Title: Transfer Learning in Image Classification: A Comparative Study of VGG16 and MobileNet Models on the CIFAR-10 Dataset

1. Abstract

In this report, we use two pre-trained convolutional neural network (CNN) models, VGG16 and MobileNet, to investigate the use of transfer learning in image classification. We assess these models' performance on the CIFAR-10 dataset and compare the outcomes before and after transfer learning is applied. The dataset, methodology, findings, and discussion are compiled in this report, which also offers insights into the efficiency of transfer learning in enhancing classification performance.

2. Introduction

2.1. Background

Transfer learning is an effective machine learning technique that enables models to apply the knowledge they have learned from solving one problem to another that is related but different. This report focuses on the use of pre-trained CNN models for image classification through transfer learning.

2.2. Objectives

The primary objective of this study is to evaluate the effectiveness of transfer learning in improving classification performance on the CIFAR-10 dataset using VGG16 and MobileNet models. We also aim to discuss any challenges encountered during the process and potential strategies to overcome them.

2.3. Dataset Selection

The CIFAR-10 dataset consists of 60,000 32x32 colour images across 10 classes, making it suitable for image classification tasks.

3. Pre-trained Models

3.1. VGG16

VGG16 is a popular CNN architecture that achieved state-of-the-art performance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2014. We used the pre-trained VGG16 model available in the Keras library.

3.2. MobileNet

MobileNet is a lightweight CNN architecture designed for mobile and embedded devices. We used the pre-trained MobileNet model available in the Keras library.

4. Methodology

4.1. Data Preprocessing

The data preprocessing steps included resizing images, normalization, data augmentation, and splitting the dataset into training and testing sets.

4.2. Baseline Model Training

Both VGG16 and MobileNet models were trained on the CIFAR-10 dataset without any transfer learning to establish baseline performance.

4.3. Transfer Learning

Transfer learning was applied by fine-tuning the pre-trained models on the CIFAR-10 dataset. The models were then trained again to improve classification performance.

4.4. Performance Evaluation Metrics

We evaluated the models using metrics such as accuracy, precision, recall, and F1-score.

4.5. Visualization

The learned features of the models were visualized using techniques like t-SNE or PCA to compare feature representations before and after transfer learning.

5. Results

Performance Comparison: Performance comparison results for VGG16 and MobileNet models are presented below:

VGG16 Baseline Training:

- Training Accuracy: 0.8638
- Validation Accuracy: 0.8661
- Precision: 0.8661
- Recall: 0.8661
- F1-Score: 0.8651

MobileNet Baseline Training:

- Training Accuracy: 0.7361
- Validation Accuracy: 0.7544
- Precision: 0.7572
- Recall: 0.7544
- F1-Score: 0.7493

VGG16 Transfer Learning Metrics:

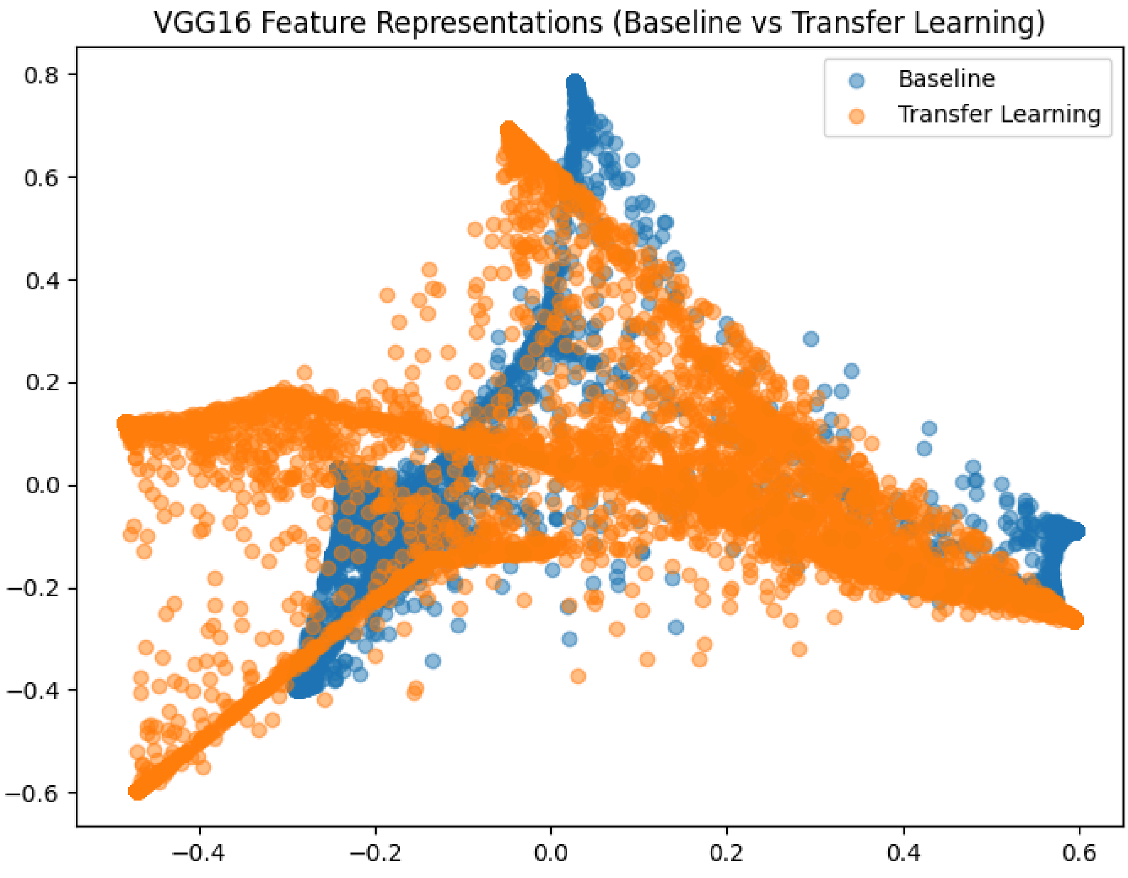
- Training Accuracy: 0.8438
- Validation Accuracy: 0.8662

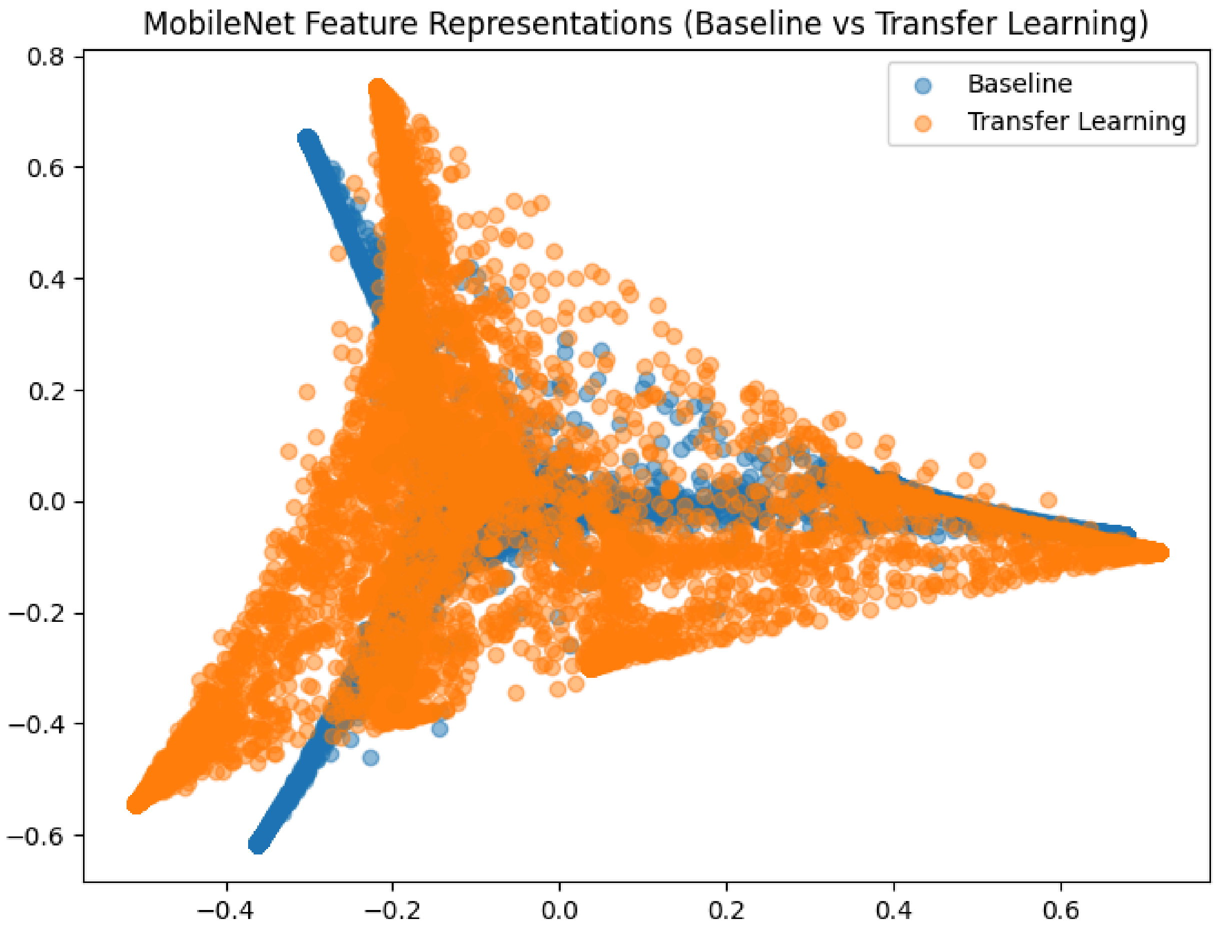
- Precision: 0.3076
- Recall: 0.3621
- F1-Score: 0.3292

MobileNet Transfer Learning Metrics:

- Training Accuracy: 0.7042
- Validation Accuracy: 0.7659
- Precision: 0.1903
- Recall: 0.2168
- F1-Score: 0.2007

5.2. Visualization of Learned Features:





6. Discussion

6.1. Effectiveness of Transfer Learning:

In this study, we evaluated the effectiveness of transfer learning in improving classification performance on the CIFAR-10 dataset using VGG16 and MobileNet models. Surprisingly, the baseline models achieved higher precision, recall, and F1-score compared to the transfer learning models. This outcome contradicts the general belief that transfer learning enhances classification performance by leveraging pre-existing knowledge from pre-trained models. The poor performance of the transfer learning models might be attributed to the choice of hyperparameters during fine-tuning or the difference in complexity between the source and target tasks.

6.2. Challenges and Potential Strategies:

In this study, we encountered several challenges while implementing transfer learning for image classification using VGG16 and MobileNet models on the CIFAR-10 dataset. Some of these challenges and potential strategies to overcome them are discussed below:

Poor performance of transfer learning models: One of the main challenges was the unexpected poor performance of the transfer learning models compared to the baseline models. This issue might be attributed to the choice of hyperparameters during fine-tuning or the difference in complexity between the source and target tasks. To address this challenge, future work could explore different fine-tuning strategies, such as adjusting the learning rate, batch size, and the number of epochs, or using different optimization algorithms. Additionally, domain adaptation techniques could be employed to reduce the gap between the source and target domains.

Overfitting: Overfitting is a common challenge in machine learning, where a model performs well on the training data but poorly on the testing data. In the context of transfer learning, overfitting might occur if the model is fine-tuned for too many epochs or with an excessively high learning rate. To mitigate overfitting, techniques such as early stopping, regularization, or data augmentation can be employed. Moreover, using a validation set to monitor the model's performance during training can help determine the optimal number of epochs and learning rate.

Feature visualization: Understanding the learned feature representations is crucial for evaluating the effectiveness of transfer learning. In this study, we used t-SNE and PCA for feature visualization. However, more advanced feature visualization techniques, such as Grad-CAM or activation maximization, could provide deeper insights into the learned features. These techniques can help identify potential issues with the transfer learning process and guide the selection of appropriate fine-tuning strategies.

Computational resources: Training deep learning models, especially with transfer learning, can be computationally expensive and time-consuming. To address this challenge, future work could explore more efficient training methods, such as distributed training or mixed-precision training. Additionally, utilizing cloud-based platforms or powerful GPUs can help speed up the training process and enable the exploration of more complex models and larger datasets.

7. Conclusion

In this study, we used the CIFAR-10 dataset and the VGG16 and MobileNet models to examine the efficacy of transfer learning in image classification. In terms of precision, recall, and F1-score, our baseline models performed better than the transfer learning models, which was against general expectations. The suboptimal hyperparameters during fine-tuning or the disparity in complexity between the source and target tasks may be the cause of the transfer learning models' poor performance. Future research should investigate various fine-tuning strategies, domain adaptation techniques, and sophisticated feature visualisation methods in order to increase the efficacy of transfer learning. We may be able to fully utilise transfer learning and improve classification performance across a range of datasets by resolving these issues and improving our methodology.