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Research Article

Comparison of Convolutional Neural Network Models for Feasibility of Selling Orchids

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Abstract

Orchid flowers are one of the most popular ornamental plants, widely appreciated for their unique features and aesthetic appeal, making them highly potential for sales in the global market. While numerous studies have explored Orchid flower characteristics and disease detection, research on the classification of Orchid salability remains unexplored. This study addresses this gap by classifying Orchid flowers into three categories: saleable, potential saleable, and not saleable. Convolutional Neural Networks (CNN), known for their effectiveness in image-based classification, were employed in this study with performance enhancement through the application of transfer learning. Two prominent transfer learning architectures, VGG-16 and ResNet-50, were implemented and compared to evaluate their suitability for Orchid salability classification. The results demonstrated that the VGG-16 model significantly outperformed ResNet-50 in all evaluation metrics. The VGG-16 model achieved an accuracy of 98%, precision of 99%, recall of 97%, and an F1 score of 98%. In contrast, the ResNet-50 model yielded lower performance, with an accuracy of 69%, precision of 68%, recall of 56%, and an F1 score of 56%. The study also observed that increasing the training epochs from 25 to 50 had no significant impact on the performance of either model. This research highlights the superior performance of VGG-16 in Orchid salability classification and underscores the potential of transfer learning in advancing ornamental plant research.

Keywords: Comparison; CNN; ResNet-50; Sellable of Orchid; VGG-16

Introduction

Orchid is one of the most popular ornamental plants around the world, and has many features and uniqueness that make it attractive and very potential in various aspects. The sales potential of orchids is vast and can cover a wide range of sectors. Orchids are widely used in the home decoration industry. People who want to beautify the interior or exterior of their homes often buy orchids as a decorative option. Orchids are also often a popular choice as gifts for various special occasions. Pasar Rebo sub-district in East Jakarta has been proclaimed as an Orchid village. Orchid cultivation has the opportunity to become an agribusiness cultivation that has economic value. Orchid cultivation locations are scattered at several points in Pasar Rebo Sub-district and at the locations there are display places where people passing by with attractive Orchid flower displays can immediately buy. The challenge for the manager is to select attractive and saleable Orchid flowers to be placed in the display room, while those that are not yet viable or have the potential to sell are placed in a different place and those that are not saleable are developed again to make them attractive and saleable. Identifying the readiness to sell flowers is not an easy task, even for experts.

There has been quite a lot of research related to the detection of Orchid flowers but none of them has discussed the detection of the readiness to sell Orchid flowers. Research on classification of orchid flower objects in 6 classes using convolutional neural network (CNN) [1]–[2], classification of flower types using CNN [3]–[9], detection of Orchid leaf disease [10], [11], detection of color and type in Orchids [12], [13], detection of Orchid growth [14]. This research uses a CNN approach to help solve the problem of Orchid flower sale readiness detection by focusing on how to classify sale readiness based on flower shape using CNN. Deep Learning is a branch of machine learning, where machine learning can teach computers to do human-like work done from the training process [15]–[16]. CNN is one type of deep learning. CNN is considered superior to other classical models because of the concept of weight sharing where parameter sharing from CNN can help reduce the number of parameters so that the parameters that require training are substantially reduced, resulting in better generalization and not experiencing overfitting [17], [18]. CNN is currently a widely developed research topic, including for flower classification. Solving image classification problems with high amounts of data can achieve optimal performance when using CNN approaches, but for low

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amounts of data, transfer learning approaches from pre-trained CNN architectures are usually used. Pre-trained CNNs that are available and widely used include VGG [19], [20] as an improvement of AlexNet [21], ResNet introduced with the concept of residual features [22], [23], and a number of other architectures such as Xception [24] and EfficientNet [25] that introduce architectures with consideration of a combination of depth, width, and resolution. Transfer learning is performed by moving the CNN model that has been trained with the original dataset to solve cases on other datasets.

VGGNet and ResNet were chosen in this study, because as in previous research it has been explained that these two architectures are quite effective for image classification [26]. Various types of images can be processed and analyzed using this CNN model by adjusting the parameters. VGG-16 and ResNet-50 both perform quite well in the classification of flower types, in this study they will be compared for the classification feasibility of selling orchids based on flower shape and color. This research will discuss the ability of ResNet-50 and VGG-16 in classifying Orchid flower images specifically into three categories namely saleable, potential saleable, and not saleable.

Method

This research begins with the data collection stage, then proceeds with preprocessing which includes resizing and augmentation [27]. After that, classification is done with the VGG-16 and ResNet-50 methods. From the model that has been built with the two architectures, it is used to predict the selling feasibility of orchids. The last stage is evaluating the results by comparing the accuracy and confusion matrix values of the two methods used.

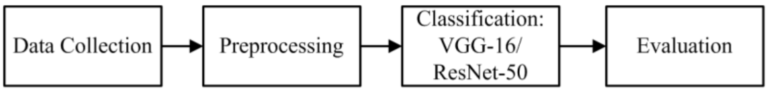

Figure 1. Research stages

A. Data Collection

This research uses private data sets, the data used has been labeled by experts into three classes, namely saleable, potential saleable, and not saleable. The retrieval was done using a cellphone camera using a white paper background with a distance of 25-40 cm. The results of data collection amounted to 140 image data consisting of 74 Sellable classes, 48 Potential Sellable classes, and 18 Not Sellable classes. **Figure 2** is the sample dataset collected in each Orchid marketability class.

(a) (b) (c)

Figure 2. Sample images of Anggek flowers (a) Sellable (b) Potential Sellable (c) Not Sellable

B. Preprocessing

After the data collection process, preprocessing is carried out to optimize the quality of the image, so as to facilitate and boost the system's ability to identify objects. The preprocessing stage in this system is divided into two stages, namely original data and augmentation data. In the original data, preprocessing is only done by resizing the image. In the preprocessing stage, the dataset is resized to a size of 224 × 224 pixels. While in augmented data, preprocessing is done with resize and data augmentation. **Figure 3** shows the flowchart of the augmentation data preprocessing process. Augmentation is the process of processing image data by modifying image data. In this system, the augmentation stages carried out are Rotation, Horizontal flip, shear range, rescale and fill mode. Preprocessing results are the output results of images that have gone through the resize process and augmentation stage.

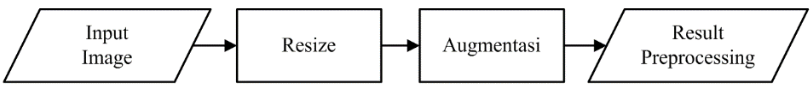

Figure 3. Preprocessing stages

C. Classification

In the classification stage, a training learning process is carried out on the image, which then outputs a model that will be stored for use in the testing process. Model building is the process of training image data in identifying objects and categorizing them according to their class. In this research, the method used is one of the branches of deep learning algorithms, namely CNN with VGG-16 and ResNet-50 architectures.

VGG-16 is a CNN architecture that won the ImageNet competition in 2014. VGG-16 is considered as one of the best architecture models to date. VGG-16 does not have a large number of hyperparameters, but VGG-16 only focuses on 3×3 convolution layer filters with stride 1 and always uses the same padding and 2×2 maxpool layer filters with stride 2. At the end of the architecture, the VGG-16 has 2 fully connected layers followed by softmax for output. The number 16 of the VGG-16 indicates that it has 16 equally loaded layers. This network is quite large and has about 138 million parameters. **Figure 4** shows the architecture of the VGG-16 [28].

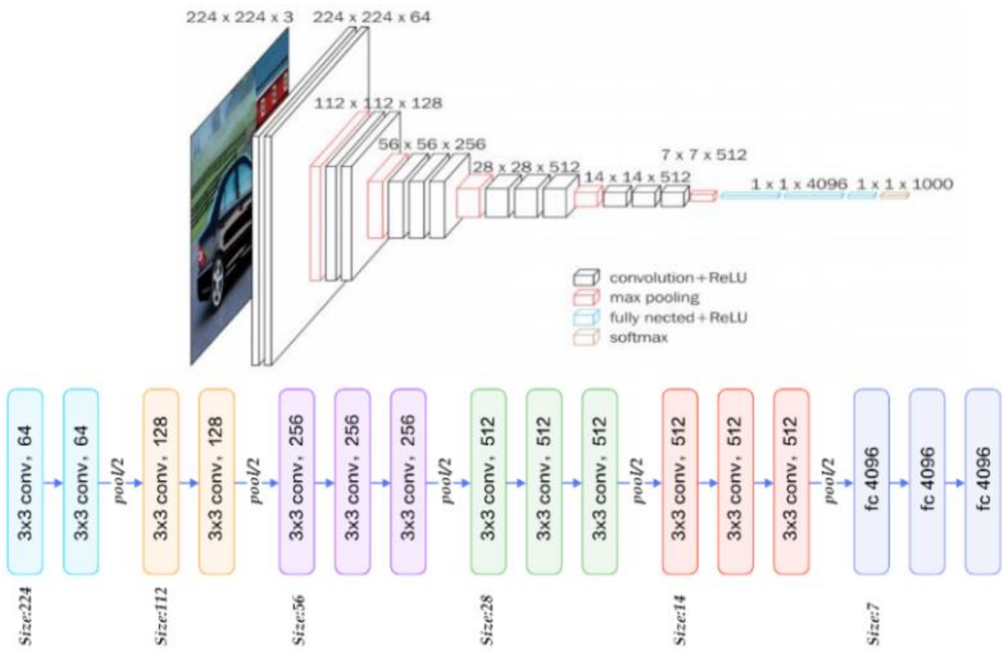

Figure 4. VGG-16 Architecture

Residual Network or ResNet was introduced by Kaiming He who won the ILSVRC (ImageNet Large Scale Visual Recognition Challenge) in 2015. The goal of this architecture is to design an ultra-deep network that is free from the missing gradient problem. ResNet50 is the most commonly used type that consists of 49 convolutional layers plus one Fully-Connected Layer [29]. ResNet-50 is a variation of the ResNet architecture that has 50 layers that have been trained on at least 1 million images in the ImageNet database. ResNet-50 consists of five stages in each of which there are convolution and identity blocks. Each convolution block consists of two convolution layers and each identity block also has three convolution layers. ResNet 50 already has more than 23 million trainable parameters. **Figure 5** shows the architecture of ResNet-50 which consists of five stages of convolution process.

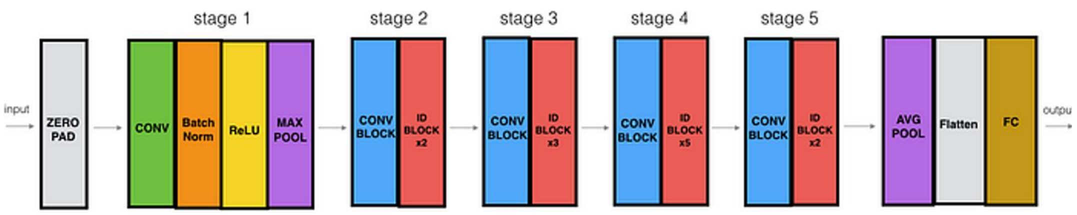

Figure 5. ResNet-50 Architecture

D. Evaluation

The designed model will be calculated based on the performance suitability of the model performance. To measure the advantages and disadvantages of the designed model using confusion matrix. Confusion matrix is one of the techniques to measure the performance of a classification model. The origin of this method is a review that is used to compare the performance results performed by a model with the classification performance results that should be using [30]. There are four confusion matrix performance measurement terms that can represent the results of the classification process, namely, True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). TP values are data that is correctly classified by the model as true values. TN is data that is correctly classified by the system as a false value. FP is false data but classified as true data and FN is true data but classified as false data [31].

The calculation of the performance of the model to be calculated is precision, recall, accuracy, and F1 score. Equations 1, 2, 3 and 4 show the calculation formulas for precision, recall, accuracy and F1 score respectively. Accuracy is defined as the level of truth in a study that shows accurate results. Precision is the success rate of data in comparing the predicted amount with the total amount of data.

$$\text{Precision} = \frac{\text{TP}}{\text{FP} + \text{TP}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{FN} + \text{TP}} \tag{2}$$

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{FP} + \text{TP} + \text{FN}} \tag{3}$$

$$\text{F1 score} = 2 \times \frac{\text{precision x recall}}{\text{precision} + \text{recall}} \tag{4}$$

Results and Discussion

The programming language used in processing is Python. The tool used in this research is Google Collaboratory. In this section, we will discuss the results obtained using transfer learning VGG-16 and ResNet-50. Before being inputted into the model, the Orchid flower image data is resized to 224×224 pixels then segmented and divided into training and testing data first. The ratio of training and testing data is 90% of the total data for training data and 10% of the total data for testing data.

A. Classification with VGG-16

A summary of the model for image classification with VGG-16 in this study is illustrated in **Table 1**.

Table 1. VGG-16 Model Summary

Layer (type)	Output Shape	Param#
vgg16 (Functional)	(None, 7, 7, 512)	14714688
conv2d (Conv2D)	(None, 7, 7, 32)	147488
max_pooling2d (MaxPooling2D	(None, 3, 3, 32)	0
dropout (Dropout)	(None, 3, 3, 32)	0
flatten (Flatten)	(None, 288)	0
dense (Dense)	(None, 3)	867
Total params : 14,863,043		
Trainable params : 148,355		
Non-trainable params: 14,714,688		

Table 1 shows the architecture of transfer learning with VGG-16. The CNN model is built by adding deeper layers to the base VGG16 model. The added layers are Conv2D which acts as a global feature collector, Dense layer with 3 units with softmax activation function. The comparison of accuracy and loss on training and validation for VGG-16 with 25 epochs and 50 epochs can be seen in **Figure 6**.

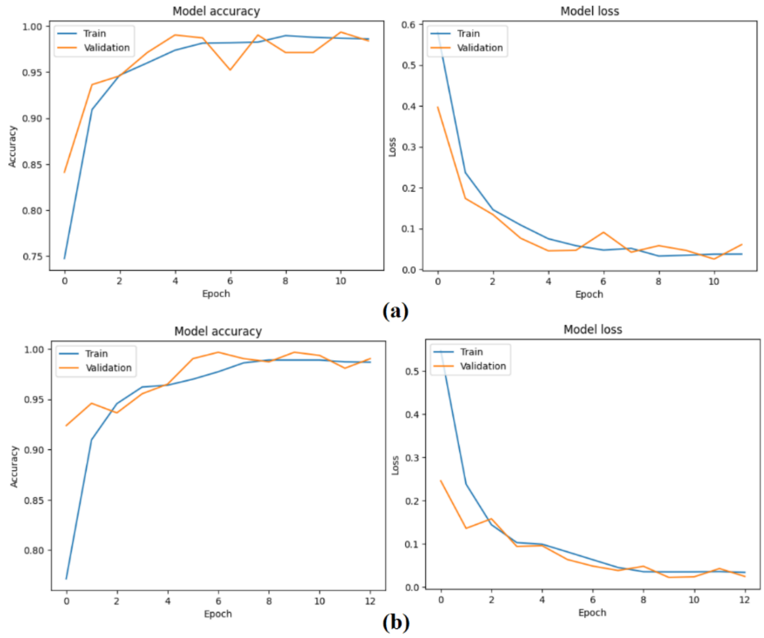

Figure 6. Accuracy and loss on training and validation with VGG-16 model with (a) 25 epochs (b) 50 epochs

From **Figure 6**, it can be seen that the accuracy starts to stabilize after the 11th epoch in the classification with 25 epochs and the accuracy with 50 epochs stabilizes after the 12th epoch. While the loss function decreases significantly during the validation and training phases.

The confusion matrix of the classification of the saleability of Orchid flowers using the VGG-16 model is illustrated in **Figure 7**, this matrix is used to illustrate the full performance of the VGG-16 model. From the matrix, it can be seen that most of the images have been correctly predicted with both 25 and 50 epochs.

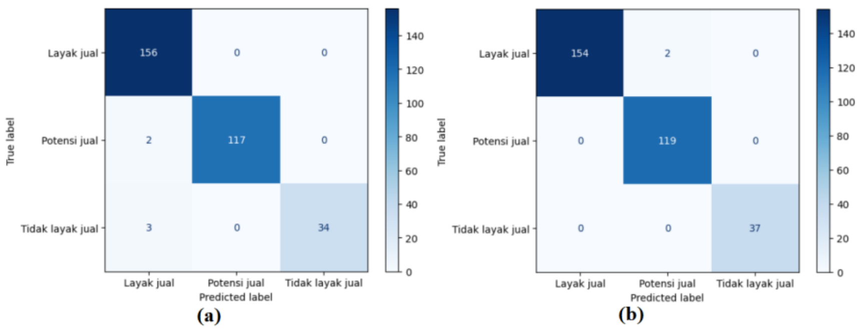

Figure 7. Confusion Matrix of VGG-16 with (a) 25 epochs (b) 50 epochs

B. Classification with ResNet-50

A summary of the model for image classification with ResNet-50 used can be seen in **Table 2**.

Table 2. ResNet-50 Model Summary

Layer (type)	Output Shape	Param#
resnet50 (Functional)	(None, 7, 7, 2048)	23587712
conv2d (Conv2D)	(None, 7, 7, 32)	589856
max_pooling2d (MaxPooling2D	(None, 3, 3, 32)	0
dropout (Dropout)	(None, 3, 3, 32)	0
flatten (Flatten)	(None, 288)	0
dense (Dense)	(None, 3)	867
Total params : 24,178,435		
Trainable params : 590,723		
Non-trainable params: 23,587,712		

Table 2 shows the architecture of transfer learning with ResNet-50. The CNN model is built by adding deeper layers to the ResNet-50 base model. The added layers are Conv2D which acts as a global feature collector, Dense layer with 3 units with softmax activation function. The comparison of accuracy and loss on training and validation for ResNet-50 with 25 epochs and 50 epochs can be seen in Figure 8.

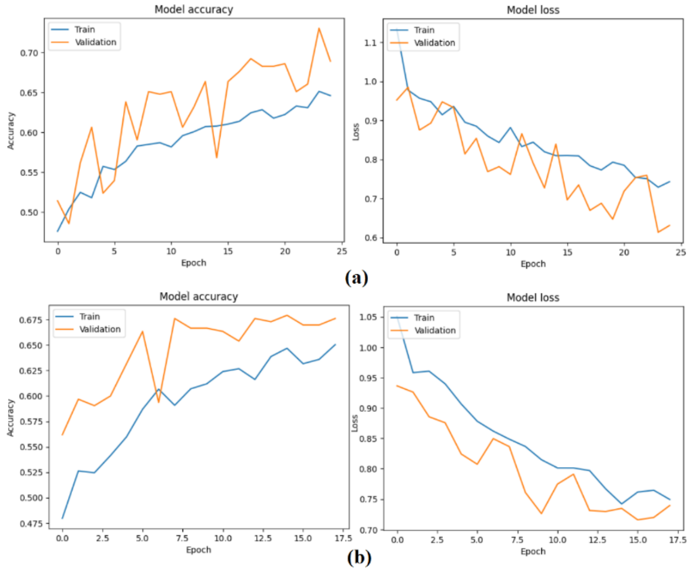

Figure 8. Accuracy and loss on training and validation with ResNet-50 model with (a) 25 epochs (b) 50 epochs

From Figure 8, it can be seen that the accuracy continues to rise after the 23rd epoch and then stabilizes in the classification with 25 epochs and the accuracy with 50 epochs continues to rise after the 17th epoch begins to stabilize. While the loss function decreased significantly during the training and validation phases.

The confusion matrix of the classification of the saleability of Orchid flowers using the ResNet-50 model is illustrated in Figure 9, this matrix is used to illustrate the full performance of the VGG-16 model. From the matrix, it can be seen that most of the images are still not predicted correctly with 25 and 50 epochs.

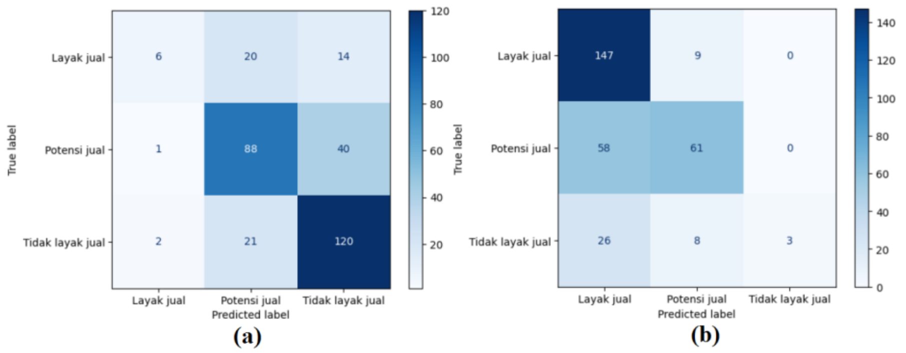

Figure 9. Confusion Matrix ResNet-50 with (a) 25 epochs (b) 50 epochs

C. Performance Comparison of VGG-16 and ResNet-50

In comparing algorithms in transfer learning using several and the results are as in Table 3.

Table 3. Comparative Metrics of VGG-16 and ResNet-50

Model	Accuracy	Precision	Recall	F1-Score
VGG-16 (Epoch 25)	0.98	0.99	0.97	0.98
VGG-16 (Epoch 50)	0.99	0.99	1	1
RasNet-50 (Epoch 25)	0.69	0.68	0.56	0.56
RasNet-50 (Epoch 50)	0.68	0.81	0.51	0.51

The results of the accuracy metric show that the VGG-16 model achieves an accuracy of 98% (epoch 25) and 99% (epoch 50), while the ResNet-50 model has an accuracy of 69% (epoch 25) and 68% (epoch 50). In terms of accuracy, the VGG-16 model performed better than the ResNet-50 model. The VGG-16 model is able to classify well. The results of the precision metric show that the VGG-16 model has a precision of 99%, while the ResNet-50 model has a precision of 68% (epoch 25) and 81% (epoch 50). In terms of precision, the VGG-16 model also performs better. Precision describes the extent to which the predicted positive results are correct, and the VGG-16 model is able to achieve a precision of around 99% for the predicted positive classes. The results of the recall metric show that the VGG-16 model has a recall of 97% (epoch 25) and 100% (epoch 50), while the ResNet-50 model has a recall of 56% (epoch 25) and 51% (epoch 50). In terms of recall, the VGG-16 model once again performed better. The results of the F1 Score metric show that the VGG-16 model has an F1 score of 97% (epoch 25) and 100% (epoch 50), while the ResNet-50 model has an F1 score of 56% (epoch 25) and 51% (epoch 50). F1 score is the harmonic mean between precision and recall, and gives equal attention to both metrics. In terms of F1 score, the VGG-16 model once again performed better.

Based on the above discussion, overall, the VGG-16 model shows better performance than the ResNet-50 model in the classification of the marketability of Orchid flowers, measured based on accuracy, precision, recall, and F1 score. The use of epoch 25 and epoch 50 has no significant difference in the VGG-16 model. However, it is important to note that model evaluation should always be considered in the context and purpose of the specific application, as well as taking into account other factors such as computational requirements, inference speed, and model size.

Conclusion

VGG-16 and ResNet-50 are two convolutional neural network architectures that are widely used in image classification applications. Both algorithms have successfully classified feasibility of selling orchids with the performance of VGG-16 algorithm outperforming ResNet-50. VGG-16 achieved higher accuracy, precision, recall, and F1 score than ResNet-50. With an accuracy of 99%, VGG-16 has a better ability to correctly classify samples compared to ResNet-50 which has an accuracy of 69%. In terms of precision, VGG-16 outperforms ResNet-50. This shows that VGG-16 has a lower tendency to give false positive predictions compared to ResNet-50. VGG-16 also showed better recall compared to ResNet-50, indicating that VGG-16 is more effective in recovering true positive samples. The F1 score produced by VGG-16 is also higher than ResNet-50 which indicates that VGG-16 is able to achieve a better balance between precision and recall. It can therefore be concluded that in the case of Orchid flower classification feasibility of selling, VGG-16 may be a better choice for use in similar applications or tasks. However, keep in mind that these results may vary depending on the dataset and other parameters used in training and evaluating the model. Therefore, the selection of the algorithm depends on the needs and characteristics of the dataset used. This research has proven that VGG-16 has a good performance in the classification feasibility of selling orchids. Future research can be conducted using a machine learning approach by extracting and selecting features to find stability in classification based on shape and color.

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References

[1] Y.-W. Chang, Y.-K. Hsiao, C.-C. Ko, R.-S. Shen, W.-Y. Lin, and K.-P. Lin, “A Grading System of Pot-Phalaenopsis Orchid Using YOLO-V3 Deep Learning Model,” 2021, pp. 498–507.

[2] Cassandra, “Multilabel Classification of Orchid Features based on Deep Learning,” University Of Twente, 2020.

[3] S. Islam, M. F. Ahmed Foysal, and N. Jahan, “A Computer Vision Approach to Classify Local Flower using Convolutional Neural Network,” in 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), 2020, pp. 1200–1204, doi: 10.1109/ICICCS48265.2020.9121143.

[4] D. S. Dewantara, R. Hidayat, H. Susanto, and A. M. Arymurthy, “CNN with Multi Stage Image Data Augmentation Methods for Indonesia Rare and Protected Orchids Classification,” in 2020 International Conference on Computer Science and Its Application in Agriculture (ICOSICA), 2020, pp. 1–5, doi: 10.1109/ICOSICA49951.2020.9243174.

[5] S. Arwatchananukul, K. Kirimasthong, and N. Aunsri, “A New Paphiopedilum Orchid Database and Its Recognition Using Convolutional Neural Network,” Wirel. Pers. Commun., vol. 115, no. 4, pp. 3275–3289, Dec. 2020, doi: 10.1007/s11277-020-07463-3.

[6] W. Sarachai, J. Bootkrajang, J. Chaijaruwanich, and S. Somhom, “Orchids Classification Using Spatial Transformer Network with Adaptive Scaling,” 2019, pp. 1–10.

[7] Y. Tian, G. Yang, Z. Wang, E. Li, and Z. Liang, "Instance segmentation of apple flowers using the improved mask R–CNN model," Biosyst. Eng., vol. 193, pp. 264–278, May 2020, doi: 10.1016/j.biosystemseng.2020.03.008.

[8] M. Alom, M. Y. Ali, M. T. Islam, A. H. Uddin, and W. Rahman, "Species classification of brassica napus based on flowers, leaves, and packets using deep neural networks," J. Agric. Food Res., vol. 14, p. 100658, Dec. 2023, doi: 10.1016/j.jafr.2023.100658.

[9] J. S. Estrada, J. P. Vasconez, L. Fu, and F. A. Cheein, "Deep Learning based flower detection and counting in highly populated images: A peach grove case study," J. Agric. Food Res., vol. 15, p. 100930, Mar. 2024, doi: 10.1016/j.jafr.2023.100930.

[10] L.-H. Li, Y.-S. Chu, J.-Y. Chu, and S.-H. Guo, "A Machine Learning Approach for Detection Plant Disease," in Proceedings of the 3rd International Conference on Vision, Image and Signal Processing, 2019, pp. 1–6, doi: 10.1145/3387168.3387238.

[11] P. Srichocksittikul and N. Nimsuk, "Design of Deep Learning Architecture for Classification of Orchid Diseases," in 2021 18th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2021, pp. 904–907, doi: 10.1109/ECTI-CON51831.2021.9454869.

[12] D. H. Apriyanti, L. J. Spreeuwers, P. J. F. Lucas, and R. N. J. Veldhuis, "Automated color detection in orchids using color labels and deep learning," PLoS One, vol. 16, no. 10, p. e0259036, Oct. 2021, doi: 10.1371/journal.pone.0259036.

[13] P. N. Andono, E. H. Rachmawanto, N. S. Herman, and K. Kondo, "Orchid types classification using supervised learning algorithm based on feature and color extraction," Bull. Electr. Eng. Informatics, vol. 10, no. 5, pp. 2530–2538, Oct. 2021, doi: 10.11591/eei.v10i5.3118.

[14] L.-B. Chen, G.-Z. Huang, X.-R. Huang, and W.-C. Wang, "A Self-Supervised Learning-Based Intelligent Greenhouse Orchid Growth Inspection System for Precision Agriculture," IEEE Sens. J., vol. 22, no. 24, pp. 24567–24577, Dec. 2022, doi: 10.1109/JSEN.2022.3221960.

[15] A. Khumaidi, Y. A. Purwanto, H. Sukoco, and S. H. Wijaya, "Using Fuzzy Logic to Increase Accuracy in Mango Maturity Index Classification: Approach for Developing a Portable Near-Infrared Spectroscopy Device," Sensors, vol. 22, no. 24, p. 9704, Dec. 2022, doi: 10.3390/s22249704.

[16] H. Naz, Z. Zhang, M. Al-Habib, F. A. Awwad, E. A. A. Ismail, and Z. A. Khan, "Posture Detection of Heart Disease Using Multi-Head Attention Vision Hybrid (MHAVH) Model," Comput. Mater. Contin., vol. 79, no. 2, pp. 2673–2696, 2024, doi: 10.32604/cmc.2024.049186.

[17] L. Duan, Y. Ren, and F. Duan, "Adaptive stochastic resonance based convolutional neural network for image classification," Chaos, Solitons & Fractals, vol. 162, p. 112429, Sep. 2022, doi: 10.1016/j.chaos.2022.112429.

[18] F. Ben Nasr Barber and A. Elloumi Oueslati, "Human exons and introns classification using pre-trained Resnet-50 and GoogleNet models and 13-layers CNN model," J. Genet. Eng. Biotechnol., vol. 22, no. 1, p. 100359, Mar. 2024, doi: 10.1016/j.jgeb.2024.100359.

[19] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," in International Conference on Learning Representations, 2015, doi: 10.48550/arXiv.1409.1556.

[20] A. Khumaidi and A. Nurpadilah, "Klasifikasi Molting Kepiting Soka Menggunakan Algoritma Convolusional Neural Network," Komputa J. Ilm. Komput. dan Inform., vol. 13, no. 2, pp. 43–50, Oct. 2024, doi: 10.34010/komputa.v13i2.13984.

[21] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," Commun. ACM, vol. 60, no. 6, pp. 84–90, May 2017, doi: 10.1145/3065386.

[22] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 770–778, doi: 10.1109/CVPR.2016.90.

[23] L. Almazaydeh, S. Atiewi, A. Al Tawil, and K. Elleithy, "Arabic Music Genre Classification Using Deep Convolutional Neural Networks (CNNs)," Comput. Mater. Contin., vol. 72, no. 3, pp. 5443–5458, 2022, doi: 10.32604/cmc.2022.025526.

[24] F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," in 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 1800–1807, doi: 10.1109/CVPR.2017.195.

[25] M. Tan and Q. V. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," in Proceedings of the 36th International Conference on Machine Learning, ICML, 2019.

[26] M. C. Younis, "Evaluation of deep learning approaches for identification of different corona-virus species and time series prediction," Comput. Med. Imaging Graph., vol. 90, p. 101921, Jun. 2021, doi: 10.1016/j.compmedimag.2021.101921.

[27] W. Herwanto, A. Khumaidi, and H. P. Putro, "Feature Extraction and Classification of Tissue Mammograms Based on Grayscale and Gray Level Co-occurrence Matrix," in 2021 International Seminar on Machine Learning, Optimization, and Data Science (ISMODE), 2022, pp. 131–134, doi: 10.1109/ISMODE53584.2022.9743131.

[28] T. Ben Abdallah, I. Elleuch, and R. Guermazi, "Student Behavior Recognition in Classroom using Deep Transfer Learning with VGG-16," Procedia Comput. Sci., vol. 192, pp. 951–960, 2021, doi: 10.1016/j.procs.2021.08.098.

[29] T. Tian, L. Wang, M. Luo, Y. Sun, and X. Liu, "ResNet-50 based technique for EEG image characterization due to varying environmental stimuli," Comput. Methods Programs Biomed., vol. 225, p. 107092, Oct. 2022, doi: 10.1016/j.cmpb.2022.107092.

[30] S. Matarneh, F. Elghaish, F. Pour Rahimian, E. Abdellatef, and S. Abrishami, "Evaluation and optimisation of pre-trained CNN models for asphalt pavement crack detection and classification," Autom. Constr., vol. 160, p. 105297, Apr. 2024, doi: 10.1016/j.autcon.2024.105297.

[31] A. Khumaidi, Y. A. Purwanto, H. Sukoco, and S. H. Wijaya, "Effects of spectral transformations in support vector machine on predicting 'Arumanis' mango ripeness using near-infrared spectroscopy," J. Ilm. Ilk., vol. 13, no. 3, 2021.