**CONVOLUTIONAL NEURAL NETWORKS ASSIGNMENT REPORT**

**INTRODUCTION**

This report delves into the use of Convolutional Neural Networks (CNNs) for the classification of a Cats and Dogs dataset. Two primary methodologies were compared: developing CNNs from scratch and employing pretrained networks. The core aim was to understand the impact of training sample size on model efficacy, particularly focusing on the challenges of overfitting in smaller datasets. Techniques such as data augmentation and regularization were employed to optimize model performance.

**PROCEDURE**

Our experimental approach involved creating and evaluating multiple models under varied conditions. For models built from scratch, we experimented with different training sizes to observe the impact on overfitting and generalization. In the case of pretrained models, we leveraged a well-established architecture, ResNet-50, pre-trained on ImageNet. We compared the performance of these models using metrics like validation accuracy and loss, focusing on how increasing the training dataset size influences these metrics.

**SCRATCH MODELS RESULTS**

The models built from scratch were evaluated under three different training sizes. The findings were as follows:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | Training Size | Validation Size | Test Size | Validation Accuracy | Validation Loss |
| 1 | 1000 | 500 | 500 | 66.00% | 0.6600 |
| 2 | 5000 | 500 | 500 | 69.00% | 0.5687 |
| 3 | 10000 | 500 | 500 | 72.60% | 0.5489 |

* **Models with Smaller Training Sets**: We noticed that models trained with fewer data (1000 samples) were prone to overfitting, as reflected in their lower validation accuracy.
* **Improvement with Larger Datasets**: Increasing the dataset size to 5000 showed a slight improvement in performance, indicating that larger datasets help in generalization. However, the most significant improvement was noted with 10000 samples, suggesting a direct correlation between dataset size and model accuracy.

**PRETRAINED MODELS RESULTS**

Leveraging the power of transfer learning, we employed the model, pretrained on ImageNet, and observed the following:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | Training Size | Validation Size | Test Size | Validation Accuracy | Validation Loss |
| 4 | 1000 | 500 | 500 | 78.40% | 0.4456 |
| 5 | 5000 | 500 | 500 | 82.20% | 0.4119 |
| 6 | 10000 | 500 | 500 | 83.60% | 0.3840 |

* **Effectiveness of Pretrained Models**: Pretrained models consistently outperformed scratch models across all training sizes. This highlights the advantage of using networks that have already learned robust features from a large and diverse dataset.
* **Scaling Training Data**: Similar to scratch models, an increase in training data size improved the pretrained model's accuracy. The jump in performance was more pronounced with pretrained models, emphasizing the synergy between large datasets and advanced network architectures.

**OBSERVATIONS AND ANALYSIS**

* **Training Size and Overfitting** -One of the critical observations from this study is the inverse relationship between training size and overfitting. Models trained with limited data struggled to generalize, whereas larger datasets substantially mitigated this issue.
* **Pretrained Networks as a Robust Solution**- The superiority of pretrained models in handling overfitting and achieving higher accuracy was evident. This underscores the effectiveness of transfer learning, particularly in scenarios with limited training data.
* **Data Augmentation and Regularization** - The application of data augmentation and dropout techniques played a significant role in improving model performance, especially for models built from scratch. These strategies were pivotal in enhancing the models' ability to generalize to new data.

**SUMMARY**

In conclusion, this study reinforces the significance of training sample size in the development of effective CNN models for image classification. It demonstrates the pronounced benefits of using pretrained networks, particularly in combating overfitting and improving predictive accuracy. The results underline the importance of choosing the right model architecture and dataset strategy, providing valuable insights for similar image classification tasks.