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Convolutional Neural Networks for Classification Motives and the Effect of Image Dimensions

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Abstract

Although Indonesian batik patterns vary by location, they usually depict local customs and cultures. Each batik has a unique quality and, to correctly identify the batik designs, you need to understand the design patterns. However, many people struggle to identify and categorize these kinds of motivation because they don't have the requisite knowledge, understanding, or access to sufficient information. This study used photo data to classify batik patterns into 15 different groups. Batik Kawung, Megamendung, Lasem, Pole, Machete, Gills, Nutmeg, Karaswasih, Cendrawasih, Geblek Renteng, Bali, Betawi, and Dayak are all included in this category. 1,350 images were used in the research. Google supports the collection of data. To provide the highest level of precision and to evaluate how image dimensions affect the classification of batik designs, this study employs convolutional neural networks (CNNs). The results of this study show that Multi-Layer Perceptron (MLP) is a well-liked deep learning method for data classification, especially in domains where picture classification is involved. The size of the images utilized affects the accuracy of computational neural network (CNN) algorithms. The results showed that the test using training data comparisons of 60%, 30% and 10% resulted in a 01.89% loss of 1.18% and a 100% improvement in accuracy.

Keywords: *Image Processing, Indonesian Batik Motifs, Convolutional Neural Networks*

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1. Introduction

Batik is an Indonesian work of art that harmoniously integrates technology and artistic expression. Batik, an exceptional inheritance from Indonesia's forebears, has flourished significantly, particularly in its remarkable designs, themes, and techniques. Batik is a renowned form of artistic expression in Indonesia, deeply ingrained in the various aspects of Indonesian culture. On 2 October 2009, UNESCO officially recognized batik as Indonesia's cultural heritage [1].

A prominent feature of Indonesian culture is batik, which displays patterns influenced by plants, animals, and everyday parts of people's lives. There are three main classifications of batik: stamped, printed, and written. Identifying stamped batik is more difficult since its designs exhibit unique recurrent patterns and are less flexible than those seen in written batik.

Additionally, stamped batik does not feature elaborate patterns that utilize the canting wax process. Therefore, it is imperative to implement a complete identification process to accurately categorize batik. This work combines computer vision and artificial intelligence methodologies to achieve optimal analysis of batik images.

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However, applying different methods to extract certain characteristics and classify systems can present challenges in identifying new patterns in batik designs [2]. Picture categorization requires the inclusion of extensive picture characteristics that will build a significant image pattern, allowing for the representation of information contained in the image. This method achieves high precision in extracting comprehensive feature data from a shot through a training process that uses a training image.

The study aimed to create a convolutional neural network (CNN) model specifically designed for the classification of Solo batik images. The analysis found that the model achieved an impressive precision of 99.07% and a negligible loss rate of 0.2% when analyzing 745 batik samples [3]. This research is expected to serve as a valuable reference point for the research and development of matrices. MobileNetV2 is an appropriate method to address the image classification problem [4].

Research on Batik Motif classification using a convolutional neural network was carried out by R. Mawan. To prolong the life of batik, this study attempts to locate batik designs on computers. Batik parang, megamendung, and kawung are the three varieties of batik that were used in this study. These three groups of batiks were created using CNN. Tests are available for accuracy and data loss. The 120 datasets were divided into half, resulting in 30 testing and 90 training datasets for each half. The accuracy of the model was 65% when CNN used grayscale and 70% of the time when CNN combined grayscale with other characteristics [5].

Calculating the fractal dimension is a basic and exact endeavor. The K-Nearest-Neighbor technique showcases the ability of a solitary batik pattern to depict several clusters. Several factions. This is more beneficial as it illustrates that a batik pattern can symbolize numerous groups without explicitly showing the complete design. The fractal dimension of batik can be determined by box-counting analysis, using the data and research findings of the study. This will be used to classify batik into many categories [6].

In his study, Fonda talked about how CNN can sort Riau batik pictures according to how they look. The things that make Riau batik. The main point of this study is to find out how to tell the difference between pictures of Riau batik and pictures that do not. Some types of batik come from Riau, and others do not. After one run, the test showed that 65% of the data were correct, with only 2.5% being wrong. CNN was used in this study to show that the method can tell the difference between Riau batik and When batik is being sorted; 65% of the time, it can be told apart from other types of batik. Most of the patterns in Riau batik are the same as those in different batiks. However, some have brighter designs that make them stand out. This greatly changes the accuracy level [7].

Ayu Ratna, Tohirn, Adi, Purwani and Rahmat conducted a study in which CNN and Cooccurrence Matrix Gray Level features were used to divide Karawang batik patterns into various groups. They used 1094 pictures as training data and found that the training picture was right 18.19% of the time. In addition to that, the findings of the study. The test used 344 batik pictures, 45 of which were from Karawang and 299 from outside of Karawang. The success rate was about 18.60%. On the other hand, the Karawang batik pictures tests that had to be named and placed in groups were properly done about 73.33% of the time [1].

The research conducted by Bariyah T, Arif Rasyidi M, and Ngatini investigates the extensive array of batik motifs that showcase a variety of patterns. The study shows that a convolutional neural network (CNN) successfully performs multilabel classification on 15 batik designs. CNN achieves an accuracy of around 91.41% on 300 test pictures using 100 epochs. The model achieved a precision of around 91.41% when evaluated on a dataset that included 300 photographs after 100 training epochs. Performing a photo test with 100 generations [8].

The results showed that using dilation morphology to enhance the edge detection image of 10 batik designs resulted in much higher accuracy when using the canny operator compared to the Robert and Sobel operators. The use of expanding morphology in the Robert, Sobel, and Canny operators improves the ability to detect fraudulent activities [9]. R. F. Alya, M. Wibowo, and P. Paradise conducted research that generated many model scenarios.

The scenarios comprised a convolutional neural network (CNN) model, a CNN model without transfer learning, and multiple models that used transfer learning. Transfer learning models were trained using two discrete learning rates: 0.0004 and 0.0001. The empirical findings demonstrate that the CNN model, M0, achieves a training accuracy of 89.64% without employing transfer learning. In contrast, the M2 model, or M1, had a training accuracy rate of 89.64%. The M2 model, which integrates the convolutional neural network (CNN) and VGG-16, achieved a training precision of 91.23% with a loss of 24.48% and a training rate of 0.0001. Furthermore, the M2 model exhibited a training precision rate of 91.23% when assessed using test data [10].

The research carried out by Sentosa, Mulyana, Cahyana, and Pramuditasari investigated the evolution of Balinese batik designs throughout the community, analyzing the many phases of this development. Researchers employed the convolutional neural network (CNN) approach to assess various elements and sensor systems in multiple predesigned Balinese batik patterns. The study used two testing models, specifically the sequential model and the VGG16 model described above, to perform picture recognition to classify Balinese batik motifs. The dataset used in this study consists of 526 image data samples[11].

Research by Ayumi, Nurhaida, and Noprisson aimed to employ convolutional neural networks (CNN) to identify batik patterns. Through experiments, it has been observed that employing feature extraction, selection, and reduction techniques results in many results. The final trials demonstrate a higher level of accuracy compared to the use of the unprocessed image dataset. Implementing feature selection and reduction techniques can improve overall operational efficiency. The optimal parameter configurations for maximum accuracy are as follows: The number of epochs is set to 200, the batch size is 20, the optimizer used is Adam, the learning rate is 0.01, the network weights are initialized using uniform lean, and the neuron activation function is linear [12].

A comparative analysis of preprocessing techniques using sharp and median filter methodologies was performed. The results demonstrated that the utilization of a convolutional neural network (CNN) for batik photo classification, with preprocessing procedures involving K-means clustering and median filter, yielded a remarkable level of accuracy. The batik pictures were categorized using a Convolutional Neural Network (CNN), with K-means clustering as the underlying method. Clustering was used to obtain preprocessed results from the median filter of [13].

Putra, Alvin Eka Naufal, Mohammad Farid Prasetyo and Vincentius Riandar conducted a study that concluded that the Xception architecture, namely variation 3, is the optimal choice for classifying spices. When there is a requirement for a quick classification model, it is advisable to employ MobileNetV2 in version 2, as it shows the fastest computing time compared to all other architectures in all versions.

However, there is a significant disparity of 5% in the maximum level of precision achieved between MobileNetV2 and Xception. If there is a requirement for a more accurate substitute for Xception with a reduced computing time, one may choose to utilize the DenseNet201 architecture. DenseNet201 exhibits a marginal 3% discrepancy in accuracy while offering superior computational efficiency compared to Xception [14].

Pratiwi researched an ensemble learning approach proposed by Renny Amalia Nurmaini, Siti Rini, Dian Palupi Rachmatullah, Muhammad Naufal Darmawahyuni and Annisa. This method aimed to classify seven different types of skin lesions by combining three sophisticated convolutional neural network models. Inception V3, Inception ResNet V2 and DenseNet 201. Skin lesions were classified into seven groups, with an average precision, precision, sensitivity, specificity and F1 score of 97.23%, 90.12%, 97.73%, 82.01%, and 85.01%, respectively. According to the proposed ensemble model, it can achieve significantly better classification outcomes compared to earlier research findings. The experimental results demonstrate that the suggested framework exhibits encouraging effects [15].

Bella, Wahyu, Ulfah, Galih, and Agus improved image categorization results utilizing convolutional neural network (CNN) techniques in their research. The researchers incorporated augmentation techniques, especially the Image Data Generator, into their model. In addition, they also incorporated a dense layer of the fully connected layer type. Following 100 epochs, the accuracy of the training data reached 96.73%, while the accuracy of the testing data reached 97%. The inability to use the augmentation process can cause a decrease in the accuracy measure of the test data to 96%. The research findings show that the methodology used in this study has excellent results, as shown by the significantly better accuracy of the test data [16].

The classification of batik is a crucial matter in picture pattern identification due to the multitude of styles and variations it encompasses. An appropriate methodology is necessary to identify the pattern. After carefully analyzing and comparing multiple algorithms and schemes discussed in academic articles, it is evident that the Convolutional Neural Networks (CNN) method exhibits a significant level of precision in detecting batik motif images during image processing.

Although the CNN approach has been used in previous studies to classify batik images, there are still unknown aspects and unmet opportunities for further progress. The unnamed subject refers to the lack of studies that specifically examined how changes in image dimensions affect the categorization of batik designs using CNN methodology. The main problem of this study is to determine the optimal approach for choosing image dimensions that achieve a balance between high accuracy and efficient computing performance in the categorization of batik images.

The reason for choosing CNN in this work, instead of alternative approaches, is explained by CNN's capacity to autonomously extract visual information without the need for laborious manual manipulation. The CNNs' capacity to independently extract and gather substantial data is an added advantage in the classification of batik, which spans a wide array of variations and styles. The objective of this study is to examine the influence of image size on the categorization of batik patterns. Convolutional neural networks (CNN) can be adapted to accommodate varying picture dimensions, facilitating a comprehensive analysis of how image resolution impacts the model's performance.

The objective of this study is to improve our understanding of how picture dimensions affect batik classification employing convolutional neural networks (CNN). In addition, this work aims to determine the ideal image size to achieve the highest level of accuracy and computational efficiency. This knowledge serves as a significant resource for future research and development endeavors. This research provides a unique advantage compared to previous studies, as it precisely investigates the impact of image dimensions and severity, leading to more extensive and pertinent conclusions.

Moreover, this study has the capacity to improve the understanding of batik classification with the application of convolutional neural networks (CNN). Moreover, it can provide valuable perspectives to establish optimal image dimensions. The long-lasting nature of this research finding as a reliable standard is an added benefit, as it can aid in the development of improved classification matrices and methods in the future.

2. Research Methods

A Convolutional Neural Network (CNN) is a commonly employed technique for constructing a Multi-Layer Perceptron (MLP) that is mostly utilized for classifying data, particularly in picture categorization. Figure 1 shows the sequential steps involved in CNN methodology [17].

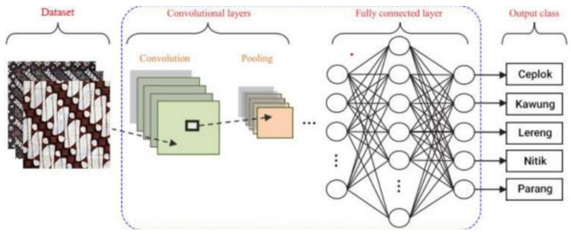

Figure 1.. Convolutional Neural Network (CNN) method

Convolution is the primary procedure in the construction of convolutional neural networks (CNN). Convolution is the iterative application of one function to the output of another function. Convolutional layers employ convolution procedures on the output of the preceding layer. Each convolutional layer transforms individual filters into segments of the input data, resulting in the generation of an activation map or a 2D feature map. Figure 2 clearly depicts the convolution process [18].

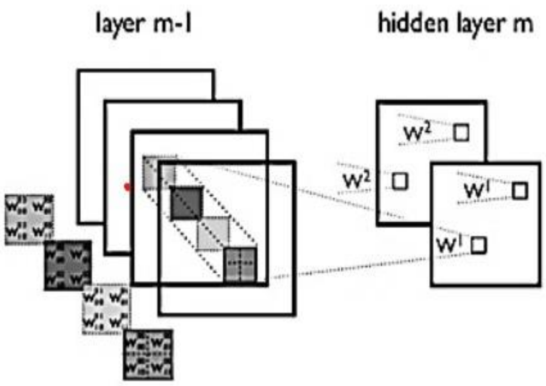

Figure 2. Convolutional Layer

The output of the convolutional layer is often expressed using Equation 1.

$$M_j^p = f\left(\sum_{i\varepsilon Mj} M_j^p * k_{ij}^p + N_j^p\right) \quad (1)$$

p represents the p-th layer, k_{ij} represents the convolutional kernel, N_j represents the bias, and M_j represents a set of input mappings. Unsupervised learning is commonly used to train different architectural elements, such as bias and kernel weights [19].

Grouping is the procedure to reduce the dimensions of a matrix by implementing grouping strategies. The pooling layer is often placed after the convolutional layer. The pooling layer consists of a filter with a defined size and stride that systematically traverses the region of the feature map. Two commonly used methods of pooling within the pooling layer are average pooling and maximum pooling. The pooling layer is commonly executed by using a 2x2 filter with a stride of two, which is applied to every slice of the input. The procedure is illustrated in Figure 3 [20].

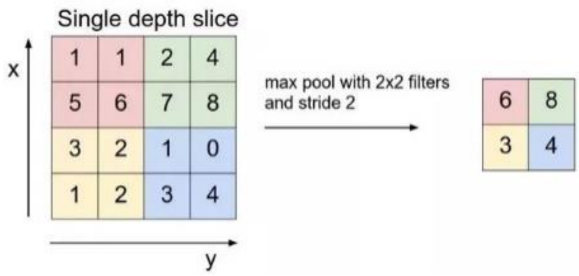

Figure 3. Process of Pooling

Before stochastic merging, it is necessary to compute the probability p for every region. The calculation formula is shown in Equation 2[19].

$$P_i = \frac{a_i}{\sum^{k\varepsilon S} j\, a_k} \quad (2)$$

Sj represents the amalgamation of region j, where F denotes the attributes, and i indicates the location of each element within region j. The stochastic variable *St* is utilized in the pooling procedure for each successive map F. Equation 3 represents the mathematical notation for the stochastic variable *St* [19].

$$a_{x\,y}^{p,k} = St(m, n, x, y) \quad (3)$$

Subsequently, a flattening approach is employed to transform the result of the Max-Pooling into a unidimensional vector. This vector can serve as input for the fully connected layer during the construction of a convolutional neural network (CNN).

The fully connected layer level is commonly used for data processing and subsequent classification. The output received from the pooling stage will be subjected to either a "flatten" or a reshape operation, yielding a vector that will be used as input for the fully connected layer stage. The procedure is illustrated in Figure 4 [21].

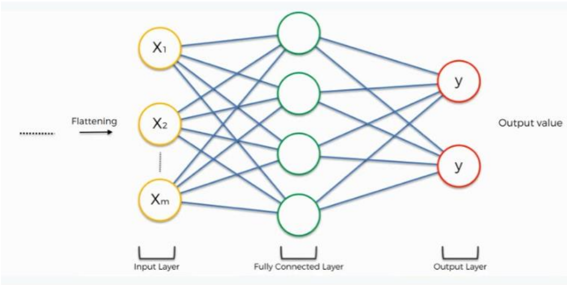

Figure 4. Full Connection and Output

3. Results and Discussions

3.1. Research

The study revealed that the convolutional neural network (CNN) technique can classify photographs of the batik motif. In addition, the size of the images used substantially affects the accuracy of the CNN method. The results showed that the experiments carried out with proportions of training data of 60%, 30%, and 10% had a loss of 01.89% and a precision of 100%, as shown in Figure 5.

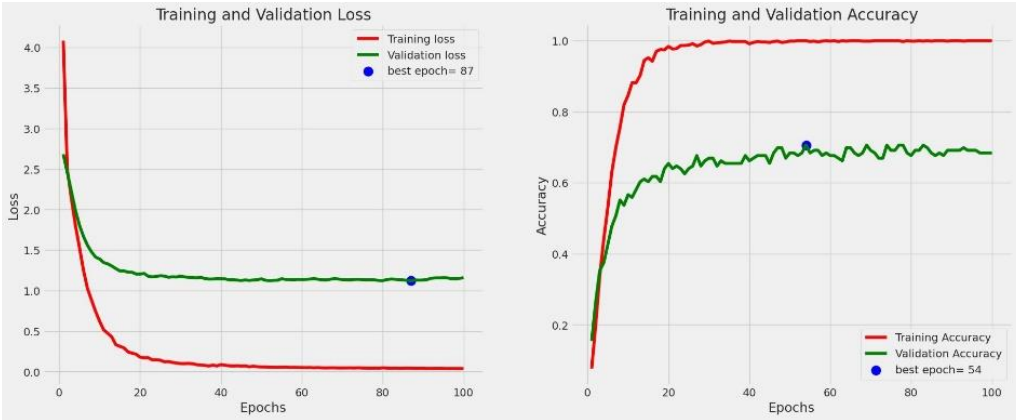

Figure 5. Loss and Accuracy Results of Training and Validation

3.2. Discussion

The study used a data set of batik photos in JPG format that comprised a wide range of subjects, dimensions, and resolutions. The objective of this work is to classify batik designs by evaluating photographic data. The research aims to analyze 15 specific categories of motif patterns, namely kawung batik, megamendung batik, lasem batik, poleng batik, tambal batik, parang batik, ikat-dyed batik, gill batik, nutmeg batik, sekar jagad batik, cendrawasih batik, geblek renteng batik, bali batik, betawi batik and dayak batik. The study used a total of 1350 photos, which were evenly distributed among the five preexisting thematic groups. Data were chosen based on their relevance to the research topic, which aims to improve the understanding of batik motif prediction in Indonesia.

The dataset named "Indonesia Batik" is available for download from the public data repository Kaggle, created by Marilia Prata. The collection comprises batik photographs obtained from various on-line platforms, including Google pictures, Pinterest, and other websites that showcase batik themes. Data for this study were collected on Tuesday, November 21, 2023, at 19.50 WIB. Figure 6 shows numerous Indonesian batik patterns, while Table 1 shows the batik motifs and their respective data quantities.

Table 1. Batik Motifs and Number of Data

No	Class	Total
1	Batik Kawung	90
2	Batik Megamendung	90
3	Batik Lasem	90
4	Batik Poleng	90
5	Batik Tambal	90
6	Batik Parang	90
7	Batik Ikat Celup	90
8	Batik Insang	90
9	Batik Pala	90
10	Batik Sekar Jagad	90
11	Batik Cendrawasih	90
12	Batik Geblek Renteng	90
13	Batik Bali	90
14	Batik Betawi	90
15	Batik Dayak	90
Total		1350

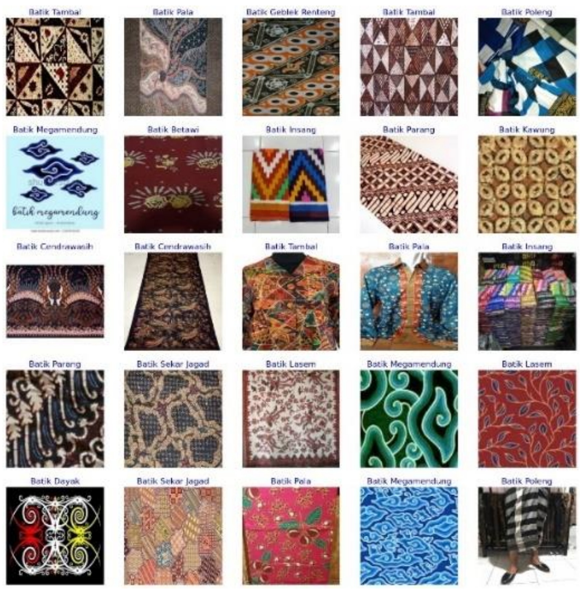

Figure 6. Samples of Indonesian Batik Motifs

Table 2. Number of Train, Test, and Validation Data Splits

No	Class	Train (60%)	Test (30%)	Validasi (10%)
1	Batik Kawung	54	27	9
2	Batik Megamendung	54	27	9
3	Batik Lasem	54	27	9
4	Batik Poleng	54	27	9
5	Batik Tambal	54	27	9
6	Batik Parang	54	27	9
7	Batik Ikat Celup	54	27	9
8	Batik Insang	54	27	9
9	Batik Pala	54	27	9
10	Batik Sekar Jagad	54	27	9
11	Batik Cendrawasih	54	27	9
12	Batik Geblek Renteng	54	27	9
13	Batik Bali	54	27	9
14	Batik Betawi	54	27	9
15	Batik Dayak	54	27	9
Total		810	405	135

Data processing involves a dual process. The first stage involves segregating the data into separate categories. This allows us to assess the effectiveness of the model obtained. Predictive skills of the model can be evaluated by partitioning the data, performing tests, and validating the functionality of the model.

The study used a partitioning system in which 60% of the data was allocated for training, 30% for testing, and 10% for validation. The training set contained 810 instances, the testing set contained 405 instances, and the validation set contained 135 instances. Table 2 shows a variety of batik patterns and the data segregation procedure.

The next step is to use the Image Data Generator library. The objective is to enhance the variety of training data and the model's capacity to analyze batik motif images. This library uses many transformations, including rotation, cropping, rotation, and rescaling, to generate different versions of photos. Table 3 shows the results obtained using data augmentation techniques.

Table 3. Data Augmentation

Image Data Generator	train_datagen	test_datagen
Rescale	1./255	1./255
Rotation Range	65	
Shear Range	0.2	
Zoom Range	0.2	
Horizontal Flip	True	
Width Shift Range	0.2	
Height Shift Raange	0.2	

Furthermore, once the data augmentation procedure is completed, the data are entered into a predetermined CNN model or architecture in Figure 7. Figure 7 shows the arrangement of the input layer in the Convolutional Neural Network (CNN). The utilization of training data occurs. The input data is processed by this convolutional layer using Rectified Linear Unit (ReLU) and max pooling functions. The output of the first layer serves as the input of the next layer, and this process is repeated for both convolutional layers. The convolution results are collected and processed in the flattened layer, producing a cohesive relationship among all pieces.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 mobilenetv2_1.00_224 (Func  (None, 7, 7, 1280)        2257984
 tional)

 conv2d (Conv2D)             (None, 7, 7, 64)          737344

 max_pooling2d (MaxPooling2  (None, 3, 3, 64)          0
 D)

 dropout (Dropout)           (None, 3, 3, 64)          0

 flatten (Flatten)           (None, 576)               0

 dense (Dense)               (None, 15)                8655

=================================================================
Total params: 3003983 (11.46 MB)
Trainable params: 745999 (2.85 MB)
Non-trainable params: 2257984 (8.61 MB)
_________________________________________________________________
```

Figure 7. CNN Architecture layers 7, 7, 64

The CNN model, depicted in Tables 4 and 5, shows the results of the training and testing data after 100 epochs. The sequential testing data have obtained a maximum accuracy of 100%. Programming uses Python, the Google Colab platform, and the necessary libraries.

Table 4. Train Epoch Results

Train Epoch	Loss	Accuracy	Val_loss	Val_accuracy
1	4.0835	0.0765	2.6823	0.1544
2	2.4929	0.1988	2.4575	0.2647
3	2.1372	0.3383	2.2265	0.3529
4	1.8056	0.4420	1.9923	0.3750
5	1.5330	0.5309	1.8072	0.4265
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
96	0.0367	1.0000	1.1559	0.6912
97	0.0375	1.0000	1.1455	0.6838
98	0.0367	1.0000	1.1451	0.6838
99	0.0371	1.0000	1.1503	0.6838
100	0.0362	1.0000	1.1579	0.6838

Table 5. Test Epoch Results

Test Epoch	Loss	Accuracy	Val_loss	Val_accuracy
1	2.0513	0.4851	1.4110	0.5515
2	0.7676	0.7673	1.3730	0.5735
3	0.4115	0.8911	1.2479	0.6250
4	0.2449	0.9381	1.2135	0.6471
5	0.1494	0.9629	1.2145	0.6618
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.

.	.	.	.	.
.	.	.	.	.
96	0.0213	1.0000	1.5818	0.6838
97	0.0230	0.9975	1.7898	0.6838
98	0.0207	1.0000	1.7080	0.6912
99	0.0195	1.0000	1.7723	0.6765
100	0.0216	1.0000	1.7403	0.6765

Figure 8 shows that after 100 epochs of experimentation, the loss is documented as 04.05%, with the most favorable epoch occurring at the 87th epoch with a value of 1.1198. Figure 9 shows the 100% accuracy result. The best epoch, which occurred in the 54th epoch, achieved 70.59%.

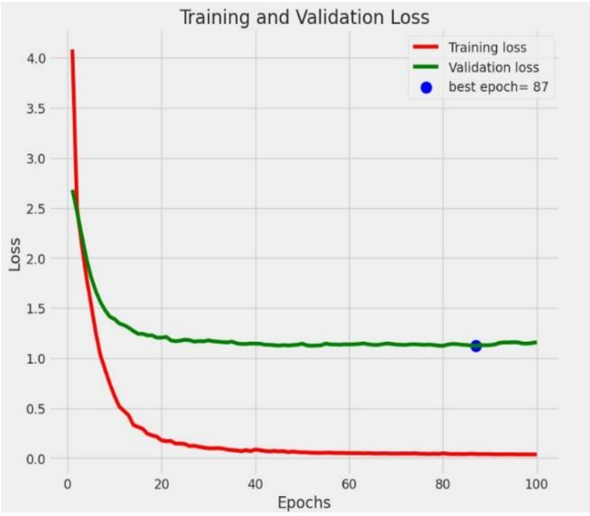

Figure 8. Loss Result

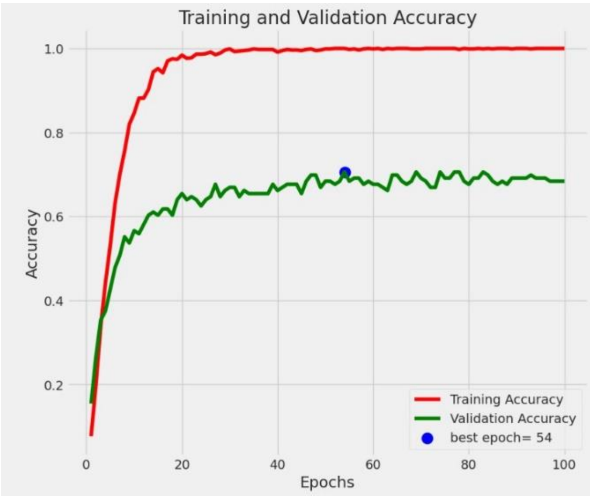

Figure 9. Accuracy Results

Upon completion of the modeling procedure, a performance evaluation is performed to validate the precision of the results. The test data are fed into the trained model to assess the model's performance. The expected results of the model are subsequently compared with the actual test data returns to generate the assessment metrics. Assessment is carried out with the confusion matrix. It showcases the model's ability to precisely categorize the data instances into the most appropriate category. The matrix has four cells: the actual positive cell (TP), the true negative cell (TN), and the false positive cell (FP). These cells show favorable anticipated predictions [12]. Figure 10 shows the confusion matrix obtained from the test data set consisting of 15 batik motif classes. Data were trained for 100 epochs.

Figure 11 shows that the convolutional artificial neural network model shows excellent recognition for each class and maintains a good balance between precision and recall. Therefore, it can be concluded that this model is quite appropriate for this classification task and provides excellent results.

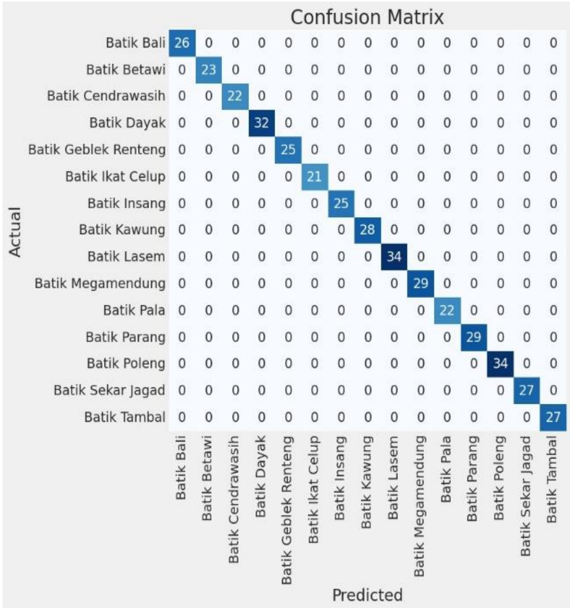

Figure 100. Confusion Matrix

Classification Report:

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	precision	recall	f1-score	support
Batik Bali	1.00	1.00	1.00	26
Batik Betawi	1.00	1.00	1.00	23
Batik Cendrawasih	1.00	1.00	1.00	22
Batik Dayak	1.00	1.00	1.00	32
Batik Geblek Renteng	1.00	1.00	1.00	25
Batik Ikat Celup	1.00	1.00	1.00	21
Batik Insang	1.00	1.00	1.00	25
Batik Kawung	1.00	1.00	1.00	28
Batik Lasem	1.00	1.00	1.00	34
Batik Megamendung	1.00	1.00	1.00	29
Batik Pala	1.00	1.00	1.00	22
Batik Parang	1.00	1.00	1.00	29
Batik Poleng	1.00	1.00	1.00	34
Batik Sekar Jagad	1.00	1.00	1.00	27
Batik Tambal	1.00	1.00	1.00	27
accuracy			1.00	404
macro avg	1.00	1.00	1.00	404
weighted avg	1.00	1.00	1.00	404

Figure 11 Classification Report.

4. Conclusions

Researchers can conclude that the convolutional neural network (CNN) technique allows the execution of classification procedures on batik images. CNN can detect complex patterns and identify significant features and can optimize image dimensions. In batik motif classification, it can be challenging due to limited data availability for model training. It can also hinder optimization, as the model requires considerable data to learn effectively. Additionally, there may be differences in the number of images accessible for each batik motif category, causing the model to show superior recognition for more common classes and lower rewards for less common classes. In this study, the image dimensions used can affect the accuracy of the CNN method. This study shows that the right image dimensions can significantly affect the accuracy of batik image classification. The findings show that using an image size of 7 x 7 pixels with 6-3-1 split data can produce an accuracy rate of 100%. The dataset in the present investigation comprises 1350 data points, each comprising images with dimensions of 7x7. To improve the precision of future research, it is recommended to use a larger amount of data and higher-resolution images.

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