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Classification of Corn Seed and Cob Quality Based on Texture and RGB Color Features Using Backpropagation Method

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ABSTRACT

The quality of agricultural products, such as corn, is greatly influenced by various factors, both environmental factors and agricultural engineering factors. This post-harvest quality affects product performance and is in line with consumer satisfaction, so it will greatly affect its selling price. Manual corn quality grouping requires a lot of time and effort. This study aims to develop a method for classifying corn kernel and cob quality based on digital image processing, using RGB color and texture features. The dataset consists of 150 corn kernel images divided into two quality categories, namely "good" and "bad". The research process involves preprocessing stages, color feature extraction using RGB color space, and texture features using the Gray Level Co-occurrence Matrix (GLCM) method. The classification model is built using the Backpropagation artificial neural network algorithm. The test results show that this method is able to achieve classification accuracy of up to 75%. The implementation of this method is expected to increase the efficiency of the corn quality selection process, reduce dependence on manual assessment, and provide significant benefits to the agricultural sector, especially farmers and the corn industry. These findings provide an important contribution to the development of digital-based post-harvest technology in Indonesia.

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Introduction

Agriculture is an important sector that contributes greatly to food security and the economy, especially in Indonesia as an agricultural country. However, one of the main challenges in this sector is ensuring the quality of the harvest to meet market standards, both for domestic consumption and export. In Indonesia, corn is the second food commodity after rice and a source of calories or a substitute for rice, besides being used as animal feed. According to the latest data from the Central Statistics Agency (BPS), the area of peeled corn harvest in Indonesia in 2024 is estimated to reach 2.58 million hectares (BPS, 2024). This figure shows an increase of around 4.34% compared to the harvest area in 2023 which was recorded at 2.48 million hectares. Corn is a food crop commodity that has an important and strategic role in national development, corn is included in cereal or grain plants that can live in tropical and subtropical climates, corn is not only used as food but also used as feed and industry, and has even begun

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to be used as an alternative fuel (biofuel) (Mujiadi, Hatmoko, & Fahmi, 2023). The quality of agricultural products, such as corn, is greatly influenced by various factors, both environmental factors and agricultural engineering factors. The main factors that influence include soil conditions, climate and rainfall, pests and diseases, and harvesting and post-harvest techniques. This post-harvest quality affects product performance and is in line with consumer satisfaction, so it will greatly affect its selling price (Sidik, Wahyuna, Rudian, & Jojo, 2023). The process of determining quality manually by farmers and middlemen is not only time-consuming but also often produces inconsistent results, because it depends on subjective human judgment.

As technology advances, digital image processing methods emerge as a potential solution to overcome challenges in measuring crop quality. Image processing enables a faster and more accurate evaluation process by utilizing certain algorithms to analyze the visual characteristics of the observed objects. The use of image processing and machine learning technology can increase the efficiency of determining harvest times, reduce losses in the supply chain, and help farmers make more informed decisions regarding agricultural product processing (Munawaroh & Fatah, 2024). This study will utilize cameras and analysis software to detect and classify the condition of corn seeds and cobs, so that the selection process can be carried out automatically and more efficiently.

To assess the quality of corn cobs and kernels, several steps can be taken, both visually and with the help of digital image processing technology to improve the accuracy of the assessment, one of which can be seen from the density of the kernels on the cobs. Good quality corn can be seen from the kernels that are fully filled, dense, and uniform along the cob. Cobs that have holes or are not fully filled can indicate less than optimal growth. The components of corn crop yields can also be influenced by genotype and environment (Nazirah, Zuhra, & Satriawan, 2022). In reality, middlemen buy corn from farmers with intact and unpeeled fruit. Middlemen will provide a range of selling prices from farmers based on the quality of their harvest, one of which is seen from the density of corn kernels. Middlemen and farmers will select the quality of corn cobs as much as possible to get different prices. This selection process requires more time and effort which also has an impact on additional costs for the sorters.

Previous studies have shown that computer vision can be a significant way to analyze grains. Research related to the classification of corn seed quality has been carried out using various methods. Classification to distinguish between broken and intact Arabica coffee beans was carried out by (Fadjeri, 2023). Coffee bean research was also conducted by (Ilhamsyah, Rahman, & Istiadi, 2018) who used the multilayer perceptron method based on LCH color features. In this study, morphological features are characteristic features to recognize coffee beans based on the type and integrity of the beans. Classification of the quality of dry nutmeg seeds can be done through dry nutmeg seed images in order to sort dry nutmeg seeds effectively. In this study, the method used was Case Based Reasoning (Alhamid, Rumui, & Anas, 2022). In research conducted by (Pebrianto & Haryanto, 2023), morphology has an important aspect in determining plant variations, such as dimensions, color, region, and seed structure in chilies. This study uses CNN as the classification method. Corn seed classification was studied by (Sari & Haryatmi, 2021) using the CNN method.

Research on the classification of export coffee beans using Backpropagation artificial neural networks (Olivya, Tungadi, & Rante, 2018) which will perform sorting, obtained 4 categories of bean quality, namely grade 1 can be exported while 2, 3, and 4 can only be sold locally. Determination of grade is determined based on the defect value that has been set based on the Indonesian National Standard (SNI). In testing 10 coffee bean images, the accuracy level obtained was 80%. The GLCM method can be used to extract features on corn seeds that can affect the high accuracy of classification. Research that applies this method is to recognize the type of corn seeds with the categories of red pozole corn, corn kernels, white corn, and colorful corn. The recognition method used is the Backpropagation algorithm and Support Vector Machine, while for feature extraction using the GLCM method consisting of contrast, energy, homogeneity, and correlation. In the calculation with the confusion matrix, the highest results were obtained in the backpropagation algorithm with an average accuracy of 97.1%, an average precision of 93.3% and an average recall of 95% (Yunarto, Pribadi, & Irsyad, 2020). Several previous studies that have been conducted to recognize the quality of corn kernels using object recognition methods discuss the analysis of the RGB intensity distribution of digital images for the classification of corn kernel quality using SSD Mobilenet and Histogram applied in IoT devices (Audy & Zaini, 2022).

In this context, research on the classification of corn kernel and cob quality based on digital image processing becomes very relevant. With reliable classification, farmers and agricultural industries can improve the efficiency of post-harvest processes, reduce product losses, and ultimately increase income. Therefore, this study aims to develop a method for classifying corn kernel and cob quality using digital image processing techniques, which is expected to have a positive impact on the supply chain and the quality of agricultural products as a whole.

Methods

This study uses an experimental method based on digital image processing to classify the quality of corn kernels on the cob based on two main visual characteristics, namely color and texture of kernel density on the cob. The backpropagation method on artificial neural networks (ANN) is applied to build a classification model that can distinguish between good and bad quality corn based on features extracted from the image. The process of the research to be carried out are shown in Figure 1.

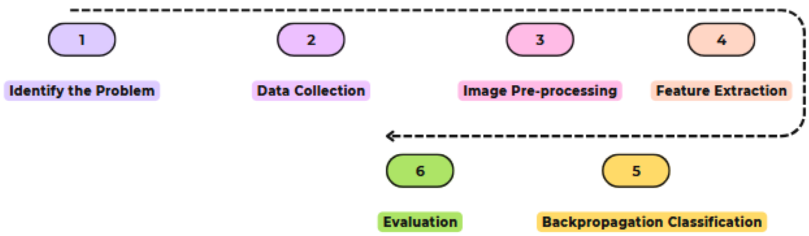


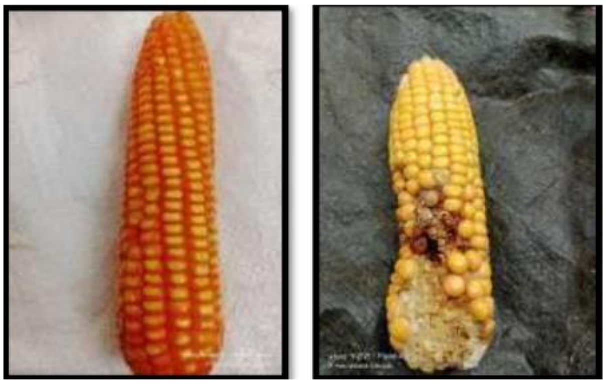
Figure 1. Research Process Steps

1. Problem Identification

Corn kernel quality is one of the important factors in determining the selling value and yield potential of corn plants. In the agricultural industry, uniform, dense, and defect-free corn kernels have a higher value than kernels that do not meet these standards. One of the main indicators of corn kernel quality is the density of kernels on the cob, which reflects the level of kernel filling and the success of nutrient absorption by the plant. In the manual selection process, the assessment of corn kernel quality is often subjective and takes a long time. This is an obstacle, especially in large-scale production. Therefore, an efficient and objective method is needed to accurately evaluate corn kernel density.

2. Dataset Collection

At this step, corn image data collection was carried out using a cellphone camera with the same lighting and location. An example of the dataset used is shown in Figure 2.



(a) (b)

Figure 2. Corn Dataset, (a) Good Quality, (b) Bad Quality

Good quality corn has a dense, orange cob texture, while poor quality corn has cobs that are not dense, hollow, and have rotten, blackish-brown kernels.

3. Image Pre-procssing

The preprocessing process aims to prepare the data to be more optimal for the feature extraction and model training stages. Pre-processing is a step to improve the quality of the transformed image to produce important features from an image (Fajar, Sulthan, & Wahyudi, 2023). The preprocessing steps include:

a. Image Resizing: Images with large resolutions require more computing power and time to process. By reducing the image size to a resolution sufficient for analysis, processing time can be reduced without losing important information.
b. Conversion to Grayscale: The image is converted to grayscale for texture feature extraction.
c. Normalization: Each image is normalized to equalize the pixel intensity scale so that the extracted features have a consistent scale.
d. Corn Seed Segmentation: Segmentation is carried out to separate corn kernels from the background, using the adaptive thresholding method or color-based segmentation method. Furthermore, the segmentation process aims to separate objects and backgrounds in the image (Asmar, Kurniawan, Ashari, Akbar, & Intam, 2023).

4. Feature Extraction

Color feature extraction is carried out to obtain attributes that represent the color and texture of corn kernels. The next feature extraction is to obtain color features by finding the proportion of dominant colors in the image (Afriansyah, Saputra, Sa'adati, & Ardhana, 2023). Calculating dominant colors is an approach that is often used to understand the main color characteristics in an image. Dominant colors are used to represent the overall color character of the image. Color feature extraction in images is carried out by comparing the RGB values that form the image (Guntara, 2022). The results of this study (Khultsum & Subekti, 2021) show an accuracy level of 96% in color feature extraction. Other studies explain that color feature extraction is used if the objects to be recognized have different colors, color parameters are obtained by normalizing each RGB (Red Green Blue) component in the image (Prastyaningsih & Kusrini, 2021).

Texture features are obtained using the Gray Level Co-occurrence Matrix (GLCM) method to calculate texture based on parameters such as contrast, energy, homogeneity, and entropy. GLCM is a technique for obtaining 2nd-order statistical values by calculating the probability of the proximity relationship between two pixels at a certain distance (d) and angle (θ) (Barburiceanu, Terebes, & Meza, 2021). Distance The working process of the GLCM method is to form co-occurrence in image data, then determine the functional characteristics of the matrix between the pixels. Co-occurrence is the occurrence of many levels of adjacent pixels with pixel values based on distance and angular orientation. The distance in question can be in pixels while the orientation is in degrees. Pixels can be determined through the distance between pixels, which is determined at 1 to 10 pixels, while the angular orientation is formed from four angular directions, namely $\mathbf{0^0}, \mathbf{45^0}, \mathbf{90^0}, \mathbf{135^0}$ (Andono & Rachmawanto, 2021).

5. Backpropagation Classification

After the features are obtained, the next step is to train the classification model using an artificial neural network with the backpropagation algorithm. The network architecture of the ANN model uses a multi-layer perceptron architecture with one input layer, one or more hidden layers, and one output layer. The number of neurons in the input layer corresponds to the number of features extracted, while the output layer consists of two neurons representing the quality class (good and bad). Backpropagation classification is a systematic for training multilayer artificial neural networks. This method has a strong mathematical basis, is objective and this algorithm obtains the form of equations and coefficient values in the formula by minimizing the sum of the squares of the error through the developed model (Armelia, Andrian, & Junaidi, 2024). Activation Function: The activation function used is sigmoid for the hidden layer and softmax in the output layer, in order to obtain the class probability. Network Training: Data is trained using the backpropagation algorithm, with parameters in the form of learning rate, momentum, and epoch which are determined based on the tuning results to achieve the best performance.

6. Evaluation

At this stage, an evaluation of the classification results will be carried out which are described in the confusion matrix. Confusion Matrix is a 2 x 2 matrix, where in general each block is divided into 4 parts. True Positives (TP) indicate a prediction with a true value according to the actual conditions that are true. False Positives (FP) indicate a prediction with a true value where the actual conditions are false. True Negatives (TN) indicate a prediction with a false value according to the actual conditions that are false. False Negatives (FN) indicate a prediction with a false value where the actual conditions are true (Amalia, Bimantoro, & Aranta, 2022). After training, the model is tested using test data to evaluate its performance. Performance measurements include metrics, namely accuracy where the percentage of test data that is successfully classified correctly by the model.

Results and Analysis

The dataset used in this study is the Bisi type of corn image collected as many as 150 images, consisting of 75 images of the "good" group and 75 images of the "bad" group. From each group of corn seed quality, 15 images were taken to be used as testing data and 15 images for training data. So the total is 30 as testing data and 120 as training data. The dataset was taken using a cellphone camera during the day. An example of the dataset used is shown in Figure 2.

1. Image Pre-processing

The steps taken at this stage are:

a. Remove Background

Remove Background is done manually using Google Remove Bg, This step aims to simplify visual data, ensure a more focused analysis on the main object, and aims to improve the accuracy of the next process. The results of removing the background are shown in Figure 3.

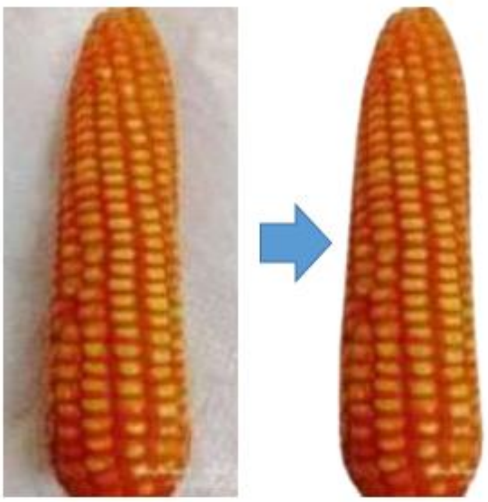


Figure 3. Remove Background

b. Image Resizing

In corn grain quality classification research, resizing helps ensure that all images have a uniform size. This is important for accurately analyzing grain density, texture patterns, or color distribution. Resizing is an important step in image preprocessing to ensure consistency, efficiency, and compatibility of subsequent analysis. Images with high resolution require more computing power and time to process.

By reducing the size of the image to a resolution sufficient for analysis, processing time can be reduced without losing important information. Resize the image from 980 x 1280 pixels to 250 x 250 pixels.

c. Convert to Grayscale

Image conversion to grayscale is one of the initial steps in image processing, especially for texture feature analysis. Texture refers to a repetitive spatial pattern that reflects the surface characteristics of an object. The results of the conversion to grayscale are shown in Figure 4.

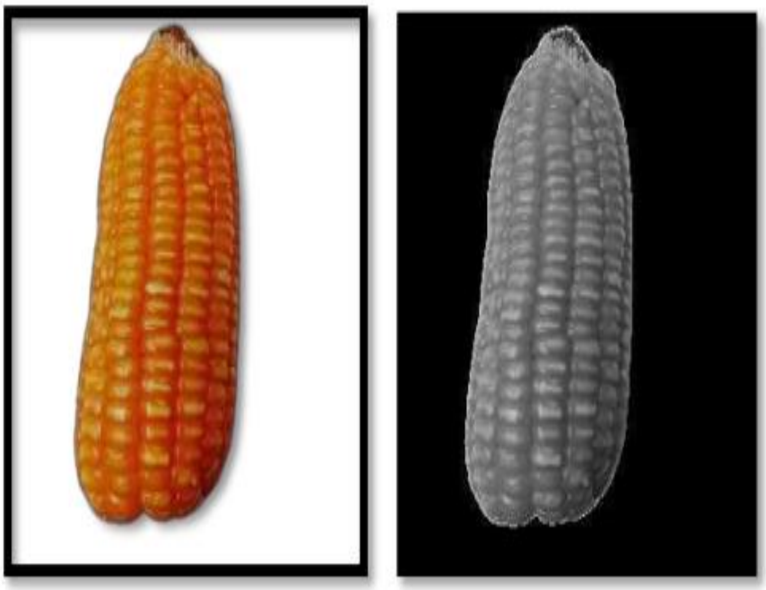


Figure 4. Grayscale Image

2. Feature Extraction

Texture feature extraction is done by applying the GLCM method. This GLCM method is used to extract the quality features of corn kernels on the cobs as previously described, where the quality will be extracted its features. There are matrices 0^0, 45^0, 90^0, 135^0. The GLCM process prepares the data class that will be saved to the *.csv file from the GLCM extraction results. And the features used are Entropy, Energy, Contrast, Correlation, and Homogeneity features. The number of features taken in the GLCM texture extraction process is 20 features. An example of the results of GLCM feature extraction is shown in Table 1.

Table 1. Examples of GLCM Feature

No.	Feature	Image1	Image 2
1.	Energi 0^0	0,6133	0,6337
2.	Contrast 0^0	0,6765	0,6863
3.	Homogenity 0^0	253,9576	262,3982
4.	Corelation 0^0	0,9589	0,9579
5.	Energi 45^0	0,9589	0,6337
6.	Contras 45^0	0,6765	0,6863
7.	Homogenity 45^0	253,9576	262,3982
8.	Corelation 45^0	0,9589	0,9579
9.	Energi 90^0	0,7631	0,7787
10.	Contras 90^0	1,0000	1,0000
11.	Homogenity 90^0	0,0012	0,0013
12.	Corelation 90^0	1,0000	1,0000
13.	Energi 135^0	0,6133	0,6337
14.	Contrast 135^0	0,6765	1,0000

15.	Homogenity 135^0	253,9556	262,3961
16.	Corelation 135^0	0,9587	0,9579
17.	Energi Mean	0,6133	0,6337
18.	Contrast Mean	0,6766	0,6863
19.	Homogenity Mean	253,9556	262,3961
20.	Corelation Mean	0,9589	0,9579

The next feature extraction is to get the color feature by finding the proportion of dominant colors in the image. Calculating dominant colors is an approach that is often used to understand the main color characteristics in an image. Dominant colors are used to represent the overall color character of the image. At this stage, each image will have 3 color feature values. The results of the color feature extraction are shown in Table 2.

Table 2. Examples of Color Feature

No.	Fitur	Image 1	Image 2
1.	R	0,3964	0,3668
2.	G	0,0104	0,0097
3.	B	0,0104	0,0200

3. Backpropagation Classification

Backpropagation is an algorithm used in machine learning to minimize errors by adjusting weights based on the difference between the output and the desired target. To carry out the classification process using the ANN method through the backpropagation algorithm, there are stages of feedforward, backpropagation or error propagation and changes in weights and biases (weight update/adjustment) (Putri, 2021). This algorithm is often used in artificial neural networks, especially in multilayer architectures, to find optimal weights. Backpropagation consists of three layers: input layer, hidden layer, and output layer. The research process of corn seed quality classification based on color features and texture features using 120 training data and 30 testing data. In this classification process, the input features used are a combination of texture features and color features, with a total of 23 features. The goal is to train data on training data which is useful for determining the quality carried out on the data to be tested. The next classification process is carried out using Python programming. At the learning stage, the model uses training data, namely x_train, y_train with the fit() function. Algorithm learning using 100 epochs or iterations and data validation are also implemented to validate the learning process against training data, and finally callbacks that will monitor the model learning process which will monitor accuracy and validation accuracy. Figure 5 is a visualization of the results of the learning process for 100 iterations which shows the results of the accuracy and error (loss) values in the model, where the results of the model learning process get an accuracy of 89%.

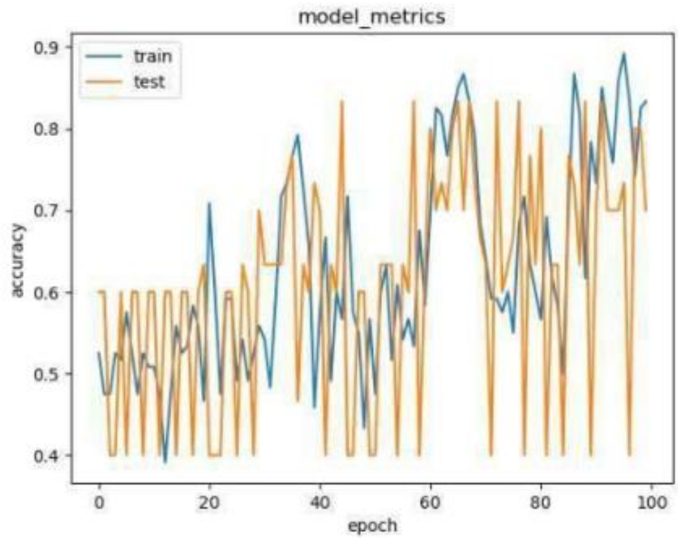


Figure 5. Visualization of Learning Model

The Confusion Matrix shown in Figure 6 displays the prediction results for the validation data, there are 13 correct data or detected label 0, there are 5 incorrectly predicted data label 1, there are 4 incorrectly predicted data detected 0, there are 8 correct data or detected label 1. In the trial stage with the backpropagation algorithm that has been implemented into the website using new data as many as 20 corn image data consisting of 10 good quality and 10 bad quality.

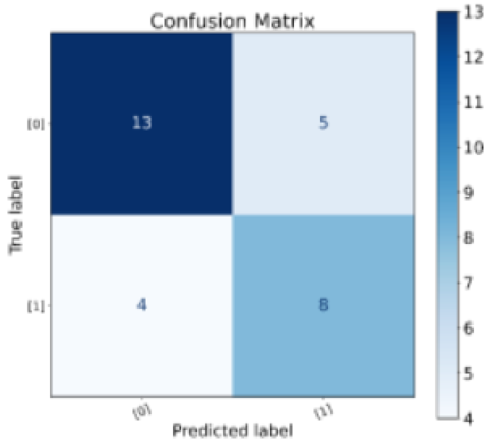


Figure 6. Confusion Matrix

The obtained model is then used in the image testing based on the Flask Web application. The test was carried out on new data of 20 corn image data consisting of 10 good quality and 10 bad quality. Table 3 is the test result on the Flask Web-based application.

Table 3. Test Results On Flask Web Application

Image	Class	Prediction Label	True Label
br1	Bad	Good	False
br2	Bad	Bad	True
br3	Bad	Good	False
br4	Bad	Bad	True
br5	Bad	Bad	True
br6	Bad	Bad	True
br7	Bad	Bad	True
br8	Bad	Bad	True

br9	Bad	Bad	True
br10	Bad	Good	False
kb1	Good	Good	True
kb2	Good	Good	True
kb3	Good	Bad	False
kb4	Good	Good	True
kb5	Good	Good	True
kb6	Good	Good	True
kb7	Good	Good	True
kb8	Good	Bad	False
kb9	Good	Good	True
kb10	Good	Good	True

Table 3 shows the results of the image integration test. The accuracy value is calculated using the following equation (1) (Seran, Rahman, & Istiadi, 2021).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} x100\% \qquad \text{...(1)}$$

$$Accuracy = \frac{15}{20} x100\% = 75\%$$

So in the test of corn seed quality classification using the web-based backpropagation neural network method, an accuracy of 75% was obtained. Because the Machine Learning Overfitting model studies the data in too much detail, so that not only the data is captured, but the noise is also recorded. The overfitting model will produce a very high accuracy value during the training process, but has low accuracy when testing.

The test accuracy of 75% indicates that the model can correctly classify most of the data, but there are still significant misclassifications. These errors can come from training data that does not cover all the feature variations in the test data, or from noise that affects the classification results. One challenge found is overfitting, where the model learns too much detail in the training data to include noise. This results in lower performance on new data compared to the training data, even though the training accuracy reaches 89%. Texture features extracted using the GLCM method provide important statistical information, such as energy, contrast, homogeneity, and correlation. Meanwhile, RGB color features provide an overview of the visual condition of the corn kernels. The combination of these two types of features is quite effective, but needs to be improved by selecting more discriminatory features.

Conclusion

The results of the research on the classification of corn kernel and cob quality based on color and texture features using the Backpropagation method can be concluded that the process of determining the quality of corn kernels based on color and texture features with a total of 150 data with a minimum image format size of 250 x 250 pixels. So the results of the classification system test obtained an accuracy value of 75% using the backpropagation method. Suggestions for improvement from this study are to increase the number and variety of datasets, including images from various environmental conditions and variations in corn seed quality, including using image augmentation such as rotation, flipping, or color intensity adjustment to increase data diversity.

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