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Classification of Riau Batik Motifs Using the Convolutional Neural Network (CNN) Algorithm

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Abstract—Riau Batik, a treasured cultural heritage, faces challenges in its preservation due to limited public awareness of its unique motifs. This research aims to bridge the knowledge gap by developing a website-based classification system that can identify and recognize Riau batik patterns, offering round-the-clock accessibility to users. By leveraging the Convolutional Neural Network (CNN) algorithm, the classification system was trained using a dataset of 1,440 images. The model was fine-tuned through optimization of batch size and epoch parameters to maximize classification accuracy. The training process culminated in a model with an accuracy of 89%, achieved using a batch size of 16 and 50 epochs. This system seeks to elevate public appreciation and knowledge of Riau Batik, thereby contributing to the preservation of its cultural and historical significance. The accessible classification tool presents a practical approach to ensuring the motifs and legacy of Riau Batik are preserved for future generations. The proposed CNN-based model demonstrates the potential to enhance digital engagement with traditional culture through modern technology, facilitating widespread recognition and appreciation of Riau's rich batik heritage.

Keywords: Classification, CNN, Deep learning, Riau Batik.

INTRODUCTION

Indonesia, a culturally rich nation, takes pride in its valuable batik art heritage, where each motif embodies a profound history and philosophy, symbolizing a significant cultural legacy. On October 2, 2009, UNESCO recognized Indonesia's batik as an Intangible Cultural Heritage, acknowledging its unique artistic and cultural value [1]. Among the many batik varieties is Riau Batik, also known as Batik Tabir, distinguished by its characteristic longitudinal stripe patterns. This batik style, celebrated for its beauty and deep cultural meaning, is a cultural treasure that warrants preservation and appreciation. As custodians of regional cultural assets like Riau Batik, Indonesians bear the responsibility of sustaining and safeguarding it. However, awareness of Riau Batik remains limited. A survey conducted with 60 participants in Riau (30 men and 30 women) revealed that 76% had little or no knowledge of Riau Batik. This lack of awareness is a significant challenge since the classification and appreciation of batik motifs require in-depth understanding of both the patterns and the philosophies they represent [2].

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Therefore, enhancing public knowledge of Riau Batik motifs is crucial to preserving this cultural heritage.

One way to increase recognition of Riau Batik motifs is through developing a website-based system capable of identifying these motifs and offering related information. A promising approach for this task is deep learning, a subset of machine learning that uses multiple layers to extract key information from raw data. The "deep" aspect of deep learning refers to the numerous layers involved in processing data [3]. In image pattern recognition, algorithms like the Convolutional Neural Network (CNN) are widely applied. CNNs are particularly adept at processing image data, including distinguishing objects from one another [4]. One reason for CNN's popularity is its ability to handle complex datasets without needing a separate feature extraction process, as feature extraction occurs internally during model development [5]. Past research has demonstrated the effectiveness of CNN in classifying batik motifs. For instance, Firman et al. achieved 90% accuracy in classifying West Java batik motifs, including Cirebon, Indramayu, and Priangan, using a dataset of 300 images [6]. Similarly, Tungki Ari et al. classified Solo batik motifs with 2,256 images across seven categories, reaching 95% accuracy [7]. In contrast, a study by Hendry Fonda, Yuda Irawan, and Anita Febriani focused on Riau Batik, achieving 65% accuracy with 168 images across 30 epochs, though this result was less accessible [8]. Comparatively, studies using the SVM algorithm for Banten Batik classification achieved only 85% accuracy [9], and the KNN algorithm for Javanese Batik classification reached just 65% [10]. These findings underscore the superiority of the CNN algorithm in achieving higher accuracy for batik image classification compared to other methods, such as SVM and KNN.

This study aims to develop a CNN-based classification model by optimizing the training process using a larger dataset of 1,440 images and fine-tuning parameters such as epochs and batch size. The results of this research are presented on a publicly accessible website, enhancing the accessibility and usability of the model. This model has the potential to greatly improve the recognition of Riau batik motifs, paving the way for a more efficient and accurate classification process. With this approach, we can envision a future where the preservation of Riau batik becomes more effective, ensuring its cultural value is maintained and cherished for generations to come.

METHOD

Figure 1 in the document illustrates the overall research methodology employed in this study, beginning with observations at local batik shops to identify common motifs and public familiarity with Riau Batik. Following this, a series of steps were conducted, including surveys, literature reviews, and dataset collection. Preprocessing of the dataset, such as image augmentation and resizing, was performed to optimize data quality for model training. The process continues with model design and training using Convolutional Neural Networks (CNN), aiming for high accuracy in motif classification. The final phase involves testing the model and deploying it on a website to allow users to classify and recognize Riau batik motifs. This structured methodology ensures systematic data handling and effective model development for achieving the research goals. Research methodology begins with observations at batik shops, then continues with surveys and identifying problems, literature studies, and collecting datasets, which are then preprocessed on the dataset, one of which is augmentation on image data. After preprocessing, the model design is carried out. The designed model will undergo a training process to evaluate the level of accuracy. Once the expected level of accuracy is achieved, the model is tested using a confusion matrix. Furthermore, the model will be implemented on the web to classify Riau batik motifs. A research method that designs these steps is needed to prepare the research methodology. In this study, the method used is CRISP-DM, illustrated in Figure 2.

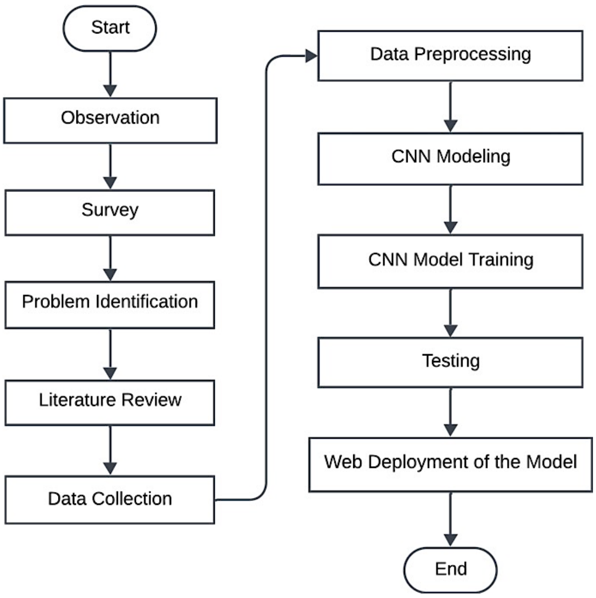

Figure 1. Research Methodology

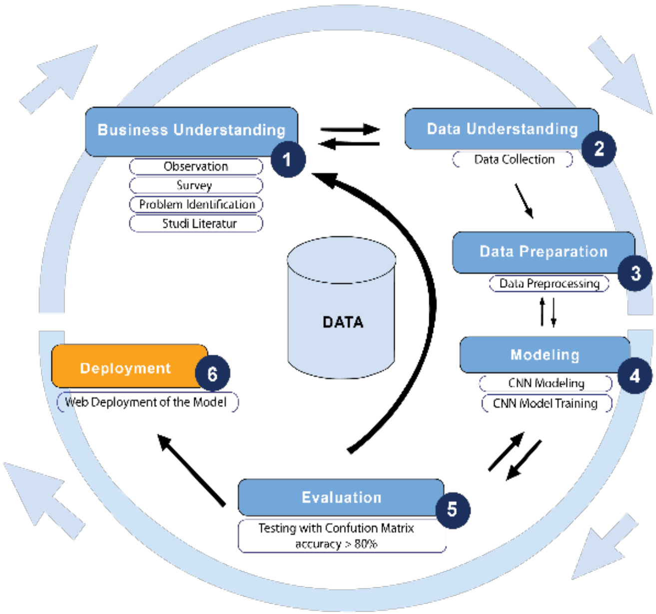

Figure 2. CRISP-DM

Figure 2 in the document depicts the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework utilized for structuring the research methodology. Establishing objectives and requirements for the project, which involves recognizing the importance of Riau Batik motifs and their preservation needs. Gathering and exploring datasets, including capturing images from batik shops and online sources. Preparing the data through preprocessing steps such as labeling, resizing images, and performing augmentation to enhance data quality. Designing and training the CNN model to classify motifs, optimizing hyperparameters like batch size and epochs. Assessing the model's performance using metrics like accuracy and confusion matrices to ensure its effectiveness. Implementing the trained model on a website for public use, facilitating Riau Batik motif recognition. The research phase employs the CRISP-DM method, a framework designed to transform business problems into structured data mining tasks. This approach facilitates the execution of data mining projects without dependence on specific applications or technologies. The method comprises six main stages: business understanding, data understanding, data preparation, modeling, evaluation, and deployment [12].

RESULT AND DISCUSSION

At this stage, the author conducted observations at two batik shops to identify Riau batik motifs commonly encountered by the public. Additionally, a public awareness survey was carried out using Google Forms, targeting 30 men and 30 women. The survey results revealed that 76% of the 60 respondents had never heard of or were unfamiliar with Riau Batik motifs. The next step involved identifying the problem, which focused on how to facilitate the classification of Riau batik motifs to make them more recognizable to the public. This challenge stems from a lack of public knowledge about these motifs. Therefore, accessible online media is needed to support public recognition of Riau batik motifs. Following this, a literature study was conducted to gather and analyze relevant information for this research, drawing from books, scientific journals, and other credible sources.

This stage focuses on the collection of datasets through two main methods: direct data capture at batik shops and data collection from the shops' social media accounts. The direct data capture involved using a personal smartphone camera to take 85 images in-store, while an additional 95 images were sourced from social media. As a result, each class contained a total of 180 images. Due to the limited dataset size, each of the 180 images was augmented by rotating it at seven different angles, leading to a comprehensive dataset of 1,440 images. The dataset was then divided into two parts: 1,152 images for training data and 288 images for testing data, following an 80% to 20% split between training and testing data. After collecting the dataset, preprocessing was carried out to enhance image quality, thereby improving the system's ability to identify objects [13]. The initial step in preprocessing involved labeling the dataset to provide each image with a name, facilitating easy recognition and differentiation. The labels used included bamboo shoots, kiambang flowers, and kundur flowers. Following the labeling process, each image was resized to 350 x 350 pixels. Resizing ensures uniformity in image size, which is a critical requirement for Convolutional Neural Network (CNN) modeling, enabling more consistent and accurate processing during the classification tasks.

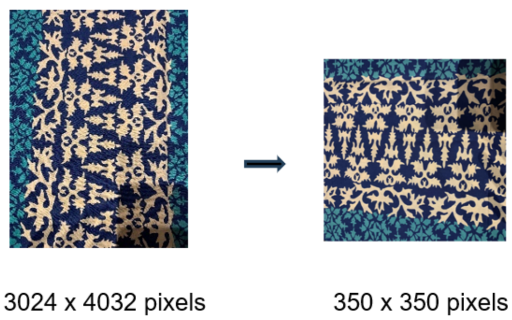

Figure 3. Resize Image

Figure 3 in the document illustrates the image resizing process applied during data preprocessing. The resizing step involves adjusting each image in the dataset to a consistent size of 350 x 350 pixels. This standardization ensures uniformity across all images used in the Convolutional Neural Network (CNN) model, facilitating improved accuracy and consistency during the training and classification stages. The image resizing process is crucial for maintaining the integrity and comparability of input data, as it allows the model to process images with uniform dimensions, ultimately enhancing its ability to learn and recognize patterns effectively within the Riau batik motifs dataset. In addition, image augmentation is also carried out during this preprocessing process. Augmentation includes rotation range, width shift range, height shift range, shear range, zoom range, and horizontal flip on the dataset to multiply the data. The author performs image augmentation automatically using the source code in Figure 3.

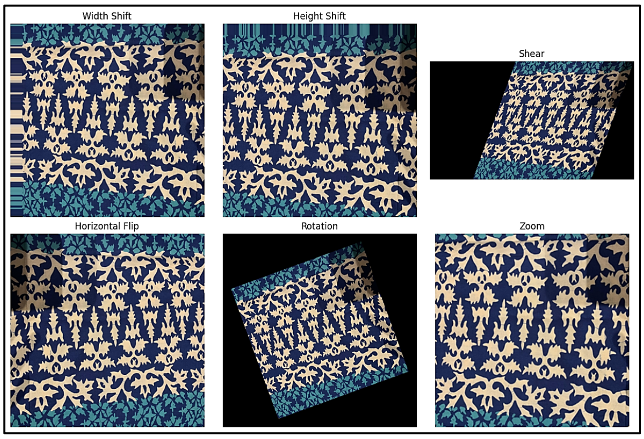

Figure 4. Image Augmentation

Figure 4 in the document depicts the image augmentation process used during data preprocessing. This process involves applying various transformations to the images in the dataset to increase its size and variability. The augmentation techniques shown include rotation, width and height shifts, shear transformations, zooming, and horizontal flips. By introducing these variations, the model is exposed to a broader range of image scenarios, improving its ability to generalize and accurately recognize different motifs of Riau Batik. This step helps to mitigate overfitting and enhances the robustness of the Convolutional Neural Network (CNN) model by simulating real-world variations that it may encounter during classification tasks. Augmentation rotation_range = 40 rotates the image up to 40 degrees, width_shift_range = 0.3 and height_shift_range = 0.3 shifts the image horizontally and vertically by up to 30%, shear_range = 0.3 applies distortion shearing, zoom_range = 0.2 zooms in or zooms out by up to 20%, horizontal_flip = True flips the image horizontally, and fill_ mode='nearest' fills in the pixels lost due to the transformation with the nearest pixel. By applying these parameter values, the resulting augmentation variations appear more significant and distinct than those of other parameter values previously tested. By using color variations, scales, and rotation in the augmentation process, the model can provide more accurate predictions when tested than if it were not augmenting. Models become more trained to recognize patterns that may appear in various image variations. The modeling stages are prepared by designing the structure of the CNN architecture and determining the number of layers that will be used to design the model. The preparation of this model was carried out after the dataset underwent the preprocessing stage. The structure of the model will consist of three layers of Convolution, three layers of Pooling, and Fully connected. The Activation function is also applied to each Convolutional Layer. The model architecture in this study can be found in Figure 4.

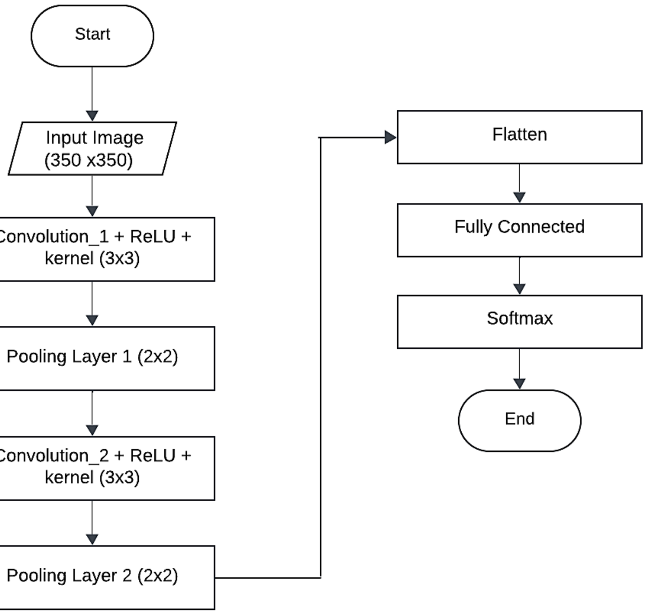

Figure 5. CNN Architecture

The Figure 5 illustrates the CNN architecture used in this study to classify Riau batik motifs. The convolutional layer utilizes a 3x3 kernel size with the ReLU activation function. For the pooling layer, MaxPooling with a 2x2 kernel size is applied. This stage, involving both the convolutional and pooling layers, is referred to as Feature Learning and produces a Feature Map. Following this, the process moves to the Classification stage, where the Feature Map matrix dimensions are flattened into a one-dimensional vector. Subsequently, a fully connected layer is added, incorporating dropout and dense layers.

Table 1. Training Trials

Training	Epoch	Batch size	Accuracy		Loss		Accuracy test
			Train	Valid	Train	Valid	
1	20	8	0.8732	0.9561	0.2955	0.2240	77%
2	20	16	0.8926	0.9518	0.2733	0.2085	81%
3	20	20	0.9140	0.8860	0.2234	0.8860	74%
4	20	24	0.7640	0.7939	0.5429	0.5471	55%
5	20	32	0.8038	0.9254	0.4663	0.2194	76%
6	30	8	0.9077	0.9912	0.2132	0.1005	84%
7	30	16	0.9464	0.9912	0.1573	0.0331	85%
8	30	20	0.9698	0.9912	0.1105	0.0375	86%
9	30	24	0.9318	0.9825	0.2019	0.0602	85%
10	30	32	0.9205	0.9430	0.2506	0.1385	83%
11	40	8	0.9709	1.0000	0.0937	0.0133	86%
12	40	16	0.9111	0.9956	0.2016	0.0443	89%
13	40	20	0.9485	0.9649	0.1135	0.1101	85%
14	40	24	0.9255	0.9912	0.2208	0.0784	85%
15	40	32	0.9395	0.9868	0.1647	0.0474	87%
16	50	8	0.8963	1.0000	0.2544	0.0457	84%
17	50	16	0.9348	1.0000	0.1721	0.0136	89%
18	50	20	0.9286	0.9868	0.1804	0.0673	88%
19	50	24	0.9647	0.9825	0.1354	0.0912	86%
20	50	32	0.9367	0.9605	0.1971	0.1071	84%

The final step employs the Softmax activation function, which determines the probability distribution for each class. At this stage, the previously created model will undergo a training process to produce a model with an optimal level of accuracy. This training process will form a model that can classify Riau batik motifs. The training data used is data that has gone through the preprocessing process. Then, the hyperparameter configuration is carried out during model training. At this stage, ten experiments will be carried out using different parameters, namely comparing batch size and epoch, to find the best parameters to provide optimal accuracy results. Based on the data presented in Table 1, the best model was obtained from the 17th experiment after twenty trainings. The model was trained in the experiment using 50 epochs and a batch size of 16. The results show that the accuracy of the training data is 0.9348 or 93%, while the accuracy of the validation data is 1.0000 or 100%. In addition, the loss value in the training data was recorded at 0.1721 or 17%, and the loss value in the validation data was 0.0136 or 1.36%. This data shows that the model trained in the 17th experiment performs well on both training and validation data, with high accuracy and low loss value. While the other experiments resulted in lower accuracy and higher loss value. The best model was chosen from the highest accuracy and the lowest loss value. The accuracy and loss graphs of the 17th training experiment can be seen in Figure 6.

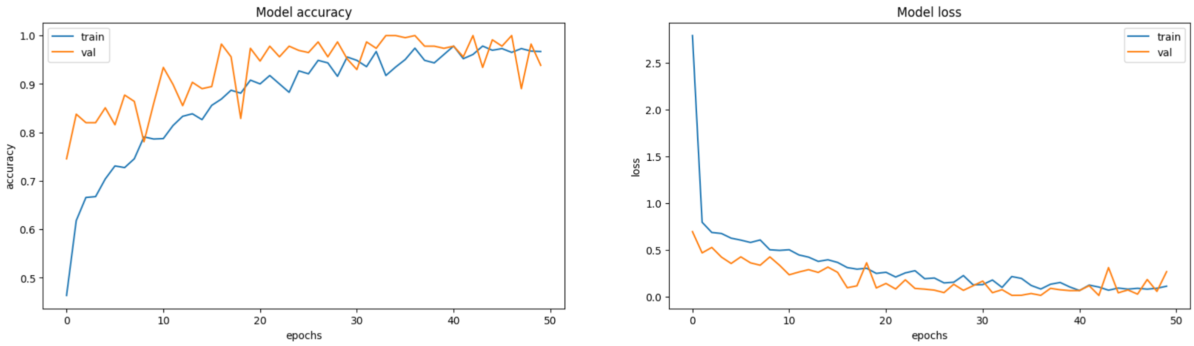

Figure 6. 17th Attempt

Figure 6 in the document displays the accuracy and loss graphs resulting from the 17th training experiment of the CNN model used for classifying Riau batik motifs. The graph on the left shows the model's accuracy across epochs, with the blue line representing training accuracy and the orange line indicating validation accuracy. A significant increase in accuracy is observed during certain epochs, reaching its peak at epoch 34 with a validation accuracy of 100% and a training accuracy of approximately 93.5%. The loss graph on the right demonstrates the model's performance in minimizing errors throughout the training process. The loss consistently decreases over the epochs, with the final loss values at epoch 50 being 0.0136 for validation loss and 0.1721 for training loss. Together, these graphs indicate that the model performed exceptionally well, showing a steady increase in accuracy and a reduction in loss, which suggests effective learning and robust classification capabilities for the Riau batik motifs. Accuracy and loss graphs are essential for evaluating model performance during training in classification tasks. The accuracy graph shows how both models make correct predictions in each epoch and iteration, while the loss graph shows how effectively the model reduces errors during training. The accuracy loss and validation loss values are considered to be a good approach of zero. The smaller the accuracy and validation loss values, the better the model is at predicting the correct outcomes [14]. By looking at these two graphs, we can understand how stable the model performance increases and decreases and determines Which model is most optimal for classification. The graph displayed results from model training using 50 epochs, batch size 16. The accuracy graph on the left shows a significant improvement in some epochs - the blue line represents the training accuracy, and the orange line represents the validation accuracy. The accuracy graph shows that the highest accuracy was achieved at epoch 34, with a value of 1.0000 for accuracy validation and 0.9348 for training accuracy. The loss chart shows a consistent decline in each epoch, with a loss value on epoch 50 of 0.0136 for validation loss and 0.1721 for training loss. Based on the graph, the model showed excellent performance with a test accuracy of 89%. An evaluation process on the test data is necessary to determine whether the trained model can recognize it. This stage requires using previously collected test data, but this test data does not undergo a preprocessing process. These test data are images that the model has never encountered before. Evaluation of model performance in this study will be carried out using the Confusion Matrix. which can be seen in Figure 7. Based on the results of the confusion matrix, we can assess the overall accuracy of the model's predictions using the accuracy metric [15].

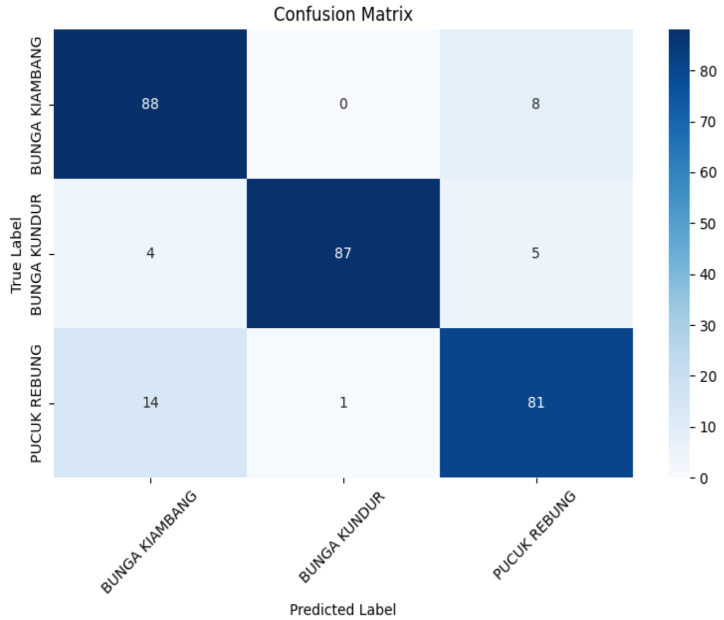

Figure 7. Confusion Matrix

	precision	recall	f1-score	support
BUNGA KIAMBANG	0.83	0.92	0.87	96
BUNGA KUNDUR	0.99	0.91	0.95	96
PUCUK REBUNG	0.86	0.84	0.85	96
accuracy			0.89	288
macro avg	0.89	0.89	0.89	288
weighted avg	0.89	0.89	0.89	288

Figure 8. Model Performance

Accuracy = $\frac{TP+TN}{TP+TN+FP+FN} = \frac{88+87+81}{288} = 89\%$

Precision = $\frac{TP}{TP+FP} = \frac{88}{88+18} = 0.83$

Recall = $\frac{TP}{TP+FN} = \frac{88}{88+8} = 0.92$

F1-score $= \frac{2 \times Precision \times Recall}{Precision + Recall} = \frac{2 \times 0.83 \times 0.92}{0.83 + 0.92} = 0.87$

Precision = $\frac{TP}{TP+FP} = \frac{87}{87+1} = 0.99$

Recall = $\frac{TP}{TP+FN} = \frac{87}{87+9} = 0.91$

F1-score = $\frac{2 \times Precision \times Recall}{Precision + Recall} = \frac{2 \times 0.99 \times 0.91}{0.99 + 0.91} = 0.95$

Precision = $\frac{TP}{TP+FP} = \frac{81}{81+13} = 0.86$

Recall = $\frac{T}{TP+FN} = \frac{81}{81+15} = 0.84$

F1-score = $\frac{2 \times Precision \times Recall}{Precision + Recall} = \frac{2 \times 0.86 \times 0.84}{0.86 + 0.84} = 0.85$

Macro AVG Precision = $\frac{\sum_{i=1}^{l} \frac{TP}{TP_i+FP_i}}{l} = \frac{(Precision_1+Precision_2+Precision_3)}{l}$

$$= \frac{0.83+0.99+0.86}{3} = 0.89$$

Macro AVG Recall = $\frac{\sum_{i=1}^{l} \frac{TP}{TP_i+FN_i}}{l} = \frac{(Recall_1+Recall_2+Recall_3)}{n} = \frac{0.92+0.91+0.84}{3} = 0.89$

Macro AVG F1-score = $\frac{\sum_{i=1}^{l} F1_i}{N} = \frac{f1score_1+f1score_2+f1score_3}{l} = \frac{0.87+0.95+0.85}{3} = 0.89$

Weighted AVG Precision = $\frac{\sum_{i=1}^{l} \frac{TP}{TP_i+FP_i} \times N_i}{l}$

$$= \frac{Precision_1 \times N_1+Precision_2 \times N_2+Precision_3 \times N_3}{l} = \frac{0.83\times96+0.99\times96+0.86\times96}{288} = 0.89$$

Weighted AVG Recall = $\frac{\sum_{i=1}^{l} \frac{TP}{TP_i+FN_i} \times N_i}{l} = \frac{Recall_1 \times N_1+Recall_2 \times N_2+Recall_3 \times N_3}{l} = \frac{0.92\times96+0.91\times96+0.84\times96}{288} = 0.89$

Weighted AVGF1-score = $\frac{\sum_{i=1}^{l} \omega_i \times F1_i}{\sum_{i=1}^{l} \omega_i} = \frac{\omega_1 \times f1score_1+\omega_2 \times f1score_2+\omega_3 \times f1score_3}{Total\ weight} = \frac{96\times0.87+96\times0.95+96\times0.85}{288} = 0.89$

Based on the figure above on the Confusion Matrix, this study's accuracy value was 89%. This deployment stage will implement the model created into a simple web, as shown in the image below.

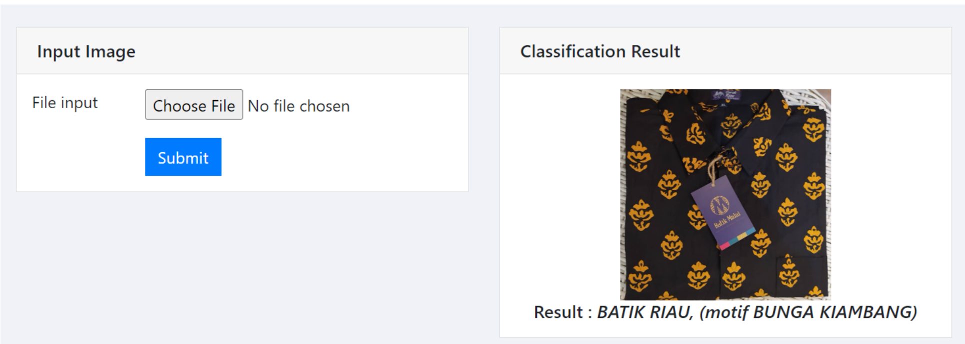

Figure 9. Model Implementation

Classifying batik images on the simple website above begins by entering a batik image file. The image is then processed, and the features are extracted so that it can classify the type of batik input.

CONCLUSION

Based on the conducted research, the CNN algorithm utilized in this study successfully classified Riau Batik motifs. The optimal model was achieved with training parameters of 50 epochs, a batch size of 16, a learning rate of 0.001, an image size of 350x350 pixels, and an architecture comprising two convolution layers, two pooling layers, and one fully connected layer. Evaluation using a Confusion Matrix revealed an accuracy of 89%. Despite this success, there are several areas that require further improvement. One key limitation is the size and diversity of the dataset, as expanding the number and variety of motifs would enhance the model's accuracy and generalization capabilities. Additionally, the current implementation relies on manually inputting images into the system via a website, which does not support real-time processing. This restricts the model's applicability in practical, real-world scenarios, where real-time image recognition would offer greater utility and efficiency.

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