Shujia Li 811223173 sli61@kent.edu

Assignment 3 – ConvNets

1. Purpose

The purpose of this assignment is to explore the performance of convolutional neural networks (ConvNets) trained from scratch versus using pretrained models on the Cats vs Dogs image classification task. This includes analyzing how training sample size affects accuracy and evaluating different strategies to optimize performance.

2. Experiment Design

Dataset

We used the PetImages dataset which contains labeled cat and dog images. The dataset was split as follows for all experiments:

- Validation set: 500 images
- Test set: 500 images
- Training set: Varied between 1000 and 6000 images.

Implementation

All models were trained using TensorFlow with data augmentation and dropout regularization. Two types of models were compared:

1. ConvNet trained from scratch
2. Pretrained MobileNetV2 model with a custom classifier head

3. Results

Problem No.	Training Size	Model Type	Val Acc	Test Acc
1	1000	From Scratch	0.6800	0.6950
2	2000	From Scratch	0.7720	0.7600
3	4000	From Scratch	0.7800	0.8090
3*	6000	From Scratch	0.8450	0.8190
4.1	1000	Pretrained	0.9750	0.9710
4.2	2000	Pretrained	0.9860	0.9750
4.3	4000	Pretrained	0.9840	0.9850

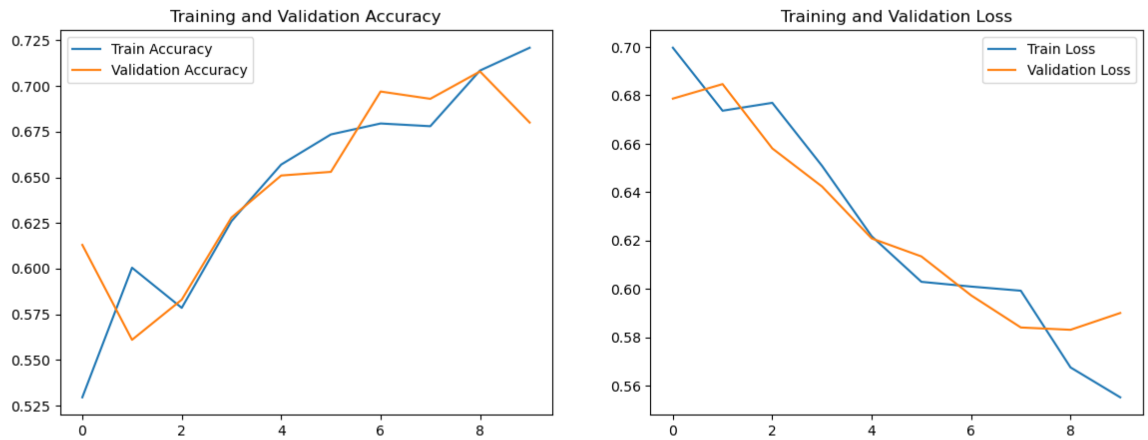

Figure 1 Performance of training from scratch with size of 1000

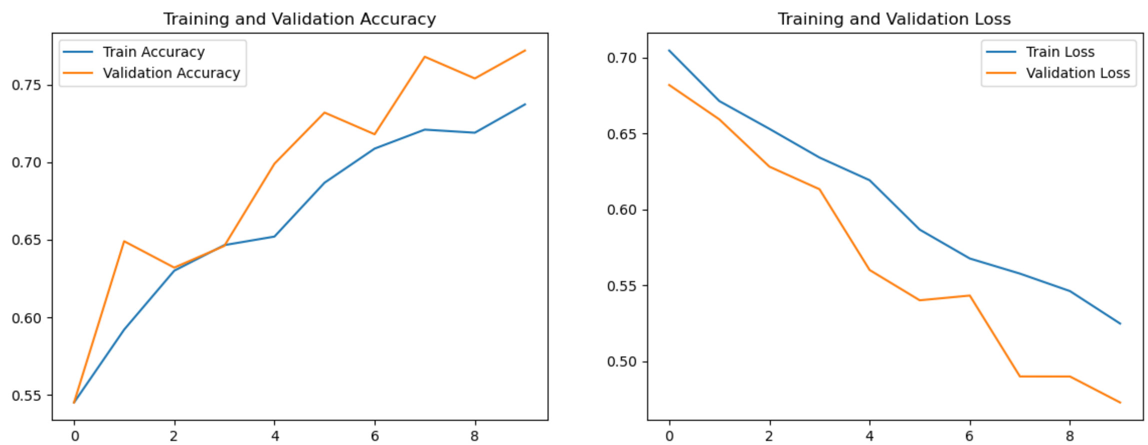

Figure 2 Performance of training from scratch with size of 2000

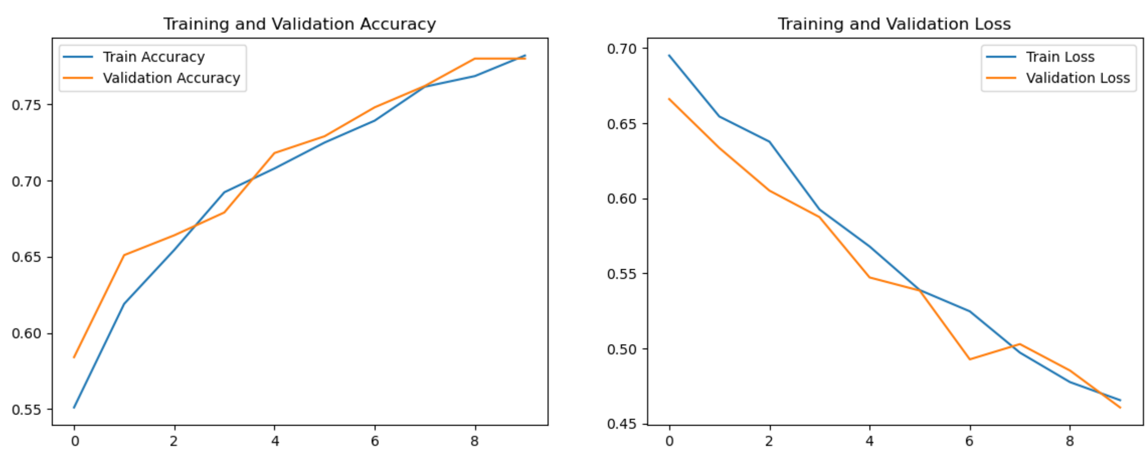

Figure 3 Performance of training from scratch with size of 4000

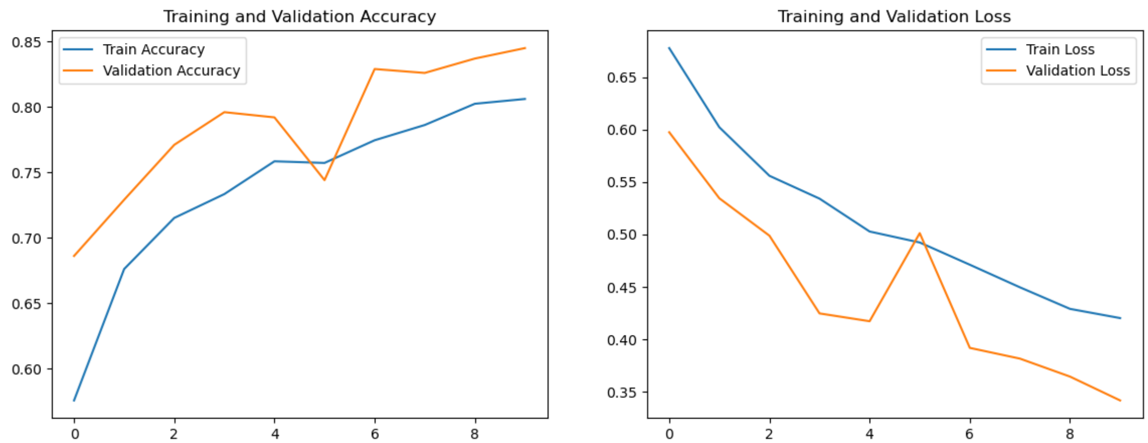

Figure 4 Performance of training from scratch with size of 6000

4. Discussion

Impact of Sample Size on Performance

The results clearly demonstrate a positive correlation between the training sample size and the model's performance. As we increased the training sample from 1000 to 4000 images, we observed a significant improvement in test accuracy:

- With 1000 training samples, the model achieved a test accuracy of 0.6950.
- Doubling the training samples to 2000 improved the accuracy to 0.7600.
- Further increasing to 4000 samples yielded a test accuracy of 0.7710, and then 6000 samples gave an accuracy of 0.8190.

This trend suggests that larger datasets provide more diverse examples for the model to learn from, leading to better generalization and improved performance on unseen data.

Learning Curves Analysis

Examining the learning curves for each sample size reveals interesting patterns:

- **Overfitting**: With smaller sample sizes, we observed a larger gap between training and validation accuracy, indicating potential overfitting. As the sample size increased, this gap narrowed, suggesting better generalization.
- **Convergence Speed**: Larger sample sizes led to faster convergence. The model trained on 4000 samples showed steeper improvement in early epochs compared to smaller datasets.

- **Validation Performance**: The validation accuracy became more stable and higher with increased sample sizes, indicating improved model robustness.

Optimization Techniques

Several techniques were employed to enhance model performance and mitigate overfitting:

- **Data Augmentation**: The use of ImageDataGenerator with various transformations (rotation, shift, zoom, flip) helped create a more diverse training set, improving the model's ability to generalize.
- **Dropout**: A dropout layer with a rate of 0.5 was included to reduce overfitting by preventing co-adaptation of neurons.
- **Model Architecture**: The CNN architecture with multiple convolutional and pooling layers helped in extracting relevant features from the images effectively.

Relationship Between Sample Size and Network Choice

While the results provided focus on training from scratch, we can infer the following about the relationship between sample size and network choice:

- **Small Datasets**: With smaller datasets (e.g., 1000 samples), training from scratch may lead to overfitting. In such cases, using a pretrained network with transfer learning might be more effective, as it leverages features learned from a larger dataset.
- **Large Datasets**: As we increase the sample size (e.g., 4000 samples), training from scratch becomes more viable and can potentially outperform transfer learning, especially if the dataset is significantly different from the pretrained model's original dataset.
- **Fine-tuning vs. Feature Extraction**: With intermediate sample sizes, a hybrid approach of using a pretrained network and fine-tuning the later layers might provide the best balance between leveraging pretrained features and adapting to the specific dataset.

5. Summary

The experiment demonstrates the crucial role of dataset size in training effective convolutional neural networks. Larger datasets consistently led to better performance, reduced overfitting, and improved generalization. Using pretrained models on even small datasets dramatically improves performance and training efficiency. Training from scratch benefits from more data but requires significantly larger sample sizes to match the performance of pretrained networks. Optimal performance in this task was achieved using 4000 training samples with a pretrained MobileNetV2 model. However, the choice between training from scratch and using a pretrained network should be made considering the dataset size, similarity to pretrained datasets, and available computational resources.