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Implementation of Convolutional Neural Network (CNN) Method in Determining the Level of Ripeness of Mango Fruit Based on Image

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Abstract: This study aims to classify the ripeness level of mango fruit using a Convolutional Neural Network (CNN) model based on digital images. This classification is important to help the automatic sorting process in the agricultural industry that relies on accuracy in determining fruit quality. Based on the literature review, CNN has been widely used in image-based object recognition because of its ability to extract visual features automatically. Previous studies have shown that CNN is effective in image classification, but the results are highly dependent on the quality of the data and the model parameters used. This research method involves collecting mango fruit images at three levels of ripeness (raw, half-ripe, ripe), which are then processed and analyzed using the Orange application with CNN architecture. Model evaluation was carried out using accuracy metrics, AUC, confusion matrix, and visualization through box plots and scatter plots to see the distribution and differences in data between classes. The results showed that the CNN model obtained an accuracy of 53.3% and an AUC value of 0.717, which indicates the model's initial ability to distinguish ripeness categories but with a fairly high level of misclassification. There is still overlapping data between classes, especially between the raw and half-ripe classes, which indicates the need for additional features and parameter refinement. In conclusion, CNN has the potential to be used in classifying the ripeness level of mango fruit, but its performance can be improved through feature development and deeper model tuning.

Keywords: Digital Image; Colour Image; Convolutional Neural Network; Model Evaluation; Mango Ripeness.

Introduction

Mango fruit is one of the tropical horticultural commodities that has high economic value and is very popular with the community, both in Indonesia and in various other countries (Bini et al., 2024; Kiloes et al., 2023). Its distinctive sweet and fresh taste makes mango the main choice as a fruit for direct consumption, as well as a basic ingredient in various processed foods and beverages. Indonesia as an agricultural country has many local mango varieties spread across a number of regions, one of which is Indramayu Regency which is known as a high-quality mango producing area. With supportive soil and climate conditions, mango production from this area is not only able to meet the needs of the domestic market, but has also reached the international export market (Tengsetasak et al., 2024). The superiority of mango in terms of taste quality, skin color, flesh texture, and aroma is the main attraction in the global market (Kiloes et al., 2022). In the context of the fruit industry and distribution, one very crucial aspect is sorting or classification based on the level of fruit ripeness. The level of ripeness of the mango greatly affects the quality and taste, so it is important to ensure

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that the fruit sent or marketed is in optimal condition (Ayyaz et al., 2023; Gelaye, 2024).

However, determining the ripeness of the mango accurately is still a challenge, especially when done on a large scale (Islam et al., 2025; Zhang et al., 2025). Manual assessment commonly carried out by farmers and traders relies on visual observations such as changes in skin colour, fruit aroma, and surface texture (Nayak et al., 2023). Unfortunately, this method has limitations because it is highly dependent on the subjectivity of observers and individual experience, and can cause inconsistencies in the assessment results.

The main problem faced in manual classification of mango fruit ripeness is the low efficiency and accuracy, especially when dealing with large volumes of fruit in a short time (Worasawate et al., 2022). In practice, each fruit must be observed one by one, which of course takes time and effort, and increases the potential for errors in classification. In addition, the absence of standard standards that can be followed by all observers causes the results obtained to vary greatly. Errors in determining the level of ripeness can result in losses in distribution and marketing, such as fruit that rots before reaching consumers or fruit that is not ripe enough for consumption. This encourages the need for technology-based solutions to replace manual methods that are no longer adequate.

Digital image processing technology and artificial intelligence now provide great opportunities to overcome these problems. One approach that is increasingly popular is the use of the Convolutional Neural Network (CNN) method, which is part of the Deep Learning technique in the Artificial Intelligence domain (Thaseentaj & Ilango, 2023). CNN is specifically designed to automatically recognize visual patterns and features from images, such as colour, shape, and texture (Bianconi et al., 2021). This method has been widely used in the fields of object recognition, face detection, and fruit and vegetable classification based on images. The advantage of CNN lies in its ability to extract visual features hierarchically and adaptively without requiring a complicated manual coding process (Hindarto, 2023; Marpaung et al., 2023; Shabir et al., 2025). Therefore, CNN is very suitable for use in this study which aims to classify the ripeness level of mango fruit through the image of its skin. Although many studies have implemented CNN in fruit classification, there are still few studies that apply it practically through a visual platform without programming such as Orange.

Orange is a graphical user interface (GUI)-based application designed to make it easier for users to analyze data and apply machine learning models without having to write code manually (Lim et al., 2022). This platform is very friendly for beginners, academics, and small and medium industry players who want to apply artificial intelligence technology on a limited scale (Osipyan et al., 2022). By utilizing the drag and drop features in Orange, users can build analysis pipelines, train models, and evaluate performance easily and quickly. The combination of the power of CNN and the ease of Orange opens up new opportunities in the application of fruit ripeness classification technology (Ibtissam, 2024). This study aims to develop an automatic classification system for the ripeness of mango fruit using the CNN method implemented in the Orange application. This system is designed to identify the ripeness of mangoes based on the visual characteristics of the fruit skin, such as dominant color, color gradation, and surface texture. The dataset used is in the form of mango fruit images categorized into three levels of ripeness, namely ripe, half-ripe, and unripe. These images are analyzed through preprocessing stages such as resizing and normalization, then processed by the CNN model built in Orange. The results of the model training are then evaluated to measure classification performance based on parameters such as accuracy and confusion matrix.

The implementation of CNN in the Orange application not only simplifies the system development process, but also speeds up the testing and validation process of the classification model (Dhiman et al., 2023). The analysis stages are carried out systematically, starting from the initial processing of image data, dataset division, model training, to evaluation of classification results. In Orange, this process is carried out by compiling nodes such as Image Embedder, Neural Network, Test & Score, and Confusion Matrix in one integrated workflow. Each stage provides visualization and numerical results that help researchers understand the performance of the model being built. The classification results obtained are then compared with the actual data to determine how well the model recognizes fruit ripeness.

The advantage of this approach lies not only in the accuracy of the classification results, but also in the speed and efficiency of data processing. Compared to manual methods, the CNN-based system in Orange is able to process images automatically and provide classification output in just seconds. This is very useful for agricultural business actors or fruit distributors who need a fast and consistent solution in sorting fruit according to ripeness. In addition, the implementation of this system can also increase the competitiveness of horticultural products in the national and international markets, because product quality can be maintained better.

With this research, it is expected to create a classification model that is not only accurate but also easy to implement by various groups. This model can be used as a tool in the process of sorting and distributing mangoes that is more efficient and reliable. Furthermore, this approach can be developed for other fruit varieties or integrated into a broader agricultural digitalization system. This research also shows that CNN technology and the Orange application have great potential in supporting the digital transformation of the agricultural sector, especially in improving the quality and efficiency of the fruit supply chain in Indonesia.

Method

Machine learning is a branch of artificial intelligence that allows computers to learn from data and make decisions or predictions without having to be explicitly programmed. In the context of this study, machine learning is used to teach the system to recognize visual patterns from images of mangoes based on their ripeness, such as skin color and texture. With the right algorithm, such as a Convolutional Neural Network (CNN), the system can be trained to automatically distinguish between ripe, semi-ripe, and unripe mangoes (Ma et al., 2024). This approach makes machine learning an effective and efficient solution to replace the manual methods that have been used to visually determine fruit ripeness.

Convolution Neural Network Method

Convolutional Neural Network (CNN) is a method in deep learning that is specifically designed to process data in the form of images. CNN works by recognizing visual patterns, such as color, shape, and texture, through a series of convolution layers that extract important features from the image. In the context of this study, CNN is used to classify the ripeness of mangoes based on their skin color images, which visually show the difference between unripe, semi-ripe, and ripe mangoes. With CNN's ability to detect and learn visual characteristics automatically, this method is very suitable for application in research that focuses on object identification based on digital images, such as in this case mangoes.

Classification Model

A classification model is a method in machine learning that is used to group data into certain categories based on the characteristics or features it has. In the context of this research, the classification model is used to identify the ripeness level of mangoes based on the analysis of fruit skin color images (Chen et al., 2020). By utilizing the Convolutional Neural Network (CNN) algorithm, this model can automatically learn visual patterns from mango images and determine whether the fruit is in the raw, half-ripe, or ripe category. The application of this classification model not only increases accuracy in the identification process, but also accelerates and simplifies the fruit selection process, especially on a large production scale in the agricultural sector or fruit distribution.

Research Stages

In this research, there are several stages of research that will be carried out, for the research stages are as follows Figure 1.

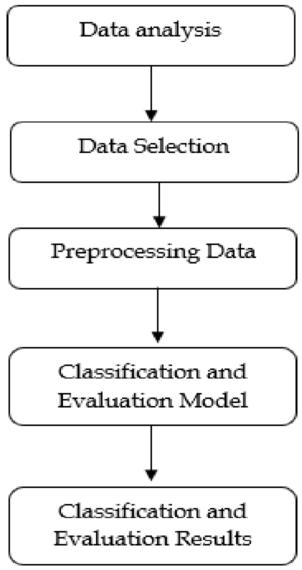


Figure 1. Research stage design

Confusion Matrix

Confusion Matrix is an evaluation tool in machine learning that is used to describe the performance of a classification model by showing the number of correct and incorrect predictions for each class. This matrix displays a comparison between actual and predicted values, making it easier to identify the level of accuracy and the types of errors that occur, such as prediction errors between classes. In this study, the Confusion Matrix was used to evaluate the ability of the CNN model to classify the ripeness level of mangoes into ripe, unripe, and semi-ripe categories visually and in a structured manner. There is a table for the confusion matrix that is the evaluation in this study, as shown in Table 1.

Table 1. Confusion Matrix is used to evaluate the capabilities of the CNN model.

Model	Acctual	
	Positive	Negative
Positive	True Positive (TP)	False Positive (FP)
Negative	False Negative (FN)	True Negative (TN)

Table 1 shows a confusion matrix that functions as an evaluation tool for the performance of the classification model built in this study. The matrix presents information about the number of mango data that were successfully classified correctly or misclassified into each ripeness class, namely ripe, unripe, and half-ripe. The rows in the matrix show the actual class of the data, while the columns show the predicted results of the model. By looking at the distribution of numbers in each cell, it can be seen how accurate the model is in recognizing each class, as well as identifying the most frequent error patterns. This evaluation is an important basis for assessing the effectiveness of the CNN method applied in processing mango images using the Orange application. In the Confusion Matrix there are also calculations to obtain accuracy, precision and recall results. The calculation Formula 1, 2, and 3.

$$Akuration = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

$$Presition = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

Result and Discussion

Data analysis is a very important initial stage in this study because it is the basis for understanding the characteristics of mango fruit images that will be used for the classification process. At this stage, researchers evaluate and observe image data based on ripeness level categories, such as ripe, unripe, and half-ripe, to ensure that each category has a balanced and relevant representation. This analysis also includes identifying visual attributes such as colour, size, and shape of the fruit that have the potential to be important features in the classification process using the Convolutional Neural Network (CNN) method. The results of this analysis will be a reference in determining the preprocessing strategy and data separation for optimal training and testing of the classification model.

Figure 2 illustrates a sample of mango fruit images used in this study to support the ripeness classification process. Each image represents one of three main categories, namely ripe, unripe, and half-ripe, which will later become the target of classification by the Convolutional Neural Network (CNN) model. The use of images as primary data aims to utilize visual features such as fruit skin colour, texture, and shape as indicators of ripeness that can be recognized by the system (Naranjo-Torres et al., 2020). These images were obtained with consistent lighting and shooting angles so that data quality is maintained and supports the model training process accurately. With these visual samples, the system can learn to recognize typical patterns from each ripeness category, which are then applied in the automatic classification process using the Orange application.

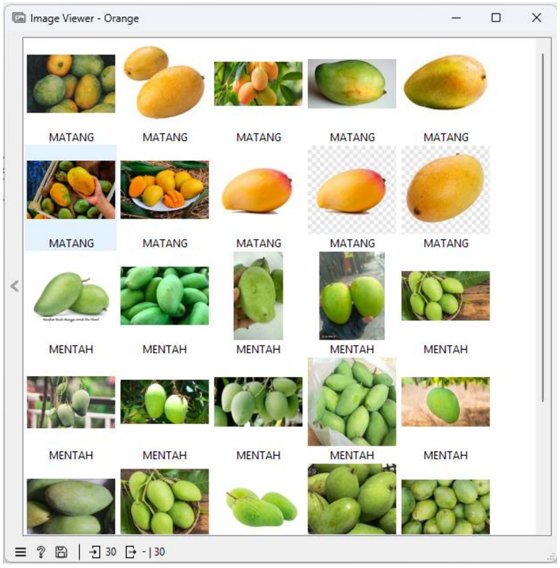


Figure 2. Display of data Convolutional Neural Network

Data Selection

Data selection is a very important initial stage in the process of classifying the ripeness level of mango fruit using the Convolutional Neural Network (CNN) method. At this stage, the selection of mango fruit images that have good visual quality and are able to clearly represent ripeness conditions, starting from the raw, half-ripe, to ripe categories (Alsirhani et al., 2023). Images that are blurry, blurry, have uneven lighting, or do not show the characteristics of a certain level of ripeness will be eliminated so as not to affect the results of model training. This selection process aims to ensure that the dataset used is truly relevant and informative for the machine learning system to be built. By using only valid and quality data, the CNN model can more easily recognize colour patterns, textures, and other visual features of each category of mango fruit. This will have a direct impact on the accuracy and consistency of the model in classifying, as well as minimizing the possibility of errors in predicting the level of ripeness when the model is implemented.

Data Preprocessing

Data preprocessing is an important stage in ensuring the quality of the dataset before training the classification model. In this study, the mango fruit images used as samples have gone through a selection process and visual inspection to ensure that the images have good resolution, sufficient lighting, and display visual features such as fruit skin colour clearly. These images do not experience distortion, blur, or noise that can interfere with model analysis. Thus, the dataset that has been collected is declared suitable for use and meets the standards for the classification process using the Convolutional Neural Network (CNN) method. This good data quality is the main foundation so that the model can learn optimally in recognizing and distinguishing the level of ripeness of mango fruit.

Classification Model Design and Evaluation

The design of the classification and evaluation model in this study was carried out by utilizing the Orange application, a GUI-based visual platform that facilitates the process of data mining and machine learning without the need for complex programming. In this process, the image of a mango that has gone through the preprocessing stage is entered into the Orange workflow, then the Convolutional Neural Network (CNN) algorithm is applied to form a ripeness level classification model. Furthermore, the model is evaluated using the Test and Score node and Confusion Matrix to measure its performance based on the parameters of accuracy, precision, recall, and classification error. This approach allows for efficient, easy-to-operate, and accurate analysis.

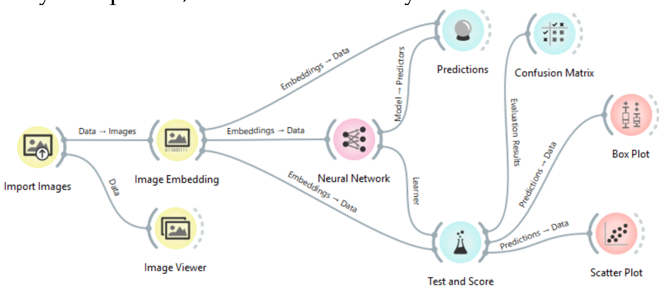


Figure 3. shows the design of the classification and evaluation model flow using the Orange application based on visual workflow.

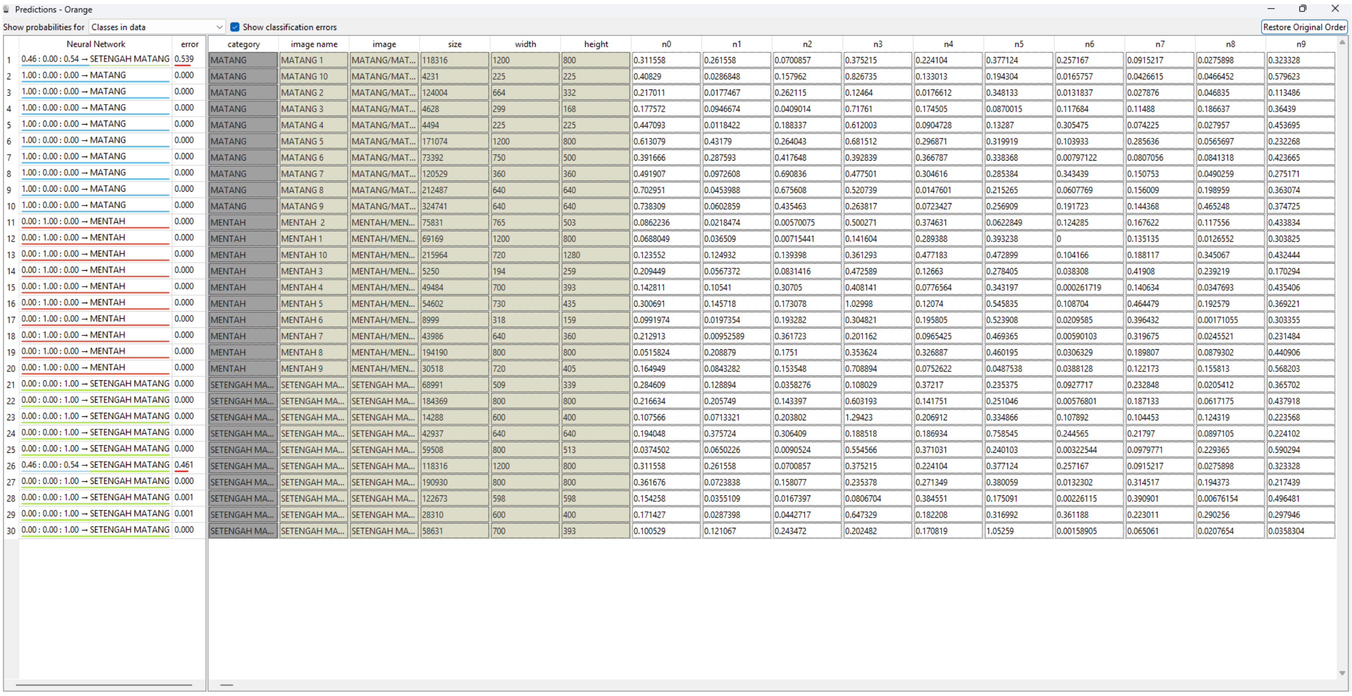
The process starts from the Import Images node which is used to import mango fruit images into the system. Furthermore, the Image Embedding node converts these images into numeric data (features) that can be processed by the machine learning model. To ensure image quality, the Image Viewer node can be used to display and verify image visualizations. The embedding data from the image is then sent to the Neural Network node which acts as a classification algorithm to learn patterns and produce a prediction model. This model is tested using the Test and Score node to measure its classification performance, including accuracy and other evaluation metrics. The Predictions node is used to display the results of the classification predictions performed by the model. The final evaluation results are visualized through three nodes: Confusion Matrix to see the accuracy of the classification in each class, Box Plot to display the distribution of evaluation scores, and Scatter Plot to illustrate the distribution of predictions between classes. This entire series helps in designing and assessing the effectiveness of the mango ripeness classification model visually and comprehensively.

Classification and Evaluation Results

Classification Results

The classification results show that the Neural Network model built using the Orange application is able to classify the ripeness level of mangoes into three categories, namely ripe, half-ripe, and unripe, with quite good performance. This model has gone through the training and testing stages, producing predictions that are then analyzed using a confusion matrix to assess the accuracy and level of classification error in each class.

Each row represents one processed fruit image data, with the "category" column showing the original label and the classification result column showing the model prediction. Predictions are classified into three classes, namely RIPE, HALF RIPE, and RAW. The error value listed shows the level of misclassification in each image, where most of the error values are 0.000, indicating that the prediction matches the original label. There are several predictions that have errors, such as in rows 1 and 26, which indicate misclassification by the model. In general, the classification results show that the model has good performance in recognizing and classifying the ripeness level of mango fruit based on images, with a high level of accuracy. Evaluation Results The evaluation results in this study were carried out using several methods to measure model performance comprehensively. First, the test and score method is used to measure the overall accuracy of the model in classifying test data. Furthermore, the confusion matrix provides a detailed description of the number of correct and incorrect predictions, making it easier to identify misclassification in each class. In addition, visualization using box plots helps in assessing the distribution and spread of data, as well as detecting outliers that may affect the model results. Finally, scatter plots are used to see data distribution patterns and relationships between variables, which can strengthen the understanding of model performance and data characteristics. This combination of evaluations ensures a more in-depth and valid analysis of the results.



	Neural Network	error	category	image name	image	size	width	height	n0	n1	n2	n3	n4	n5	n6	n7	n8	n9
1	0.46 : 0.00 : 0.54 → SETENGAH MATANG	0.539	MATANG	MATANG 1	MATANG/MAT...	118316	1200	800	0.311558	0.261558	0.0700857	0.375215	0.224104	0.377124	0.257167	0.0915217	0.0275898	0.323328
2	1.00 : 0.00 : 0.00 → MATANG	0.000	MATANG	MATANG 10	MATANG/MAT...	4231	225	225	0.40829	0.0286848	0.157962	0.826735	0.133013	0.194304	0.0165757	0.0426615	0.0466452	0.579623
3	1.00 : 0.00 : 0.00 → MATANG	0.000	MATANG	MATANG 2	MATANG/MAT...	124004	664	332	0.217011	0.0177467	0.262115	0.12464	0.0176612	0.348133	0.0131837	0.027876	0.046835	0.113486
4	1.00 : 0.00 : 0.00 → MATANG	0.000	MATANG	MATANG 3	MATANG/MAT...	4628	299	168	0.177572	0.0946674	0.0409014	0.71761	0.174505	0.0870015	0.117684	0.11488	0.186637	0.36439
5	1.00 : 0.00 : 0.00 → MATANG	0.000	MATANG	MATANG 4	MATANG/MAT...	4494	225	225	0.447093	0.0118422	0.188337	0.612003	0.0904728	0.13287	0.305475	0.074225	0.027957	0.453695
6	1.00 : 0.00 : 0.00 → MATANG	0.000	MATANG	MATANG 5	MATANG/MAT...	171074	1200	800	0.613079	0.43179	0.264043	0.681512	0.296871	0.319919	0.103933	0.285636	0.0565697	0.232268
7	1.00 : 0.00 : 0.00 → MATANG	0.000	MATANG	MATANG 6	MATANG/MAT...	73392	750	500	0.391666	0.287593	0.417648	0.392839	0.366787	0.338368	0.00797122	0.0807056	0.0841318	0.423665
8	1.00 : 0.00 : 0.00 → MATANG	0.000	MATANG	MATANG 7	MATANG/MAT...	120529	360	360	0.491907	0.0972608	0.690836	0.477501	0.304616	0.285384	0.343439	0.150753	0.0490259	0.275171
9	1.00 : 0.00 : 0.00 → MATANG	0.000	MATANG	MATANG 8	MATANG/MAT...	212487	640	640	0.702951	0.0453988	0.675608	0.520739	0.0147601	0.215265	0.0607769	0.156009	0.198959	0.363074
10	1.00 : 0.00 : 0.00 → MATANG	0.000	MATANG	MATANG 9	MATANG/MAT...	324741	640	640	0.738309	0.0602859	0.435463	0.263817	0.0723427	0.256909	0.191723	0.144368	0.465248	0.374725
11	0.00 : 1.00 : 0.00 → MENTAH	0.000	MENTAH	MENTAH 2	MENTAH/MEN...	75831	765	503	0.0862236	0.0218474	0.00570075	0.500271	0.374631	0.0622849	0.124285	0.167622	0.117556	0.433834
12	0.00 : 1.00 : 0.00 → MENTAH	0.000	MENTAH	MENTAH 1	MENTAH/MEN...	69169	1200	800	0.0688049	0.036509	0.00715441	0.141604	0.289388	0.393238	0	0.135135	0.0126552	0.303825
13	0.00 : 1.00 : 0.00 → MENTAH	0.000	MENTAH	MENTAH 10	MENTAH/MEN...	215964	720	1280	0.123552	0.124932	0.139398	0.361293	0.477183	0.472899	0.104166	0.188117	0.345067	0.432444
14	0.00 : 1.00 : 0.00 → MENTAH	0.000	MENTAH	MENTAH 3	MENTAH/MEN...	5250	194	259	0.209449	0.0567372	0.0831416	0.472589	0.12663	0.278405	0.038308	0.41908	0.239219	0.170294
15	0.00 : 1.00 : 0.00 → MENTAH	0.000	MENTAH	MENTAH 4	MENTAH/MEN...	49484	700	393	0.142811	0.10541	0.30705	0.408141	0.0776564	0.343197	0.000261719	0.140634	0.0347693	0.435406
16	0.00 : 1.00 : 0.00 → MENTAH	0.000	MENTAH	MENTAH 5	MENTAH/MEN...	54602	730	435	0.300691	0.145718	0.173078	1.02998	0.12074	0.545835	0.108704	0.464479	0.192579	0.369221
17	0.00 : 1.00 : 0.00 → MENTAH	0.000	MENTAH	MENTAH 6	MENTAH/MEN...	8999	318	159	0.0991974	0.0197354	0.193282	0.304821	0.195805	0.523908	0.0209585	0.396432	0.00171055	0.303355
18	0.00 : 1.00 : 0.00 → MENTAH	0.000	MENTAH	MENTAH 7	MENTAH/MEN...	43986	640	360	0.212913	0.00952589	0.361723	0.201162	0.0965425	0.469365	0.00590103	0.319675	0.0245521	0.231484
19	0.00 : 1.00 : 0.00 → MENTAH	0.000	MENTAH	MENTAH 8	MENTAH/MEN...	194190	800	800	0.0515824	0.208879	0.1751	0.353624	0.326887	0.460195	0.0306329	0.189807	0.0879302	0.440906
20	0.00 : 1.00 : 0.00 → MENTAH	0.000	MENTAH	MENTAH 9	MENTAH/MEN...	30518	720	405	0.164949	0.0843282	0.153548	0.708894	0.0752622	0.0487538	0.0388128	0.122173	0.155813	0.568203
21	0.00 : 0.00 : 1.00 → SETENGAH MATANG	0.000	SETENGAH MA...	SETENGAH MA...	SETENGAH MA...	68991	509	339	0.284609	0.128894	0.0358276	0.108029	0.37217	0.235375	0.0927717	0.232848	0.0205412	0.365702
22	0.00 : 0.00 : 1.00 → SETENGAH MATANG	0.000	SETENGAH MA...	SETENGAH MA...	SETENGAH MA...	184369	800	800	0.216634	0.205749	0.143397	0.603193	0.141751	0.251046	0.00576801	0.187133	0.0617175	0.437918
23	0.00 : 0.00 : 1.00 → SETENGAH MATANG	0.000	SETENGAH MA...	SETENGAH MA...	SETENGAH MA...	14288	600	400	0.107566	0.0713321	0.203802	1.29423	0.206912	0.334866	0.107892	0.104453	0.124319	0.223568
24	0.00 : 0.00 : 1.00 → SETENGAH MATANG	0.000	SETENGAH MA...	SETENGAH MA...	SETENGAH MA...	42937	640	640	0.194048	0.375724	0.306409	0.188518	0.186934	0.758545	0.244565	0.21797	0.0897105	0.224102
25	0.00 : 0.00 : 1.00 → SETENGAH MATANG	0.000	SETENGAH MA...	SETENGAH MA...	SETENGAH MA...	59508	800	513	0.0374502	0.0650226	0.0090524	0.554566	0.371031	0.240103	0.00322544	0.0979771	0.229365	0.590294
26	0.46 : 0.00 : 0.54 → SETENGAH MATANG	0.461	SETENGAH MA...	SETENGAH MA...	SETENGAH MA...	118316	1200	800	0.311558	0.261558	0.0700857	0.375215	0.224104	0.377124	0.257167	0.0915217	0.0275898	0.323328
27	0.00 : 0.00 : 1.00 → SETENGAH MATANG	0.000	SETENGAH MA...	SETENGAH MA...	SETENGAH MA...	190930	800	800	0.361676	0.0723838	0.158077	0.235378	0.271349	0.380059	0.0132302	0.314517	0.194373	0.217439
28	0.00 : 0.00 : 1.00 → SETENGAH MATANG	0.001	SETENGAH MA...	SETENGAH MA...	SETENGAH MA...	122673	598	598	0.154258	0.0355109	0.0167397	0.0806704	0.384551	0.175091	0.00226115	0.390901	0.00676154	0.496481
29	0.00 : 0.00 : 1.00 → SETENGAH MATANG	0.001	SETENGAH MA...	SETENGAH MA...	SETENGAH MA...	28310	600	400	0.171427	0.0287398	0.0442717	0.647329	0.182208	0.316992	0.361188	0.223011	0.290256	0.297946
30	0.00 : 0.00 : 1.00 → SETENGAH MATANG	0.000	SETENGAH MA...	SETENGAH MA...	SETENGAH MA...	58631	700	393	0.100529	0.121067	0.243472	0.202482	0.170819	1.05259	0.00158905	0.065061	0.0207654	0.0358304

Figure 4. shows the results of the classification of the ripeness level of mango fruit using the Neural Network model in the Orange application.

Test and Score Results

Test and score is an evaluation method used to measure model accuracy by comparing model predictions to test data whose classes are already known. This method provides an overview of how well the model can classify new data correctly.

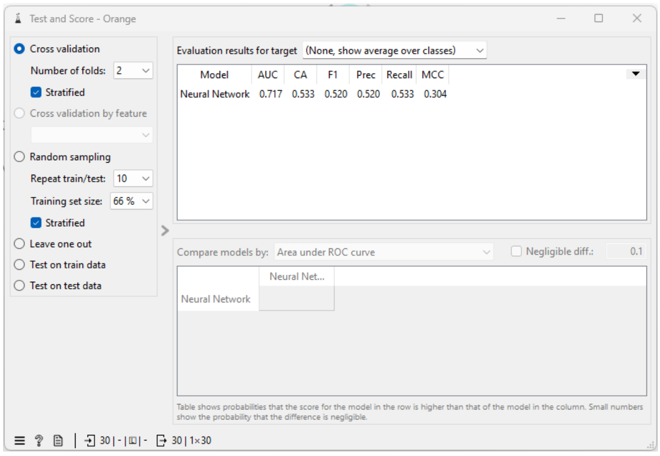


Figure 5. Display of CNN application to mango ripeness

The evaluation results of the mango ripeness classification process using the Orange application show that the Neural Network model used has moderate performance. Based on testing with the Test and Score node, the model produces an AUC value of 0.717, which shows a fairly good ability to distinguish between ripeness classes. The classification accuracy of 53.3% shows that more than half of the data can be correctly classified by the model. The F1-score (0.520), precision (0.520), and recall (0.533) values illustrate the balance between the model's ability to recognize and predict classes correctly. Although the MCC value is only 0.304, this still shows a positive correlation between predictions and actual labels. With the support of visualization from the Confusion Matrix, Box Plot, and Scatter Plot, these results provide a fairly clear picture of the model's performance in detecting the ripeness level of mangoes, as well as identifying areas that still need to be improved to achieve more optimal accuracy. 2) Confusion Matrix Results Confusion matrix is an evaluation tool that presents information about the number of correct and incorrect predictions for each class in tabular form. Through this matrix, evaluation metrics such as true positive, false positive, true negative, and false negative can be seen which help understand model performance in more detail.

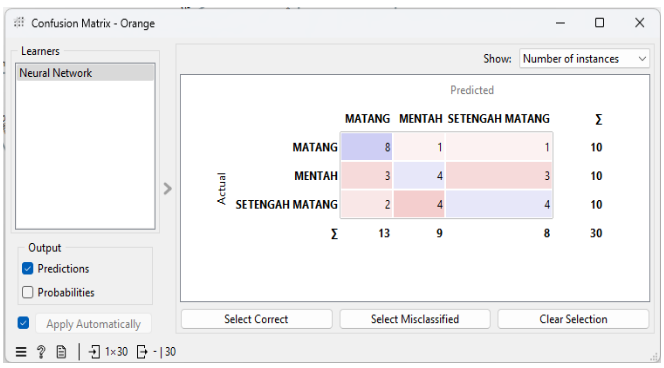


Figure 6. Display of data analysis NCC fruit ripeness

The image above shows the results of the Confusion Matrix evaluation of the Neural Network model in the study of mango fruit ripeness classification using Orange. Of the total 30 fruit images, each class (Ripe, Unripe, and Half-Ripe) is represented by 10 images. The model successfully classified 8 ripe fruit images correctly, but incorrectly classified 1 as unripe and 1 as half-ripe. For the raw class, only 4 images were correctly classified, while 3 were incorrectly classified as ripe and 3 as half-ripe. Meanwhile, of the 10 half-ripe images, only 4 were correctly classified, 2 were classified as ripe, and 4 as unripe. These results indicate that the model still has difficulty in distinguishing between the unripe and half-ripe classes, as seen from the large number of cross-classification errors between the two classes. This evaluation confirms that although the model shows promising initial performance, improvements are still needed to improve classification accuracy, especially for classes that tend to be visually similar.

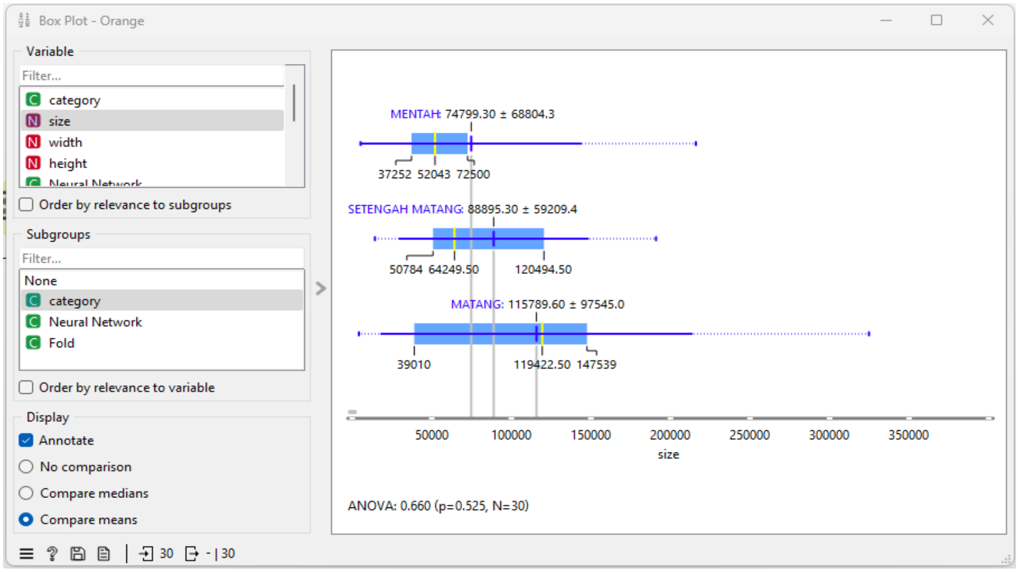


Figure 7. Display the distribution of model evaluation scores

Box Plot Results

The Box Plot in the evaluation results is used to display the distribution of model evaluation scores, such as accuracy or AUC, from the validation process that is carried out repeatedly. This visualization helps identify variations in model performance and detect extreme values or inconsistencies between test iterations.

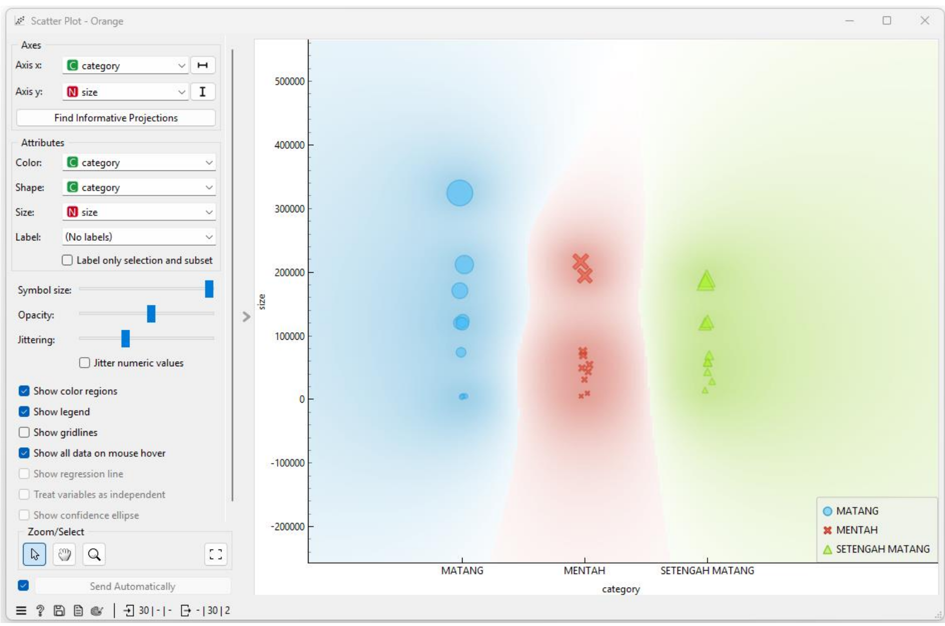


Figure 8. Display of scatter plot

The Box Plot image above shows the distribution of size feature values from mango fruit images based on three categories of ripeness levels: Raw, Half-Ripe, and Ripe. It can be seen that the Ripe category has the largest average size of around 115,789.60 with a fairly wide data distribution, while the Raw category has the smallest average size of around 74,799.30. This Box Plot also shows the distribution of data (quartiles) and extreme values (outliers) that appear in each category. Although there are differences in the average size values between categories, the ANOVA test results show a p-value of 0.525 (greater than 0.05), which indicates that the difference in size between ripeness levels is not statistically significant. This shows that the size feature alone is not enough to strongly distinguish the ripeness level of mangoes in the classification model. 4) Scatter Plot Results Scatter Plot is used to visualize the distribution of data and the relationship between two variables in the classification process, for example between model predictions and actual values. In the context of mango fruit classification, scatter plots help identify patterns, misclassifications, and separation between classes based on the features used.

The Scatter Plot image above shows the distribution of mango fruit sizes based on three ripeness categories, namely Ripe, Unripe, and Semi-Ripe (Mehta & Kaur, 2024; Okere, 2023). Each category is given a different symbol and color: a blue circle for Ripe, a red cross for Unripe, and a green triangle for Semi-Ripe. From this visualization, it can be seen that the data for the Ripe category tends to have a larger size, while the Unripe category has a narrower size distribution and is in a smaller size range. The Semi-Ripe category is in between the two, both in terms of position and size. Although there is a visual separation between the categories, some points appear to overlap, especially between the Unripe and Semi-Ripe categories, indicating potential misclassification due to similarity in feature values (Karki et al., 2024; Kayaalp, 2024). This visualization provides additional insight into the extent to which the size feature can help distinguish ripeness levels in a classification model.

Conclusion

Based on the classification and evaluation results, it can be concluded that the Convolutional Neural Network (CNN) model is able to recognize basic patterns from mango fruit images to classify their ripeness levels into three categories, but its performance is still moderate. With an accuracy value of 53.3% and an AUC of 0.717, the model shows promising initial capabilities, but is not yet reliable enough for precise classification, especially because there are still errors in distinguishing between unripe and half-ripe mangoes. Evaluation through Confusion Matrix, Box Plot, and Scatter Plot indicates overlapping data and a lack of discriminatory features between classes. Therefore, improvements are needed by adding relevant features and refining model parameters so that classification can be carried out more accurately and consistently. In addition, the evaluation results also show that although the CNN model has captured some basic visual characteristics of mango fruit images, the visual complexity between ripeness levels is still a challenge. The overlapping values in the Box Plot visualization and the spread of adjacent data in the Scatter Plot indicate that the model requires additional information or a stronger feature representation to distinguish classes more effectively. This opens up opportunities for further development, such as the use of data augmentation techniques, color or texture feature extraction, and exploration of more complex CNN architectures so that classification results are more optimal.

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