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Classification for Papaya Fruit Maturity Level With Convolutional Neural Network

Nurmalasari-[1*)], Yusuf arif Setiawan-[2], Widi Astuti-[3], M. Rangga Ramadhan Saelan-[4], Siti Masturoh-[5], Tuti Haryanti-[6]

[1,5,6]Sistem Informasi, [2]Ilmu Komputer, [3]Bisnis Digital, [4]Sains Data
Universitas Nusa Mandiri
nurmalasari.nmr@nusamandiri.ac.id, yusufarif@live.jp, widiastuti.wtu@nusamandiri.ac.id, rangga.mgg@nusamandiri.ac.id, siti.uro@nusamandiri.ac.id , tuti@nusamandiri.ac.id
(*) Corresponding Author

Abstract

Papaya California (Carica papaya L) is one of the agricultural commodities in the tropics and has a very big opportunity to develop in Indonesia as an agribusiness venture with quite promising prospects. So the quality of papaya fruit is determined by the level of maturity of the fruit, the hardness of the fruit, and its appearance. Papaya fruit undergoes a marked change in color during the ripening process, which indicates chemical changes in the fruit. The change in papaya color from green to yellow is due to the loss of chlorophyll. The papaya fruit is initially green during storage, then turns slightly yellow. The longer the storage color, the changes to mature the yellow. The process of classifying papaya fruit's ripeness level is usually done manually by business actors, that is, by simply looking at the color of the papaya with the normal eye. Based on the problems that exist in classifying the ripeness level of papaya fruit, in this research, we create a system that can be used to classify papaya fruit skin color using a digital image processing approach. The method used to classify the maturity level of papaya fruit is the Convolutional Neural Network (CNN) Architecture to classify the texture and color of the fruit. This study uses eight transfer learning architectures with 216 simulations with parameter constraints such as optimizer, learning rate, batch size, number of layers, epoch, and dense and can classify the ripeness level of the papaya fruit with a fairly high accuracy of 97%. Farmers use the results of the research in classifying papaya fruit to be harvested by differentiating the maturity level of the fruit more accurately and maintaining the quality of the papaya fruit.

Keywords: Convolutional; Classification; Maturity Level; Neural Network

Abstrak

Pepaya California (Carica papaya L) merupakan salah satu komoditas pertanian didaerah tropis yang mempunyai peluang sangat besar untuk dikembangkan di Indonesia sebagai usaha agribisnis dengan prospek yang cukup menjanjikan. Sehingga tuntutan terhadap kualitas buah pepaya sangat ditentukan oleh tingkat kematangan buah, kekerasan buah dan penampakannya. Buah pepaya mengalami perubahan warna yang nyata selama proses pematangan, yang menunjukan terjadinya perubahan-perubahan secara kimiawi dalam buah. Perubahan warna pepaya dari hijau menjadi kuning disebabkan hilangnya klorofil. Selama proses penyimpanan awalnya buah pepaya berwarna hijau, kemudian berubah menjadi sedikit kuning. Semakin lama penyimpanan warna berubah menjadi kuning matang. Proses pengklasifikasian tingkat kematangan buah pepaya biasanya dilakukan oleh pelaku usaha secara manual yaitu hanya dengan cara melihat warna pepaya dengan mata secara biasa. Berdasarkan permasalahan yang ada dalam pengklasifikasian tingkat kematangan buah papaya maka dalam riset ini kita membuat suatu sistem yang dapat digunakan untuk mengklasifikasikan warna kulit buah pepaya dengan menggunakan pendekatan pengolahan citra digital. Metode yang digunakan untuk pengklasifikasian tingkat kematangan buah pepaya dengan Arsitektur Convolutional Neural Network (CNN) untuk mengklasifikasikan tekstur dan warna buah. Penelitian ini menggunakan delapan arsitektur transfer learning dengan 216 simulasi dengan batasan parameter seperti optimizer, learning rate, batch size, jumlah layer, epoch dan dense dan dapat melakukan klasifikasi pada tingkat kematangan buah pepaya dengan akurasi cukup tinggi yaitu 97%. Hasil penelitian digunakan oleh para petani dalam mengklasifikasikan buah pepaya yang akan dipanen dengan membedakan tingkat kematangan buah dengan lebih akurat dan menjaga mutu buah pepaya.

Kata kunci: Convolutional; Klasifikasi; Tingkat Kematangan; Neural Network

INTRODUCTION

The development of science and technology in digital image processing makes it possible to process agricultural and plantation products automatically with the help of image processing applications (Ismail & Malik, 2022). So digital image processing technology is used to determine the ripeness level of the papaya fruit with better precision and efficiency. This research is to create an artificial intelligence model for papaya farmers in determining the maturity level of California papaya (Carica Papaya L) when the harvesting process is carried out (K. Dozono, S. Amalathas, 2022).

Farmers often use their instincts when harvesting papaya to determine which fruit is ripe, half-ripe, or unripe. This instinct is the farmer's tacit knowledge (Dalkir, 2013), a practical and intuitive ability obtained cumulatively from years of trial and error experience during harvesting. Unfortunately, this tacit knowledge is difficult to transfer to others, so every harvest process must involve the farmer (He, 2017).

At the individual level, tacit knowledge is closely related to skills or expertise. Includes pattern recognition acquired through cumulative experience which is performed against a background of unconsciousness, is difficult to articulate, and forms the basis of valuable individual expertise (Gunawan Gunawan, Hidayat, & Purnomo, 2013). This tacit exists within each person, individually, is unique, unwritten, but known. Relying on tacit knowledge, of course, farmers will face many limitations at the field level, so this intelligence must be transferred to machines (Goldstein et al., 2018).

Therefore, to facilitate the classification of papaya maturity levels and for the benefit of the agricultural industry so that the cost of funds becomes more efficient, the Convolutional Neural Network (CNN) method can be applied. As we know, the CNN method can produce a significant level of accuracy because it has network depth and has been widely applied to image data (Hinton, 2012).

CNN can be used for fruit classification, quality control, and harvesting (Cuong et al., 2022). Papaya maturity classification can be facilitated using the Convolutional Neural Network (CNN) method, which has been widely applied to image data and can produce a significant level of accuracy (Al-Masawabe, Samhan, AlFarra, Aslem, & Abu-Naser, 2021; Behera, Rath, & Sethy, 2021).

CNN architectures vary depending on the authors' application, work, and wishes, so new modifications are always possible. The future of CNN is predicted to be in the robotic harvesting sector (Naranjo-Torres et al., 2020). Therefore, researchers used the CNN method in this study to classify papaya's ripeness level based on the tacit knowledge of papaya farmers of as many as three classifications: ripe, half-ripe, and unripe.

RESEARCH METHODS

Convolutional Neural Networks (CNN) are a special category of deep learning algorithms that can accept as input several sample images and perform convolution operations to extract features from the input images and can distinguish each object from the other (Alganci, Soydas, & Sertel, 2020). The structural architecture of the CNN network (Figure 1) is similar to the structure of the neuronal connectivity of the human brain.

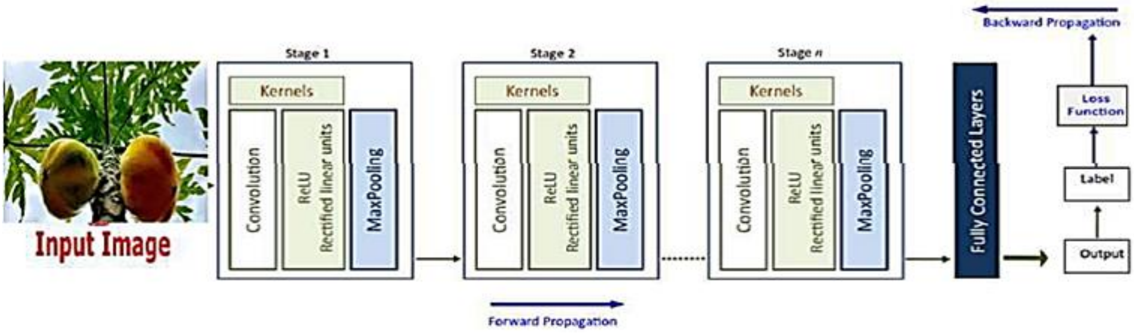

Figure 1. The general architecture of a convolutional neural network

The tools and materials used in this research are software and hardware, equipped with supporting hardware and software. At the same time, the material used is the image of a California papaya with the Latin name Carica Papaya L.

The data used in this study are papaya images obtained from three papaya gardens

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belonging to the Lubuk Makmur farmer group in Mugirejo village, North Samarinda sub-district, Samarinda city and one papaya garden belonging to the Tunas Karya farmer group in Sungai Meriam village, Anggana sub-district, Kutai Kartangera district, East Kalimantan.

The dataset used in this study is 1,500 papaya images divided into three labels with 500 images each, namely ripe, half-ripe, and unripe. Images were taken using the farmer's cellphone at various times, weather, and conditions, in the morning, afternoon, and evening. The papaya image is taken when the fruit remains on the tree. The dataset is in JPG format with HDR quality, and the average image size is 4MB.

Determination of the maturity level is determined by each farmer who owns the papaya garden. The farmers have an average of more than five years of experience, and all supply modern markets or mini-markets for Samarinda and Balikpapan in East Kalimantan Province. From a deep understanding of the fruit that can be harvested uniformly, they have opinions and validation methods that are almost the same.

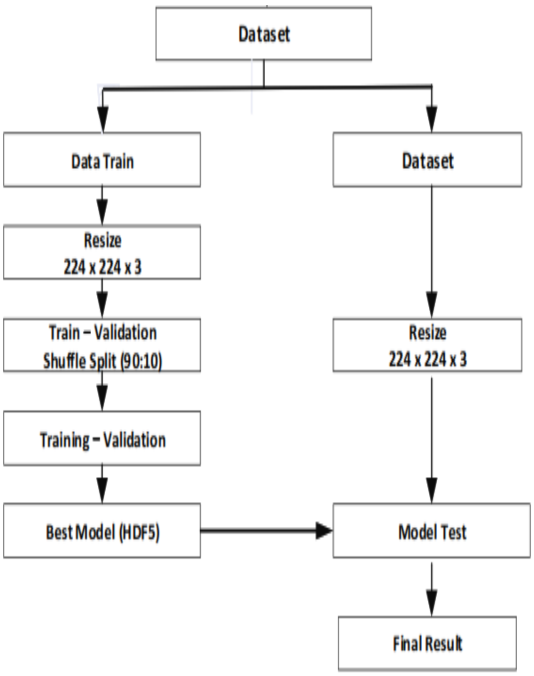

Figure 2. CNN Algorithm flowchart

The CNN structure consists of feature extraction consisting of a convolutional layer, usually followed by a pooling layer and a softmax classifier. The convolutional layer extracts feature from images, while the pooling layer reduces dimensions and computation time. This architecture can achieve a form of regulation by itself. The extracted features are then inserted into the upper softmax layer for classification (You et al., 2017).

Experiment Scenario

Researchers carried out several scenarios in conducting experiments on eight transfer learning models, namely:

a. DenseNet201 model architecture
b. InceptionV3 model architecture
c. MobileNet model architecture
d. NasNetMobile model architecture
e. ResNet50V2 model architecture
f. VGG16 model architecture
g. VGG19 model architecture and
h. Xception model architecture

This experiment is to get the best method to classify papaya's ripeness level. The benchmarks we want to get are as follows:

a. Has the highest hdf5 (training accuracy) score
b. Has the highest test accuracy value
c. The smallest hdf5 (weight) file size

Metrics Performance

As an experimental evaluation tool, this study looks at the output results generated by the performance of the proposed classification method, namely the output of the confusion matrix, precision, recall, accuracy, and kappa score.

Confusion matrix

The confusion matrix, also known as the error metric, provides comparative information on the classification results performed by the system (model) with the actual classification results.

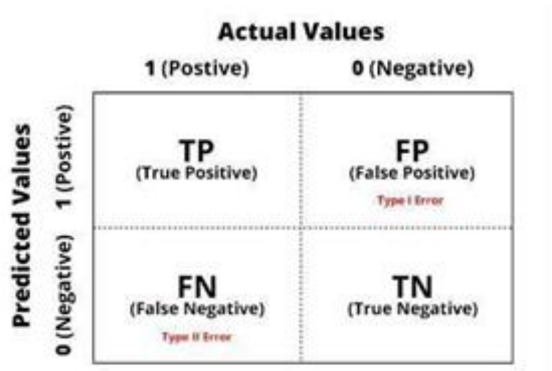

Figure 3. Confusion Matrix

Based on Figure 3, the confusion matrix will obtain accuracy, precision, recall, FI score, and specificity.

The accuracy value is the percentage of the number of data records that are properly and correctly classified using the algorithm and the results of the classification after testing the dataset (W. Abbes, D. Sellami, S. Marc-Zwecker, 2021) (Q. Li, W. Li, J. Zhang, 2018). Accuracy is applied to assess an algorithm's performance in classifying an image (Tharwat, 2018). In the decision value reference, if the value is 0, it means the value is bad; if it is 1, it is very good. And if the accuracy value is close to 1, it shows a high accuracy value; if it is close to 0, the accuracy value is low. Accuracy equation:

$$\text{Accuracy} = \frac{TP+TN}{TP+TP+FP+FN} \quad \text{.....} (1)$$

Precision (precision value) is the proportion of cases predicted to produce positive results, where the value is also positive in the actual data [93]. Precision is also called positive prediction volume (PPV), the ratio of the total positive predictions to all the correct positive predictions. Precision values range between 0 and 1. The precision with a value of 1 is the highest or best value, and 0 is the lowest or worst. The precision equation is as follows:

$$\text{Precision} = \frac{TP}{TP+FP} \quad \text{.....} (2)$$

Recall (Sensitivity) is the proportion of cases that are positive and predicted correctly (W. Abbes, D. Sellami, S. Marc-Zwecker, 2021). Sensitivity is called another name for recall. It is the ratio of true positives to the total number of positive samples. Withdrawal values range between 0 and 1, a recall value of 1 means the value is high or best, and 0 is low or worst.
The sensitivity equation is as follows.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad \text{.....} (3)$$

F1 Score

According to Sokolova (2006), cited by researchers (Tharwat, 2018), the F-measure is the F1-score, representing the average harmonic precision and recall. The value is between 0 (worst) and 1 (best). It has shown little value if there is little precision or drawdown.

The F1-score equation is as follows.

$$\text{F1 score} = 2\,\frac{Precision.Recall}{\text{Precision+Recall}} \quad \text{.....} (4)$$

Cohen's kappa is a measurement test tool that states consistency between two measurement methods or measures consistency between two measurement model tools.

And it can also be used as a measurement tool by two raters. Cohen's kappa coefficient is only applied to the measurement results of qualitative (categorical) data (Powers, 2020).

RESULTS AND DISCUSSION

The total dataset is 1,500 images of 3 (three) classes/levels of ripeness of the papaya fruit produced from the farmers' Xiaomi mobile phones with a display resolution of 1080 x 2408 pixels (Full HD). The number of images of papaya fruit for each class can be seen in Table 1.

Table 1. Total Data Based on the Level of Papaya Maturity

No.	Maturity level	Amount
1	Ripe	500 Images
2	Half ripe	500 Images
3	Unripe	500 Images
	Total	1.500 Images

At the experimental preprocessing stage, 1,215 images of train sample data were obtained, and 135 images of validation sample data. If it is made in the form of a data distribution table based on the experimental process, it can be seen in Table 2.

Table 2. Distribution of Data Based on the Experimental Process

No.	Dataset	Amount of Data
1	*Data training*	1.215
2	*Data validation*	135
3	*Data testing*	15

Ten models with training scores and threshold testing above 90% and kappa scores above 85% as shown in the following table 3:

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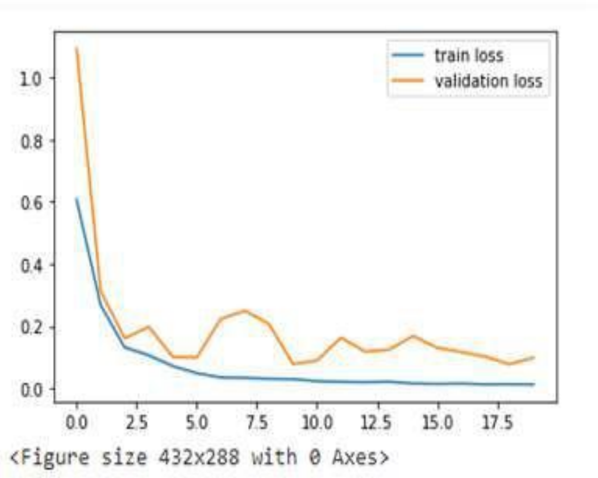
Table 3. Simulation Results

No.	Architecture	Optimizer	Layer	Batch Size	Training Score %	Testing Score%	Kappa Score%	Size Hdf5 (MB)
1	VGG16	Adam	-7	35	97,69	97	95	164,60
2	VGG16	Adam	-7	32	96,92	96	94	164,60
3	VGG16	Adam	-7	37	97,69	93	90	164,60
4	VGG16	Adam	-10	32	99,23	93	90	178,20
5	DenseNet201	Adam	-7	32	99,23	92	88	142,90
6	DenseNet201	RMSprop	-10	35	96,92	92	88	118,80
7	ResNet50V2	RMSprop	-5	35	93,84	92	88	143,40
8	VGG19	Adam	-10	35	96,92	92	88	229,90
9	VGG16	Adam	-10	35	99,23	92	88	178,20
10	DenseNet201	Adam	-5	37	96,92	91	86	141,00

Of the ten highest simulations, it can be seen that the VGG16 transfer learning model has the best/highest performance. We describe the explanation regarding the performance of VGG16 in the classification of papaya fruit maturity levels as follows:

a. Accuracy and Loss Graph

In the classification with the VGG16 architectural model, the training and validation process is carried out using 20 (twenty) epochs, the last 7 (seven) layers of training, and using the Adam optimizer displays a training score of 97.69%, a testing score of 97%, 95% kappa score with a weight measure files of 168.60 MB. The results of the training and validation process are shown in Figure 4.



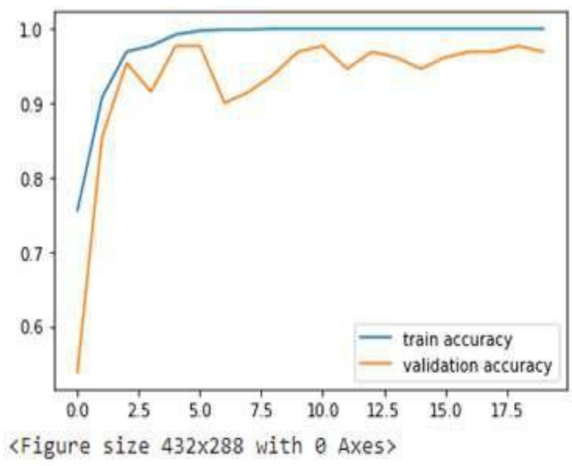


Figure 4. Graph of VGG16 Training and Validation Results

In Figure 4 point (a), the loss graph shows that the training and validation loss processes experience a fairly good balance. It can be seen that the train loss line and the validation loss line move rhythmically, not moving away from each other, and the lines do not overlap. In general, in the training and validation process in each epoch process, validation loss values were increased (val_loss improved). Likewise (b), the accuracy graph shows a fairly good balance in the accuracy training and validation processes. It can be seen that the accuracy train line and the accuracy validation line move in rhythm and do not move away from each other.

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b. Confusion Matrik

Evaluation of the performance of the VGG16 method uses the hyperparameter model in classifying the level of maturity of papaya images. This experiment was carried out at three levels of ripeness of papaya fruit, as many as 150 images. It can be seen that the model already understands the maturity level by representing 50 images that are considered ripe. In the recognition level of half-ripe, from 50 images, one is still identified as unripe. Meanwhile, the model recognizes 46 images as unripe at the half-ripe recognition level, and four images are still half-ripe. The model performance is quite good, which is also indicated by the kappa score of 95%. Based on the experiments, it has produced a confusing matrix image performance, as shown in Figure 5.

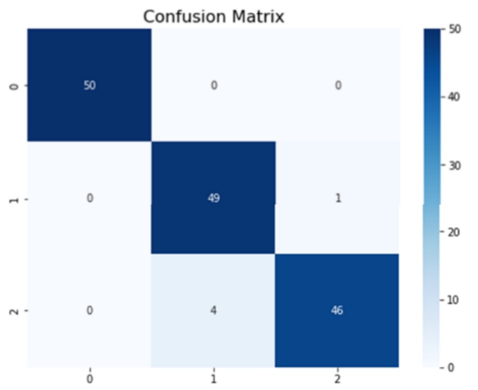

Figure 5. Graph of the VGG16 Confusion Matrix

Figure 6. Prediction Image from Testing Model Vgg16

e. Image Analysis

The experimental results presenting image recordings of testing results from training show that the model is sufficiently trained to recognize objects even though the accuracy level is still 97%. The difficulty is distinguishing fruit that has just ripened or been exposed to sunlight so that the model still reads unripe fruit as half-ripe fruit. The image of the testing results from the training data can be seen in Figure 6.

CONCLUSIONS AND SUGGESTIONS

Conclusion

This study uses eight transfer learning architectures with 216 simulations with parameter constraints such as optimizer, learning rate, batch size, number of layers, epoch, and dense and can classify the level of ripeness of papaya fruit with a fairly high accuracy of 97%. There are still deficiencies related to model recognition in unripe fruit growing half-ripe or fruit that is half-ripe but still young. For this reason, it is necessary to add a dataset so that the algorithm can better recognize the differences in fruit from unripe to half-ripe. Tacit knowledge is an ability that comes from trial and error, it is difficult to explain how, but it can be felt, and the results can be validated. For this reason, AI (Artificial Intelligence) can bridge the rare capabilities of experts so that they can help process activities in the field.

Suggestion

The best model obtained from the research results can be further improved by adding to the number of existing datasets. The implementation of this AI (Artificial Intelligence) model should be developed in the form of an application so that it can support increased fruit production and create a digital ecosystem at the farmer level.

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