Identification of Banana Ripeness using Convolutional Neural Network Approaches

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2023 International Conference on Computer, Control, Informatics and its Applications (IC3INA) | 979-8-3503-9487-0/23/$31.00 ©2023 IEEE | DOI: 10.1109/IC3INA60834.2023.10285749

***Abstract*— Digital images have been widely used for computer vision systems of ripe bananas. Consumers or industrial companies need computer vision-based applications to determine the ripeness of bananas. The computer vision system is challenging because it processes images and must find a good method. In Saranya's 2022 research, the Convolution Neural Network method is accurate. We propose to improve the CNN architecture to identify banana ripeness. We use the dataset from the Saranya 2022 research, and we augment the dataset to make it large. Proposed CNN architecture: We have 97.95% accuracy with the adam optimizer. Our proposed CNN architecture results are better than Saranya's 2022 research.**

Keywords— ***Ripe bananas, Architecture CNN, Augmentation, Identification, Convolution neural network***

I. Introduction

Many people consume bananas; of the many types of fruit, 16% are bananas. The level of maturity of the fruit influences its quality of the fruit. The quality of bananas is a concern for consumers and industrial companies. The effectiveness and speed in determining the maturity level of bananas is research that continues to be developed. Because the ripeness of the fruit greatly affects the market price. Several studies have developed algorithms that are effective in determining the maturity level of bananas, starting from machine-learning methods [1-4], Neural Network [5-7], and deep learning/Convolution Neural Network (CNN) [8-11].

The results of the accuracy of each of the previous studies are *k*-NN, SVM 96.6% [1], Nearest Centroid 73.33% [3], *k*-NN 93.33% [4], Artificial Neural Network 97.53% [5], Neural Network 95.24% [6], Neural Network 97.75% [7], CNN 96.14% [8], NASNetMobile 96.18% [9], CNN 98.25% [10], CNN 92.2% [11]. Many studies have been carried out regarding identifying banana ripeness, one of which was carried out by Saranya et al., 2022. We want to develop banana ripeness research using a different CNN architecture to produce good precision. Based on previous research, the highest accuracy is the method CNN 98.25% [10]. Therefore, we propose the CNN method based on the research architecture [8] to identify the ripeness of bananas. We differ from previous studies in the number of convolution layers and neurons in each convolution layer. We use datasets from research [7-8]. Evaluate the different CNN architectures in the identification of banana ripeness. The study aims to propose a CNN architectural approach to identify the ripeness of bananas. The contribution of this study makes a different CNN architecture for identifying banana ripeness and augmenting banana data.

II. Related Work

In general, research has been carried out on the level of ripeness of bananas. The stages in computer vision are feature extraction and classification/identification. Several previous studies of feature extraction using the Principal Component Analysis (PCA) feature [1]. PCA feature extraction takes the eigenvalue features from image pixels and is used to reduce the size of the image eigenvalues. Another feature extraction method takes the image's HSV (Heu-Saturation-Value) color value [3-4], or from RGB (Red, Green, Blue) color values and textures [6-7]. The feature extraction process greatly affects the classification of banana ripeness. The classification method that has high accuracy is deep learning/CNN. The CNN method processes feature extraction and classification in one architecture. The feature used is the value of each image pixel processed by convolution. The convolution feature extraction method has good results because it represents a broad image [8-11]. Therefore we propose a feature extraction and classification method using CNN. Table 1 describes previous research on recognizing banana ripeness or something else.

TABLE I. The State-of-the-Art

Feature extraction	Algorithms	Results
Principal Component Analysis [1]	k-Nearest Neighbor, Support Vector Machine (SVM), and Decision Tree (DT)	Accuracy is 96.6%
pre-trained deep convolution neural network Inception V3 [2]	Support Vector Machine learning algorithm to get ripening banana	
The mean color HSV image [3]	Classified using Nearest Centroid Classifier (NCC)	Accuracy is 73.33%
The mean, median, range, standard deviation, and variance of the RGB color, HSV image [4]	The K-Nearest Neighbor classification algorithm	The accuracy is 93.333%
The ripeness factor (RF) of the banana fruit, and contrast image [7]	The SVM, the naive Bayes, the KNN, the decision tree	Accuracy is 97.75%
Convolutional Neural Network [8]	CNN	Accuracy is 96.14%
Convolutional Neural Network [9]	MobileNet V2 and NASNetMobile to classify the ripeness of the banana	The NASNetMobile the highest accuracy achieved is 96.18%
Convolutional Neural Network [10]	MobileNet V2 and RestNet, an Android application display	Accuracy is 98.25%

	the ripeness banana live image	
Color RGB statistics [12]	Mobile application identified the ripeness of banana fruit	Accuracy is 96.15%
Image alcohol content [13]	ANFIS for classification tool the banana ripeness level from alcohol level and RGB values image	Accuracy is 99.07%
Wavelet features and image chlorophyll values [14]	ANN classification model	Accuracy is 95.5%
Color feature [15]	K-Means clustering to determine banana ripeness states and the Decision Tree algorithm to classify banana shelf-life	Accuracy around 52%
Feature colors of CIELa*b [16]	The fuzzy model classification	Accuracy is 93.11%
CNN [17]	CNN	Accuracy is 91.9%
CNN [18]	Deep Learning	Accuracy is 98%
Feature statictic RGB, CIELab and CIELuv [19]	ANN	Accuracy is 97.44%
Feature binary result morphological operation [20]	ANN	Accuracy is 97%
Yolov3 [21]	Object detection CNN	Accuracy is 96%
Transfer learning Inception V3 [22]	Classification leaf variants of cassava	Accuracy is 95.76%

III. RESEARCH METHODHOLOGY

A. Dataset

We use public datasets from research [7-8], types of maturity levels of bananas, namely Green 104 images, Midripen 88 images, Overripen 33 images, and Yellowish-green 48 images. We did the augmentation by rotating and flipping it [8]. After augmenting our dataset, it becomes like Table 2. Table 2 describes the initial data of 273 images. After augmentation, it becomes 952 images. Figure 1 is an example of a banana ripeness dataset, Figure 1a Green, Figure 1b Midripen, Figure 1c Overripen, and Figure 1d Yellowish-green. The dataset used as input in CNN is the image of Figure 1, with a size of 128x128.

TABLE II. DATASET

No	Type	Training	Testing	Total
1	Green	198	38	236
2	Midripen	192	36	228
3	Overripen	224	40	264
4	Yellowish-green	192	32	224
	Total	806	146	952

(a) (b)

(c) (d)

Fig. 1. Types of Ripeness Banana

B. Propose

We propose the CNN architecture concerning research [8]. The difference between this research and the previous one is the number of convolution layers and neurons in each layer. Figure 2a is the research architecture [8], Figure 2b and Figure 2c architecture We propose. Figure 2a has a Dropout layer, while the proposed architecture does not exist. The total parameters of each of the previous research architectures and our proposals are in Table 3. We evaluate the architecture by calculating the loss function and accuracy values. We do data augmentation and build different CNN architectures (Figure 3).

Figure 2a the research architecture [8], the input image size is 64x64, the architectural layers of research [8] are three times the convolution screen with the number of neurons 32, 16, 16, max-pooling screen, two times the convolution screen with the number of neurons 16, 16, and screen max-pooling, the final image size of the research architecture [8] is 10x10.

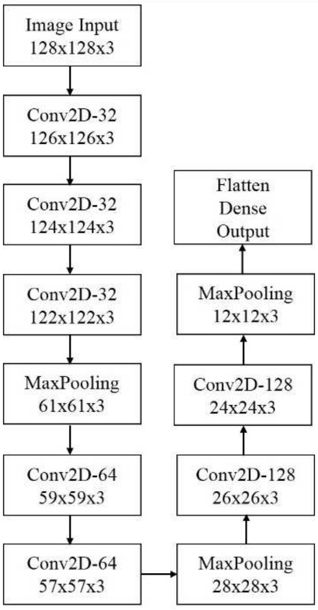
TABLE III. CNN ARCHITECTURE PARAMETERS

No	Architecture	Total
1	First proposal	5016132
2	Second proposal	19171908

Layer	Size Image	Neuron
Input	64x64x3	-
Conv2D	62x62x3	32
Conv2D	58x58x3	16
Conv2D	54x54x3	16
MaxPooling	27x27x3	-
Conv2D	25x25x3	16
Conv2D	21x21x3	16
MaxPooling	10x10x3	-
Dropout	-	-
Flatten	-	-
Dense	-	16
Output	-	4

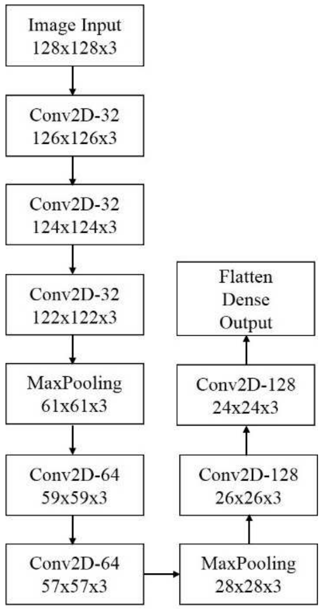
(a)

Layer	Size Image	Neuron
Input	128x128x3	-
Conv2D	126x126x3	32
Conv2D	124x124x3	32
Conv2D	122x122x3	32
MaxPooling	61x61x3	-
Conv2D	59x59x3	64
Conv2D	57x57x3	64
MaxPooling	28x28x3	-
Conv2D	26x26x3	128
Conv2D	24x24x3	128
MaxPooling	12x12x3	-
Flatten	-	-
Dense	-	256
Output	-	4



(b)

Layer	Size Image	Neuron
Input	128x128x3	-
Conv2D	126x126x3	32
Conv2D	124x124x3	32
Conv2D	122x122x3	32
MaxPooling	61x61x3	-
Conv2D	59x59x3	64
Conv2D	57x57x3	64
MaxPooling	28x28x3	-
Conv2D	26x26x3	128
Conv2D	24x24x3	128
Flatten	-	-
Dense	-	256
Output	-	4



(c)

Fig. 2. CNN Architecture

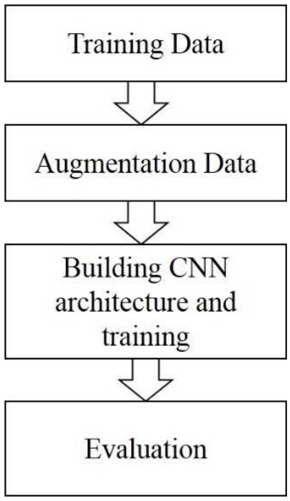


Fig. 3. Research Process

Figures 2b, 2c are our proposed architecture; the input image size of both of our proposals is the same, 128x128, and has the following architecture screen: three convolution layers with the number of neurons 32, 32, 32, max-pooling layer, two convolution layers with the number of neurons 64, 64, screen max-pooling, two convolution layers with several neurons 128, 128, and in the last layer in the first architecture there is a max-pooling layer and the final image size is 12x12, while in the second architecture there is no max-pooling layer and the final image size is 24x24.

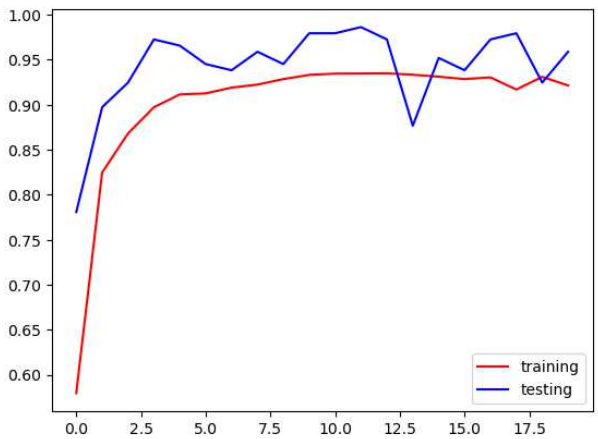
IV. Results and Discussion

We propose an approach to identifying ripe bananas by building a CNN architecture. The basic CNN architecture that we made is based on research [8]. We propose two CNN architectures to determine the best accuracy in identifying banana ripeness. We use categorical cross-entropy loss function and accuracy to evaluate the proposals. We use two optimizer models (rmsprop and adam) with default learning rate values. We trained 20 epochs, and each epoch read 200 images. Table 4 is the result of the accuracy of the data test. We try to use research architecture [8] in our data with an input size of 128x128, with an accuracy above 90% (Table 4).

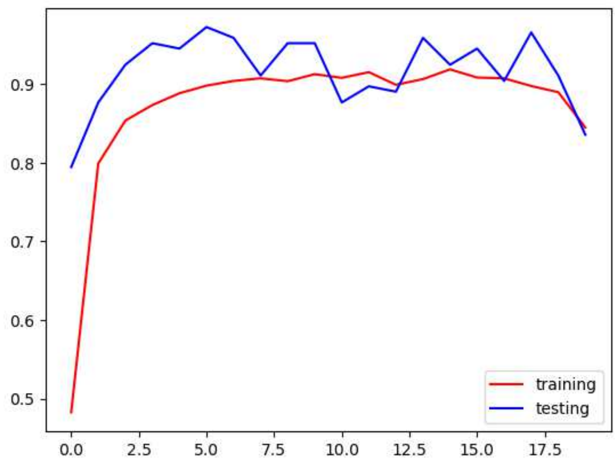
The proposed first CNN architecture has the highest accuracy for both optimizers (rmsprop and adam).

Figure 4 displays the accuracy performance of the two CNN architectures for identifying ripe bananas with the optimizer='rmsprop'. Figure 4a, and Figure 4b are the accuracy of our proposed CNN architecture with optimizer='rmsprop'. Figure 5 shows the accuracy of the CNN architecture with the optimizer='adam'. Figure 5a, and Figure 5b are the accuracy of our proposed CNN architecture with optimizer='adam'. In line terms, based on Figure 4 and Figure 5, the CNN model built has good performance because the lines in the graphs of Figure 4 and Figure 5 during training and testing do not have a high difference in accuracy.

We used the banana dataset from research [8], and the results accuracy are in Table 4. We trained and validated the banana data with the CNN VGG19 and VGG16 transfer learning methods, the evaluation results are in Table 4. We display the results of the model evaluation in a confusion matrix as shown in Figure 6. We conducted training and evaluation 5 times, and the average evaluation results are in Table 4 and Figure 6. The evaluation results for the first CNN architecture that we propose have the best average recal and precision, 0.87 and 0.87. Meanwhile, the evaluation of the second CNN architecture was not good, namely in the prediction of the Yellowish-green class, it only had recal and precision, 0.79 and 0.82. The research [7] has an accuracy of 97.75%, and the results of our research have almost the same accuracy, namely 97.95%.

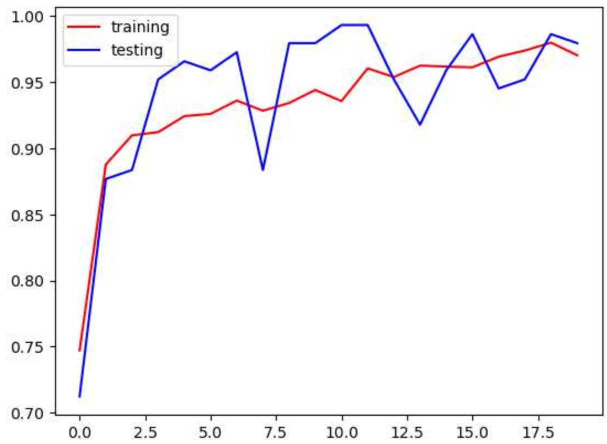


(a)

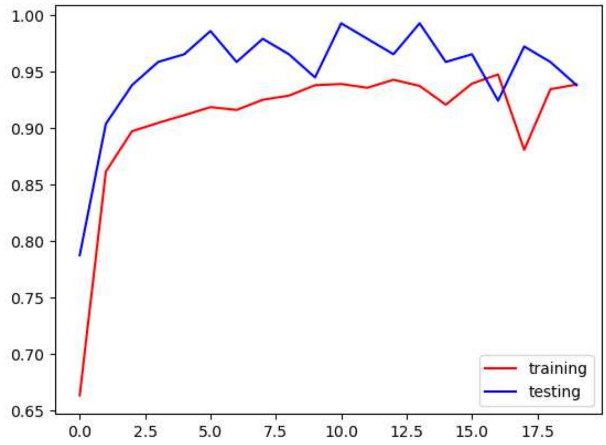


(b)

Fig. 4. Accuracy Optimizer='rmsprop' Architecture (a) First Proposal (b) Second proposal



(a)



(b)

Fig. 5. Accuracy Optimizer='adam' Architecture (a) First Proposal (b) Second proposal

TABLE IV. ACCURACY RESULTS

No	CNN	Accuracy (%)	
		Optimizer='rmsprop'	*Optimizer='adam'*
1	Research [8]	-	92.85
2	First proposal	95.9	97.95
3	Second proposal	83.6	93.8
4	VGG19	78.77	80
5	VGG16	78.1	86

Class	Green	Midripen	Overripen	Yellowish
Green	38	0	0	0
Midripen	0	28	0	8
Overripen	0	0	40	0
Yellowish	0	9	0	23

First proposal

Class	Green	Midripen	Overripen	Yellowish
Green	38	0	0	0
Midripen	0	30	2	4
Overripen	0	0	40	0
Yellowish	0	21	0	11

Second proposal

Class	Green	Midripen	Overripen	Yellowish
Green	38	0	0	0
Midripen	0	27	3	6
Overripen	0	9	31	0
Yellowish	6	5	0	21

VGG19

Class	Green	Midripen	Overripen	Yellowish
Green	38	0	0	0
Midripen	1	26	4	5
Overripen	0	1	39	0
Yellowish	2	7	0	23

VGG16

Fig. 6. Confusion Matrix Evaluation

V. Conclusion

We propose the CNN method approach to identify banana ripeness. We propose two CNN architectures. The highest accuracy of the CNN architecture that we propose is 97.95%. The best architecture is the first proposal by optimizer='adam'.

Experiment using the optimizer='rmsprop' on the proposed CNN architecture results in accuracy under the optimizer='adam'. Suggestions for further research modify the CNN architecture to produce good precision.

Acknowledgment

Thanks to Universitas Islam Lamongan for providing research funding.

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