Investigation of Transfer Learning Freeze Model Perfomance in Different Epoch

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Abstract: This research aimed to investigate the performance of transfer learning in the Oxford Flower 102 class data. The study used a Resnet 34 model with three different epochs, 10, 15, and 20. The training data was augmented by applying random rotation, cropping, mirroring, and normalization, while the test data was augmented by resizing and normalizing. The model was trained using cross-entropy as a measure of accuracy. The results showed that the model with 20 epochs achieved the highest accuracy of 97.96%. The training loss was 0.0884, while the validation loss was 0.1008. The model with 15 epochs showed an accuracy of 97.48% with a training loss of 0.126 and a validation loss of 0.00965. The model with 10 epochs showed an accuracy of 97.84% with a training loss of 0.1505 and a validation loss of 0.1052. These results indicate that increasing the number of epochs can improve the accuracy of transfer learning in image classification, but there is also a risk of overfitting. This study provides insights into the potential of transfer learning in image classification and the impact of different epochs on the model's performance.

Keywords: Transfer learning, Freeze model, Epoch.

Introduction

Artificial Intelligence is becoming an integral part of the life of modern society. Artificial intelligence is the intelligence shown by machines, in contrast to the natural intelligence displayed by humans and other animals. Some of the activities designed to be carried out are speech recognition, learning, planning and problem solving. The term is often applied to system development projects instilled with the characteristics of human intellectual processes, such as the ability to reason, find meaning, generalize, or learn from past experiences.

Artificial intelligence is used in repetitive activities, with the use of artificial intelligence in activities like this can save costs. Artificial intelligence can learn from existing data patterns without having to be given complex commands. Artificial intelligence that can learn from these data patterns is then referred to as machine learning. Machine learning itself is quite useful in learning patterns from data, but *machine learning* only creates linaer models and simple correlations of data(*Deep Learning vs. Machine Learning: Beginner's Guide | Coursera*, n.d.).

To overcome problems in machine learning, a new method was developed in the form of deep learning. Deep learning is a method based on artificial neural networks. According to IBM deep learning is part of machine learning, which is basically a neural network with three or more layers. This neural network seeks to simulate the behavior of the human brain although its capabilities are still far from that of humans, allowing to learn from large amounts of data even in complex cases(Najafabadi et al., 2015). While a single layer of neural networks can still make estimates, additional hidden layers can help optimize and refine accuracy.

Deep learning is commonly used in many data processing such as images and languages. The field of image processing itself is currently very

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developed and is needed in the industrial field, for example the automotive industry that requires autonomous car systems or self-driving. In determining the distance, the car uses the image obtained from the camera to determine the distance which is then made a decision from the existing artificial intelligence system. Computer vision is a field of artificial intelligence that trains computers to interpret and understand the visual world. Computer vision uses digital images from cameras and videos as well as deep learning models, machines can accurately identify and classify objects then react to what they see.

Computer vision itself functions to gain knowledge from data in the form of images and videos which are then used for making certain decisions both automatically and manually. Computer vision usually uses deep learning methods such as CNN, RNN, and transfer learning. Transfer learning is machine learning in which a model developed for a task is reused as a starting point for a model on a second task.

Transfer learning performs well in image classification, but it needs performance improvements to get better accuracy. Performance Improvement from Transfer learning is carried out using hyperparameter tuning, one of the hyperparameters that can be used is epoch. and this study focuses on the impact of epochs on transfer learning freeze model performance.

Transfer Learning

Transfer learning is a machine learning method that leverages a model that has been trained with a specific dataset and then used for a new model. Transfer learning is commonly used as a pre-trained model(Han et al., n.d.). Transfer learning can be used directly without changing the built-in architecture of the transfer learning model, but it can also be used by modifying the model architecture by adding and retrieving portions.

In the process of training the transfer learning model, there are two training schemes, the first is to freeze the model, which will result in the absence of gradient calculations. The freeze model is faster in training. While the unfreeze or finetuning model is ordinary training while still doing gradient calculations. Fine tuning models are slower in conducting training.

Transfer learning is widely used in various fields of machine learning such as computer vision(Sharma & Parikh, n.d.), natural languege procesing(Alyafeai et al., 2020) and reinforcement learning(Zhu et al., 2020). In the field of computer vision, especially in the field of image classification, transfer learning is widely used to create models with high accuracy. In the field of image classification transfer learning has a lot of models, among the transfer learning models in the field of image classification are Alexnet, VGG16, ResNet34(Gao et al., 2021), Mobilenetv2 and others.

Adam Optimization

Adam optimization is a popular optimization algorithm used in deep learning and machine learning. It was introduced by Diederik Kingma and Jimmy Ba in their paper "Adam: A Method for Stochastic Optimization" (Kingma and Ba, 2014). Adam combines the advantages of both Momentum optimization and RProp optimization to achieve faster convergence. It calculates adaptive learning rates for each weight and updates the weights based on these learning rates, thus achieving convergence faster than other optimization algorithms. The algorithm calculates the moving average of the gradient and the squared gradient and uses these values to update the weights. It also uses bias correction techniques to correct the moving average and the squared gradient estimates (Kingma and Ba, 2014). Adam optimization is computationally efficient and is widely used in many deep learning models, including convolutional neural networks and recurrent neural networks. The algorithm has been shown to outperform traditional optimization algorithms such as SGD and Adagrad in a variety of tasks (Kingma and Ba, 2014)

Epoch

Epoch is a one-time learning process on all training data in machine learning. Each epoch uses gradient descent to update weights and minimize function loss. This process is carried out repeatedly for several epochs until an optimal solution or stopping criteria are reached. The model will learn and improve performance each time through a single epoch. The exact epoch value will affect the speed of training and the accuracy of the model. Too little epoch will cause underfitting and too much will lead to overfitting.

Materials and Methods

Methodology for Investigating the Impact of Different Epochs on Transfer Learning Freeze Model Performance in Oxford Flower 102 Class using Cross Entropy Accuracy Measurement

1. Data Collection: The Oxford Flower 102 class dataset will be used for this study. This dataset consists of 102 different flower categories and includes images of flowers with various attributes such as color, shape, and size.
2. Transfer Learning: A pre-trained deep learning model, such as VGG16 or ResNet, will be used for transfer learning. The model will be frozen at a certain layer and fine-tuned for flower classification.
3. Epochs: Three different values for epochs will be used in this study, namely 3, 5, and 10. For each value, the model will be trained and evaluated.
4. Cross Entropy: Cross entropy will be used as the evaluation metric for model performance. Cross entropy measures the difference between the predicted and actual distribution of class labels, and a lower value indicates better performance.
5. Performance Comparison: The accuracy of the model will be recorded and compared for each value of epochs. The results will be visualized using graphs and tables to compare the model's performance in terms of accuracy.

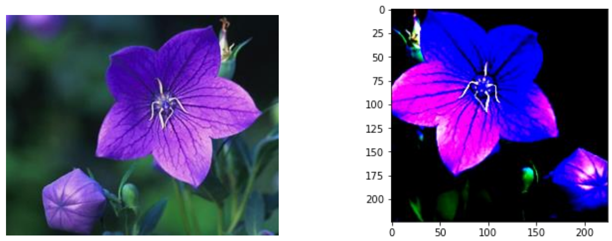
Results and Discussion

In this stage the data is divided into two parts, training data and validation data Then the data is augmented, namely by changing the image size, *crop center*, random rotation, random horizontal mirroring, changes to tensors and normalization.

The training data is carried out augmentation as follows.

1. Random rotation of 30°
2. picture cropped with a size of 224 to 224 pixels×
3. image is mirrored horizontally randomly
4. image converted to tensor
5. The image is normalized by each chanel so that the average becomes 0.485, 0.456, 0.406 and the standard deviation becomes 0.229, 0.224, 0.225.

so that the following results are obtained



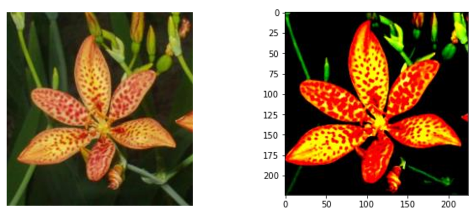
(a) (b)

Figure 1. Image samples for training data (a) Images before augmentation, (b) images after augmetasi

The test data is carried out augmentation as follows.

1. Change image size to 256pixel× 256
2. Gamber cut center with size 224 ×224 pixels
3. Gamber converted to tensor
4. Gamber normalized each channel so that the average became 0.485, 0.456, 0.406 and the standard deviation became 0.229, 0.224, 0.225.

so that the following results are obtained



a) (b)

Figure 2. Image samples for validation data (a) Images before augmentation, (b) images after augmeation.

The freeze model for the Resnet 34 model uses several parameters. The epochs used in all models are three, namely, 10, 15, and 20. Training in each model used *tunning parameters.* The parameters used are as follows: grad_clip = 0.1, weight_decay = 1e-4. Max_lr used in the *freeze* model is the 10E-4.

To measure the performance of each epoch of the model, the results of training the model are as follows:

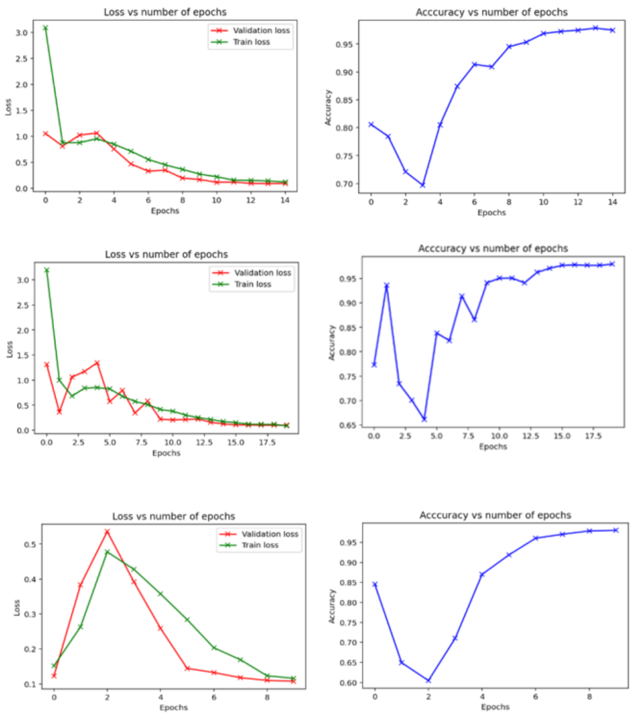


Figure 3 (a) epoch accuracy score 10, (b) epoch accuracy score 15, (c) epoch accuracy score 20, (d) loss function score for epoch 10, (e) loss function score for epoch 15, (f) *loss function* score for epoch 20

Tabel 1. Accuracy, *training* loss, and *validation loss* scores for *freeze* models

No	Epoch number	Accuracy	*Training loss*	*Validation loss*
1	10	97.84%	0.1505	0.1052
2	15	97.48%	0.126	0.00965
3	20	97.96%	0.0884	0.1008

Discussion

The results of this study showed that the performance of the Resnet 34 model using a freeze model with different epochs can have an impact on the accuracy of the model. The results showed that the highest accuracy was obtained when using an epoch of 20 with an accuracy of 97.96%. While the lowest accuracy was obtained when using an epoch of 15 with an accuracy of 97.48%. These results suggest that increasing the number of epochs can increase the accuracy of the model.

Additionally, the results of the training and validation loss also showed an interesting pattern. The training loss of the model decreased with an increase in the number of epochs. The training loss for the 10 epochs model was 0.1505, for the 15 epochs model was 0.126, and for the 20 epochs model was 0.0884. This result indicates that the longer the model is trained, the lower the training loss will be.

However, the validation loss showed a different pattern. The validation loss of the 20 epochs model was higher compared to the validation loss of the 10 and 15 epochs models. This result indicates that the model may be overfitting when using a large number of epochs. Overfitting occurs when a model is too complex and has learned the training data too well, leading to poor generalization to new data.

Overall, the results of this study suggest that there is a trade-off between the number of epochs and the accuracy of the model. While increasing the number of epochs can increase the accuracy of the model, it can also lead to overfitting and reduce the generalization ability of the model. Therefore, it is important to carefully consider the number of epochs used in training models. Further research is needed to investigate this trade-off and to find the optimal number of epochs for a specific task.

Conclusions

In this study, the performance of transfer learning on Oxford Flowers 102 dataset was investigated by training a ResNet-34 model with three different epochs, 10, 15, and 20. The results showed that the accuracy of the model increases with the increase in the number of epochs, with the highest accuracy of 97.96% obtained at 20 epochs. However, the training loss decreased with the increase in the number of epochs, with the lowest value of 0.0884 obtained at 20 epochs. The validation loss also decreased with the increase in the number of epochs, with the lowest value of 0.1008 obtained at 20 epochs.

In conclusion, the increase in the number of epochs has a positive effect on the accuracy of the transfer learning model, while the training loss and validation loss decreased with the increase in the number of epochs. These results suggest that using a larger number of epochs can help improve the performance of transfer learning models

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