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Ambon Banana Maturity Classification Based On Convolutional Neural Network (CNN)

Yuha Aulia Nisa[1)*], Christy Atika Sari[2)], Eko Hari Rachmawanto[3)], Noorayisahbe Mohd Yaacob[4)]
[1,2,3)]University of Dian Nuswantoro, Indonesia,
[4)]Malaysia-Japan International Institute of Technology (MJIIT),University of Technology Malaysia (UTM), Malaysia
[1)]yuhaaul1901@gmail.com, [2)]christy.atika.sari@dsn.dinus.ac.id,[3)]eko.hari@dsn.dinus.ac.id,
[4)]noorayisahbe@utm.my

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Abstract: The banana (Musa paradical), is an excellent fruit produced nationally and high in vitamins. In Indonesia, banana production is at a higher level than other fruit products. However, one of them is the issue with bananas' post-harvest, which arises when they are produced in huge quantities on a large scale or by an industry that sorts bananas. So far, the determination of the maturity level of bananas is done by relying on visual analysis limited to the color of the skin by the human eye. However, this identification approach has several drawbacks. First, this method requires significant effort in the banana sorting process. In addition, the perception of the fruit's maturity level can vary, because humans can experience fatigue and lack of consistency in judgment. In addition, human judgment is also influenced by subjective factors that can affect the final result. Considering this problem, developed a system to classify the ripeness level of Ambon bananas. This system utilizes image enhancement features to increase contrast, which is implemented using a Convolutional Neural Network (CNN). The classification process is carried out through image processing using MATLAB R2022a software, which forms the basis of a classification system with 4 classes which include 486 images of unripe Ambon bananas, 235 images of half-ripe Ambon bananas, 309 images of perfectly ripe Ambon bananas, 184 images of rotten Ambon bananas. The dataset analyzed in this study totaled 1214 data divided into 1093 training data and 121 test data. The CNN method is used in this data classification, and the results show an accuracy rate of 95.87%.

Keywords: Banana, Classification, Convolutional Neural Network, Maturity, Image Enhancement

INTRODUCTION

The scientific name for bananas is Musa Paradisiaca, which is included in the Musaceae family (Galani, 2019). Bananas are a fruit that is commonly found throughout the world because it grows abundantly in tropical and subtropical areas. Each banana has characteristics that make it easy to recognize its type and ripeness. Size and color are important indicators for distinguishing species and determining ripeness. In Indonesia, banana varieties are quite diverse. One of the banana types that is quite popular in Indonesia is the Ambon banana. Its distinctive feature is its flesh, which is yellowish-white cream in color, very tender, and soft to the touch. Its inherent sweetness and lack of sourness make it a sought-after ingredient in a variety of dishes and desserts, adding a natural sweetness and rich texture.

*name of corresponding author

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Classification of the maturity level of the Ambon banana based on color has an important role in agriculture and the food industry because the commodity of the Ambon banana has high economic value and is generally consumed when it reaches a certain level of maturity (Maimunah et al., 2019), (Tamatjita & Sihite, 2022). Therefore, in the process of cultivating Ambon bananas, observation of color is an important key, especially at the nursery stage. This involves careful monitoring of the fruit's color characteristics. The color of the fruit at this stage can be an early indicator to determine the level of maturity desired. Seeds that have the color of the fruit according to the level of maturity expected will have a greater chance of achieving optimal yields.

Along with the growth and development of Ambon bananas, the skin color gradually changes. Farmers and producers must understand these changes to identify the right time to harvest (Evans et al., 2020). For example, at the beginning of development, Ambon banana skin is usually green, and over time the color starts to change to yellow. Then when it reaches a certain level of maturity, the yellow color will be brighter and evener, indicating that the fruit is ready to be harvested. Unfortunately, banana farmers still classify the type and ripeness of bananas manually. Banana sorting is a postharvest problem for bananas produced industrially or on a large scale. The color of a banana can indicate how ripe the fruit is, but the human eye isn't always good at distinguishing between colors. The color seen by humans cannot be used as a benchmark for determining the ripeness of bananas (Sabilla et al., 2019). Until now, the determination of the ripeness level of bananas still relies on the use of the human eye to observe changes in fruit skin color. However, in this identification process, there are several weaknesses, including the need for a larger workforce to synchronize, and the results of perceptions of fruit maturity levels can vary because humans can experience fatigue, inconsistency, and subjective judgments.

The problem can be solved in a way, that the author tries to utilize a technique in deep learning to detect objects in images (Le et al., 2019). This technique involves classifying the maturity level of bananas using the Convolutional Neural Network (CNN) algorithm. This is because CNN tries to resemble the human visual cortex in image recognition so that CNN can process information from the image (Gupta et al., 2022), (Picon et al., 2019). The use of this algorithm utilizes the ability of convolution layers to capture visual images to obtain a high level of accuracy in determining the level of fruit maturity (Peng et al., 2021). The process begins by providing training data containing images of Ambon bananas at various maturity levels to the CNN algorithm. During the training, CNN will identify visual patterns related to color changes and physical characteristics of Ambon bananas during the approval process. The result of this training is the CNN model which has a high level of accuracy in specifying the maturity level of Ambon bananas from the image.

This can help optimize harvest time, reduce wastage of resources, and increase overall crop yields (Sulistyowarni et al., 2020). In addition, this model can also be used in the automation of inventory management and distribution processes, thereby enabling high-quality Ambon banana products to be more easily identified and marketed to consumers. Thus, the application of deep learning, especially through the CNN algorithm, has a positive impact on increasing efficiency and productivity in Ambon banana cultivation and industry.

LITERATURE REVIEW

Many studies have discussed the development of fruit maturity classification systems which still have several weaknesses, so further research has been carried out to complement the existing weaknesses, below is the discussion. The classification accuracy obtained in this study to identify the ripeness level of bananas using the raw NIR spectrum region was 94.35% on the validation set. In addition, the average classification accuracy achieved to identify green bananas at different maturity levels using the PLSDA model based on differences in spectral subsets is more than 91.53%. One weakness of this research is the limited sample size. The study only used a total of 177 bananas for analysis. A larger sample size would have provided more robust and reliable results. Additionally, the study focused on a specific cultivar of bananas, and it would be beneficial to include different cultivars to assess the generalizability of the models (Chu et al., 2022).

The research results showed that the banana ripeness classification system based on color characteristics using the K-NN method achieved an accuracy of 90.9%. This system is able to accurately classify the ripeness of bananas into three categories: unripe, ripe and overripe. The color features used in the classification process are the RGB and HSV values extracted from fruit skin images. The

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Euclidean Distance formula is used to calculate the shortest distance between test data and training data. The weakness of this study is that only 10 test data were used (Adenugraha et al., 2022).

This research focuses on classifying the maturity levels of bananas using skin images and the HSI color space transformation features with the K-NN method. The study used the Raja banana and achieved an accuracy of 91.33% with a standard deviation of +/- 4.52% and a value of k=4. The study suggests further research to improve accuracy by exploring better features and extraction methods. The weaknesses of this research include the limited dataset used, as it only consists of 300 data sets with three categories of banana ripeness levels. Additionally, the study could benefit from further development and improvement in terms of features and extraction methods to enhance accuracy values (Thoriq et al., 2022).

Research resulted in various variations of distance and k value in the K-NN method to classify the quality of California papaya fruit. The results show that features such as R, G, minor axis, major axis, and defect area produce the most optimal results. Utilization of the Euclidean distance with a k value of 7 gives the best performance, with an accuracy of 86.67%, a precision of 87.50%, and a recall of 80.00%. These findings indicate that the combination of the right features and optimal K-NN parameters can produce significant classification results in identifying the quality of California papaya fruit, which has the potential to provide benefits to the agricultural and distribution industries. The weakness of this study is that the amount of data used in this study still needs to be added using only 150 images(Al Rivan et al., 2021).

Banana Fruit Ripeness Classification Based on Color Features with the SVM Method achieves an accuracy of 75%. The average value of RGB and LAB features is obtained from the dataset, and the SVM model is trained and tested using these features. This shows that 75% of the tested banana images are correctly classified as ripe, while the remaining 25% are classified as unripe. The study only used a dataset of 80 banana images. A larger sample size would provide more robust results and increase the generalizability of the findings (Muhammad et al., 2019).

Based on previous related research, there are limitations to the data set used, including the sample size and techniques used, as well as other factors such as processing difficulty. Therefore, researchers formulated a new concept to increase the efficiency of the image training process, by adopting an image enhancement technique that focuses on increasing image contrast based on the color of banana peels. In this research, efforts were made to overcome these limitations, but still focused on achieving goals in developing a classification method for the ripeness level of Ambon bananas. The research has carried out 12 trials with 1214 images with consistent test results showing 100% accuracy. The results of this study indicate that with the application of this new approach the level of accuracy reaches 95.87%.

METHOD

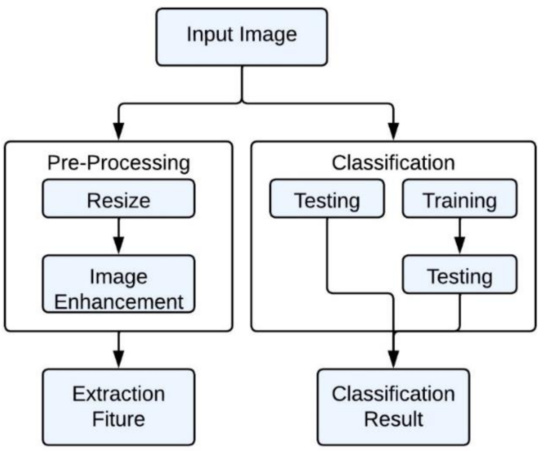

Fig. 1 Research Methodology

Data Collection

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Collection of Ambon banana image datasets in .jpg format with a size of 224 x 224 x 3 totaling 1,214 sample images. Based on This image data set, is broken down into 4 classes which include 486 images of unripe Ambon bananas, 235 images of half-ripe Ambon bananas, 309 images of perfectly ripe Ambon bananas, and 184 images of rotten Ambon bananas. The dataset collection is private because it is taken in real-time by storing banana samples by taking pictures for 4 days. The unripe banana dataset used for research was taken from the Kaggle platform. The training data of 1093 images was used to train a model or algorithm to classify Ambon bananas into appropriate categories based on color and level of ripeness. Apart from that, test data of 121 images was used to test the performance of the trained model, thus ensuring that the model could perform accurate classification on data that had never been seen before. Then this data can determine the value of the level of accuracy which can influence the results of classifying the maturity level of Ambon bananas.

Pre-processing

The image data obtained underwent a preprocessing stage to improve the quality of the previous image (Saragih & Emanuel, 2021). This preprocessing stage aims to make the results of the next process more optimal. The other stages are as follows:

a. Resize
   The resizing process plays a crucial role in image processing, involving adjusting the image dimensions to the desired size. In research involving 224 x 224 x 3 images, this step has significance in a variety of contexts, especially in the realms of machine learning and image processing. Changing the image dimensions to a size suitable for the CNN network, namely 224 x 224 pixels with three color channels (RGB), is an important step to ensure the image is ready for the training stage. By carrying out this resizing process, the images can be integrated into the learning algorithm and undergo further analysis to support research objectives.
b. Image Enhancement
   At the Image Enhancement stage, a process is carried out to obtain images that are more easily interpreted by the human eye (Human Visual System/HVS) (Yuan et al., 2021). Image enhancement is also used to improve the visual quality of images (Chakraborty et al., 2019). One important aspect of image enhancement is contrast enhancement, which aims to increase the difference between the different brightness levels of an image. When it comes to increasing contrast, there are several methods used to increase the distance between pixels that represent light and dark areas in an image.

Extraction Feature

In the process of classifying the maturity level of Ambon bananas using the Convolutional Neural Network (CNN) algorithm, there is an image feature extraction process (Aruraj et al., 2019). These features play a role in describing the visual characteristics of the Ambon banana image which will then be processed by the CNN algorithm for classification. The features used in the program, such as Mean, Variance, Kurtosis, Minimum, Standard Deviation, Entropy, Skewness, and Maximum.

Each feature provides different information about the distribution of pixel intensity in the image (Fu et al., 2020), including information about the brightness, variation, distribution, and shape of the image. The mean and standard deviation reflect the average brightness level and the variation in pixel intensity in the image. Kurtosis and skewness describe the shape of the pixel intensity distribution, while entropy measures the level of image complexity. The minimum and maximum represent the lowest and highest pixel intensity values in the image.

To get the Mean value, the calculation is done by the formula:

$$M = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

Where n is the number of elements in the dataset, and x_i is the value of the to-i element in the dataset.

To get the Variance value, the calculation is done by the formula:

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$$variance = \frac{\sum_{i=1}^{n}(x_i - m)^2}{n} \tag{2}$$

Where n is the number of elements in the dataset, x_i is the value of the to-i element in the dataset, and m is the average value of the dataset.

To get the Standard Deviation value, the calculation is done by the formula:

$$std = \sqrt{\frac{\sum_{i=1}^{n}(x_i - m)^2}{n}} \tag{3}$$

Where n is the number of elements in the dataset, x_i is the value of the to-i element in the dataset, and m : the average value of the dataset.

To get the Kurtosis value, the calculation is done by the formula:

$$k = \frac{\sum_{i=1}^{n}(x_i - m)^4}{n \times std^4} \tag{4}$$

Where n is the number of elements in the dataset, $x_i$is the value of the to-i element in the dataset, m is the average value of the dataset, and std : standard deviation of the dataset.

To get the Minimum value, the calculation is done by the formula:

$$Min = \min(x_1, x_2, \dots, x_n) \tag{5}$$

Where n is the number of elements in the dataset, and $x_i$is the value of the to-i element in the dataset.

To get the Entropy value, the calculation is done by the formula:

$$-\sum_{i=1}^{N} p(x_i) \,.\, \log_2(p(x_i)) \tag{6}$$

Where N is the number of possible different values in the dataset, x_i is the intensity value of the pixel value at the to- i position, and px_i is the probability of occurrence of the value x_i in the dataset.

To get the Skewness value, the calculation is done by the formula:

$$Skewness = \frac{\sum_{i=1}^{n} (\mathcal{X}_i - \bar{\mathcal{X}})^3}{n \cdot \mathcal{S}^3} \tag{7}$$

Where n is the number of elements in the dataset, $\mathcal{X}_i$ is data value in the to-i position, $\bar{\mathcal{X}}$ is the average of the data, and $\mathcal{S}$ is standard deviation of the data

To get the Maximum value, the calculation is done by the formula:

$$Max = \max(x_1, x_2, \dots, x_n) \tag{8}$$

Where n is the number of elements in the dataset, and $x_i$is the value of the to-i element in the dataset.

Classification of Convolutional Neural Networks (CNN)

The designed system is the classification of fruit maturity levels. A Convolutional Neural Network (CNN) is a type of artificial neural network architecture specifically designed for image processing and analysis (Kuang et al., 2019)(Wu et al., 2020). CNN is very effective at recognizing complex visual patterns in images, making it a powerful tool for a variety of image-processing tasks, including fruit

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ripeness classification. In the context of fruit ripeness classification, CNN serves as a machine learning model that understands and distinguishes changes in color, texture, and other visual characteristics that occur during the fruit ripening process (Mukhiddinov et al., 2022)(Risdin et al., 2020).

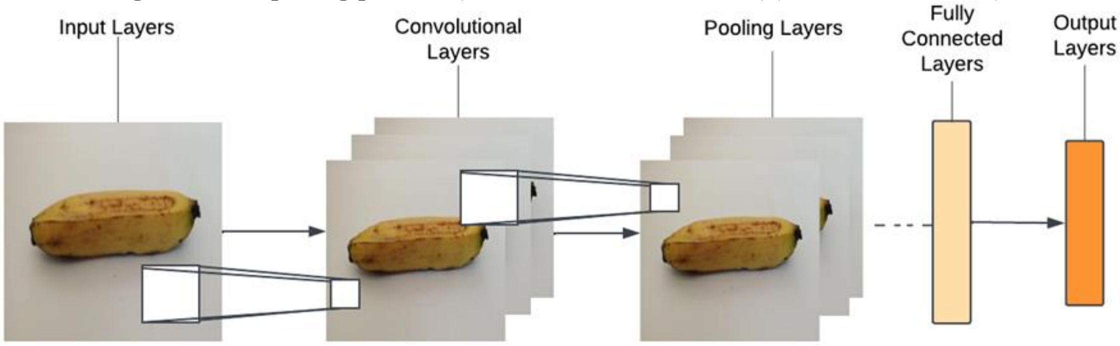

Fig. 2 Structure CNN Using Dataset

Based on Fig. 2, the first convolution layer will recognize basic patterns such as lines and edges in the banana image (Tripathi, 2021). The activation layer will add a dimension of non-linearity by activating the neurons based on the pattern found. Merging the layers will help reduce the resolution of the image, retaining important information, such as the shape and texture of the banana. Then, the next convolution layer will be more complex, recognizing more specific features, such as spots or the texture of a banana peel. This process will continue through several layers, with dropout layers possibly used to prevent overfitting. Ultimately, the fully connected layer will link identified features to neurons to generate outputs, such as classifying bananas into different maturity-level categories.

Accuracy

Accuracy is a measure that is commonly used to evaluate the extent to which the results of predictions or classifications produced by a method match the actual original data. The purpose of calculating accuracy is to evaluate the success of the system and allow comparisons between different studies using different methods. This allows for the possibility of conducting comparisons with alternative studies using different methods. These measures offer performance benchmarks, aid informed decision-making, and increase confidence in model results. Despite this simplicity, accuracy may have limitations in dealing with class imbalance or error types. Nonetheless, it remains important in evaluating model efficacy, promoting comparability, and advancing research efforts.

RESULT

The banana image used as the dataset in this study was obtained from a personal dataset because real-time image capture uses a smartphone in .jpg format and for the Ambon banana dataset it was taken on the Kaggle site. All of these images were collected together to send into 4 classes of all data containing 1214 Ambon bananas, which included 489 unripe bananas, 235 half-ripe bananas, 309 perfectly ripe bananas, and 184 rotten bananas. The dataset consists of training and testing data. The training data has a total of 1093 images, while the test data has a total of 121 images. Data training and data testing are used to train the CNN model.

After becoming a dataset as needed. The dataset goes through a preprocessing process taking into account the amount of data, the preprocessing process for changing the data size is done by changing the original image size to 224 x 224 x 3 pixels which has a uniform size including three color channels (RGB). After that, the image enhancement process is carried out to get an increase in contrast from the original image. The purpose of increasing the image compared to increasing the contrast is to make the image sharper, clearer, and easier to recognize by increasing the difference between the various levels of brightness in the image using the CNN method to produce a class classification of banana maturity levels.

Table 1. Class of each level maturity

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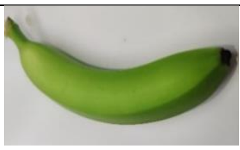
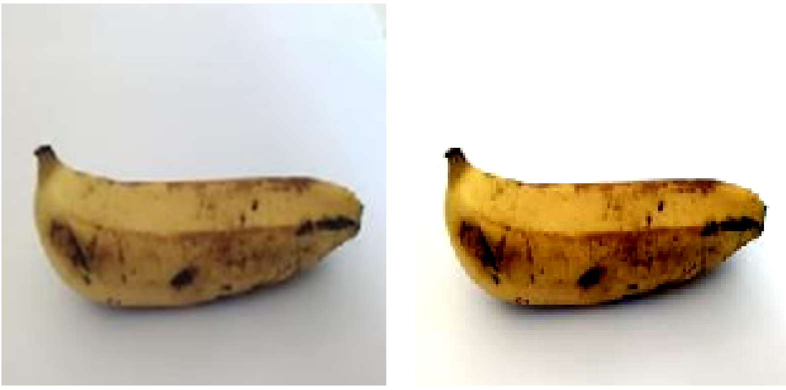
Image	Banana Maturity Level	Description
	Unripe Banana	Ambon banana peel has a color that tends to be green.
	Half-ripe Banana	Half-ripe Ambon banana skin is yellowish-green
	Perfectly Ripe Banana	Ambon banana peels that have reached perfect maturity have an overall yellow color.
	Rotten Banana	Ambon banana peels that are starting to rot brown and speckled



Original Image Image Enhancement
Fig. 3 Image Enhancement

Based on Fig. 3, after increasing the contrast, feature extraction can be produced in Table 1 in a more concise numerical form to determine the characteristics of the image, as well as calculate the image value. Based on Table 2, there is an input image in .jpg format from the original Ambon banana image that has gone through the previous resizing process, then proceeded to the image refinement process to obtain increased contrast in the image so that the image can be seen more clearly. This program uses the CNN method to produce class classifications of banana maturity levels. In Table I, feature extraction produces image data processing in a more concise numerical form that reflects the important characteristics of the image. The following is the result of feature extraction from the image of a training banana as shown in Table 3.

Table 2. Extraction Feature

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Banana Class	Mean	Variance	Kurtosis	Standard Deviation	Entropy	Skewness	Min	Max
unripe_banana	202.57	4307.24	3.66341	65.6296	6.54843	-1.33365	0	255
ripe_banana	192.666	2003.15	6.94759	44.7566	6.69179	-1.92677	0	249
rotten_banana	182.908	8361.05	2.65143	91.4388	5.60843	-1.22383	0	254
halfripe_banana	216.551	4456.79	4.83009	66.7592	5.00658	-1.81538	0	255

Table 3. Training Option

Hyperparameters	Result
Optimization Function	adam
MaxEpochs	8
Frequency	30
MiniBatchSize	8

It can be seen from Table 3 that the accuracy and validation of graphical visualization and plotting of the accuracy of the results for the number of iterations. Models that have undergone training using the MatLab R2022a software obtain an accuracy of 95.87%. Information is explained in Fig.4 and Fig. 5 uses the 'adam' optimization function, MaxEpochs 8, and MiniBatchSize 8 in conducting training. Based on the results of training and testing, training accuracy measures the degree to which the model successfully recognizes the training data correctly, while training loss measures how well the model minimizes the difference between the predicted results and the actual values in the training data. It can be seen from Table 3 that the test has been carried out correctly on the ripeness classification of Ambon bananas.

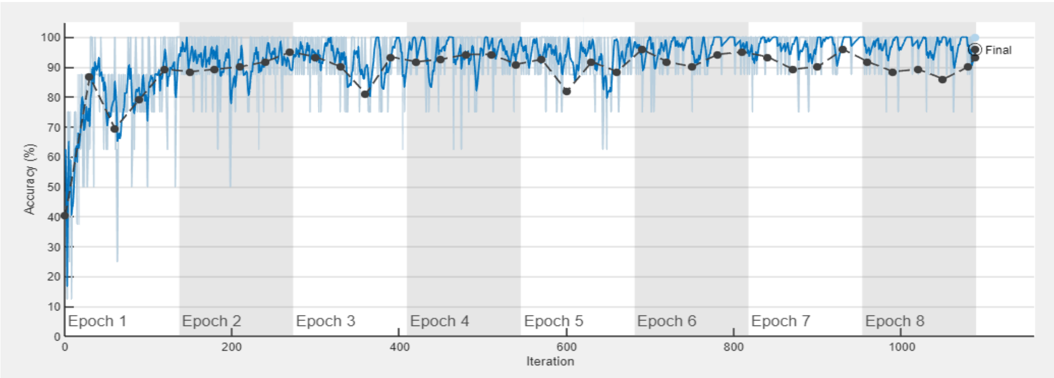

Fig. 4 Accuracy Training

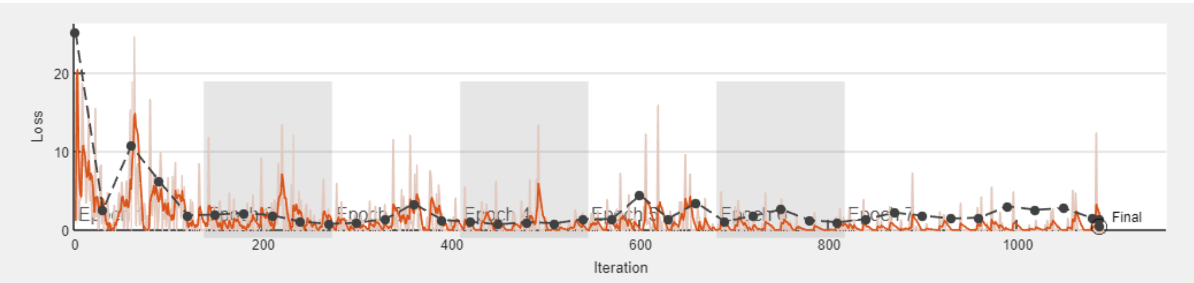

Fig. 5 Loss Training

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Based on Table 4, Banana ripeness classification uses training data which is used to train the model to understand visual characteristics such as color that reflect the level of banana ripeness, so that it can classify new bananas based on the input image. The banana maturity classification results reflect the model's ability to recognize and differentiate bananas based on their level of maturity. For example, when feeding an image of a banana into a model, the model will provide a prediction of the ripeness of the banana, such as “unripe,” “half-ripe,” “ripe,” or “rotten.”

Table 4. Sample of Ambon Banana Class Classification

Image Files .jpg	Ambon Banana Class Classification (CNN)		
	Original Ambon Banana class	Ambon Banana Class Classification	True or False
9.jpg	Unripe	unripe_banana	True
17.jpg	Unripe	unripe_banana	True
56.jpg	Unripe	unripe_banana	True
62.jpg	Half-ripe	halfripe_banana	True
20.jpg	Half-ripe	halfripe_banana	True
30.jpg	Half-ripe	halfripe_banana	True
3.jpg	Perfectly Ripe	ripe_banana	True
18.jpg	Perfectly Ripe	ripe_banana	True
24.jpg	Perfectly Ripe	ripe_banana	True
4.jpg	Rotten	unripe_banana	True
14.jpg	Rotten	unripe_banana	True
48.jpg	Rotten	unripe_banana	True

Differences in classification results are usually reflected in the accuracy and consistency of the model in recognizing different ripeness of bananas. The higher the training accuracy, the better it is at classifying banana ripeness. Thus, the banana maturity classification results measure the extent to which the data can differentiate the level of banana maturity based on the images provided. This training produces excellent accuracy. All sample images were classified correctly resulting in training of 95.87%. In the 12 trials that have been carried out, the Testing results have consistently shown 100% accuracy.

DISCUSSIONS

This research focuses on the development and evaluation of a sophisticated classification system to differentiate the maturity level of Ambon bananas. The dataset used is very extensive, consisting of more than a thousand images with dimensions of 224 x 224 pixels and three RGB color channels. This data is broken down into four different ripeness classes of bananas: ripe, half-ripe, unripe, and rotten. The evaluation phase includes in-depth testing by repeating the process 12 times using 3 samples from each level of maturity of Ambon bananas had been seen in Table 4, extraordinary results were obtained with a 100% success rate. The method used relies on Convolutional Neural Network (CNN) and image enhancement techniques to strengthen contrast, increase detail, and sharpen pixel intensity differences.

CONCLUSION

The research was conducted with a total dataset of 1214 images of Ambon bananas measuring 224 x 224 x 3 consisting of 4 classes of banana maturity levels, namely ripe bananas, half ripe bananas, unripe bananas, and rotten bananas. on sample testing that has been carried out to achieve a success rate of 100%. This research succeeded in creating a classification system for the maturity level of Ambon bananas in terms of banana color using the Convolutional Neural Network (CNN) algorithm which is enriched with image enhancement techniques to increase contrast to help sharpen detail and pixel differences. intensity level in the image. The results showed that this approach resulted in an accuracy value of 95.87%. This research is expected to help the agricultural sector which has the potential to revolutionize the sorting and management of banana products. Speed and accuracy in classifying maturity levels can provide more efficient distribution and higher quality standards for end consumers, as well as make a valuable contribution to the agricultural industry as a whole.

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