Journal of Soft Computing Exploration

Homepage: https://shmpublisher.com/index.php/joscex

p-ISSN: 2746-7686
e-ISSN: 2746-0991

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Website based classification of Karo Uis types in north Sumatra using convolutional neural network (CNN) algorithm

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Article Info

Article history:

Received Nov 26, 2024
Revised Dec 17, 2024
Accepted Dec 20, 2024

Keywords:

Uis Karo
Classification
Convolutional Neural Network
Deep Learning
Web-based System

ABSTRACT

Indonesia is one of the largest archipelagic countries in the world. It has abundant cultural diversity including nature, tribes. One of the tribes in Indonesia is the Batak Karo tribe. Batak Karo is a tribe that inhabits the Karo plateau area, North Sumatra, Indonesia. Batak Karo has various cultures, one of which is a traditional cloth known as uis. Unfortunately, the Karo Batak community, especially the younger generation, has insufficient knowledge of the types of uis. Thus, a solution that is easily accessible both in terms of time, cost and experts in recognizing Uis is needed. This research aims to build a website-based application that can classify the types of Karo Uis. This research uses Convolution neural network (CNN) using Alex Net architecture, to get the best model this research compares several hyper parameters, namely learning rate of 10^{-1} to 10^{-4}, and data division with a ratio of 70:30 and 80:20. The best model falls on a ratio of 70:30 and a learning rate of 10^{-4} with an accuracy of 98%, and a validation accuracy of 99%, then the model is stored in h5 format in this study successfully builds and implements the model into a web-based application.

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https://doi.org/10.52465/joscex.v5i4.500

1. INTRODUCTION

Indonesia is one of the largest archipelagic countries in the world, rich in cultural diversity encompassing various aspects of nature, ethnic groups, cultures, and religious beliefs. On average, each ethnic group has its own regional language and customs that carry unique values which cannot be separated [1]. One of the ethnic groups, the Batak Karo, inhabits the highlands of Karo in North Sumatra. The Batak Karo people possess various cultural elements, including music (such as the Karo drum), dance (known as "landek"), and traditional cloth known as "uis" [2].

Uis Karo is a traditional fabric used in daily life as well as in various Batak Karo ceremonial events. Each uis fabric symbolizes a different message depending on its type and intended use. The symbolism found in the uis fabric can be seen in its patterns, colors, and designs [3]. Uis Karo is generally divided into two types:

uis nipes (thin fabric) and uis kapal (thick fabric). However, there are many types and motifs of uis with specific functions, such as uis arinteneng, uis gatip, uis beka bulu, uis jujung–jujungen, and nipes benang ireng, which are used during weddings, while uis Batu Jala is used in the koro-koro ceremony, uis teba is used during funerals, and uis julu, jongkit, kelam-kelam, and gara-gara are used in traditional ceremonies [4], [5].

Currently, there is a growing lack of awareness about the patterns of uis Karo, largely because uis Karo is used only in traditional events. Some members of the Karo community have even replaced traditional Karo cloth with batik or songket fabrics for everyday wear [6]. This is supported by several studies. In a research Merselina Sembiring at all, some reasons for the lack of knowledge about uis Karo were identified: the younger generation of Karo people has limited knowledge about the use of uis Karo in traditional ceremonies, there is a lack of interest among the younger generation of the Karo community to learn about the meanings of various types of uis, and the younger generation of Karo people has begun adopting modern clothing styles, making them feel disconnected from using uis Karo in daily life [7]. Additionally, in a research Wesnina, a survey of 100 young Karo people revealed that only 69.5% understood the types of uis Karo, while 72% recognized its characteristics, and only 55% knew it's uses [8].

Previous research indicates that public awareness of Karo Uis fabric remains limited. Despite this, there is a pressing need for an approach to enhance understanding of Uis fabric patterns. One of the key challenges is that many traditional Karo fabrics share similar designs and colors, making it difficult to differentiate between them. Traditionally, identifying these fabrics requires consultation with weavers or individuals with specialized knowledge of Uis [8]. To address this issue, it is essential to implement a solution that is accessible in terms of time, cost, and expert involvement, particularly for younger generations or the general public, including fabric vendors, to improve their understanding of Uis fabric patterns.

Convolutional Neural Network (CNN) is one of the algorithms in deep learning. CNN consists of layers of interconnected linear units. The value of a CNN is computed through weight derivatives and is widely used in computer vision applications. A commonly used dataset is MNIST from TensorFlow, where the digit values on a fully connected layer are connected to image intensity values to perform classification [9].

TensorFlow is a framework for machine learning and deep learning that operates on a large scale and is applied to heterogeneous systems for building Convolutional Neural Network (CNN) models[10]. Several studies have utilized CNN for image classification tasks. This is evidenced by several studies, such as, CNN was implemented for classifying Solo batik motifs, achieving a validation accuracy of 99% and an overall accuracy of 95% [11]. Second, CNN with the Alex Net architecture was used to classify citrus disease with an accuracy of 94% [12]. Third, for Alzheimer's disease classification, CNN with the Alex Net architecture achieved an accuracy of 95% [13]. Fourth, batik classification was conducted utilizing transfer learning with the VGG-16 architecture. The study incorporated data augmentation techniques, specifically Random Erasing and Grid Mask, resulting in an accuracy of 96.88% [14]. Lastly, the application of the Convolutional Neural Network (CNN) algorithm utilizing transfer learning with the Efficient-B1 for rice leaf disease classification motif batik at Indonesian got accuracy 89% loss 33% and implement the model to android[15].

However, TensorFlow does not come with a user interface that can facilitate user interaction with the system and cannot be accessed on other operating systems. To enable the model to be accessed from different operating systems, a web service is used. A web service is a data application (database), a set of tools that can be accessed remotely by various devices through a specific intermediary, serving as a connection between the model that has been developed and the website-based user interface [16].

Based on the issues surrounding uis Karo and the application of CNN, the researcher hypothesizes that a CNN model, integrated with a website-based application, could be a solution to increase public awareness about uis Karo patterns. This would be easily accessible, cost-effective, and independent of the availability of experts, offering a means to promote understanding of uis Karo in everyday life.

2. METHOD

This study focuses on the development and evaluation of a model, as well as its implementation in a web application for classifying uis Karo. The research process is divided into several stages, including data collection, image preprocessing, augmentation, exploratory data analysis (EDA), splitting the dataset into training and testing data, designing the convolutional neural network (CNN) model, model evaluation, and the implementation of the model in the web application. The flowchart of this research process is presented in the figure 1.

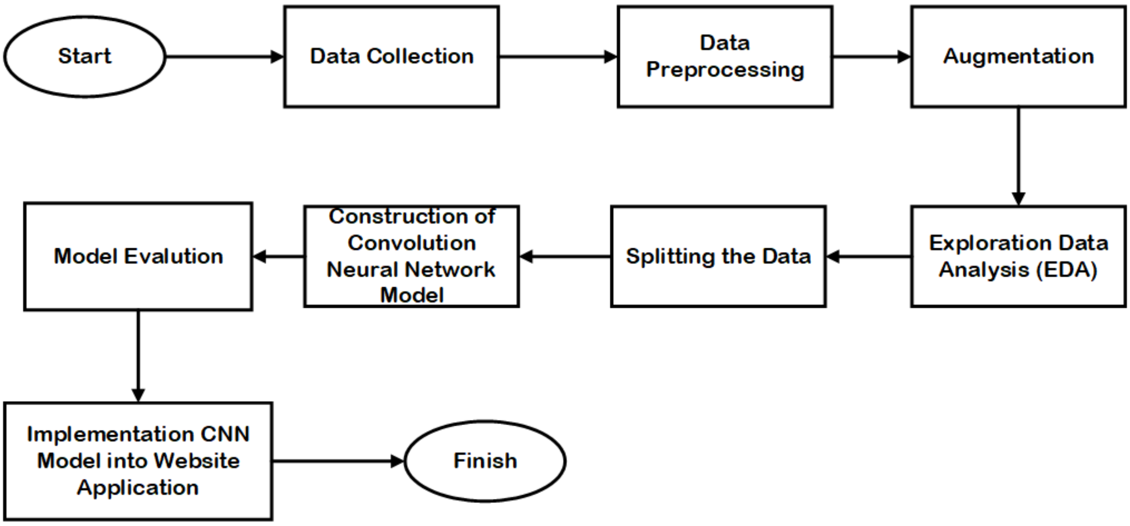
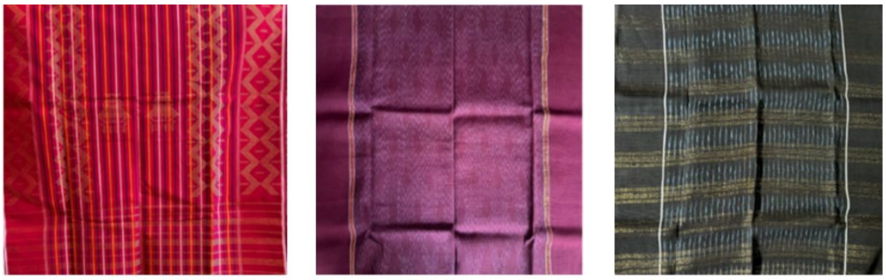


Figure 1. Research Flowchart

Data Collection

In this study, image data were collected through direct observation of traditional Karo weavers on Jl. Karya Pelita, Deli Serdang, as well as Karo cloth vendors in Pancur Batu. A total of 208 images in JPG format were obtained. The data collection process involved capturing images at a distance of 90 cm for vertical orientations and 80 cm for horizontal orientations, utilizing a POCO F4 smartphone equipped with a 64 MP camera featuring optical image stabilization (OIS). The types of Karo textiles, locally referred to as *uis Karo*, included *gara-gara*, *gatip diberu*, *gatip jongkit*, *kelam-kelam*, *nipes beka buluh*, *nipes benang ireng*, and *nipes motif litap-litap lembu*. Examples of the collected data are presented in Figure 2.



a) Nipes Beka Bulu b) Gara - Gara c) Gatip Diberu

Figure 2. Example of captured image

Preprocessing Data

Before the data is used for model building, the data goes through several processes to improve accuracy, the next steps are, performing background removal, resizing the image and image augmentation. Background removal is used to remove unwanted features in the data, then resizing the image with dimensions 227 x 227 and Augmentation is a process carried out on the image with the aim of multiplying the dataset by modifying and changing the condition of the image data from the image dataset that has been collected [17].

Augmentation techniques used in the research are image rescaling, rotation, zooming and random noise. Rescaling image is the process of normalizing pixels with a range between (0 to 255), rotating the image at a specified degree, zooming the image at a specified range Adding random noise involves altering pixels randomly in the image to introduce noise effects, simulating conditions of poor quality or low resolution. These three processes are implemented to enhance the model's generalization capability by introducing new variations in the training data used.

Exploratory Data Analyst

Exploratory Data Analyst (EDA) is a critical phase in the data science process that involves analyzing datasets and summarizing their main characteristics through visualizations and statistical techniques. First introduced by John Tukey [18], EDA emphasizes understanding patterns, identifying anomalies, and gaining insights into the data before applying formal statistical or machine learning models. In this study, EDA focused on analyzing the color diversity within each class of the dataset to examine variability.

Convolutional Neural Networks

Convolutional Neural Networks (CNN) is an extension of Artificial Neural Networks, distinguished by their unique structure, which includes input layers, convolutional layers, activation functions, and pooling layers. For classification tasks, CNNs also utilize fully connected layers with activation functions [19]. The research employed the Alex Net architecture, originally developed by a research team at the University of Toronto in 2012 [20], Alex Net consists of 8 convolutional and pooling layers arranged hierarchically, followed by 3 fully connected layers [21]. The diagram of the Alex Net architecture is shown at figure 3. To optimize the model's accuracy, several hyperparameters were fine-tuned, as detailed in Table 1.

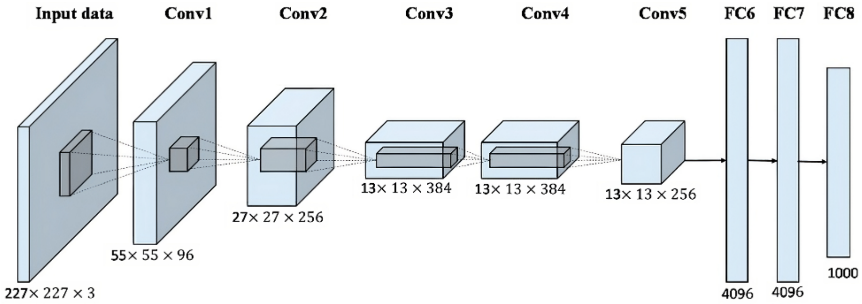


Figure 3. Architecture alexnet

Table 1. Hyperparameter

Name	Kind / Values
Loss Function	Categorical Cross Entropy
Loss Optimization	Adaptive Moment Estimation (ADAM)
Batch Size	32 (default)
Learning Rate	10^{-1}, 10^{-2}, 10^{-3}, 10^{-4}
Epochs	25, 50
Ratio (train data and test data)	70:30, 80:20

Model Testing and Evaluation

The trained model will be tested using test data that has been divided previously. Further testing to see the performance of the model in detecting the type of uis karo using confusion matrix [22]. The metrics considered during testing are training accuracy, test accuracy, training loss, test loss and F1-Score value. The accuracy value is obtained based on the result of the correct difference between the predicted model and the actual class. The loss value is obtained by calculating the distance between the model prediction and the actual class. Finally, the F1-Score value is obtained by calculating the harmonic mean of the precision and recall values to measure the overall performance of the model [22]–[24].

Web Application Development and Model Implementation

After identifying the best-performing model during evaluation, it was saved in H5 format for deployment. The implementation involved creating a centralized model accessible via an API or endpoint. This endpoint was used for transmitting data between the model and the web application.

3. RESULTS AND DISCUSSIONS

Exploratory Data Analysis

The prepared data intended for the model was first analyzed to understand its characteristics. During this EDA phase, the researcher performed a color analysis by calculating the range (max - min) of pixel values and the average for each class, the results of these calculations are presented in Table 2. The standard deviation of pixel values in each image was used for these calculations. This measure was chosen as the pixel value distributions were not normal, meaning their standard deviations were not equal to 1. An example of the distribution a channel in image is illustrated in Figure 4.

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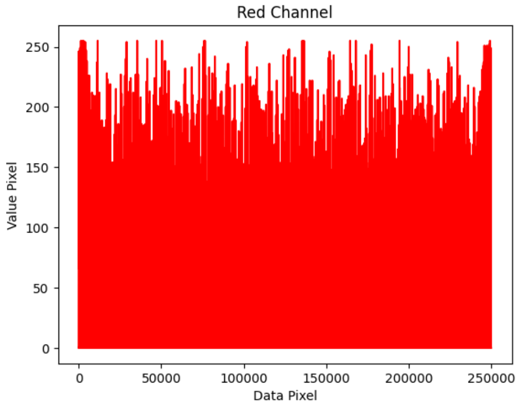

Figure 4. Distribution red channel from image

Table 2. Result standard deviation for each class

Classes	**Distance | Min – Max |**			**Average**		
	R	**G**	**B**	**R**	**G**	**B**
Gara – Gara	32,09	22,41	34,44	52,52	43,90	34,44
Gatip Diberu	22,60	19,77	22,32	43,45	45,22	43,99
Gatip Jongkit	23,54	21,66	23,13	51,85	37,43	44,04
Kelam - Kelam	27,54	21,69	26,08	35,69	35,46	35,70
Nipes Beka Buluh	33,50	16,37	15,42	87,90	45,02	45,24
Nipes Benang Ireng	31,10	26,35	23,53	68,24	49,99	50,00
Nipes Motif Litap Litap Lembu	55,81	60,12	35,99	70,94	37,28	35,40

Based on Table 2, the average values of each class across the RGB channels reveal significant homogeneous variations, particularly in the red channel. The red channel exhibits a notable mean value difference, with the Nipes Beka Buluh class having an average of 87.90, while the *Kelam-Kelam* class shows a much lower mean of 35.69, indicating a substantial difference. The green channel also demonstrates homogeneous variations, albeit less pronounced than those observed in the red channel. Meanwhile, the blue channel displays even smaller variations compared to the red and green channels, but differences between classes remain evident. These findings underscore the variability in pixel intensity across different channels, which could significantly influence the model's ability to classify image data effectively.

Convolutional Neural Network Model Training

Model training was conducted based on predefined architectures and hyperparameters using Google Collab. The outcomes of training, including hyperparameter settings and testing results for each model, are shown in Table 3.

Table 3. Measurement Result Train Model

Epochs	**Ratio**	**Learning Rate**	**Accuracy**	**Val accuracy**	**Loss**	**Val Loss**
25	70:30	$\mathbf{10^{-1}}$	0.1453	0.1428	13.283	13.279
		$\mathbf{10^{-2}}$	0.1232	0.1428	2.0531	2.0512
		$\mathbf{10^{-3}}$	0.8783	0.8685	0.2794	0.3079
		$\mathbf{10^{-4}}$	0.9863	0.8990	0.0677	0.4066
	80:20	$\mathbf{10^{-1}}$	0.1378	0.1428	15.109	15.101
		$\mathbf{10^{-2}}$	0.1492	0.1428	2.2345	2.0532
		$\mathbf{10^{-3}}$	0.9121	0.9142	0.2345	0.1926
		$\mathbf{10^{-4}}$	0.9921	0.9885	0.0460	0.0509
50	70:30	$\mathbf{10^{-1}}$	0.1265	0.1428	16.604	16.594
		$\mathbf{10^{-2}}$	0.1330	0.1428	2.0541	2.0536

	$\mathbf{10^{-3}}$	0.9477	0.9180	0.1301	0.2270
	$\mathbf{10^{-4}}$	0.9807	0.9942	0.0269	0.0367
80:20	$\mathbf{10^{-1}}$	0.1264	0.1428	11.608	11.597
	$\mathbf{10^{-2}}$	0.1378	0.1428	2.0336	2.0331
	$\mathbf{10^{-3}}$	0.8799	0.8857	0.3340	0.2704
	$\mathbf{10^{-4}}$	1	0.9814	0.0292	0.0406

The table 3 reveals that models trained with learning rates of 10^{-1} and 10^{-2} exhibited underfitting, as evidenced by high loss values during training. While the number of epochs significantly influenced training accuracy, it had a negligible effect on validation accuracy. For instance, at 50 epochs, validation accuracy was consistently lower than training accuracy, indicating overfitting. However, the gap between validation and training accuracy was not substantial. The best-performing model was achieved at 50 epochs with a 70:30 train-test ratio and a learning rate of 10^{-4}. This model was selected because its training accuracy exceeded its validation accuracy while maintaining a minimal difference. Visualization of the performance metrics for the best model, based on Table 3, is presented in Figure 5.

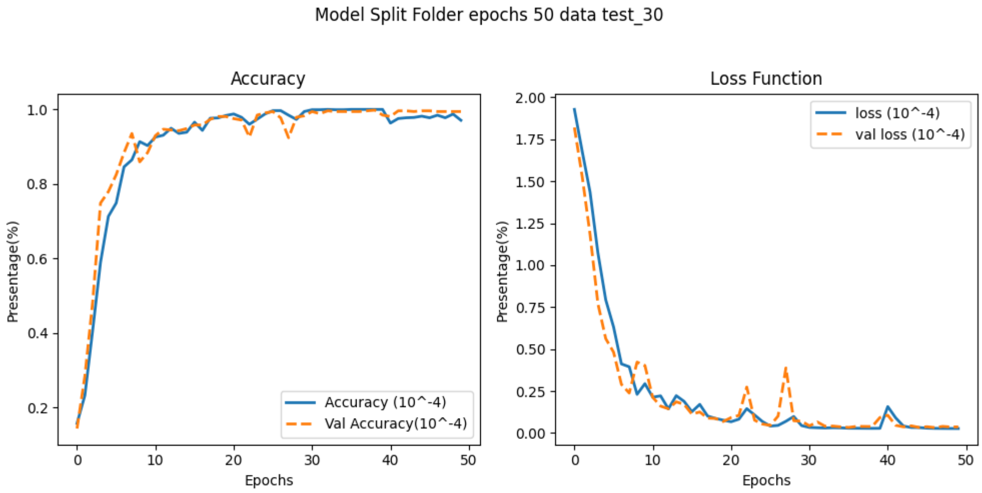

Figure 5. Visualization for the best model

Once the optimal model has been obtained, the next step involves conducting a comparative analysis with previous studies to identify differences or research gaps. This comparison is based on the accuracy achieved by the models. Further details regarding the results of this comparison are presented in the following table 4.

Table 4. Accuracy Model Comparison

Research Title	Architecture	Epoch	Accuracy	Val accuracy
Penerapan Algoritma Convolutional Neural Network Untuk Klasifikasi Motif Citra Batik	-	100	99%	94%
Implementasi Data Augmentation Random Erasing dan Grid Mask pada CNN untuk Klasifikasi Batik	VGG16	60	85%	-
Implementasi Convolutional Neural Network (CNN) Klasifikasi Motif Batik Menggunakan Efficientnet-B1	Efficientnet-B1	10	98%	70%
Website Based Classification of Karo Uis Types in North Sumatra Using Convolutional Neural Network (CNN) Algorithm	**Alex Net**	**50**	**98%**	**99%**

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Evaluasi Model

After selecting the best-performing model, the next step was to evaluate its performance on the test dataset. The evaluation process utilized a confusion matrix, as illustrated in figure 6. Based on the figure 6, performance metrics for each class, including Accuracy, Precision, Recall, and F1-score, were calculated. The results of these metrics for each class are presented in Table 5.

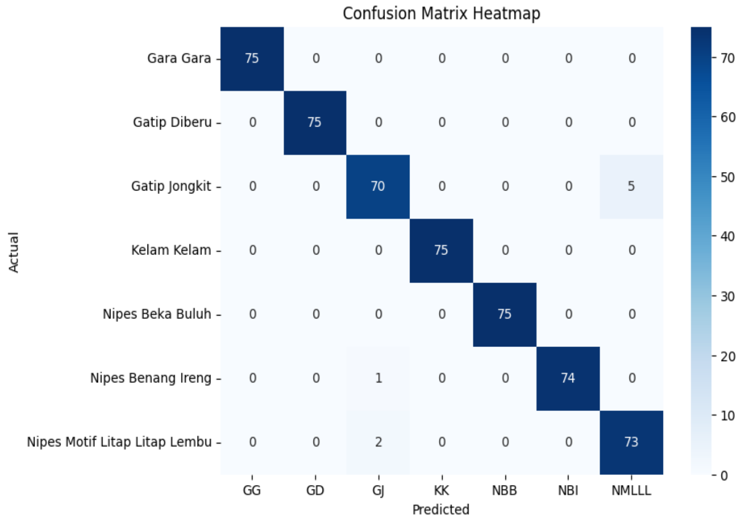

Figure 6. Visualization confusion matrix

Table 5. Result calculation Precision, Recall and f1-score

Classes	Precision	Recall	F1-Score
Gara – Gara	100%	100%	100%
Gatip Diberu	100%	100%	100%
Gatip Jongkit	96%	93%	95,8%
Kelam - Kelam	100%	100%	100%
Nipes Beka Buluh	100%	100%	100%
Nipes Benang Ireng	100%	99%	99%
Nipes Motif Litap -Litap Lembu	94%	97%	95%
Average	**98%**	**98%**	**98%**
Accuracy		**98%**	

The confusion matrix presented in Figure 6 highlights instances of misclassification within the test dataset. One notable case involves the Gatip Jongkit class, where five images were misclassified as Nipes Motif Litap-Litap Lembu. This error likely stems from the close resemblance in color between these two motifs. Despite this, the model demonstrated strong performance on the test data, achieving over 90% correct predictions. As shown in Table 6, the model attained an average Recall (Hit Rate) of 98%, Precision (the accuracy of positive predictions) of 98%, and an F1-Score of 98%. These metrics suggest that the model effectively classifies UIS Karo patterns with high reliability.

Website Application Development and Model Implementation

After implementing the best model, it is stored in an H5 format for seamless integration into the web services. The website system is built using a microservices architecture, comprising two primary components: the frontend and the backend. The frontend, developed with the React.js framework, serves as the user interface, while the backend, created using the Flask framework in Python, handles the system's logic and provides endpoints for the frontend to consume, as detailed in Table 6. Communication between these components is facilitated through APIs.

Table 6. Endpoint webservices from website application

No	Endpoint	Method	Description
1.	/predict	POST	Show result prediction base on model
2.	/name_uis?=<name >	GET	Show result of uis data base on name given
3.	/all_uis	GET	Show results all data for uis karo

Users can interact with the website system by uploading images, which are then processed for classification. Figure 7 illustrates the flowchart outlining how users interact with the system. Figure 8 depicts the homepage, offering an overview of the website, while figure 9 shows the page where users can upload images for classification by the application. The classification results, along with their corresponding processes, are also provided.

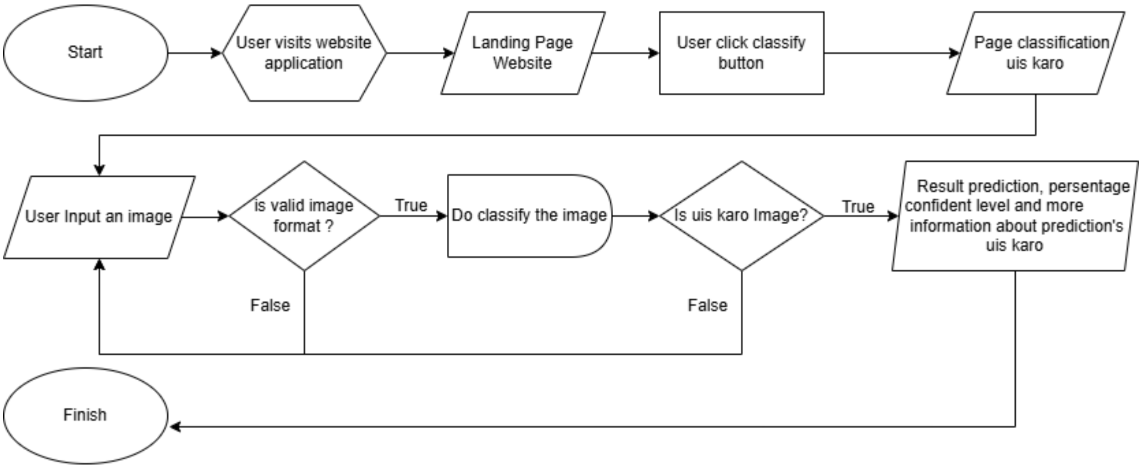

Figure 7. Flowchart how the user interaction with website System

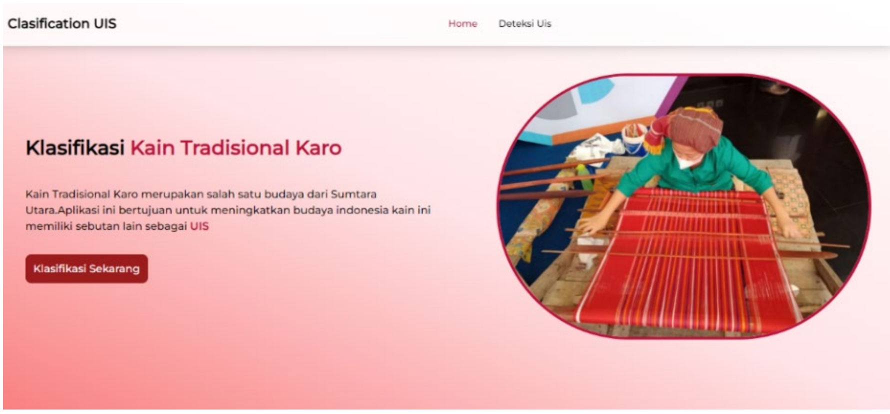

Figure 8. Main page website application

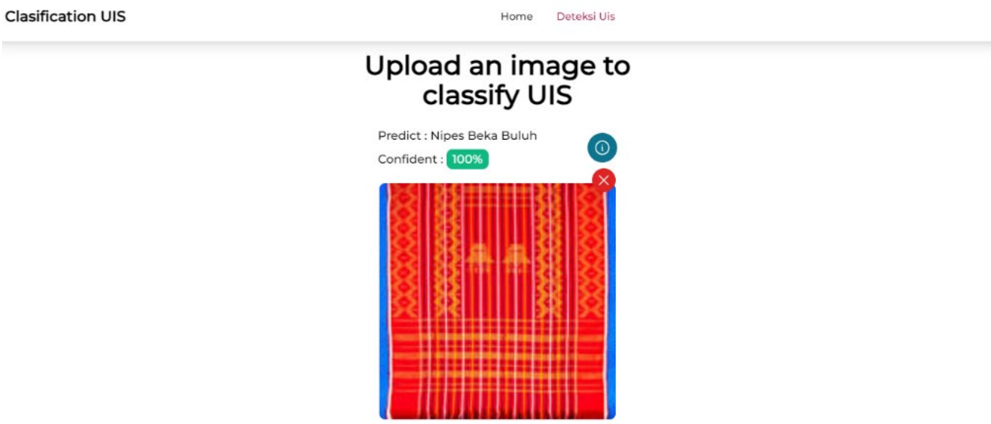

Figure 9. Classification page from website application

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4. CONCLUSION

Based on the results obtained from this study, it can be concluded that the evaluation of the model is promising and suitable for implementation in a system. The research findings on the classification of *uis Karo* reveal significant insights. Analyzing RGB data demonstrates notable variations, particularly in the red channel, where average values differ significantly between image classes. For instance, the *Nipes Beka Buluh* class has an average red channel value of 87.90, whereas the *Kelam-Kelam* class shows a much lower average of 35.69, highlighting considerable heterogeneity within the dataset. To address this variation, a Convolutional Neural Network (CNN) model employing the Alex Net architecture was developed. The model was trained for 50 epochs using a 70:30 data split ratio and a learning rate of 10^{-4}. Evaluation results indicate that this CNN model achieved an impressive overall accuracy of 98%, with a validation accuracy of 99%. Additionally, this study developed a web-based application using React.js and Flask, deployed locally, to enhance the recognition of traditional Karo fabrics. The application includes features such as the classification of *uis Karo* types through scanning, information on the function of each fabric, and detailed characteristics of each *uis Karo* fabric.

To further enhance the performance of the CNN model, several areas require improvement. Increasing the dataset by incorporating additional variations or motifs is essential. Expanding the *uis Karo* classes, as some types were not captured during data collection, will provide broader coverage. Optimizing the model through techniques such as L1 and L2 regularization or exploring alternative optimization methods will help prevent overfitting. Finally, utilizing transfer learning by applying pre-trained features can effectively mitigate overfitting and underfitting challenges, ensuring a more robust model for future developments.

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