

SUMMARY REPORT – ASSIGNMENT 3

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Introduction

This work studies on the use of CNN for binary image classification between cat and dog images. The goal is to measure trained from scratch models with transfer learning architectures and see how sample size changes training regimes. The study attempts, by systematic testing, to find the best dataset size and model configuration providing most accurate and generalizing results. It also studies the contribution of data augmentation and transfer learning in alleviating overfitting, enhancing Modell ability.

Dataset Overview

We conduct the experiments on the Microsoft Research Cats and Dogs, a standard computer vision benchmark dataset. It includes 25,000 labeled photographs, half of which are dogs and the other cats. For this analysis, subsets of varying length (1,000, 1,400, 1,600, 1,800, and 2,000 images) were sampled for the training portions of the dataset, while validation and test sets remained constant at five hundred images each. This uniform arrangement guarantees a fair performance comparison between all models, trained with different data sizes.

Data Preprocessing

All images were pre-processed in order to feed the CNN with compatible inputs. The following steps were implemented:

- Reading and parsing image files of the dataset.
- All images are rescaled to 150×150 pixels.
- Data normalization: making values of pixels to be within $[0, 255]$ to $[0, 1]$ for numerical stability.
- Partitioning data into training, validation, and test sets.
- Performing augmentation like rotation, flipping and zooming of images to generate more variations in dataset and enhance generalization.

Model 1: Training from Scratch

Step 1: Base Training Set (1,000 images)

A CNN baseline model was built and trained from scratch with 1,000 training images. This model was composed of the stacked convolutional and pooling network layers followed by dense layers for binary classification.

Performance Summary:

- Training Accuracy: 72.2%
- Validation Accuracy: 72.0%
- Test Accuracy: 67.6%

These findings reflect slight overfitting, i.e. the training accuracy was higher than the validation and test accuracies. Data augmentation was incorporated for the purpose of generalization and resulted in a small performance gain in all test metrics.

Step 2: Expanded Training Sample

Amplifying the training set size will enhance the stability and the accuracy of learning. Regularization, early stopping, dropout layers were added to the CNN model to avoid overfitting.

Performance Summary:

- Training accuracy: 70.9% to 97.4%
- Validation Accuracy: 71.9% -> 97.4%
- Test Accuracy: 85.0%

We also observed that adding more data (and regularization) improved the generalization of model a lot which shows that a bigger dataset is better for training from scratch.

Stage 3: Optimizing the Sample for Maximum Accuracy

Additional experiments were performed for various sample sizes to find out the optimal size of training dataset having optimum performance. We kept data augmentation and early stopping to stabilize training.

Performance Summary:

- Training Accuracy: 99.97%
- Validation Accuracy: 76.3%
- Test Accuracy: 90.1%

The model performed exceedingly well with 1,800–2,000 training samples but a gap between the train and validation accuracies suggested slight overfitting. In general, the scratch-trained CNN showed consistent accuracy and powerful generalization.

Pretrained Network: Transfer Learning Approach

As for the model used to transfer learn, we chose VGG16 pretrained (with ImageNet). The base network was frozen (i.e., no further backpropagation allowed) and a custom classification head, consisting of a dense layer with ReLU as activation function, dropout regularization and sigmoid output actioned for fine-tuning on Cats vs Dogs dataset.

Here all the input images were rescaled to 224×224 pixels as per the input of VGG16. The model was optimized using the RMSprop (learning rate = 1e-4) and binary cross entropy loss. Data augmentation was kept maintaining the variety of training inputs. The experimental results indicated fast convergence and surprising performance, which further verifies the superiority of pretrained models, especially for small datasets.

Results and Performance Analysis

Table 1: Scratch-Trained CNN Performance

Model & Sample Size	Method	Validation Accuracy	Test Accuracy	Validation Loss	Test Loss
Model 1 (1000)	Without Augmentation	68.0%	71.2%	0.601	0.575
Model 1 (1000)	With Augmentation	77.6%	70.4%	0.512	0.602
Model 2 (1400)	Without Augmentation	70.2%	68.0%	0.550	0.623
Model 2 (1400)	With Augmentation	81.8%	76.6%	0.428	0.531
Model 3 (1600)	With Augmentation	80.8%	79.8%	0.419	0.445
Model 4 (1800)	With Augmentation	78.6%	75.8%	0.447	0.536
Model 5 (2000)	With Augmentation	84.0%	81.8%	0.398	0.500

Table 2: Pretrained Model Performance (VGG16)

Model & Sample Size	Validation Accuracy	Test Accuracy	Validation Loss	Test Loss
Model 6 (1000)	97.2%	96.0%	3.175	7.235
Model 7 (1400)	98.6%	98.0%	1.427	4.092
Model 8 (1600)	97.4%	98.0%	2.418	2.123
Model 9 (1800)	98.8%	97.8%	1.373	3.125
Model 10 (2000)	98.4%	97.2%	1.344	3.517

Comparative Analysis: Scratch vs. Pretrained Models

These results unequivocally show that pretrained architectures are preferable to trained-from-scratch models. The scratch-trained best model had a test accuracy of around 82%, but all pretrained models achieved over 97% on tests, even when

using less training data. The pretrained VGG16 model exploited learned representations on large-scale datasets which led to a faster learning rate and better feature extraction, resulting in higher accuracy. Even though pretrained models experienced some mild overfitting, with slightly higher validation losses, their accuracy and stability imply robust generalization.

Conclusion:

This experiment demonstrates that CNNs are strongly architected for image classification and also underlines the power of data augmentation and transfer learning. Although models learnt from scratch scaled well with more data and regularization, pretrained architectures (eg VGG-16) provided better quality and efficiency especially when we only have limited amount of data. Finally, the results of the study confirm that transfer learning greatly improves performance on small computer vision tasks. It would be interesting for future work to see if both types of deep layers can be fine-tuned or if niche architectures (such as ResNet [16] and EfficientNet [46]) should be experimented with in order to obtain an even better generalization behavior and computational efficiency.