# Benchmarking a New Dataset of Traditional Balinese Carving Ornaments for Image Classification Task

Made Windu Antara Kesiman<sup>1</sup>, I Gede Mahendra Darmawiguna<sup>2</sup>, I Gede Rusdy Mahayana Putra<sup>3</sup>, Ni Luh Putu Kurniawati<sup>4</sup>

{antara.kesiman@undiksha.ac.id<sup>1</sup>, mahendra.darmawiguna@undiksha.ac.id<sup>2</sup>, rusdy.mahayana.putra@undiksha.ac.id<sup>3</sup>}

Virtual, Vision, Image, and Pattern Research Group, Universitas Pendidikan Ganesha, Jalan Udayana No. 11 Singaraja Bali 81116<sup>123</sup>

**Abstract.** In the framework of the development of an automatic Balinese carving ornament recognition application, a valid image dataset is needed. This paper describes the improved new dataset of traditional Balinese carving ornaments and presents the benchmarking results in an image classification task. The improvement of the new dataset involves the increased number of image samples and involves the validation and addition of the number of ornament classes. Some frequently used feature extraction methods, for example, Gabor Filter, Zoning, Histogram of Gradient, Neighborhood Pixels Weights, and Kirsch edge, were tested to benchmark the image classification task for this new dataset. The benchmark results showed that this new dataset has a fairly high technical challenge for feature extraction methods in the pattern recognition field. The new proposed dataset will support further research steps in building a classification and recognition system for Balinese carving ornaments.

Keywords: benchmark, dataset, image classification, Balinese carving ornament

## **1** Introduction

The development of computer vision technology, especially in pattern recognition, has now appeared to create socio-cultural-based applications to support the tourism industry sector. Meanwhile, to the ancient manuscript collections that have been the center of attention of researchers in document image analysis [1], other cultural objects have now begun to be analyzed by researchers. They are traditional textile motif patterns, basic movement patterns of traditional dances [2], [3], and traditional carving ornament patterns [4]. The aim of those researches was not only to preserve the nation's cultural heritage but also to increase the interest of tourists in exploring the cultural object by offering and using some technology-based tourism programs and applications.

The first challenge faced by researchers to build a cultural-based pattern recognition system is the absence of a dataset of those cultural objects. Nevertheless, the challenge of building a new dataset is not easy either [5]. With all existing socio-cultural rules and limitations, the efforts to

build datasets for those cultural objects must be carried out to support the research program. One of the Balinese cultural objects rich in patterns and motifs is carving ornaments. This paper describes the contribution of a new image dataset of traditional Balinese carving ornaments and presents the initial benchmark for image classification task for those images of ornament. This dataset will be very useful in helping the researchers develop applications for automatic carving ornament pattern recognition for the wider community, especially for tourists. This work was under the Project of DIORAMA (Digital Image of Ornament Analysis) from Virtual, Vision, Image, and Pattern Research Group.

The following section will briefly describe the traditional Balinese carving ornaments. The standard dataset construction for images of Balinese carving ornament will be presented in section 3. Section 4 will show the initial benchmarking results and performances for the image classification task by using our proposed dataset. The last section will draw some conclusions.

## 2 Traditional balinese carving ornaments

Traditional Balinese carving ornaments are the embodiment of human and natural beauty carved as various decorations into the parts of Balinese buildings and temples. The forms of ornaments, the color combinations, the carving process, and placement contain specific meanings and purposes. Based on the book of Arsitektur Traditional Daerah Bali (Traditional Balinese Architecture) [6], it is stated that Balinese carving ornaments are divided into two main categories, namely plant (flora) ornaments and animal (fauna) ornaments.

Ornaments of type flora (see **Figure 1**) are carved in the forms of plants with various meanings or expressions. This flora category is further divided into three subcategories, namely 1) Keketusan, 2) Kekarangan, and 3) Pepatraan. Keketusan takes the most important part of a plant carved in a repetitive pattern to beautify its prominence. Kekarangan shows the shape of a plant, and it is focused on the beauty of that plant. There are several classes of Kekarangan, namely Karang Simbar, Karang Bunga, and Karang Suring [7]. Kekarangan is also carved by taking the forms of animal beauty. Pepatraan is carved based on the name/type of the plant that is embodied. Pepatraan allows the possibility of using the name of the plant from the country of origin. Several classes of Pepatraan exist, namely Patra Wangga, Patra Sari, Patra Pidpid, and others.



Fig. 1. Examples of ornament of type flora – keketusan (batu-batuan and kakul-kakulan), kekarangan and patra wangga.

Ornaments of type fauna (see **Figure 2**) display the beauty of fauna, and in its placement, it is generally accompanied or equipped with related ornaments of type flora. Ornaments of type fauna are displayed in various decorative ways with their respective names. They appear in the

form of sculptures or reliefs combined with decorations of various ornaments of type flora. Ornaments of type fauna can be divided into two subcategories: Pepatraan and Kekarangan. Pepatraan type fauna can be categorized into four classes: Patra Naga, Patra Garuda, Patra Singa, and Patra Kera. Kekarangan in type fauna can be categorized into seven classes, namely Karang Boma, Karang Sae, Karang Gajah, Karang Goak, Karang Tapel, Karang Bentulu, and Karang Batu.



**Fig. 2.** Examples of ornament of type fauna – patra naga, patra garuda, patra singa, patra kera, and karang boma.

## **3 Dataset construction**

The new image dataset of Balinese carving ornaments proposed in this paper was the improved version of the previous dataset introduced by Putra et al. [4]. This previous dataset only consisted of 18 classes of ornaments. The sample images were captured using a DSLR Nikon D5300 camera with ISO 500, and a pixel dimension of 6000 x 4000 pixels. The validation of class name sample images was done by the experts and practitioners in Balinese carving.

#### 3.1 Image corpus and samples

The new image dataset of Balinese carving ornaments would improve the previous dataset in terms of class variety, verification of class label, and the number of image samples from each ornament class. The new dataset consisted of 25 classes (see Table 1 and 2). Two classes from the previous dataset, namely Karang Daun and Karang Guling, were deleted. Karang Guling class was included in Patra Punggel class, while Karang Daun class was divided into two new classes, namely Karang Simbar and Karang Bunga. Seven new other classes were also added, namely Patra Tali Ilut, Patra Wangga, Patra Api, Karang Boma, Karang Sae, Karang Bentulu, and Karang Batu. Three previous class names were corrected: Patra Mesir, Mote-motean, and Pidpid. In terms of the quantity of sample images, all sample images from the existing class of the previous dataset were still used, and five new sample images were added for each class in the new dataset. All sample images were then manually cropped into pixel dimensions of 300 x 200 (see **Figure 3**).



Fig. 3. The capturing and cropping process of a sample image: patra *tali ilut*.

No	New Class Nome	Old Dataset			New Dataset			
INO	New Class Mallie	Nb Train Set	Nb Test Set	Total Samples	Nb Train Set	Nb Test Set	Total Samples	
1	Batu-Batuan	7	5	12	10	7	17	
2	Batun-timun	10	6	16	13	8	21	
3	Kakul-kakulan	6	4	10	9	6	15	
-	Karang-Daun	10	6	16	Deleted	Deleted	Deleted	
4	Karang-Gajah	8	6	14	11	8	19	
5	Karang-Goak	8	5	13	11	7	18	
6	Karang-Tapel	16	5	21	19	7	26	
-	Karang Guling	21	5	26	Deleted	Deleted	Deleted	
7	Patra Mesir	7	5	12	10	7	17	
	(Prev: Kuta Mesir)							
8	Mas-Masan	10	5	15	13	7	20	
9	Mote-motean	4	4	8	7	6	13	
	(Prev: Mute-mutean)							
10	Patra-Banci	8	5	13	11	7	18	
11	Patra-Cina	5	4	9	8	6	14	
12	Patra-Punggel	8	5	13	11	7	18	
13	Patra-Samblung	6	5	11	9	7	16	
14	Patra-Sari	7	5	12	10	7	17	
15	Patra-Ulanda	11	5	16	14	7	21	
16	Pidpid	16	5	21	19	7	26	
	(Prev: Pipid)							
17	Patra Tali Ilut	Not available	Not available	Not available	3	2	5	
18	Patra Wangga	Not available	Not available	Not available	3	2	5	
19	Patra Api	Not available	Not available	Not available	3	2	5	
20	Karang Simbar	Not available	Not available	Not available	3	2	5	
21	Karang Bunga	Not available	Not available	Not available	3	2	5	
22	Karang Boma	Not available	Not available	Not available	3	2	5	
23	Karang Sae	Not available	Not available	Not available	3	2	5	
24	Karang Bentulu	Not available	Not available	Not available	3	2	5	
25	Karang Batu	Not available	Not available	Not available	3	2	5	
	TOTAL	168	90	258	212	129	341	

Table 1. Class name and number of image samples for dataset

No	Class Name	Sample Image	No	Class Name	Sample Image	No	Class Name	Sample Image
1.	Batu-batuan	<u></u>	9.	Patra Wangga		17.	Karang Simbar	
		And the second		Wangga			Simba	ALC:
2.	Kakul-	IC CIC	10.	Patra Sari	and way	18.	Karang	- Mar
	kakulan						Bunga	
3.	Mas-masan		11.	Patra	Car	19.	Karang	and the second
				Punggel			Boma	
4.	Mote-		12.	Patra	POUS C	20.	Karang Sae	
	motean			Samblung				
5.	Pidpid	TATA MA	13.	Patra Ulanda	(a) () ()	21.	Karang	
		Carry .			- Provide		Gajah	Contraction of the second
6.	Batun Timun		14.	Patra Cina		22.	Karang Goak	
					1233			
7.	Patra Tali	0000	15.	Patra Banci	23052	23.	Karang Tapel	0
	llut							( ST
8.	Patra Mesir	Elle Ile	16.	Patra Api-	The states	24.	Karang	100
				apian	Creation State		Bentulu	
						25.	Karang Batu	202
								S MO

Table 2. Image samples for each class in the new dataset

#### 3.2 Ground truth data format

The class labeling process for each image sample was validated by three practitioners and educators as experts in the Balinese art carving domain. Three experts labeled each sample image based on their expertise. Each sample image file was named *CLASSLABEL\_XXX*.jpg, where *XXX* is the three digits number of the sample image. For example, Batu-batuan\_001.jpg, Mote-Motean\_003.jpg, etc.

## 4 Benchmarking methods and results

#### 4.1 Methods

The initial benchmarking process of the image classification task for the new dataset of traditional Balinese carving ornaments was performed in three different methods/schemes as follow:

Method A: Gabor Filter and Zoning as feature extraction method with the neural network as a classifier (see **Figure 4**). In this method, the Gabor filter was combined with the Zoning method to extract features of ornament images based on the previous finding by Putra et al. [4]. In our experiment, the sample images were first pre-processed into greyscale images and resized into the dimension of 500 x 500 pixels. The Gabor filter was first applied with a combination of parameters, namely wavelength of 4 or 8, the orientation of 0, 45, ..., 315, aspect ratio of 0.5 or 0.9, and bandwidth of 0.5 or 1. All Gabor filtered images were then converted into a binary image by using Otsu's binarization method [8]. Seven types of Zoning methods (horizontal, vertical, block, left diagonal, right diagonal, radial, and circular) were applied on each binarized image with a zone area of 50 pixels. The extracted features from each image and Zoning type were finally concatenated to build a final feature vector of dimension 13,120.



Fig. 4. Feature extraction steps with gabor filter and zoning.

A neural network with a single hidden layer of 500 neurons trained a classifier. This network used 0.0001 for regularization strength and 0.0001 for step size for parameter values during the training process. The network was trained until 40,000 epochs.

Method B: Histogram of Gradient (HoG) [9] and Neighborhood Pixels Weights (NPW) [10] on Kirsch Edge image (see **Figure 5**). This combination of features was proposed by Kesiman et al. [11]. The same pre-processing step as Method A was applied. The HoG feature was calculated with the parameter values of 5 for bin size and step, 10 for cell size, and 9 for the number of orientations. The NPW feature of level 3 with a block size of 50 was calculated over the Kirsch edge image in four different directions. All HoG and NPW features were concatenated to build a final feature vector of dimension 79,100. The same neural network was used to train a classifier, but only with a hidden layer of 100 neurons. A neural network with a single hidden layer of 500 neurons was used to train a classifier. This network used 0.0001 for regularization strength and 0.0001 for step size for parameter values during the training process. The network was trained until 40,000 epochs.

Method B: Histogram of Gradient (HoG) [9] and Neighborhood Pixels Weights (NPW) [10] on Kirsch Edge image (see **Figure 5**). This combination of features was proposed by Kesiman et al. [11]. The same pre-processing step as Method A was applied. The HoG feature was calculated with the parameter values of 5 for bin size and step, 10 for cell size, and 9 for the number of orientations. The NPW feature of level 3 with a block size of 50 was calculated over the Kirsch edge image in four different directions. All HoG and NPW features were concatenated to build a final feature vector of dimension 79,100. The same neural network was used to train a classifier, but only with a hidden layer of 100 neurons.



Fig. 5. Feature extraction steps with hog, kirsch edge, and npw.

#### 4.2 Results

Table 3 shows the initial benchmarking results of the image classification task for the new dataset of traditional Balinese carving ornaments. Although this experiment aimed not to compare the benchmarks of the two versions of the dataset, it is also important to note that the benchmark for the image classification task using the previous dataset was 41.14% [4]. Other than that, the benchmark of the previous dataset was calculated by averaging the performance values from several parameters in the K-Fold validation experiments [4]. Whereas for the new dataset, the benchmark was calculated using a fixed train/test set.

With the new, improved dataset, the benchmark was now lower. This is undoubtedly due to the increased number of classes, from 18 classes to 25 classes. The applied feature extraction methods and the classifier systems now face significantly increased challenges in gaining their best performance to classify the sample images of Balinese carving ornaments. This initial benchmark value did not justify the highest possible performance achieved with the proposed method but only provided a preliminary overview of the new challenges in the new dataset.

**Table 3.** Benchmark of image classification task

No	Methods	Correct Classification
1	Method A	35.66 %
2	Method B	23.26 %

# **5** Conclusions

A new dataset of traditional Balinese carving ornaments for the image classification task was proposed in this paper. This new dataset has high social-cultural value and offers new technical challenges in image classification tasks in the field of pattern recognition. From the initial benchmarking results, it can be seen that some well-known and frequently used feature extraction methods for pattern recognition have not been able to achieve high enough classification results. This is due to the visual characteristics possessed by each ornament class varying greatly. The characteristics of these datasets will create new interesting challenges for researchers in the pattern recognition field. The dataset will be publicly available for all research and academic purposes on the Virtual, Vision, Image, and Pattern Research Group website (https://research.undiksha.ac.id/vvip-rg/).

Acknowledgments. The authors thank Balinese families, students, and experts (I Komang Subrata, S.Pd, M.Pd, I Nyoman Karyana, S.Pd, and I Made Suyatna, S.Sn) who helped in collecting and validating the dataset for this work. This research is supported by DIKTI Penelitian Dasar Unggulan Perguruan Tinggi (PDUPT) 2021 Research Funding Program.

## References

[1] M. W. A. Kesiman and G. A. Pradnyana, "A Complete Scheme of Word Spotting System for the Balinese Palm Leaf Manuscripts," in *2019 11th International Conference on Information Technology and Electrical Engineering (ICITEE)*, Pattaya, Thailand, Oct. 2019, pp. 1–5. doi: 10.1109/ICITEED.2019.8929937.

[2] M. W. A. Kesiman, I. M. D. Maysanjaya, I. M. A. Pradnyana, I. M. G. Sunarya, and P. H. Suputra, "Revealing the Characteristics of Balinese Dance Maestros by Analyzing Silhouette Sequence Patterns Using Bag of Visual Movement with HoG and SIFT Features," *Journal of ICT Research and Applications*, vol. 15, no. 1, pp. 89–104, 2021, doi: 10.5614/itbj.ict.res.appl.2021.15.1.6.

[3] M. W. A. Kesiman, I. M. D. Maysanjaya, I. M. A. Pradnyana, I. M. G. Sunarya, and P. H. Suputra, "Profiling Balinese Dances with Silhouette Sequence Pattern Analysis," in *2020 International* 

*Conference on Computer Engineering, Network, and Intelligent Multimedia (CENIM)*, Surabaya, Indonesia, Nov. 2020, pp. 423–428. doi: 10.1109/CENIM51130.2020.9297893.

[4] I. G. R. M. Putra, M. W. A. Kesiman, G. A. Pradnyana, and I. M. D. Maysanjaya, "IDENTIFIKASI CITRA UKIRAN ORNAMEN TRADISIONAL BALI DENGAN METODE MULTILAYER PERCEPTRON," *SINTECH Journal*, vol. 4, no. 1, pp. 29–39, Apr. 2021, doi: 10.31598/sintechjournal.v4i1.552.

[5] M. W. A. Kesiman, J.-C. Burie, J.-M. Ogier, G. N. M. A. Wibawantara, and I. M. G. Sunarya, "AMADI\_LontarSet: The First Handwritten Balinese Palm Leaf Manuscripts Dataset," in *15th International Conference on Frontiers in Handwriting Recognition 2016*, Shenzhen, China, Oct. 2016, pp. 168–172. doi: 10.1109/ICFHR.2016.39.

[6] I. N. Gelebet, I. G. N. A. Puja, and Proyek Inventarisasi dan Dokumentasi Kebudayaan, *Arsitektur tradisional daerah Bali*. Denpasar: Departemen Pendidikan dan Kebudayaan, 1981.

[7] N. K. A. Dwijendra, *Arsitektur rumah tradisional Bali: berdasarkan asta kosala-kosali*, Cet. 1. Denpasar, Bali: Kerjasama Bali Media Adhikarsa [dengan] Udayana University Press, 2008.

[8] Global image threshold using Otsu's method - MATLAB graythresh - MathWorks France. Accessed: Feb. 20, 2018. [Online]. Available: https://fr.mathworks.com/help/images/ref/graythresh.html?requestedDomain=true

[9] A. Aggarwal, K. Singh, and K. Singh, "Use of Gradient Technique for Extracting Features from Handwritten Gurmukhi Characters and Numerals," *Procedia Computer Science*, vol. 46, pp. 1716–1723, 2015, doi: 10.1016/j.procs.2015.02.116.

[10] S. Kumar, "Neighborhood Pixels Weights-A New Feature Extractor," *International Journal of Computer Theory and Engineering*, pp. 69–77, 2009, doi: 10.7763/IJCTE.2010.V2.119.

[11] M. W. A. Kesiman, S. Prum, J.-C. Burie, and J.-M. Ogier, "Study on Feature Extraction Methods for Character Recognition of Balinese Script on Palm Leaf Manuscript Images," Cancun, Mexico, Dec. 2016.