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The Role Of Gray Level Co-Occurrence Matrix In Convolutional Neural Network Transfer Learning For Coffe Bean Classification

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Abstract— This research explores the impact of the Gray Level Co-Occurrence Matrix on enhancing Convolutional Neural Networks for categorizing coffee beans, focusing on a case study from Permadi Pandansari. The data used in this study is training data for 2 types of coffee beans of 400 images, while test data for 2 types of coffee beans is 100 images, so the total is 500 images of coffee beans. The extraction process used is the extraction of texture and color obtained from the extraction of the Grey Level Co-Occurrence Matrix. Followed by the deep learning method used for grouping is Convolutional Neural Network using VGG-16 transfer learning. To maximize the results, this study also applies ADAM optimization and also ReLU and Softmax activation. The results of the feature extraction test are determined by the values of accuracy, precision, recall, F1-Score and also Cross Validation. This research investigates the influence of the Gray Level Co-Occurrence Matrix on enhancing Convolutional Neural Network performance in coffee bean classification, centered on a case study from Permadi Pandansari. The dataset comprises 500 coffee bean images, with 400 images for training and 100 for testing, representing two types of coffee beans. Texture and color features were extracted using the Gray Level Co-Occurrence Matrix, followed by classification using CNN with VGG-16 transfer learning. To optimize performance, ADAM optimization, along with ReLU and Softmax activation functions, was applied. The effectiveness of the feature extraction was evaluated through accuracy, precision, recall, F1-score, and cross-validation metrics.

Keywords — E-Learning, Student Interaction, EUCS, classification, Artificial Neural Network, Multilayer Perceptron.

1. INTRODUCTION

Coffee beans are the main ingredient of coffee drinks, not only drinks, in this day and age coffee beans are widely used for things outside drinks, for example as food flavorings, beauty products, and others [1]. According to International Coffee Organization (ICO) data, coffee consumption in Indonesia reached the largest record in the 2020/2021 period. The figure obtained at that time became the fifth largest in the world. In addition, based on the Indonesian Statistics report, in 2021 coffee production increased by 1.62% or 774.6 thousand tons. This is certainly proof that the coffee industry in Indonesia continues to grow and has great potential for the economy. Coffee beans can be classified by type based on the characteristics possessed by coffee beans. Regulations concerning coffee classification exist, as outlined in SNI 01-2907-2008, where section 4 provides a classification of coffee beans by type. In Indonesia, coffee is generally categorized into two main types: Arabica and Robusta [2]. This classification based on type greatly affects the taste or aroma of coffee in subsequent processing. Therefore, the qualification or grouping of coffee beans is an important stage to create a taste according to the consumer's wishes.

In this coffee bean grouping, there are various ways to get good and correct coffee bean grouping results, the way that can be applied as a development of the current era is the application of Artificial Intelligence (AI) [3]. Artificial Intelligence (AI) is a finding of artificial intelligence that is currently widely used, one of its applications can use machine learning methods where one of the types of machine learning that can be applied to coffee bean grouping is deep learning [4].

The deep learning method chosen in the grouping/classification of coffee beans this time is the Convolutional Neural Network or commonly abbreviated as CNN [5]. CNN is often used to process images or detect objects, but in this study a transfer learning model is inserted to try something new which of course with the hope of optimizing the results, the transfer learning technique used is VGG16. Specifically, the VGG16 used for modeling this time is a type of VGG16 that has undergone a pretrained process, this is intended so that the best trained VGG16 architecture can be directly used to shorten the time and also not widen the research aspect, where for this research focuses on the extraction of the Grey Level Co-Occurence Matrix [6]. The Grey Level Co-Occurence Matrix itself occurs before the classification process using CNN transfer learning, the feature extraction process is carried out first to obtain the definition of texture and color. But before that, the image data must also go through the preprocessing stage first, namely converting to an ash scale for each image that initially has RGB features. Supporting information on the classification of arabica and robusta coffee types was obtained from Permadi Coffee, as a coffee bean processing place located in Pasuruan Regency, East Java and has been established since 2013, in that place test data will also be obtained. The information on the grouping of coffee beans used includes the color and texture of the coffee beans themselves which can distinguish them from each type of coffee [7].

2. METHODOLOGY

The data in this study is divided into training data and testing data, where the data is obtained directly with the coffee bean object at the Permadi Pandansari Coffee House [8]. For data collection, the device used is a camera from the Oppo A92 android. The number of training data and testing data is compared to 80% and 20%, so that from a total of 500 images, there are 400 training data and 100 testing data for all balanced arabica and robusta coffee beans [9]. The data processing process will go through the following stages:

Prepocessing

Preprocessing is an initial step conducted prior to further data processing, aimed at shaping the coffee bean image dataset to fit the specific requirements [10]. The preprocessing stage that occurred in this study was to change the image into an ash scale [11]. The progress of preprocessing can be seen in the following image:

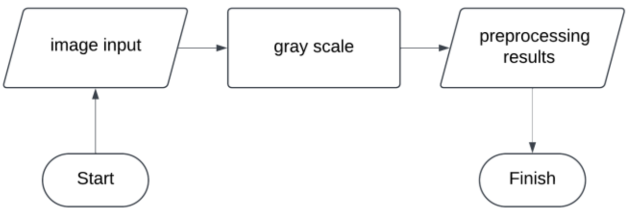

Fig. 1. Stages of prepocessing

The image illustrates that the original image is in RGB format, followed by a conversion step to grayscale, resulting in a new grayscale image that will be used in further processing.

Processing

Processing is the core process for image processing, in this stage will extract the Grey Level Co-Occurrence Matrix, with the following scenario:

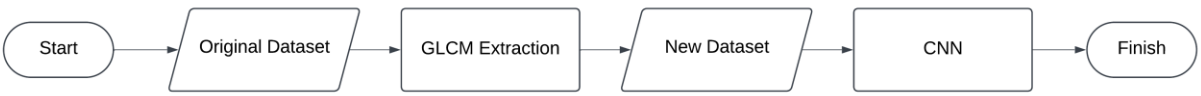

Fig. 2 GLCM Scenario.

Scenario in the picture. 2, is the scenario of GLCM extraction, for color and texture extraction. The Gray Level Co-Occurrence Matrix (GLCM) method according to Rahmanti (2017) is a technique to obtain 2nd order statistical values by calculating the probability of the proximity relationship between two pixels at a certain distance (d) and angle (θ) [12]. By obtaining the attraction value, use the following 4 search features:

$$\text{Contrast: } \sum i \sum [i,j]2P[i,j]$$

Contrast is a representation of the value of the variation in grayness levels, The contrast value scale in GLCM depends on certain settings, such as the number of grayness levels, but when it is likened to a scale of 0 to 1 [13]. In this case, a contrast value close to 0 indicates very low contrast, while a value close to 1 indicates high contrast.

$$\text{Homogenity: } \sum i \sum j = \frac{P[i,j]}{1+|i-j|}$$

Homogeneity is used to measure the degree of similarity of variation in the grayness intensity of the image, The interpretation of the homogeneity value also depends on the image being analyzed and its texture characteristics [14]. For example, in images with very fine or uniform textures, the homogeneity value tends to be close to 1, while in images with coarse or non-uniform textures, the homogeneity value tends to be lower.

$$\text{Energy: } \sum i \sum j P2[i,j]$$

Energy is used to see the degree of uniformity of the texture that the image has. The interpretation of energy values in images with complex textures, which have a strong and focused intensity pattern, tends to have high energy values (close to 1). In contrast, in images with smooth or homogeneous textures, which have weak or fragmented intensity patterns, the energy value tends to be lower.

$$\text{Correlation: } \frac{\sum i \sum j\ (i-\mu i)(j-\mu j)p(i,j)}{\sigma i\ \sigma j}$$

Where:

$\mu i = \sum i \sum j\ ip(i,j)$

$\mu j = \sum i \sum j\ jp(i,j)$

$\sigma i = \sqrt{\sum i \sum j\ (i - \mu i)2\ p(i, j)}$

$\sigma j = \sqrt{\sum i \sum j\ (j - \mu j)2\ p(i, j)}$

Correlation represents the linear relationship of the grayish image degree, the value for a correlation itself ranges from -1 to 1.

With a description of the value:

i = row

j = column

P = probability/occurrence μ = mean

σ = mediation (sigma)

A correlation value of -1 indicates the presence of a negative linear dependence between pixel intensities along the specified direction in the image. A correlation value of 1 indicates a positive linear dependence between pixel intensities along that direction. After the extraction value is obtained, it will continue using the classification process using the CNN transfer learning method, namely VGG-16 with adam optimization. The CNN method used in this study is a fully-connected layer with ReLU and Softmax activation.

Testing: The tests carried out in this study include determining the value of accuracy, precision, recall, F1 Score, and also Cross Validation

3. RESULTS AND DISCUSSION

After completing the method's stages, the results are displayed visually, showing the extracted image values as follows:

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FIG. 3 VISUALIZATION OF GLCM

This visualization displays the results of extraction from the GLCM features where the features displayed are contrast, correlation, energy and also homogeneity with each angle reference of 0°, 45°, 90°, 135°. This is the meaning of the truth of a model that has displayed the extraction results in accordance with the wishes of this study, which is 4 GLCM feature extractions.

After going through the preprocessing and processing stages, the model will be trained using image data first to determine the results of the loss value and accuracy of a VGG16 CNN transfer learning modeling with the addition of ADAM optimization. The results of the test will produce accuracy values as well as graphs as follows:

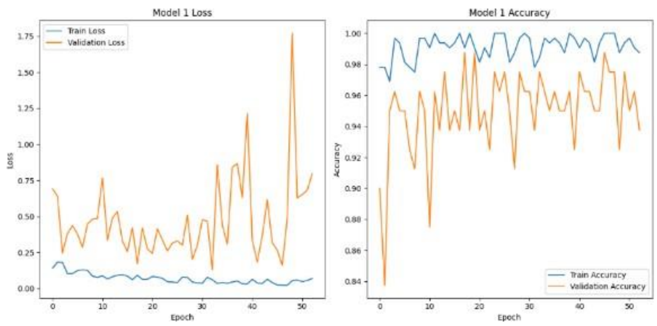
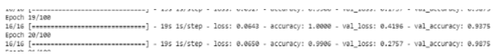


Fig. 4. GLCM Loss and Accuracy Value

The image above explains the loss graph and also accuracy, where the value is obtained from the results of training data, for the training value can be seen at the time of running the epoch, which is as follows:



```
Epoch 19/100
16/16 [==============================] - 19s 1s/step - loss: 0.0643 - accuracy: 1.0000 - val_loss: 0.4196 - val_accuracy: 0.9375
Epoch 20/100
16/16 [==============================] - 19s 1s/step - loss: 0.0650 - accuracy: 0.9906 - val_loss: 0.2757 - val_accuracy: 0.9875
```

Fig. 5 Epoch GLCM

This study uses the number of epochs of 100 with early stopping, early stopping here aims to prevent the model from experiencing overfitting. However, as an example in Fig. 5, he is shown 2 examples of epoch results which when viewed from the twentieth epoch, the training data has a loss value of 0.0650 and an accuracy value of 0.9906.

The model also undergoes a testing phase using cross-validation to ensure consistent results, with the cross-validation test producing the following graph :

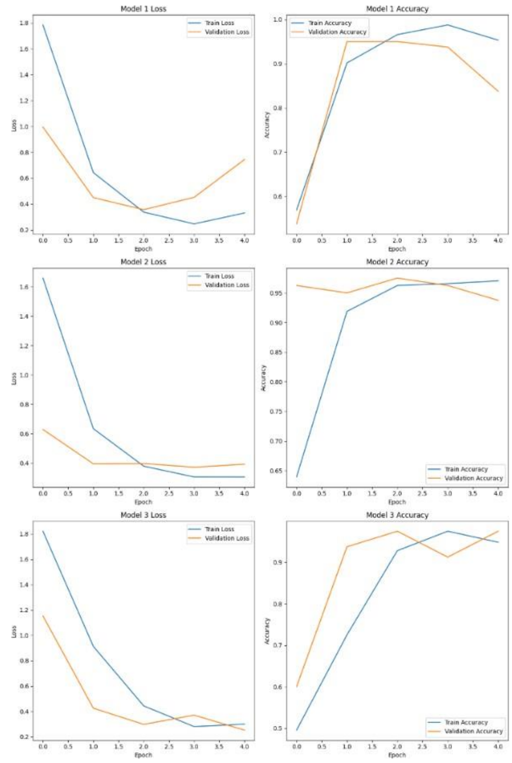


Fig. 6 Cross Validation GLCM

The test was conducted with a 3-fold cross-validation, showing that training data loss and validation data remained stable around the middle epochs, though there was a noticeable gap at the start and end of the epochs. Accuracy displayed an inverse relationship to the loss. The resulting confusion matrix is as follows:

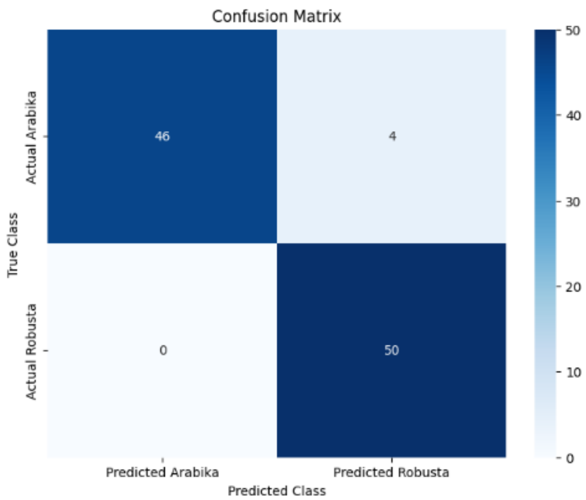


Fig.. 7 Confusion Matrix GLCM

The figure above indicates that there were no instances where Arabica was predicted but the actual result was Robusta. Predictions accurately identifying Arabica matched the actual Arabica data 46 times, while predictions correctly identifying Robusta matched the actual Robusta data 50 times. There were 4 instances where Robusta was predicted, but the actual result was Arabica. This brings the total data tested in the confusion matrix to 100, matching the test batch size (0 + 46 + 50 + 4 = 100). For reference, Arabica is considered the positive class, and Robusta the negative class :

Value:

False Positive (FP) : 0 True Positive (TP): 46 False Negative (FN): 4 True Negative (FP): 50 For value:

Precision:

TP / (TP + FP) = 46 / (46+0) = 46 / 46 = 1

Recall:

TP / (TP + FN) = 46 / (46+4) = 46 / 50 = 0.92

F1 Scoree = 2 * (Recall*Precission) / (Recall +

Precission)

= 2 * (92%*100%) / (92% + 100%)

= 95.83%

For example, Robusta is used as a positive camp and Arabica is used as a negative camp, so:

Value:

False Positive (FP) : 4 True Positive (TP): 50 False Negative (FN): 0 True Negative (FP): 46 For value:

Precision:

TP / (TP + FP) = 50 / (50+4) = 50 / 54 = 0.92

Recall:

TP / (TP + FN) = 50 / (50+0) = 50 / 50 = 1

F1 Scoree = 2 * (Recall*Precission) / (Recall

+ Precission)

= 2 * (100%*92%) / (100% + 92%)

= 96.15%

The calculation proved to be the same as the following image obtained through a function in python:

```
F1 score for arabika: 0.9583333333333334
F1 score for robusta: 0.9615384615384615
Macro-averaged F1 score: 0.9599358974358974
Micro-averaged F1 score: 0.96
```

Fig. 8 F1 Scoree GLCM

So the value for precision from this study is 1 (100%) for arabica and 0.92 (92%) for robusta, the precision itself here is the result of the ratio of positive predictions compared to the overall positive predicted results. However, for the recall value in this study of 0.92 (92%) for arabica and 1 (100%) for robusta, where this value comes from the ratio of positive correct predictions compared to the overall positive correct data. And for F1-Score, they are worth 95.83% of arabica coffee beans and 96.15% of robusta coffee, respectively.

4. CONCLUSION

Based on the model and also the test of the use of GLCM extraction with the CNN transfer learning grouping method, the values obtained using the CNN transfer learning method are as follows:

Table 1. Conclusion Table

	Arabica	Robusta
Accuracy	98.75/19s	98.75/19s
Precision	100%	92%
Recall	92%	100%
F1 Scoree	95.83%	96.15%

The results of the test using the extraction of the Grey Level Coocurence Matrix feature which was then classified using the Convolutional Neural Network method with the type of Visual Geometric Group transfer learning with a weight of 16 (VGG16) can be said to be good if it will be used for a modeling that can later be developed into a system.

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