FN 6 FP 4/FN	-
Unique	RESULTS AND DISCUSSION Tables 3-5 show the performance of each classification model that has	-
Unique	A minimum accuracy of 85.4% is produced by squeezenet1_0 while densenet201 provides the best	-
Unique	All models also produce a top-2 accuracy of more than 95% which indicates that	-
Unique	in the top-3 at least 8 times out of 15 criteria in terms of accuracy,	-
Unique	In terms of the number of layers in the model, DenseNet and ResNet show	-
Unique	DenseNet tends to continue to increase while ResNet is volatile but shows an increasing	-
Unique	The same improvement was not shown by VGG where in terms of accuracy both	-
Unique	However, as the number of layers increases, the resulting increase in performance is less	-
Unique	included in the top-3 as many as 11 times of all criteria, outperforming all other	-
Unique	vgg16_bn 0.916 0.980 0.999 vgg19_bn 0.916 0.983 0.997 Bulletin of Electr Eng & Inf ISSN:	-
Unique	0.892 0.856 squeezenet1_1 0.833 0.838 0.843 0.930 0.833 0.841 vgg16_bn 0.943 0.806 0.942 0.991 0.886	-
Unique	0.989 vgg19_bn 0.811 0.928 0.858 0.932 0.950 0.960 Next, we look at the confusion matrix	-
Unique	The densenet169 model was chosen as the representative because it provides the best overall	-
Unique	Ceplok pattern followed by a Kawung pattern predicted as a Banji pattern and a Banji	-
Unique	5 2 Parang 0 0 0 0 160 0 Sekar Jagad 0 0 0	-
Unique	Confusion matrix for densenet169, top 3 most confused patterns are highlighted □ ISSN: 2302-9285	-
Unique	4, August 2020 : 1430 – 1437 1436 Figure 6 shows some examples of	-
Unique	As a point of fact, the Kawung pattern is very closely related to Ceplok	-
Unique	the similarity of several other pictures of the Ceplok family in the training data on	-
Unique	caused by the small size of the pattern in the image so that the main	-
Unique	To overcome this problem, the quality and quantity of the training data need to	-
Unique	CONCLUSION From the results of this study, we have seen that CNN can be	-

Unique	In future research, we will try to apply CNN to the problem of multiclass	-
Unique	In general, basic batik patterns such as those used in this study are often	-
Unique	It will be very interesting to know whether CNN is able to overcome these	-
Unique	model must be able to handle unknown categories which are often known as open set	-
Unique	category that is not in the training data, then the model will still pair the	-
Unique	Thus, it would be better if the model returns "unknown" for patterns that it	-
Unique	ACKNOWLEDGEMENTS This research was supported by Lembaga Penelitian dan Pengabdian Masyarakat Universitas Internasional Semen	-
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Bulletin of Electrical Engineering and Informatics Vol. 9, No. 4, August 2020, pp. 1430~1437 ISSN: 2302-9285, DOI: 10.11591/eei.v9i4.2385 1430 Journal homepage: http://beei.org Batik pattern recognition using convolutional neural network Mohammad Arif Rasyidi, Taufiqotul Bariyah Department of Informatics, Universitas Internasional Semen Indonesia, Indonesia Article Info ABSTRACT Article history: Received Dec 4, 2019 Revised Mar 6, 2020 Accepted Mar 23, 2020 Batik is one of Indonesia's cultures that is well-known worldwide. Batik is a fabric that is painted using canting and liquid wax so that it forms patterns of high artistic value. In this study, we applied the convolutional neural network (CNN) to identify six batik patterns, namely Banji, Ceplok, Kawung, Mega Mendung, Parang, and Sekar Jagad. 994 images from the 6 categories were collected and then divided into training and test data with a ratio of 8:2. Image augmentation was also done to provide variations in training data as well as to prevent overfitting. Experimental results on the test data showed that CNN produced an excellent performance as indicated by accuracy of 94% and top-2 accuracy of 99% which was obtained using the DenseNet network architecture. Keywords: Batik Classification CNN Pattern recognition Corresponding Author: Mohammad Arif Rasyidi, Department of Informatics, Universitas Internasional Semen Indonesia, Jl. Veteran, Gresik, Jawa Timur 61122, Indonesia. Email: mohammad.rasyidi@uisi.ac.id

1. INTRODUCTION

Indonesia is an archipelago that has diverse cultures such as music, dance, and art. One of the most well-known Indonesian arts in the world is Batik. Batik is a pictorial fabric that is made specifically by writing or applying wax to the fabric which is then processed in a certain way. Because of the high philosophy and aesthetic values contained in it, batik has received world recognition by being designated as one of the world's cultural heritage by UNESCO in 2009 [1]. The word "batik" itself comes from the Javanese word "amba", which means to write and "nitik" which means to give a point. The word batik refers to the technique of making patterns using canting or stamp and fabric dyeing by using a color barrier material, called "malam" (wax) which is applied onto the fabric. In Indonesia, batik has a variety of different patterns in each region. There are thousands of batik patterns that have been created by craftsmen and artists in Indonesia. These patterns can be divided into two main categories, namely geometric and non-geometric patterns. Some examples of geometric patterns include Ceplok, Banji, Parang, Kawung, and Mega Mendung patterns. While the patterns that are classified as non-geometric patterns include Semen, Cuwiri, Lunglungan, and Buketan. In batik, the pattern functions as a characteristic that identifies the type of batik. These patterns are usually arranged repeatedly to illustrate the basic pattern on the fabric as a whole [2]. The diversity of batik patterns in Indonesia has the potential to develop the tourism sector in Indonesia. Many tourists, both domestic and foreign, are interested in batik and want to find out more about the detailed information, such as history, place of manufacture, and so forth. However, often this information is difficult to find. What's more, not everyone knows the name of the batik pattern they want to find out more about. Detailed information about batik, including the pattern, will be easier to obtain if we know the name of the batik pattern, both from books and online information sources, such as search engines. However, we Bulletin of Electr Eng & Inf ISSN: 2302-9285 Batik pattern recognition using convolutional neural network (Mohammad Arif Rasyidi) 1431 often find pictures of batik but do not know the name of the pattern which makes it difficult for us to find more information about the batik. Therefore, it is necessary to build a system that can facilitate he recognition of Indonesian batik patterns. The system can also be used as a learning medium for students as an effort to preserve Indonesian culture. Furthermore, the system can also be integrated with other

systems. For example, as a component for automatically classifying batik in an online store. In designing the system, a model that is able to classify batik patterns is needed. In a previous study, Nurhaida compared several types of feature extraction methods to classify four batik patterns. The best results are given by gray level co-occurrence matrices (GLCM) with an average accuracy of 80% [3]. In another study, Kasim et al. used artificial neural networks and GLCM to classify seven batik patterns with the highest accuracy of 90.48% [4]. The classification of batik patterns was also carried out by Alkaff et al. using scale invariant feature transform and support vector machine [5]. The study resulted in an accuracy of 95% for the four predicted patterns. From these previous studies, it can be seen that the classification methods used had produced a fairly good accuracy. However, the training data used in these studies were very limited. Nurhaida [3], for example, used training data with a total of 40 images for four batik patterns. Similar to Nurhaida's research, in Kasim's research [4], the dataset used was limited in number, namely 20 images for each pattern, while Alkaff [5] employed a total of 160 images for all patterns. The images used in these studies were also very organized so that the performance of the resulting model may be different if used with real-world data where images can have varying levels of lighting, distortion, and perspective during image capture. Another thing we note is that most previous studies had focused more on feature extraction process. Traditionally, image recognition starts with the extraction of features from the images to be processed. These features will then be used as training data for machine learning algorithms during training or as inputs for models during prediction. Common feature extraction methods that are used for batik pattern recognition include GLCM [3, 6-9], scale-invariant feature transform (SIFT) [5, 10-12], multi texton histogram (MTH) [13], Gabor and log-Gabor [6], and local binary pattern (LBP) [6]. In this study, we propose the implementation of convolutional neural network (CNN) for batik pattern identification. CNN is a state-of-the-art method that has been widely used for image classification. In contrast to image recognition methods in general, CNN generally does not require a separate feature extraction process. Feature extraction on CNN is done internally in conjunction with the model development process. Thus, in this study, the images are used directly without first extracting their features. In previous studies, CNN has often been reported to deliver excellent performances. Seo and Shin, for example, used CNN to classify fashion images resulting in 93% accuracy [14]; Fang et al. applied them to classify retinal tomographic images with more than 92% accuracy [15], while Ptucha et al. employed them for handwriting recognition with a character error rate of 4.7% [16]. In other studies, Putri and Fanany used CNN to generate photographs from sketches [17] while Fairuz et al. utilized them for finger vein identification [18], where good results had been reported in both works. Based on these related researches, the CNN method is deemed appropriate for this batik pattern identification problem. 2. RESEARCH METHOD Convolutional neural network is a type of deep learning commonly used to analyze visual images. Although it was introduced more than three decades ago [19], the construction of deep CNN models has only become popular in recent years. This is supported by the development of information technology, especially hardware that is capable of supporting the process. In this study, we use CNN for batik pattern identification. The steps we use to employ CNN to solve this problem are illustrated in Figure 1. Figure 1. Research methodology 2.1. Data collection At this stage, we have collected 944 images of batik patterns that will be used in building the classification model. These images have been obtained from various sources, such as search engines, online stores, as well as direct image taking in shops and batik artisans nearby. There are six batik patterns used in this study, namely Banji, Ceplok, Kawung, Mega Mendung, Parang, and Sekar Jagad with the composition shown in Table 1. Some examples of batik pattern images can be seen in Figure 2. These images are then divided into two datasets namely training and test sets with a ratio of 8:2. Thus, the training and test sets consist of 756 and 188 images respectively. Table 1. The composition of dataset Pattern Image count Banji 87 Ceplok 114 Kawung 135 Mega Mendung 226 Parang 191 Sekar Jagad 191 Total 944 Figure 2. Some examples of batik patterns used in this study 2.2. Image augmentation Deep learning requires a large amount of data to be able to produce good performances. Thus, naturally, to improve the quality of the resulting model and to avoid overfitting, we need to collect larger amounts of data. However, this may be difficult to do because of limited costs, time, and so on. In the construction of image classification models, one alternative method that can be used to provide variations to the data is image augmentation. With image augmentation, during the training process, the image given to the model will be modified with small random transformations without losing its original content. Transformations that can be done include rotation, reflection, magnification, lighting, and so on, as well as their combinations. Some examples of transformation in the augmentation process can be seen in Figure 3. In this study, random transformations for each image in the training data are performed at each iteration during the training process. Thus, the classification model will be faced with different training data on each iteration. This is done to prevent overfitting so that the resulting model can be more accurate when dealing

with images that it has never seen before. Random transformations are also carried out five times for each image in the test data so that the total number of images to be tested on the resulting model is 940 images. Unlike the augmentation of training data, augmentation of the test data is only done once. Thus, all models produced will be evaluated using the same test data. The transformation parameters for image augmentation in this study are shown in Table 2. Original Image Flip Horizontal Flip Vertical Rotate Zoom Lighting Warp Figure 3. Some examples of random transformations used in image augmentation Table 2. Image augmentation parameters Transformation Value Horizontal Flip True/False Vertical Flip True/False Max Rotation 45° Max Zoom 1.3 Max Lighting 0.3 Max Symmetric Warp 0.2 2.3. Model training In the construction of CNN models, network architecture plays a very important role. In previous studies, many CNN architectures have been developed and tested to produce good performances in the field of image classification. In this study, we implement the following CNN architectures and their variations: AlexNet [20], VGG (vgg16_bn and vgg19_bn) [21], ResNet (resnet18, resnet34, resnet50, resnet101, and resnet152) [22], SqueezeNet (squeezenet1_0 and squeezenet1_1) [23], and DenseNet (densenet121, densenet169, densenet201, and densenet161) [24]. We use models that have been previously trained on the ImageNet database to speed up the learning process then modify it to accommodate our problem of identifying batik patterns. Each model is trained for eight cycles using the 1cycle policy [25]. 2.4. Testing Each model produced is then tested using test data that have been prepared previously. The results of this test will then be summarized in the form of a confusion matrix with the format shown in Figure 4. Based on the confusion matrix, accuracy, precision, and recall are calculated according to the following formula: ∑ ∑ ∑ □ ISSN: 2302-9285 Bulletin of Electr Eng & Inf, Vol. 9, No. 4, August 2020 : 1430 – 1437 1434 where: TP = True Positive FN = False Negative FP = False Positive = Number of data Other than those metrics, top-2 accuracy as well as top-3 accuracy is also reported for comparison. Actual Class C1 TP 1 FP 2/FN 1 FP 3/FN 1 FP 4/FN 1 FP 5/FN 1 FP 6/FN 1 C2 FP 1/FN 2 TP 2 FP 3/FN 2 FP 4/FN 2 FP 5/FN 2 FP 6/FN 2 C3 FP 1/FN 3 FP 2/FN 3 TP 3 FP 4/FN 3 FP 5/FN 3 FP 6/FN 3 C4 FP 1/FN 4 FP 2/FN 4 FP 3/FN 4 TP 4 FP 5/FN 4 FP 6/FN 4 C5 FP 1/FN 5 FP 2/FN 5 FP 3/FN 5 FP 4/FN 5 TP 5 FP 6/FN 5 C6 FP 1/FN 6 FP 2/FN 6 FP 3/FN 6 FP 4/FN 6 FP 5/FN 6 TP 6 C1 C2 C3 C4 C5 C6 Prediction Figure 4. Sample confusion matrix 3. RESULTS AND DISCUSSION Tables 3-5 show the performance of each classification model that has been built. A minimum accuracy of 85.4% is produced by squeezenet1_0 while densenet201 provides the best accuracy of 94.3%. All models also produce a top-2 accuracy of more than 95% which indicates that all of them have a very good performance in recognizing the tested batik patterns. Overall, the DenseNet network architecture shows the best performance compared to other network architectures. This is indicated by all variations of DenseNet (densenet121, densenet169, densenet201, and densenet161) included in the top-3 at least 8 times out of 15 criteria in terms of accuracy, precision, and recall, which is more than all other architectures. In terms of the number of layers in the model, DenseNet and ResNet show an increase in performance as the number of layers increases. DenseNet tends to continue to increase while ResNet is volatile but shows an increasing general trend too. The same improvement was not shown by VGG where in terms of accuracy both vgg16 and vgg19 showed equivalent results. However, as the number of layers increases, the resulting increase in performance is less significant. For DenseNet for example, the performance of densenet121 to densenet201 continues to improve in terms of accuracy, however, the best overall performance is actually demonstrated by densenet169 which is included in the top-3 as many as 11 times of all criteria, outperforming all other DenseNet variants. Table 3. Accuracy of each model. Top 3 values are highlighted Model Accuracy Top-2 accuracy Top-3 accuracy alexnet 0.856 0.957 0.980 densenet121 0.936 0.984 0.999 densenet161 0.940 0.995 1.000 densenet169 0.941 0.990 0.999 densenet201 0.943 0.994 0.999 resnet18 0.901 0.970 0.988 resnet34 0.884 0.967 0.990 resnet50 0.923 0.989 0.997 resnet101 0.906 0.973 0.995 resnet152 0.933 0.990 1.000 squeezenet1_0 0.854 0.967 0.990 squeezenet1_1 0.862 0.959 0.979 vgg16_bn 0.916 0.980 0.999 vgg19_bn 0.916 0.983 0.997 Bulletin of Electr Eng & Inf ISSN: 2302-9285 □ Batik pattern recognition using convolutional neural network (Mohammad Arif Rasyidi) 1435 Table 4. Precision of each model. Top 3 values are highlighted Model Banji Ceplok Kawung Mega Mendung Parang Sekar Jagad alexnet 0.755 0.798 0.836 0.904 0.856 0.904 densenet121 0.884 0.804 0.930 1.000 0.940 0.994 densenet161 0.920 0.876 0.889 1.000 0.940 0.966 densenet169 0.922 0.861 0.913 1.000 0.936 0.966 densenet201 0.863 0.861 0.933 0.991 0.975 0.961 resnet18 0.867 0.770 0.872 0.996 0.940 0.887 resnet34 0.905 0.741 0.859 0.986 0.887 0.888 resnet50 0.837 0.804 0.926 1.000 0.946 0.948 resnet101 0.835 0.752 0.902 0.982 0.919 0.982 resnet152 0.927 0.846 0.880 0.996 0.940 0.959 squeezenet1_0 0.789 0.752 0.816 0.930 0.892 0.856 squeezenet1_1 0.833 0.838 0.843 0.930 0.833 0.841 vgg16_bn 0.943 0.806 0.942 0.991 0.886 0.896 vgg19_bn 0.820 0.859 0.930 1.000 0.933 0.880 Table 5. Recall of each model. Top 3 values are highlighted Model Banji Ceplok Kawung Mega Mendung Parang Sekar Jagad alexnet 0.822 0.824 0.658 0.919 0.931 0.920 densenet121 0.933 0.952 0.768 0.970 0.988 0.983 densenet161 0.889 0.904 0.877 0.957 0.981 0.989 densenet169 0.922 0.944 0.813 0.957 1.000 0.989 densenet201 0.911 0.944 0.813 0.979 0.994 0.977 resnet18 0.800 0.856 0.794

0.949 0.981 0.943 resnet34 0.744 0.872 0.787 0.889 0.981 0.954 resnet50 0.911 0.920 0.806 0.953 0.981 0.943 resnet101 0.900 0.920 0.774 0.919 0.988 0.926 resnet152 0.844 0.880 0.897 0.979 0.981 0.943 squeezenet1_0 0.833 0.776 0.658 0.911 0.925 0.954 squeezenet1_1 0.722 0.784 0.729 0.957 0.875 0.966 vgg16_bn 0.922 0.832 0.845 0.949 0.919 0.989 vgg19_bn 0.811 0.928 0.858 0.932 0.950 0.960 Next, we look at the confusion matrix of densenet169 in more detail as shown in Figure 5. The densenet169 model was chosen as the representative because it provides the best overall performance compared to the other models. From the confusion matrix, it can be seen that the pattern where the model makes the most mistakes is the Kawung pattern which is often wrongly predicted as a Ceplok pattern followed by a Kawung pattern predicted as a Banji pattern and a Banji pattern predicted as a Kawung pattern. Actual Class Banji 83 0 6 0 1 0 Ceplok 0 118 3 0 0 4 Kawung 7 19 126 0 3 0 Mega Mendung 0 0 3 225 5 2 Parang 0 0 0 0 160 0 Sekar Jagad 0 0 0 0 2 173 Banji Ceplok Kawung Mega Mendung Parang Sekar Jagad Prediction Figure 5. Confusion matrix for densenet169, top 3 most confused patterns are highlighted Figure 6 shows some examples of images where the model makes prediction errors on these patterns. As a point of fact, the Kawung pattern is very closely related to Ceplok where Kawung is one of the families of the Ceplok pattern. Thus, the prediction error of Kawung as a Ceplok pattern might be due to the similarity of several other pictures of the Ceplok family in the training data on the Kawung pattern. On the other hand, the prediction error of Banji and Kawung patterns may be caused by the small size of the pattern in the image so that the main pattern of Banji and Kawung does not appear significantly in the image. To overcome this problem, the quality and quantity of the training data need to be improved in future studies. Actual: Kawung Prediction: Ceplok Actual: Kawung Prediction: Banji Actual: Banji Prediction: Kawung Figure 6. Some examples of the most confused patterns 4. CONCLUSION From the results of this study, we have seen that CNN can be applied to the problem of identifying batik patterns and has shown excellent performance. In future research, we will try to apply CNN to the problem of multiclass classification on batik patterns. In general, basic batik patterns such as those used in this study are often combined to form new patterns. Therefore, one batik fabric can contain more than one pattern at a time. It will be very interesting to know whether CNN is able to overcome these problems. Another problem that we will try to overcome is the problem where the resulting model must be able to handle unknown categories which are often known as open set recognition problems. In the current application, if the model is given an image with a new category that is not in the training data, then the model will still pair the image to a pattern that it has encountered before. This is dangerous because the model will give users the wrong information. Thus, it would be better if the model returns "unknown" for patterns that it has never learned before. ACKNOWLEDGEMENTS This research was supported by Lembaga Penelitian dan Pengabdian Masyarakat Universitas Internasional Semen Indonesia. REFERENCES [1] KADIN Indonesia Foundation and Indonesia Batik Museum Institute, “Indonesian batik,” UNESCO, 2019, [Online], Available at: https://ich.unesco.org/en/RL/indonesian-batik-00170. [2] A. Haake, “The role of symmetry in Javanese batik patterns,” Computers & Mathematics with Applications, vol. 17, no. 4-6, pp. 815-826, 1989. [3] I. Nurhaida, R. Manurung, and A. M. 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