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Implementation of Transfer Learning in CNN for Classification of Nut Type

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Abstract: Nut has a high nutritional value and is widely used as an ingredient in cooking and snacks. Nut is included in the group of grains and has many types. Each type of nut has different nutritional content. Some types of nuts can also cause allergies or negative reactions in certain people, so it is important to identify the type of nut to be consumed. There are many types of nut that are different from each other, but some of them are similar. This makes it difficult to distinguish between the types of nuts, so there is a need for technology that can accurately identify nut types. Transfer Learning method is used to utilize trained models and applied to nut type classification. The two CNN models used are Inception V3 and Xception. The dataset consists of 11 types of nuts consisting of 1,320 data. The data is divided into 60% for training data and 40% for validation data. Preprocessing is done to ensure the image size is consistent and clarify the focus on the data image to be tested. The training results show that the Xception model is superior to Inception V3, with an accuracy of 86.36% on the validation data, while Inception V3 only reached 74.05%. Xception is able to predict nut types more precisely.

Keywords: Transfer Learning, Convolutional Neural Network, Nut Classification,Inception V3, Xception

INTRODUCTION

Nut is one of the best sources of plant-based protein for the human body. In addition, nut also contains many nutrients, such as vitamins, fiber, healthy fatty acids and minerals. The unique flavor and texture make nut often consumed as cooking ingredients and snacks. Nut is included in the group of grains and has many types. There are many types of nut that are different from each other, but there are some that are similar. This makes it difficult to distinguish the type of nut. Each type of nut has a different nutritional content. Some types of nut can also cause allergies or negative reactions in certain people, so it is important to identify the type of nut to be consumed. Therefore, a technology such as Artificial Intelligence (AI) is needed that can improve accuracy and efficiency in classifying nut types.

One of the technology options that can be utilized is through the use of Deep Learning (DL). Deep learning (DL) is an artificial intelligence (AI) approach that mathematically mimics the brain mechanism in capturing significant patterns from big data (Yudistira, 2021). This technology uses an artificial neural network consisting of many layers (Deep Neural Network) to predict data and analyze data, such as pattern recognition, prediction and classification.

Classification technique that is often used to classify image data is Convolutional Neural Network (CNN). Convolutional Neural Network (CNN) is one type of algorithm in deep learning that can receive input in the form of images and is able to identify objects in the image, so that it can be used as a tool to distinguish each existing image (Iswantoro & Handayani UN, 2022). The use of Convolutional Neural

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Network (CNN) in solving data classification problems was chosen because it has a high level of accuracy (Marifatul Azizah et al., 2018). Furthermore, the method used to improve the performance of the CNN algorithm is the transfer learning method. This method is used to take concepts from predefined models and apply them to new problems. Transfer learning is a technique that utilizes a trained model to classify new datasets without the need to train the data from scratch (Fuadi & Suharso, 2022).

Some previous research has successfully implemented CNN to classify objects in images, such as research conducted by Nur Fadilla to classify vehicle types with the CNN method. The images used for the study were 120 images. The accuracy result obtained was 94.44% with four convolution layers with a filter size of 3x3 (Fadlia & Kosasih, 2019). Another research was conducted by Moch Kholil using CNN, namely to classify infection diseases in chickens based on feces images using CNN. In this study, 95.40% of chicken feces images were predicted to have coccidiosis, 94.97% of chicken feces images were predicted to be healthy, 90.21% of chicken feces images were predicted to have Newcastle disease and 96.50% of chicken feces images were suspected of having pullorum disease (Kholil et al., 2022). CNN research was also conducted by D. Iswantoro to classify corn plant diseases using the CNN method with the number of input images of 150x150 getting an accuracy of 97.5% for training data, while for testing data with 50 data resulted in an accuracy rate of 94% (Iswantoro & Handayani UN, 2022).

From this background, the author has an idea to conduct research by applying the Transfer Learning method and using CNN architecture to classify nut based on its type.

LITERATUR REVIEW

In recent studies, the novelty of implementing transfer learning using Convolutional Neural Network (CNN) in nut type classification has gained attention. Research by Gustavo Thiodorus and friends (et al., 2021) has conducted research using transfer learning and the residual network model to classify food/non-food images, and the results show high accuracy. In addition, (Saputra et al., 2022)) also successfully used transfer learning with the MobileNetV2 model to classify traditional weapons in Central Java, achieving an accuracy of 98.64%. And in previous research, (Firmansyah, 2021) used CNN in transfer learning to classify flowers with an accuracy rate of 64%. All these research results show significant developments in the application of transfer learning in nut type classification and related fields. (Wijaya et al., 2021) conducted a research using transfer learning on a convolutional neural network (CNN) to diagnose COVID-19 and pneumonia in X-ray images. The study showed improved performance of the Xception model in detecting these conditions after freezing certain CNN layers and retraining the outflow/output part of the model for classification based on the desired conditions.

METHOD

This study uses an experimental type of research. The authors analyzed the accuracy of the CNN algorithm for classifying nut types.

Dataset

In this study, the authors used a nut type dataset consisting of 1320 images and covering 11 types of nuts. This dataset is obtained from the following link: https://www.kaggle.com/datasets/ruopengan/11-common-nut-types-for-image-classification.

Work Procedures

The following image processing work procedure using the convolutional neural network algorithm can be completed with the following steps:

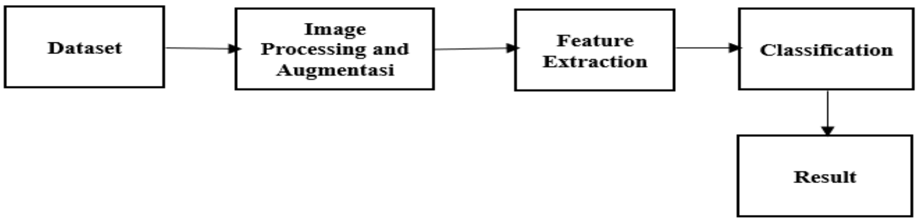

Fig. 1. Work Procedure for Nut Type Classification

Dataset

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Identification The test data images from the dataset are classified in each folder with labels according to the types of nuts, such as almonds, brazilnuts, hazelnuts, and so on.

Image Processing and Augmentasi

Pre-processing of the test image data was performed with all the images of the nut types collected in one dataset and loaded for scaling at a fixed size of 300 X 300 pixels to make them suitable for further processing in the deep learning pipeline.

Feature Extraction

Split the dataset into a training subset of 792 images and a validation subset of 528 images out of a total of 1320 images with 60% training data and 40% validation data from the dataset.

Classification

The next step is to input images for processing to classify the types of beans using transfer learning models, namely Inception V3 and Xception. Training the model by initializing the parameters for training, such as the number of epochs.

Result

Performing performance analysis, including a comparison between the Inception V3 and Xception implementations by comparing the classification results provided by the model on the training and validation subsets.

RESULT

The results of this research include the process of data preparation, preprocessing, testing, and discussion, as well as the proposed model of nut type classification.

Data Preparations

This dataset consists of 1320 images covering 11 types of nuts, including almond, brazil nut, cashew, chestnut, hazelnut, macadamia, peanut, pecan, pine nut, pistachio, and walnut. These images will be used for training and testing the CNN model architecture.

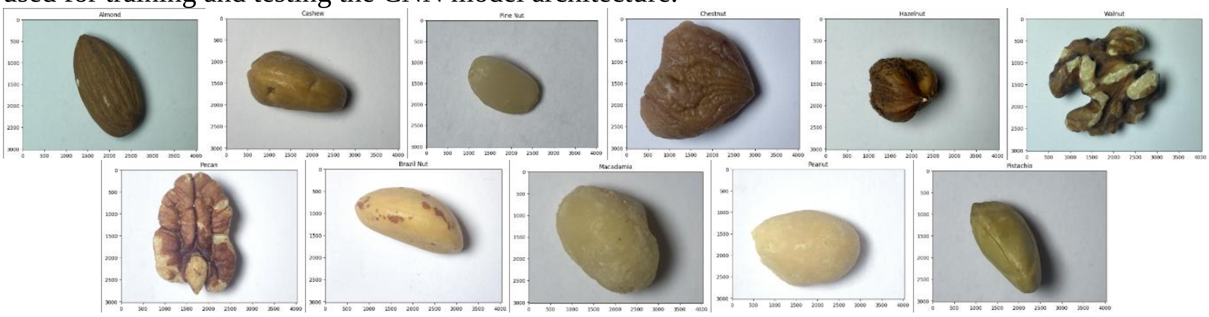

Fig. 2. Dataset of Nut Types

Preprocessing

Before the data can be used to train the CNN model, a data preprocessing process is carried out. The data preprocessing stage is the first stage carried out on the image by resizing the image (scaling) to 300 x 300 pixels, rotating the image to clarify the focus on the data image to be tested. All models used in this study were trained with the Adam optimizer.

In developing a deep learning model, data is required to train the model. Therefore, the data will be separated into two parts, namely training data to train the model, and validation data to test the model that has been created. In addition, the data will be divided into 60% for training data and 40% for validation data.

Training Process

The next step is to conduct training using two models, namely Xception and Inception V3. The dataset to be used is the nut type, which will be divided into train data and validation data. The train data is generated by dividing the original dataset consisting of 1,320 data into 60% train data and 40% validation data, resulting in 792 train data and 528 validation data.

In each model, there are iterations (epochs) that determine the amount of training to achieve a high level of accuracy. Information on the number of epochs can be found in Tables 1 and 2.

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Table 1. Data Training Results on Inception V3 Model

Epoch	Data *Train*		Data *Validation*	
	Loss	*Acc*	Val *Loss*	Val *Acc*
1	2.2684	0.2298	2.4363	0.0938
2	1.5987	0.4684	3.3609	0.1125
3	1.1434	0.6528	5.8213	0.0500
4	0.9423	0.7348	4.9658	0.1000
5	0.7863	0.7992	6.8499	0.0500
⋮	⋮	⋮	⋮	⋮
27	0.2051	0.8007	1.7809	0.5250
28	0.1467	0.8109	1.0271	0.631 3
29	0.1858	0.7808	3.0114	0.3125
30	1.0637	0.7159	0.9262	0.7405

Table 2. Data Training Results on Xception Model

Epoch	Data *Train*		Data *Validation*	
	Loss	*Acc*	Val *Loss*	Val *Acc*
1	1.4440	0.5492	3.5784	0.1312
2	0.7748	0.8422	5.0153	0.0750
3	0.5591	0.8788	5.6806	0.0875
4	0.6324	0.9192	4.8684	0.1063
5	0.5463	0.9293	5.2630	0.0625
⋮	⋮	⋮	⋮	⋮
27	0.0378	0.9937	1.6486	0.5938
28	0.0217	0.9962	1.5154	0.5875
29	0.0231	0.9862	0.6992	0.7937
30	0.0516	0.9785	0.3936	0.8636

From the table above, it can be seen that the results of training and validation data with the number of iterations (epochs) 30 produce accuracy and loss values. Accuracy is a measure that explains how well the trained model can classify validation data correctly, while the loss value is a measure of the error produced by the model when predicting validation data.

In addition, the author gets a graph of the movement of accuracy and loss values on the training and validation data generated for each iteration (epoch) is as follows:

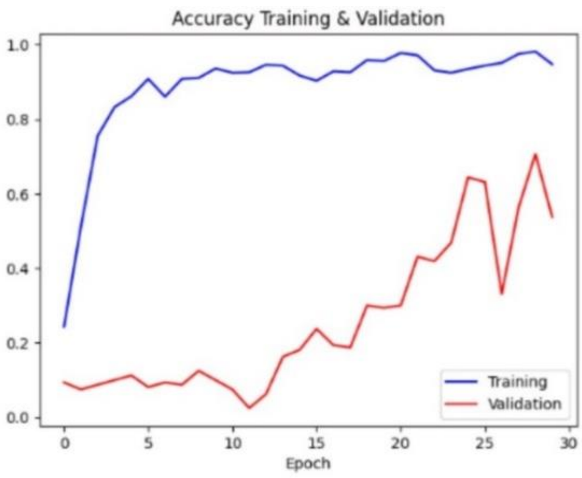

Fig. 3. Graph of Accuracy of Training and Validation on Inception V3 Model

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Fig. 4. Graph of Loss Training and Validation on Inception V3 Model

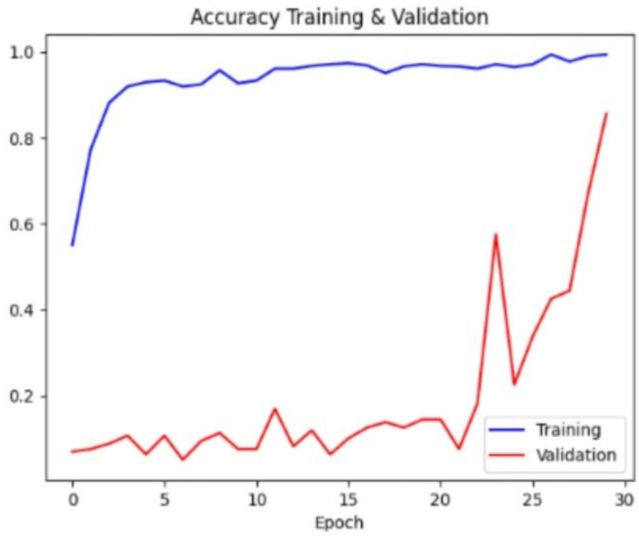

Fig. 5. Graph of Training Accuracy and Validation on the Xception Model

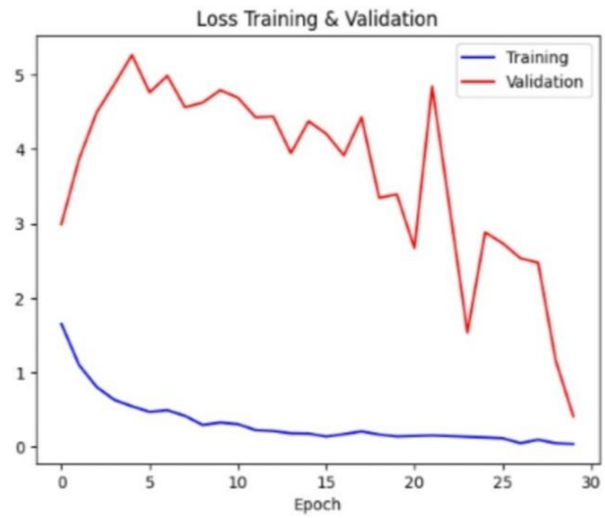

Fig. 6. Graph of Loss Training and Validation on Xception Model

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It was found that the loss rate was close to zero or low, while the accuracy rate continued to increase. This shows a positive result. The more iterations (epochs) used, the higher the accuracy on the training data, while the resulting loss rate on the research data will be lower. From the results of the training and validation data, the Confusion Matrix results are obtained as follows.

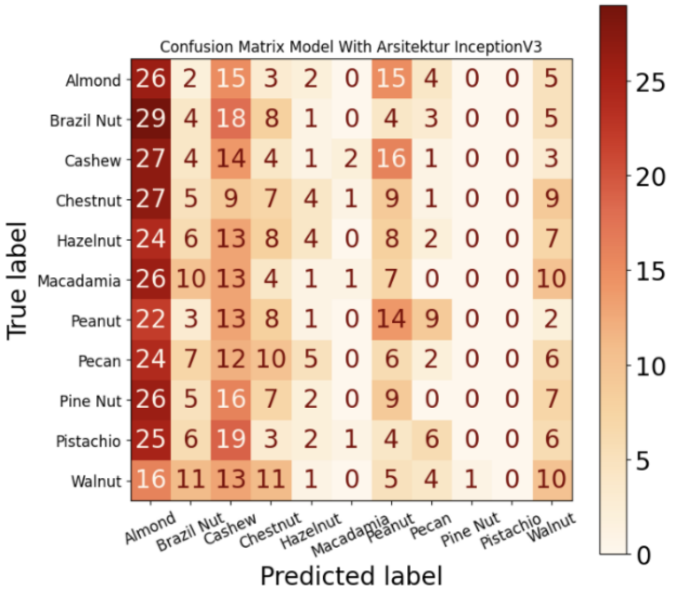

Fig. 7. Confusion Matrix Result on Inception V3 Model

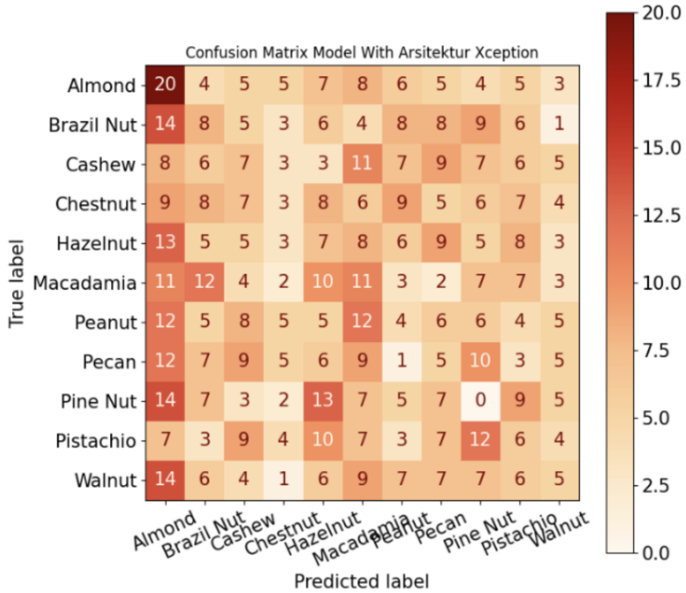

Fig. 8. Confusion Matrix Result on Xception Model

Based on Figures 7 and 8 which are the results of the confusion matrix in the Inception V3 and Xception models, it can show the correct data prediction for the classification of nut type. The amount of correctly predicted data is shown in the brown square. While the number of incorrect predicted data is shown in the white colored square.

Testing Process

After going through the training process using 792 training data, both models were tested using 528 validation data to measure how accurate their performance is. The following are the test results on the two models generated from this research:

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Table 3. Inception V3 Model Accuracy Result

Data	Sum of Data	*Epoch*	
		Loss Value	Accuracy Value
Training	792	1.0637	71.59%
Validation	528	0.9262	74.05%

Table 4. Xception Model Accuracy Result

Data	Sum of Data	*Epoch*	
		Loss Value	Accuracy Value
Training	792	0.0516	97.85%
Validation	528	0.3936	86.36%

The Inception V3 model, listed in Table 3, shows the loss value of the training data obtained is 1.0637 and the validation data is 0.9262. The lower the loss value, the better the model performance. However, the accuracy result obtained is 71.59% on training data and 74.05% on validation data. This shows that the model has relatively low accuracy and can indicate that the Inception V3 model has not provided satisfactory results in classifying the dataset used.

On the other side, Table 4 displays the Xception model. In this table, it can be seen that the loss training value obtained is 0.0516 and the validation data is 0.3936. While the accuracy results obtained are 97.85% on training data and 86.36% on validation data. This shows that the Xception model is able to classify well on the same dataset.

DISCUSSIONS

The problem at hand is the classification of nut type. The main challenge is to create a classification model that is able to learn the different characteristics between different type of nut. Other problems include the collection of sufficient nut datasets, appropriate data preprocessing, and the application of effective transfer learning methods. The utilization of transfer learning techniques using pre-trained models is a promising solution to this problem. However, further research is needed to prove the reliability of pre-trained models in performing nut type classification.

The result of this research has not achieved the expected level of success in designing the two pre-trained models, Inception V3 and Xception, to perform nut type classification. After going through the training process using 792 training data, the two models were tested using 528 validation data to measure how accurate their performance is. However, the test results show that the accuracy of both models is still not optimal. The Inception V3 model achieved an accuracy of 74.05%, while the Xception model achieved an accuracy of 86.36%.

CONCLUSION

This research uses Transfer Learning method with Convolutional Neural Network (CNN) model to classify nut type based on image. The pre-trained models used are Inception V3 and Xception. The results show that Xception has better performance with 86.36% accuracy on validation data, while Inception V3 only reaches 74.05%. However, the accuracy of both models still needs to be improved by increasing the amount of data and variety of nut type in the dataset as well as exploring other model architectures.

The author can provide suggestions for further development by trying different model architectures. Besides Xception and Inception V3, there are many choices of neural network model architectures that can be used for transfer learning. Future research can explore other model architectures such as ResNet and VGG-16 to classification of nut type. By conducting a broader comparison, it is expected to find a more optimal architecture for this classification task. In addition, in future research, it is important to increase the amount of data and variety of nut types that have not been included in the dataset used to classify nut types. The more and varied types of nuts in the dataset, the better the transfer learning model can learn and be able to achieve more optimal accuracy results.

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