Inception-V3 Versus VGG-16 in Rice Classification Using Multilayer Perceptron

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Inception-V3 Versus VGG-16: in Rice Classification Using Multilayer Perceptron

Ichsan Firmansyah[1], Rika Rosnelly[2], Wanayumini[3]

[1,2,3]*Magister of Computer Science, Potensi Utama University*
JL. KL. Yos Sudarso Km. 6,5 No. 3-A, Medan

[1]ichsanfirmansyah1989@gmail.com

[2]rikarosnelly@gmail.com

[3]wanayumini@gmail.com

***Abstract*— Rice is an intriguing research topic, particularly in computer vision fields, because it is a staple food consumed in many parts of the world. Different rice varieties can be classified using the rice grain image based on their textures, sizes, and colors. To extract features from rice images, we used two popular pre-trained convolutional neural network models, Inception V3 and VGG 16. The extracted features are then used as transfer learning in six variations of multilayer perceptron models, using rectified linear units as the activation function and adaptive moments as the loss function. The results show that the VGG 16 network performs better than the Inception V3, with 0.5% higher accuracy, precision, and recall value. Also, using the VGG 16 network produces a lower misclassification percentage, compared to the Inception V3 network, with a difference of 2.6%.**

***Keywords*— feature extraction, inception v3, multilayer perceptron, rice classification, transfer learning, vgg 16**

I. INTRODUCTION

Rice is a common staple food in many parts of the world, and it comes in a variety of textures, sizes, and colors [1]. By utilizing computer vision, rice grain images can be classified based on these features to facilitate the identification of different types of rice [2]. In this study, rice images consisting of five varieties were used as data to be classified based on the results of their respective feature extractions. We use a convolutional neural network (CNN) pre-trained model to extract the rice features as an input for classification.

In pattern recognition, choosing the appropriate features to process is crucial in improving the overall accuracy of the classification [3]. Because of its ability to process images in a minimalized step, the use of CNN as a tool for image processing gave birth to many pre-trained networks such as Inception V3 (IV3) and VGG 16 (VGG16) [4]. By using the CNN network model, a transfer learning model can be generated, where the data is pre-trained and the results are transferred to a new dataset [5]. In this research, we use two network models (IV3 and VGG16) to extract the rice image features and use them as input to the multilayer perceptron (MLP) classification algorithm to classify the rice varieties.

In establishing a good performance model in transfer learning, one of the most important aspects we need to consider is the relation between the source domain (pre-trained model) and the target domain (classifier) [6]. As Inception V3 and VGG 16 use a convolutional neural network architecture, this network utilizes layers and neurons in its feed-forward process [7]. Multilayer perceptron also uses layers, neurons, and a feed-forward process in its classification [8]. These factors signify the close relationship between Inception V3, VGG 16, and multilayer perceptron thus will grant a good performance classification model when combined.

In the classification process, we use the Adam (adaptive moment estimation) optimization functions, combined with the ReLu activation function, to design six models with different hidden layers configurations between 25, 50, and 100 layers to classify the data from the feature extraction. We compare the results using confusion matrix evaluation values to see which model produces better classification performance.

II. METHODS

A. Inception V3

Inception V3 (IV3) is a networks based on pre-trained CNN algorithms that can be used to extract image features based on previous training data sets [9]. With a combination of nine and twenty-two Inception modules-Convolutional Layers, IV3 uses them to process the features from an image [10]. As one of the variations of GoogleNet, IV3, based on 7x7 convolution factorization, consists of 2 or 3 convolution layers with 3x3 dimensions [11]. Following that, a linear layer and a softmax layer were used to output the semantic concepts from the input image [12].

Some studies have shown IV3's ability to transfer the extracted features to a machine learning algorithm, such as chest image-based Covid-19 classification using MLP algorithm (with an accuracy of 94.08%) [13] and facial expression-based human emotions recognition using MLP algorithm (with an accuracy of 81.11%) [14].

B. VGG 16

Another pre-trained CNN model that is often used in feature extraction is VGG 16 (VGG16) [15]. Suggested by Simonyan and Zisserman, VGG16 is a CNN model with a five blocks architecture, where each block consists of three convolutional layers and a pooling layer [16]. The VGG-16 network has 16 homogeneous convolution layers, divided into smaller convolution filters measuring 3x3, where every two or three convolution layers, one pooling layer is inserted [17].

Some studies have shown VGG16's ability to transfer the extracted features to a machine learning algorithm, such as identifying digital identity cards with facial recognition using SVM (with an accuracy of 93.51%) [18]; gait recognition using MLP (with an accuracy of 99.10%) [19]; and prostate recognition with ultrasound image using SVM (with an accuracy of 98%) [20].

C. Multilayer Perceptron

In MLP, the role of the activation function is crucial in optimizing classification performance because using different activation functions can cause a significant performance value in the classification process [21]. Using logistic regression as its classifier base, MLP receives input through an input layer, forwarded to two or more hidden layers, which are then processed using weights and biases to produce an output in the form of classification [22]. This feed-forward process will activate the neurons containing the input using an activation function, such as rectified linear unit (ReLu) [23], which produces an output of 0 if x < 0 and 1 for others [24].
ReLu is often applied to modify or increase the values sent in the neural network architecture to achieve better network convergence [25]. Equation (1) shows how to use the ReLu function in the MLP algorithm, where x is the neuron value and t is the time stamp [26].

$$f_{ReLu} = Max(0, x)_t \qquad (1)$$

Adam is one of the MLP activation functions that can optimize and efficiently solve a regression problem in the learning process [27]. To use this optimation function, we can refer to equation (2), where θ is the criterion value, t is the time stamp, α is the step size, η is the first-moment gauge, and μ_t is the second raw moment gauge [28].

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{u}_t + \varepsilon}} \hat{a}_t \qquad (2)$$

D. Dataset

The dataset used in this study is an image dataset of five types of rice, namely Arborio, Basmati, Ipsala, Jasmine, and Karacadag [29]. The researchers only used the first 100 images from 75000 rice images in this study, for a total of 500 images. These five types of rice have different grain characteristics, seen from the length and width [30]. Table I shows the technical information regarding the grain characteristics of the five types of rice used in this study.

TABLE I
CHARACTERISTICS OF RICE GRAINS

Variety	Length (cm)	Width (cm)
A	0.6-0.75	0.3-0.4
B	0.85-0.115	0.35-0.45
I	0.9-0.11	0.4-0.55
J	0.65-0.1	0.25-0.35
K	0.45-0.6	0.3-0.4

Notes: A = Arborio, B = Basmanti, I = Ipsala, J = Jasmine, K = Karacadag

E. Feature Extraction

This dataset of 500 rice images was extracted with each feature using the IV3 and VGG16 networks. The output produced by each of these networks' feature extraction differs. The IV3 network generates 2048 features, while the VGG16 network generates 4096 features. Figure 1 shows the feature extraction process using the IV3 and the VGG16 networks.

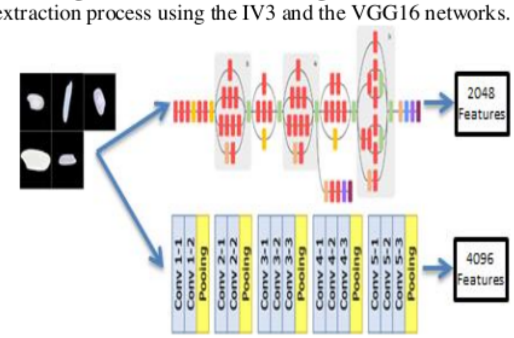

Fig. 1 IV3 and VGG16 feature extraction

F. Classification Model

After getting the feature extraction results from both pre-trained models, the MLP algorithm uses them as input neurons in its architecture. In classifying the feature extractions into Arborio, Basmati, Ipsala, Jasmine, or Karacadag rice types, six MLP models were formed with three hidden layers with variations in the number of neurons 100-50-25, 100-25-50, 50 -100-25, 50-25-100, 25-100-50, 25-50-100, with a ReLu and Adam function. The configuration of the classification model utilized in this research is shown in Table II.

TABLE II
CLASSIFICATION MODEL CONFIGURATION

Model	Hidden Layer	Activation Function	Loss Function
Model 1	100-50-25	ReLu	Adam
Model 2	100-25-50	ReLu	Adam
Model 3	50-100-25	ReLu	Adam
Model 4	50-25-100	ReLu	Adam
Model 5	25-100-50	ReLu	Adam
Model 6	25-50-100	ReLu	Adam

The IV3 and VGG16 networks' feature extraction results are sent to each of the aforementioned models, where they are processed using the ReLu function based on equation (1) in the hidden layer. The MLP model uses the Adam function to update its weight and bias based on equation (2) [28].
To obtain the tabulations of the predicted output and actual output ratio, we use 10-fold cross-validation to evaluate the classification results of each MLP model. Using equations (3) to (5), we use accuracy, precision, and recall values the confusion matrix table as a reference to determine the best performance model. These values are then used as a reference to determine the performance of each model based on the input used.

III. RESULTS

A. Features Statistic

From processing the rice image dataset, we obtained the mean, median, and dispersion values from the extraction results of each model. The statistics of the mean values from the IV3 network are as follows: highest values = 2.94429, average values = 0.296121087, and lowest values = 0.00503133; and the VGG16 network are as follows: highest values = 3.62072, average values = 0.432702989, and lowest values = 0. The statistics of the median values from the IV3 network are as follows: highest values = 2.95732, average values = 0.251893286, and lowest values = 0; and the VGG16 network are as follows: highest values = 3.6203, average values = 0.4292222562, and lowest values = 0. The statistics of the dispersion values from the IV3 network are as follows: highest values = 4.16392, average values = 0.911582276, and lowest values = 0.162651; and the VGG16 network are as follows: highest values = 22.3383, average values = 1.383258709, and lowest values = 0.0171457. Table III shows the tabulation of the mean, median, and dispersion values from the feature extraction of both networks.

TABLE III
STATISTICS OF FEATURE EXTRACTION

Statistic	Network	Lowest Value	Average Value	Highest Value
Mean	IV3	0.00503133	0.296121087	2.94429
Mean	VGG16	0	0.432702989	3.62072
Median	IV3	0	0.251893286	2.95732
Median	VGG16	0	0.4292222562	3.6203
Dispersion	IV3	0.162651	0.911582276	4.16392
Dispersion	VGG16	0.0171457	1.383258709	22.3383

The IV3 network produces 2048 feature extraction results, compared to 4096 feature extractions generated by the VGG16 network. This is in accordance with the form of the IV3 architecture, which produces an output of 2048 neurons, and is also in accordance with the form of the VGG16 architecture, which produces an output of 4096 neurons. Judging from the distribution of the mean values between the IV3 and VGG16 networks, it can be seen that the VGG16 networks produced a higher average value, namely 0.432702989 compared to 0.296121087; the median value was higher, namely 0.429222562 compared to 0.251893286; and a higher average dispersion value, which is 1.383258709 compared to 0.911582276, when compared to the IV3 network. This illustrates that the average value distribution of the feature extraction results in the VGG16 network, which uses an output of 4096 neurons, is higher than the IV3 network, which uses an output of 2048 neurons.

B. Model Evaluation

Using information from each model's feature extraction, we obtained the evaluation of the classification of rice types on the six MLP models in the form of a confusion matrix table. Table IV shows the results of rice-type classification using IV3 network feature extraction data, while Table V shows the results of rice-type classification results using VGG16 network feature extraction data.

TABLE IV
IV3 CONFUSION MATRIX RESULTS

Model		A	B	I	J	K
Model 1	A	98	0	0	0	2
	B	0	99	1	0	0
	I	0	0	100	0	0
	J	0	1	1	98	0
	K	1	0	1	0	98
Model 2	A	96	0	1	0	3
	B	0	98	2	0	0
	I	1	1	98	0	0
	J	0	2	1	97	0
	K	1	0	0	0	99
Model 3	A	98	0	0	0	2
	B	0	97	1	2	0
	I	1	1	98	0	0
	J	1	2	0	97	0
	K	1	0	1	0	98
Model 4	A	97	0	0	0	3
	B	0	99	1	0	0
	I	0	0	100	0	0
	J	0	1	0	98	1
	K	1	0	1	0	98
Model 5	A	95	0	0	1	4
	B	0	98	2	0	0
	I	0	0	100	0	0
	J	0	4	0	96	0
	K	1	0	0	0	99
Model 6	A	96	0	0	0	4
	B	0	99	1	0	0
	I	1	0	99	0	0
	J	0	1	0	99	0
	K	2	0	1	0	97

Notes: A = Arborio, B = Basmanti, I = Ipsala, J = Jasmine, K = Karacadag

TABLE V
VGG16 CONFUSION MATRIX RESULTS

Model		A	B	I	J	K
Model 1	A	98	0	0	0	2
	B	0	99	0	1	0
	I	0	0	99	0	1
	J	0	0	0	100	0
	K	1	0	0	0	99
Model 2	A	96	0	0	1	3
	B	1	97	0	2	0
	I	1	0	99	0	0
	J	0	1	0	99	0
	K	2	0	0	0	98
Model 3	A	97	0	0	0	3
	B	0	99	0	1	0
	I	0	0	100	0	0
	J	0	1	0	99	0
	K	1	0	0	0	99
Model 4	A	97	0	0	0	3
	B	0	99	0	1	0
	I	0	0	100	0	0
	J	0	0	0	100	0
	K	1	0	0	0	99
Model 5	A	95	0	0	1	4
	B	0	99	0	1	0
	I	1	0	99	0	0

	J	0	0	0	100	0
	K	1	0	0	0	99
Model 6	A	96	1	0	0	3
	B	0	99	0	1	0
	I	1	0	98	0	1
	J	0	1	0	99	0
	A	97	0	0	0	3

Notes: A = Arborio, B = Basmanti, I = Ipsala, J = Jasmine, K = Karacadag

The accuracy, precision, and recall values obtained from each MLP model classification result using IV3 and VGG16 network feature extraction are summarized to determine the model with the best performance. Table VI shows the evaluation value of the classification results of each MLP model using the data from the feature extraction of the IV3 and VGG16 network.

TABLE VI
IV3 AND VGG16 CLASSIFICATION EVALUATION

Model	Accuray (%)		Precision (%)		Recall (%)	
	IV3	VGG16	IV3	VGG16	IV3	VGG16
Model 1	98.6	99	98.6	99	98.6	99
Model 2	97.6	97.8	97.6	97.8	97.6	97.8
Model 3	97.6	98.8	97.6	98.8	97.6	98.8
Model 4	98.4	99	98.4	99	98.4	99
Model 5	98.4	98.4	98.4	98.4	98.4	98.4
Model 6	97.6	98.2	97.6	98.2	97.6	98.2
Average	98.03	98.53	98.03	98.53	98.03	98.53

We add up the total prediction errors of each network (IV3 and VGG16) from the confusion matrix displayed in Tables 3 and 4 and tabulate the results in Table VII.

TABLE VI
IV3 AND VGG16 CLASSIFICATION ERRORS

Data Output	Predicted Output	Error	
		IV3	VGG16
Arborio	Basmanti	0	1
	Ipsala	1	0
	Jasmine	1	2
	Karacadag	18	18
Basmanti	Arborio	1	1
	Ipsala	8	0
	Jasmine	4	7
	Karacadag	0	0
Ipsala	Arborio	0	0
	Basmanti	8	8
	Jasmine	2	2
	Karacadag	0	0
Jasmine	Arborio	3	3
	Basmanti	2	0
	Ipsala	0	0
	Karacadag	0	2
Karacadag	Arborio	1	0
	Basmanti	11	3
	Jasmine	0	0
	Ipsala	2	0

The results in Table 6 shows that the misclassification of Arborio variety is highest (41 error), and the lowest is the Jasmine variety (10 error). From a total of 500 predictions of rice types using the feature extraction results of each IV3 network, we calculate a total error of 50 or a value of 10%. From a total of 500 predictions of rice types using the feature extraction results of each VGG16 network, we get a total error of 37 or a value of 7.4%

IV. CONCLUSIONS

Using a pre-trained network such as IV3 or VGG16 is more efficient and effective than manually extracting the features. We can use the pre-trained model to bypass the feature extraction process to gain a similar output for the classification process. The output dimensions of the IV3 and VGG16 networks affect the distribution of feature extraction values from the rice image. The VGG16 network has larger output dimensions and produces higher mean, median, and dispersion values than the IV3 network. The classification performance of the MLP algorithm using the VGG16 network shows better accuracy, precision, and recall values than the IV3. The number of misclassifications also supports this, where the error percentage from the VGG16 network feature extraction is lower than the IV3 network. When combined with the VGG16 network, the MLP algorithm performs more effectively when categorizing the rice varieties Arborio, Basmati, Ipsala, Jasmine, and Karacadag using the 100-50-25 neurons configuration, using the ReLu activation function and Adam optimization function.

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