

ULOS FABRIC CLASSIFICATION USING ANDROID-BASED CONVOLUTIONAL NEURAL NETWORK

ARIF FADLY SIREGAR AND TUGA MAURITSIUS

Information System Management Department, BINUS Graduate Program
Bina Nusantara University
JL. K. H. Syahdan No. 9, Kemanggis, Palmerah, Jakarta 11480, Indonesia
arif.siregar@binus.ac.id; tmauritsus@binus.edu

Received November 2020; revised March 2021

ABSTRACT. *Indonesia is a country with diverse ethnic, religious, and cultural backgrounds. Among the tribes in Indonesia, one of them is the Batak tribe. The Batak tribe has a variety of cultures, one of which is ulos fabric. Every ulos fabric has meaning, and its patterns also have different meanings. However, in today's world, ulos fabric has begun to be forgotten. Many of ulos models and types are circulating, yet people can barely recognize them and sometimes they even do not know that it is a ulos fabric pattern. So to preserve the culture of this ulos fabric, we tried to classify the ulos fabric using the convolutional neural network method. We selected Convolutional Neural Network (CNN) because it shows better results in image recognition in recent years. We get the accuracy of around 87.27% in different factors. The model is then deployed to Application Programming Interface (API) to be used in android application that can predict the ulos fabric. The aim of the application and research is to help the people to recognize the ulos fabric pattern by taking pictures of it and then they will get information about the function of the ulos fabrics and its history that lies behind it.*

Keywords: Ulos fabric, Batak tribe, Convolutional neural network, Machine learning, Deep learning, Android

1. **Introduction.** Indonesia is the largest country in Southeast Asia which has a diversity of ethnicities and cultures [1]. According to the indonesia.go.id website, Indonesia has 1,340 ethnic groups based on BPS (Badan Pusat Statistik, a Central Bureau of Statistics in Indonesia) census data in 2010 and one of them is the Batak tribe. The Batak tribe is one of the tribes in the Sumatra area, or more precisely North Sumatra. With a population of around 8,466,969, based on the census data, the Batak tribe has a percentage of around 3.58 percent of the total population in Indonesia in 2010 [2].

From the large population of the Batak tribe, the Batak tribe has several sub-ethnicities such as Angkola, Karo, Mandailing, PakPak, Tapanuli, Simalungun, Toba, and Dairi. The sub-ethnic group has a surname or family name, such as Siregar, Lubis, Nasution, and Daulay. All of that is from Mandailing sub-ethnic group alone. The Batak people have many cultures in each of these sub-ethnicities. The cultures that exist in the Batak tribe also vary, from musical instruments, dances, to clothing. Each has their own characteristics in each Batak sub-ethnicity [3].

Among Batak cultures, one of the most well-known Batak cultures by the wider community is the ulos fabric. Ulos fabric is a woven fabric that was made directly by the ancestors of the Batak tribe since ancient times. According to its meaning, ulos means a blanket that is useful for warming the body and protecting its users from exposure to cold air, which is the original function of the ulos fabric used by the Batak people. In addition

to being used as a scarf, nowadays ulos fabric is often used as a beautiful garment with distinctive and attractive motifs.

Ulos fabric has several types of motifs such as Bintang Maratur, Mangiring, Ragi Hotang, Sibolang, and Suri-suri. The motifs of the ulos fabric have their own unique meanings and characteristics. For example, ulos Sibolang is given to pay respect to someone for their services. Ulos Mangiring is used to carry his child, with the hope that the child who is wearing this ulos will continue to be accompanied by his parents and some others with their own different meaning [4].

The Batak tribe nowadays usually uses ulos fabric as a complement for formal events such as weddings, mourning, and other traditional events and people have started to leave this tradition due to decreased cultural interest and the lack of media to introduce this ulos fabric culture. Today's people are more active with technology and one of the most frequently used technologies is smartphone.

Based on data from katadata.co.id, smartphone users in Indonesia in 2019 have reached 92 million people. Smartphones have become a medium of communication, information, entertainment, and education in Indonesia. Because of that, for the sake of preserving the culture of ulos, the author creates an android application that can be used to classify ulos based on the motifs or patterns of each. The application is expected to be an educational tool for the public and also as a reference for business needs. According to Causey [5], ulos is one of the exotic cultures and has a selling value. Besides that, the application built is expected to help in preserving the culture. With the development of the era where the image of ulos fabric has more variants, ulos fabric will be more difficult to be identified by the public. One method that can be used to classify ulos fabrics is convolutional neural network or often abbreviated as CNN. CNN is a type of neural networks that is commonly used for data image such as detecting and recognizing objects in an image [6].

In recent years, results of CNN in image classification have gained immense success. CNN is one of the best methods to classify and recognize images in Machine Learning (ML) [7]. In various visual learning, image detection and pattern finding tasks CNN has shown great success as compared to other methods. This is the reason in this study we focused and selected the CNN method to classify and recognize ulos fabric patterns. With the help of CNN people are able to find ulos fabric patterns by just taking a picture [8].

Apart from CNN, there is a method for classifying images, namely the Scale-Invariant Feature Transform (SIFT). According to Yan et al. in their journal comparing CNN with SIFT [9], it was found that CNN's performance was slightly better than SIFT and that the application of CNN has also been widely practiced by academics and succeeded in solving problems in image classification. One example of that is Li et al. who apply CNN to the world of medicine with the aim of research being to classify kidney images into Interstitial Lung Disease (ILD) by looking at the structure and shape of the kidney [10]; other CNN applications are carried out by Wicaksono et al. for example, who apply CNN to classifying batik by looking at the patterns of the batik [11]. In this study, the authors want to build an android application that can classify the ulos fabric by photographing it, and then the results of the image will be processed using the CNN method to determine the type of ulos fabric being photographed.

2. Literature Review.

2.1. Ulos. Ulos is a woven fabric originated from the Batak tribe in the form of a shawl. This fabric is a symbol of blessing, affection, and unity. In accordance with the Batak saying "Ijuk pangihot ni hodong, ulos pangihot ni holong" which means "If palm fiber is the binding of the fronds on the stem, then ulos is the binding of affection between

people". Literally, ulos is a blanket that can warm the body and protect the body from exposure to cold air. According to the ancestral beliefs of the Batak tribe, there are three sources that give heat to humans, namely the sun, fire and ulos. Of the three sources of heat, ulos are considered the most comfortable and familiar with everyday life. Once upon a time, the ancestors of the Batak tribe were mountain people, that is how history has been pinned to them. This is due to their habit of living and farming in mountainous areas. Living in the highlands means that they must be prepared to fight against the chill of the weather. This is where the history of ulos begins [4].

Ulos fabric did not immediately become sacred at the beginning of its appearance. In accordance with natural law, ulos has also gone through a fairly long process that takes a long time, before finally becoming a symbol of the Batak tribe as it is today. Unlike ulos that is considered as sacred as we know, in the past, ulos were even used as blankets or sleeping mats by the ancestors of the Batak tribe. According to the official Indonesian tourism website, the ulos fabric currently has a very important role for the Batak community. Ulos is not only used for clothing, but is also used in several rituals and ceremonies such as birth, death and marriage. Now the ulos fabric is an inseparable part of the traditional life of the Batak tribe.

2.2. Convolutional neural network. Basically Convolutional Neural Network (CNN) is with a number of convolution layers with the ReLU or Tanh activation function commonly used in the training process. In a traditional neural network feedforward we connect each neuron to the output of neurons in the next layer, usually called the fully-connected layer or affine layer.

On CNN, there are no steps required to take on traditional neural networks, instead we use the convolution method through the input layer to calculate output. Each layer applies a different filter, usually consisting of hundreds or thousands of filters and combining the results of the convolution operation. During the training process, CNN automatically learns the value of applying filter results to the convolution operator based on the desired task. For example, in image classification, CNN can learn to detect edges of image pixels in the first layer, then use these edges to detect simple shapes in the second layer, and then use the results of feature extraction in the previous filter to detect features at a higher level [12].

2.2.1. Input layer. The computer looks at the input image on the input layer by looking at the number of pixels it has from an input image. Rating depends on the volume dimensions of height \times width \times depth, where depth refers to the channel of an image (RGB). For example, if we have an image of 227×227 , the array representation will show $227 \times 227 \times 3$. Each depth is given a range of values from 0 to 225, which represents the intensity of the pixels in each channel. Furthermore, with these numbers the neural network can analyze and predict the possibility of the image entering into a specific class output.

2.2.2. Convolution layer. According to Lecun et al., the convolution layer is the main block in CNN which consists of various filters that are initialized randomly to perform convolution operations that function as feature extractions to study feature representations from an image input. In the convolution layer, neurons are arranged into feature maps. Each neuron in the feature map as a receptive field, is connected to neurons from the previous convolution layer through a series of weights that are trained, also known as filter banks [13].

2.2.3. *Dropout.* Dropout is a technique used to reduce overfitting in neural networks by preventing complex adaptations to training data. The idea is to derive random units from the neural network. Dropout refers to the removal of random and temporary units, both in the hidden layer or visible layer, and all the connections between input and output.

Each node is given the probability of p , which represents the probability of keeping the node. The value given is in the range between 0 and 1. For example, you can set each unit in the hidden layer with a probability of 0.5. That means, for each unit, there is a 50% chance the unit will be maintained in and 50% chance it will be dropped from the neural network.

2.2.4. *Fully connected layer.* Fully connected layer is a traditional multi-layer perceptron that uses the softmax activation function at the output layer. The term “fully connected” states that every neuron in the previous layer is connected to every neuron in the next layer.

The output of the convolution and pooling layer represents the high level features extracted from image input. This layer basically gets input volume (convolution, ReLU or pooling layer) and produces an N dimension vector where N is the number of classes. The goal is to use these features to classify images into various classes based on what has been initialized in the training data.

The main difference from the traditional multilayer perceptron is that the input layer is not a vector, but rather the value of the activation volume taken as input. Fully connected layer can be defined as follows.

If $l - 1$ is a fully connected layer, then

$$y_i^{(l)} = f(z_i^{(l)})$$

where

$$z_i^{(l)} = \sum_{j=1}^{m_1^{(l-1)}} w_{i,j}^{(l)} y_{i,j}^{(l-1)}$$

or

$$y_i^{(l)} = f(z_i^{(l)})$$

with

$$z_i^{(l)} = \sum_{j=1}^{m_1^{(l-1)}} \sum_{r=1}^{m_2^{(l-1)}} \sum_{s=1}^{m_3^{(l-1)}} w_{i,j,r,s}^{(l)} \left(y_i^{(l-1)} \right)_{r,s}$$

The purpose of fully connected as a whole is to set the weight parameters or to make a stochastic likelihood representation of each class based on activation map generated by a series of convolutional, non-linearity, rectification, and pooling layers.

2.2.5. *Softmax.* The softmax function calculates the probability distribution of events above ‘ n ’ from various events. In general, this function will calculate the probability of each destination class through all available classes. Then the probability of doing a calculation is very helpful for determining the destination class of the given input.

The main advantage of using softmax is the probability range output. The range will be 0 to 1, and the sum of all probabilities will be equal to one. If the softmax function is used for a multi-classification model, softmax can return the probability of each class and the target class will have a high probability. The softmax function is defined as follows:

$$F(x_i) = \frac{\text{Exp}(x_i)}{\sum_{j=0}^k \text{Exp}(x_j)}$$

where $i = 0, 1, 2, \dots, k$.

2.3. **API.** API (Application Program Interface) is a method used as a liaison between two applications to be able to communicate with each other [14]. In general, an application that is commercial or open-source must have an API for public use. By using an API, other parties can access data or information without having to know how the application was built. The API has the following types.

2.3.1. *Web API.* Web API or Web Service is a type of API that uses http as a communication line and usually exchanges data in JSON format. The use of Web APIs today is a common thing, where now there are more than 13,000 types of APIs that can be used for various types of purposes, such as checking traffic and weather conditions.

2.3.2. *SOAP.* SOAP is the earliest method used to exchange data. SOAP was built in 1998 to create a messaging framework that is used to communicate between applications on the web. SOAP uses Web Service Definition Language (WSDL) and XML in communicating.

2.3.3. *XML RPC.* XML remote procedure control is a derivative of SOAP and is still widely used because it uses the http line and still uses the XML data format in communicating. However, RPC settings are very strict because the user must know the name of the procedure to be used and the parameters contained in the procedure.

2.4. **CRISP-DM.** CRISP-DM is a framework to define the processes and tasks that you should do to create a successful data mining project [15]. The data mining process based on CRISP-DM consists of 6 phases.

2.4.1. *Business understanding.* Business understanding is an understanding of the substance of data mining activities that will be carried out, the needs of the business perspective. Its activities include determining business goals or objectives, understanding business situations, determining data mining goals and making strategic plans and research schedules.



FIGURE 1. CRISP-DM

2.4.2. *Data understanding.* Data understanding is the phase of collecting initial data, studying data to be able to recognize data that will be used, identifying problems related to data quality, and detecting an interesting subset of data to make an initial hypothesis.

2.4.3. *Data preparation.* Data preparation or often referred to as a labor-intensive phase. Activities undertaken include selecting tables and fields to be transformed into new databases for data mining material (raw data sets).

2.4.4. *Modeling.* Modeling is the phase of determining data mining techniques to be used, determining data mining tools, data mining techniques, data mining algorithms, and determining parameters with optimal values.

2.4.5. *Evaluation.* Evaluation is the interpretation phase of data mining results shown in the modeling process in the previous phase. Evaluation is carried out in depth with the aim of adjusting the model obtained to fit the objectives to be achieved in the first phase.

2.4.6. *Data deployment.* Data deployment deployment is the phase of preparing reports or presentations of knowledge gained from evaluations in the data mining process [9].

3. Methodology. The main contribution of this study is to identify ulos fabric patterns and state what a specific pattern means. An application is developed which will identify the ulos patterns. It will be beneficial for different industries like it can be used for educational purpose as well as for industrial or cultural purpose also. This purpose will be achieved with the help of CNN.

In this study, we have used the CRISP-DM methodology to achieve this task. This is chosen because CRISP-DM has the stages of business understanding which is at this stage focusing on understanding the objectives of the project and the needs from a business perspective [16]. Because of that, the authors apply the steps contained in the CRISP-DM as a methodological reference.

3.1. Business understanding. This stage is the stage to understand the project objectives and the needs of business objectives. The aim of the author is to develop an application that can identify ulos fabric so that it can be used as an educational tool as well as business and cultural needs so that the ulos fabric can be remembered and preserved.

3.2. Data understanding. This stage is the initial stage of collecting data and finding the insight first. At this stage, the writer will take and collect data image ulos fabric from the Internet as well as photos with a good image quality level and classify the images by type.

3.3. Data preparation. This stage is a stage that includes all activities to create a final dataset. At this stage the writer will do the process of cropping to get the best image quality. Cropping is done only taking parts of the image that have ulos patterns. Like the image of the ulos fabric pattern on the fabrics that are being worn by humans, the part of the image taken is the back of the image and removing other parts such as the face, hands and feet. Resizing the image is changed to 180×180 pixels because it is the ideal size in this case. The next process gives a size batch of 10 and does not change the color of the digital image.

3.4. Modeling. At this stage there will be modeling classification using a Convolutional Neural Network (CNN). The first process is carried out by reading the data set that has been processed in the previous stage. From the data set, training data and test data will be

taken. The training data is then used to conduct CNN training. The CNN training process is carried out by starting with parameter initialization and repeated according to the specified maximum repetition. The output of this process is the best model for classification. The accuracy of the model can be determined by validating it using test data.

After reading the data, the next step is to conduct training on the CNN model. The input size for CNN is a $180 \times 180 \times 3$ color image. The number of convolutional layers is one of the parameters that determine the accuracy of the classification model.

The main parameters used in CNN training are optimization, the number of epochs, the number of convolutional layers, the number of filters in each layer, the size of the kernel, and the number of neurons in the hidden layer used. The working principle of the training process on CNN is the same as any artificial neural network in general, namely by carrying out the process of forward propagation and backward propagation as many iterations as specified or if the stop conditions are met. In this study, the updating of the weight value was carried out with the optimizer Adam.

The input training on CNN is the data set that has been read in the previous process. Parameter initialization is done by determining the number of epochs, optimization and kernel size in each convolutional layer. Convolutional is carried out for matrix input using a filter that has been assigned a size. The result of the convolutional process is a matrix as many as the number of filters. The results convolutional are then pooled to reduce the size of the matrix.

Neurons in the pooling layer are the result of the process pooling using the method max-pooling against the previous convolutional layer. The size pooling each of convolutional layer used 2×2 with stride 1, which means that each 2×2 square will be pooled (taking the largest value to be passed on to neurons in the pooling layer) and the square will shift two to the right or down. This size was chosen because if you use a smaller size (1×1), the process pooling is not the same. This causes the features produced to be the same as the features map resulting from the convolutional process and the feature's sensitivity to changes input is still high. Meanwhile, if the size kernel pooling is larger, a lot of information from the image will be lost. In the activation function, the function that will be used after pooling is the relay function. The process is carried out as many as the convolutional layer that has been defined.

The results from the convolutional layer serve as input for the fully-connected layer. Each matrix component of the output matrix is a convolutional layer considered as one input value for the fully-connected layer. Fully-connected layer is built by two layers. This is a general hidden layer in the form of one dimensional neurons of artificial neural networks that consist of neurons that are connected to each other with neurons in the previous layer. Each of the neurons uses the Tanh activation function. The output of the layer is the last layer that consists of 4 neurons representing 6 types of tested ulos fabric patterns. This is fully connected to the previous layer. This is the softmax layer, so that the activation of each neuron added value will be one [17].

3.5. Evaluation. At this stage, an evaluation of the model that has been made before will be carried out. The test carried out is tested using the confusion matrix method which is useful for evaluating the classification methods and testing the accuracy of a model. There are 4 terms in the confusion matrix, namely True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). True Negative (TN) value is the amount of negative data that is detected correctly, while False Positive (FP) is negative data but is detected as positive data. Meanwhile, True Positive (TP) is positive data that is detected correctly and False Positive (FP) is positive data that is detected incorrectly.

		Actual Condition		
		Actual Positive	Actual Negative	
Output of Classifier	Total Samples			
	Classify Positive	TP	FP	PPV (Precision)
Classify Negative		FN	TN	
		TPR (Recall)	TNR (Specificity)	ACC
				F-measure
				MCC

FIGURE 2. Confusion matrix

The **ROC** graph summarizes all of the confusion matrices that each threshold produced.

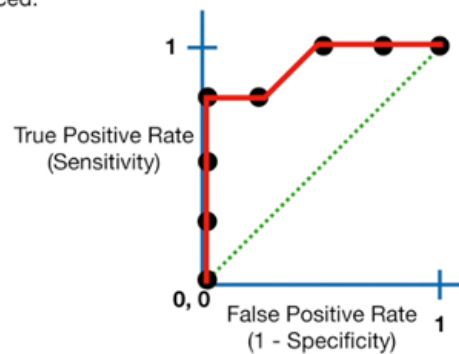


FIGURE 3. ROC curve

For performance visualization, the author will use the ROC curve and AUC models. ROC (Receiver Operating Characteristics) is a performance measurement tool for classification problems in determining the threshold of a model and if the higher the true positive rate and the smaller the false positive rate, the threshold will be great. Whereas AUC (Area Under Curve) is the area under the ROC curve or integral of the ROC function. AUC is usually used to compare one model to another and we choose the model with the largest AUC, because for each point it has a higher TP and/or a lower FP.

3.6. Deployment. In the preprocessing stage, modeling to training data will be carried out in the Google Colaboratory cloud because Google Colaboratory provides free GPU services to its users as a back-end computing and can be used for free and give a lot of RAM and storage. Apart from that, Google Colab has many libraries for deep learning such as Keras, TensorFlow, PyTorch and OpenCV. After the CNN modeling stage is complete, authors build an android application using the Android Studio IDE which can classify the ulos fabric by integrating the application with an API that the author built using the Flask framework. Flask framework is the backend framework that used python as a programming language that means can be loaded the model of CNN that author

created before. After that, the android application can find out the types and details of the ulos fabric by taking a picture or pick from gallery.

4. Comparison with the Old Models. In this section a comparison with the old models is presented. However, the models available are not able to give a clear result about the automatic identification of the ulos patterns. There are models available to create new patterns but not to identify the previous ones [18]. After the app is developed a manual comparison will be done by using previous image detecting systems.

5. Result and Discussion. This chapter will discuss the implementation of the CNN layer architectural model to measure the success in classifying ulos fabrics. Hyperparameter testing will be carried out first which will then be used as neural network input in testing the CNN model. The last most optimal CNN model will be compared with the Alexnet pretrained model.

5.1. Pre-processing and data augmentation. Do the cropping of each image to separate the area of the retinal pixel intensity by the pixel boundary. Then each size of the input retina image will be converted to $180 \times 180 \times 3$. This change in input size is obtained from conducting experiments to get the right results. Authors also normalized each image to help identify candidate objects from the ulos fabric to be clearer than the image original. The stage of pre-processing can be seen in Figure 4.

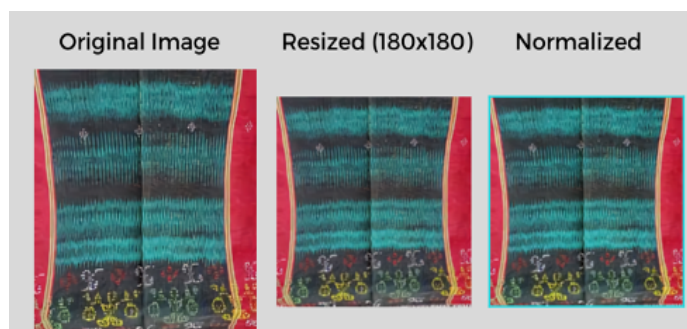


FIGURE 4. Pre-processing data

The authors decided to limit the use of the pre-processing method because each logic applied to this phase is the same as applying to a number of image inputs that will be training. That will cause the initialization process at the beginning of the neural network training to be slower because the memory consumption required is quite large. In addition, data augmentation is also applied by performing random flipping, rotation and zooming as shown in Figure 5.

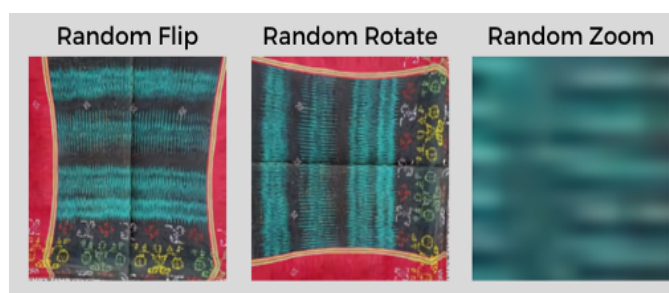


FIGURE 5. Augmentation data

5.2. Layer architecture design. The initial step in this study is to search for hyper-parameters from epoch and mini-batch to optimize CNN model architecture, which will be tested in the next experiment, but before looking for the best hyperparameter it is necessary to create a CNN layer architecture first.

The layer architecture of CNN that authors have created uses 3 layers and 1 fully-connected layer where the first layer is initiated with filter = 16, kernel size = 3 and stride = 1, then on the second layer using filter = 32, kernel size = 3 and stride = 1 and the third layer uses filter = 64, kernel size = 3 and stride = 1 and the three layers have no padding and use ReLU activation. Then the model is built using a pooling layer in the form of max pooling in each convolution layer. The pooling layer is used to reduce the dimensions of the feature map (down sampling). So it can overcome overfitting and speed up the computation, because there are fewer parameters that need to be updated. After that the authors added a dropout of 0.2 to prevent overfitting and accelerate the learning process. Then the authors add flatten to reshape features into a vector so that it can be used as input from the fully-connected layer. To see the summary model built, it can be seen in Figure 6.

```

Model: "sequential_1"

```

Layer (type)	Output Shape	Param #
sequential (Sequential)	(None, 180, 180, 3)	0
rescaling (Rescaling)	(None, 180, 180, 3)	0
conv2d (Conv2D)	(None, 180, 180, 16)	448
max_pooling2d (MaxPooling2D)	(None, 90, 90, 16)	0
conv2d_1 (Conv2D)	(None, 90, 90, 32)	4640
max_pooling2d_1 (MaxPooling2D)	(None, 45, 45, 32)	0
conv2d_2 (Conv2D)	(None, 45, 45, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 22, 22, 64)	0
dropout (Dropout)	(None, 22, 22, 64)	0
flatten (Flatten)	(None, 30976)	0
dense (Dense)	(None, 128)	3965056
dense_1 (Dense)	(None, 5)	645

```

Total params: 3,989,285
Trainable params: 3,989,285
Non-trainable params: 0

```

FIGURE 6. Model summary

5.3. Testing of epoch parameters. Experiments were carried out on the parameter of epoch with the value variables given as follows:

$$epoch = \{10, 30, 50, 80, 100\}$$

The results of the epoch parameter experiment obtained the following results.

In Table 1, it can be seen that the achievement of training epoch obtained the optimal value at epoch = 100 with the best accuracy of 87.27%. The smallest value is obtained at epoch = 10 with an accuracy of 64.45%. So the value of epoch 100 was chosen because it has more optimal accuracy results than other values.

TABLE 1. Evaluation of epoch parameters testing

Epoch	Mini-Batch	Accuracy	Time (s)
10	10	64.45%	115
30	10	78.18%	293
50	10	76.36%	465
80	10	80.00%	721
100	10	87.27%	932

5.4. **Testing of mini-batch parameters.** After getting the optimal epoch parameter value, the next step is to conduct mini-batch parameter testing, and the experiment was carried out with the following variable values:

$$minibatch = \{10, 20, 30\}$$

From this experiment using epoch 100 and the test results obtained can be seen in Table 2 as follows.

TABLE 2. Evaluation of mini-batch parameters testing

Epoch	Mini-Batch	Accuracy	Time (s)
100	10	87.27%	932
100	20	78.18%	860
100	30	75.55%	856

In Table 2, it can be seen that the value of a mini-batch will not necessarily result in a higher level of accuracy than a mini-batch that has a low value. The decrease in accuracy may occur due to the sometimes unstable neural network training. It can be seen that mini-batch = 30 has a lower level of accuracy than mini-batch 10 and 20. So the authors choose mini-batch = 10 as the optimal value for the mini-batch parameter.

5.5. **CNN model testing.** After designing the ideal CNN layer architecture and getting the optimal value of the epoch hyperparameter and mini-batch, then the CNN model is tested, which gives an accuracy rate of 87.27% as shown in Figure 7.

In Figure 7, it can be seen that the accuracy value during training reaches a very high accuracy value of almost 1.0 and the accuracy value when validation reaches a value of 0.87. According to the authors, the validation test results obtained are quite high, it is just that the curve when the validation is not stable enough, possibly due to the number of datasets that is not too large and for the loss levels resulting from testing this model can be seen in Figure 8.

In Figure 8, it can be seen that the loss level during training data is very small, even close to 0. However, during validation, the loss level is unstable and when the 80th epoch has a very high loss level. This may indicate that the number of datasets is still insufficient so that it cannot identify more diverse data or hyperparameters that are still not optimal but the loss value is getting smaller at the 100th epoch.

5.6. **Deployment.** After testing the model, the accuracy rate is quite high at 87%, so the next step is to do the deployment. The model that has been built is saved into a .h5 file format, then build an API (Application Programming Interface) using the Flask framework. This framework was chosen because it was built in the python language which supports the tensorflow and hard libraries, and this framework is lightweight because it only needs to add the required libraries [19]. This API was built to be used by the

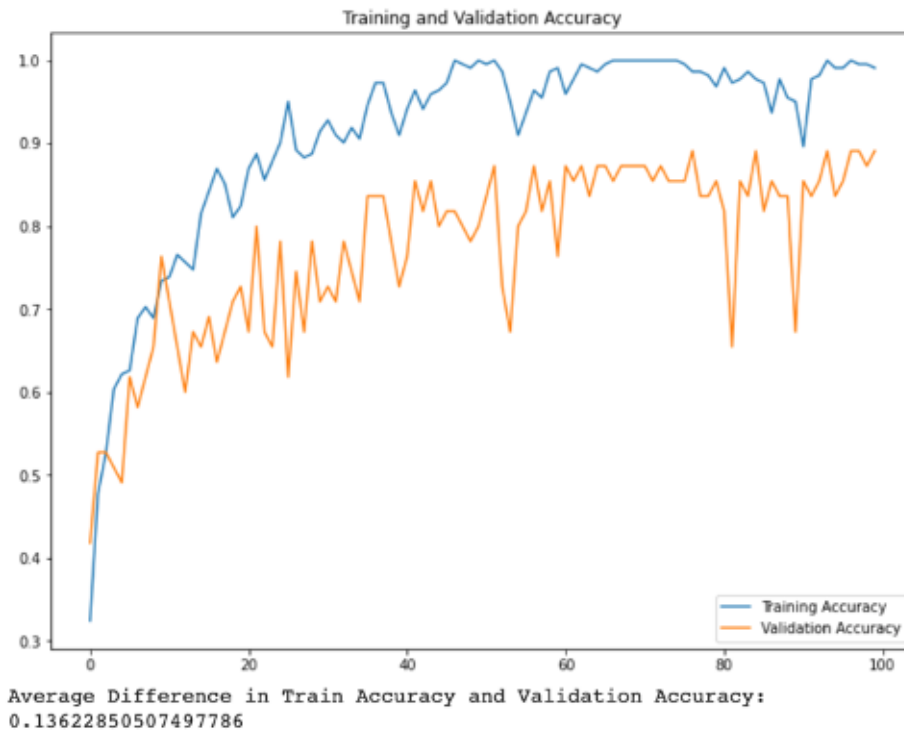


FIGURE 7. Training and validation accuracy

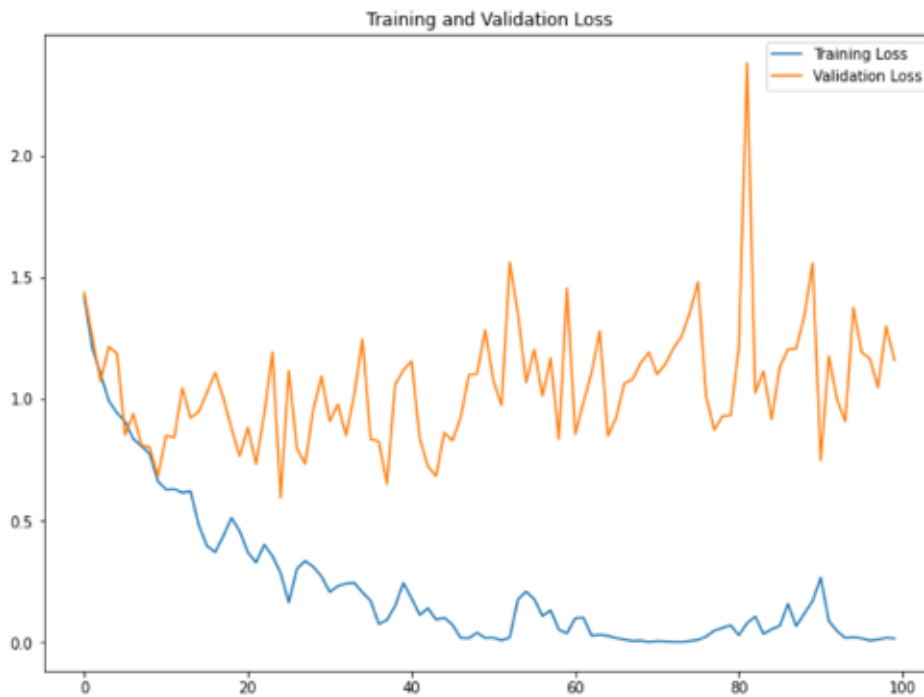


FIGURE 8. Training and validation loss

android application that the author built to be able to predict the ulos fabric that was photographed by the user by means of Android sending the encoded image to Base64 format and sent to the API that had been built. Furthermore, the API will get a data request that has been sent and decoded from the Base64 format to the image. The API

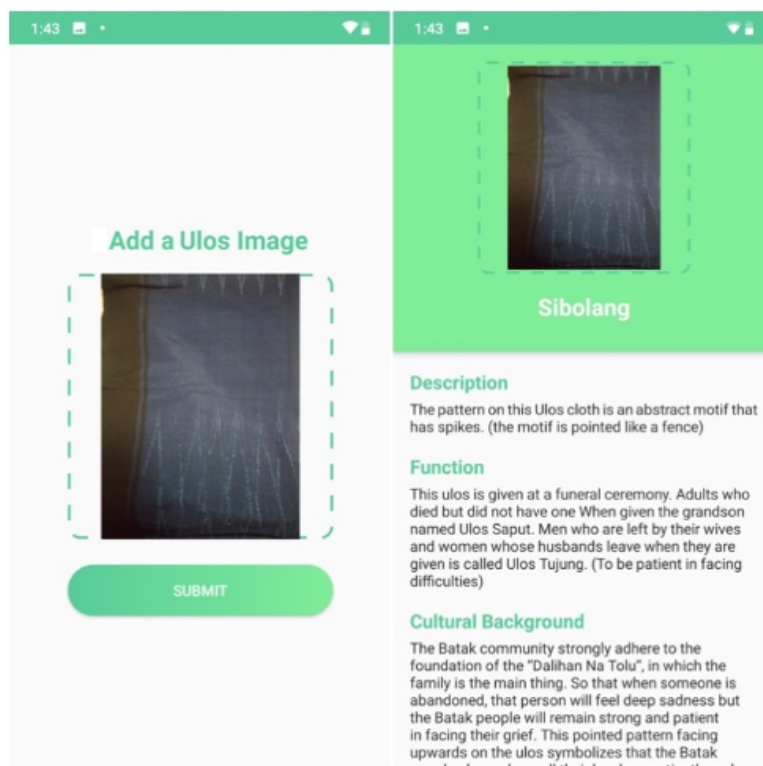


FIGURE 9. Ulos android application

will classify the image by using the prediction function of the previously built model. After the application gets a response from the API regarding the prediction results of an image, it will display information about the ulos fabric as shown in Figure 9.

In Figure 9, you can see an image of the application that the author built to find out the name and description, function and cultural background of the ulos cloth by adding an image from the gallery or the user's camera as seen in the image on the left, then after the user adds the image and presses the submit button, it will send the image data to the API that has been built to be predicted. After getting the results, the application built displays information about the ulos cloth.

6. Conclusion. Based on the results of the research that has been done it can be clearly concluded that there is no app or software available in literature to identify and state the meaning of the ulos fabric patterns.

Some important factors to develop such app are determination of hyperparameters epoch and minibatch are very important in providing more accurate accuracy, where in this case, epoch = 100 and minibatch = 10 are the most optimal hyperparameter that get an accuracy value of 87.27%. The training process at CNN is greatly helped by the existence of Google Colaboratory. With Google Colaboratory, the training process can be carried out in the cloud without requiring high specification hardware. It speeds up the training process that is carried out.

For the API that we have created and the android application built we are with the hope that people can get to know more and not forget about the history of the ulos cloth. In addition, this application can be expected to become an educational tool in introducing ulos cloth culture. As it is the first application in this area of research and development. It will be a great contribution towards the modern trends of ulos fabric identification and presenting their meaning.

REFERENCES

- [1] A. Ananta, E. N. Arifin, M. S. Hasbullah and N. B. Handayani, *Demography of Indonesia's Ethnicity*, Institute of Southeast Asian Studies, 2015.
- [2] R. Wiryasaputra, *Tribes in Indonesia Indonesia Wikipedia*, The Free Encyclopedia, 2011.
- [3] R. O. Tampubolon, Understanding meanings deeply, *Joged*, doi: 10.24821/joged.v10i2.1885, 2018.
- [4] Y. Erlyana, Visual study of variety of pattern in ulos cloths, *Dimensi*, vol.1, pp.35-46, 2016.
- [5] A. Causey, Ulos or saham? Presentations of Toba Batak culture in tourism promotions, *Indones. Malay World*, doi: 10.1080/13639819808729914, 1998.
- [6] M. I. Jordan and C. M. Bishop, Neural networks, in *Computer Science Handbook*, 2nd Edition, 2004.
- [7] Y. Sun, B. Xue, M. Zhang, G. G. Yen and J. Lv, Automatically designing CNN architectures using the genetic algorithm for image classification, *IEEE Trans. Cybern.*, 2020.
- [8] Z. Chen, J. Zhang, R. Ding and D. Marculescu, ViP: Virtual pooling for accelerating CNN-based image classification and object detection, *2020 IEEE Winter Conference on Applications of Computer Vision*, pp.1180-1189, 2020.
- [9] K. Yan, Y. Wang, D. Liang, T. Huang and Y. Tian, CNN vs. SIFT for image retrieval: Alternative or complementary?, *MM 2016 – Proc. of 2016 ACM Multimed. Conf.*, pp.407-411, doi: 10.1145/2964284.2967252, 2016.
- [10] Q. Li, W. Cai, X. Wang, Y. Zhou, D. D. Feng and M. Chen, Medical image classification with convolutional neural network, *2014 13th Int. Conf. Control Autom. Robot. Vision (ICARCV)*, pp.844-848, doi: 10.1109/ICARCV.2014.7064414, 2014.
- [11] A. Y. Wicaksono, N. Suciati, C. Fatichah, K. Uchimura and G. Koutaki, Modified convolutional neural network architecture for Batik motif image classification, *IPTEK J. Sci.*, vol.2, no.2, pp.26-30, doi: 10.12962/j23378530.v2i2.a2846, 2017.
- [12] I. M. A. Agastya and A. Setyanto, Classification of Indonesian Batik using deep learning techniques and data augmentation, *Proc. of 2018 3rd Int. Conf. Inf. Technol. Inf. Syst. Electr. Eng. (ICITISEE2018)*, pp.27-31, doi: 10.1109/ICITISEE.2018.8720990, 2018.
- [13] Y. Lecun, Y. Bengio and G. Hinton, Deep learning, *Nature*, vol.521, no.7553, pp.436-444, doi: 10.1038/nature14539, 2015.
- [14] J. Best, Application Programming Interface (API), in *Breaking Digital Gridlock*, 2018.
- [15] T. Mauritsius, A. S. Braza and Fransisca, Bank marketing data mining using CRISP-DM approach, *Int. J. Adv. Trends Comput. Sci. Eng.*, doi: 10.30534/ijatcse/2019/71852019, 2019.
- [16] A. Azevedo and M. F. Santos, KDD, SEMMA and CRISP-DM: A parallel overview, *IADIS Eur. Conf. Data Min.*, pp.182-185, <http://recipp.ipp.pt/bitstream/10400.22/136/3/KDD-CRISP-SEMMA.pdf>, 2008.
- [17] F. Chollet, *Keras: The Python Deep Learning Library*, Keras.Io, 2015.
- [18] C. Nugroho, I. K. Nurhayati, K. Nasionalita and R. M. U. Malau, Weaving and cultural identity of Batak Toba women, *J. Asian Afr. Stud.*, 2020.
- [19] K. Relan, Beginning with Flask, in *Building REST APIs with Flask*, Berkeley, CA, Apress, 2019.