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Ambarella Fruit Ripeness Classification based on EfficientNet Models

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ABSTRACT

Evaluating the fruit's maturity level is crucial to acquiring high-quality fruit. The skin color of some fruits may be used as one of the numerous indicators to determine whether they have achieved their peak degree of ripeness. Similar to other fruits, the skin color of an Ambarella fruit indicates its maturity. However, determining the ripeness of the Ambarella fruit was assessed manually, which is time-consuming, inefficient, taxing, requires a large number of employees, and has the potential to result in discrepancies. This study aims to classify the ripeness of the Ambarella fruit using the deep learning approach, specifically using the Convolutional Neural Network (CNN). The new family of EfficientNetV2 is trained to classify the Ambarella fruit ripeness. The pre-trained models are utilized in this work, and the training was done via transfer learning through fine-tuning. EfficientNetV2B0 achieves the highest accuracy of 100% despite having a smaller size than the other EfficientNetV2 models used in this work.

I. INTRODUCTION

Agriculture is a significant contributor to Indonesia's economy, which relies heavily on the sector [1][2]. Indonesia produces numerous marketable agricultural products, such as rice [3], vegetables [4], and fruits [5]. Various kinds of fruit are produced in Indonesia, such as pineapple, banana, mangoes, oranges, watermelon, rambutan, salak, and many others [6]. Among all other fruits, the Ambarella fruit, or *Spondias dulcis* Parkinson, is one of the fruits grown in Indonesia [7]. The Ambarella fruit, known as Kedondong in Indonesia, is widely known and cultivated in various tropical countries, such as Asia, Pacific Islands, Central America, South America, Australia, Africa, and the Caribbean [7], [8]. Ambarella is one of a kind since every component of the plant, such as the fruit, leaves, panicles, and bark, may be consumed and put to good use [7]. Some treatments for hemorrhoids, diabetes mellitus, blood purifiers, indigestions, sores, burns, and wounds use the fruit, bark, and leaves of the Ambarella plant [7], [9]–[11].

Evaluating the fruit's maturity level is crucial to acquiring high-quality fruit for farmers to sell or the food industry, supermarkets, and retail stores [12], [13]. The skin color of certain fruits, including mangoes, tomatoes, Carica papaya, grapes, palm oil, cape gooseberry, apples, and bananas, can be used as one of several indicators to detect when the fruit has reached its peak level of maturity [12], [14]–[19]. Similar to other fruits, the ripeness of Ambarella fruit can be seen through its skin color [8], [9], [20]. In determining fruit ripeness, the manual method is still used [14], [21], [22], and this applies to the Ambarella fruit, as the ripeness is still assessed manually [20]. Manually determining fruit maturity is time-consuming and taxing, calls for a large number of employees, is inefficient, and has the potential to result in discrepancies [21]–[25]. An accurate and reliable model that can automatically determine the ripeness of fruits is considered necessary [13].

Technologies like computer vision, machine learning, and deep learning have emerged due to technological advancement. The emergence of these technologies creates opportunities for the agricultural sector, such as the management of water and soil, detection of crop disease, detecting fruits, and classifying the ripeness or maturity of fruits [13], [26]–[30]. These methods open up the possibility of classifying the Ambarella fruit ripeness automatically. Previous works show that machine learning or deep learning can successfully classify the ripeness of various fruits. The work of Castro et al. proposed using machine learning methods to classify the ripeness of cape gooseberry based on different color spaces and principal components from the combination of the color spaces [12]. The accuracy of Artificial Neural Network (ANN), k-Nearest Neighbors, Decision Tree, and Support Vector Machine (SVM) were compared. The result shows that training SVM using the L*a*b color space yields the highest accuracy. The work of Khojastehnazhand, Mohammadi, and Minaei proposed a maturity detection and volume estimation for apricot [31]. To determine the maturity and volume, the authors used two classifiers: Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA). Both classifiers were trained using three types of color features, the R, G, and B channels, grayscale, L*, a*, and b*, to determine the maturity of the fruit. The results show that by using the G channel, grayscale, L*, and b* color features, the highest accuracy of LDA is 90.4%, and QDA is 92.3%.

Worasawate, Sakunashinha, and Chiangga's work use machine learning to automatically classify the ripeness stage of the "Nam Dok Mai Si Tong" mango fruit [32]. Gaussian Naïve Bayes (GNB), Support Vector Machine (SVM), and Feed-forward Artificial Neural Network (FANN) were trained using the biochemical data and tested using the electrical data of the mango fruit. The results show that the highest mean accuracy was achieved by using the FANN, which is 89.6%. Saragih, Gloria, and Santoso's work use color feature to classify the ripeness of ambarella fruit [20]. The SVM and k-NN were trained using three color features: the HSV, RGB, and L*a*b*. Both models were trained to classify ripeness stages: unripe, mid-ripe, ripe, and overripe. The SVM achieved the highest accuracy of 96.67% by using the L*a*b color feature, while the k-NN only achieved an accuracy of 70% using the same color features.

The previous works use the machine learning approach to classify the ripeness or maturity of different fruits. However, deep learning methods are known for image classification, proven capable of classifying fruit ripeness, and widely used in various research. The work of Ashtiani et al. compares the performance of five Convolutional Neural Network (CNN) models, which are DenseNet, ResNet-18, Inception-v3, AlexNet, and ResNet-50, to classify the ripeness of mulberry fruit [33]. Aaherwadi et al. propose a method to predict banana maturity using deep learning methods, specifically CNN [13]. The authors use the proposed CNN and the AlexNet model to classify three different stages of banana ripeness: unripe, ripe, and over-ripe. The proposed CNN achieves an accuracy of 98.25%, and the AlexNet achieves 81.75% on the original banana dataset. However, improvement happens by augmenting the original dataset. The proposed CNN achieves 99.36%, while the AlexNet achieves 99.44% accuracy. Sharjito, Elwirehardja, and Prayoga propose classifying oil palm fresh fruit bunch using lightweight CNN models [23]. The lightweight MobileNetV1, EfficientNetB0, MobileNetV2, and NASNet Mobile. A novel approach to image augmentation was proposed, called the 9-angle crop. The highest accuracy was achieved by the EfficientNetB0, which is 89.8%.

The previous works show that machine and deep learning methods can classify different ripeness stages of various fruits. However, a further experiment using the latest CNN model is needed. The work of [23] uses a new model, which is EfficientNet, although currently, EfficientNetV2 exists. EfficientNetV2 is a new CNN model with better parameter efficiency and faster training speed than previous models [34]. This paper intends to utilize the new EfficientNetV2 to classify the Ambarella fruit's ripeness stages and as a continuation of the previous work by [20].

The EfficientNetV2 in this work used the models provided by Keras. Currently, there are seven kinds of EfficientNetV2 provided by Keras, which are EfficientNetV2B0, EfficientNetV2B1, EfficientNetV2B2, EfficientNetV2B3, EfficientNetV2S, EfficientNetV2M, and EfficientNetV2L. This work investigates the performance of the EfficientNetV2B0, EfficientNetV2B1, and EfficientNetV2B2, as the output model size is relatively small.

II. METHOD

The experiment in this work follows several steps. Figure 1 shows the steps in this work.

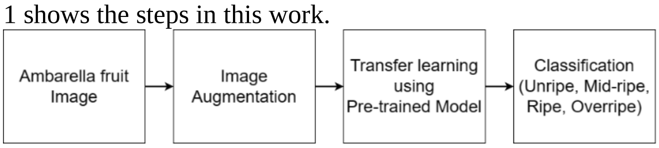

Fig. 1. Workflow for classification of Ambarella fruit ripeness

In Figure 1, the workflow for the experiment is that the ambarella fruit image goes through the augmentation stage, used as input for each pre-trained model, and lastly, the classification result shows the ripeness stage of the fruit in the image.

The Ambarella fruit in this work uses the dataset in [20]. However, in this work, several images are added by rotating the image and flipping horizontally or vertically. Overall, there are 374 images of Ambarella fruit used as the dataset. The dataset is split into training and validation. The training dataset uses 70% of the total dataset, while the validation dataset uses 30%. Figure 2 shows several images in the training dataset, while Figure 3 shows the images for validation.

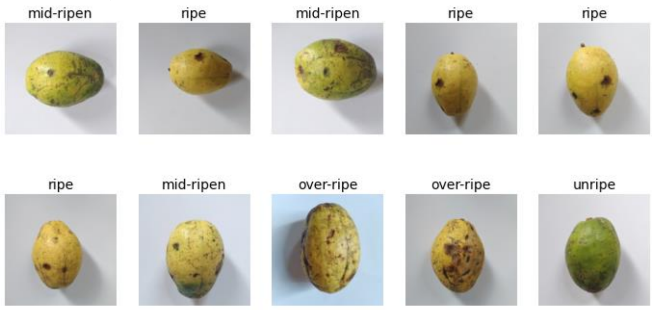

Fig. 2. Sample images of Ambarella fruit for training [20]

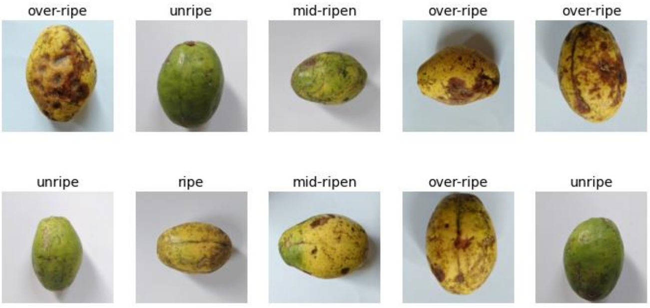

Fig. 3. Sample images of Ambarella fruit for validation [20]

Each image in the dataset has a size of 320 × 320 pixels. Later in the training and validation, each image is resized into the appropriate input size of each model. In the training stage, each image goes through the image augmentation stage. Image augmentation is a technique for creating a variance of an image from the original image while keeping the essential information in the newly created image [35], [36]. Image augmentation reduces overfitting while training the model [35]. This work uses six image augmentation techniques: translation, rotation, brightness, contrast, flip, and zoom. Image augmentation is applied only in the training stage. Figure 4 shows an example of applying image augmentation to an image.

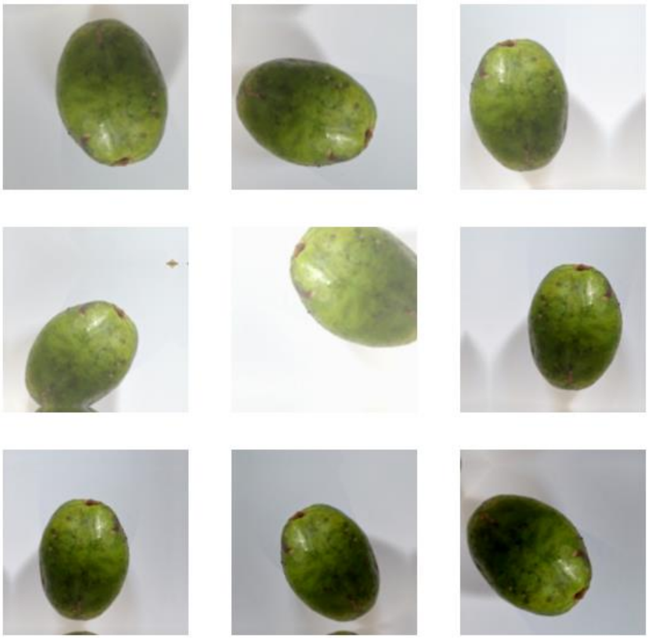

Fig. 4. Examples of applying image augmentation to an image [20]

The Ambarella fruit ripeness was classified by training three different EfficientNetV2 models. Tan and Le [34] proposed the EfficientNetV2. The EfficientNetV2 models were created to have faster training time and more efficient parameters than the earlier models. The authors proposed an enhanced technique for progressive learning that increases image size and regularization simultaneously during the model's training. Using the proposed approach, the resulting EfficientNetV2 achieved excellent performance on several benchmarking datasets, such as ImageNet and CIFAR/Flowers/Cars. This work experiments on three EfficientNetV2 models, which are EfficientNetV2B0, EfficientNetV2B1, and EfficientNetV2B2. The reason for choosing the three models is that those models have a relatively smaller model size than the other available EfficientNetV2 models. The models in this work are pre-trained using ImageNet, a dataset comprising millions of images with a thousand classes. Each pre-trained EfficientNetV2 models are accessible through the Keras library.

The transfer learning approach, specifically fine-tuning, was implemented in this study to train each model. The transfer learning by fine-tuning approach benefits from the pre-trained models by adjusting their parameters to the current dataset [33]. The transfer learning through fine-tuning approach was initially done by replacing the original last layers of each model to match the classes of the custom dataset, which in this case are four classes (unripe, mid-ripe, ripe, and unripe), as the default last layers have 1000 classes. In the training stage, two phases were done. The first phase is called the "warm-up" training, in which all layers are frozen, and the second phase is unfreezing the last layers of the pre-trained model, which allows updating the weights [37]. Unfreezing the last layers was done block-wise, as proposed by the work of [38]. Fine-tuning the top blocks of the pre-trained model creates a better classifier and saves computational power and time [38]. Therefore, in this work, the unfreezing was done to the last block of each model.

The EfficientNetV2B0, EfficientNetV2B1, and EfficientNetV2B2 have different blocks, which are 21, 27, and 28, respectively, where EfficientNetV2B0 with the least amount. Each block consists of convolutional, pooling, batch normalization, and dropout layers. The unfreezing was done to the last block of each model, with added layers of average global pooling layer, dropout layer with a probability of 30%, and softmax layer. Adding the dropout layer is another approach to reduce overfitting when training a model [38]. Each model was first trained for 10 epochs and then fine-tuned for 10 epochs. The initial learning rate used to train each model is 10^{-2} and is decreased to 10^{-4} in the fine-tuning stage.

III. Result and Discussion

This section shows the results of transfer learning by fine-tuning each EfficientNetV2 model. The results of each model's accuracy assessment on the training and validation datasets are presented in Table 1.

Table 1. Results of Ambarella fruit ripeness classification

Model	Before Fine-Tuning		After Fine-Tuning	
	Training (%)	*Validation (%)*	*Training (%)*	*Validation (%)*
EfficientNetV2B0	**96.18**	**98.21**	97.33	**100**
EfficientNetV2B1	95.04	96.43	**97.71**	99.11
EfficientNetV2B2	93.89	95.54	96.57	99.11

Table 1 shows that for the training dataset, EfficientNetV2B0 achieves the highest accuracy of 96.18% before fine-tuning, whereas EfficientNetV2B1 and EfficientNetV2B2 achieve 95.04% and 93.89%, respectively. Regarding validation accuracy, EfficientNetV2B0 achieves the highest as well, which is 98.21%. The validation accuracy achieved by EfficientNetV2B1 and EfficientNetV2B2 is higher than the training accuracy, which is 96.43% and 95.54%, respectively. Notably, the relatively close results between training and validation accuracy imply that overfitting did not occur throughout the training procedure [33]. Overall, each model achieves excellent accuracy results in the training and validation dataset.

The following results after the fine-tuning show that each model achieved an increment in the accuracy for the training and validation dataset. EfficientNetV2B1 obtains the highest accuracy for the training dataset, 97.71%, after the fine-tuning. The increment obtains by the EfficientNetV2B1 is 2.67%. In addition, EfficientNetV2B0 obtains 97.33%, an increase of 1.15%, while EfficientNetV2B2 achieves 96.57%, an increase of 2.68%. Regarding the accuracy of the validation dataset, EfficientNetV2B0 obtains the most remarkable accuracy of 100%, which is an improvement of 1.79%. The accuracy of both EfficientNetV2B1 and EfficientNetV2B2 is 99.11%, a gain of 2.68% and 3.57%, respectively. In this case, EfficientNetV2B2 achieves a significant improvement. Although EfficientNetV2B1 and EfficientNetV2B2 have more layers than EfficientNetV2B0, EfficientNetV2B0 proves to achieve the highest accuracy. The work of [36] obtained a similar result, where the most miniature model, MobileNetV2, achieves the highest accuracy compared to MobileNet, InceptionV3, Xception, and Inception Resnet V2, which are deeper models.

Comparing each model's size, EfficientNetV2B0 is the smallest at 31.05 megabytes (MB). In contrast, EfficientNetV2B1 and EfficientNetV2B2 have a size of 35.26 MB and 43.82 MB, respectively. To utilize a pre-trained model on a mobile device, such as a smartphone or Raspberry PI, the EfficientNetV2B0 is appropriate, as it has a combination of excellent accuracy with minimum computation. As for EfficientNetV2B1 and EfficientNetV2B2, it also makes sense to utilize them for mobile devices due to their relatively small size and sufficient accuracy.

The results achieved in this work are an improvement from the previous work [20]. In the previous work, the highest accuracy achieved by the Support Vector Machine (SVM) was 96.67%. The deep learning approach, in this case, using the pre-trained CNN models, can significantly increase the accuracy without manually extracting the image's color features and experimenting with different color features. Therefore, pre-trained CNN models are suggested for further experiments and, hopefully, for production use.

Figure 5 shows several results of predicting the Ambarella fruit ripeness using the trained EfficientNetV2B0 using several images from the validation dataset.

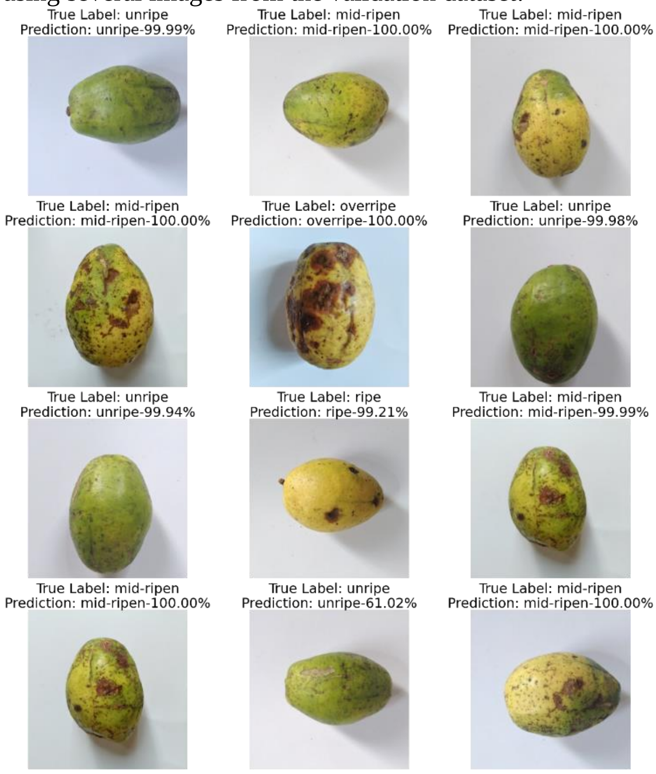

Fig. 5. Results of classifying Ambarella fruit ripeness using EfficientNetV2B0

As shown in Figure 5, the trained EfficientNetV2B0 can correctly classify each Ambarella fruit ripeness. Overall, the prediction confidence of each image is relatively high; nevertheless, one confidence is just 61.02%; nonetheless, the classification is accurate. The results show that the model can classify the ripeness of Ambarella fruit in an image. The EfficientNetV2B0 has shown via this study's experiments that despite its small size, it can classify accurately.

IV. CONCLUSION

In this study, an approach to classify the ripeness of Ambarella fruit has been proposed. The classification of four stages of ripeness: unripe, mid-ripen, ripe, and overripe; was done using three pre-trained EfficientNetV2 models, EfficientNetV2B0, EfficientNetV2B1, and EfficientV2B2. The models were trained using transfer learning through fine-tuning approach, as they can benefit from the weights learned from the ImageNet dataset. Fine-tuning was performed block-wise, and the unfreezing was done to the last block of each model. Overall, EfficientNetV2B0 achieved the highest accuracy, which is 100%, on the validation dataset, while EfficientNetV2B1 achieved the highest accuracy of 97.71% on the training dataset. The lowest accuracy was achieved by the EfficientNetV2B2, which is 96.57%. Despite the small size, the EfficientNetV2B0 has proven to achieve high performance;

therefore, it is possible to use it for mobile devices. Nonetheless, EfficientNetV2B1 and EfficientNetV2B2 achieved great accuracy; although the size is relatively bigger than EfficientNetV2B0, it is possible to use them for mobile devices.

The future aim is to collect more datasets with various backgrounds, as the current dataset lacks variety. Additionally, there is a possibility to train a model for detecting the Ambarella fruit in the image to detect and crop the Ambarella fruit automatically.

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