Assignment-2

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Introduction:

Image categorization, a key task in the field of computer vision, has a wide range of uses, from diagnosing medical images to operating self-driving cars. CNNs have a reputation for excelling in various datasets and are particularly adept at image classification tasks due to their high performance. Nevertheless, CNN's performance can be greatly impacted by factors such as data quality, sample size, and network architecture. Thus, this research examines the impact of these variables on the enhancement of image classification models.

Context:

Deep learning models, particularly CNNs, have shown great performance in image categorization. Usually, to prevent overfitting and get good results, training Convolutional Neural Networks (CNNs) from the beginning demands a substantial labeled dataset. When there is a lack of labeled data, transfer learning methods like pretrained networks can help by leveraging information from bigger datasets. Understanding how the size of the training data relates to the choice of network architecture is essential for successful implementation of these models in real-world scenarios.

Approach:

In this study, we investigated how changes in sample size and network selection affect performance in image classification assignments. In the beginning, a basic CNN structure was utilized because it was anticipated to be simpler to teach. A dataset consisting of 1,000 images was utilized, with 500 images allocated for training and 500 for validation. Overfitting was reduced by implementing strategies such as enlarging the dataset and applying data augmentation techniques. Afterwards, the dataset increased in size, and modifications were made to the network architecture.

We also tested different training datasets to find the best input size for accurate predictions. A pretrained model, VGG16, was used to evaluate the difference in performance between training from the beginning and using a pretrained network.

Results and Findings:

Training from Scratch:

The CNN trained from scratch performed reasonably well with a small dataset of 1,000 images, with data augmentation playing a key role in minimizing overfitting. Increasing the training dataset size further improved performance, underscoring the significance of sample size when training CNNs from scratch.

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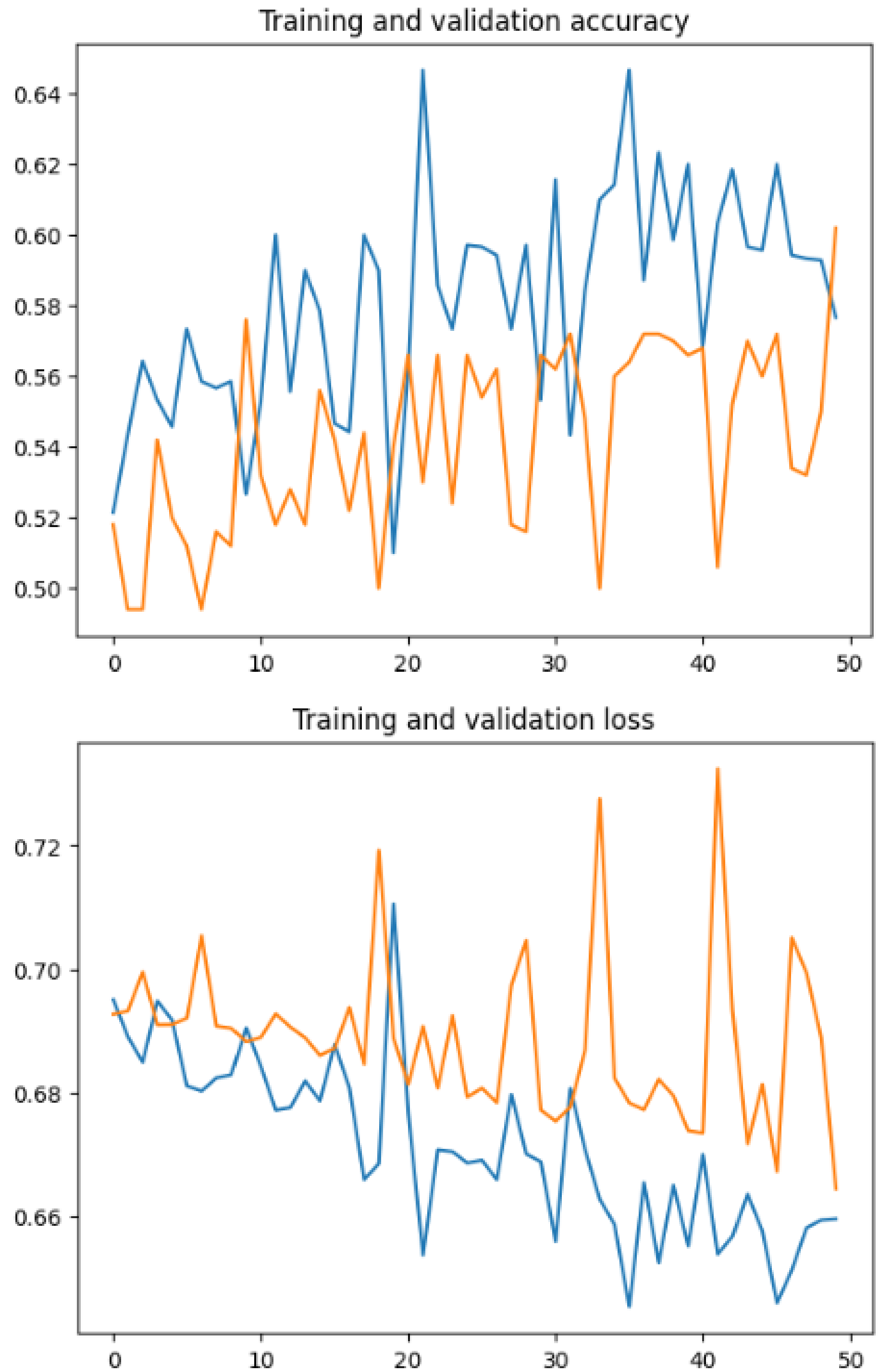


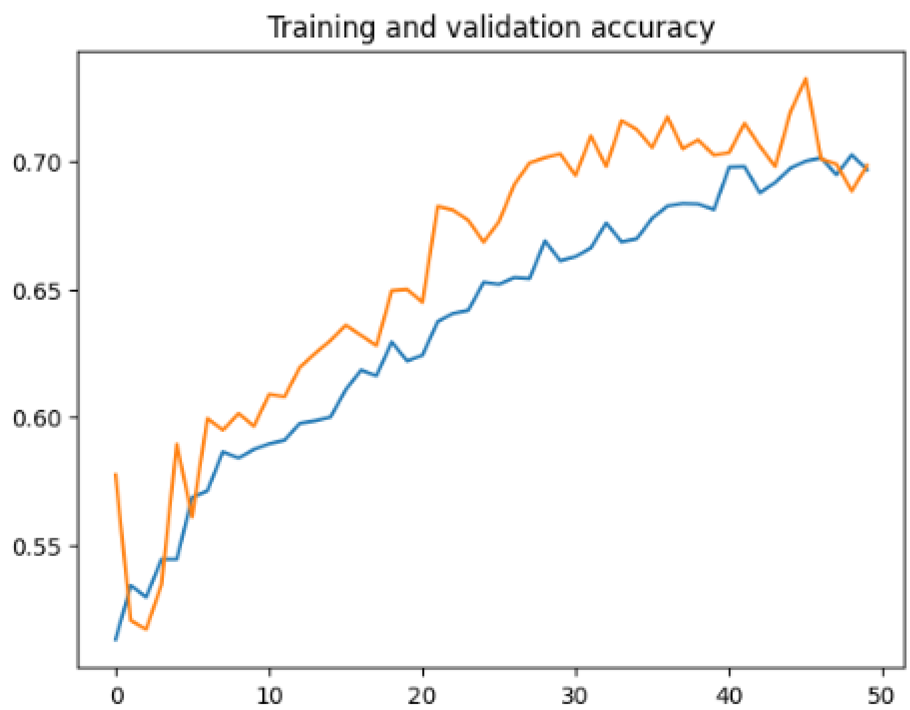
CNN for 1000 samples

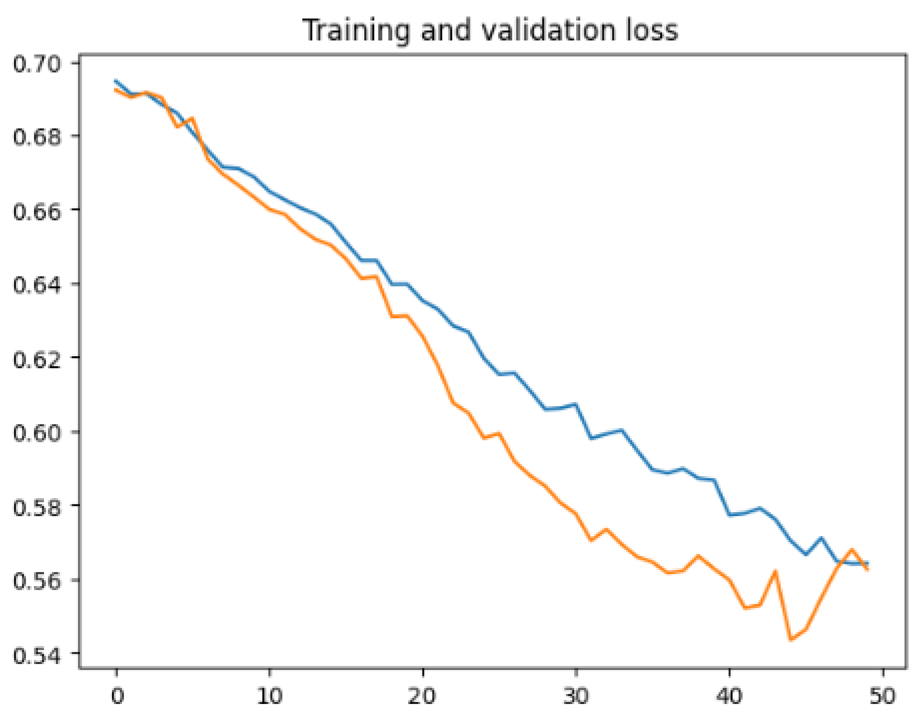
Optimal Training Sample Size:

Through experimentation, we determined the optimal dataset size for achieving the best prediction results. A balance between a sufficiently large dataset, moderate model complexity, and appropriate regularization techniques yielded the most effective results in preventing overfitting.

Pretrained Network:

From a performance perspective, the VGG16 pretrained model outperformed the model trained from scratch with limited data. The model's accuracy was fine-tuned with our dataset, illustrating the effectiveness of transfer learning in cases where labeled data is limited.





VGG Accuracy and Loss for 1000 samples

Sno.	Method	Training size	Training accuracy	Validation Accuracy	Test Accuracy
1	Training from Scratch	1000	58.4	60.2	61

2	After Augmentation	1000	65.64	59.2	60.33
3	Optimizing the model	5000	70.3	68.2	65.66
4	With augmentation	5000	76.55	73.40	70.9
5	VGG16 Pretrained Model	1000	85.45	87	85.66
	Augmentation	1000	87	88	87.5
6.		5000	86.96	89.60	88.33
7		10000	86.5	91.15	91.8

Conclusion:

This study highlights the importance of both training sample size and network architecture in image classification. With sufficient data and proper regularization, CNNs can deliver strong results, although transfer learning with pretrained models proves to be an effective alternative when data is limited. Understanding the interaction between these components allows for the design of models that balance performance with the availability of data and computational resources. Future research could explore new optimization techniques and network architectures to enhance classification accuracy across various datasets and applications.