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# Classification of Palm Oil Ripeness Level using DenseNet201 and Rotational Data Augmentation

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**Abstract**−Indonesia is a country in Southeast Asia with the largest palm oil production in the world. Based on Indonesian Central Statistics Agency data, in 2022 Indonesia produced 46,8 million Tons of Crude Palm Oil (CPO). To produce a high-quality oil, palm oil fruit must be harvested in an optimal condition. But, even a experienced and trained person found it difficult to identify whether the fruit is ripe or raw. In this research theres two type of classification which is ripe and raw, this is because palm oil milling factory only accept pure ripe palm oil fruit and not half ripe or almost ripe. The data that is used in this reseacrh was collected from two sources, the first source is from https://www.kaggle.com/datasets/ahmadfathan/kematangansawit and the second source was collected manually by going to palm oil plantation. The total of data that is used for this research is 1000 data and 1000 augmented data. Dense Convolutional Network (DenseNet) that is used in this research is a CNN architecture that was first introduced in 2017. Compared to DenseNet121 and DenseNet169, DenseNet201 is proven to have a higher level of accuracy. The 90:10 data scheme succeeded in getting the highest accuracy with a total accuracy of 97.50% with a learning rate of 0.001 and a dropout of 0.01.

**Keywords**: Palm Oil; DenseNet201; Classification; Augmentation; Rotate

## 1. INTRODUCTION

Indonesia is a country in Southeast Asia with the largest palm oil production in the world. Sumatra and Borneo is the islands that have the most palm oil plantation in Indonesia compared to other islands in Indonesia [1]. Based on Indonesian Central Statistics Agency data, in 2022 Indonesia produced 46,8 million Tons of Crude Palm Oil (CPO) [2]. To produce a high quality oil, palm oil fruit must be harvested in an optimal condition [3]. Palm oil fruit maturity level is very important to decide the quality and quantity of the oil that will be produce from the fruit [4]. But, even a experienced and trained person found it difficult to identify whether the fruit is ripe or raw [5].This is because the traditional way to identify the ripeness of the fruit with only human vision is not effective and can lead to wrong classification [6]. Misidentifying the maturity of palm oil results in many palm oil being returned to plantation owners by palm oil mills factory[7]. Classification of the maturity level of palm oil suitable for harvest is very important to estimate the oil content in the palm fruit. The difference in palm maturity levels can be seen from the color of the palm, black indicates raw and red indicates ripe [8]. The difference between ripe and raw pal oil fruit in Figure 1.

**Figure 1.** Ripe and raw palm oil fruit

Machine Learning is a branch of Artificial Intelligence (AI) that uses principles from computer science and statistics to create models that reflect a number of data patterns [9]. Deep Learning is a part of Machine Learning that uses Deep Neural Networks to solve deeper Machine Learning solutions. Since now Deep Learning has developed very rapidly in many fields, one of which is Computer Vision or Image Processing [10].

In the year 2017, Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q made *Dense Convolutional Network* (DenseNet) as one of the CNN architecture [11]. DenseNet has many different version such as DenseNet121, DenseNet169 and DenseNet201, every version of DenseNet has their own characteristic and excess [12]. Compared to DenseNet121 and DenseNet169, DenseNet201 is proven to have a higher level of accuracy [13]. In research conducted by Tiwari in 2022, it was proven that DenseNet201 has higher accuracy in classifying compared to other architectures such as VGG-16, EfficientnetB7, Xception, Resnet50, InceptionV3, and MobileNetV2 [14].

In 2022 Suci Ashari has done a palm oil classification using deep learning with CNN architecture and get 92% of the accuracy without using any augmentation data and optimizer [15]. To reduce overfitting in the model, data augmentation will be used to increase the amount of training data by using information that already exists in the previous training data [16]. Rotate is a data augmentation technique in which an image is rotated according to a specified angle and creates a new image based on an existing image in the dataset [17]. Rotation is done by rotating the image clockwise or counterclockwise between 1° and 359° [18]. Before augmentation, preprocessing is used to process the original image data before being processed by the algorithm used [19].

Apart from augmentation, Hyperparameter Optimizer is also used to assist in reading images and improving performance to avoid overfitting. The Adamax optimizer is proven to be able to perform more precise classifications compared to other optimizers such as Adam, N-Adam, and SGD [20]. Based on the explanation that has been described, in this research a ripeness classification system for palm fruit was created using one of the methods of the CNN architecture, namely DenseNet201, using rotate data augmentation. With the aim of helping palm oil farmers in classifying maturity of oil palm fruit.

## 2. RESEARCH METHODOLOGY

In research, it is necessary to create or explain the flow for each stage of the research that will be carried out. This research methodology is useful as a guide in conducting research. The flow of each process becomes instructions or guidelines that will direct the research from start to finish. Research methodology also aims to ensure that research is carried out in a structured manner

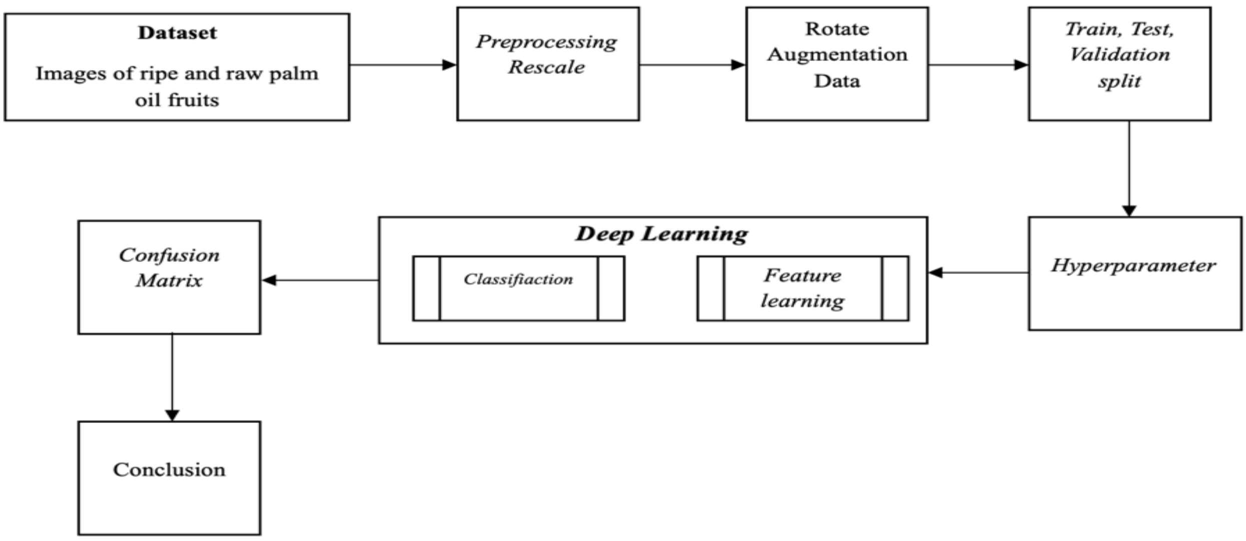



**Figure 2.** Research steps and methods

Figure 2 illustrates the research design for classification using the DenseNet201 architecture CNN method and Each step in this research starts from data collection to the results and conclusions of this research.

### 2.1 Dataset

In this step, the researcher collects data where the data will be used as input data. The data collection process was carried out by combining secondary data from Kaggle (https://www.kaggle.com/datasets/ahmadfathan/kematangansawit) and primary data that had been collected by researchers directly from palm oil plantations in Siak Sri Indrapura. The palm oil dataset used in this research has 2 classes, namely ripe with 500 images and raw with 500 images.

### 2.2 Preprocessing Rescale

In the preprocessing stage, researcher used rescale preprocessing which functions to adjust the brightness of pixels with a size of 1/255. This preprocessing is used by changing the range of values from 0 and 255 to 0 and 1

### 2.3 Rotate Augmentation

To increase the number of datasets, data augmentation is carried out. The augmentation that used is rotate 90°, where the image will be rotated at a multiple of 90°. The number of pictures or images is 1000 images, where each class, namely ripe and raw has 500 images each**.** Each image will be rotated by 90°, 180°, and 270°.

### 2.4 Data Split

From the total existing dataset, the data was divided into 3 parts, namely train, test and validation. Where the validation data gets 20% of the total images in the dataset with the data distribution scheme (90:10), (80:20), and (70:30).

### 2.5 Hyperparamter Optimizer

The optimizer hyperparameter used in TensorFlow library is Adamax with a SoftMax activation system with 3 different layer dropout experiments, namely 0.001, 0.01 and 0.1. Likewise with the learning rate, experiments were carried out with 3 different learning rates, namely 0.001, 0.01 and 0.1, each using 20 epochs.

### 2.6 Deep Learning

In the research that will be carried out, the application of deep learning using the CNN method will be used. This method was chosen because it was proven to be able to carry out good and accurate classification. In CNN there are several architectural models, in this research the model used is DenseNet201. The DenseNet201 architecture consists of 201 deep layers which are capable of loading a pre-trained model with image sources from the CIFAR100 dataset which consists of 6000 color images with a size of 32x32 pixels and consists of 100 classes which form a network with a wide scope for learning feature representation for many types of images [21]. The DenseNet201 architecture can be seen on Figure 3.

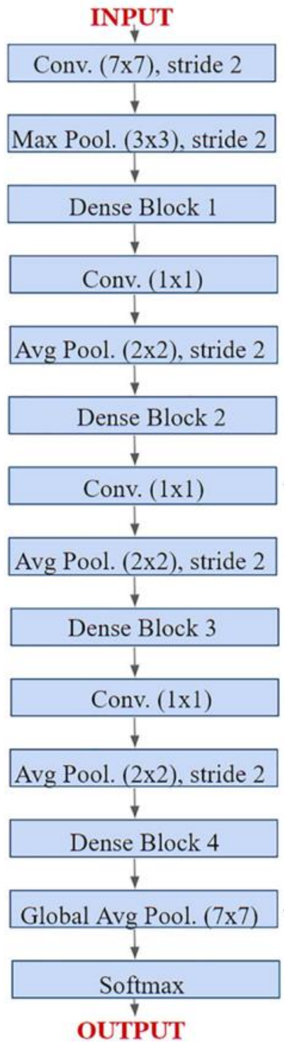



**Figure 3.** DenseNet201 architecture

a. Convolution 7x7 with *stride* = 2
b. Max Pooling 3x3 with *stride* = 2
c. *Layer Dense Block* 1, with Convolution 1x1 and 3x3 with 6 repetition.
d. Transition Layer 1,with 2 operation:
   1. Convolution 1x1.
   2. 2x2 Average Pool with stride = 2
e. *Layer Dense Block* 2, with Convolution 1x1 and 3x3 with 12 repetition.
f. *Transition Layer* 2, with 2 operation:
   1. Convolution 1x1.
   2. 2x2 Average Pool, with stride = 2
g. *Layer Dense Block* 3, with Convolution 1x1and 3x3 with 48 repetition.
h. *Transition Layer* 3, with 2 operation:
   1. Convolution 1x1
   2. 2x2 Average Pool, with stride= 2
i. *Layer Dense Block* 4, Convolution 1x1 and 3x3 with 32 repetition.
j. Global Average Pool 7x7.
k. SoftMax Activision.

### 2.7 Implementation and Testing

This stage is carried out to evaluate and analyze the results of the modeling that has been created. At this stage the researcher uses a confusion matrix which consists of accuracy, precision, recall, and f1-score, where the value is obtained from a formula with the following components in Table 1.

**Table 1.** Confusion matrix

| | | **Prediction** | |
|---|---|---|---|
| | | Positif | Negatif |
| **Actual** | Positif | *True Positive (TP)* | *False Negative (FN)* |
| | Negatif | *False Positive (FP)* | *True Negative (TN)* |

Table 1 shows the formula of The Confusion Matrix consists of Accuracy, Precision, Recall and F1-Score which can be calculated based on the values of TP, TN, FP and FP, each of which has the following formula:

a. Accuracy function is to describe the level of accuracy of the model in carrying out classification.

$$Accuracy = \frac{TP + TN}{TP + TP + FP + FN} \tag{1}$$

b. Precision functions is to calculate the ratio of the amount of data that has been predicted correctly to the total predicted data.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

c. Recall functions is to evaluate the comparison of the amount of correctly predicted data with all actual data.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

d. F1-Score functions to calculate the average of the Precision and Recall comparisons that have been calculated previously.

$$F1 - Score = \frac{2 \times Recall \times Precision}{Recall + Precision} \tag{4}$$

## 3. RESULT AND DISCUSSION

The classification of palm oil ripeness model is run on a MacBook Pro with an M1 Processor, 8 GB of RAM, and MacOS Ventura 13.6.4 operating system with an average running time of 15 minutes. This research is using DenseNet201 with data testing to get a model with the best accuracy.

### 3.1 Data Collecting

In this research the dataset of palm oil ripeness collected from 2 resources. The first resource is form www.kaggle.com that has 2 classes which is ripe with 249 images and raw with 363 images. The second resource is collected manually by going to palm oil plantation in Siak Sri Indrapura by taking pictures with Samsung a52 phone camera, the camera was pointed directly to the palm oil fruit that still on the tree, this is done to increase the amount of data from each classes.

**Table 2.** The total of datasets

| **Name** | **Ripe** | **Raw** |
|---|---|---|
| Primary Data | 251 | 137 |
| Secondary Data | 249 | 363 |
| Augmented Images | 500 | 500 |
| **Total** | 1000 | 1000 |

Table 2 shows the total amount of the dataset after 2 resources is combined the amount of images of palm oil images add up to 1000 images where each class has 500 images. Rotate data augmentation data is also used to increase the amount of data, the augmentation adding 1000 more images to the dataset where each classes has 500 augmented images. Table 2 contains the number of datasets from each classes and the total of all the datasets.

### 3.2 Preprocessing

The preprocessing that used in this research is rescaling and resize. Rescaling is used to change the color scale from 0-255 to 0-1. Resize is used for changing the size of image based on the algorithm that used which is DenseNet201 with the size of 224x224.


**Figure 4.** Preprocessing image

Figure 4 shows the result of the rescale and resize preprocessing where all of the images with different sizes will be resized into the size of 224x224. The resize preprocessing is done to match the DenseNet201 requirements where the input images should be the size of 224x224.

### 3.3 Rotate Augmentation

The augmented data that used is rotate augmentation data. The augmentation will add 500 images to each of the classes which is ripe and raw. Rotate data augmentation is an augmentation technique that rotates an image by a predetermined angle such as 90°, 180°, and 270. After the augmentation data will increase from 1000 images to 2000 images and this will affect the level of accuracy that will be produced from the model.

```
1. pipeline = Augmentor.Pipeline(input_dir, output_dir)
2. pipeline.rotate90(probability=1)
3. pipeline.rotate180(probability=1)
4. pipeline.rotate270(probability=1)
5. num_of_augmented_images = 1000
```

**Figure 5.** Rotate data augmentation

Figure 5 explain the implementation of rotate augmentation. The code in lines 2, 3 and 4 functions to set the rotation angle for the data to be augmented. The code in line 5 is used to adjust the amount of data that will be augmented from the dataset.

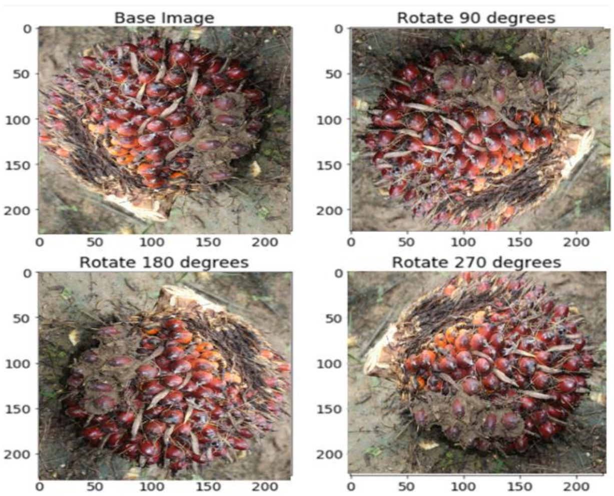



**Figure 6.** Augmented image

Figure 6 shows the result of the augmented images from tha dataset. The images will be augmented into 3 different angels such as 90°, 180°, and 270°. This is done to increase the amount of dataset and variations of the data.

### 3.4 Data Split

Data splitting that used in this research is using 3 experimental schemes. Data is divided into training data, test data and validation data.

**Table 3.** Data Split

| Data Split | Train Data | Test Data | Validation Data |
|---|---|---|---|
| (90;10);20 | 720 | 80 | 200 |
| (90;10);20 Augmented | 1440 | 160 | 400 |
| (80;20);20 | 640 | 160 | 200 |
| (80;20);20 Augmented | 1280 | 320 | 400 |
| (70;30);20 | 560 | 240 | 200 |
| (70;30);20 Augmented | 1120 | 480 | 400 |

Table 3 shows the result of the data after data splitting is done. Validation data was taken from 20% of the total palm oil images in two classes of ripe and raw. Training data and test data are divided into 3 different schemes such as (90:10), (80:20) and (70:30).

### 3.5 DenseNet201 Implementation

Testing uses the Tensorflow Library in Keras using the Python programming language. Testing was carried out on Google Colab by calling the DenseNet201 library. Testing was carried out with 57 schemes by changing the test parameters, namely learning rate and drop out value. The learning rates used are 0.1, 0.01, and 0.0001. For dropout, 0.1, 0.01 and 0.001 are used. Figure 7 is showing the DenseNet201 algorithm library used from TensorFlow.

```
1. from keras.applications import DenseNet201
2. base_model=tf.keras.applications.DenseNet201(include_top=False,
   weights="imagenet",input_tensor=Input(shape=(224,224,3)))
```

**Figure 7.** DenseNet201 algorithm

### 3.6 Training Result

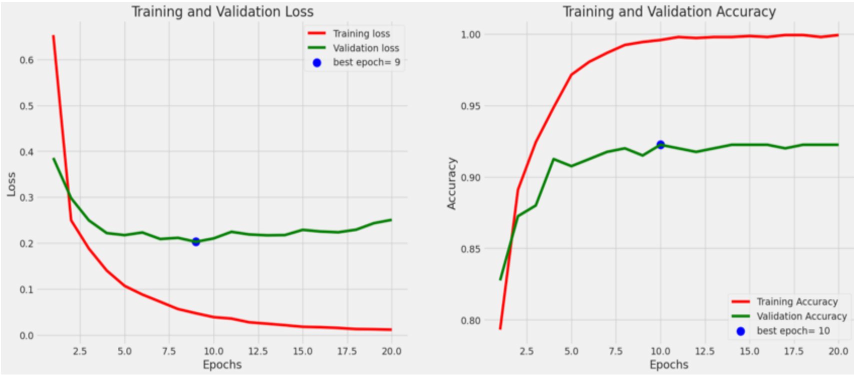
In this step DenseNet201 is used with preprocessing data from the TensorFlow library to increase the accuracy. The number of epoch that is used in this step is 20 epoch, Adamax Hyperparameter is also used in this step with SoftMax Activision. This process uses Google Collab with Google GPU runtime so that the DenseNet201 model training process can be done more quickly. Table 4 shows the training results using DenseNet201.

**Table 4.** Training result

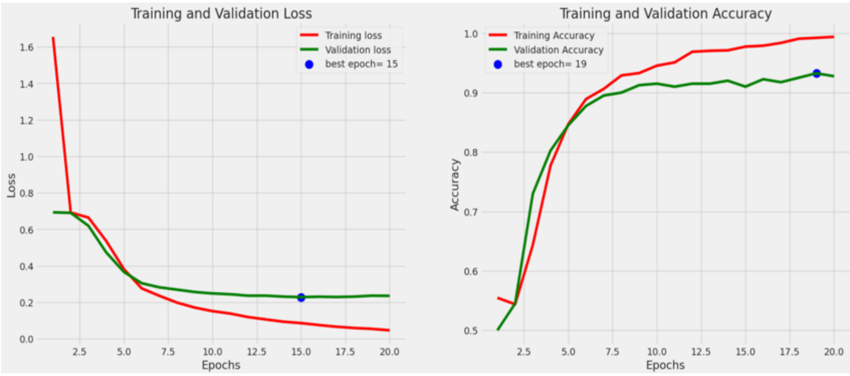
| No | Data Split | Learning rate | Dropout | Augmented | Not Augmented |
|---|---|---|---|---|---|
| 1 | 90;10 | - | - | - | - |
| 2 | | 0,001 | 0,001 | 93,12% | 93,75% |
| 3 | | 0,001 | 0,01 | **97,50%** | 92,50% |
| 4 | | 0,001 | 0,1 | 90,62% | **95,00%** |
| 5 | | 0,01 | 0,001 | 49,38% | 92,50% |
| 6 | | 0,01 | 0,01 | 91,87% | 92,50% |
| 7 | | 0,01 | 0,1 | 92,25% | 93,75% |
| 8 | | 0,1 | 0,001 | 86,25% | 73,75% |
| 9 | | 0,1 | 0,01 | 77,50% | 72,50% |
| 10 | | 0,1 | 0,1 | 53,75% | 85,00% |
| 11 | 80;20 | - | - | - | - |
| 12 | | 0,001 | 0,001 | **95,31%** | 92,50% |
| 13 | | 0,001 | 0,01 | 91,87% | **93,12%** |
| 14 | | 0,001 | 0,1 | 90,62% | 92,50% |
| 15 | | 0,01 | 0,001 | 88,13% | 85,62% |
| 16 | | 0,01 | 0,01 | 89,06% | 91,25% |
| 17 | | 0,01 | 0,1 | 91,56% | 85,62% |
| 18 | | 0,1 | 0,001 | 50,00% | 45,63% |
| 19 | | 0,1 | 0,01 | 50,94% | 45,63% |
| 20 | | 0,1 | 0,1 | 78,12% | 79,37% |
| 21 | 70;30 | - | - | - | - |
| 22 | | 0,001 | 0,001 | 91,04% | 90,42% |

| | | | | |
|---|---|---|---|---|
| 23 | 0,001 | 0,01 | 93,25% | **92,50%** |
| 24 | 0,001 | 0,1 | 91,04% | 89,17% |
| 25 | 0,01 | 0,001 | 92,50% | 88,75% |
| 26 | 0,01 | 0,01 | **93,33%** | 88,75% |
| 27 | 0,01 | 0,1 | 50,83% | 88,75% |
| 28 | 0,1 | 0,001 | 50,00% | 90,00% |
| 29 | 0,1 | 0,01 | 47,50% | 75,83% |
| 30 | 0,1 | 0,1 | 79,58% | 47,92% |

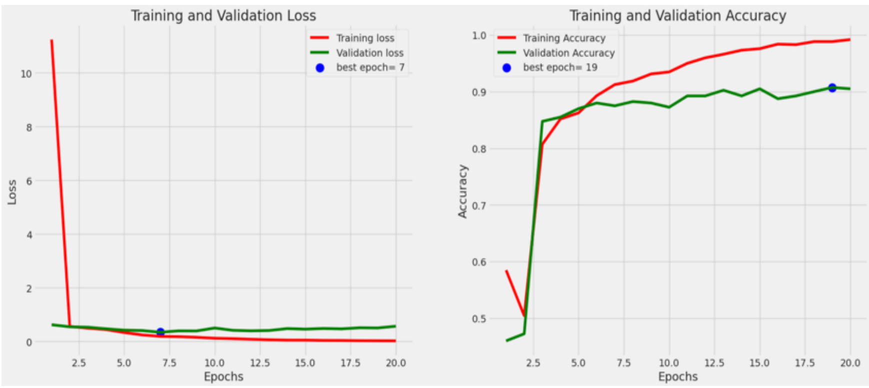
Based on the data in Table 4, it is proven that data augmentation with appropriate learning rates and dropout can improve accuracy. However, there are some training outcomes where the accuracy rate is higher when augmentation is not used. This occurs because the learning rates and dropout rates are not suitable for the type of data present.




(a)




(b)



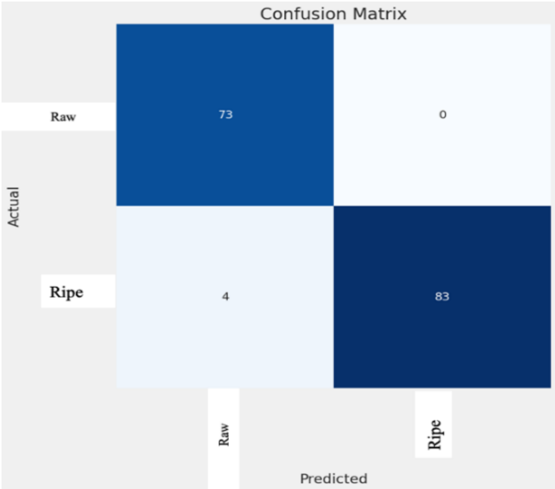

(c)

**Figure 8.** Accuracy and loss graph of (a) 90:10, (b) 80:20, and (c) 70:30

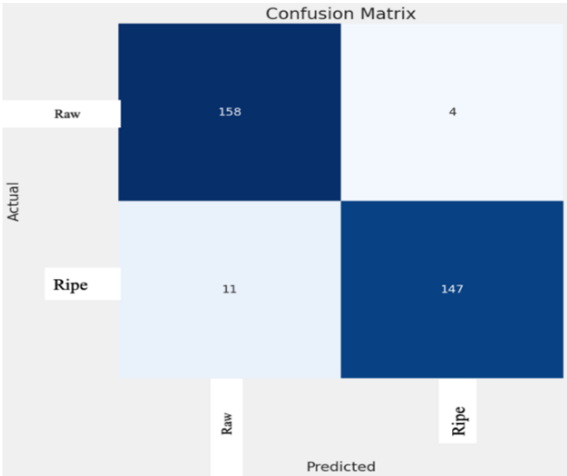
Figure 8 shows a graph of training results from the highest accuracy from each scheme. As shown in Table 4 The results in the 90:10 data scenario had the best results, with the highest validation accuracy level of 97,50% with 0,001 learning rate and 0,1 dropout. The 80:20 data scenario has the highest validation accuracy of 95,31% with 0,001 learning rate and 0,001 dropout, then the 70:30 scenarios have a highest validation accuracy of 93,33% with 0,01 learning rate and 0,01 dropout.

### 3.7 Confusion Matrix

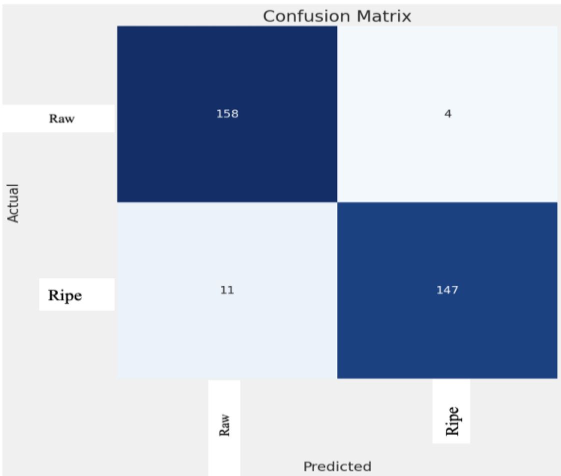
In testing this model, the Confusion Matrix method was used to measure the level of model accuracy on the test data provided with 1000 image data consisting of 500 images labeled as ripe and another 500 images labeled as raw. This test was carried out on each of the best models that had been saved from 70:30, 80:20, and 90:10 data scenarios against the previously trained model. Figure 9 is the confusion matrix result of the highest value for each scheme.




(a)




(b)




(c)

**Figure 9.** Confusion matrix of (a) 90:10, (b) 80:20, (c) 70:30

Based on Figure 9, from the result of confusion matrix from the highest accuracy of each scheme, The results obtained by calculating precision, recall, f1-score and accuracy values for each data scheme using the classification_report() function in the Scikit Learn library can be seen in Table 5.

**Table 5.** Confusion Matrix table

| Scheme Data | Class | Precision | Recall | F1-Score | Accuracy |
|---|---|---|---|---|---|
| 90:10 | Raw | 95% | 100% | 97% | 97% |
| | Ripe | 100% | 95% | 98% | |
| 80:20 | Raw | 93% | 98% | 95% | 95% |
| | Ripe | 97% | 93% | 95% | |
| 70:30 | Raw | 95% | 92% | 93% | 93% |
| | Ripe | 92% | 94% | 93% | |

Table 5 shows the confusion matrix table that has been made.The number of the precission, recall, f1-score and accuracy obtained from the results that shown on Figure 9.

## 4. CONCLUSION

In the experiment that was carried out to identify ripeness of palm fruit using the DenseNet201 model, the DenseNet201 algorithm which was used by comparing augmented and non-augmented data was added by changing the learning rate and dropout parameters. It was found that the modified DenseNet201 model provided better accuracy with augmentation compared to DenseNet201 without modification. The number of drop outs and learning rate have a big influence on the accuracy value during the experiment. The 90:10 data scheme succeeded in getting the highest accuracy with a total accuracy of 97.50% with a learning rate of 0.001 and a dropout of 0.01. Meanwhile, the 80:20 data scheme achieved the highest accuracy with an accuracy rate of 95.31% and also a better model than the 90:10 scheme, this is because the 80:20 is not overfitting and have better training accuracy and validation accuracy. The 70:30 data scheme with an accuracy rate of 93.33%. Data augmentation has proven to be important in increasing the level of accuracy of the model in classifying, most of the results from training show a higher level of accuracy when the model is given data augmentation. Apart from data augmentation, Adamax hyperparameters also play an important role in improving accuracy and reducing overfitting. From the research results, it was concluded that DenseNet201 was quite good and suitable for use for classifying palm fruit maturity.

## REFERENCES

[1] D. Suryani, A. Yulianti, E. L. Maghfiroh, and J. Alber, “Klasifikasi Kualitas Produk Kelapa Sawit Menggunakan Metode Naïve Bayes” 2022
[2] F. Murgianto, E. Edyson, A. Ardiyanto, S. K. Putra, and L. Prabowo, “Potential Content of Palm Oil at Various Levels of Loose Fruit in Oil Palm Circle,” Jurnal Agro Industri Perkebunan, pp. 91–98, Oct. 2021, doi: 10.25181/jaip.v9i2.2161.
[3] R. Sinambela, “A RIPENESS STUDY OF OIL PALM FRESH FRUIT AT THE BUNCH DIFFERENT POSITIONS,” Jurnal Keteknikan Pertanian, vol. 8, no. 1, pp. 9–14, Aug. 2020, doi: 10.19028/jtep.08.1.9-14.
[4] K. O. Purnama, D. Setyaningsih, E. Hambali, and D. Taniwiryono, “Processing, Characteristics, and Potential Application of Red Palm Oil - A review,” International Journal of Oil Palm, vol. 3, no. 2, pp. 40–55, May 2020, doi: 10.35876/ijop.v3i2.47.
[5] D. Cherie, R. Rini, and M. Makky, “Determination of the optimum harvest window and quality attributes of oil palm fresh fruit bunch using non-destructive shortwave infrared spectroscopy,” in AIP Conference Proceedings, American Institute of Physics Inc., Sep. 2019. doi: 10.1063/1.5125538.
[6] M. Rifqi, “DETEKSI KEMATANGAN TANDAN BUAH SEGAR (TBS) KELAPA SAWIT BERDASARKAN KOMPOSISI WARNA MENGGUNAKAN DEEP LEARNING,” Jurnal Teknik Informatika, vol. 14, no. 2, 2021, doi: 10.15408/jti.v14i2.23295.
[7] M. Y. M. A. Mansour, K. D. Dambul, and K. Y. Choo, “Object Detection Algorithms for Ripeness Classification of Oil Palm Fresh Fruit Bunch,” International Journal of Technology, vol. 13, no. 6, pp. 1326–1335, 2022, doi: 10.14716/ijtech.v13i6.5932.
[8] Z. Ibrahim, N. Sabri, and D. Isa, “Palm Oil Fresh Fruit Bunch Ripeness Grading Recognition Using Convolutional Neural Network” 2018
[9] N. Giarsyani, A. Fathan Hidayatullah, and R. Rahmadi, “KOMPARASI ALGORITMA MACHINE LEARNING DAN DEEP LEARNING UNTUK NAMED ENTITY RECOGNITION : STUDI KASUS DATA KEBENCANAAN,” 2020.
[10] D. Hindarto and H. Santoso, “Plat Nomor Kendaraan dengan Convolution Neural Network.”, 2021
[11] A. Fahrezantara, S. Rizal, N. Kumalasari, and C. Pratiwi, “Pemanfaatan Convolutional Neural Network Dalam Klasifikasi Penyakit Tanaman Singkong Menggunakan Arsitektur Densenet.”, 2023
[12] A. M. Simarmata, P. Salim, N. J. Waruwu, and J. Jessica, “Densenet Architecture Implementation for Organic and Non-Organic Waste,” sinkron, vol. 8, no. 4, pp. 2444–2449, Oct. 2023, doi: 10.33395/sinkron.v8i4.12765.
[13] M. K. Bohmrah and H. Kaur, “Classification of Covid-19 patients using efficient fine-tuned deep learning DenseNet model,” Global Transitions Proceedings, vol. 2, no. 2, pp. 476–483, Nov. 2021, doi: 10.1016/j.gltp.2021.08.003.
[14] A. Tiwari, M. Poduval, and V. Bagaria, “Evaluation of artificial intelligence models for osteoarthritis of the knee using deep learning algorithms for orthopedic radiographs,” World J Orthop, vol. 13, no. 6, pp. 603–614, 2022, doi: 10.5312/WJO.V13.I6.603.

[15] S. Ashari, G. J. Yanris, and I. Purnama, “Oil Palm Fruit Ripeness Detection using Deep Learning,” Sinkron, vol. 7, no. 2, pp. 649–656, May 2022, doi: 10.33395/sinkron.v7i2.11420.
[16] L. Perez and J. Wang, “The Effectiveness of Data Augmentation in Image Classification using Deep Learning,” Dec. 2017, [Online]. Available: http://arxiv.org/abs/1712.04621
[17] K. Alomar, H. I. Aysel, and X. Cai, “Data Augmentation in Classification and Segmentation: A Survey and New Strategies,” J Imaging, vol. 9, no. 2, Feb. 2023, doi: 10.3390/jimaging9020046.
[18] M. E. H. Chowdhury et al., “Can AI Help in Screening Viral and COVID-19 Pneumonia?,” IEEE Access, vol. 8, pp. 132665–132676, 2020, doi: 10.1109/ACCESS.2020.3010287.
[19] U. Khultsum and G. Taufik, “Komparasi Kinerja DenseNet 121 dan MobileNet untuk Klasifikasi Citra Penyakit Daun Kentang,” JURIKOM (Jurnal Riset Komputer), vol. 10, no. 2, p. 558, Apr. 2023, doi: 10.30865/jurikom.v10i2.6047.
[20] D. Alamsyah and D. Pratama, “IMPLEMENTASI CONVOLUTIONAL NEURAL NETWORKS (CNN) UNTUK KLASIFIKASI EKSPRESI CITRA WAJAH PADA FER-2013 DATASET,” Jurnal Teknologi Informasi, vol. 4, no. 2, 2020.
[21] R. A. Saputra and dan D. Faisal Adhinata, “Model Deteksi Kebakaran Hutan dan Lahan Menggunakan Transfer Learning DenseNet201,” vol. 05, p. 2023, 2023, doi: 10.52985/insyst.v5i2.317.