# Classification of Melinjo Fruit Ripeness Using a Convolutional Neural Network (CNN) Based on Digital Images

**Anggi Ade Kurniawan[1]*, Setyoningsih Wibowo[2]*, Nur Latifah Dwi Mutiara Sari[3]***
* Informatika, Universitas Persatuan Guru Republik Indonesia Semarang
kurniawananggi392@gmail.com [1], setyoningsihwibowo@upgris.ac.id [2], nurlatifah@upgris.ac.id [3]

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**ABSTRACT**

The subjective and ineffective manual sorting of melinjo fruit, a key ingredient in Indonesian cuisine, results in inconsistent quality. This study aims to create and evaluate an automated classification system for judging the ripeness of Gnetum gnemon fruit in order to solve these issues and offer a reliable and objective quality control method. The approach was to create a customized Deep Convolutional Neural Network (Deep-CNN). The model was trained and evaluated using a simple dataset of 5,718 images that were separated into three maturity levels: raw, semi-ripe, and fully ripe. Twenty percent of the dataset was used for testing, and the remaining 80 percent was used for training. Image preparation techniques like contrast enhancement and scaling to 250x250 pixels were applied in order to optimize the model's input data. The evaluation was conducted using a test dataset consisting of 1,144 photos. After eight epochs of training with the Adam optimizer, the generated Deep-CNN model demonstrated remarkable efficacy with a final classification accuracy of 99.91%. The high level of performance that remained throughout the testing phase confirmed the model's strong ability to accurately identify the ripeness levels of melinjo fruit. The previously unresolved issue of automated melinjo classification is addressed in this work with a tailored and remarkably accurate (99.91%) solution. Its primary advantage is that it provides a trustworthy and unbiased technical alternative to subjective hand sorting. This directly meets industry needs by offering a scalable method to improve operational effectiveness, standardize product quality, and increase the commercial value of melinjo fruit of agricultural products.



## I. Introduction

The melinjo plant (Gnetum gnemon L.) makes a substantial contribution to the Indonesian economy, especially through its most well-known processed product, emping (Gnetum Gnemon Chips) [1]. Emping's flavor, color, and crispiness are all greatly influenced by the ripeness of the melinjo seeds used as raw materials [2]. Currently, the majority of the methods used to classify seeds based on their level of maturity are manual and have significant drawbacks [3]. With categorization accuracy relying on each worker's visual perception and experience, this process is not only time-consuming and labor-intensive but also highly subjective, potentially leading to inconsistent final product quality [4].

Numerous problems facing the agriculture sector could potentially be automated with the help of Convolutional Neural Networks (CNN) and other advancements in computer vision technology [5]. CNN is particularly helpful for classification tasks because of its ability to automatically extract complex visual information directly from images [6]. Numerous studies have effectively employed CNN to precisely assess the level of ripeness of a range of fruit commodities, such as bananas [7], tomatoes [8], oranges [9] and coffee [10]. These findings demonstrate that CNN is a highly reliable method for classification applications based on agricultural images.

Melinjo is a commercially important product in Indonesia, and its quality is heavily influenced by the fruit's ripeness.

However, traditional manual sorting techniques are inefficient and subject to subjective errors. Numerous studies have successfully used Convolutional Neural Networks (CNN) to automate the ripeness classification of various fruits, including oranges, tomatoes, and bananas, often with high accuracy. Studies specifically addressing the application and improvement of this method for melinjo maturity classification (Gnetum Gnemon) fruit are still scarce, though. This research gap highlights the possibility of applying well-proven technical solutions to a unique, economically significant, but little-known local problem. This research gap highlights the possibility of applying well-proven technical solutions to a unique, economically significant, but little-known local problem. This work aims to design, build, and evaluate a particular CNN model for automatically classifying the ripeness of melinjo fruit using digital photographs. The study's objectives were to develop a CNN model specifically for this task, apply it to a functional prototype with a graphical user interface (GUI), and assess the system's performance quantitatively to validate its suitability for demonstrates its potential applicability for industrial fruit sorting systems.

Unlike many previous studies that focus on commonly investigated fruits, this research specifically addresses the ripeness classification of melinjo fruit (*Gnetum gnemon*), a locally significant agricultural commodity in Indonesia that has received limited attention in computer vision–based studies. The novelty of this work lies not in proposing a new algorithm, but in the application of a tailored Convolutional Neural Network (CNN) architecture combined with a practical MATLAB-based graphical user interface (GUI) to support objective, automated, and scalable ripeness assessment. Furthermore, the dataset used in this study was collected as primary data under controlled conditions, providing a reliable empirical basis for evaluating the effectiveness of CNN-based classification for melinjo fruit.

## II. METHODS

According to the flowchart, this study uses a CNN architecture with three convolutional blocks. The Deep-CNN structure undergoes three successive cycles of Convolution, Batch Normalization, ReLU activation, and Max Pooling operations during model training. After these iterations, the network uses Fully Connected layers and Softmax activation to complete the final classification, producing a Classification Output.


Figure 1. Flowchart of the proposed model

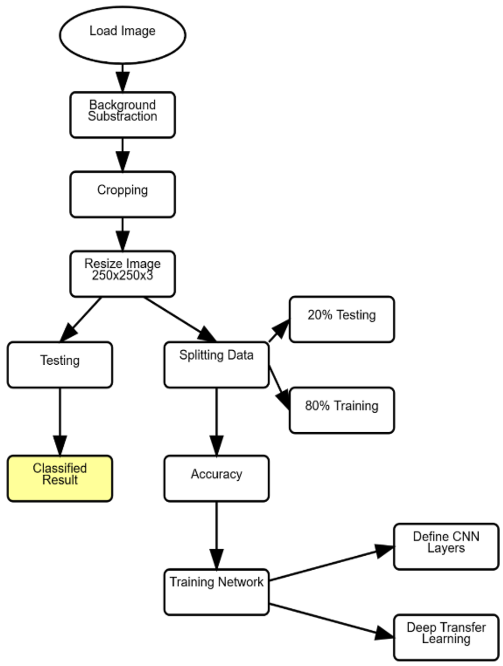


Figure 2. Methods

The dataset is then preprocessed using background subtraction and image segmentation techniques to obtain consistent background features [11]. The processed data is then cropped and resized to ensure optimal data clarity. The dataset is split into 80% training data and 20% testing data for the subsequent training phase, which entails processing through CNN (Define Transfer Layers) layers and developing a defined architecture [12].

The CNN architecture is composed of a series of layers, including a convolutional layer ('convolution2dLayer'), a max-pooling layer ('maxPooling2dLayer'), a ReLU activation function ('reluLayer'), and a batch normalization layer ('batchNormalizationLayer'). The final classification stage combines softmax activation and fully connected layers, as shown in Figure 2. Network training uses the train network function, which processes the training images by combining the training data, the designated layers, and the designated parameters. During the accuracy evaluation phase, the trained network classifies the validation dataset using a classification function. The accuracy level is ascertained by comparing the predicted labels (Predd) and the actual labels (Valid). The accuracy percentage obtained in the MATLAB user interface is then displayed by the set function. The trained model's output is then exported to facilitate the classification of new input data. The same preprocessing methods, like cropping and resizing adjustments, are applied to new test data to guarantee consistency with the training data set.

### *A. Data Collection*

A compilation of 5,718 sample melinjo fruit image files in the 250 × 250 x 3.jpg format. This image dataset is divided into three classes: 1,920 images of melinjo fruit that is immature, 1,890 images of melinjo fruit that is half-ripe, and 1,908 images of melinjo fruit that is fully ripe. The dataset used in this study was collected directly by the author as primary data. A total of 4,574 images were used to train a model designed to classify melinjo fruits according to their color characteristics and maturity stage. 1,144 images were used to further test the model's ability to correctly identify novel fruits that it had never seen before. This dataset further allows the determination of accuracy values that affect the classification results for the ripeness level of melinjo fruit.

### *B. Pre-processing*

The obtained image data is then subjected to pre-processing to improve the quality of the original image [13]. This pre-processing stage aims to optimize the results of subsequent processing stages. Other actions include the following:

1) RGB image cropping is used to alter the center of the melinjo fruit object in order to make the image in the dataset more consistent and focused. This cropping process was done by hand to ensure that the fruit was positioned correctly in the frame.
2) A crucial stage in image processing is resizing, which modifies a picture's size to meet specific specifications. Three color channels (red, green, and blue) and a consistent size of 250 pixels wide by 250 pixels tall were used to create photographs of melinjo fruit to help with classification. This step is essential for image processing and machine learning because it guarantees that the images are in the right format for models that use convolutional neural networks. The images are resized for training purposes and can be used to evaluate the freshness of the fruit.

### *C. Data Augmentation Strategy*

To improve the robustness and generalization capability of the proposed CNN model, data augmentation was applied during the dataset preparation stage. Data augmentation aims to artificially increase the diversity of training samples by introducing controlled variations that simulate real-world conditions. In this study, image augmentation was performed offline using MATLAB functions prior to the training process.

The augmentation techniques included random rotation within a range of −20° to +20°, horizontal flipping, random scaling between 0.8 and 1.2, and random horizontal and vertical translations within ±10 pixels. These transformations were selected to preserve the essential visual characteristics of melinjo fruit while introducing variations in orientation, size, and position.

It is important to note that data augmentation was applied exclusively to the training dataset, while the validation and testing datasets remained unchanged. This strategy was adopted to prevent data leakage and to ensure that the evaluation results reflect the model's true generalization performance on unseen data.

### *D. Extraction Features*

Melinjo fruit's level of maturity is classified using the Convolutional Neural Network (CNN) algorithm, and an image feature extraction process is carried out. [14]. These features give the melinjo fruit images a clear representation, which CNN uses to classify them. The program examines a variety of statistical values, such as mean, variance, kurtosis, minimum, standard deviation, entropy, skewness, and maximum, in order to analyze the data. To help understand the brightness level, degree of variation, pixel arrangement, and overall shape of the image, each of these numbers represents a different feature of the pixel brightness distribution [15]. The standard deviation shows how much the brightness varies, while the mean value shows how bright the melinjo fruit photos are on average. While kurtosis and skewness reveal details about the structure of the brightness distribution, entropy shows how complex the image is. The minimum and maximum values indicate the image's lowest and highest brightness levels. These statistical features are presented for descriptive analysis of image characteristics and dataset interpretation, while the CNN model performs end-to-end feature learning directly from raw image data.

Statistical features are computed using the following formula:

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

1) *Mean*, Calculated using the standard arithmetic mean formula, where $N$ represents the total number of dataset elements and $X_i$ shows each element value.

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

2) *Varians*, measure the spread of data by using a formula that combines N(dataset size), $X_i$, (individual element values) and M (data group average).

$$std = \sqrt{\frac{\sum_{i=1}^{n} (X_i - M)^2}{N}} \tag{3}$$

3) *Standard Deviation*, determines the distribution of data by taking the square root of the variance, utilizing N(dataset size), $X_i$ (element value), and M (the mean of the data set).

$$k = \frac{\sum_{i=1}^{n} (X_i - M)^4}{N \times std^4} \tag{4}$$

4) *Kurtosis*, assesses the distribution shape using a formula that includes N (dataset size), $X_i$, (element value), M (the average of the data group), and S (standard deviation).

$$Min = \min(x_1, x_2, \ldots, x_i) \tag{5}$$

5) *Minimum* value identifies the smallest element in a dataset, where $N$ represents the size of the dataset and $X_i$ represents each element value.

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

6) *Entropy calculations measure*, information content using a formula that involves $N$ (number of possible values), $X_i$(pixel intensity value), and $PX_i$(probability of occurrence for each value).

$$skewness = \frac{\sum_{i=1}^{n} (X_i - \bar{X})^3}{N \times S^3} \tag{7}$$

7) Skewness, evaluates distribution asymmetry using parameters including $N$ (dataset size), $X_i$ (data value), $X$ (average data), and S (standard deviation).

$$Max = \max(x_1, x_2, \ldots, x_i) \tag{8}$$

8) *Maximum value calculations identify*, the largest element in a dataset, where $N$ represents the size of the dataset and $X_i$ represents each element value.

### *E. Classification Convolutional Neural Networks*

The categorization of fruit maturity stages is the main emphasis of the system's design. Convolutional neural networks, or CNNs, are a particular kind of artificial neural network designed to work with images and carry out operations like processing and analysis [16][17]. CNN's exceptional ability to identify intricate visual patterns in photographs makes it ideal for image processing tasks like determining the freshness of melinjo fruit. In this case, CNNs serve as machine learning models that can recognize and distinguish between color, texture, and other visual attributes that change as melinjo fruit ripens [18].

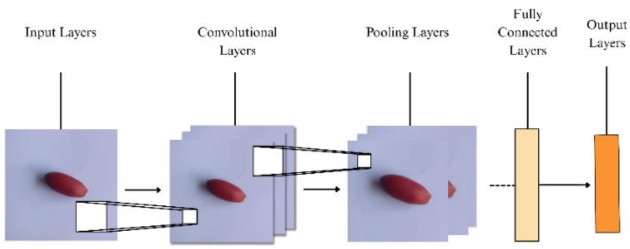


Figure 3. Proposed CNN Structure

Figure 3 shows that the first convolutional layer is responsible for identifying the melinjo fruit image's basic features, such as edges and lines[19]. The activation layer introduces non-linearity by activating neurons based on the patterns discovered. The pooling layer is crucial to this process because it reduces image resolution without sacrificing crucial details like the texture and shape of the melinjo fruit. Convolutional layers get better at identifying finer details as they develop, like the melinjo fruit peel's texture and surface patterns. In this sequential process, each layer builds on the one that came before it. Sometimes dropout layers are used to prevent the model from becoming too obsessed with specific details. In the end, a fully connected layer takes the features it has learned and connects them to neurons, which then produce results that tell us the ripeness of the fruits.

The proposed classification system employs a Convolutional Neural Network (CNN) architecture designed to directly process RGB images of melinjo fruit with a fixed input size of 250 × 250 × 3 pixels. The network consists of three convolutional blocks, each composed of a convolutional layer, batch normalization, and a ReLU activation function. Max-pooling layers are applied after the first and second convolutional blocks to progressively reduce spatial dimensions while preserving discriminative features.

The convolutional layers use 3 × 3 kernels with an increasing number of filters (8, 16, and 32) to capture low-level to mid-level visual features such as edges, color transitions, and texture patterns related to fruit ripeness. Batch normalization is employed to stabilize the learning process and improve convergence. The extracted features are then passed to a fully connected layer followed by a softmax activation function to produce the final classification output across the predefined ripeness categories.

TABLE I
CNN ARCHITECTURE

| Layer | Type | Kernel / Units | Output Description |
|---|---|---|---|
| Input | Image Input | 250 × 250 × 3 | RGB Image |
| Conv1 | Convolution | 3 × 3, 8 filters | Feature extraction |
| BN1 | Batch Normalization | – | Training stabilization |
| ReLU1 | Activation | – | Non-linearity |
| Pool1 | Max Pooling | 2 × 2 | Spatial reduction |
| Conv2 | Convolution | 3 × 3, 16 filters | Deeper features |
| BN2 | Batch Normalization | – | Normalization |
| ReLU2 | Activation | – | Non-linearity |
| Pool2 | Max Pooling | 2 × 2 | Dimensionality reduction |
| Conv3 | Convolution | 3 × 3, 32 filters | High-level features |
| BN3 | Batch Normalization | – | Normalization |
| ReLU3 | Activation | – | Non-linearity |
| FC | Fully Connected | 3 units | Ripeness classes |
| Softmax | Softmax | – | Probability output |
| Output | Classification | – | Final class |

### F. Accuracy Evaluation

Accuracy is a commonly used baseline metric to assess how well a method's classifications or predictions correspond to the actual ground truth data. System performance is evaluated and cross-study comparisons using different methodologies are provided by accuracy computations. Comparing various research strategies that use different methods is made easier as a result. This statistic provides a performance benchmark, encourages informed decision-making, and increases confidence in model results for melinjo fruit maturity assessment. When dealing with differences in mistake categories or class imbalance, accuracy may have disadvantages despite its simplicity. To assess model effectiveness, facilitate cross-study comparison, and advance research on melinjo fruit categorization systems, accuracy is still essential.

## III. Result and Discussion

The photographs of melinjo fruit that made up the study's dataset were gathered by the author. Three classes were created from the collected photos of 5,718 melinjo fruit samples: 1,920 immature melinjo fruits, 1,890 half-ripe melinjo fruits, and 1,908 fully ripe melinjo fruits. The dataset, which was divided into training and test data, contained 1,144 test data points and 4,574 training data points. Both training and test data were used to train the CNN model for melinjo fruit ripeness classification.

The dataset was preprocessed after it was compiled, taking into consideration its volume. Three color channels (RGB) were added during preprocessing, and the original images were resized to a constant 250 x 250 x 3 pixel size. Image enhancement was then used to increase the contrast of the original photos. Contrast enhancement attempts to make images sharper, clearer, and more recognizable by emphasizing the differences between the image's different brightness levels. The CNN method was then used to categorize the melinjo fruit's maturity levels.

TABLE II
MATURITY LEVEL OF EACH CLASS

| Picture | Melinjo Maturity Level | Information |
|---|---|---|
|  | Unripe Melinjo | Young melinjo fruit has green skin with a hard and dense texture. |
|  | Half-ripe Melinjo | The skin of half-ripe melinjo fruit has a yellowish green color with a slightly softer texture compared to unripe melinjo fruit. |
|  | Ripe Melinjo | Perfectly ripe melinjo fruit is reddish brown in color with a soft and tender texture all over the surface of the fruit. |

As indicated in Table 2, the original melinjo fruit image's input image in.jpg format was resized before being subjected to a contrast enhancement technique to increase image clarity. The CNN approach is used by the algorithm to categorize the melinjo fruit's level of ripeness. As demonstrated in Table 3, the feature extraction technique yields a more concise numerical representation of picture data, emphasizing the salient characteristics of the image of melinjo fruit.

TABLE III
EXTRACTION FEATURES

| Melinjo Class | Mean | Variance | Kurtosis | Standard Deviation | Entrophy | Skewness | Min | Max |
|---|---|---|---|---|---|---|---|---|
| Unripe_melinjo | 161.16 | 3650.14 | 2.83492 | 60.416426 | 5.430057 | -1.863840 | 0 | 253 |
| halfripe_melinjo | 159.05 | 2975.65 | 5.12432 | 54.549583 | 5.296077 | -2.191477 | 0 | 240 |
| ripe_melinjo | 152.51 | 3304.52 | 3.01474 | 57.484981 | 5.362829 | -1.896352 | 0 | 240 |

Finding, calculating, and collecting distinguishing features in an image is part of feature extraction functionality in image processing. Feature extraction attempts to reduce image complexity by transforming visual data into a more straightforward representation where important information is captured through distinguishing features. Many image analysis programs, machine learning models, and classification techniques then use these gathered features as input.

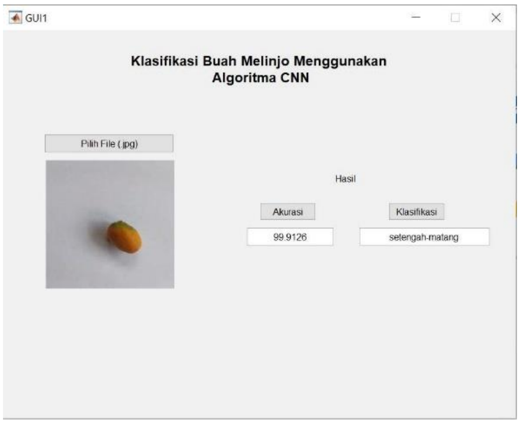


Figure 4. Melinjo Fruit Ripeness Classification GUI

The model trained using MATLAB R2022a software achieved 99.91% accuracy in classifying the ripeness of melinjo fruit. The GUI interface in Figure 4 illustrates how the training process accurately classified half-ripe melinjo fruit samples. Although classification accuracy was used as the primary evaluation metric in this study, it remains a widely adopted performance indicator in image-based classification tasks, particularly when the dataset is relatively balanced across classes. In the presented dataset, the number of samples for each ripeness category is comparable, reducing the risk of biased accuracy measurements.

The use of additional metrics such as precision, recall, F1-score, and confusion matrix analysis can provide more detailed insights into class-wise performance. However, given the extremely high accuracy achieved and the balanced class distribution, overall accuracy serves as a sufficient indicator of the model's effectiveness at this stage. Future studies may extend the evaluation framework by incorporating more comprehensive performance metrics to further analyze classification errors and decision boundaries.

TABLE IV
SAMPLE RESULT OF CLASSIFICATION OF MELINJO RIPENESS

| **Image Name** | **Real Name** | **Classification Name** | **True/False** |
|---|---|---|---|
| **Image Name** | **Real Name** | **Classification Name** | **True/False** |
| 1.jpg | Unripe Melinjo | Unripe Melinjo | True |
| 4.jpg | Unripe Melinjo | Unripe Melinjo | True |
| 17.jpg | Half-ripe Melinjo | Half-ripe Melinjo | True |
| 24.jpg | Half-ripe Melinjo | Half-ripe Melinjo | True |
| 42.jpg | Ripe Melinjo | Ripe Melinjo | True |
| 98.jpg | Ripe Melinjo | Ripe Melinjo | True |

With a 99.91% accuracy level, the Training Model produced classification results that we tested six times using different image sources, resulting in six correct answers or a 100% correct value. Figure 5's training progress visualization demonstrates the model's performance with the Adam optimization function, MaxEpochs 8, and MiniBatchSize 8. The experimental results demonstrate that the proposed CNN model achieved a high classification accuracy of 99.91% on the validation dataset. This performance indicates that the model successfully learned discriminative visual features associated with different ripeness stages of melinjo fruit, particularly color distribution and surface texture.

The high accuracy can be attributed to several factors, including the use of batch normalization, an appropriate input resolution, and data augmentation techniques that enhance model generalization. Nevertheless, the possibility of overfitting cannot be entirely excluded, given the relatively controlled imaging conditions and the limited number of training epochs. However, the consistency between training and validation accuracy curves suggests that the model maintains stable learning behavior without significant divergence.

Misclassification cases, although rare, predominantly occur between the half-ripe and fully ripe categories, which share similar visual characteristics. This observation aligns with human perception challenges in distinguishing intermediate ripeness stages and highlights potential areas for further refinement of the classification system.

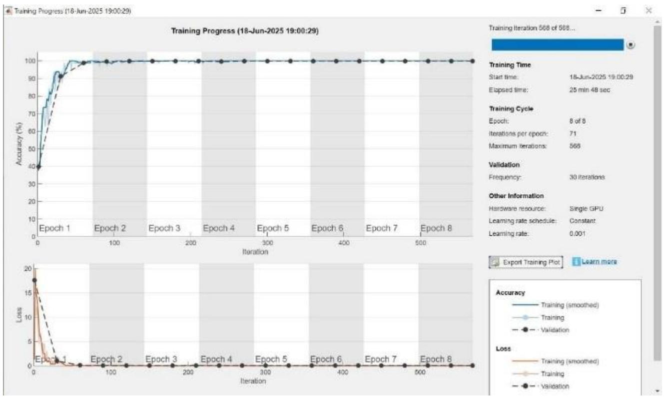

Figure 5. Training Accuracy and Loss

Variations in categorization outcomes frequently reflect the accuracy and dependability of the model in identifying different melinjo ripeness levels. Improving training accuracy greatly increases the model's efficacy in classifying melinjo ripeness. As a result, the findings show that the model can distinguish between ripeness stages according to the dataset's visual characteristics. Outstanding accuracy was the outcome of the training program's outstanding success.

CNN is an advanced image processing technique that can automatically extract valuable information from input images. Its strength in feature extraction is attributed to its ability to directly learn hierarchical representations from images of unripe melinjo fruit [20]. They are very successful at classifying melinjo fruit because they are able to identify and extract significant characteristics and patterns from the data. The study looked at the performance of the classification stage in addition to feature extraction. In the discussion that follows, Table 3 displays the results of the previously mentioned test. The system demonstrated a high degree of accuracy in the classification tests. This indicates a 99.91% accuracy rate for the measurement. Additionally, the CNN accuracy produced during the testing phase is routinely used to generate percentage accuracy numbers. The CNN accuracy produced during the testing phase also consistently generates percentage accuracy values. The training system for melinjo fruit ripeness classification demonstrated an accuracy of approximately 99%, as indicated by the CNN.

The website-based information system that outlines the implementation of this research system includes an overview of the study, the research findings, and the stages of the research process carried out in the Matlab program. This website aims to make it easier for readers to understand the benefits and performance studies of running. The Melinjo fruit ripeness classification research webpage's main display looks like this:

Home Page

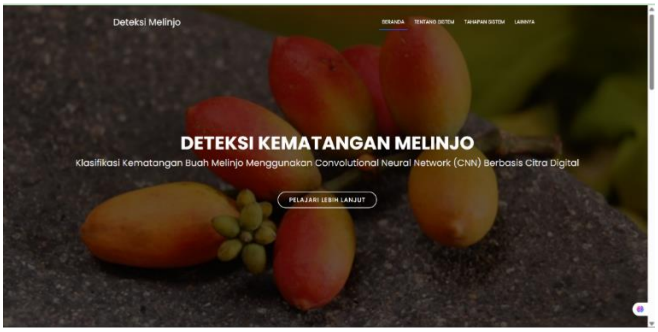

Figure 6. Website Homepage

This page contains information about the features and specifications of this research, explaining the research title, the software used, and the catagories of the melinjo fruit ripeness clasification results.

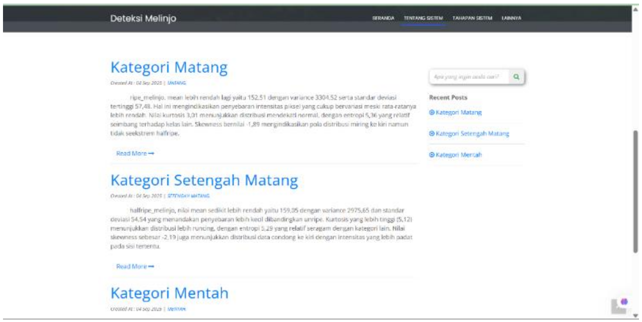

Figure 7. About the System Page

This page contains an explanation of the categories of melinjo ripeness classification processed in this study. Readers can see the numerical classification results from the training results in Matlab, which are summarized into descriptive paragraphs as shown in Figure 7.

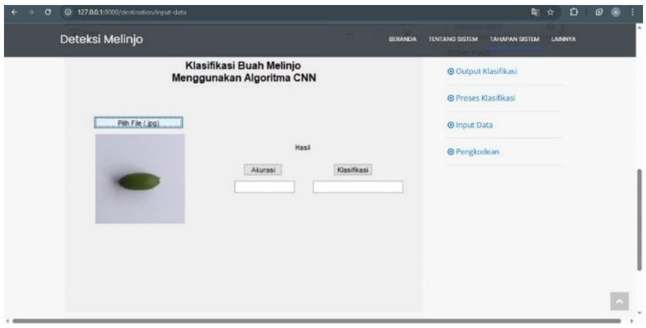

Figure 8. System Stage Page

This page contains the steps taken by researchers in classifying melinjo fruit using the available data set, starting from coding to set the rules, logic, and system indicators, inputting the data set, and waiting for the classification process to complete.

Despite the promising results, this study has several limitations. First, the dataset was collected under relatively controlled conditions, which may not fully represent the variability encountered in real industrial environments, such as changes in lighting, background complexity, and fruit orientation. Second, the validation strategy relied on a single hold-out data split (80:20), which, while commonly used, may limit the strength of generalization claims.

Future research may address these limitations by incorporating cross-validation strategies, evaluating the system under real-time industrial conditions, and extending the proposed approach to other agricultural commodities or melinjo varieties. Additionally, integrating the model into edge-based or embedded systems could further enhance its practical applicability in automated fruit sorting processes.

Another limitation of this study is the reliance on a single evaluation metric and a hold-out validation strategy. While this approach provides a clear and interpretable performance measure, it does not fully capture class-specific misclassification patterns. Future research will focus on integrating confusion matrix analysis, precision, recall, and F1-score metrics, as well as cross-validation schemes, to strengthen the robustness and interpretability of the evaluation process.

## IV. CONCLUSION

A substantial dataset of 5,718 Melinjo images with a resolution of 250 × 250 x 3 pixels was used for this investigation. Based on the degree of maturity, the photos were carefully divided into three groups: fully ripe, partially ripe, and unripe fruit. A remarkable 99.91% success rate was attained in the sample testing that was conducted. The study presented a classification framework that uses a Convolutional Neural Network (CNN) to evaluate the ripeness of melinjo fruit based on color. Image preprocessing techniques that highlight pixel intensity and detail variations and improve contrast were used to support the model. According to the findings, this methodology produced an accuracy rate of 99.91%.

The results showed that this methodology yielded a 99.91% accuracy rate. The study's findings are anticipated to have a significant impact on the agricultural sector, potentially altering the handling and sorting of melinjo fruit products. The efficiency of distribution networks and the establishment of higher standards of quality for end users could both be enhanced by the ability to swiftly and precisely assess the maturity levels of melinjo fruits. This capability helps to enhance the agricultural industry overall in addition to making it simpler for the industry to process and sell melinjo fruits.

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