ASSIGNMENT 3: CONVOLUTION

Spring 2025 ADVANCED MACHINE LEARNING (BA-64061-001)

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ASSIGNMENT 3 SUMMARY: Convolution Networks

INTRODUCTION:

In this assignment, we applied the usage of Convolutional Neural Networks (CNNs) to the binary image classification task using the Cats vs Dogs dataset. Our goal was to compare performance across models trained from scratch and those that use pretrained architectures, on varying sizes of training samples. We began with a small training set of 1000 images and then gradually extended the training set to check how it affected the accuracy. For improving performance and preventing overfitting, strategies like data augmentation and dropout regularization were employed. The scratch-trained model got better with more data, but pre-trained networks were better even with small data sets. This exercise helped demonstrate how data size and model initialization impact deep learning performance in computer vision tasks.

GOAL:

This assignment aims to investigate how training sample size affects model performance by using convolutional neural networks (CNNs) to identify photos of dogs and cats. It entails contrasting models that were created from scratch with those that used pretrained networks. The emphasis is on applying methods such as regularization and data augmentation to lessen overfitting and increase accuracy in various contexts.

METHODLOGY:

The Cats vs. Dogs dataset, a well-known binary image classification dataset, was used for this assignment. Training, validation, and test sets were the three categories into which the dataset was separated. At first, there were 1000 photos in the training set and 500 images in each of the validation and test sets.

These were the primary steps involved in the method:

1. Preparation of Data

After being extracted, the dataset was arranged into distinct folders for testing, validation, and training. To make sure the data was properly formatted, a simple exploratory analysis was conducted.

2. Data Augmentation

Using picture augmentation methods like rotation, zoom, horizontal flipping, and rescaling to lessen overfitting brought on by the tiny training sample.

3.Training Models from Scratch

TensorFlow/Keras was utilized to construct a customized CNN architecture. Several convolutional and pooling layers preceded by thick layers made up this structure. The dataset with varying training sizes was used to train the model, which was constructed with binary cross-entropy loss.

4.Training a Model using a Pretrained Network

On top of a pretrained convolutional foundation (such as VGG16), custom dense layers were applied. Depending on the training phase, the convolutional layers were either frozen or fine-tuned to assess transfer learning performance.

5.Assessment of Performance

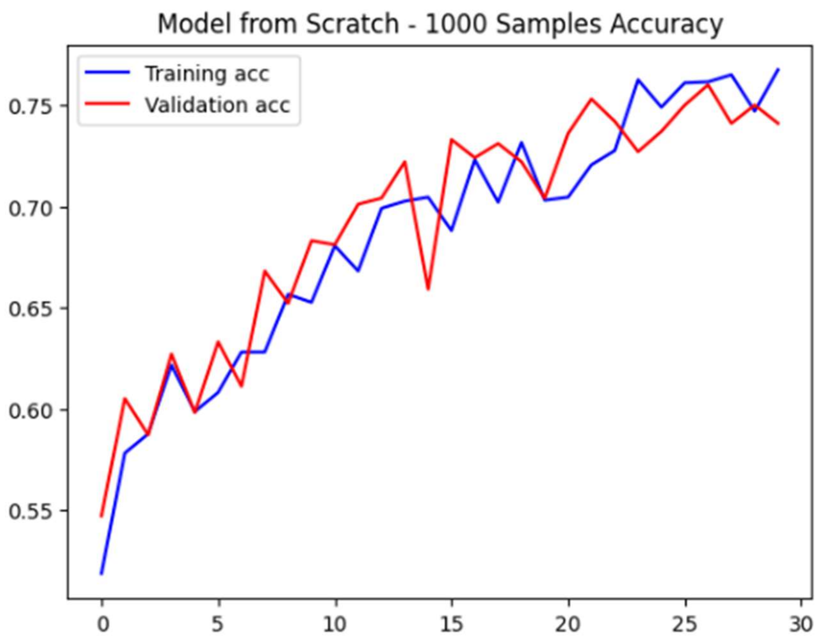
In order to assess the accuracy and loss of both models (pretrained and scratch) on test and validation data, they were trained on different sample sizes. The best training strategy and sample size were identified by plotting and summarizing the results.

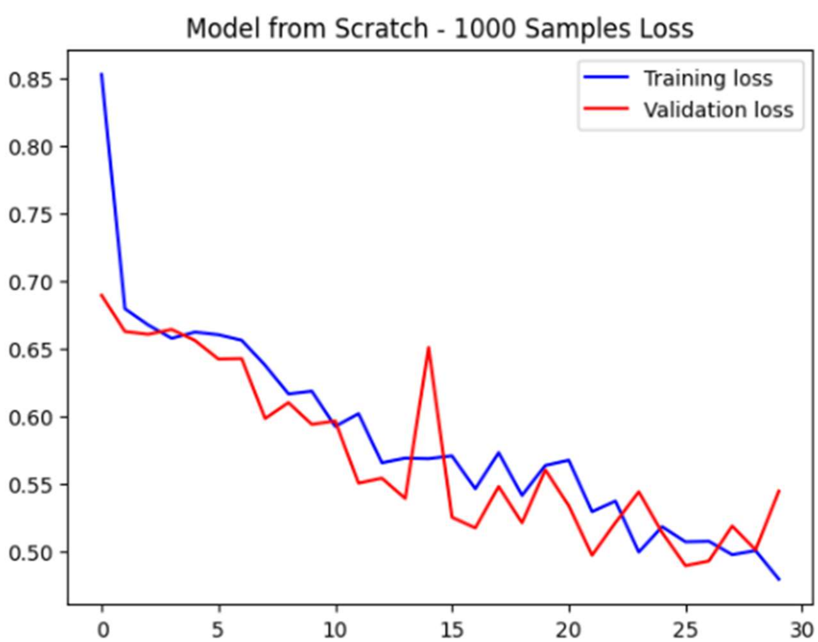
RANDOM SAMPLE IMAGES:

SUMMARIES OF EXPERIMENTS:

EXPERIMENT-1: Training with a Small Dataset from Scratch

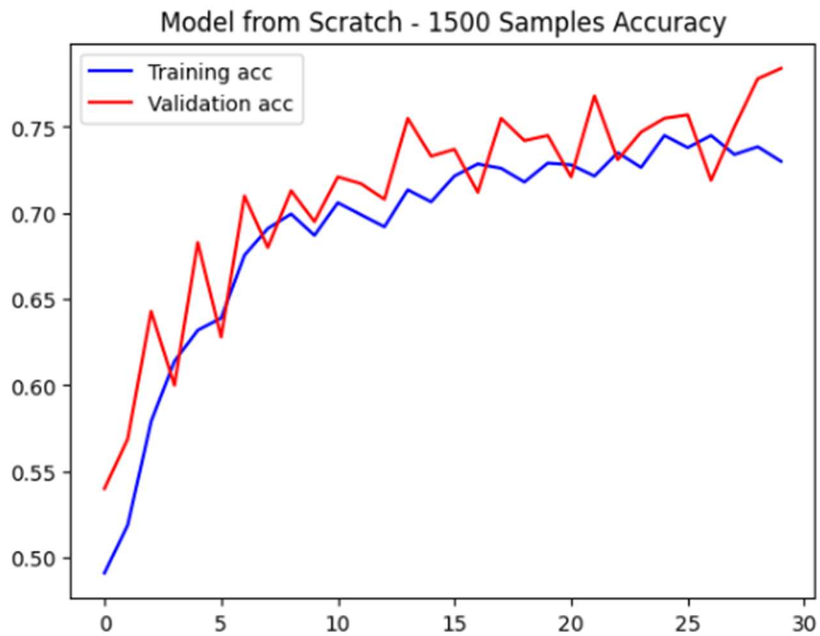
Goal: To use a small dataset of 1000 photos to train a CNN model from scratch.
Result: As a result, there were indications of overfitting and the model performed moderately. Although efforts were made to regularize, the validation accuracy was lower than anticipated.
Technique used: To lessen overfitting, dropout layers and data augmentation were used.

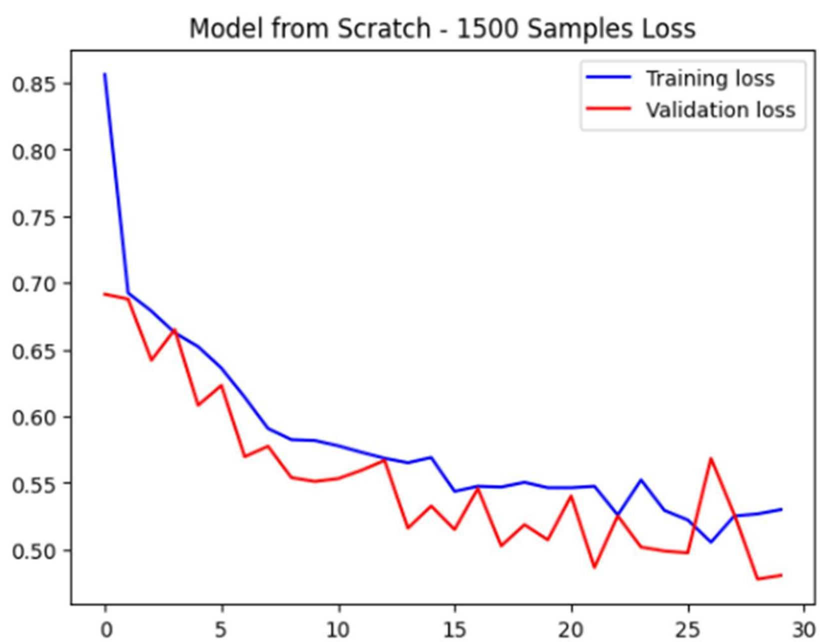




EXPERIMENT-2: Training with a Small Dataset from Scratch

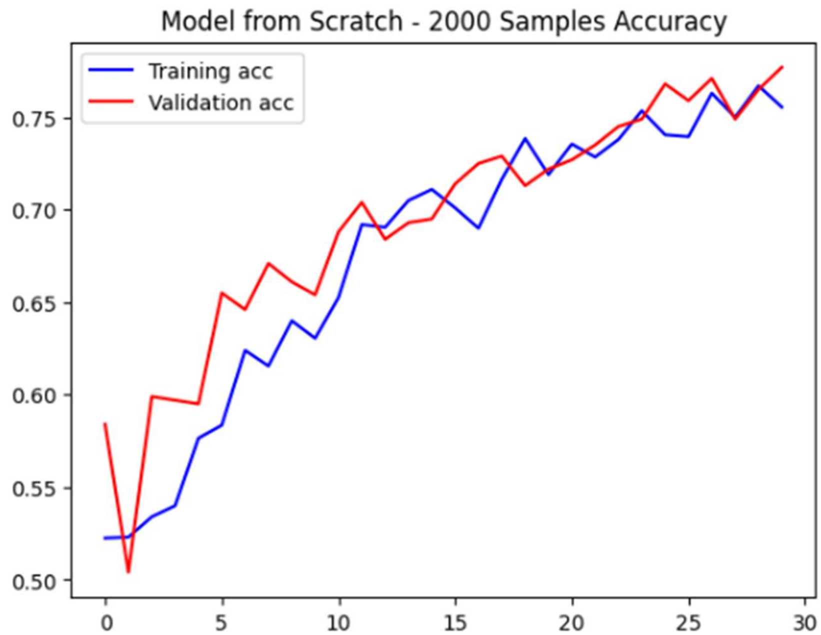
Goal: To see how a scratch-trained CNN performs when the training dataset is increased to 1500.
Result: The model demonstrated considerable gains in accuracy and generalization with additional training samples. Less overfitting resulted in more steady training.
Technique used: The same CNN architecture and augmentation approaches were applied to a larger dataset.

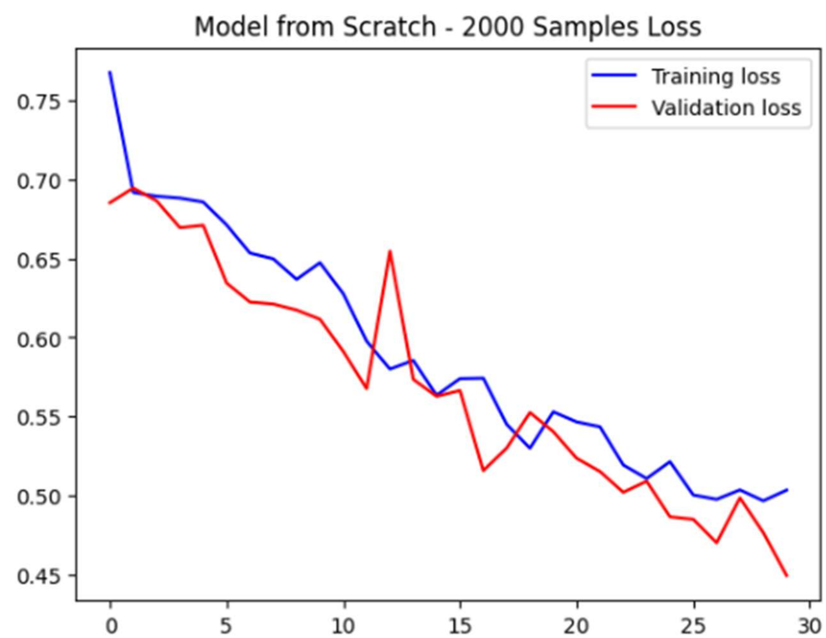




EXPERIMENT-3: Optimal training sample size from Scratch

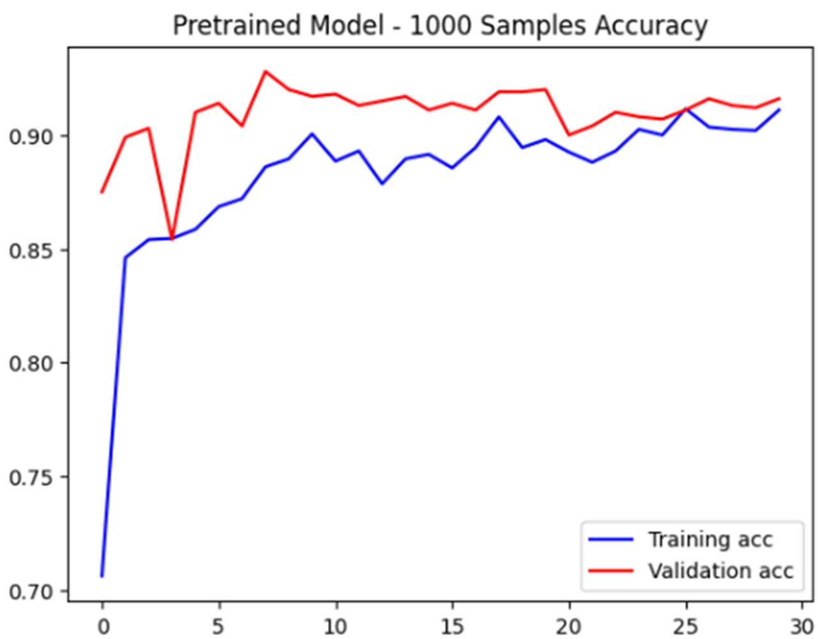
Goal: To find the Optimal training sample size for a scratch-trained model while balancing overfitting and performance is the aim of this study.
Result: The model's peak performance was achieved at the ideal dataset size. After that, training time rose, and accuracy gains were negligible.
Method: Consistent model structure and regularization were assessed over a range of training sizes.

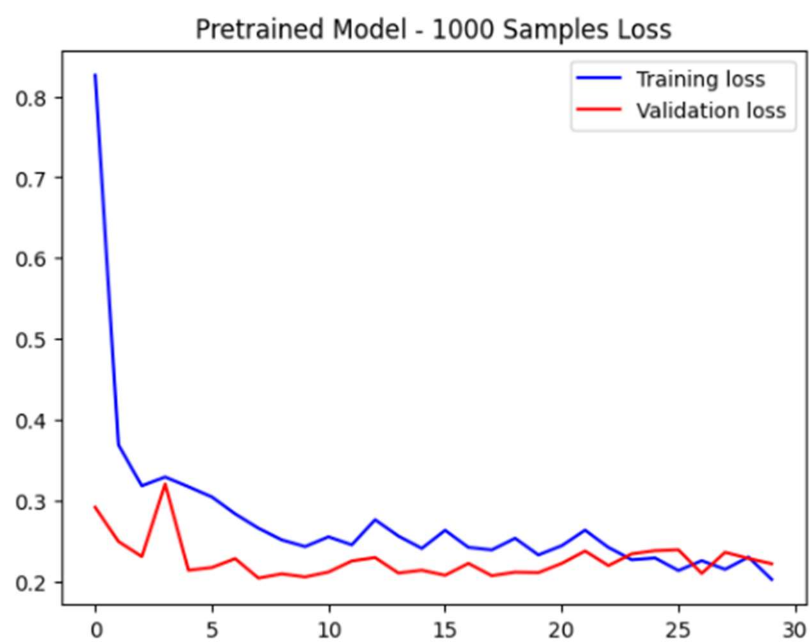




EXPERIMENT-4: Network Pretrained (Small Dataset)

Goal: To assess pretrained CNN's performance on a short dataset consisting of 1000 photos.
Result: The pretrained model outperformed the scratch-trained one by demonstrating superior generalization and high accuracy.
Method: Custom dense layers were placed on top of a frozen pretrained base (such as VGG16).





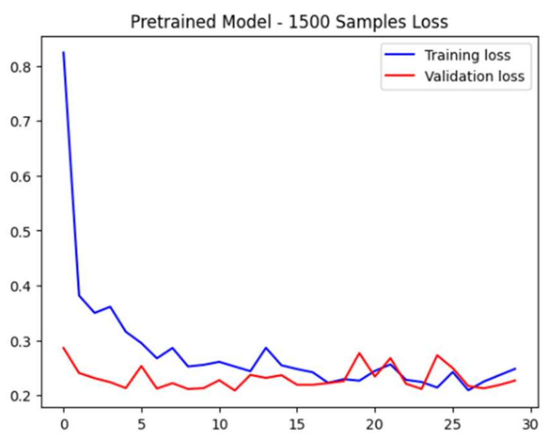
EXPERIMENT-5:

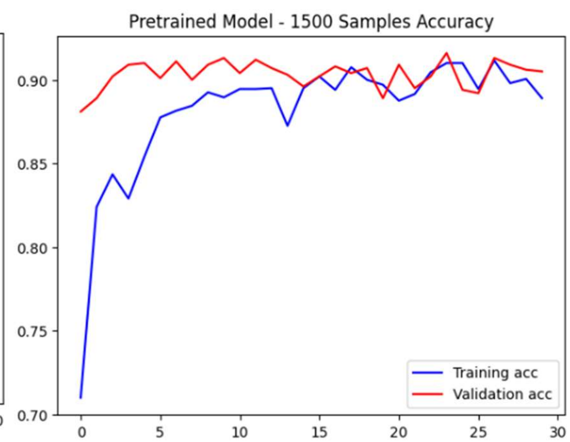
Network Pretrained with Different Sample Sizes (1500 and 2000)

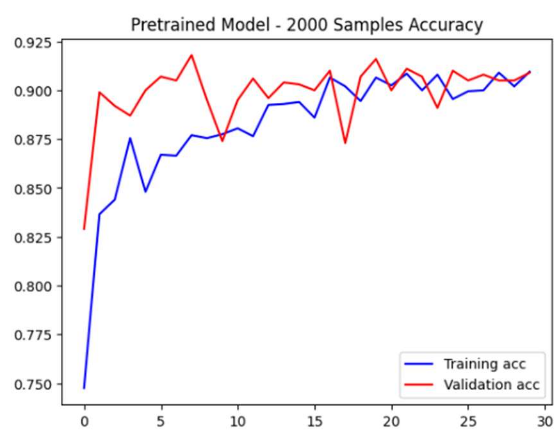
Goal: The goal is to investigate the effects of varying sample sizes on pretrained models.

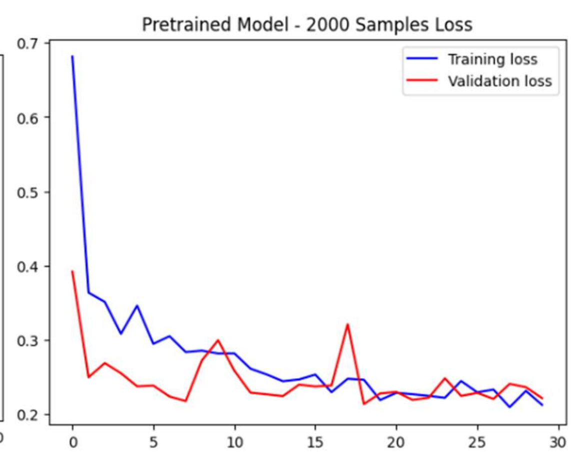
Result: Despite using less data, the pretrained model continuously delivered strong results. Results on larger datasets were further enhanced by fine-tuning.

Method: The method employed was transfer learning combined with regularization and fine-tuning of certain convolutional layers.







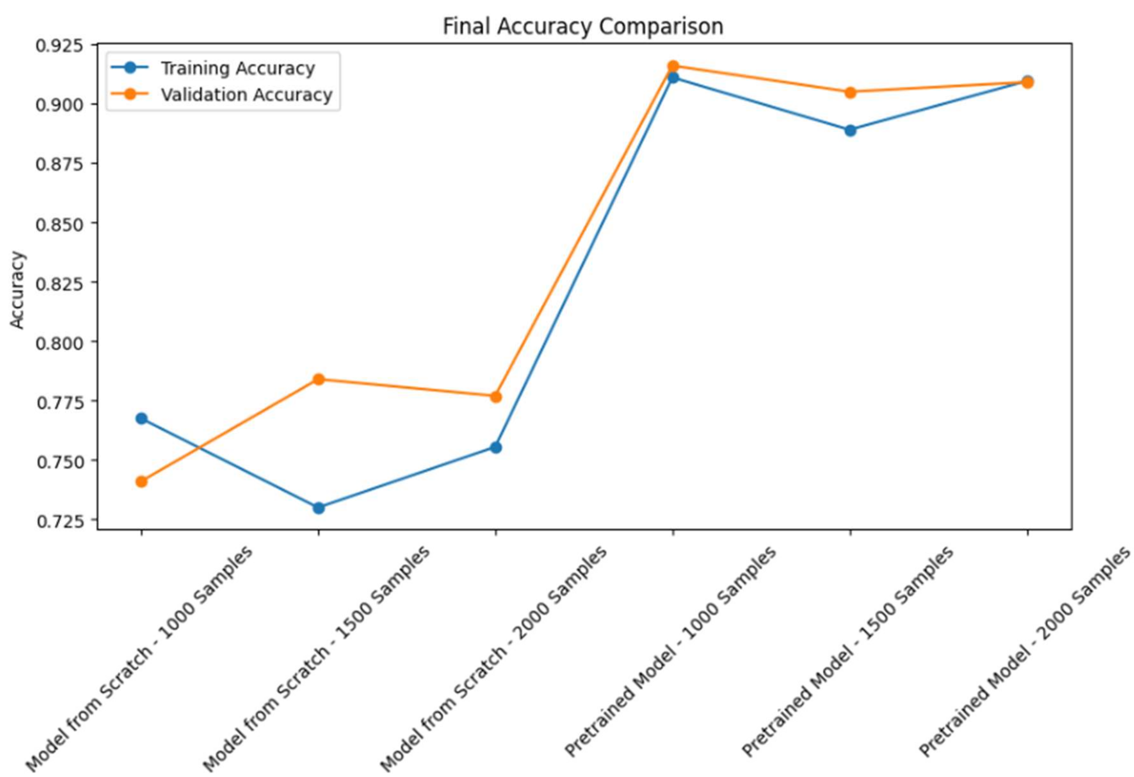


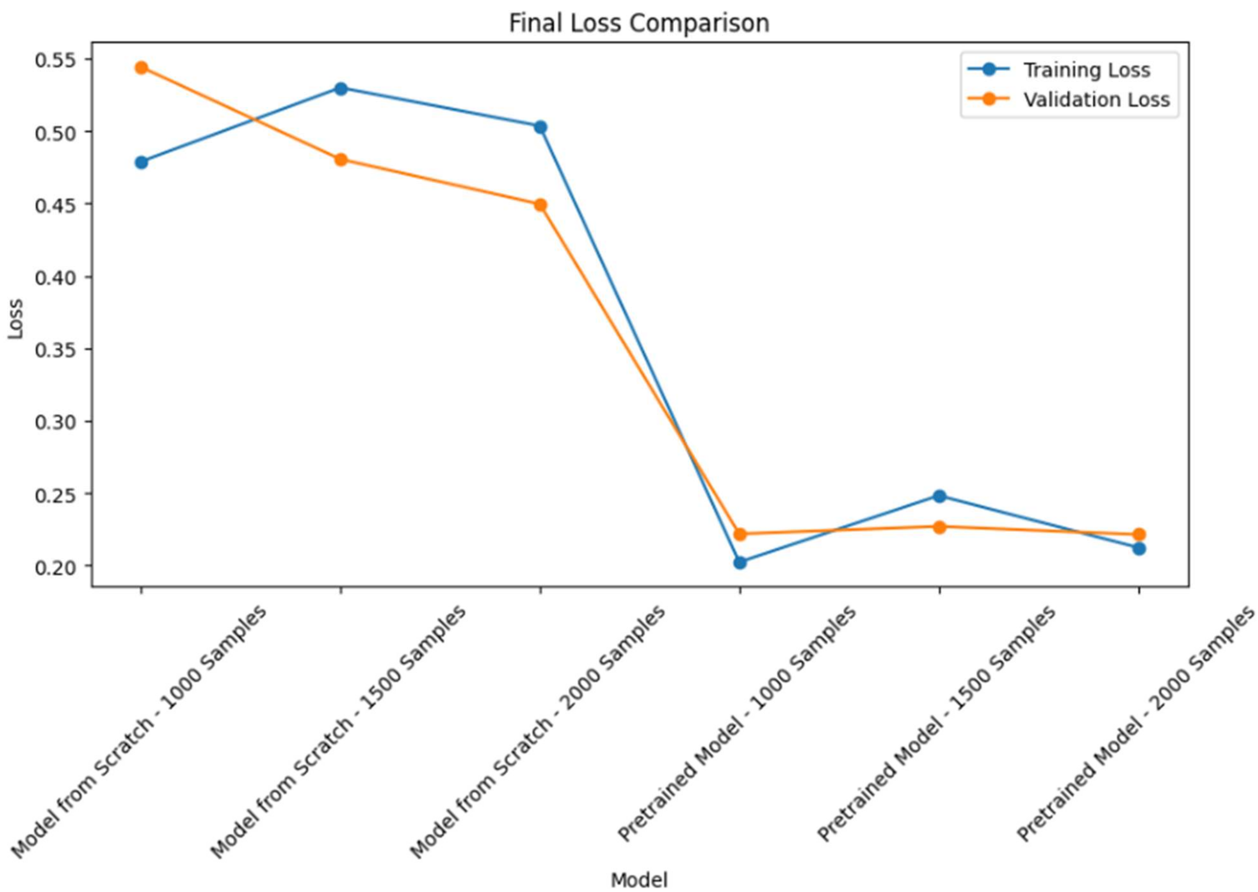
CONCLUSION:

The practical effects of model selection and training sample size on CNN performance for image classification were illustrated in this assignment. More data and work were needed for models that were trained from scratch to generalize effectively. Conversely, even with smaller datasets, pretrained models offered improved accuracy. Techniques for regularization and data augmentation were essential in the fight against overfitting. Overall, transfer learning turned out to be more reliable and effective, particularly in situations with little data.

FINAL THOUGHTS:

Scratch-trained models performed better when the dataset size was increased, but this came at the cost of increased computation and training time. Pretrained models required fewer resources to reach high accuracy and demonstrated great baseline performance. When new data became available, pretrained models could be fine-tuned to achieve even greater results. Model robustness was increased across all configurations with the use of data augmentation. The secret to getting the best results is striking a balance between training approach, data availability, and model complexity.




Final Loss Comparison
Training Loss
Validation Loss
Loss
0.55
0.50
0.45
0.40
0.35
0.30
0.25
0.20
Model from Scratch - 1000 Samples
Model from Scratch - 1500 Samples
Model from Scratch - 2000 Samples
Pretrained Model - 1000 Samples
Pretrained Model - 1500 Samples
Pretrained Model - 2000 Samples
Model

FINAL SUMMARY:

Multiple dataset sizes were used to test pretrained and scratch training methods. Training from scratch performed well on larger datasets but poorly on smaller ones. Pretrained models performed better every time, providing more efficiency and generalization. Reducing overfitting, data preparation, augmentation, and dropout were crucial. According to the results, transfer learning is the best strategy for handling small amounts of data in picture classification tasks.

Model Type (Scratch/Pretrained Model)	Sample Sizes	Training Accuracy	Validation Accuracy	Training Loss	Vallidation Loss
From Scratch	1000	0.7625	0.7480	0.4959	0.4952
From Scratch	1500	0.7065	0.7450	0.5788	0.5232
From Scratch	2000	0.7475	0.7800	0.4990	0.4756
Pretrained Model	1000	0.9115	0.9130	0.2103	0.2318
Pretrained Model	1500	0.9075	0.9100	0.2180	0.2265
Pretrained Model	2000	0.8960	0.9130	0.2334	0.2114

KEY LEARNINGS:

Pretrained weights greatly aid deep learning models, particularly in situations with sparse data. To achieve similar outcomes, building models from scratch takes more effort, data, and tuning. Regularization and augmentation can help reduce overfitting, which is still a significant problem. The size of the dataset and the resources available determine the best training approach. The significance of review and experimentation in deep learning workflows was reaffirmed by this assignment.

CODE OUTPUT: Link for the code PDF