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CLASSIFICATION OF C. ANNUUM AND C. FRUSTECENTS RIPENING STAGES: HOW WELL DOES DEEP LEARNING PERFORM?

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ABSTRACT: Chilli is one of the world's most widely grown crops. Among all of the chilli variants, C. *annuum* and C. *frustescents* are the most prevalent and consistently liked variants in Asia, where it is appreciated for its strong taste and pungency. Nevertheless, harvesting at the proper ripening stage according to their colour, size, and texture is essential to ensure the best quality, marketability, and shelf life. Currently, visual inspection is the primary method used by farmers, which is time-consuming and complicated. Even though automated chilli classification using computer vision and intelligent methods has received scholars' attention, the classification of C. *annuum* and C. *frustescents* ripening stages using deep learning models has not been extensively studied. Hence, this study aims to investigate the effectiveness of three deep learning models, namely EfficientNetB0, VGG16 and ResNet50, in classifying chilli ripening stages into unripe, ripe, and overripe classes. We also introduce a huge dataset comprising 9,022 images of C. *annuum* and C. *frustescents* chilli under various growth stages and imaging conditions which provides sufficient samples for the deep learning modelling. The experimental results show that the ResNet50 model outperforms other models with more than 95% accuracy for all classes.

ABSTRAK: Cili merupakan salah satu tanaman terbanyak ditanam di dunia. Antara semua varian cili, C. annuum dan C. frustescents adalah yang paling meluas ditanam dan merupakan varian paling pedas di Asia, kerana rasanya yang kuat. Namun begitu, penuaian pada peringkat cili matang mengikut warna, saiz dan teksturnya adalah penting bagi memastikan kualiti, kebolehpasaran dan jangka hayat terbaik. Pada masa ini, pemeriksaan visual adalah kaedah utama yang diguna pakai petani bagi memeriksa cili, tetapi ia memakan masa dan rumit. Walaupun pengelasan cili secara automatik menguna pakai kaedah komputer dan pintar mendapat perhatian sarjana, kajian tentang klasifikasi cili jenis C. annuum dan C. frustescent pada peringkat matang menggunakan model pembelajaran mendalam masih belum begitu meluas. Oleh itu, kajian ini bertujuan bagi mengkaji keberkesanan tiga model pembelajaran mendalam, iaitu EfficientNetB0, VGG16 dan ResNet50, dalam mengklasifikasi kematangan cili pada beberapa peringkat matang cili seperti belum masak, masak dan terlalu masak. Kami juga memperkenalkan set data yang besar terdiri daripada 9,022 imej cili C. annuum dan C. frustescents pada pelbagai peringkat pertumbuhan dan keadaan imej, bagi menyediakan sampel yang cukup untuk membina model pembelajaran mendalam. Hasil dapatan eksperimen mendapati model ResNet50 mengatasi model lain dengan peratusan 95% lebih tepat berbanding semua kelas.

KEYWORDS: *Transfer Learning, Deep Learning, Fruit Classification, Chilli Fruit Dataset, EfficientNetB0, VGG16, ResNet50.*

1. INTRODUCTION

Chillies have been used as part of the human diet as spice, condiments, and vegetables for their appealing colour, flavour, and spice since the advancement of civilisation. The largest producer and exporter of chilli is India, followed by China and other countries [1-2]. Chilli is a famous cash-value crop in Malaysia and has been recorded as among the top ten crops from 2016 to 2020 [3]. This is due to its massive utilisation in the food industry for producing sauces, soups, processed meats, nibbles, candies, and soft beverages [4]. However, there is a bottleneck in chilli production due to manual sorting and grading to determine whether the chilli is in perfect condition. Chilli fruit ripening stages can be categorised according to the chilli's bioactive compound [4]. L. A. Martínez-López et al. [5], studied the ripening stages of 34,066 chilli genes at four time intervals, which were 10, 20, 40, and 60 days, respectively, after anthesis (DAA). The authors found that 10 and 20 DAA represent the early and middle stages of fruit growth, 40 DAA is when chillies reach the breaking stage (mature-green), and 60 DAA is when the fruits are fully ripened. However, the study by Olatunji & Afolayan [6] revealed that the taxonomic status of C. *frustescents* and C. *annuum* is unclear because they are morphologically related. In the experiment, the authors used the International Board for Plant Genetic Resources Descriptors for Capsicum (IPGRI,1995), in which the maturation stage classification is based on multiple traits, such as fruit colour, fruit shape, fruit surface, seed colour, and seed size. The fruit colour ranges from light yellow to green for the intermediate maturation stage and red for the mature stage. Nevertheless, the chilli fruit sorting differs according to consumer specifications and preferences. This means that chillies can be sorted according to numerous parameters, and based on these facts, the manual classification process can be time-consuming. Furthermore, individual perception and exhaustion may lead to inconsistencies in the selection and sorting decisions [7-8]. Therefore, a rapid, effective, and intelligent system is required to categorise the ripening stage in chilli harvesting.

Automated chilli fruit classification study has received significant attention in recent years. In Khuriyati et al. [9], the authors used artificial neural networks (ANN) and image processing to sort and grade red peppers. The result showed 84.46% accuracy when trained and tested using 190 and 288 images, respectively, whereas Sudianto et al. [7], used You Only Look Once (YOLO) method via transfer learning models to detect and classify the quality of A- and B-grade chillies in real-time. The authors showed that the classification accuracy for grade A chillies was higher than for grade B chillies, with 99.4% and 75.6% accuracies, respectively. The same method was applied by Abdul Manan et al. [8] to classify chilli plants and fruit (bird's eye). A comparison with two other models, Faster R-CNN and RetinaNet, has shown that the YOLO model outperformed other models by achieving 75.69% accuracy. Purwaningsih et al. [10], used a simple CNN network to classify chilli images as feasible or unsuitable. The authors showed that the network was able to produce 80% accuracy when classifying images under a controlled environment. Cruz-Domínguez et al. [11] used ANNs to recognise dried chilli peppers based on their patterns. The study produced an accuracy of only 82.13%, which may be attributed to the simple classification network. Other studies related to transfer learning-based deep learning models, such as EfficientNetB0, VGG16, and ResNet50 for fruit and vegetable classification were discussed in [12-17]. The results produced by the deep models were much better than their simple machine learning based counterparts in [9-11], but the performance of these models in classifying C. *annuum* and C. *frustescents* images under controlled and various imaging conditions into three ripening stages has yet to be explored. Furthermore, there are limited publicly available chilli images under different imaging conditions. Inspired by these facts, this study aims to investigate the efficacy of transfer learning-based EfficientNetB0, VGG16, and ResNet50 models to classify C. *annuum* and C.

frustescents images with the aforementioned conditions. Additionally, the objective is to develop a chilli image dataset that is large enough to facilitate deep learning modelling. The findings in this paper will create opportunities for producing more robust classifiers for automated chilli classification.

This paper is organised as follows: Section 2 describes the method used in this study. This includes the detail on the compilation of the chilli fruit dataset and explanation of the three deep learning models of EfficientNetB0, VGG16, and ResNet-50. Section 2 also includes deliberation on the experimental setup for the classification. Section 3 presents the experimental results, followed by discussions. Finally, Section 4 concludes the paper.

2. METHOD

2.1. Chili Fruit Dataset

The dataset used in this study consists of 9,022 images of C. *annuum* and C. *frustescents*, of which 1496 are original chili images whereas 7526 are the augmented image counterparts. The original images were captured using an Oppo Reno4 V11.1 smartphone under various growth stages and imaging conditions, such as various chilli shapes, different distances from chilli to the camera (10cm and 15cm) and different camera settings such as ISO 100, ISO 200, white balance, 5000, and 6000. Other varying parameters considered in this study include different image sizes, scales, orientations and flipping effects, which were performed during the image augmentation process.

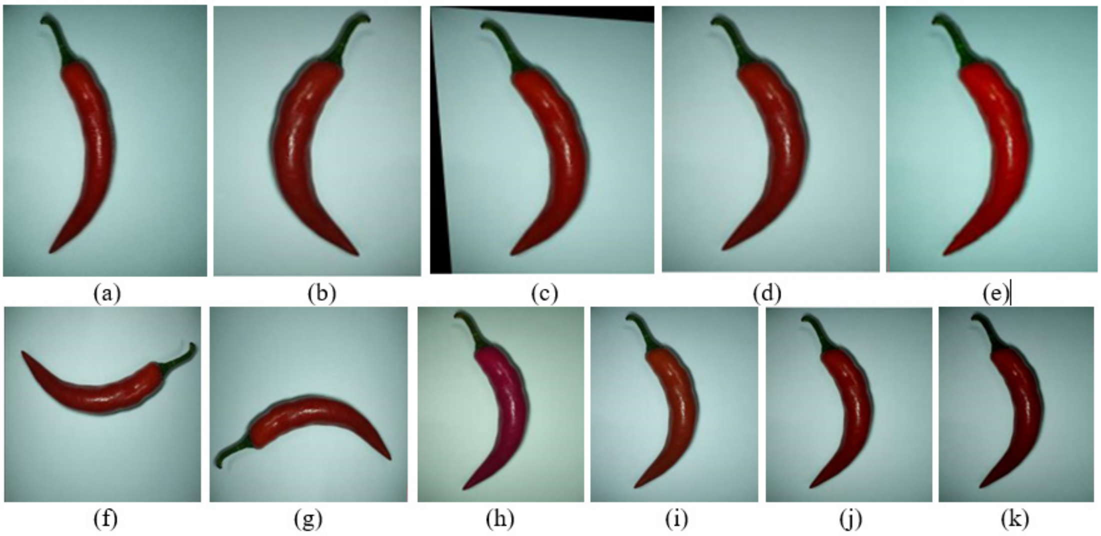

Fig. 1. Samples of ripe C. *annuum* images. (a) Original image; (b) Horizontal flipped; (c) Shear at 20% angle vertical and horizontal (20°,20°); (d) Saturation adjust to -50% (e) Saturation adjust to +50%; (f) 90° rotated clockwise; (g) 90° rotated counter-clockwise; (h) Hue adjust to -25°; (i) Hue adjust to +25°; (j) Brightness adjust to 20% brighter and (k) Brightness adjust to 20% darker.

In this study, the original chili images were resized to 224 x 224 pixels, horizontally flipped, sheared at a 20% angle, image saturated between -50% and +50%, rotated 90° clockwise and anti-clockwise, hue changed at -25° and +25°, and brightness adjusted by 20% brighter and darker, as shown in Fig. 1, using Roboflow software. The reason for producing images under various imaging conditions is to replicate actual varying scenarios and to provide sufficient samples that support deep learning modelling. The images were labelled and grouped into three stages of maturity, which are unripe, ripe, and overripe classes, respectively. Table 1 shows the total number of images acquired for each chilli variety.

Table 1: Chillies quantities per type

Images	Train	Test	Total
Original Dataset:			
C. *annuum*	415	103	518
C. *frustescents*	783	195	978
Augmented Dataset:			
C. *annuum*	3251	811	4062
C. *frustescents*	2771	693	3464
Combine Dataset:			
C. *annuum*	3666	914	4580
C. *frustescents*	3554	888	4442

2.2. Deep Learning Models

In this study, a transfer learning approach was applied to the three state-of-the-art deep learning models, namely EfficientNetB0, VGG16, and ResNet-50. The performance of these models in classifying C. *annuum* and C. *frustescents* ripening stages were compared. These models were selected due to their exceptional performance in classifying the maturity of other fruits and vegetables, as discussed in Miraei Ashtiani et al. [12], Duong et al. [17] and Suharjito et al. [18]. The utilisation of the transfer learning approach is expected to produce faster and better results than using the model from scratch, as discussed in Pardede et al. [16], Szyc [19] and Zhu et al. [20]. The EfficientNet was developed by Tan & Le [21] and currently consists of 8 models, ranging in quality from B0 to B7. Each version was upgraded from the previous version using a different compound coefficient, with EfficientNetB0 as the baseline. As a result, the model consistently scales the depth, width, and resolution to produce more efficient results with better accuracy. The first stage in the compound scaling approach is to find a grid to discover the relationship between the various scaling dimensions of the baseline network under a fixed resource limitation. This method determines a reasonable scaling factor for the depth, width, and resolution dimensions. Using these coefficients, the baseline network is then scaled to the desired target network [22]. The convolutional layer is the first layer in the architecture, and the remaining layers are mobile inverted bottleneck convolutional (MBConv) building blocks with squeeze-and-excitation optimisation layers, as shown in Fig. 2. The recommended input image dimension for this model is 224x224x3.

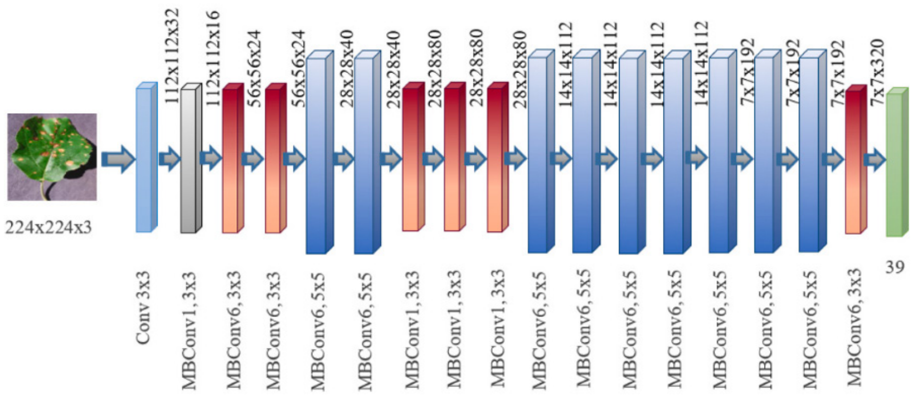

Fig. 2. EfficientNetB0 Schematic Diagram [22].

The VGG-16 architecture, as shown in Fig. 3, comprises a combination of convolution layers, maximum pooling and fully connected (FC) layers [22]. The convolutional layers have a RELU activation function. All the information from these layers was passed to the max-pooling layer that functions to reduce the dimensions of the feature maps. Finally, the classification output was compiled by the FC layers, which are the last three layers in the architecture. These layers represent the required output classes, which for this study were the three classes of the chilli fruit ripening stages. Nevertheless, the recommended default input image size is 224x224x3.

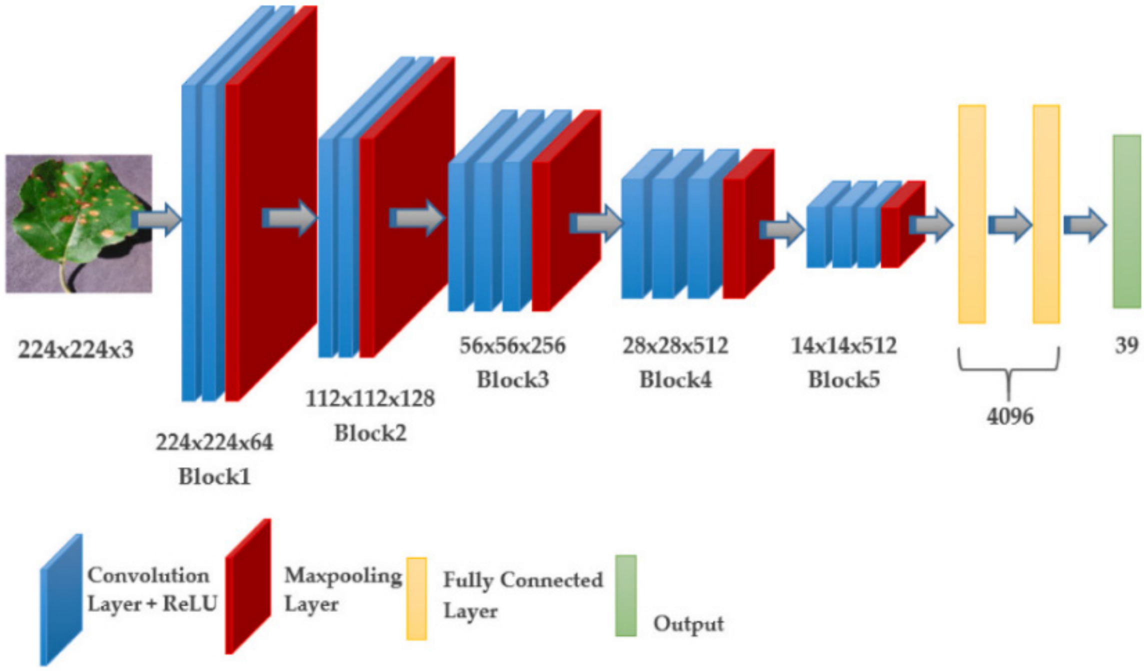

Fig. 3. VGG16 Schematic Diagram [22].

ResNet50 model is a potential remedy for the issue of numerous non-linear layers failing to learn identity mappings and degradation. The network architecture has several stacked residual units, as shown in Fig. 4. The network is constructed using residual units as building blocks and consists of convolution and pooling layers. This architecture accepts 224 x 224 pixels input images, following the recommendation in [21] and uses the same 3 x 3 kernels as the VGG16.

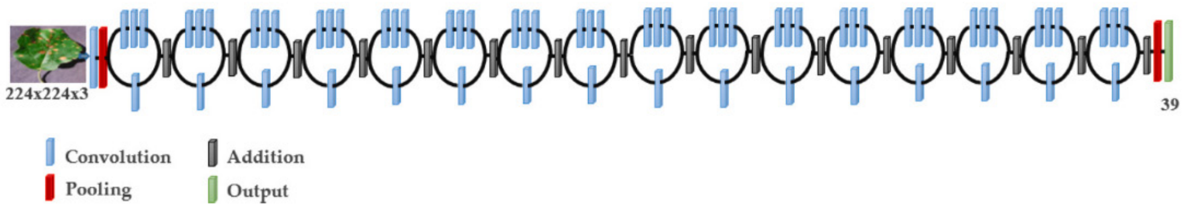

Fig. 4. ResNet50 Schematic Diagram [22].

2.3. Experimental Setup

This experiment was performed using an x64-based processor with an Intel(R) Core(TM) i5-10200H CPU operating at 2.40GHz, an NVIDIA GeForce GTX 1650 graphics card, and 8GB of RAM. These deep learning models were compiled by GPU using Jupyter Notebook alongside the Keras and TensorFlow framework. The proposed flow chart of C. *annuum* and

C. *frustescents* ripening stages classification is shown in Fig. 5. The transfer learning used in EfficentNetB0, VGG-16, and ResNet50 models improves the classification accuracy and shortens the training time [23-24]. The hyperparameters, namely batch size, learning rate, and the number of epochs used in the experiments, were selected based on the outcome achieved during the training and the recommended values in [24-25]. For this study, the appropriate values for batch size, learning rate, and the number of epochs are 32, 0.0001 and 30 respectively. Normalisation and batch size were a consideration in the experiment setup. All deep learning models were executed using Stochastic Gradient Descent (SGD) for optimisation and softmax function for classification. Holdout cross-validation is applied in the experiment, where the entire dataset is partitioned randomly into a training set and a testing set with a distribution of 80% and 20%, respectively.

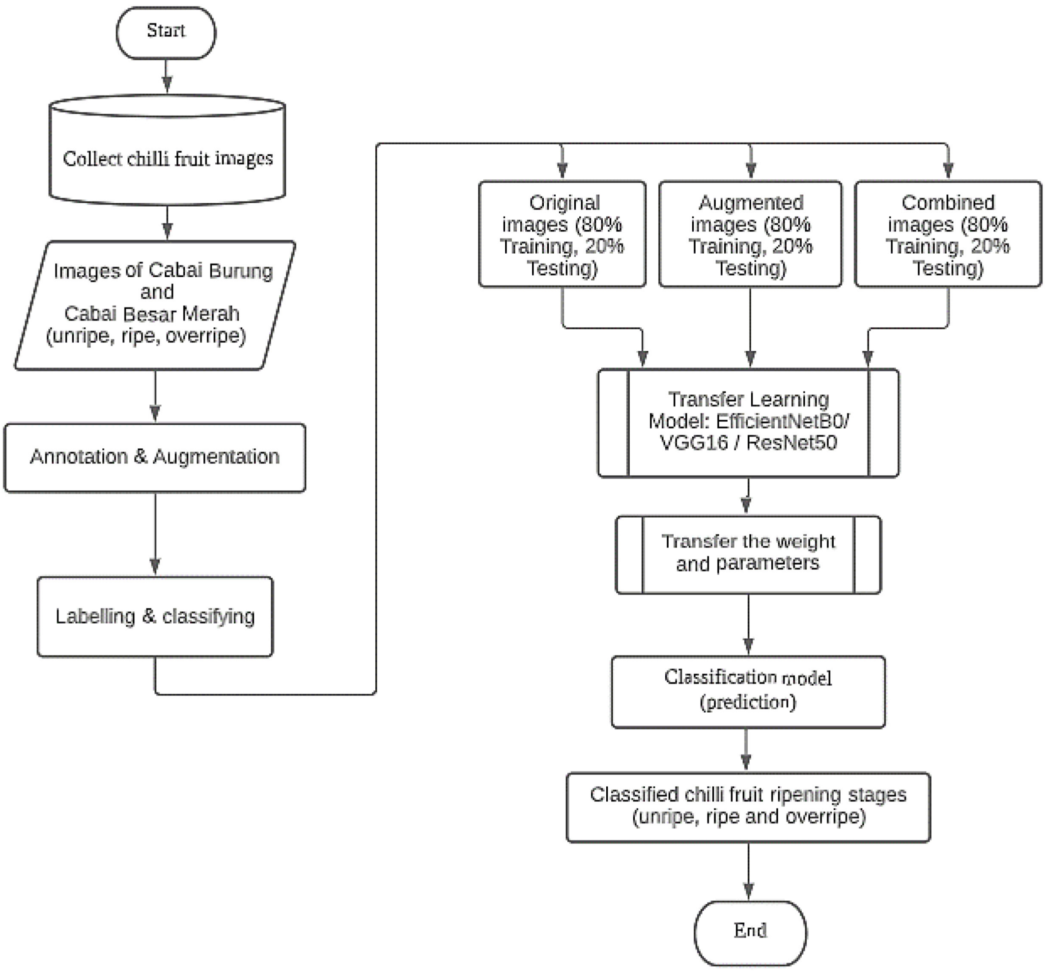

Fig. 5. Chilli Fruit Ripening Stage Classification Flow Chart.

3. RESULTS AND DISCUSSION

The performance of the models is evaluated using accuracy, precision, recall, and F1-score. Accuracy generally assesses the performance of the classification model and precision represents the accuracy of the forecasts. Recall is the true positive rate and the F1 score is a weighted harmonic mean of recall and precision, where 1.0 is the best result and 0 is the lowest. These parameters can be calculated using the values from the confusion matrices, as shown in Tables 2-4. In these tables, P.O., P.R., P.U., A.O., A.R. and A.U represent predicted overripe, predicted ripe, predicted unripe, actual overripe, actual ripe and actual unripe, respectively. The

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experiments were performed using three datasets, where the first dataset consisted of original images only, the second dataset consisted of augmented images only and the third dataset consisted of a combination of original and augmented images. All chilli fruit images were trained and tested with 30 epochs and divided randomly at a ratio of 80:20. Figs. 6-8 show that the ResNet50 model outperforms EfficentNetB0 and VGG-16 models when classifying C. *frustescents* images. The ResNet50 model produced 98% to 99% accuracy, while VGG16 had a slightly lower range of accuracy percentages. The EfficientB0 model produced a wide range of accuracy, ranging from 56% to 96%. It is shown in Fig. 7 that the EfficientNet model has poor stability compared to ResNet and VGG16 models, especially when tested using only the original images. This shows that the EfficientNet model needs more images to work well.

Table 2: Confusion matrix obtained using original images.

Variety	Model	EfficientNetB0			VGG16			ResNet50		
C. *frustescents*		P.O.	P.R.	P.U	P.O.	P.R.	P.U	P.O.	P.R.	P.U
	A,O.	0.66	0.31	0.03	0.98	0.01	0.01	1.00	0.00	0.00
	A.R.	0.18	0.74	0.08	0.03	0.97	0.00	0.03	0.88	0.09
	A.U	0.00	0.60	0.40	0.01	0.02	0.97	0.00	0.00	1.00
C. *annuum*		P.O.	P.R.	P.U	P.O.	P.R.	P.U	P.O.	P.R.	P.U
	A.O.	0.63	0.37	0.00	0.98	0.02	0.00	1.00	0.00	0.00
	A.R.	0.45	0.48	0.07	0.00	0.84	0.16	0.06	0.87	0.07
	A.U	0.20	0.60	0.20	0.00	0.40	0.60	0.00	0.10	0.90

Table 3: Confusion matrix obtained using augmented images.

Variety	Model	EfficientNetB0			VGG16			ResNet50		
C. *frustescents*		P.O.	P.R.	P.U	P.O.	P.R.	P.U	P.O.	P.R.	P.U
	A.O.	0.97	0.03	0.00	0.99	0.00	0.01	1.00	0.00	0.00
	A.R.	0.03	0.93	0.04	0.00	0.98	0.02	0.00	0.97	0.03
	A.U	0.00	0.02	0.98	0.00	0.01	0.99	0.00	0.01	0.99
C. *annuum*		P.O.	P.R.	P.U	P.O.	P.R.	P.U	P.O.	P.R.	P.U
	A.O.	0.99	0.01	0.00	0.99	0.01	0.00	1.00	0.00	0.00
	A.R.	0.03	0.90	0.07	0.02	0.81	0.17	0.03	0.94	0.03
	A.U	0.00	0.05	0.95	0.00	0.08	0.92	0.00	0.04	0.96

Table 4: Confusion matrix obtained using combined images.

Variety	Model	EfficientNetB0			VGG16			ResNet50		
C. *frustescents*		P.O.	P.R.	P.U	P.O.	P.R.	P.U	P.O.	P.R.	P.U
	A.O.	0.99	0.01	0.00	0.97	0.02	0.01	1.00	0.00	0.00
	A.R.	0.03	0.91	0.06	0.00	0.98	0.02	0.00	0.97	0.03
	A.U	0.01	0.02	0.97	0.02	0.01	0.97	0.00	0.02	0.98
C. *annuum*		P.O.	P.R.	P.U	P.O.	P.R.	P.U	P.O.	P.R.	P.U
	A.O.	1.00	0.00	0.00	0.98	0.02	0.00	1.00	0.00	0.00
	A.R.	0.02	0.90	0.08	0.02	0.91	0.07	0.03	0.92	0.05
	A.U	0.00	0.06	0.94	0.00	0.06	0.94	0.00	0.05	0.95

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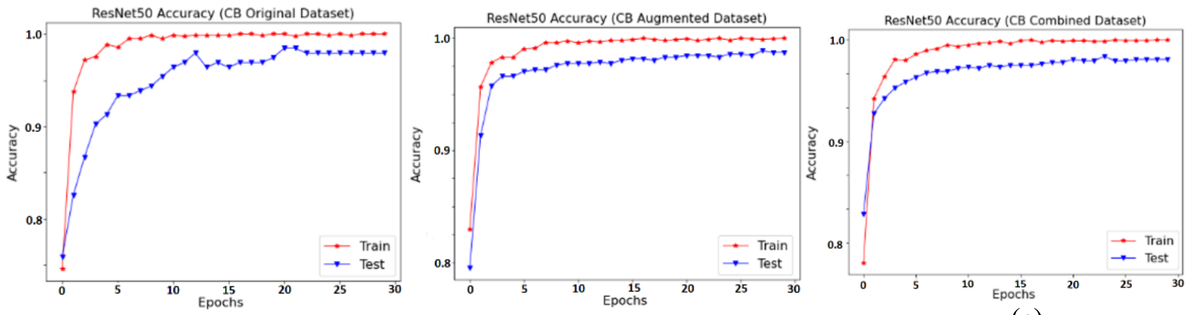
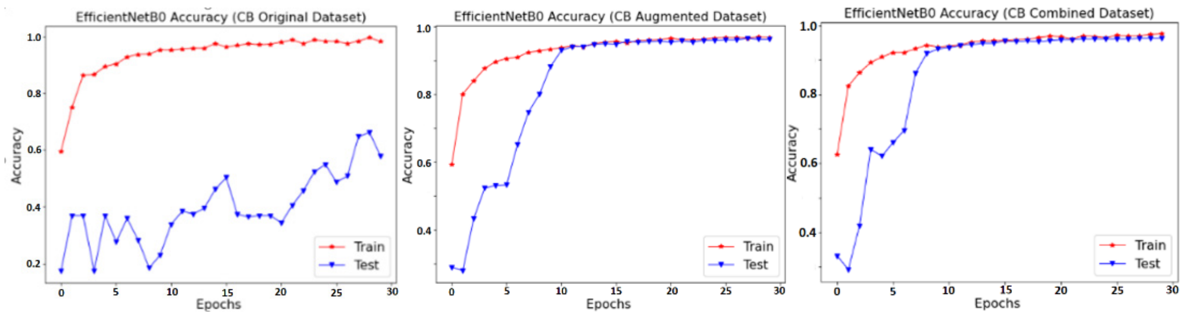


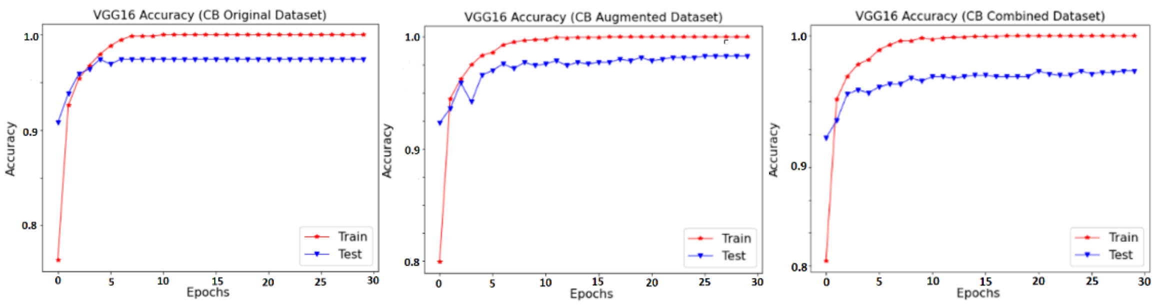
(a) (b) (c)

Fig. 6. The accuracy produced by ResNet50 model for classifying (a) original images, (b) augmented images and (c) combined images of C. *frustescents*.



(a) (b) (c)

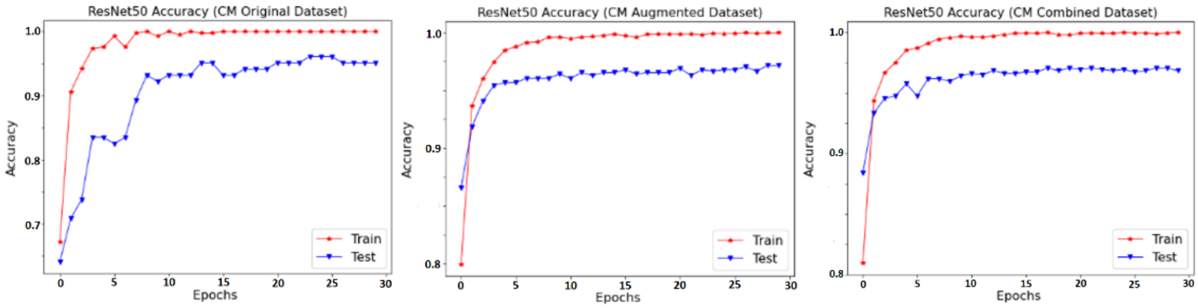
Fig. 7. The accuracy produced by EfficientNetB0 model for classifying (a) original images, (b) augmented images and (c) combined images of C. *frustescents*.



(a) (b) (c)

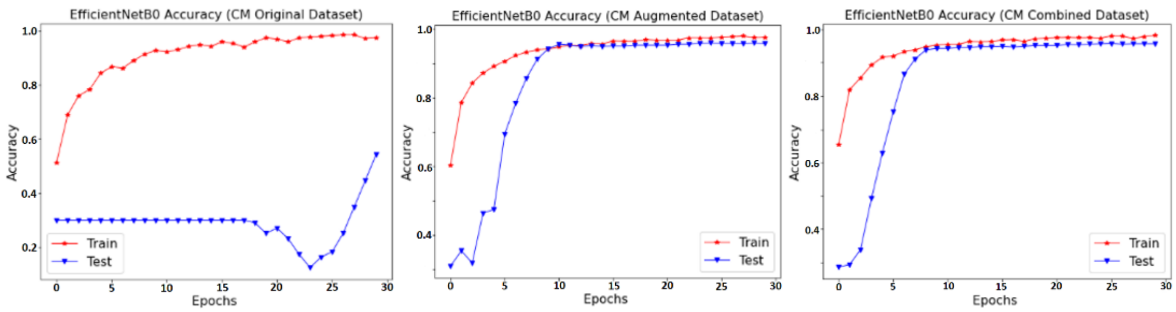
Fig. 8. The accuracy produced by VGG16 model for classifying (a) original images, (b) augmented images and (c) combined images of C. *frustescents*.

The same trend was observed when classifying C. *annuum*, as shown in Fig. 9-11. The ResNet50 model produced an accuracy ranging from 95% to 97%, while VGG16 had a slightly lower range of accuracy percentages. As expected, the EfficientNetB0 model produced a wide range of accuracy, ranging from 54% to 96%, where the lowest accuracy was produced when tested with only the original images. In terms of stability, it is shown that the ResNet50 and VGG16 models are better than the EfficientNet model. However, it is observed that VGG16 failed to generalise the testing set because the testing accuracy was much lower than the training accuracy. The performances matrices for all deep learning models for C. *frustescents* and C. *annuum* are presented in Table 2-4.



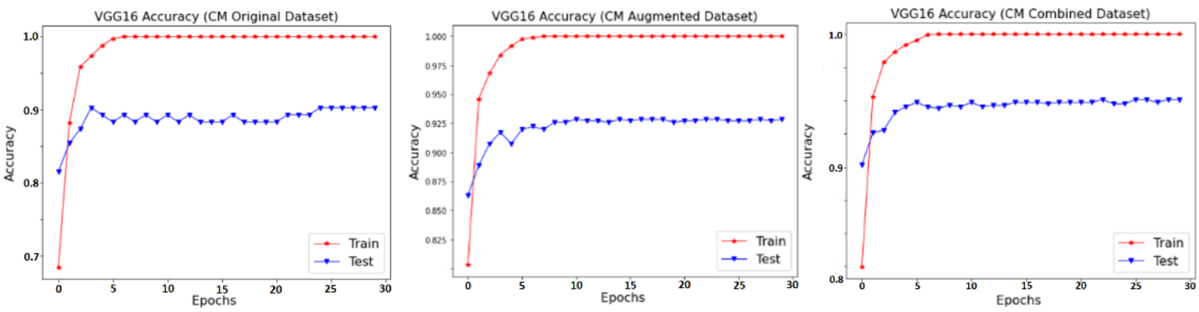
(a) (b) (c)

Fig. 9. The accuracy produced by ResNet50 model for classifying (a) original images, (b) augmented images and (c) combined images of C. *annuum*.



(a) (b) (c)

Fig. 10. The accuracy produced by EfficientNetB0 model for classifying (a) original images, (b) augmented images and (c) combined images of C. *annuum*.



(a) (b) (c)

Fig. 11. The accuracy produced by VGG16 model for classifying (a) original images, (b) augmented images and (c) combined images of C. *annuum*.

Tables 5-7 show that the classifiers produced higher accuracy when classifying C. frustescents than C. annuum. It is also shown that positive predictive values for C. frustescents is slightly higher than C. annuum. The same trend is observed for recall. This is because of the distinctive sizes of C. frustescents fruits used in the data collection, making them easier to be classified. The experiment results also showed that the total number of images used for classification is vital for good classification. The performance of the classifiers when classifying 1496 original images is poorer than classifying 7526 augmented images, especially for EfficientNetB0. This means that the data used to train EfficientNetB0 is insufficient.

Table 5: Classification performance using original images

Variety	Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score	Loss
C. *frustescents*	EfficientNetB0	57.95	67.00	60.00	0.57	0.197
	VGG16	97.44	97.00	97.00	0.97	0.081
	Resnet50	97.94	98.00	96.00	0.97	0.049
C. *annuum*	EfficientNetB0	54.37	52.00	44.00	0.45	0.267
	VGG16	90.29	79.00	81.00	0.80	0.124
	Resnet50	95.14	92.00	92.00	0.92	0.071

Table 6: Classification performance using augmented images

Variety	Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score	Loss
C. *frustescents*	EfficientNetB0	96.16	96.00	96.00	0.96	0.207
	VGG16	98.30	98.00	98.00	0.98	0.065
	Resnet50	98.72	99.00	99.00	0.99	0.037
C. *annuum*	EfficientNetB0	95.68	95.00	95.00	0.95	0.198
	VGG16	92.85	91.00	91.00	0.91	0.064
	Resnet50	97.16	97.00	96.00	0.97	0.046

Table 7: Classification performance using combined images

Variety	Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score	Loss
C. *frustescents*	EfficientNetB0	96.33	96.00	96.00	0.96	0.188
	VGG16	97.33	97.00	97.00	0.97	0.057
	Resnet50	98.55	98.00	98.00	0.98	0.035
C. *annuum*	EfficientNetB0	95.73	95.00	95.00	0.95	0.176
	VGG16	95.08	94.00	94.00	0.94	0.052
	Resnet50	96.82	96.00	96.00	0.96	0.042

4. CONCLUSION

The efficacy of transfer learning models, namely EfficentNetB0, VGG16 and ResNet50, in classifying three stages of ripening chilli fruit for C. *frustescents* and C. *annuum* from a dataset consisting of 9,022 images in a controlled environment and under various imaging conditions is demonstrated. The experiment results show that ResNet50 is superior to the other two deep learning models. Nevertheless, the other two models, EfficientNetB0 and VGG16 also presented good results of over 90%. However, EfficientNetB0 has difficulty classifying an original dataset for both chilli fruit types. This is because the dataset used for training is small, consisting of less than 1,000 images, and also due to various illumination effects. In conclusion, transfer learning algorithms have shown the potential to be used in classifying chilli fruit ripening stages. The performance can be improved by using a large dataset and various augmentation images for training to produce better performance.

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