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Transfer Learning VGG16 for Classification Orange Fruit Images

Dhiya Mahdi Asriny, Riyanto Jayadi

Information Systems Management Department, Binus Graduate Program – Master of Information Systems Management, Bina Nusantara University, Jl. Kebon Jeruk Raya no 27 Kebon Jeruk, Jakarta, 11530, Indonesia

dhiya.asriny@binus.ac.id; riyanto.jayadi@binus.edu

Abstract. Fruit quality selection is essential in increasing sales and market competitiveness. Currently, human perception manually selects siamese orange fruit. Human perception has defects, including inaccuracy and inconsistent results, which are limitations in the selection process. Another problem is the decreasing agricultural land allocated and the declining interest in Indonesia's farmer labor. In this research, we use the convolutional neural network-VGG16 as a proposed modeling that might assist in selecting and recognizing Siamese citrus fruit quality. The proposed convolutional neural network-VGG16 successfully identified the quality of siamese citrus based on image data used in this research. The five classes of images are used, including immature oranges, good oranges grade 1, good oranges grade 2, damaged oranges, and rotten oranges. Five deep learning-based methods were examined in this research: LeNet-5, VGG16 Fine Tuning, VGG19, AlexNet, and VGG16 Proposed Model. A primary dataset of 1000 siamese orange image data was used to evaluate the models, including 200 images in each category. For LeNet-5, modeling obtained an accuracy of 95.49%. For VGG16 Fine Tuning modeling obtained an accuracy of 85.50%. The accuracy rate for VGG19 modeling is 95.49%. In comparison, AlexNet modeling had a 95.99% accuracy rate. Finally, the VGG16 Proposed Model obtained a result of 97.50%, showing that it outperformed other CNN deep learning modeling approaches used in this research in terms of results.

Keywords: Orange Classification, Deep Learning, Convolutional Neural Network, VGG16

1. Introduction

The agricultural industry in Indonesia broadly consists of farming, plantations, fishing, livestock farming, and forestry. One fruit frequently grown in Indonesia is oranges (Wijaya et al., 2015; Park 2021). According to Shahbandeh (2022), oranges are one of the commodities with the fifth-highest production rate in the world, after bananas, watermelons, apples, and grapes. Based on statistics from (USDA, 2022), forecasts that due to favorable weather, the orange output rate increased by 1.4 million from the previous year to 48.8 million in 2021/22. Due to the increasing productivity of Siamese oranges in Indonesia annually, the demand for oranges in Indonesia has also grown significantly. According to Badan Pusat Statistik Indonesia, Siamese oranges are one of the commodities with the third-highest productivity level, after mangoes and bananas (Indonesia Statistical Agency, 2018). In comparison to 2017, the productivity of Siamese oranges increased by 242,851 or 11.22% in 2018. Orange fruits are now among the top commodities in Indonesia as a result of the growth due to their significant economic impact.

Siamese oranges are often graded manually, which is done under the assumption that individuals control the entire process. Orange fruits are directly seen visually throughout the selection process. The effect of human psychological situations, human optical limitations, and a lack of consistency in selecting Siamese orange fruits are all limitations of manual orange selection. In addition, there are issues with labor supply, particularly in agriculture. The problem is that the labor supply of young farmers is decreasing while the number of farmers who are elderly (55 years or older) continues to rise. The aging of farmers and the declining interest of workers in agriculture due to the low average level of education based on comparisons with labor in other areas is known as the "aging farmer" phenomenon (Susilowati, 2016). The number of farmers in Indonesia fell to 28.5% in 2019. Low salaries and the limited supply of agricultural land are credited for the younger generation's declining interest in becoming farmers (Bayu, 2021).

Researchers are currently using computer vision to identify fruit, an extensively used application (Bhargava & Bansal, 2018). It has been extensively developed to use computer vision to analyze images for work-related purposes, such as an automatic fruit harvest detection system (Onishi et al., 2019), fruit maturity detection systems (Mazen & Nashat, 2019), fruit classifications system (Albarrak et al., 2022; Asriny et al., 2020), and others. Frequently, fruit attributes like color features (San et al., 2019; Zawbaa et al., 2014), texture features (Capizzi et al., 2016; San et al., 2019), and shape (Jana & Parekh, 2017; Zawbaa et al., 2014) features may be used to identify them.

Convolutional neural networks (CNN) with the VGG16 architecture is used in this research to identify the qualities of Siamese orange fruits. The main goal of this research is to propose modeling convolutional neural network-VGG16 by including many dropout layers and the use of appropriate hyperparameters in order to improve the convolutional neural network-VGG16 performance in classifying Siamese orange image data. Additionally, the proposed convolutional neural network-VGG16 modeling may automatically identify orange quality when integrated into the system, making it easier for farmers and orange collectors to select oranges that would provide the highest possible profit. The Siamese orange fruit images are classified using the model into five classes: immature oranges, good oranges grade 1, good oranges grade 2, damaged oranges, and rotten oranges. Previous studies show that CNN with the VGG16 architecture effectively classifies image data or detects objects and performs well (Pardede et al., 2021; Pathak & Makwana, 2021; Rismiyati & Luthfiarta, 2021). There was much research using the convolutional neural network-VGG16, but no previous studies on using the convolutional neural network-VGG16 to classify orange images have been discovered. Convolutional neural network (CNN) using VGG16 architecture is used in this research to classify characteristics in the quality of Siamese orange fruits. Furthermore, to determine the most effective model for identifying Siamese orange image data, this study compares each result with the models generated using various models and scenarios.

The paper is compiled as follows. Related works are described in Section 2. The methodology is described in Section 3. The results and discussion are described in Section 4. The final section, Section 5, explains the concluding remarks.

2. Related Works

Numerous earlier researchers have researched image processing with orange objects using various of techniques and orange item types. Using the principle component analysis (PCA) approach, Li et al. (2011), with the working title "Detection of common flaws on orange using hyperspectral reflectance imaging" discovered faults in citrus fruits with an accuracy of 91.5% and 93.7%. In 2015, Romadhon & Widyaningrum researched employing the Learning Vector Quantization approach for orange image classification, which had an accuracy of 76% but utilized a different object from the one used in this study. The Edited Multi Seed Nearest Neighbor Technique and Linear Regression approaches were used to carry out the orange selection procedure in Jhawar, "Orange Sorting by Applying Pattern Recognition on Colour Image," which produced accuracy rates of 89.90% and 97.89%. Using the Artificial Network-Harmony Search (ANN-HS) and K-Nearest Neighbors (kNN) methods, Sabzi et al. (2017), "A New Approach for Visual Identification of Orange Varieties using Neural Networks and Metaheuristic Algorithms", successfully identified orange fruits with accuracy rates of 94.28% and 70.88%. Research conducted by Asriny et al. (Asriny et al., 2020) under the title “Orange Fruit Images Classification using Convolutional Neural Networks” classified the quality of oranges into five classes using a convolutional neural network with a classical architecture (LeNet-5) that compares two activation functions, namely ReLu and Tanh and uses k-fold cross validation to validate the data to be used by the model, with accuracy rates of 96% and 93.8%. A recent study entitled "Image Retrieval Based on Deep Learning" by Ghaleb et al. (2022) obtained an accuracy of 93.33% for Corel1K datasets, 94% for Cifar-10 datasets, 85.5% for Cifar-100 datasets, and 99.9% for 70k Mnist datasets by suggesting CNN modeling to make classification more accurate.

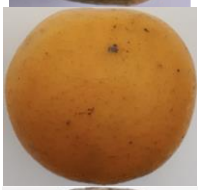
Furthermore, the use of the deep learning technique for image classification is covered in this research. A convolutional neural network with the VGG16 architecture is one of the most well-known techniques. Considering that the architecture can analyze complex image data quickly, the objective is to generate a classification of image data that is more accurate. Research that applies the convolutional neural network method with the VGG16 architecture was first introduced by (Simonyan & Zisserman, 2015) with the research title “Very Deep Convolutional Networks for Large-Scale Image Recognition”. The VGG16 architecture was included in the 2014 ILSVRC competition. The research used datasets from ImageNet to classify images on a big scale (Yin, et al., 2015). VGG16 modeling is accurate and outperforms competing methods in the challenging recognition built around visual data. It is broadly applicable to several tasks and datasets. The accuracy values were 7.3% and 7.4% for the test data with seven nets and a single net, respectively. Based on the result of this research, VGG16 can be used to handle massive amounts of data.

Convolutional Neural Network-VGG16 for Road Extraction from Remotely Sensed Images is the name of research by Ganakwar & Date (2020). This work examined the application of VGG16 to distinguish extracted road pictures from remote sensing photographs (RSIs). The study also compared picture recognition techniques using K-means, CNN, and MFPN. VGG16 was used, and the results were superior to other approaches due to its accuracy score of 97.08%. Another study, titled "Classification of Fruits Using Convolutional Neural Networks and Transfer Learning Models," was carried out by Pathak & Makwana. Apples, bananas, and oranges were classified as good or bad in the research, and the suggested modeling was contrasted with numerous CNN architectures, including VGG-16, VGG-19, LeNet-5, and AlexNet. With a score of 90.81% accuracy, VGG16 came in second place. Meanwhile, the proposed modeling resulted in an accuracy of 98.23%. Although there has been much research using convolutional neural networks, researcher have yet to discover any papers using convolutional neural networks VGG16 to classify orange images. Based on previous research, this research utilized convolutional neural networks VGG16, a type of deep learning technique, to analyze image data to classify orange fruit quality.

3. Research Methodology

The primary data for this research comes from images of siamese oranges taken using a smartphone camera with a 16 Megapixel resolution. The Siamese orange image data is placed on white paper with sufficient room lighting to equalize the conditions in each image. Balancing the conditions of each Siamese orange image is done to achieve the focus of siamese orange imagery and good and high image quality. The five classes of images are used, including immature oranges, good oranges grade 1, good oranges grade 2, damaged oranges, and rotten oranges (shown in Table. 1). Each category of fruit is taken several images by rotating and repositioning the orange object. The images are stored in files with the.jpg extension, and the sizes range from 2448x2448 to 4608x3456 pixels. The data used in this research is 1000 siamese orange image data, including 200 images in each category. For each orange category, 80% of the data is used for training and 20% for testing purposes. Image data performed pre-processing steps, including cropping and resizing the image to 500x500 pixels.

Table. 1: Samples of each category throughout the dataset of orange fruit

Dataset	Variable	Variable Definition
	Immature Oranges	The image represents an immature orange.
	Good Oranges Grade 1	The image of a good oranges grade 1 is a ripe orange with good quality, and there are no significantly damaged or rotten parts. This variable is widely used for the consumption of drinks.
	Good Oranges Grade 2	The image of a good oranges grade 2 is a good quality orange, and there are no significantly damaged or rotten parts. This variable is widely used for daily consumption (eaten).
	Damaged Oranges	The image of a damaged orange is an orange that is ripe or immature, but some parts are damaged due to pests or impacts.
	Rotten Oranges	The image of a rotten orange is a ripe orange, and some parts are rotten due to loss of moisture, dry air, or infection with bacteria.

The design of the CNN-VGG16 model to be used in this research is shown in Fig. 1, including the convolution layer, pooling layer, dropout layer, flatten layer, and dense layer. The design from previous literature was used as a reference, and added one process after the pooling layer: dropout regularization.

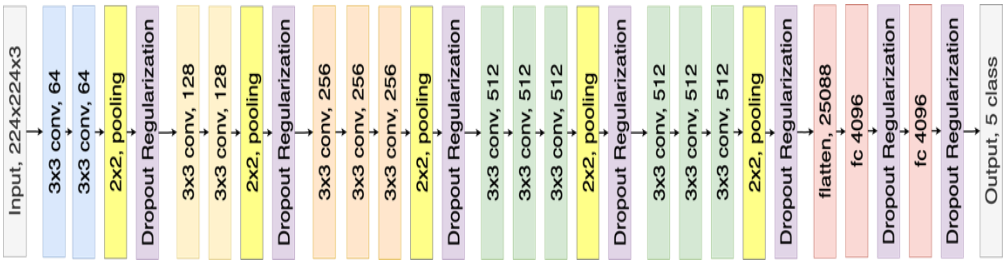


Fig. 1: Proposed architecture using VGG16

With downsampling techniques, the pooling layer aims to reduce the number of parameters (in the feature map) and avoid overfitting. Dropout regularization is a technique that eliminates some neurons from the layer or hidden layers that have been "active" in the layer; these neurons are chosen randomly during the training process (Abhirawan et al., 2017). The multidimensional shape of the array is transformed using flatten layers into a vector format so that it may be input for fully connected layers.

The convolution process is carried out five times in this research, aiming to train the model and see the performance of the model that has been designed. The CNN-VGG16 model study is unique in adding a dropout layer after the pooling layer for each convolution process. The activation function that we used is ReLU (Rectified Linear Unit). Each convolution's kernel is 3x3 in size, while the pooling layer is 2x2 in size. It has a size of 64 filters for the first and second convolutions.

The 128 filters are used in the third and fourth convolutions. The 256 filters in the fifth, sixth and seventh convolutions are examined. The 512 filters are used from the eighth through the thirteenth. However, there are two steps in the use of 512 filters. The first part use a 3x3 kernel, a 2x2 max pooling process, and a dropout regularization for the eighth, ninth, and tenth convolution processes. After the convolution process is finished, 512 filters reuse the second part, for the eleventh, twelfth, and thirteenth-layer convolutions, in the same conditions. This research used 25088, 4096, and 4096 nodes of neurons in hidden layers, which were carried out in steps for fully connected layers. Classifying into five classes use a softmax classifier, which makes it simple to classify by calculating the probability of all labels and aims to provide intuitive results. Finally, a python script using the Keras and TensorFlow libraries are used to implement the research model. Each model conduct training using the provided data set to improve and enhance its ability to classify input data.

Table. 2: Hyperparameter used for the VGG16 proposed model

Hyperparameter	Value
Epoch	30
Batch Size	128
Optimizer	Adam
Learning Rate	0.0001
Validation Split	0.2

4. Result and Discussion

The performance of the model and the proposed model are compared in the experiments done for this work utilizing a variety of CNN architectures, including LeNet-5, VGG16 Fine Tuning, VGG19, and AlexNet. The model development process is evaluated based on two metrics, namely loss and accuracy, to measure performance. The loss function indicates the model's error against the prediction value, while accuracy is used to identify the percentage of data classified correctly. Categorical cross-entropy, a technique for multi-class classification tasks, was also used in this research.

The hyperparameters used for these models (LeNet-5, VGG16 Fine Tuning, VGG19, and AlexNet) are similar to conditions such as using a Dropout of 0.01, a learning rate of 0.0001, the optimizer is adam, and 30 epochs as the optimal number of iterations. The dropout value utilized in this study was chosen after considering the results of various tests conducted by researchers that examined the impact of the dropout value on model performance. Based on the experiments' findings, this study determined that a suitable Dropout number to use was 0.01. While ReLu is the activation function used in each model.

Table. 3: The accuracy of CNN architectures: VGG16 fine tuning, VGG19, AlexNet, and VGG16 proposed model

Model	Trainable Parameters	Loss Value	Accuracy Value
LeNet-5	1.106.437	0.093	95.49%
VGG16 Fine Tuning	109.521.701	0.306	85.50%
VGG19	125.445	0.273	95.49%
AlexNet	23.960.965	0.121	95.99%
VGG16 Proposed Model	134.281.029	0.091	97.50%

This research assesses the performance of the used architecture based on loss values and accuracy using experiments from this study. LeNet-5 has a loss value of 0.093, VGG16 Fine Tuning has a loss value of 0.306, VGG19 a loss value of 0.273, AlexNet a loss value of 0.121, and VGG16 Proposed Model a loss value of 0.091. Each architecture completed has a relatively low loss value. As a result, the modeling-based tests conducted for this research are excellent and have successfully identified orange image data. The accuracy value accurately reflects the classification level. Each model is in Table. 3 obtain a low loss value rate and, therefore, a high accuracy; the outcomes are generally positive. LeNet-5 obtained an accuracy of 95.49%, VGG16 Fine Tuning obtained an accuracy rate of 85.50%, whereas VGG19 obtained a rate of 95.49%, AlexNet at 95.99%, and VGG16 Proposed Model obtained the most excellent accuracy of 97.50%. Based on accuracy values, loss values, and trainable parameters, the study's findings demonstrate that the VGG16 Proposed Model approach is more effective and good at classifying orange image data. With more epochs being used, the performance of the VGG16 proposed model is highly detailed, as shown in Fig. 2.

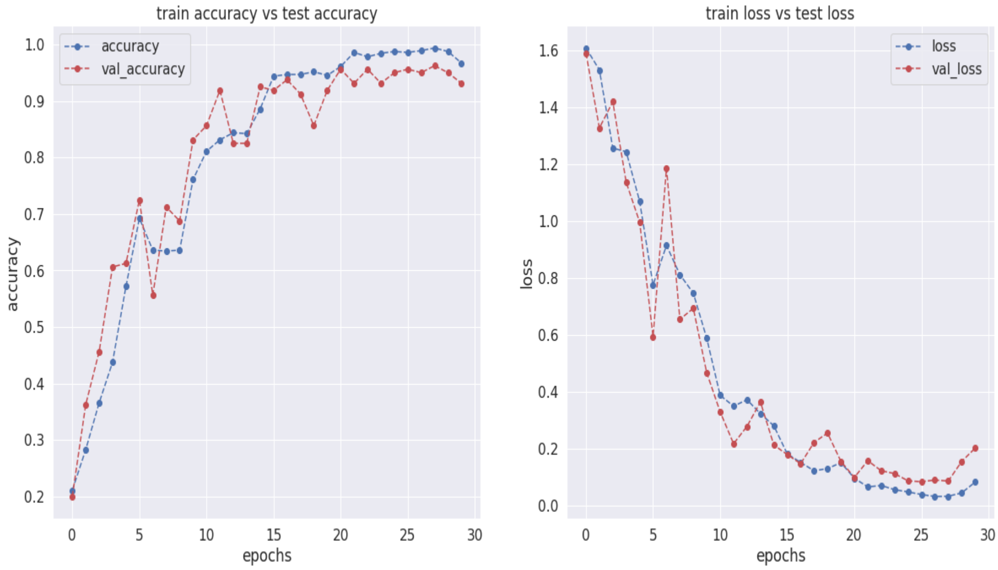


Fig. 2: Accuracy and loss of data training and testing of VGG16 proposed model

The proposed VGG16 model is often near to zero because of the increased motion caused by the increased number of epochs used. As the testing data increases, the accuracy value gets closer to 1 (the maximum value). Using the number of epochs used during the model training process positively correlates to accuracy. Instead, there is a negative correlation between the loss value and the number of epochs used. With this, we might increase the number of epochs used during the model training process to reduce loss value. In doing so, this study able to build a CNN VGG16 model that can provide high accuracy and accurately classify image data.

Table. 4: Results of data classification testing of VGG16 proposed model

Immature oranges	40	0	0	0	0
Good oranges grade 1	0	37	3	0	0
Good oranges grade 2	0	0	40	0	0
Damaged Oranges	0	0	0	40	0
Rotten oranges	0	0	0	2	38
	Immature oranges	Good oranges grade 1	Good oranges grade 2	Damaged oranges	Rotten oranges

As shown in Fig. 2, the performance of the proposed model VGG16 during training dropped compared to the loss value, but it was almost 1 for the accuracy value while using epoch 25. It is proven based on the loss value graph in the testing data, which showed a slight reduction after the 25 epochs. It may be inferred from feeding that using many epochs is only sometimes necessary if the research uses an epoch count of 25; feasible that the model performs at its peak level in this research. The results of the classification of testing data obtained from the VGG proposed model are shown in the **错误!未找到引用源。**.

The proposed VGG16 model classification results show inaccuracies in the good oranges grade 1 class of as many as three images classified into the good oranges grade 2 and inaccuracies in the rotten orange class of two images classified into the damaged orange class. The siamese orange imagery data was accurately identified using the VGG16 proposed models. It is envisaged that this research offer farmer or orange collectors a new alternative other than traditional or manual ways of classifying or selecting siamese oranges.

5. Conclusion

In this research, we evaluated the effectiveness of different deep learning models, particularly Convolutional Neural Networks, to classify siamese orange image data, including LeNet-5, VGG16 Fine Tuning, VGG19, AlexNet, and VGG16 Proposed Model. The accuracy obtained with LeNet-5 was 95.59%. The accuracy of the VGG16 Fine Tuning modeling was 85.50%. An accuracy value of 95.49% was obtained using VGG19 modeling. The accuracy for AlexNet modeling was 95.99%. At the same time, the accuracy of the VGG16 Proposed Model is 97.50%. The proposed VGG16 model consists of 23 layers, with each convolution layer using 3x3 filters, five pooling layers placed after the convolution layer with a size 2x2, a dropout layer with a size of 0.01, a softmax classifier to classify image data, and three sizes on the hidden layer, consisting of 25088, 4096, and 4096 nodes. In order to get the most excellent and accurate model performance in this study, it also applied an activation function, ReLu. According to the results of the experiments, the VGG16 Proposed Model has provided more excellent performance due to its higher accuracy than other modeling approaches. Further work can be improved by training the model on a particular task or domain to produce better accuracy. Utilizing many image datasets so that the model becomes more recognized of the dataset object and produces a maximum level of accuracy. Adding preprocessing phases to create better data, such as segmenting data from image data and reducing noise. Furthermore, the subsequent research can develop the modeling into an application that will let farmers or collectors of siamese citrus fruits select the fruit more easily and quickly.

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