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Research Article

Classification of lombok pearls using glcm feature extraction and artificial neural networks (ann)

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Abstract

In this study, the second-order Gray Level Co-occurrence Matrix (GLCM) and Pearl image classification were used using the Artificial Neural Network (ANN). No previous research combines the GLCM method with artificial neural networks in Pearl image classification. The number of images used in this study is 360 images with three labels, namely 120 A images, 120 AA images, and 120 AAA images. The epochs used in this study were 10, 20, 30, 40, 50, 60, 70, and 80. The test results at epoch 10 get 80.00% accuracy, epoch 20 got 90.00% accuracy at epoch 30 gets 93.33% accuracy, epoch 40 get 94.44% accuracy, while epoch 50 got 95.55% accuracy, epoch 60 got 96.66% accuracy, epoch 70 got 96.66% accuracy while epoch 80 got 95.55% accuracy. The combination of the proposed methods can produce accuracy in the classification of Pearl images, such as the results of the classification test.

Keywords: Pearl Image; Image Classification; GLCM; ANN.

Introduction

Pearls are one of the objects that have a high selling value. Especially now, pearls have been used as exquisite jewelry in fashion. Pearl value depends on several aspects. Good pearls have features, such as size, luster, shape, and texture that are not deformed or discolored and have a perfectly round shape. The ideal pearl is perfectly round and smooth, but there are also a variety of other conditions [1], [2]. In the pearl industry, most pearl-producing companies mainly rely on manual classification. Experienced professionals classify pearls according to size, texture, shape, luster, and other characteristics [2]. Although manual selection has the advantage of selecting pearls, the manual process takes quite a long time and has broad insight related to the types of pearls based on their quality [3]. In image classification, handcrafted features are easy to design only if the classification rules are simple. However, for pearl classification, it is pretty challenging to get clear classification rules, let alone create compelling, handcrafted features [2].

In recent years, with the rapid development of machine vision technology, the use of machine vision can be used to replace manual measurements made by humans, which is caused by several factors such as fatigue, time constraints, and human emotions in increasing the accuracy and efficiency of measurement for pearls [4]. In classification learning, an artificial neural network (ANN) is the most widely used model because of its ability to solve large data sets and powerful computations[5], on research [2] designing an automatic pearl classification machine using the Back Propagation Neural Network (BPNN) and multi-stream convolutional neural network (MS-CNN) methods, next upgrade[6] how to classify pearls automatically using Multiview pearl images where MVGAN is used to petrify MSCNN in Pearl image classification then segmented by shape by Xinying Liu et al. [7] .

In this study, we apply an Artificial Neural Network (ANN) to improve classification accuracy in Pearl's images [6] based on the Gray-Level Co-Occurrence Matrix (GLCM) [8] to get the value of contrast, correlation, energy, homogeneity of texture values, Texture value is used as a feature that distinguishes one image from another then classify using the proposed architectural network to get the results of the Pearl image classification from the previous method.

Method

Several studies related to Pearl's image have carried out image classification based on shape, size, and even color, in this study resulted in a category using each proposed method. However, there has been no research on classifying Pearl images based on feature extraction. Therefore, this study presents a new performance path in organizing Pearl imagery based on features using the GLCM[8] method with four components to obtain accuracy. The feature extraction results using the proposed method are classified using the artificial neural network method to get the results of the accuracy value. In this stage, the problem identification stage is, Issues raised from previous journal references to get problems related to pearl image classification, with as a basis for problems for needs analysis, system design, and implementation, The purpose of this research is how to get the accuracy and classification of pearl images based on feature extraction, in this case, we use the GLCM method in feature extraction to get the values that exist in the image and classify them using an artificial neural network.

To support the results in this experiment, we need a flow or process in the research that aims to be more structured according to the design and method proposed in feature extraction and image classification of Lombok pearls. The scheme of this research is shown in Figure 1.

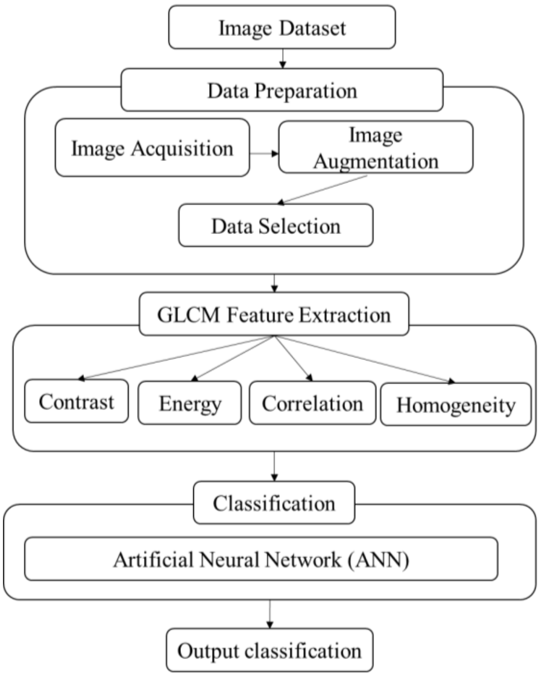


Figure 1. Pearl image classification flow

A. Dataset

This study uses a different dataset, namely the image of the Lombok pearl. The Pearl image dataset is taken using a digital camera. The pearl image was taken based on the primary dataset of image capture at a distance of 19.5 cm from the camera using a green background and using 4 LED lights with 5 watts of power installed on the left and right of the object at a distance of 20 cm, Each pearl has a different shape and size, so it needs to be grouped according to the label, in this dataset has 3 Pearl labels, namely label A, label AA and label AAA, the number of datasets is 360 images, 270 as training images and 90 test images, pearl image is taken with four sides, top side, bottom side, left side and right side by rotating the pearl this is done to increase data accuracy and to get a valid dataset, in the retrieval of image data is very influential with the results of the classification, the results of this research classification are compared with previous studies [6]. The example in the pearl image dataset is shown in Figure 2.

Image A Image AA Image AAA

Figure 2. Example of Pearl Image

B. Data Preparation

In this study, before distributing the data, the data was prepared through 3 stages, namely:

- Image Acquisition is made because the images taken are not by their respective labels, so grouping is needed
- Image Augmentation is done to change the image or modify the image with the aim that the transformed image is different so that the computer perceives the image as the same
- The next stage is data sharing; pearl image data has 360 images with 270 training images and 90 test images or three training images on one side of the test image.

C. Feature Extraction

In this study, feature extraction is performed to identify one image with another in feature extraction on pearl images using statistical characteristics of order 2. GLCM is a characteristic extraction method to obtain feature values by calculating the occurrence of the same matrix in image pixels. The features contained in GLCM are carried out based on the parameters contrast, correlation, energy, and homogeneity. GLCM can be used to extract an image[11][15][14][16].

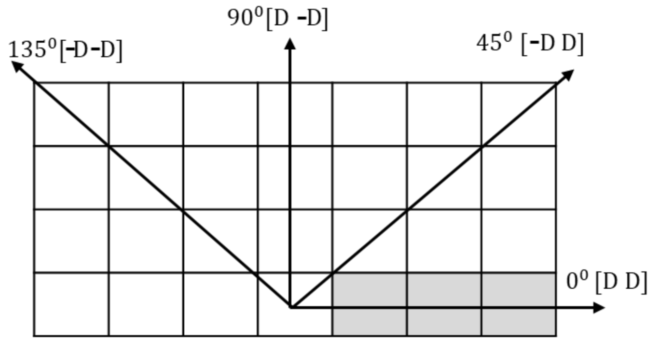


Figure 3. The direction of rotation of GLCM

At this stage, feature extraction is carried out using order two on the image based on grayscale to get the contrast, correlation, energy, and homogeneity values to represent each image with an image rotation of 0^0 [8] [17][18] (as shown in Figure 3).

a) Correlation

$$\sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \frac{(i - m_r)(j - m_c)p_{ij}}{\delta r \; \delta c} \tag{1}$$

b) Contrast

$$\sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \, (i - j)^2 p_{ij} \tag{2}$$

c) Homogeneity

$$\sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \, Pi^2 j \tag{3}$$

d) Energy

$$\sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \frac{p_{ij}}{1 + [i - j]} \tag{4}$$

D. (Artificial Neural Network) ANN

Artificial Neural Network Architecture. The Artificial Neural Network (ANN) classification method was chosen because ANN can think like a human and process information from an image [19]. This study uses a Multi-layer Backpropagation Neural Network [8]. This method has three stages, including the input, hidden, and output layers [12]. The input layer can accept input in the form of images and produce feature extraction values. Feature extraction is based on four features used in order 2 in GLCM [20][21].

In contrast, the hidden layer uses two hidden layers and one output. It considers the number of neurons in use by activating the sigmoid function to get the final result in the output layer [5]. The architecture used in this study is shown in Figure 4.

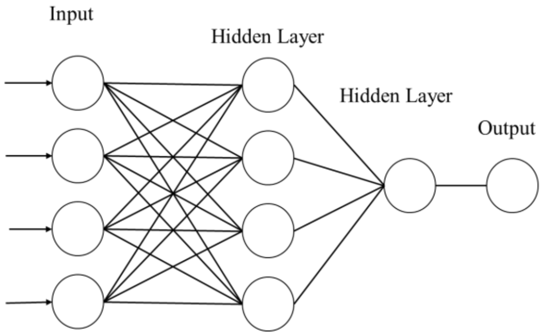


Figure 4. Artificial Neural Network Architecture

The output layer results are then compared with the original class or label to obtain the accuracy of classification results from the ANN classification method. In the classification, of course, there are several that affect the qualification results, including the amount of data used, the number of neurons used, the weight value, the learning rate, and the amount of incorrect or correct data to produce accuracy according to the proposed method to measure the level of accuracy in the classification using the Confusion matrix [22] Table 1.

Table 1. Confusion Matrix

	Actual: Yes	Actual: No
Predicted: Yes	True Positive (TP)	False Positive (FP)
Predicted: No	False Negative (FN)	True Negative (TN)

The matrix elements are characterized based on the predicted label True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The True Negative (TN) value is the number of harmful data that was detected correctly, while the False Positive (FP) is harmful data but seen as positive data[23].

$$Recall = \frac{TP}{TP + FN} x\ 100\% \tag{5}$$

$$\text{Precision } = \frac{TP}{TP + FP} x 100\% \tag{6}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FB + FN} x\ 100\% \tag{7}$$

Results and Discussion

To determine the value of the results of the proposed method, training and testing were carried out using the Matlab R2020a 64-bit software and device specifications using Win 11 Home, Ryzen 5 Ram 8 GB Processor.

A. Feature Extraction

The pearl image is performed feature extraction using the proposed method using GLCM in the 2nd order to get a value of 4 features based on Contrast, Correlation, and Energy Homogeneity with the angle used in the image 0^0, as shown in Figure 3. The results of the Pearl image extraction on the training data are in Table 2 for label A, Table 3 for label AA, and Table 4 for label AAA. From Table 2, Table 3, and Table 4, we get the feature values in pearls, with the provisions of 4 features.

Table 2. Feature Extraction Label A

File Name	Contrast	Correlation	Energy	Homogeneity
A (1).JPG	0.15876	0.73405	0.58052	0.94691
A (2).JPG	0.29696	0.75692	0.54715	0.8969
A (3).JPG	0.18505	0.83057	0.78547	0.95196
A (4).JPG	0.19407	0.69993	0.52466	0.93489
A (5).JPG	0.31094	0.68575	0.33198	0.88571
-	-	-	-	-
-	-	-	-	-
A (120).JPG	0.20037	0.73128	0.57959	0.93514

Table 3. Feature Extraction Label AA

File Name	Contrast	Correlation	Energy	Homogeneity
AA (1).JPG	0.13042	0.7262	0.84387	0.96817
AA (2).JPG	0.12256	0.73579	0.83803	0.96967
AA (3).JPG	0.13982	0.74281	0.71659	0.95894
AA (4).JPG	0.13002	0.74771	0.77512	0.96403
AA (5).JPG	0.15447	0.73044	0.69893	0.95612
-	-	-	-	-
-	-	-	-	-
AA (120).JPG	0.11178	0.79342	0.88662	0.98362

Table 4. Feature Extraction Label AAA

File Name	Contrast	Correlation	Energy	Homogeneity
AAA (1).JPG	0.15447	0.73044	0.69893	0.95612
AAA (2).JPG	0.13103	0.62907	0.77085	0.96209
AAA (3).JPG	0.23385	0.69424	0.37303	0.91181
AAA (4).JPG	0.22395	0.69252	0.39638	0.91365
AAA (5).JPG	0.20676	0.70089	0.43909	0.9206
-	-	-	-	-
-	-	-	-	-
AAA (120).JPG	0.2164	0.68139	0.46856	0.91903

Correlation states the size of the linear relationship of the adjacent pixel gray level values [24]. In Table 2, Table 3, and Table 4, it can be seen that the contrast feature is shallow due to the neighboring values that are close to one pixel to another. At the same time, the energy is seen based on the level of similarity in texture, homogeneity is high if the pixel pair has a constant gray value, and the entropy value provides information in the form of top features of coarse or delicate textures. If the entropy value is getting closer to 1, then the degree of roughness of the surface is getting higher and vice versa.

B. Discussion

After the feature value is obtained, classification is performed to get accurate results using ANN. The training results were obtained with an epoch ten learning rate of 0.1 and an accuracy of 90.74%, with 25 incorrect data and 245 correct data from 270 data. In epoch 20 training, the learning rate was 0.1 and got an accuracy of 90.37% with 26 inaccurate data and 244 accurate data from 270. While in the training epoch 30, the learning rate was 0.1 and got an accuracy of 91.48% with 23 incorrect data and 247 correct data from 270 data, in training epoch 40 learning rate was 0.1 and getting 95.18% accuracy with 13 inaccurate data and 257 accurate data from 270 data, while in epoch 50 training the learning rate was 0.1 and got 97.77% accuracy with six incorrect data and 264 correct data from 270 data, on epoch 60 activity the learning rate was 0.1 and got 98.14% accuracy with five inaccurate data and 265 accurate data from 270 data, on epoch training 70 learning rate 0.1 and getting 98.51% accuracy with four incorrect data and 266 correct data from 270 data. On epoch 80 training, the learning rate was 0.1 and got 98.88% accuracy with three inaccurate data and 267 accurate data from 270 data, with a detailed summary in Table 5 results of training accuracy.

Table 5. Results of training accuracy

NO	EPOCH	Time Elapsed	Amount of Incorrect Data	Accuracy
1	10	0:00:00	25	90.74%
2	20	0:00:00	26	90.37%
3	30	0:00:00	23	91.48%
4	40	0:00:00	13	95.18%
5	50	0:00:00	6	97.77%
6	60	0:00:01	5	98.14%
7	70	0:00:01	4	98.51%
8	80	0:00:02	3	98.88%

From Table 5, the overall training results with 50 neurons with a learning rate of 0.1 results in the highest accuracy of 98.88% at 80. Epochs. To see how far the proposed method is, the testing stages are carried out on the test data, on the Lombok pearl test data with as many as 90 images with 30 label A images, 30 AA label images, and 30 AAA label images using the network architecture obtained in training. Based on the results of the tests, different accuracy results are obtained, with epoch ten learning rate of 0.1 and getting 80.00% accuracy, while at epoch 20, the learning rate is 0.1 and brings an accuracy of 90.00%. At epoch 30, the learning rate is 0.1 and gets an accuracy of 93.33%, at epoch 40 learning rate is 0.1 gets 93.33% accuracy, at epoch 50 learning rate is 0.1 and gets 95.55% accuracy, while at epoch 60, the learning rate is 0.1 and gets an accuracy of 96.66%, at epoch 70 learning rate 0.1 and getting 96.66% accuracy, while at epoch 80 the learning rate is 0.1 and gets 95.55% accuracy. With a detailed summary in Figure 5.

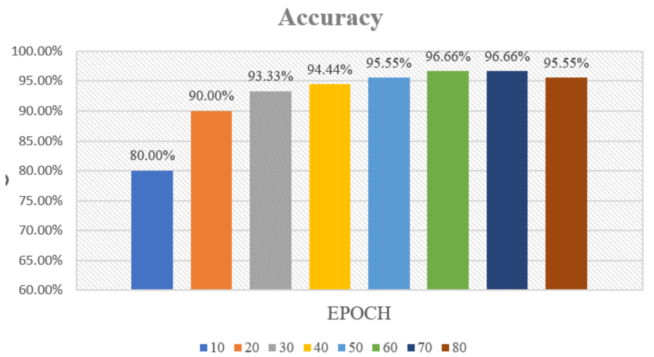


Figure 5. Testing Results of Test Data

In this study, we tried to conduct training and testing with higher ages but with lower accuracy results, and we tried higher neurons on the ANN network architecture. From Figure 5, we get the overall test results with 50 neurons with a learning rate of 0.1 for the highest accuracy results of 96.66% at epochs 60 and 70. However, the results obtained experienced the same accuracy and decreased because the image used is still relatively small. The more datasets and neurons are used, the accuracy will increase. Therefore iterations 10, 20, 30, 40, 50, 60, 70, and 80 with a learning rate of 0.1 can significantly increase pearl image classification using feature extraction and artificial neural networks.

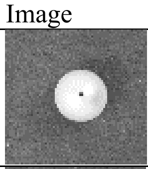
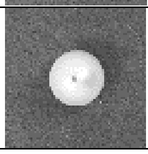
The test results using a combination of the GLCM method with classification using ANN can be described as a Confusion Matrix Table with the results in the form of Accuracy 96.66%, Precision 0.966, and Recall 0.966, as shown in the following table.

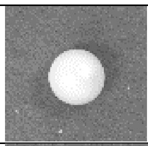
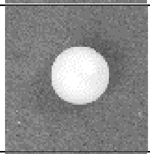
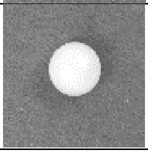
Table 6. Confusion Matrix

		Ground Truth		
PREDICTION		A	AA	AAA
	A	30	0	0
	AA	2	28	0
	AAA	1	0	29

As for the example of the results of the Pearl image classification on the test image with incorrect results in the image classification as Table 7, the results of image classification of several ideas are considered wrong with their respective labels, such as type should be classified as A. Still, after performing feature extraction based on four GLCM of features using artificial neural network classification, it is considered type AA because features are almost the same as label A, as well as other images that are considered wrong.

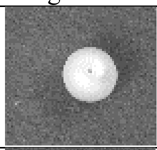
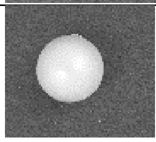
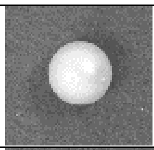
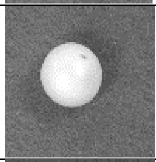
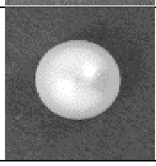
Table 7. The results of image classification are wrong

RGB Image	Grayscale Image	label	Classification Results
		A	AA
		A	AA

		AA	A
		AA	A
		AAA	A

While the sample results from the Pearl image classification on the test image with the correct results in the image classification are shown in Table 8.

Table 8. Image classification results are correct

RGB Image	Grayscale Image	label	Classification Results
		A	A
		A	A
		AA	AA
		AA	AA
		AAA	AA

Conclusion

Based on the results of the experiments carried out, the training results with 270 Pearl images, the highest accuracy was obtained at epoch 80 learning rate 0.1 and obtained an accuracy of 98.88% with three incorrect data and 267 correct data from 270 data, while the test obtained high accuracy at epoch 60 and 70 with a learning rate of 0.1 and got an accuracy of 96.66%. In this study, it still has a drawback, namely, the greater the value of the neuron used, the less good the accuracy results and even getting a low accuracy value. Therefore, for further research, it is recommended to use other methods or add methods in feature extraction with all views / Multiview in the pearl image, including size, texture, shape, luster, and other characteristics, to get better accuracy results

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