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Implementation of Convolutional Neural Network CNN Algorithm to Detect Coffe Fruit Maturity

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ABSTRACT

Fruit ripeness detection is important in the agriculture and food processing industries to ensure optimal product quality. Proper fruit ripeness can affect flavour, texture and nutrition, making it a key focus in production process monitoring and control. The fruit ripeness detection process still needs to be done manually, which can be inefficient and inaccurate. This research aims to address these challenges by implementing the CNN algorithm with VGG-19 architecture to detect coffee fruit ripeness automatically. The process involves collecting datasets of fruit images with various ripeness levels, image pre-processing including cropping and resizing, training the CNN VGG-19 model with feature learning and hyperparameter optimisation and evaluating model performance using a confusion matrix. This experiment aims to evaluate the model's performance in detecting fruit ripeness and measure the speed and efficiency of the CNN-based detection system with VGG-19 architecture. The results of this research are expected to help develop a better system for identifying fruit ripeness.

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1. INTRODUCTION

Agriculture is an important sector in the global economy, providing food for the world's growing population. In crop production, especially coffee fruit, fruit maturity is important in determining its quality and selling value [1]. Manually determining fruit maturity by farmers is often time and labour-consuming and prone to human error, which can result in losses in the supply chain [2].
The development of technology in artificial intelligence, especially in image processing and pattern recognition, has contributed significantly to the automation of various processes, including object recognition and ripeness detection in fruits [3]. One technique widely used in image processing is convolutional neural networks (CNN), which can perform classification and object detection with high accuracy.

Implementing CNN to detect coffee fruit ripeness still requires more in-depth research. Some challenges include variations in the fruit's colour, shape, and texture, affecting the algorithm's performance [4]. In addition, selecting the right architecture of the CNN is also a key factor in improving detection accuracy and reliability. The use of the VGG-19 architecture, a CNN known for its reliability and high performance in image recognition, was the focus of the study [5]. Implementing the CNN algorithm using the VGG-19 architecture is expected to obtain a system that can detect the ripeness of coffee fruit with high accuracy.

This research will also consider the practicality and effectiveness of the algorithm implementation. Thus, the results of this research are expected to significantly contribute to the development of automation systems that can help improve efficiency and productivity in the agricultural industry, especially in coffee fruit production. Image processing can be used to identify fruit ripeness. Using captured images, Arif Patriot found a way to identify the ripeness of mango fruit by using GLCM and LAB colour value features, each of which has an accuracy of 62.5% [1]. The GLCM value is a grayscale-level co-occurrence matrix consisting of features such as contrast, correlation, energy, and homogeneity of the grayscale image. LAB values are the average colour value standard deviation. KNN is used to classify the maturity of mango fruit [1].

Another research related to image processing and pattern recognition is identifying the maturity of the manalagi mango fruit [2], where the image used is manalagi fruit, which is classified into three classes: 38 ripe mangoes, 12 semi-ripe mangoes, and 50 unripe mangoes. The identification is based on the input image being prepared, the equalisation histogram being created, and the standard deviation feature being retrieved. In the last step, identification or classification is done using Euclidean distance with 84% accuracy[2]. Based on the background explained by utilising several advances in deep learning architecture to maximise the computational process, this study uses the VGG-19 architecture to detect fruit ripeness. The dataset used is taken from Kaggle, which amounts to 600 images.

2. METHOD

Figure 2.1 Flow of crips dm method This research will produce a model to detect the maturity of coffee fruit; the data used is taken from Kaggle, which is then divided into training data and testing data.

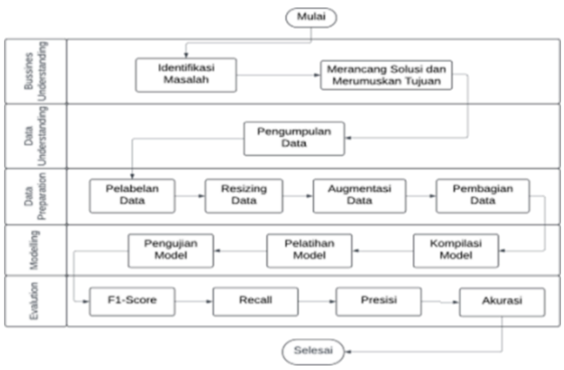

Figure 1. Research Methodology

This research focuses on improving the quality and consistency of fruit ripeness detection, which can reduce the risk of errors in the fruit sorting and distribution process. To achieve this research, an algorithm is used to perform classification, namely the CNN (convolutional neural network) algorithm. The results of this classification will later notify the user that the fruit is included in the category of not ripe, young ripe, or ripe.

3. RESULT AND DISCUSSION

Tests were carried out with variations in division ratios of 90:10, 80:20, 70:30, 60:40, 50:50:

Table 1. Testing Results

Ratio	Accuracy	Precision	Recall	F1-Score
90:10	83%	84%	83%	83%
80:20	86%	86%	86%	86%
70:30	83%	83%	83%	82%
60:40	85%	84%	85%	85%
50:50	84%	84%	84%	84%

The same image size is 224xx224 px and has hyperparameters, including batch size and epoch. This aims to measure the overall performance of the model under different conditions. Based on the explanation above, from the tests that have been carried out, it can be concluded that the best model performance in detecting the ripeness of coffee fruit in tests with a ratio of 80:20 using a variation of image size 224x224 px, batch size 16, epoch 30. obtained accuracy results of 86%, 86% for precision value, 86% for recall value, and 86% for f1-score value. CNN models with VGG-19 architecture can classify quite well.

4. CONCLUSION

Based on the training and testing modelling results, the Convolutional Neural Network algorithm using VGG-19 architecture is successfully applied to detect the maturity of coffee fruit. The research was conducted using variations in the ratio of the division of test data and training data with a division ratio of 90:10, 80:20, 70:30, and 60:40. After testing in research using a confusion matrix to evaluate test results. After evaluation, it was found that the test with the best performance had a ratio of 80:20 with an image size of 224x224, batch size 16, and epoch 30. The model has achieved an accuracy value of 86%, precision of 86, recall of 86%, and f1-score of 86%.

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