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Applications of Convolutional Neural Networks and Transfer Learning for Enhancing the Accuracy of Dragon Fruit Classification

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Abstract

This paper discusses the application of Convolutional Neural Network (CNN) and Transfer Learning (TL) methods to improve the accuracy of dragon fruit classification. The application of the CNN method in real-time testing for classifying three types of dragon fruit only achieved an accuracy rate of 33.3%. Therefore, the CNN and TL methods using the Stochastic Gradient Descent (O-SGD) optimizer and the Root Mean Square Propagation (O-RMSProp) optimizer are proposed to improve the accuracy rate in classifying three types of dragon fruit: ripe, unripe, and rotten. The results of applying the CNN method with O-SGD at epoch 100 yielded an accuracy of 27.18%, val accuracy of 27.27%, loss of 1.407, and val loss of 1.405, while O-RMSProp at epoch 100 yielded an accuracy of 99.11%, val accuracy of 100%, loss of 0.073, and val loss of 0.058. Meanwhile, the application of the TL method with O-SGD at epoch 100 yielded an accuracy of 89.35%, val accuracy of 91.82%, loss of 0.462, and val loss of 0.443. TL with O-RMSProp at epoch 100 yielded an accuracy of 100%, val accuracy of 100%, loss of 0.002, and val loss of 0.003. The performance of the TL method with O-SGD and O-RMSProp is more accurate in classifying three types of dragon fruit compared to the CNN O-SGD and O-RMSProp models. This research contributes to improving the accuracy level of the CNN classification method to ±99-100%, and the application of this technology is an effort to enhance production quality and support smart agriculture in Banyuwangi Regency.

Keywords: Dragon Fruit, CNN, TL, Classification, Accuracy

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1. Introduction

The East Java Province's largest dragon fruit-producing region is Banyuwangi [1]. According to data obtained by the Banyuwangi Central Statistics Agency, harvests of dragon fruit exceeded 408,093 tons in 2021 and 272,324 tons in 2022 [2]. Up to 80% of East Java's dragon fruit production is generated by banyuwangi [3]. Due to the benefits of anthocyanins, dragon fruit is produced [4], hypercholesterolemia [5], anti-free radicals [6], anti-bacterial [7], bioactive substances (carbonic acid, beta-carotene) [8], betacyanin [9], ascorbic acid [10], oleic acid, organic acids, phenols and esters [11]. In addition, dragon fruit can lower blood pressure [12], increase hemoglobin [13], lower leukocytes [14], cure cancer [15], and has antimicrobial, antifungal, anti-inflammatory, anticancer, antilithic, anti-fertility, and antidiabetic properties [16].

Dragon fruit production is sold in local markets (5%), regencies (25%), provinces (40%), exports (30%), and the cities of Surabaya, Malang, Jakarta, Bandung, and Bali [17]. However, the price of dragon fruit sold in the market faces several problems. The first is the price during the October-April season, which is ±Rp 5,000-8,000 per kilogram with a loss of ±Rp 2,000-5,000 per kilogram. The second is the use of artificial lighting outside the season from May to September from 10:00 p.m. to 5:00 a.m., which requires electricity costs of 600,000 per night and 6,400,000 per month. The third is the quality of fresh fruit production during and outside the season, which only reaches 50% due to diseases and pests affecting dragon fruit. The selling price during the season reaches 10,000/kg [18], and outside the season it is 35,000/kg [19].

The selling price of dragon fruit is influenced by color, where ripe dragon fruit shows signs such as dark red color, shiny skin, shrinking crown or cap, large round volume, and wrinkles at the base of the fruit. Based on the ripeness category, dragon fruit farmers make mistakes in determining ripe and unripe dragon fruit. This is influenced by several factors such as fatigue and varying levels of concentration among individuals [20].

Several efforts have been made to determine and increase dragon fruit production using artificial intelligence [21]. The use of electricity from 2020 to 2024 resulted in a production of 19,069-98,436 tons per year [22]. Although production increased, farmers' electricity costs reached 4,600,000 per month [23]. The comparison of dragon fruit production with electricity is 28,905 kg/ha and without electricity is 15,736 kg/ha (28). Adding 12-18 watts of lamp power affects the harvest yield by 8. 22 Mg/g [24], variations in yellow LED lights produce 7.56 flowers [25], dragon fruit lighting increases production during the season [26], CNN classification of dragon fruit has 70% training data and 30% testing data [27], [28], IoT and CNN monitoring applied to dragon fruit with accuracies of 0.976, 0.981, 0.986 [29], development of a sorting robot using CNN, and classification of ripeness based on color features using the SVM algorithm [30].

From the approach taken to enhance dragon fruit production, it appears that the Convolutional Neural Network-Transfer Learning (CNN-TL) classification system with Stochastic Gradient Descent (O-SGD) and Root Mean Square Propagation (O-RMSProp) optimizers for selecting three types of dragon fruit has not been implemented. The CNN-TL classification system with two optimization techniques is used to accelerate accuracy based on the classification results of 3 types of fruit at ±99-100% and maintain the quality of the harvest. The types of fruit are divided into the categories of rotten, ripe, and unripe. The application of this technology is an effort to improve production quality and support smart agriculture in Banyuwangi Regency.

2. Methods

2.1 Dataset

Four hundred and fifty dragon fruit datasets were gathered in the initial phase of the experimental technique study processes. In the second process, the datasets were separated into three groups: 150 ripe, 150 unripe, and 150 rotten. The CNN-TL algorithm coding on Kaggle is used in the third step. Testing the CNN-TL training data using 450 datasets apiece is the fourth process. Optimizing the CNN-TL training data outputs to increase accuracy and convergence with O-SGD and O-RMSProp is the fifth step. The training data must be saved in.h5 file type for the sixth procedure. In the final phase, the CNN-TL algorithm was used to test the data in.h5 files in real time. The CNN-TL classification results were tested in real time with a camera in the eighth stage, and the results for raw, ripe, and rotten dragon fruit were viewed in real time in the ninth phase.

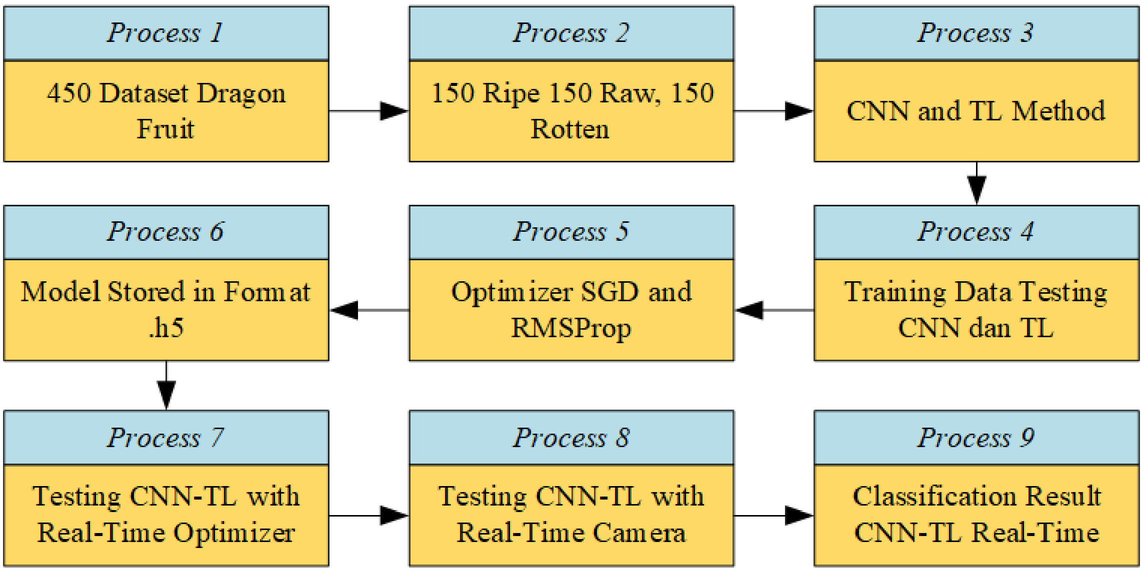

Figure 1. Research Method

The system process begins with the collection of sample data from the Esp camera capture, which yields variables in three class groups. Next, the acquired data is fed into the process by saving the picture dataset to the directory/datasets/input and separating it into train and test sets. The convolution process, which is a matrix multiplication process, is used to acquire values for each kernel, also known as a filter, and then calculates the coordinate values for training and validation purposes. The training dataset findings are then utilized to build a model. The dragon fruit sorting classification system employs a validation or object matching method that has been modified to the previously stored model.

2.2 Convolution Feature

The convolution feature is a method for transforming an image into a new image result in the form of mathematical data. Convolution is the sum of the multiplication of comparable or equivalent image elements (with similar coordinates) in two matrices or vectors. Convolution is the result of multiplying each kernel and point of the input function. A kernel is often a tiny matrix whose members are numbers. The kernel works by shifting the function x(i). The convolution result is calculated by adding each point in the function and expressing it as y(i) [31].

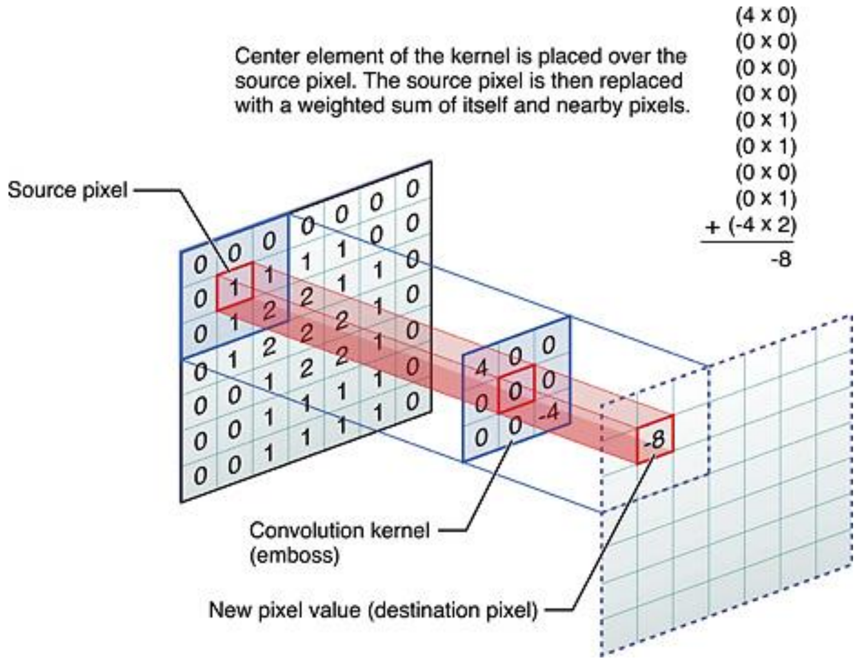

Figure 2. Convolution Feature

2.3 Confusion Matrix

The confusion matrix is a function that is used to assess the performance of classification models in machine learning. The confusion matrix is also used to calculate other matrices, including the accuracy function, recall function, and

F1_score function. The function elements of this matrix result are known as the confusion matrix [32].

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \times 100\% \quad (1)$$

where:

TP : True Positive

TN : True Negative

FP : False Positive

FN : False Negative

2.4 Loss Function

The loss function, also known as cross-entropy loss, is a function that is commonly used to determine how well a model will perform. It can then be estimated using the error from the previously created model [33].

$$H(x, y) = -\sum_{i=1}^{n} yi \log xi \quad (2)$$

where:

H (x, y) : Actual loss probability and prediction values

∑_(i=0)^n : Epoch

yi : Original probability or original possibility

xi : Prediction probability or prediction likelihood

Log : The log is equal to zero

2.5 Data Testing

Testing the training by automatically monitoring the model's accuracy and loss numbers using Kaggle code. Real-time testing involves testing with dragon fruit samples, then using a camera to watch the classification class shown on the monitor. The test results are then documented and evaluated. Real-time testing correctly classifies each type of dragon fruit as ripe, unripe, or rotten. The data used contains three types of dragon fruit classes, and the visual data was collected using an esp32 camera. There are 450 data points, comprising 150 rotting photographs, 150 unripe images, and 150 ripe images. During the training process, the data will be split into 80% training and 20% validation test data.

3.Results and Discussion

The classification results with the number of layers used in the CNN-TL method are 13, with details of Conv2D being 1 layer (conv2d_570), MaxPooling2d is 2 layers (max_pooling2d_35 and max_pooling2d_36), dropout is 2 layers (dropout_17 and dropout_18), BatchNormalization is 2 layers (batch_normalization_575 and batch_normalization_576), flatten is 1 layer (flatten_6), and Dense (fully connected) is 5 layers (dense_32, dense_33, dense_34, dense_35, and dense_36).

3.1 CNN Optimizer SGD and RMS Prop

Tabel 1 shows the results of the best training test obtained from the CNN method with SGD Optimizer. With parameter values accuracy, val_accuracy, loss, val_loss.

Tabel 1. CNN Results with SGD Optimizer

Epoch	*Accuracy* (%)	Val *Accuracy* (%)	*Loss*	Val *Loss*
5	27,24	27,27	1.424	1.423
10	27,28	27,27	1.708	1.709
20	27,24	27,27	2.171	2.174
50	27,29	27,27	1.720	1.720
100	27,18	27,27	1.407	1.405

Tabel 2 shows the results of the best training test obtained from the CNN method with the RMSprop Optimizer. With parameter values accuracy, val_accuracy, loss, val_loss.

Tabel 2. CNN Results with Rmsprop Optimizer

Epoch	*Accuracy* (%)	Val *Accuracy* (%)	*Loss*	Val *Loss*
5	47,62	47,27	1,314	1,323
10	74,50	77,27	1,005	1,021
20	79,42	80	0,710	0,690
50	98,66	100	0,282	0,307
100	99,11	100	0,073	0,058

3.2 TL Optimizer SGD dan RMS Prop

Tabel 3 shows the results of the best training test obtained from the Transfer Learning method with SGD Optimizer. With the parameter values of accuracy, val_accuracy, loss, val_loss, the accuracy value obtained using the SGD optimizer is low.

Tabel 3. TL Results with SGD Optimizer

Epoch	*Accuracy* (%)	Val *Accuracy* (%)	*Loss*	Val *Loss*
5	28,58	30,91	1,633	1,528
10	32,89	43,63	1,503	1,371
20	70,58	83,63	0,854	0,776
50	58,47	80,90	0,994	0,895
100	89,35	91,82	0,462	0,443

Tabel 4 shows the results of the best training test obtained from the Transfer Learning method with the RMSprop Optimizer. With the parameter values accuracy, val_accuracy, loss, val_loss, the accuracy of the RMSprop optimizer for all epochs is 100%.

Tabel 4. TL Results with Optimizer RMSProp

Epoch	*Accuracy* (%)	Val *Accuracy* (%)	*Loss*	Val *Loss*
5	100	100	1,607	2,304
10	100	100	1,106	6,986
20	100	100	4,907	5,502
50	100	100	1,206	0,001
100	100	100	0,002	0,003

Figure 3A shows a graph of epoch 100 testing against accuracy as an example of the results of testing the CNN method with the SGD optimizer. With train and validation parameters. The accuracy and validation values obtained were in the range of 82% with very fluctuating graph results. Epoch 100 testing against loss as an example of the results of testing the CNN method with the SGD optimizer. With train and validation parameters, the loss value decreased but at an initial value of 1, or 147%, and ended up falling to a value of 1.43, or 143%. The confusion matrix as a test of the validity of the model produced from the training process of the CNN method with the SGD optimizer to all readable classes or predicted that all classes were rotten with a total of 30 data for each class.

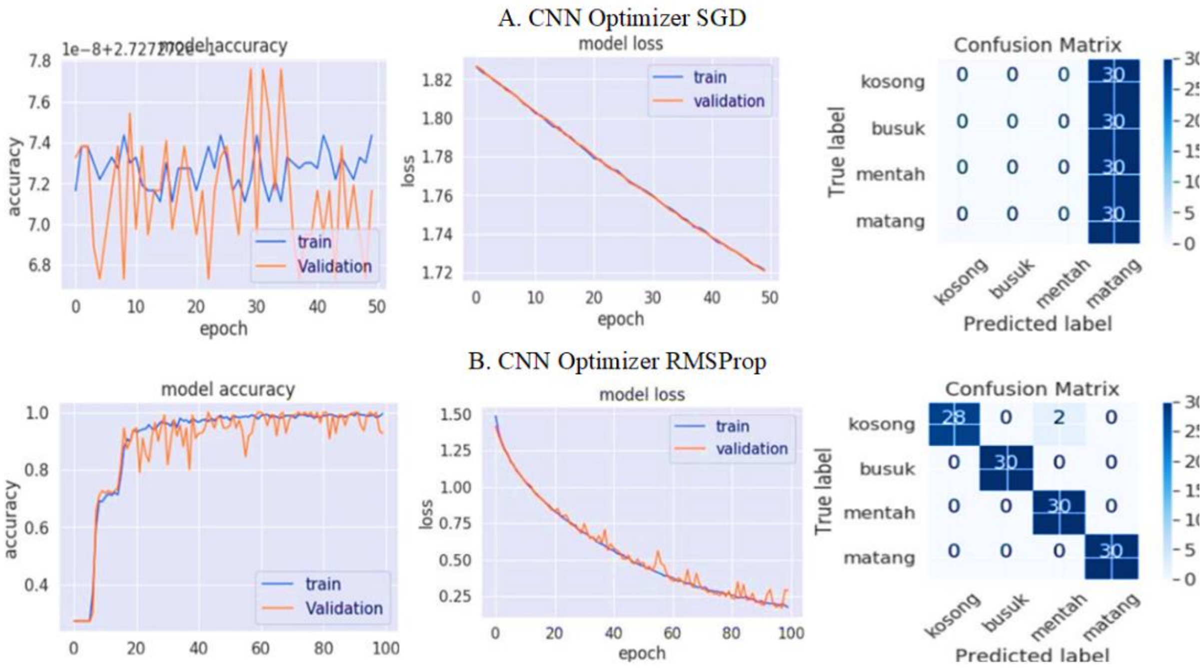

Figure 3. (a) CNN Optimizer SGD and (b) CNN Optimizer RMSProp

Figure 3B shows a graph of epoch 100 testing against accuracy as an example of the results of testing the CNN method with the RMSprop optimizer. With train and validation parameters. At epoch 10, the accuracy increased to 0.7 or 70% and rose again at epoch 18 with an accuracy increase of 0.92 or 92%. Testing epoch 100 against loss as an example of the test results of the CNN method with the RMSprop optimizer. With train and validation parameters. The loss decreases from a value of 1.50 or 150% and slows down gradually to a low point of 0.2 or 20%. Confusion matrix as a test of the accuracy of the model produced from the training process of the CNN method with the RMSprop optimizer with the predicted class raw twice.

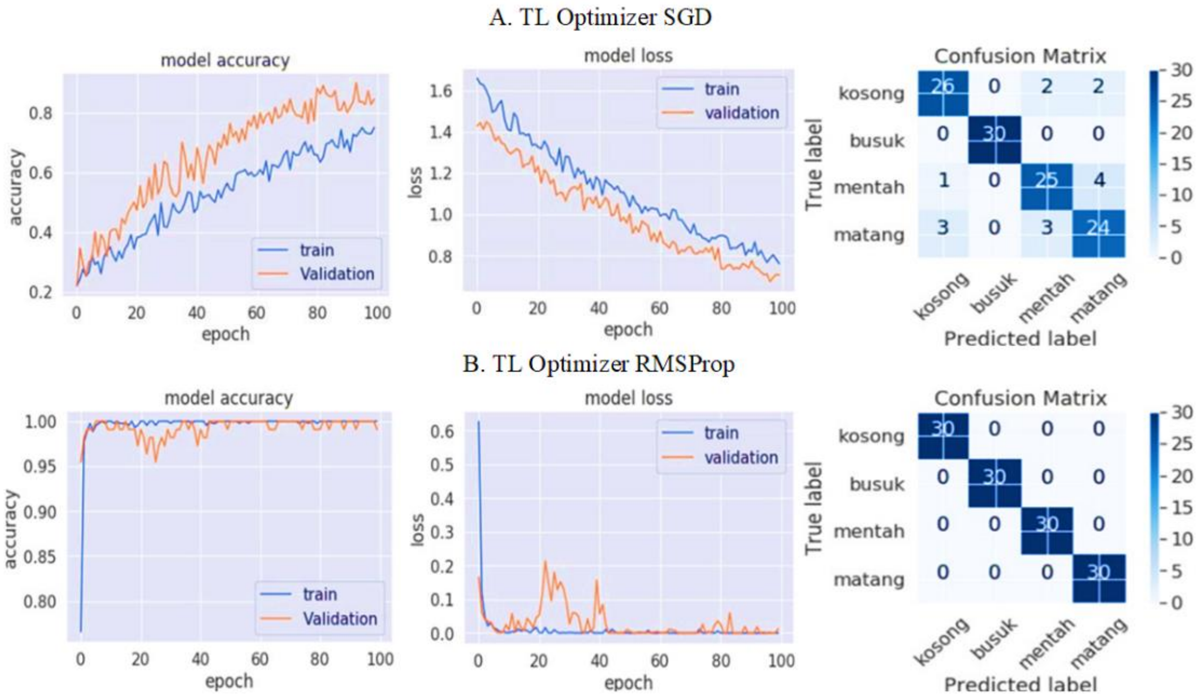

Figure 4. (a) TL Optimizer SGD and (b) TL Optimizer RMSProp

Figure 4A shows a graph of epoch 100 testing against accuracy as an example of the results of testing the Transfer Learning method with the SGD Optimizer. With the train and validation parameters, the accuracy increases slowly and fluctuates from epoch 1 to epoch 100. The graph of epoch 100 testing against loss as an example of the test results of the Transfer Learning method with SGD Optimizer. With the train and validation parameters, the loss value decreases from 1.6 or 160% to 0.8 or 80%. The confusion matrix as a test of the accuracy of the model produced from the Transfer Learning method training process with the SGD Optimizer shows that all predictions for the rotten class are correct, but for the raw class, only 25 predictions are correct and 5 are incorrect. Similarly, for the ripe class, only 24 predictions are correct and 6 are incorrect.

Figure 4B shows a graph of epoch 100 testing against accuracy as an example of the results of Transfer Learning method testing with the RMSprop Optimizer.

With train and validation parameters, the accuracy results for epoch 1 immediately increased to 0.98 or 98% and remained stable until epoch 100. The graph of epoch 100 testing against loss as an example of the test results of the Transfer Learning method with the RMSprop Optimizer. With train and validation parameters, the loss decreased to 0.05 or 5%, and the validation loss increased from 0.05 in epoch 18 to a loss of 0.2 or 20%. Confusion matrix as a test of the accuracy of the model produced from the Transfer Learning method training process with the RMSprop Optimizer, to all correct class predictions.

4. Conclusion

The Transfer Learning (TL) technique with O-SGD and O-RMSProp significantly outperforms the CNN O-SGD and O-RMSProp models for classifying three types of dragon fruit: ripe, unripe, and rotten. At epoch 100, the CNN method with O-SGD achieved an accuracy of 27.18%, val_accuracy of 27.27%, loss of 1.407, and val loss of 1.405. In comparison, O-RMSProp with CNN at epoch 100 achieved much higher performance, with an accuracy of 99.11%, val_accuracy of 100%, a loss of 0.073, and val_loss of 0.058.

On the other hand, the TL method using O-SGD at epoch 100 yielded an accuracy of 89.35%, val_accuracy of 91.82%, loss of 0.462, and val_loss of 0.443. However, the TL method using O-RMSProp at epoch 100 produced 100% accuracy, 100% val_accuracy, 0.002 loss, and 0.003 val_loss, demonstrating the best results overall. The CNN-TL technique with O-RMSProp achieved the most accurate and consistent classification results.

This research highlights the effectiveness of Transfer Learning combined with O-RMSProp optimization in enhancing classification accuracy for dragon fruit, making it a valuable tool for smart agriculture. The application of this technology can improve the sorting of dragon fruit based on ripeness, helping farmers achieve better pricing and reduce waste.

For broader adoption, challenges such as infrastructure, cost, and farmer training must be addressed. Future research should focus on optimizing the system for scalability, ensuring its affordability, and exploring its application across different agricultural sectors. This technology holds great potential in revolutionizing agricultural practices and supporting the growth of smart agriculture in Banyuwangi and beyond.

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