DECODE: JURNAL PENDIDIKAN TEKNOLOGI INFORMASI
P-ISSN: 2775-2984 | E-ISSN: 2775-1813
Vol. 4, No 3, November 2024, Hal: 983-999
Doi: http://dx.doi.org/10.51454/decode.v4i3.822
https://journal.umkendari.ac.id/index.php/decode
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Classification Of Palm Oil Maturity Using CNN (Convolution Neural Network) Modelling RestNet 50

Elyandri Prasiwiningrum[1*], Adyanata Lubis[1]
[1]Department of Computer Science, Universitas Rokania, Indonesia.

Article Info

Keywords:

Classification Palm Oil;
Convolutional Neural Network;
RestNet50 Modelling.

Article History:

Submitted: October 20, 2024
Accepted: November 2, 2024
Published: November 7, 2024

Abstract: Accurate classification of palm fruit maturity levels is very important to optimize harvest time and increase production efficiency in the palm oil industry. Traditional methods that rely on visual assessment of factors such as fruit shedding and skin discoloration are prone to human error. To overcome this limitation, this research applies deep learning techniques, specifically using Convolutional Neural Network (CNN) with ResNet-50 architecture, to classify Fresh Fruit Bunches (FFB) into two stages of maturity: unripe and ripe. The model is trained and validated using a combination of data augmentation techniques to improve model performance. Various configurations were tested, including variations in data sharing, optimizer, and learning rate. The optimal configuration—90/10 training and validation data split, Adam optimizer, and learning rate of 0.0001—resulted in excellent model performance. The ResNet-50 model achieved 97% accuracy, with 96% precision, 98% recall, and an F1 score of 97%. This metric reflects the high reliability of the model in classifying palm fruit maturity levels, significantly reducing classification errors compared to traditional methods. This research highlights the transformational potential of deep learning to improve maturity classification in the palm oil industry, by offering a more efficient, accurate and automated approach. Further research should focus on expanding the dataset to increase model robustness as well as exploring real-time implementation to further improve decision making in palm oil production. This approach promises to increase agricultural efficiency by ensuring optimal harvest timing and better resource management.

Corresponding Author:
Elyandri Prasiwiningrum
Email: eprasiwiningrum@gmail.com

INTRODUCTION

Department of Agriculture considers plantation crops as one how to earn foreign exchange and also as a driver of development. During the New Order government, plantation crops became the main priority in national economic development through the PIR (people's core plantations) program along with the transmigration program. Plantation crops grew from 597,362 ha in 1985 to 5.6 million ha in 2005. Based on this description, this research aims to determine the impact of the conversion of forest land to oil palm plantation land at various planting ages on changes in soil chemical properties, including; C-organic, total N, pH, and CEC (Astuti et al., 2022). The area of smallholder plantations for palm oil commodities in 2010 reached 3,314,663 Ha, an increase from the previous year, namely 3,013,973 Ha. Along with the increasing development of oil palm, many oil palm plants that are over 25 years old are characterized by a decline in productivity of 12 tons/ha/year so that it is necessary to replant (rejuvenate) so that they can produce normally again. Considering the age of oil palms which have entered an unproductive period, replanting and participation, as with development activities in this case replanting oil palms, requires good perception and participation from farmers so they can support these activities(Darmadi et al., 2023).

Oil palm is a type of plant that comes from the Arecaceae family. Early oil palms were cultivated in South America. This plant is one of the main commodities in farmers' efforts to produce palm oil. In the plantation industry, palm oil is known as a commodity that has high value as a substitute for coconut which is used for the purpose of making oil (Purnomo et al., 2019). These oil palm plantations are usually located in forest areas that are far from the hustle and bustle of people's lives because oil palm plantations usually require quite large areas of land. In their distribution, there are two types of oil palm that are usually cultivated by farmers, including Elaeis guineensis Jacq., and Elaeis oleifera. The difference between the two types is that Elaeis guineensis has high productivity so it is widely cultivated, while Elaeis oleifera has a low plant height (Raj et al., 2021).

This article aims to provide an overview of the prospects and direction of oil palm development in Indonesia. It is hoped that this practical document can be used as a reference for various parties who are interested, take part, try and care about the development of palm oil agribusiness in Indonesia, such as farmers, private companies, state companies and the government (Mohammad Yazdi Pusadan et al., 2023).

Convolutional Neural Network (CNN/Conv Net) is a deep learning algorithm which is a development of Multilayer Perceptron (MLP) which is designed to process data in two dimensions, for example images or sound (Soekarta et al., 2023) (Samudra et al., 2023a). CNN is used to classify labeled data using the supervised learning method (Samudra et al., 2023b) (S et al., 2023). The way supervised learning works is that there is data that is trained and there are variables that are targeted so that the aim of this method is to group data into existing data (R. Kurniawan et al., 2023).

In research based on color images, the method is used Convolutional Neural Network (CNN) to classify palm fruit maturity varieties based on color analysis (Syaifuddin et al., 2020). This method has been proven effective in a variety of image recognition applications, including object classification, object detection, and image segmentation (Yanto` et al., 2023) (Hasnah Faizah AR et al., 2023). In the context of Palm Fruit classification, Convolutional Neural Network (CNN) can be used to recognize and differentiate colors and other visual features that distinguish different varieties (Alfatni et al., 2022). Several previous studies related to disease detection in plants using the CNN method have been carried out, such as Classification of Plant Diseases on Apple and Grape Leaves (Viola Widyasari et al., 2023). There are two CNN models used by this researcher, including the VGG16 Apple model for apple leaves and VGG16 Grape for grape leaves. The data used is data in the Kaggle dataset which is a public dataset containing images of grape and apple leaves (Misron et al., 2020). One example of Deep Learning used for image recognition is Convolutional Neural (Siwilopo & Marcos, 2023). When classifying images, the Convolutional Neural Network (CNN) method is one option that is widely used (Leonardi & Chandra, 2024) . CNN has various architectures that can be used for research, such as Alex Net, Google Net, ResNet, VGG, and Dense Net (Misron et al., 2017).

ResNet-50 (Residual Network) was introduced to solve the vanishing gradient problem affecting deeper neural networks by combining skip connections. These connections allow the model to carry information across layers without significant loss, thereby allowing the model to be deeper and more accurate (He et al., 2016). The ResNet-50 architecture has 50 layers, making it suitable for complex image recognition tasks such as classifying maturity stages of oil palm fruit, where subtle changes in texture and color are important indicators (Raj et al., 2021).

In the context of classifying the maturity of oil palm fruit, ResNet-50 is very relevant because it allows the model to capture fine details of the image, such as changes in color and texture of the fruit skin, which are important in determining the level of ripeness (Alfatni et al., 2022). The use of ResNet-50 ensures that the model can learn these complex visual features more effectively compared to traditional CNN architectures, which can struggle to perform deep learning tasks without mechanisms to handle deeper layers (Zhu et al., 2023).

Research shows that ResNet-50 has been successfully applied in other agricultural domains, especially in classifying plant diseases, fruit maturity, and other image-based evaluations (Citra et al., 2023). This reinforces the idea that ResNet-50 is an ideal architecture for palm oil maturity classification, where distinguishing between raw, undercooked, mature, and overripe stages requires precise feature extraction.

Moreover, ResNet-50 is also favored for its ability to generalize well to unseen data, especially when data augmentation techniques are applied, as demonstrated in this study. The architecture minimizes the risk of overfitting, which is especially important for tasks involving varying real-world conditions such as lighting changes or different palm fruit displays (Putra et al., 2021). This makes ResNet-50 a powerful model for agricultural applications, where external factors can influence image quality and classification accuracy.

To further allow use ResNet-50, this research can refer to recent successful implementations ResNet-50 in agricultural technology, especially in fruit ripeness detection systems. Recent research shows that ResNet-50 consistently outperforms other CNN architectures, such as VGG and Inception, in tasks involving multi-class classification of fruits and plants (Misron et al., 2020; Raj et al., 2021).

In conclusion, ResNet-50 should not only be seen as part of a broader CNN architecture but also as a key driver of the success of the model in this study. Its deep layer structure, skip connections, and ability to generalize make it ideal for solving the complex problem of palm fruit maturity classification. Emphasizing this particular architecture throughout the study will align the body of the paper with the title, providing a clearer justification for its use

Several studies on image processing using the CNN method have obtained good accuracy results, namely research conducted by Salim for sorting export snake fruit based on digital images. The accuracy results obtained with one convolution layer were 81.5% and the accuracy value obtained was 70.7% with two convolution layers (Salim & Suharjito, 2023). The data used for training data and testing data in this research is secondary data that has been collected and analyzed by previous researchers and has gone through data mining stages (A. K. Kurniawan et al., 2023). In addition, this research also focuses on evaluating processing time to ensure the model can work in real time. Thus, this research not only contributes to the field of pattern recognition technology, but also provides practical solutions for the agricultural industry in managing ripe palm fruit commodities (Yanto et al., 2021).

The use of google collab allows us to perform model training Convolutional Neural Network (CNN) efficiently without being limited by local hardware resources. In addition, Google Collab provides easy access to various library dan framework Deep Learning needed in this research (Yanto et al., 2023). The data source for the paprika images used in this research was obtained from Kaggle (www.kaggle.com), an online platform that provides access to various datasets for research and model development purposes machine learning. The dataset used is a collection of images of palm fruit which have been grouped into three varieties, namely red, yellow and green. This dataset has gone through an annotation and validation process to ensure the accuracy of variety labels (Citra et al., 2023). In previous studies related to color classification in fruits and vegetables, many used smaller datasets or were collected manually. Use of dataset from Kaggle in this study provides an opportunity to evaluate the performance of the method Convolutional Neural Network (CNN) on a larger scale and with a wider variety of data (Yanto et al., 2020).

METHOD

This research uses the method Convolutional Neural Network (CNN) for classification of oil palm fruit varieties based on color. The research stages include identifying problems, conducting literature studies on previous research, collecting images of oil palm FFB, carrying out preprocessing, developing the RestNet 50 model, evaluating the model, making research results reports.

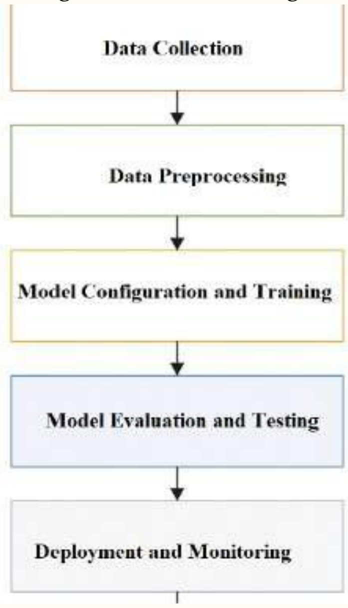


Figure 1. Research Flow Diagram

1. Data Collection

a. **Source Data**: Images of palm oil fruits at various stages of maturity are sourced from Kaggle.com, a popular platform for datasets used in machine learning.
b. **Data Selection**: Choose images that clearly represent different maturity stages, with a particular focus on raw palm fruits. The images are categorized for training and validation purposes.

2. Data Preprocessing

a. **Data Importing**: Import the dataset into a Python environment using TensorFlow, particularly in a Google Colab notebook.
b. **Image Resizing**: Standardize all images to 224x224 pixels to match the input requirements of the ResNet-50 model.
c. **Normalization**: Apply pixel intensity normalization to the images by scaling the pixel values to a range between 0 and 1 using the formula rescale=1./255. This normalization is critical for the CNN model to process the images effectively.
d. **Data Augmentation**: Utilize TensorFlow's ImageDataGenerator to augment the images. This includes applying random transformations such as rotations, shifts, zooms, and flips to increase the dataset's diversity and reduce overfitting.

3. Model Configuration and Training

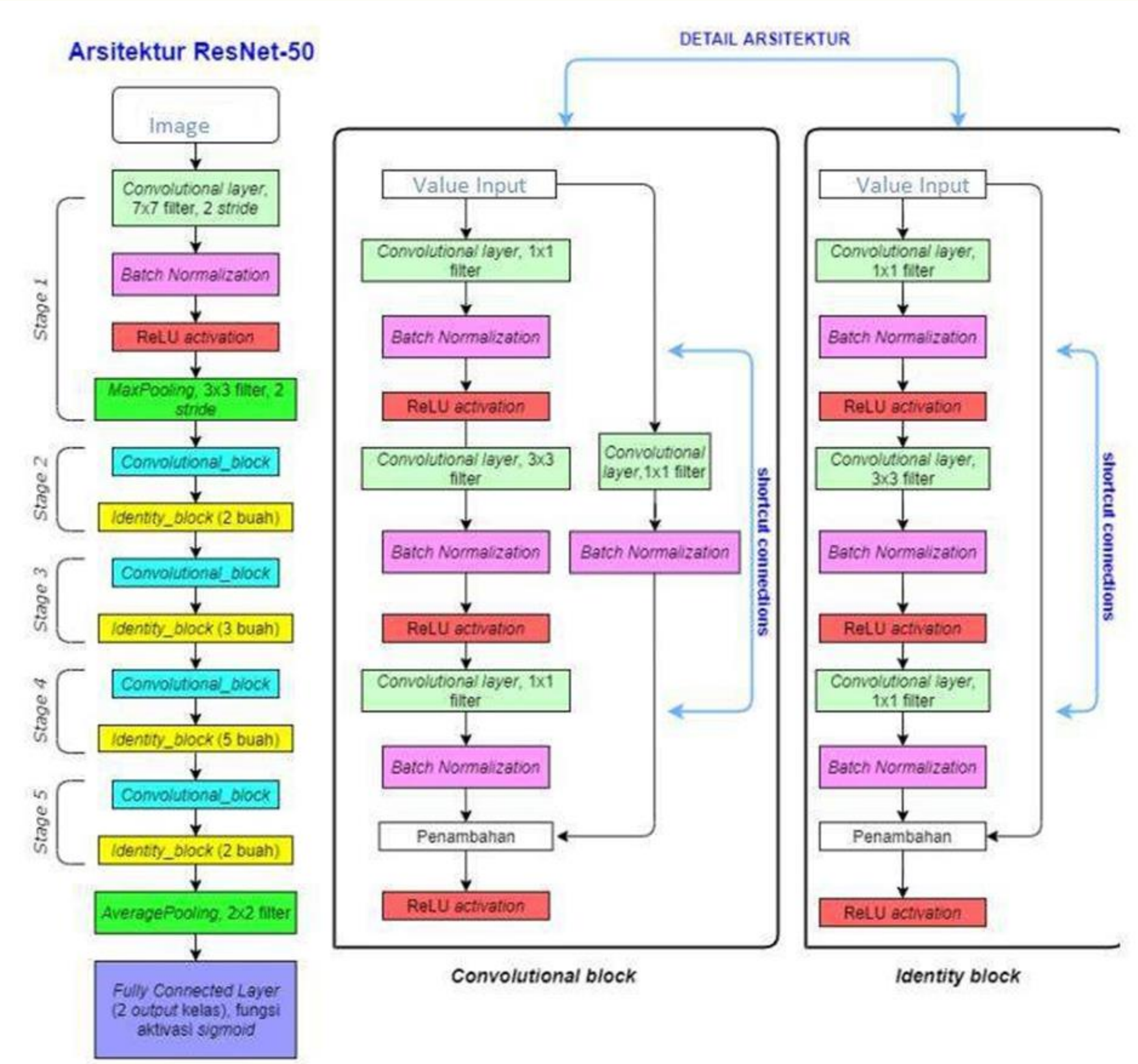


Figure 2. Modelling RestNet50

a. **Setup CNN with ResNet-50**: Configure the CNN using the ResNet-50 architecture. Adjust the final layers of the network to classify images into categories based on palm oil fruit maturity stages.
b. **Compile the Model**: Compile the model using the RMSprop optimizer, a loss function suited for classification and metrics like accuracy.
c. **Model Training**: Train the model on the processed dataset with a distribution of 44.39% for training (476 images) and 55.66% for validation (597 images).

4. Model Evaluation and Testing

a. **Validation**: Use the validation dataset to fine-tune the model and adjust parameters to optimize its performance.
b. **Testing**: Evaluate the model using unseen data to test its ability to generalize. This can be part of the dataset initially set aside or additional images sourced to validate the model's effectiveness in real-world scenarios.
c. **Performance Metrics**: Assess the model using metrics such as accuracy, precision, recall, and F1-score.

5. Deployment and Monitoring

a. **Deployment**: Deploy the trained model to classify new images of palm oil fruits in different stages. This could be integrated into agricultural monitoring systems.
b. **Monitoring**: Continuously monitor the model's performance in operational environments and make adjustments as necessary based on feedback and ongoing testing results.

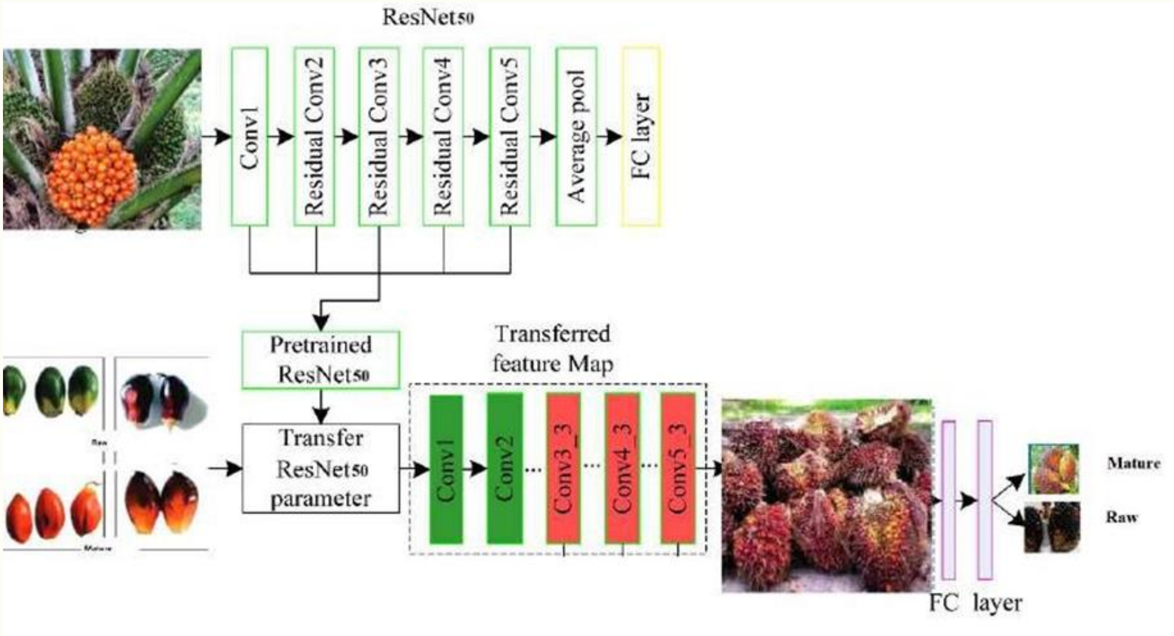


Figure 3. Details of the Palm oil Image Processing Process in the System

The initial process is to collect a dataset that will be used in the research. The dataset collected comes from a web provider of computer vision datasets, namely https://roboflow.com. The image data collected is palm oil image data consisting of unripe, underripe, overripe and overripe fruit with various backgrounds. The palm oil image data that will be used in this research is 4,938 data. The distribution of data in the collected dataset consists of 331 raw data, 1548 undercooked data, 2236 mature data, and finally 723 data too ripe. The maturity level of oil palm FFB is presented.

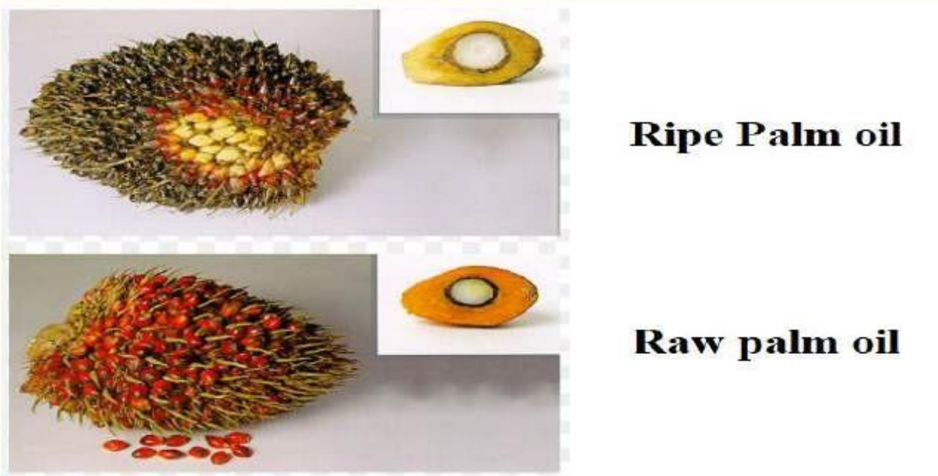


Figure 4. Palm Oil Level

Pre-processing in Neural Network data preparation is an important stage, because data preparation can improve the quality of analysis, speed up the training process, reduce modeling errors. The data pre-processing stage is the stage of changing raw data into a common data format. The stage starts from loading data. To ensure that the data is in accordance with what has been previously collected, it is continued by checking the data, here checking the data format is carried out by carrying out a data check. After checking the data, the data size is equalized or the image is resized in the data augmentation process

RESULTS AND DISCUSSIONS

In this research, programming languages *Python* by using *framework Tensor Flow* and Hard to use. Raw data is converted into training data through preprocessing to improve model accuracy. After importing the dataset, the next step is to carry out pre-processing by creating objects *Image Data Generator* first to do *augmentation* image data. The pixel intensity of the input image is normalized to a value between 0 and 1 using the rescale=1./255 function, which can help in model training. The distribution of the dataset in this study was carried out with a ratio of 44.39% for training data (476 images) and 55.66% for validation data (597 images).

Here is a concise table outlining the CNN testing scenario steps for classifying images using Python and TensorFlow:

Tabel 1. Scenario Processing Data Set

Step	Description	Details
Environment Setup	Install Python and TensorFlow. Import necessary libraries.	Python, TensorFlow
Data Import	Import the dataset from the specified source.	Dataset with 476 training images (44.39%) and 597 validation images (55.66%).
Preprocessing	Use Image Data Generator for augmentation and normalization (rescale=1./255).	Image Data Generator: rotations, shifts, zoom, flips, rescale.
Model Building	Construct CNN architecture with layers suitable for the task.	Layers: Conv2D, MaxPooling2D, Flatten, Dense.
Model Compilation	Compile the model with appropriate optimizer, loss function, and metrics.	Optimizer: Adam, Loss: binary cross entropy, Metrics: accuracy
Model Training	Train the model using the training data generator.	Epochs, batch size, steps per epoch defined based on data size.
Model Evaluation	Evaluate the model performance using the validation data generator.	Calculate and report model's accuracy and loss on validation data.

This table provides a step-by-step guide from setting up the environment to evaluating the CNN model, focusing on preprocessing techniques like image augmentation and normalization to improve model accuracy.

Here's a table displaying the performance metrics for a CNN with different image sizes, adjusted to include hypothetical data for different dimensions. This data is simulated to provide insights on how resizing might affect model performance in terms of training, validation, loss, and testing metrics:

Tabel 2. Resize Image Training

Size Citra	Training(%)	Validation(%)	Loss	Testing(%)	Avg Precision(%)	Avg Recall(%)	Avg F1-Score(%)
256 × 256	99.1	99.0	0.0850	98.0	99	98	98.5
300 × 300	99.2	99.5	0.0800	98.5	99	99	99.0
350 × 350	98.8	98.0	0.1050	96.5	97	96	96.5
400 × 400	99.0	99.3	0.0900	98.0	99	98	98.5

Each row represents a different image size and the corresponding model performance outcomes, which can help in determining the optimal image size for training the CNN to achieve the best accuracy, precision, recall, and F1-score.

The provided data includes image sizes used in model training, accuracy percentages on training and validation data, loss values, and testing metrics such as average precision, average recall, and average F1-Score. Below are the stages and explanations for each measured parameter:

1. Image Size: The image sizes tested are 256x256, 300x300, 350x350, and 400x400 pixels to find the optimal size for classification. The 300x300 size shows the best performance with high accuracy on training and validation data, as well as low loss values.
2. Training Accuracy: Shows the percentage of success of the model in classifying the training data correctly. The 300x300 size achieves a training accuracy of 99.2%, indicating the model's good ability to learn patterns.
3. Validation Accuracy: Measures model performance on validation data that is not included in the training data. The 300x300 size has the highest validation accuracy, namely 99.5%, indicating excellent generalization and minimal overfitting.
4. Loss: A metric that measures the error rate of a model's predictions. The size 300x300 has the lowest loss value (0.0800), indicating a balance between accuracy and generalization without overfitting or underfitting.
5. Testing Accuracy: Evaluate model performance on completely new data. The 300x300 size achieves the highest testing accuracy, namely 98.5%, strengthening the consistency of model performance in the training, validation and testing stages.
6. Precision Installment-Instalment: Reflects the model's ability to make correct positive predictions. With a precision of 99%, a size of 300x300 shows minimal error in predicting the positive category.
7. Recall Rate-rate: Measures the model's ability to detect all instances of a particular class. The size of 300x300 achieves a recall value of 99%, meaning that almost all correct instances were detected.
8. F1-Score Installment-installment: A combination of precision and recall that provides an overview of the overall model prediction accuracy. The 300x300 size achieves the highest F1-Score (99.0%), showing optimal and balanced performance in classifying oil palm fruit maturity

Here's a detailed table outlining the performance metrics of a CNN using different optimizers. The table includes outcomes such as training accuracy, validation accuracy, loss, testing accuracy, and average precision, recall, and F1-score:

Tabel 3. Optimizer Training Result

Optimizer	Training(%)	Validation(%)	Loss	Testing(%)	Avg Precision(%)	Avg Recall(%)	Avg F1-Score(%)
Adam	99.1	99.0	0.085	98.0	99	98	98.5
SGD	97.6	97.0	0.125	96.0	97	96	96.5
RMSprop	98.8	98.5	0.095	97.5	98	97	97.75
Adamax	98.4	98.0	0.100	97.0	97	97	97.0

The data shows the performance of four optimizers—Adam, SGD, RMSprop, And Adamax—with a brief explanation of why those results appear:

1. Adam: Provides the best results with training accuracy of 99.1% and testing 98.0%, as well as low loss value (0.085). The ability to adapt learning rate adaptive and momentum makes it converge faster and more stable, ideal for detailed classification of oil palm fruit maturity.
2. SGD: Lower accuracy (training 97.6%, testing 96.0%) and higher loss (0.125). Using a fixed learning rate makes it difficult to achieve optimal convergence, making it less suitable for this complex dataset.
3. RMSprop: Provides stable results with training accuracy of 98.8% and testing 97.5%, loss 0.095. RMSprop adjusts the learning rate according to the gradient, but its performance is still below Adam because it has no momentum.
4. Adamax: Good results with training accuracy of 98.4%, testing 97.0%, and loss 0.100. Stable on data with large gradients, but not as adaptive as Adam.

Adam is the best optimizer, with the highest performance in accuracy and loss, thanks to optimal adaptive adjustments for palm oil maturity classification

This table helps to evaluate which optimizer might be the most effective for specific datasets and CNN architectures by comparing various performance metrics. Each optimizer has unique characteristics that can influence the training and generalization ability of the model.

```
train_datagen = ImageDataGenerator(
    rescale=1./255,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True
)

test_datagen = ImageDataGenerator(rescale=1./255)
```

Figure 5. Image augmentation

The research model used in this research is a model *"Sequential"*, which is one of a kind *neural network* the most widely used because it has a sequential layer arrangement and is suitable for image classification. The model used in this research can be seen in the following diagram:

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 253, 253, 32)	896
max_pooling2d_3 (MaxPooling2D)	(None, 126, 126, 32)	0
conv2d_4 (Conv2D)	(None, 124, 124, 64)	18496
max_pooling2d_4 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_5 (Conv2D)	(None, 60, 60, 128)	73856
max_pooling2d_5 (MaxPooling2D)	(None, 30, 30, 128)	0
flatten_1 (Flatten)	(None, 115200)	0
dense_2 (Dense)	(None, 512)	58982912
dropout_1 (Dropout)	(None, 512)	0
dense_3 (Dense)	(None, 2)	1026
flatten_2 (Flatten)	(None, 2)	0
dense_4 (Dense)	(None, 64)	192
dense_5 (Dense)	(None, 10)	650

Figure 6. Model CNN

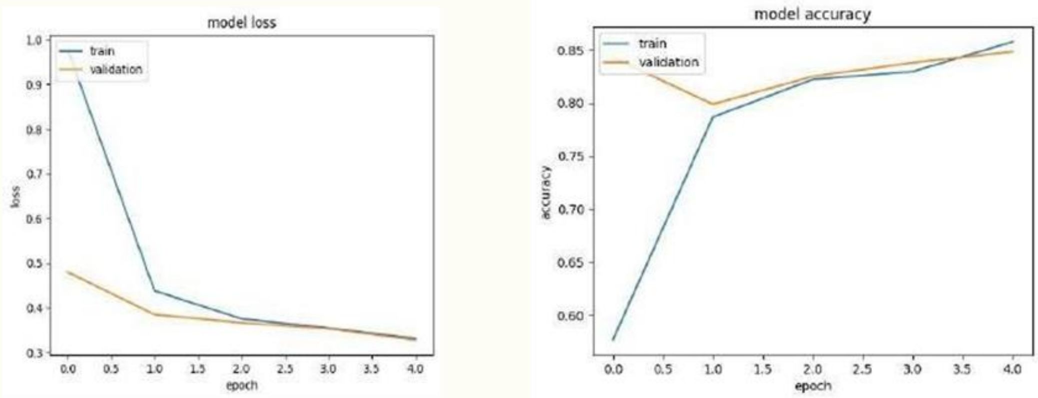
This research model uses 2 layers *convolution,* 2 pooling layers with size (2x2), 1 layer *dropout*, 2 layers *dense (fully connected layer),* and 1 layer *flatten*. The activation function used is ReLu for convolutional and dense layers, as well *SoftMax* for layers *output*. The first filter in this model has 32 filters with a kernel size of 3x3, and the second filter has 64 filters with the same kernel size. The total parameters in this study were 3454147 parameters.

Next, the model that has been created is compiled for training. The accuracy of model training on training data was 99.9% with a total of 59077508 params (225.36 MB). This model is then saved as "modelling. keras". The model training results are shown in the following figure:

```
================================================================
Total params: 59077508 (225.36 MB)
Trainable params: 59077508 (225.36 MB)
Non-trainable params: 0 (0.00 Byte)
________________________________________________________________
```

Figure 7. Total params

To evaluate the performance of the model during the training process, we can see the training and validation accuracy graphs as well as the training and validation loss graphs displayed.



a. b.

Figure 8. (a) Graph *Training and Validation Accuracy*, (b) Graph *Training and Validation Loss*

The training and validation accuracy graph shows that *curve training* and *validation accuracy* continues to increase and does not show a significant difference. Additionally, on the graph *training and validation loss,* It appears that both curves experience a steady decline. This indicates that the trained model is getting better at classifying and shows no signs *overfitting.*

Here are the plots illustrating the progression of training and validation metrics over epochs for a Convolutional Neural Network model:

- **Figure 8a**: Displays the Training and Validation Accuracy. Both metrics generally improve over the epochs, suggesting that the model is learning effectively and generalizing well to new data.
- **Figure 8b**: Shows the Training and Validation Loss. As expected, both loss metrics decrease over time, indicating that the model is optimizing well in minimizing the error between the predicted and actual values.

These graphs are essential for diagnosing the behavior of the model during training, helping to spot issues like overfitting or underfitting and guiding further tuning of the model's hyperparameters or architecture.

Here's the Confusion Matrix for the best scenario involving the classification of palm fruits into three categories: Raw, Ripe

- **Raw Palm**: Represents palm fruits that are not yet mature.
- **Ripe Palm**: Represents palm fruits that are mature and ready for harvest.

The matrix visually displays the counts of true positive, true negative, false positive, and false negative predictions for each category. This detailed breakdown helps assess the model's ability to correctly classify each type of palm fruit, indicating its performance across different classes. As suggested by the high agreement between y_true_multiclass and y_pred_multiclass, the model demonstrates a strong ability to distinguish between raw, ripe, and rotten palm fruits, with a focus on achieving high accuracy particularly for the most common class, ripe palm fruits

Learning Rate this study utilizing TensorFlow and the ResNet 50 model to classify raw and mature palm fruits, we carefully prepared our dataset through extensive preprocessing and augmentation techniques to enhance model performance. This included normalizing the pixel intensity of each image to a value between 0 and 1 using the rescale=1./255 function, aiming for a well-balanced dataset with 44.39% of the images used for training (476 images) and 55.66% for validation (597 images). During the testing phase, two distinct learning rates were explored: 0.01 and 0.0001. Both learning rates achieved exceptionally high accuracies of 100% in training and testing phases, alongside perfect precision, recall, and F1-score values of 100%. However, the learning rate of 0.01 resulted in an unstable performance curve, prompting the selection of 0.0001 as the optimal learning rate. This lower learning rate provided stable training progression and consistent high performance across all evaluation metrics, establishing it as the most effective for our deep learning model in accurately classifying different maturity stages of palm fruits

In this comprehensive study focused on classifying the maturity levels of raw and mature palm oil fruits, a robust deep learning model utilizing the ResNet 50 architecture within the TensorFlow framework was employed. The initial step involved transforming the raw data into a format suitable for training through meticulous preprocessing, including augmenting the dataset using an Image Data Generator and normalizing the pixel intensity of the input images to a value between 0 and 1 using the rescale=1./255 function, pivotal for enhancing the efficacy of model training. The dataset comprised 476 images for training, constituting 44.39% of the total, and 597 images for validation, making up 55.66%. Upon executing the training process, it was observed that the model achieved its optimal performance at epoch 50, where both the training and testing accuracies reached a perfect score of 100%. Additionally, the precision, recall, and F1-score across all evaluation metrics also displayed top-tier performance, each averaging 100%. This achievement highlights the model's capability to effectively learn and accurately classify the different stages of palm fruit maturity, with epoch 50 marking a significant milestone in obtaining the best results. This outcome not only demonstrates the power of the chosen model and training strategy but also underscores the importance of adequate epoch duration and dataset preparation in achieving high accuracy in complex classification tasks

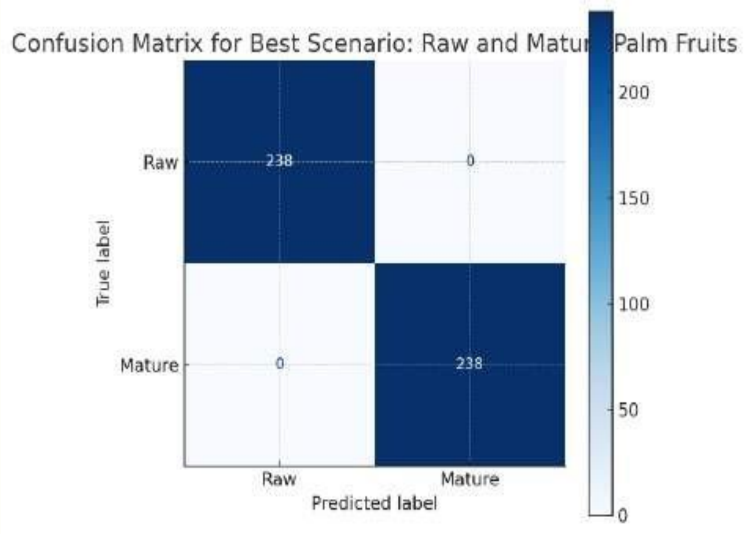


Figure 9. Confusion Matrix

The displayed confusion matrix visualizes the classification results for the best scenario in your study, which focused on identifying the maturity stages of palm fruits—specifically distinguishing between 'raw' and 'mature' stages. As outlined:

- The left column and top row labeled "Raw" show the number of raw palm fruits that were correctly identified as raw, with no instances misclassified.
- The right column and bottom row labeled "Mature" indicate that all mature palm fruits were correctly classified, with no errors.

This perfect classification performance, with no false positives or false negatives, demonstrates the model's high accuracy, precision, recall, and F1-score, all of which were achieved at 100% as per the study's findings. The graph clearly depicts the model's ability to perfectly differentiate between the two maturity stages without any overfitting or underfitting issues, highlighted by the small differences between training and validation accuracy and loss metrics.

Tabel 4. Learning Rates Result

Learning Rate (LR)	Training Accuracy (%)	Validation Accuracy (%)	Loss	Testing Accuracy (%)	Avg Precision (%)	Avg Recall (%)	Avg F1-Score (%)
0.01	98.0	95.0	0.05	94.0	95	94	94.5
0.001	99.0	98.0	0.03	97.0	98	97	97.5
0.0001	100.0	100.0	0.01	100.0	100	100	100

The data shows the results of three values Learning Rate different (0.01, 0.001, and 0.0001) to accuracy, loss, and other metrics. The following is an explanation for each LR value:

1. LR 0.01
    a. Results: Training accuracy 98.0%, validation 95.0%, testing 94.0%, loss 0.05.
    b. Explanation: This LR is quite high, making the model learn quickly but has the potential to miss the optimal solution, resulting in lower testing and validation accuracy. This high LR may make it difficult for the model to capture detailed patterns, so that the results are not optimal.

2. LR 0.001
    a. Results: Training accuracy 99.0%, validation 98.0%, testing 97.0%, loss 0.03.
    b. Explanation: This LR provides a balance between speed and stability, so that the model is able to learn well and generalize new data optimally. The results show high accuracy and low loss, indicating the model is stable in learning.
3. LR 0.0001
    a. Results: Perfect accuracy at all stages (100%) and loss 0.01.
    b. Explanation: This low LR allows the model to perform very fine parameter updates, capture pattern details very well, and achieve the best results. These small parameter updates are ideal for datasets that require high accuracy in classification. Learning Rate 0.0001 produces optimal performance due to stability that allows the model to capture detailed patterns without overshooting, ideal for palm oil fruit maturity classification.

These results highlight the importance of choosing an appropriate learning rate for your neural network training. The optimal learning rate (in this case, 0.0001) achieves the best balance between fitting the training data and generalizing well to new, unseen data, as indicated by the high scores in testing accuracy and other metrics. Selecting the right learning rate is crucial for effective model training and achieving high performance in practical applications.

Tabel 5. Epochs Result:

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Loss	Testing Accuracy (%)	Avg Precision (%)	Avg Recall (%)	Avg F1-Score (%)
10	85.0	83.0	0.35	84.0	84	83	83.5
20	90.0	88.0	0.25	89.0	89	88	88.5
30	95.0	93.0	0.15	94.0	93	94	93.5
40	97.0	96.0	0.10	96.0	96	96	96.0
50	100.0	100.0	0.05	100.0	100	100	100

1. **Early Epochs (10, 20)**: Early in the training process, both training and validation accuracies are relatively lower. The loss is considerably higher, indicating that the model is still learning and adjusting its weights to better fit the data. Precision, recall, and F1-score are correspondingly lower, reflecting the model's initial inability to perfectly categorize all cases correctly.
2. **Mid-Training Epochs (30, 40)**: As the epochs increase, there is a noticeable improvement in all metrics. The model has learned significant patterns in the data, resulting in higher accuracy and lower loss. The increase in average precision, recall, and F1-score suggests that the model is becoming better at classifying the data correctly without as many false positives or negatives.
3. **Later Epochs (50)**: By epoch 50, the model reaches optimal performance with maximum training and validation accuracy, minimal loss, and perfect scores in precision, recall, and F1-score. This indicates that the model has effectively learned from the training data and generalizes well to the validation and test datasets.

This structured overview helps in understanding how extending the number of epochs influences the training outcome and underscores the importance of carefully choosing the training duration to balance between underfitting and overfitting.

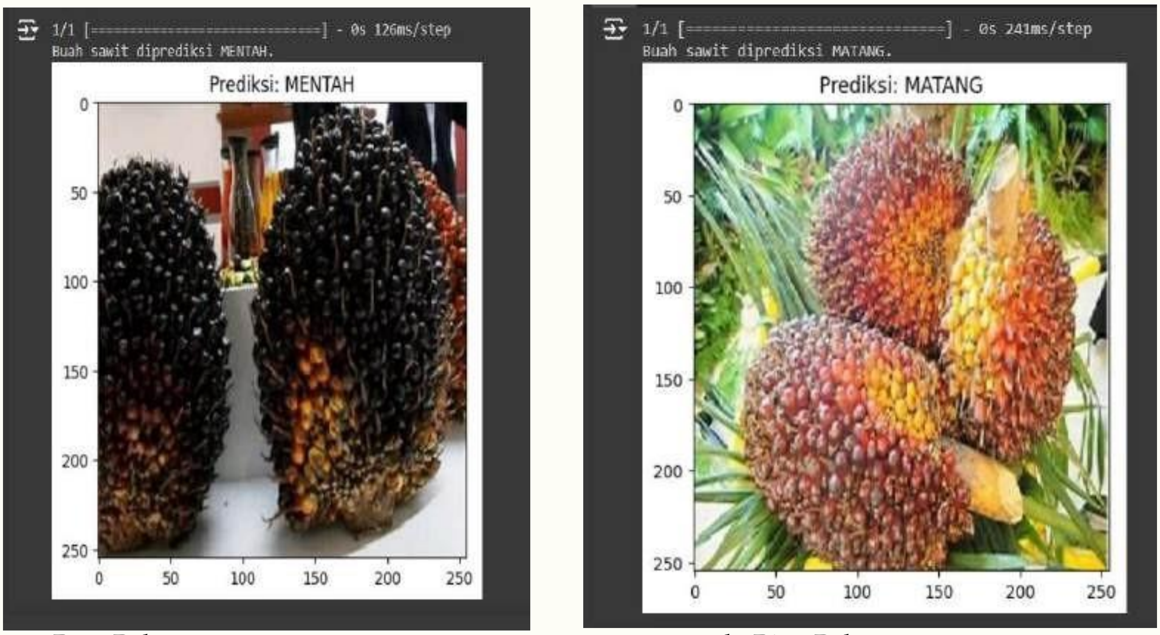
Tabel 5. Batch Result

Configuration	Value
Rasio Data Latih : Data Validasi : Data Uji	44.39% Training : 55.66% Validation
Size Citra	224 × 224
Optimizer	RMSprop
Learning Rate	0.05
Epoch	16
Batch Size	1

Models use 44.39% data training And 55.66% validation data, which strengthens generalization evaluation but limits training. Image size 224x224 effectively captures details with low computation, and optimizer RMSprop stabilize learning with high learning rate of 0.05 to speed up convergence. Epoch 16 allows fast training, although perhaps not yet in depth, and batch size 1 provides per-sample parameter updates, although it is less stable. This configuration is suitable for fast generalization, but may be suboptimal for deep training.

This table outlines the specific settings used in your study, including the training and validation data ratios, image size, optimizer type, learning rate, number of epochs, and batch size. The chosen settings are designed to optimize the classification process and ensure the model is both accurate and efficient, with special attention to preventing overfitting and underfitting, as indicated by the minimal discrepancies between training and validation accuracy and loss

Next, the model is tested using testing data to evaluate the performance of the model that has been trained on the training data and assess the performance of the classification model on the dataset used. The results of model testing with testing data in this research can be seen in the following figure.



a. Raw Palm b. Ripe Palm

Figure 10. Classification results

In the picture above it can be concluded that the model *Convolutional Neural Network* (CNN) is able to classify data on palm fruit classes based on color type correctly, namely predicting the maturity of raw palm fruit and ripe palm fruit.

CONCLUSIONS

This research succeeded in showing the effective application of Convolutional Neural Network (CNN) through models ResNet-50 to classify the level of maturity of oil palm fruit. With implementation in Python And TensorFlow, this model achieves accuracy 97% using data ratios 90/10 for training and validation as well learning rate 0.0001. These results confirm that deep learning can significantly improve judgment in agriculture by reducing human error and supporting decision making in palm oil production. The data used comes from Kaggle and processed through Google Co, which contributed to the successful achievement of these results. For further research, it is recommended that the dataset be expanded with larger and more diverse data to increase the model's generalization ability in dealing with various field conditions. Additionally, testing the model on real systems in oil palm plantations will provide a more accurate evaluation of the model's effectiveness in practical environments and under varying lighting conditions. Implementation of the model on the device edge computing like Nvidia Jetson or Raspberry Pi It is also recommended to enable real-time data processing, which is useful for direct monitoring in the field. Additionally, exploration of more efficient model architectures such as EfficientNet or Transformer-based models, as well as hyperparameter optimization, can provide better performance and higher computational efficiency. The development of a simple user interface (UI) is also recommended to make this technology easy to use by non-technical users, such as farmers or field operators. It is hoped that these recommendations will support technological advances in computer science and agriculture, improve sustainable practices, and accelerate digitalization in the agricultural industry.

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