Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 8, Number 3, July 2024
DOI : https://doi.org/10.33395/sinkron.v8i3.13854
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Classification of Avocado Ripeness Levels Using CNN Method

Gamma Wira Wibowo[1)*], Edy Mulyanto[2)]
[1,2)] University of Dian Nuswantoro, Indonesia
[1)]gammawirawibowo@gmail.com, [2)]edy.mulyanto@dsn.dinus.ac.id,

Submitted : Jul 11, 2024 | **Accepted** : Jul 22, 2024 | **Published** : Jul 27, 2024

Abstract: This research aims to develop a model for classifying the ripeness level of avocados using the Convolutional Neural Network (CNN) algorithm. The dataset comprises images of avocados categorized into three classes: unripe, ripe, and overripe. The CNN model is trained to classify the images into one of these three categories. The results indicate that the developed model can classify avocado images with high accuracy. The primary tool used for developing and implementing this method is MATLAB R2022a. The CNN algorithm is utilized to recognize and classify the ripeness level of avocados. This process involves several image processing steps, starting with preprocessing, image enhancement, and segmentation to isolate the avocado area. The dataset used in this research consists of 452 images distributed in 3 classes (unripe with 142, ripe with 66, and rotten with 244), with 80% used for training and 20% for testing. After 10 accuracy tests, the results indicate an accuracy rate of 90%. Additionally, features extracted from the images include color, shape, size, and texture characteristics, such as Mean, Standard Deviation, Kurtosis, Skewness, Variance, Entropy Value, Maximum Pixel, and Minimum Pixel. This research contributes to the field of agricultural technology by providing a robust method for the automatic classification of avocado ripeness. The findings are expected to facilitate accurate and efficient recognition of avocado ripeness, thereby supporting agricultural practices and market operations. Future research could explore the use of data augmentation techniques to further improve the accuracy and generalization of this model.

Keywords: *Avocado, Ripening, Image Processing, Classification, CNN*

INTRODUCTION

Image classification is a process of grouping all pixels in an image into groups so that they can be interpreted as a specific property. The presence of digital image classification has resulted in various studies using various algorithms. However, research on algorithm optimization, especially on testing objects that have almost the same test value for each object, has not been specifically discovered at this time. Algorithm optimization is certainly necessary, especially for test data objects that have almost the same values. The test objects should also use objects that have almost the same level of similarity, both in terms of shape and color (Alfiantama et al., 2024).

Classification of avocado ripeness levels can be realized through designing an algorithm that adjusts the parameters of the avocado object. The type of avocado ripeness itself can be differentiated based on its color and shape. On this basis, the author researched the optimization of the Convolutional Neural Networks algorithm with avocado fruit objects to produce a classification of fruit ripeness based on color. The author chose the CNN method because it has advantages, including this method. CNN has

*name of corresponding author

e-ISSN : 2541-2019
p-ISSN : 2541-044X

several advantages, including that this algorithm is strong against noisy training data and is effective if the training data is large. This is because CNN tries to resemble image recognition with the human visual cortex so that it can process information about images. However, CNN, just like other deep learning methods, has a drawback, namely the model training process is quite long but can be overcome by using hardware such as GPUs (Damayanti. 2021).

In general, Convolutional Neural Networks (CNN) are not much different from ordinary neural networks. CNN consists of neurons that have weight, bias, and activation function. Convolutional layers also consist of neurons arranged in such a way as to form a filter with length and height (pixels). Apart from developing a digital image classification that can distinguish types of avocado ripeness, this research also aims to measure the accuracy of the optimization that has been added to the CNN method for classifying avocados based on ripeness (Fung. 2020).

Object Recognition is a general science in the fields of computer vision and robot vision. In previous years in the field of neuroscience, CNNs have played a key role in solving many problems related to object identification and recognition (Hanafi et al., 2019). As the visual system of our brain shares many features with CNN properties it is very easy to model and test the object classification and identification problem domains. CNN is usually a forward architecture feed; conversely, the visual system is based on CNN (CNN) to couple repeated connections to each convolutional layer. This method has the potential to recognize visual differences between Avocado species, as proven in this study.

LITERATURE REVIEW

Classification is the job of assessing data objects to put them into a certain class from several available classes. In classification there are two main jobs carried out, namely: first, building a model as a prototype to be stored as memory, and second, using the model to carry out recognition classification or prediction on another data object so that it is known which class the data object belongs to in the model. Easy to store (Jia et al., 2020). An example of an application that is often encountered is classifying animal types, which have several attributes. With these attributes, if there is a new animal, the animal's class can be immediately identified. Another example is how to diagnose melanoma skin cancer, namely by building a model based on existing training data, and then using the model to identify a new patient's disease so that it is known whether the patient has cancer or not.

Convolutional Neural Networks (CNN) is a development of Multilayer Perceptrons (MLP) designed for 2D data processing. The CNN method is included in the deep neural network learning type because of the depth of the network and is widely used for image data. MLP is not suitable for image classification because it does not store spatial information in image data and treats each pixel as an independent function. CNN was first developed as a recognition by Kunihiko Fukushima, an NHK broadcast science researcher at the Kida Research Institute in Setagaya, Tokyo. This concept was developed by Ian Le Chun, a researcher at AT&T Bell Labs in Homedale, New Jersey, USA. The LeNet CNN model has been successfully used by LeChun in caller identification and handwriting studies. In 2012, Alex Krizowski won the Amazing Video ID Challenge of ImageNet 2012 on the CNN program. This breakthrough is an opportunity to demonstrate deep learning methods for classifying objects in photos, especially CNNs (Namrudin. 2023).

The working principle of the CNN method is similar to MLP, but in the CNN method, each neuron is represented in two dimensions, while MLP is different, where each neuron has only one dimension. The MLP has layers (red and blue squares), and each layer contains ji neurons (white circles). MLP takes one-dimensional input data and distributes it over a network to produce output. Each connection between neurons in two adjacent layers has a one-dimensional weight parameter that determines the quality of the pattern. It performs linear operations on the weight values available at each data input level and then uses non-linear operations called trigger functions to change the calculation results. In CNN, the data distribution in the data network is two-dimensional, so CNN has several linear parameters and weights. With CNNs, the linear operations and weighting parameters are different for CNNs because the data sent through the data network is two-dimensional (Ningrum. 2023).

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 8, Number 3, July 2024
DOI : https://doi.org/10.33395/sinkron.v8i3.13854
e-ISSN : 2541-2019
p-ISSN : 2541-044X

METHOD

This study uses the Deep-CNN model with 15 two-dimensional layers along with several parameters, which are visualized in the flowchart above. The training process is carried out in the Deep-CNN model consisting of Convolution, Batch Normalization, ReLU, and Max Pooling which are repeated 3 times. Then do the complete classification process. After repetition, a complete classification process is carried out, Fully Connected, Softmax, and Classification Output. Further explanation of the process is in Figure 1.

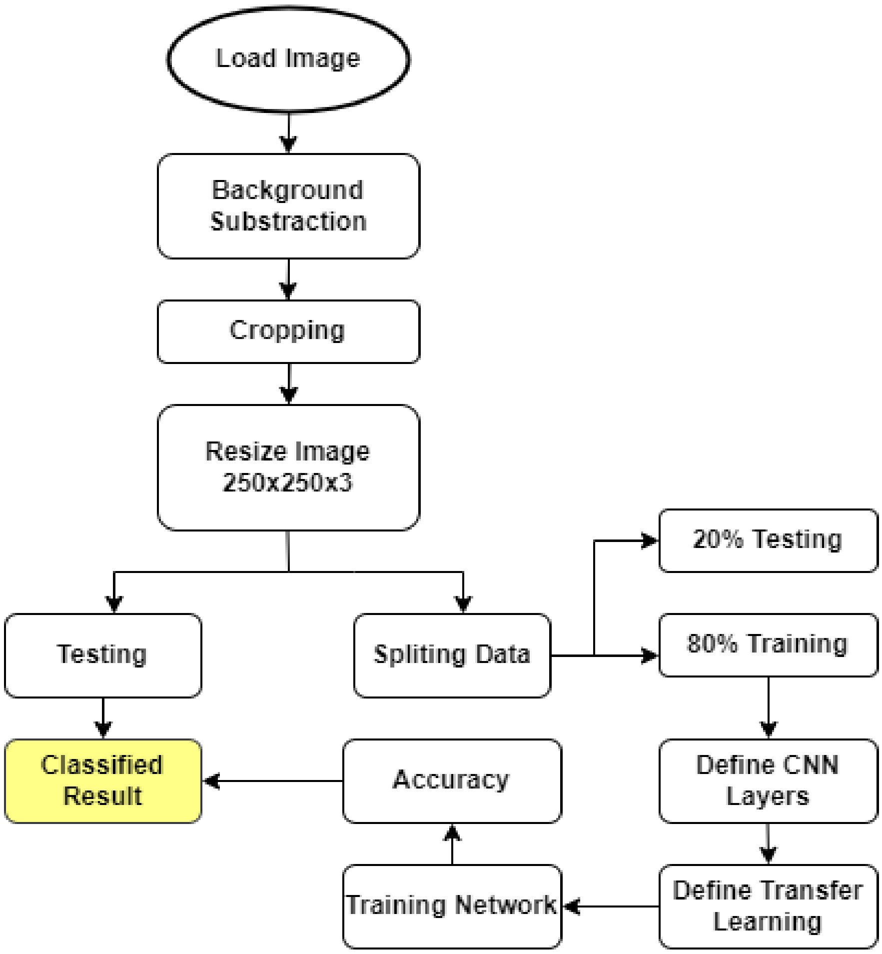

Figure 1. Classification Feature Architecture

Furthermore, the data is processed with Background Subtraction and image segmentation to obtain data with a homogeneous background (Reswan. 2024). From these data continue the process of cropping and resizing to get clear data. 80% of the training data and 20% of the testing data are processed for the training process further to processing the CNN (Define T ransfer Layers) layer and defining the Architecture to be used. Multiple convolutional layers (`convolution2dLayer`), batch normalization (`batchNormalizationLayer`), ReLU activation (`reluLayer`), and max-pooling (`maxPooling2dLayer`) are defined to form a CNN. The last fully connected layer with softmax activation is defined for classification as in Figure 1. CNNs are trained using the `train network` function with training data, layers, and options to process training images. In the Accuracy calculation step, the trained network is used to classify validation data using the classify function. Accuracy is calculated by comparing the predicted label (Predd) with the actual label (Valid). The percentage accuracy is then displayed in the MATLAB user interface using the set function (Jia. 2020). The results of the training data are then exported for the classification process of the data entered. The new data that will be tested will also undergo an adjustment process with the cropping and resizing process.

*name of corresponding author

(a) (b) (c)

Figure 2. Avocado dataset (a : rotten avocado, b : ripe avocado, c : unripe avocado)

The dataset plays a critical role in image classification tasks. A dataset is a curated collection of digital images along with corresponding labels that define the classes or categories of the images. The success of an image classification model heavily depends on the quality, diversity, and size of the dataset used for training. The dataset was taken with a total of 452 files with image extensions (.jpg) as shown in the sample in Figure 2. The dataset is processed to the classification stage with the first process grouping data based on the type of species. There are 3 folders containing -+60-250 data that have been prepared for training sessions Furthermore, the data is processed with Background Subtraction and image segmentation to obtain data with a homogeneous background (Rusli. 2024. 20% of the data has been used for training and 80% for testing.

Pre-processing

Preprocessing was performed on the obtained image data to enhance its quality (Saragih & Emanuel, 2021). This preprocessing stage plans to make the consequences of the following system more ideal. The following are the remaining stages:

a. Resize

The resizing system assumes a pivotal part in picture handling, including changing the picture aspects to the ideal size. This step is important in many different areas of research involving 250 x 250 x 3 images, particularly in the fields of machine learning and image processing. Changing the picture aspects to a size reasonable for the CNN organization, to be specific 224 x 224 pixels with three variety channels (RGB), is a significant stage to guarantee the picture is prepared for the preparation stage. The images can be incorporated into the learning algorithm and further analyzed to support research objectives by resizing them.

b. Picture

Upgrade A procedure is carried out at the Image Enhancement stage to produce images that are more readily interpreted by the human eye (Human Visual System, or HVS) (Yuan et al., 2021). Picture upgrade is additionally used to work on the visual nature of pictures (Chakraborty et al., 2019). Contrast enhancement, which aims to increase the difference between the various brightness levels of an image, is one important aspect of image enhancement. With regards to expanding contrast, there are a few techniques used to build the distance between pixels that address light and dull regions in a picture.

Extraction Feature

A process of image feature extraction (Basiroh and Lestari 2020) Takes place when the Convolutional Neural Network (CNN) algorithm is used to classify the maturity level of avocados (Aruraj et al., 2019). The avocado image's visual characteristics are described by these features, which will then be processed by the CNN algorithm for classification. Mean, Variance, Kurtosis, Minimum, Standard Deviation, Entropy, Skewness, and Maximum are some of the features utilized in the program. Each element gives different data about the conveyance of pixel power in the picture (Fu et al., 2020), including data about the brilliance, variety, appropriation, and state of the picture. The image's variation in pixel intensity and brightness are depicted by the mean and standard deviation. Kurtosis and skewness portray the state of

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 8, Number 3, July 2024 e-ISSN : 2541-2019
DOI : https://doi.org/10.33395/sinkron.v8i3.13854 p-ISSN : 2541-044X

the pixel power conveyance, while entropy estimates the degree of picture intricacy. The things used to calculate the extraction are the pixels of each input image dataset's. The image's lowest and highest pixel intensity values are represented by the minimum and maximum. The formula is used to figure out the Mean value:

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

Where n is the number of elements in the dataset, and xi is the value of the to-i element in the dataset. To get the Variance value, the calculation is done by the formula:

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

Where n is the number of elements in the dataset, xi 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:

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

Where n is the number of elements in the dataset, xi is the value of the to-i element in the dataset, and m : is the average value of the dataset. To get the Kurtosis value, the calculation is done by the formula:

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

Where n is the number of elements in the dataset, xi 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:

$$Min = \min(x_1, x_2, \dots, x_n)$$

Where n is the number of elements in the dataset, and xi is the value of the to-i element in the dataset. To get the Entropy value, the calculation is done by the formula:

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

Where n is the number of possible different values in the dataset, xi is the intensity value of the pixel value at the to- i position, and pxi is the probability of occurrence of the value xi in the dataset. To get the Skewness value, the calculation is done by the formula:

$$Skewness = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^3}{n \cdot S^3}$$

Where n is the number of elements in the dataset, $\mathcal{X}i$ is the data value in the to-i position, $\bar{\mathcal{X}}$ is the average of the data, and S is the standard deviation of the data To get the Maximum value, the calculation is done by the formula:

$$Max = \max(x_1, x_2, \dots, x_n)$$

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 8, Number 3, July 2024
DOI : https://doi.org/10.33395/sinkron.v8i3.13854
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Where n is the number of elements in the dataset, and xi is the value of the to-i element in the dataset.
A common method for assessing the degree to which a method's predictions or classifications match the actual original data is known as accuracy. Calculating accuracy serves to assess the system's efficacy and facilitate comparisons among various studies employing various approaches. As a result, comparisons with other studies can be made using a variety of approaches. These metrics provide benchmarks for performance, make it easier to make educated choices, and boost confidence in model results. Despite its simplicity, accuracy may not be able to deal with class imbalances or different types of errors. Nonetheless, it continues to play a significant role in assessing model efficacy, encouraging comparability, and progressing research efforts (Ruswandi. 2022)

RESULT

This study aims to classify images of avocados based on their species using the Convolutional Neural Network (CNN) architecture. This method utilizes deep learning techniques that can extract important features from images automatically for classification purposes. CNN can recognize complex visual patterns in images, such as the unique characteristics of each type of lovebird (Sabuj. 2023). This research involves implementing CNN with the appropriate architecture and configuration, as well as training the model using a lovebird image dataset that has been labeled with its species. The main goal is to create a model that can distinguish between types of Avocados based on their visual characteristics. The results of this study can be used for various applications, including the introduction of bird species in the field of ornithology and natural observations. The preprocessing method are sample characterization is shown below,

Table 1. Extraction Result

Datasets	Mean	Variance	Standard Deviation	Entropy	Kurtosis	Pixel Minimum	Pixel Maximum	Skewness
Mentah_2	162.349	1940.2	44.0477	6.48983	4.41454	21	234	-1.65276
Mentah_30	162.287	1881.85	43.3803	6.26406	4.66621	21	241	-1.74538
Matang_98	161.039	1752.52	41.8631	6.49412	5.48385	17	219	-1.85543
Matang_139	158.802	2188.46	46.781	6.89509	4.54057	2	218	-1.79119
Busuk_10	155.203	2256.1	47.4984	6.35968	5.98303	2	223	-2.03582
Busuk_50	156.164	2829.05	53.1888	6.70679	4.3069	1	213	-1.54522

The extraction results show that the dataset has characteristics. The raw avocado datasets are greener or brighter than mature or rotten ones. And in the Rotten avocados dataset the color is more brown or darker in color. This is shown by the pixel extraction results.

The CNN method in image classification is very useful in recognizing and classifying visual objects based on complex features that are difficult to identify manually CNN is widely used in various applications of pattern recognition, image classification, object detection, image segmentation, and other image processing (Saputra. 2023). Its strengths lie in its ability to deal with differences in size, rotation, and other variations in image data, as well as its ability to extract hierarchical features useful in visual analysis. Before being processed, we collect the dataset and prepare it to be processed using Matlab 2024. The following is a sample of the raw dataset as shown in Figure 2. Extraction has been carried out on 15 image categories of each Avocado species as shown in Table 1.

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 8, Number 3, July 2024 e-ISSN : 2541-2019
DOI : https://doi.org/10.33395/sinkron.v8i3.13854 p-ISSN : 2541-044X

Table 2 Feature Extraction

ANALYSIS RESULT				
	Name	**Type**	**Activations**	**Learnable Prope...**
1	image input 250x250x3 image with 'zero center' nor….	image input	250(S) x 250(S) x 3(C) x 1(B)	-
2	conv_1 8 3x3 convolutions with stride [1 1] and …	Convolution	250(S) x 250(S) x 8(C) x 1(B)	Weig… 3 x 3 x 3 .. Bias 1 x 1 x 8
3	batchnorm_1 Batch normalization	Batch normalization	250(S) x 250(S) x 8(C) x 1(B)	Offset 1 x 1 x 8 Scale 1 x 1 x 8
4	relu_1 ReLu	ReLu	250(S) x 250(S) x 8(C) x 1(B)	-
5	maxpool_1 2x2 max pooling with stride [2 2] and pa…	Max Pooling	125(S) x 125(S) x 8(C) x 1(B)	-
6	conv_2 16 3x3 convulations with stride [1 1] and …	Convulation	125(S) x 125(S) x 16(C) x 1(B)	Weig… 3 x 3 x 8 .. Bias 1 x 1 x 16
7	batchnorm_2 Batch normalization	Batch normalization	125(S) x 125(S) x 16(C) x 1(B)	Offset 1 x 1 x 16 Scale 1 x 1 x 16
8	relu_2 ReLu	ReLu	62(S) x 62(S) x 16(C) x 1(B)	-
9	maxpool_1 2x2 max pooling with stride [2 2] and pa…	Max Pooling	62(S) x 62(S) x 16(C) x 1(B)	-
10	conv_2 32 3x3 convulations with stride [1 1] and …	Convulation	62(S) x 62(S) x 32(C) x 1(B)	Weig… 3 x 3 x 16 .. Bias 1 x 1 x 32
11	batchnorm_3 Batch normalization	Batch Normalization	62(S) x 62(S) x 32(C) x 1(B)	Offset 1 x 1 x 32 Scale 1 x 1 x 32
12	relu_3 ReLu	ReLu	62(S) x 62(S) x 32(C) x 1(B)	-
13	FC 3 fully connected layer	Fully Connected	1(S) x 1(S) x 3(C) x 1(B)	Weights 3 x 123008 Bias 3 x 1
14	softmax softmax	Softmax	1(S) x 1(S) x 3(C) x 1(B)	-
15	Classoutput crossentropyex	Classification Output	1(S) x 1(S) x 3(C) x 1(B)	-

The feature extraction function in image processing refers to the process of identifying, calculating, and compiling representative features of an image. The goal of feature extraction is to simplify the image representation in such a way that the most relevant information can be represented by the features. These features can then be used as input for machine learning algorithms, classification, or other image analysis tasks. CNNs are powerful algorithms for image processing that automatically learn relevant features from the input images. CNNs excel at feature extraction due to their ability to learn hierarchical representations directly from raw images (Sri. 2021). This makes them highly effective for image classification tasks, allowing them to capture relevant information and patterns within the data. Besides

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 8, Number 3, July 2024
DOI : https://doi.org/10.33395/sinkron.v8i3.13854
e-ISSN : 2541-2019
p-ISSN : 2541-044X

extraction, there are also classification features that we also test directly. The results of the trial are shown in Table 3. Out of 18 classification tests, false results occurred twice. This means the accuracy is equal to 90%. The generated CNN Accuracy test also produces the same percentage of accuracy. Around 90% of CNN accuracy tests are recorded during the training system.

Experiments were carried out to find out that Badami Avocado Fruit is included in the maturity level that has been previously classified. Six experiments were conducted to determine whether the test data and predictions were accurate. In the first experiment, the program was given as input a rotten fruit, and the prediction result was rotten. In the second experiment, the program was given as input a rotten fruit, and the prediction result was rotten. In the third experiment, the program was given the input of a ripe fruit and the predicted results were ripe. In the fourth experiment, the program was given the input of a ripe fruit and the predicted results were ripe. In the fifth experiment, the program was given a raw fruit and a raw prediction result as input. In the sixth experiment, the program was given as input a raw fruit and a raw prediction result. In Table 2, the trials carried out and the prediction results from the trials are explained. The images used are taken from one example of each classification result such as ripe, raw, and rotten (Ningrum. 2024). From the test results, images of ripe avocados, images of raw avocados, and images of rotten avocados were obtained. The image of a ripe avocado has a dominant green color with a hint of green. Image of raw avocado with a dominant green image with a slight green tint. The image of a rotten avocado is dominant with black and a little green.

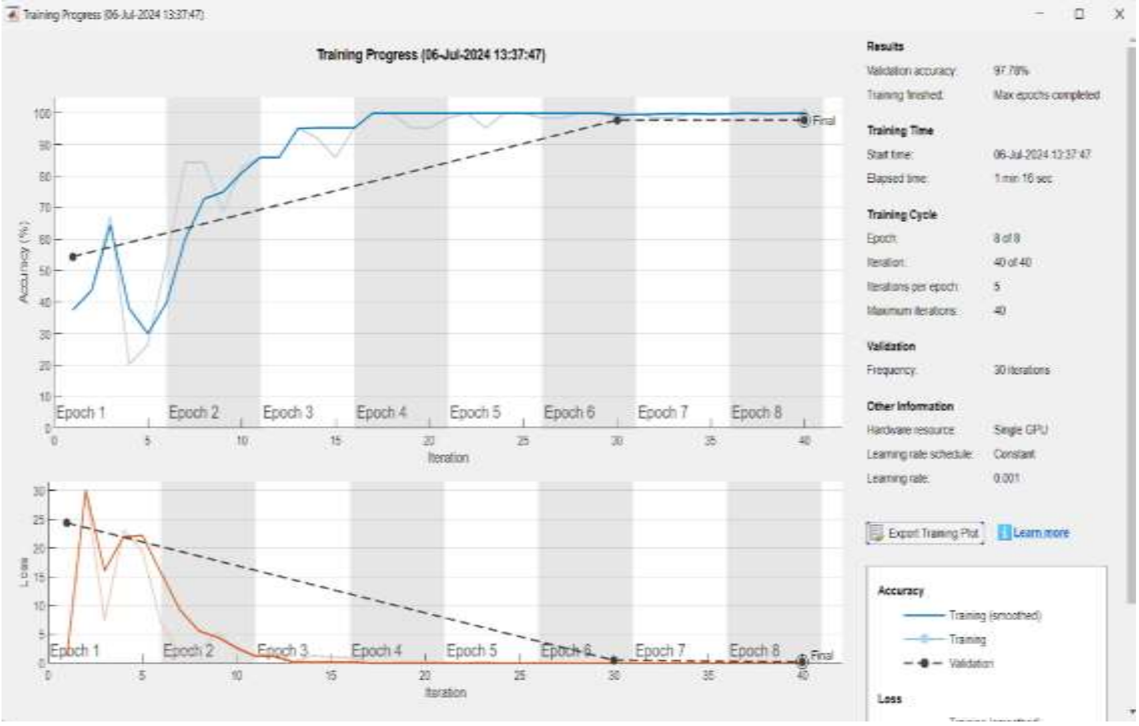

Figure 3. The graph on the left represents the accuracy testing, and the graph on the right represents the loss testing. The x-axis indicates the number of data points, and the y-axis represents the time in minutes.

The image is tested based on the determined Avocado classification. The results of the experiments carried out show the results of the model building and feature extraction processes carried out. The use of the Convolutional Neural Network (CNN) model provides good results in the programs created. The highest accuracy was 97.2% for testing and 94.6% for training. The lowest data loss is 0.5 for testing and 0.1 for training. This proves that the model used is very good and close to accurate. Figure 3 depicts a comparison of accuracy and loss in the classification process. The high and low levels of testing are due to the GPU time running in processing in carrying out image recognition with the GPU on a good device (Damayanti. 2021).

*name of corresponding author

DISCUSSION

The study used a total of 452 images which were distributed in 3 classes (unripe with 142, ripe with 66, and rotten with 244), through sample testing with a success rate of one hundred percent. Using the Convolutional Neural Network (CNN) algorithm, which is enhanced with image enhancement techniques to help sharpen detail and pixel differences. Intensity level in the image, this research was successful in creating a classification system for the maturity level of avocados in terms of avocado color. According to the findings, this method achieved an accuracy level of 90%. The agricultural sector is expected to benefit from this research, which has the potential to transform the process of sorting and managing avocado products. Classifying maturity levels with speed and precision can help the agricultural industry as a whole and improve distribution efficiency and quality standards for end consumers.

CONCLUSION

In research carried out in which the classification of avocado ripeness levels was searched by applying the CNN model, after carrying out several experiments, the accuracy results were 90% and the loss results were 10% of the test results on the testing data. This shows that the use of the CNN model in classifying avocado ripeness is quite good. The test results for avocado fruit are quite good, where the test image results and the image input results after processing show similarities. From the results of testing the Image of Avocado Fruit, quite good results can be found where the level of maturity of the Avocado Fruit follows the estimates made according to the classification of Avocado Fruit maturity. Maybe in future research, we can apply machine learning methods to compare better results between machine learning and deep learning. The use of CNN requires a lot of images in its processing so the existing dataset must be large and by the classification of each image.

REFERENCES

Alfiantama, I., Ilham, M., & Putra, A. (2024, January). Klasifikasi Tingkat Roasting Biji Kopi Dengan Metode CNN. In *Seminar Nasional Teknologi & Sains* (Vol. 3, No. 1, pp. 285-290).

Aruraj, A., Alex, A., & George, S. T. (2019). Welcome to “2019 International Conference on Signal Processing and Communication (ICSC).” 2019 International Conference on Signal Processing and Communication, ICSC 2019, c, v. https://doi.org/10.1109/ICSC45622.2019.8938305

Basiroh, Basiroh, and Wiji Lestari. 2020. “Analysis of Plant Fragaria Xananassa Disease Diagnoses Using Production Rules Base on Expert System.” *Jurnal Pilar Nusa Mandiri* 16(1): 25–32.

Chakraborty, S., Raman, A., Sen, S., Mali, K., Chatterjee, S., & Hachimi, H. (2019). Contrast Optimization using Elitist Metaheuristic Optimization and Gradient Approximation for Biomedical Image Enhancement. Proceedings - 2019 Amity International Conference on Artificial Intelligence, AICAI 2019, 712–717. https://doi.org/10.1109/AICAI.2019.8701367

Damayanti, S. A., Arkadia, A., & Prasvita, D. S. (2021). Klasifikasi Buah Mangga Badami Untuk Menentukan Tingkat Kematangan dengan Metode CNN. In *Prosiding Seminar Nasional Mahasiswa Bidang Ilmu Komputer dan Aplikasinya* (Vol. 2, No. 2, pp. 158-165).

Fu, L., Duan, J., Zou, X., Lin, J., Zhao, L., Li, J., & Yang, Z. (2020). Fast and accurate detection of banana fruits in complex background orchards. IEEE Access, 8, 196835–196846. https://doi.org/10.1109/ACCESS.2020.3029215

Fung, K. L. Y. et al. (2020). Ultramicroscopy Accurate EELS background subtraction – an adaptable method in MATLAB.Ultramicroscopy, Vol. 217, No. June, P. 113052. Doi: 10.1016/j.ultramic.2020.113052

*name of corresponding author

 e-ISSN : 2541-2019
p-ISSN : 2541-044X

Hanafi, M. H., Fadillah, N., & Insan, A. (2019). Optimasi Algoritma K-Nearest Neighbor untuk Klasifikasi Tingkat Kematangan Buah Alpukat Berdasarkan Warna. *IT Journal Research and Development*, *4*(1), 10-18.

Jia, W., Tian, Y., Luo, R., Zhang, Z., Lian, J., & Zheng, Y. (2020). Detection and segmentation of overlapped fruits based on optimized mask RCNN application in apple harvesting robot.Comput. Electron. Agric., Vol. 172, No. March, p. 105380. Doi: 10.1016/j.compag.2020.105380.

Namruddin, R., Mirfan, M., & Irfandi, I. (2023). Klasifikasi Kesegaran Buah Apel Menggunakan Metode Convolutional Neural Network (CNN) Berbasis Android. *Prosiding SISFOTEK*, *7*(1), 295-302.

Ningrum, B. N. T. C., Ni'mah, E. N., Arifin, M. P., & Dara, M. A. D. W. (2024, January). KLASIFIKASI DAN PENGENALAN POLA PENYAKIT CABAI DENGAN METODE CNN (Convolution Neural Network). In *Seminar Nasional Teknologi & Sains* (Vol. 3, No. 1, pp. 125-132).

Reswan, Y., Toyib, R., Witriyono, H., & Anggraini, A. (2024). Klasifikasi Tingkat Kematangan Buah Nanas Berdasarkan Fitur Warna Menggunakan Metode K–Nearest Neighbor (KNN). *JURNAL MEDIA INFOTAMA*, *20*(1), 280-287.

Rusli, H. N. (2024). Pengembangan Aplikasi Klasifikasi Tingkat Kematangan Buah Apel Berdasarkan Warna Kulit Buah Apel dengan Metode Convolutional Neural Network. *KALBISIANA Jurnal Sains, Bisnis dan Teknologi*, *10*(2), 178-185.

Ruswandi, M., Mulyana, D. I., & Awaludin, A. (2022). Optimasi Klasifikasi Kematangan Buah Alpukat Menggunakan KNN dan Fitur Statistik. *Smart Comp: Jurnalnya Orang Pintar Komputer*, *11*(2), 210-219.

Sabuj, H. H., et al. (2023). A Comparative Study of Machine Learning Classifiers for Speaker's Accent Recognition.2023 IEEE World AI IoT Congr. AIIoT 2023, Pp. 627–632. Doi: 10.1109/AIIoT58121.2023.10174511

Saputra, J., Sa'adati, Y., Ardhana, V. Y. P., & Afriansyah, M. (2023). Klasifikasi Kematangan Buah Alpukat Mentega Menggunakan Metode K-Nearest Neighbor Berdasarkan Warna Kulit Buah. *Resolusi: Rekayasa Teknik Informatika dan Informasi*, *3*(5), 196-203.

Sri, M. S., Naik, B. R., & Sankar, K. J. (2021). Object Detection Based on Faster R-Cnn. Int. J. Eng. Adv. Technol.. Vol. 10, No. 3, Pp. 72–76.Doi: 10.35940/ijeat.c2186.0210321

Yuan, F., Zhan, L., Pan, P., & Cheng, E. (2021). Low bit-rate compression of underwater image based on human visual system. Signal Processing: Image Communication, 91(May 2020), 116082. https://doi.org/10.1016/j.image.2020.116082

.

*name of corresponding author