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ARTIFICIAL INTELLIGENCE MEETS CULTURAL TRADITIONS: IDENTIFYING DAYAK KENYAH PAMPANG 'LAMIN' MOTIFS

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Article Info

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Abstract

The Dayak tribe, particularly the Kenyah Dayak, have a rich cultural tradition characterized by their distinctive longhouses known as "Lamin." These traditional structures serve as vital communal spaces and are adorned with intricate carvings and paintings referred to as "Kalung" or "necklace." These Kalung motifs, traditionally comprising hornbill, dragon, crocodile, tiger, and arch, hold profound cultural significance, serving both as protection against malevolent spirits and as symbols of status. Regrettably, many remain unaware of the diversity of motifs within the Dayak Kenyah culture.

In response to this knowledge gap, our research endeavors to leverage technology for the identification and recognition of Dayak Kenyah wall decorative motifs. In recent years, image identification techniques have witnessed significant advancements, driven by artificial intelligence (AI) methodologies. To address this research objective, we draw upon a growing body of knowledge in the field of AI. Previous studies, such as the work conducted by Ardianto et al. (2020), have successfully applied AI techniques, specifically Naïve Bayes and Support Vector Machine (SVM), to diverse domains. For instance, Ardianto et al. (2020) employed these methods to analyze sports learning curriculum data extracted from Twitter, achieving promising results with the Naïve Bayes-SMOTE approach.

This research contributes to the preservation and appreciation of the Dayak Kenyah culture by utilizing AI-based image recognition techniques. By harnessing the power of AI, we aim to create a tool that allows the public to discern and identify the intricate motifs adorning Dayak Kenyah longhouses. Through this technological approach, we

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hope to foster a deeper understanding of the cultural significance of these motifs while also promoting their preservation and recognition. Our study represents a novel application of AI in the realm of cultural heritage preservation, enriching the cultural tapestry of the Dayak Kenyah tribe and contributing to the broader discourse on heritage preservation through technology.

Introduction

The longhouse called “Lamin” is the traditional house of the Dayak tribe, including the Kenyah Dayak. This Lamin is in the form of an elongated box, in the form of a house on stilts to avoid moisture from the soil. Each Lamin has a motif, the art of carving and painting is called a “Kalung” or "necklace". Meanwhile, the motifs used to consist of five motifs, namely hornbill (burung enggang or tebengaang), dragon (legunan or naga), crocodile (buaya), tiger (lenjau or harimau), arch (lengkungan). The "kalung" functions as an antidote to evil spirits, and a status symbol, so its use should not be senseless [1]. However, lots of people do not know because the motives of the Dayak Kenyah tribe are diverse.

Therefore, this research helps the public to identify the Dayak Kenyah wall decorative motifs with technology. Several studies in image identification by applying various artificial intelligence (AI) methods are continuously being carried out and applied in various fields by researchers. Ardianto et al. (2020) have applied the Naïve Bayes and SVM methods to sports learning curriculum data taken from Twitter. The results showed that the Naïve Bayes-SMOTE method had an accuracy

of 70.32% and an AUC of 0.954. Meanwhile, SVM-SMOTE has got 66.92% accuracy and 0.832 AUC. However, the Naïve Bayes method has obtained the highest accuracy value compared to the SVM method with an accuracy ratio of 3.4% [2]. Ahmed & Hussein (2020) have also applied the radial basis function neural networks (RBFNN) and SVM-based SSA methods on 100 leaf images with 16 shape data each and each shape consists of 64 vectors obtained from contour normalization. On the other hand, when SVM is used with selected features, the accuracy reaches 93%, outperforming the RBFNN classifier. When SSA is used with SVM, it achieves 96.67 significant performance improvements compared to the RBFNN classifier and SVM classifier. This shows that there is great potential and benefit from feature extractors using RBFNN and classifiers using SVMbased SSA [3].

Then, Chiu et al. (2020) have applied PCA, Multilayer Perceptron, Transfer Learning, and SVM to data analysis of patients with breast cancer (2009-2013) from Manuel Gomes, Department of Obstetrics and Gynecology, University Hospital Center of Coimbra, Portugal. A total of 569 pieces of data were collected with 212 diagnosed patients and 357 healthy individuals. Interactive image processing techniques and linear program-based classifiers were used to digitize breast cancer cells and to analyze the size, shape, and texture of the cell nuclei accurately and automatically. When the number of instances is increased by three to six times (699 and 569 instances), this method achieves an accuracy of 97%, which indicates that the good performance of the method goes hand in hand despite the difference in the number of attributes [4]. Van et al. (2020) have also implemented the SVM Classifier with datasets from Case Western Reserve, University Bearing Data Center (2014). The three fault conditions include outer, inner races, and ball which are labeled as ORF, IRF, and BF, respectively. For each type of disturbance condition, the disturbance size can be 0.007, 0.014, or

0.021 milli-inches with a total of 10 conditions/classes considered. From these results, the proposed PSO-LSWSVM classifier (accuracy = 95.33%) is better than KNN (accuracy = 83.05%), PNN (accuracy = 84.77%), and PSO-LSRBFSVM (accuracy = 86.84%) [5].

Afterwards, Jaman et al. (2020) have applied the SVM Algorithm to identify the rice varieties types on the market. This study aims to distinguish the Mekongga rice variety from other varieties. This research was conducted using 70 image datasets. It goes through several stages such as preprocessing, image segmentation, feature extraction, classification, and then evaluation. The results showed that the classification resulted in an accuracy of 94.28% on test data from 35 rice images [6]. Han et al. (2020) applied the SVM method on 1.6 million records in the data set in the dataset description, with no neutral class involved in the training set. 50% of the data has a negative tag while the other 50% has a positive tag. The FK-SVM method was proposed and compared with HIST. The classification accuracy of the proposed method is verified by using the Twitter data set with the effect of the sentiment analysis method. The experimental results show that the average accuracy of the FK-SVM method on the Twitter sentiment corpus is 87.20%, a large increase based on the HIST-SVM and PLSA-SVM methods [7].

This paper aims to identify the image of the decorative wall Lamin motif of the Dayak Kenyah tribe in order to help introduce one of the cultural heritages to the community. This paper consists of four parts. First, the motivation for writing this article. Second, explain form feature extraction and SVM method. Third, explain the experimental results. Finally, conclusions from the experiment and plans for further research.

2. Method

2.1. Digital image processing

Digital image processing is a scientific discipline that studies matter relating to image quality improvement such as contrast enhancement, color transformation, restoration, and transformation images i.e., rotation, translation, scale, geometric transformation, performing feature selection i.e., feature images. optimal. Image processing also performs the process of retrieving information and describing or recognizing objects contained in the image, compressing, or reducing data for the purpose of storage, transmission, and processing time [8]–[10]. There are, several types of noise in an image such as speckle, salt, and pepper. Where, salt and pepper shaped like black and white spots. Then, the noise speckle can change its constant value. Furthermore, image improvement aims to improve image quality so that it has a better format so that a processing technique is needed [11]– [14].

In this study, the image processing technique of the decorative wall Lamin motif of the Dayak Kenyah tribe has been applied, starting with image acquisition, namely capturing, or scanning images from analog to digital. In this study, the image capture tool that has been used is the Canon EOS REBEL T6 18-55mm. Next, improve image quality by adjusting the brightness and contrast levels. Because digital image acquisition has several problems, for example noise occurs or objects disturbing, so it is necessary to adjust light brightness and contrast levels. Then, motif image segmentation has been carried out to separate certain objects that are desired and not in the matrix values of 1 (foreground) and 0 (background). In this study, thresholding techniques based on differences in the gray level of the image have been used in segmentation. The stages of digital image processing can be seen in Fig. 1.

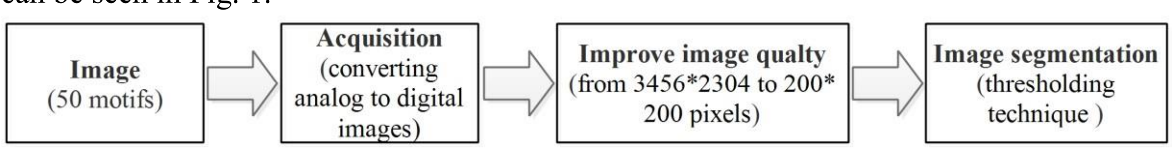


Fig. 1. The Digital Image Processing Stages

2.2. Feature extraction

Feature extraction is the image indexation database process. Mathematically, each feature extraction is an encoding of an *n*-dimensional vector called a feature vector. The feature vector component is calculated by image processing and analytical techniques are used to compare one image with another. Feature extraction is classified into 3 types consisting of low, middle, and high levels. First, the low-level is a feature extraction based on visual content such as color and texture. Second, the middle-level is an extracted based on the image area determined by segmentation, while the high-level is a feature extraction based on semantic information contained in the image. The steps for the feature extraction process can be seen in Fig. 2.

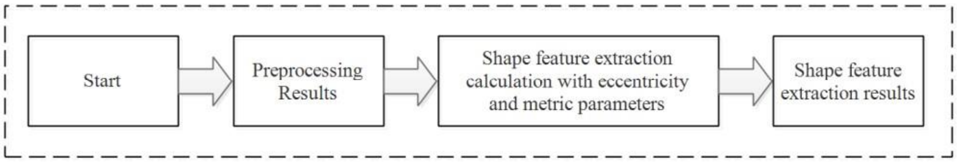


Fig. 2. The Feature Extraction Stages

In this study, the calculation of shape feature extraction uses eccentricity and metric parameters which have a range of values [0 … 1] where close to 0 (round or circular object) and 1 (elongated or close object) to facilitate the classification of decorative wall Lamin images. The eccentricity parameter is used to distinguish the object shape by calculating the comparison of the minor and major elliptical foci distance values. Calculating the eccentricity parameter value using Equation 1 and looking for the center point or centroid of the coordinate object (x, y) using Equation 2. Finding the image circumference value by calculating the shape outermost pixels that produce the minor and major axis values using Equation 3 and calculating the gradient of the line perpendicular to the diameter using Equation 4.

$$e = \sqrt{1 - \frac{b}{a^2}^2}$$

$$\overline{x_i} = \frac{\sum x}{\text{circumference}}, \bar{y}_i = \frac{\sum y}{\text{circumference}}$$

$$diameter\ gradient = \frac{(y_2 - y_1)}{(x_2 - x)}$$

$$diameter\ gradient\ straight = \frac{-1}{\text{diameter gradient}}$$

(1) $\bar{x}_i$ is the major axis; b , $\bar{y}_i$

(2)

(3)

(4)

Where, e is eccentricity; a, is the minor axis; ΣX is the Sigma of the sum x series; ΣY is the Sigma of the sum y series; y is the vertical coordinate point; x is the horizontal coordinate point.

First, calculate the image number pixels to get the area. Second, finding the image circumference value is done by counting the image outermost pixels. Third, the area and perimeter values that have been obtained are then used in metric calculations using Equation 5 [8], [15]–[17].

(5) $$M = \frac{4\pi\ x\ A}{c^2}$$

Where, M is a metric; A is area; c is circumference; 4π is 4.phi=3.14

2.3. Support Vector Machine (SVM)

The Support Vector Machine (SVM) method was first introduced by Vapnik in 1992 as a harmonious series of superior concepts in the pattern recognition field. The SVM method works on the principle of Structural Risk Minimization (SRM) to find the best hyperplane that separates two classes in the input space [4], [13], [18]. Therefore, the SVM method can also be a technique for making predictions, both in the case of regression and classification. The SVM technique is used to obtain the optimal hyperplane function to separate observations that have different target variable values. This hyperplane can be a line in two dimensions and can be a flat plane in multiple dimensions [19], [20]. The basic concept of SVM is also a harmonious combination of computational theories that have existed decades before, such as the hyperplane margin introduced by Aronszajn in 1950. The basic principle of SVM is a linear classifier and was further developed to work on non-linear problems by incorporating the concept of kernel trick or transforming lowdimensional features into higher-dimensional features in high-dimensional workspaces [21]. The SVM flowchart can be viewed in Fig. 3.

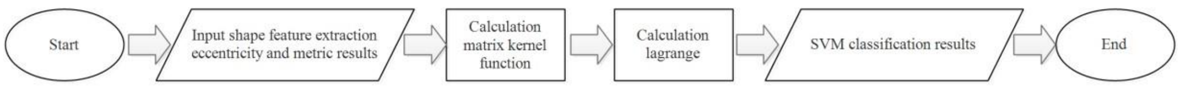


Fig. 3. The SVM method flowchart

In this study, the first step is to input the eccentricity and metric extracted data to calculate the polynomial kernel function to obtain the K matrix. Second, calculate the Lagrange multiplier and obtain the classification results. The kernel function is carried out by maintaining the data topology, where two data that are closely spaced in the input space will also be closely spaced in the feature space. Conversely, two data that are far apart in the input space will also be far apart in the feature space. Furthermore, the learning process in SVM in finding support vector points only depends on the dot product data that has been transformed into a new, higher-dimensional space [21]–[23]. The kernel function used can be seen in Equations 6, 7, and 8.

Linear (6)

$$K(x, y) = x.y$$

Gaussian/RBF (7)

$$K(x, y) = exp\frac{-||x-y||^2}{2.\sigma^2}$$

Polynomial (8)

$$K(x, y) = (x.y + c)^d$$

2.4. Performance Accuracy

In this study, the accuracy performance aims to see classification errors so that the percentage accuracy of the classification results can be known. The accuracy of the decorative wall Lamin motifs as a result of the classification is tested by formulating a contingency matrix called an error matrix or confusion matrix. The accuracy is determined empirically by selecting a sample for each pixel from the classification results and checking the label against the specified class from the reference data [17], [24], [25]. Calculation of accuracy using Equation 9.

$$Accuracy = \frac{\sum right\ image}{\sum test\ image} \times 100\% \quad (9)$$

Where, the correct test images are divided by the test images.

2.5. Image datasets

In this study, the Dayak Kenyah tribe decorative wall Lamin motifs have five motifs consisting of tebengaang or hornbills, legunan or dragon, crocodile, lenjau or tiger, arch or circle which have been obtained from the Pampang Village tourist, Samarinda, East Kalimantan. Meanwhile, the decorative wall Lamin motifs can be seen in Fig. 4.

Tebengaang or Hornbills (Be brave, loyal, and humble)

Legunan or Dragon (Heroism, holy and powerful beings, and guardians from calamity)

Crocodile (Strength and shrewdness in hunting and fighting)

Lenjau or Tiger (Leadership, courage, chastity, nobility, authority, and resisting reinforcements that protect the Dayak Kenyah community)

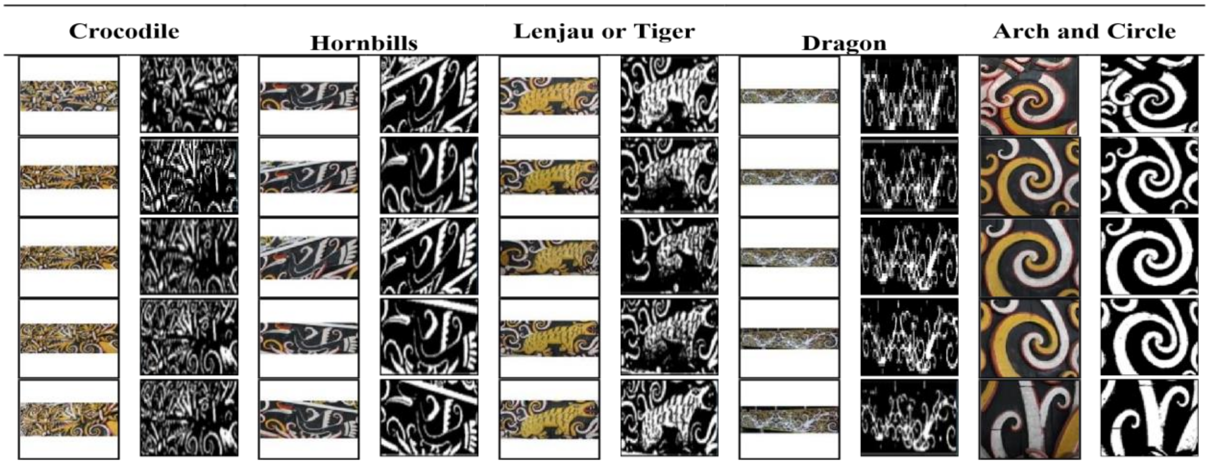
Arch or Circle (Unity and brotherhood between Dayak tribes) strength,

Fig. 4. The decorative wall Lamin of the Dayak Kenyah tribe images

3. Results and Discussion

This section describes the detection analysis results of the decorative wall Lamin images by applying the shape feature extraction based SVM method. In this experiment, the five motifs with a total of 50 images have been prearranged in the shape feature extraction and classification. First, converting analog to digital images where each motif has 10 images. Then, it has been made in five parts images with 10 motifs each including crocodile (1-10), hornbill (11-20), tiger (21-30), dragon (31-40), and arch (41-50). Second, image quality improvement by changing the original image size from 3456*2304 pixels to 200*200 pixels using Photoshop software has been prepared. Third, segmentation using a thresholding technique based on differences in the image gray level has also been applied. The segmentation of 50 motif results can be seen in Table 1. Then, the threshold matrix segmentation in binary results can be seen in Table 2.

Table 1. The decorative wall Lamin image segmentation results



Tebengaang or **Legunan or**

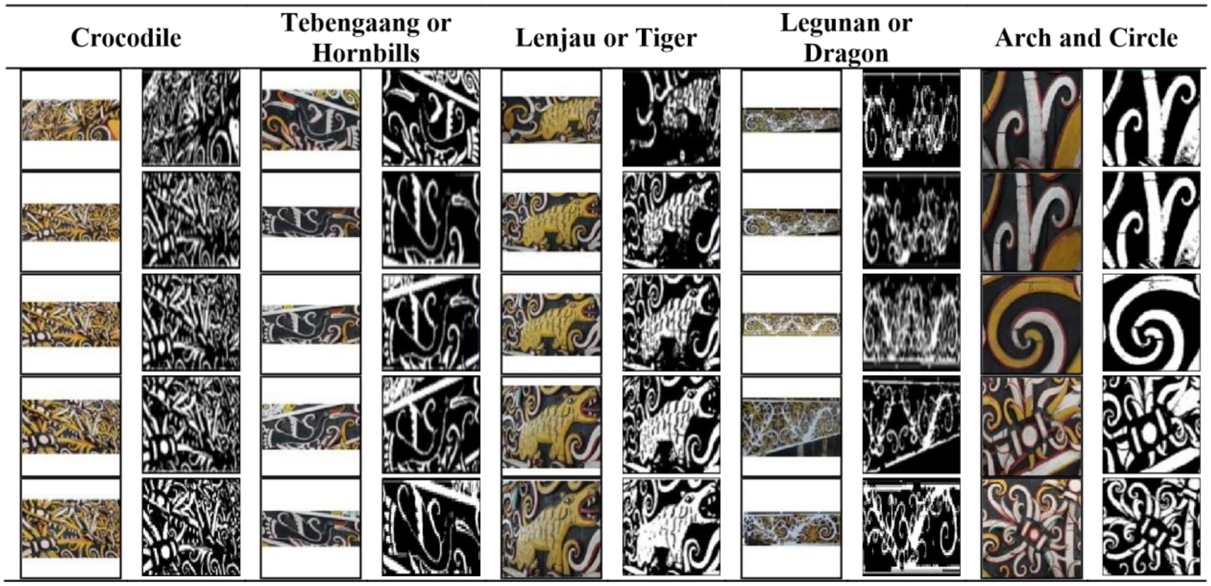


Table 2. The motifs segmentation results

			B1-B10 (Crocodile)				
	31048	30763	29929 35060 37954 37089 58867 66139			72709	73042
			E1-E10 (Tebengaang or Hornbills)				
	39240	46232	56684	43126 51110 62437 37123	43472	51646	38972
				H1-H10 (Lenjau or Tiger)			
Motifs segmentation value in (%)	31882	33434	30741	34006 34852 30836 36984	39331	43814	46112
				N1-N10 (Legunan or Dragon)			
	34676	37839	40528	41317 46744 39534 40899	39972	60899	42566
				P1-P10 (Arch and Circle)			
	20834	38787	36449	38074 33612 34491 32459	32510	43875	46816

Fourth, the shape feature extraction calculation using eccentricity and metric parameters has been observed. In this experiment, the eccentricity parameter has been used to calculate the oval or elongated object. Meanwhile, the metric parameter to calculate the object's roundness has been applied. The shape feature extraction results value can be seen in Fig. 5.

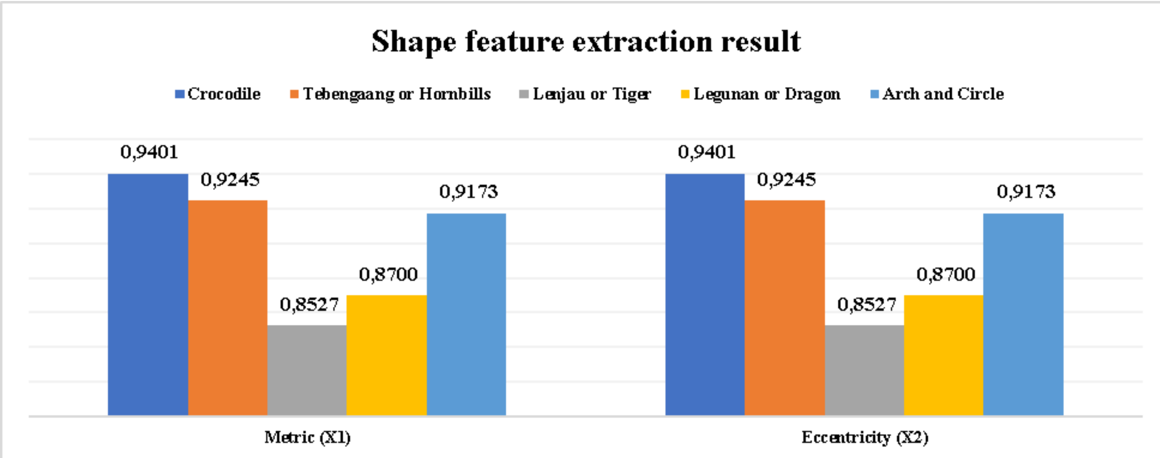


Fig. 5. Shape feature extraction results

In this experiment, the SVM method to find α, w, and b values in order to get the best hyperplane has been applied. After the shape features image classifying in the matrix values identified, then it is used as training data for 50 data with a ratio of 60%:40% (27 training: 5 crocodiles, tigers, dragons, arch and 7 hornbills; 23 testing: 5 crocodiles, tigers, dragon, arch and 3 hornbills); 70%:30% (32 training: 6 crocodiles, tigers, arch, 7 dragons, and hornbills; 18 testing: 4 crocodiles, tigers, arch, 3 dragons and hornbills); and 80%:20% (40 training: 8 crocodiles, hornbills, tigers, dragons, and arch; 10 testing: 2 crocodiles, hornbills, tigers, dragons, and arch).

Several parameters to find the best hyperplane model such as training data samples $x = x_1, x_2, \ldots x_n$, $y = y_1, y_2, \ldots y_n$, linear kernel, Gaussian/RBF, and Polynomial have been defined. In linear and Gaussian/RBF kernels the default parameter that has been used is C=1. Meanwhile, in the polynomial kernel, the default parameters that have been used are C=1 and d=3. Next, calculate the x value (shape feature) of each x_1 (metric) and x_2 (eccentricity) image. Based on the calculation of the K matrix used to find the value of the Lagrange multiplier (a), weight (w) and bias have been achieved. Then, the three values are SVM models for classification that have been used and their accuracy measured. The overall kernel accuracies can be seen in the 80% test using the Polynomial kernel with an accuracy of 85%. The SVM results can be seen in Fig. 6.

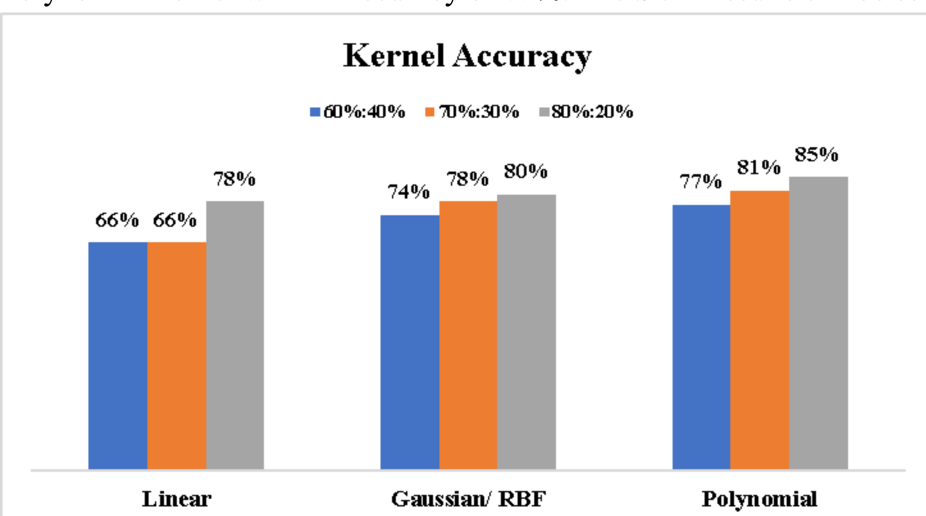


Fig. 6. Kernel accuracy comparison results

4. Conclusion

Image identification on the decorative walls Lamin Dayak Kenyah tribe using the shape feature extraction and the Support Vector Machine (SVM) methods has been implemented. The image capture tool is used a Canon

EOS REBEL T6 18-55mm. Image quality improvement is done by adjusting the brightness and contrast levels. Furthermore, the motif image segmentation with thresholding technique based on differences in the image gray level has been consumed. In this study, the shape feature extraction calculation using eccentricity and metric parameters that have a range of values [0 … 1] has also been applied. Based on the experimental results, the eccentricity parameter has the highest value of 0.6979 on the arch image, and the lowest value on the tiger image, which is 0.0270. Meanwhile, the highest value of the metric parameter is 0.9953 in the arch image and the lowest value is in the dragon image at 0.4150. Furthermore, the SVM method produces a value from each image and has been tested for accuracy with 3 kernels, namely the linear kernel, Gaussian/RBF, and polynomial. Based on the test, the best accuracy has been obtained with a data scheme of 60:20 (60%) consisting of 27 training and 23 testing of 50 images with an accuracy of 72.5%. The accuracy of the data ratio is 70:20 (70%) consisting of 32 training and 18 testing of 50 images with an accuracy of 75%. The accuracy of the data ratio is 80:20 (80%) consisting of 40 training and 10 testing of 50 images with an accuracy of 81%. The application of a combination of artificial intelligence and optimization methods will be the next research.

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Declarations

Author contribution. The contribution or credit of the author must be stated in this section.

Conflict of interest. The authors have no conflicts of interest to declare.

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