Advanced Machine Learning Assignment 3

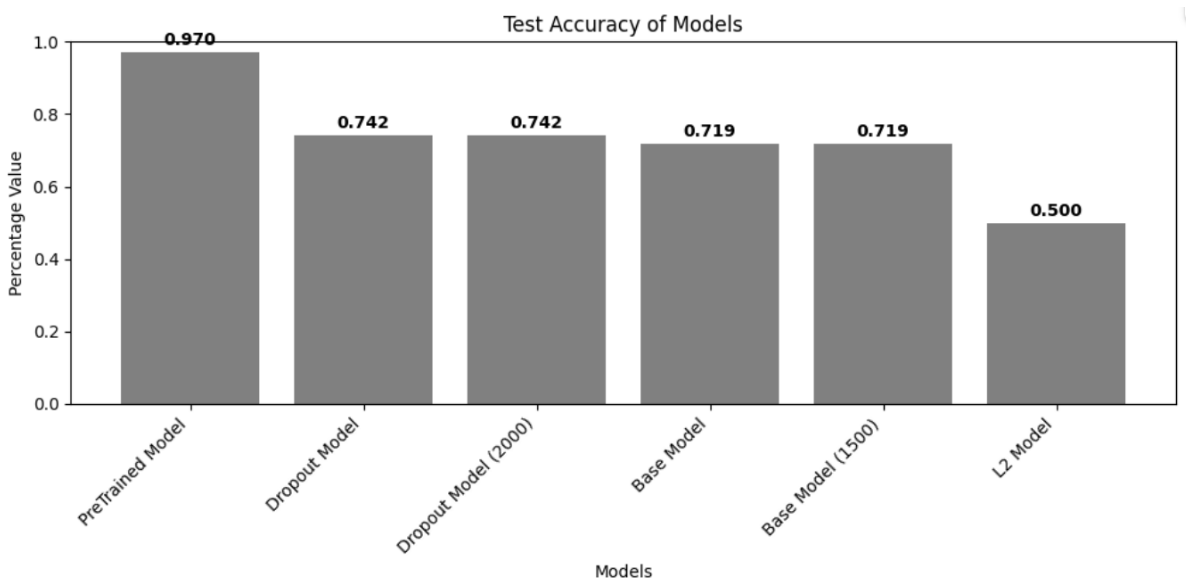
Convolution

(Arcot Balraj Tanmaiyee | tarcotba@kent.edu | 811321962)

Overall Summary

The general synopsis displays models with varying setups and training techniques. The baseline models, which served as the basis for comparison, were trained using 1000 and 1500 images, respectively. In order to reduce overfitting during training, the dropout models, which were applied to 1000 and 2000 pictures, included a 50% dropout rate. Additionally, to manage model complexity and avoid overfitting through weight penalization, an L2 regularization model was employed to train on 1000 photos.

Model	Training Image count	Training Accuracy	Validation Accuracy	Testing Accuracy
Base	1000	0.97	0.73	0.72
Dropout	1000	0.81	0.69	0.74
L2	1000	0.48	0.50	0.50
Model 2	1500	0.97	0.77	0.72
Model 3	2000	0.98	0.79	0.74
Pretrained	Same	0.98	0.97	0.97



In this study comparing CNN models for classifying images of cats and dogs, performance was generally enhanced by increasing training data. The pretrained VGG16 model demonstrated greater accuracy across all measures (training, validation, and testing). Dropout regularization prevented overfitting to a modest extent, however L2 regularization severely hindered model performance. The findings show the trade-offs between regularization strategies and training data size in order to achieve optimal model performance, and they emphasize the value of pretraining and fine-tuning for picture classification tasks, particularly when training data is few.

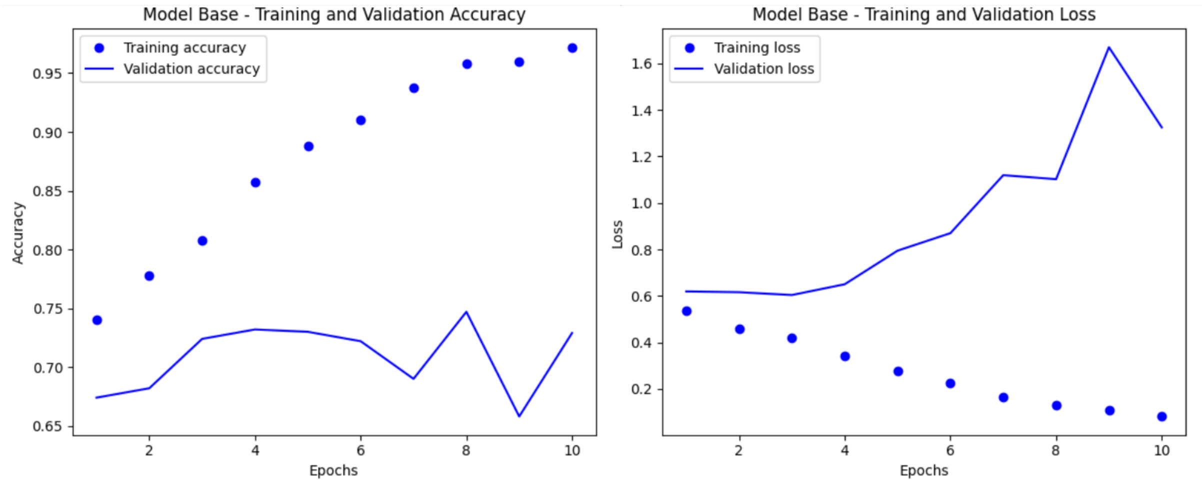
Analysis

Model 1:

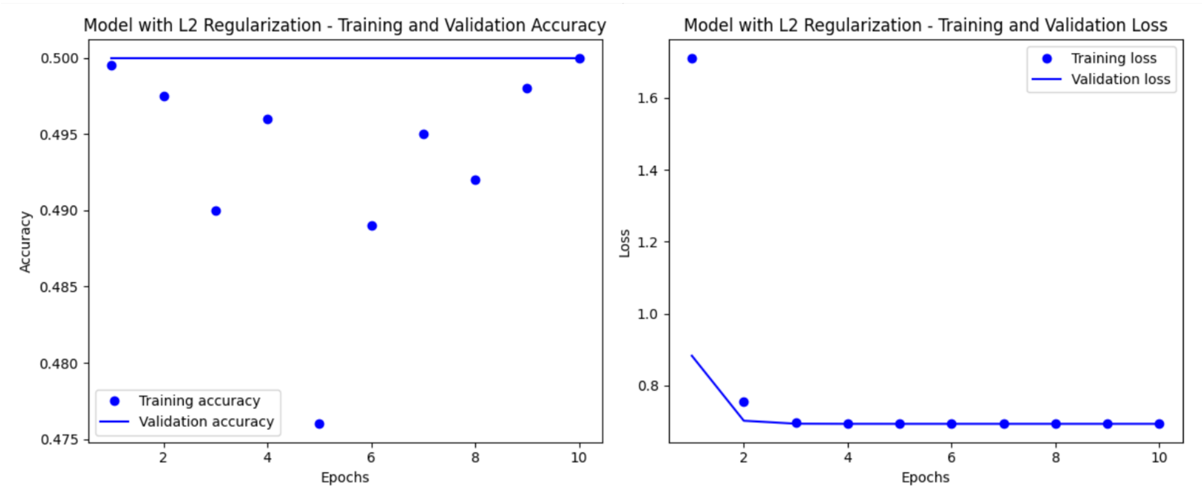
Model with initially a training sample of 1000, a validation sample of 500, and a test sample of 500. To reduce overfitting and improve performance, two techniques (Dropout and L2 Methods) are used and compared and the best performance is obtained.

Model	Training Image count	Training Accuracy	Validation Accuracy	Testing Accuracy
Base	1000	0.97	0.73	0.72
Dropout	1000	0.81	0.69	0.68
L2	1000	0.48	0.50	0.50

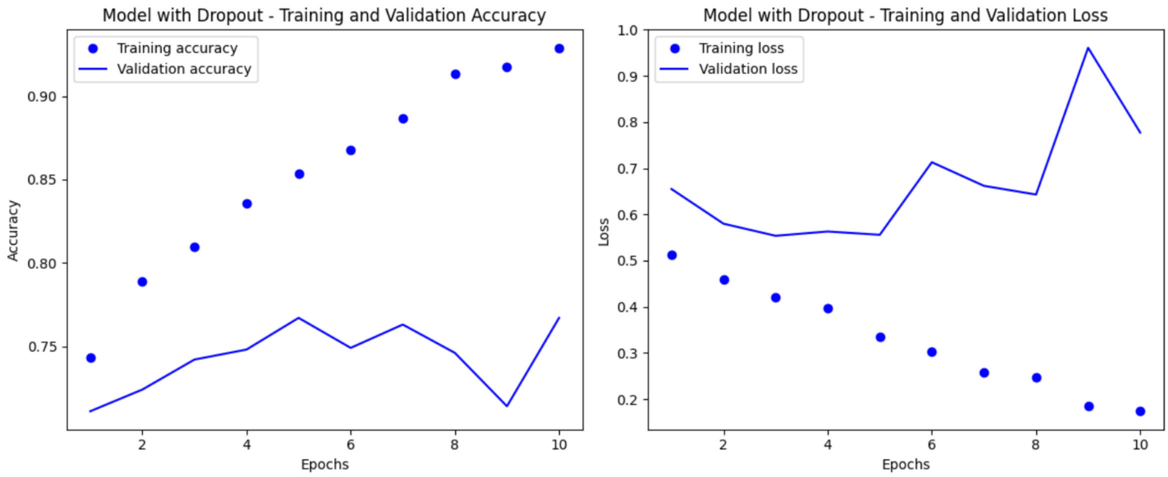
Base Model:



L2 Model:



Dropout Model:



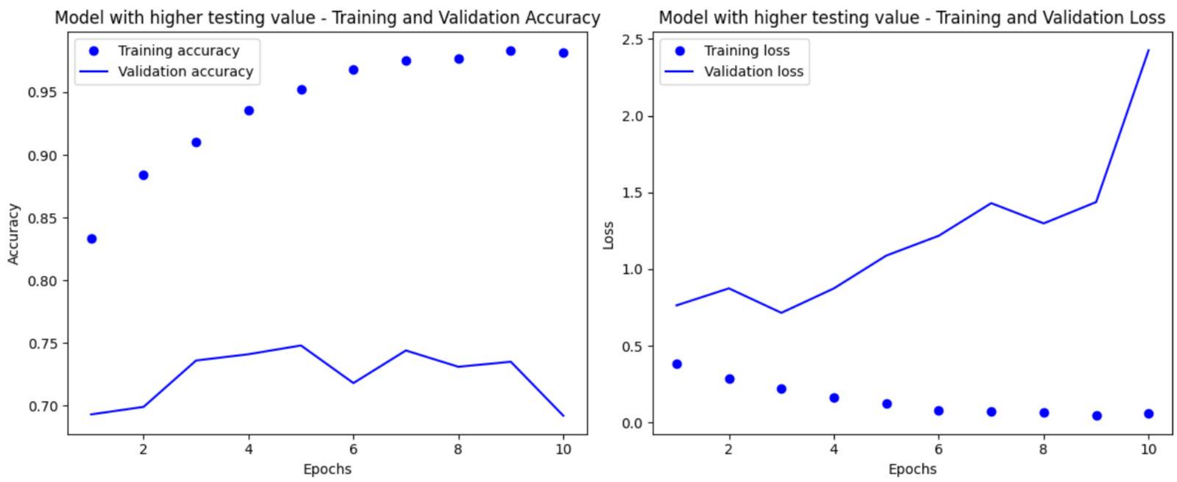
From the above figures and table, it is observed that, despite having the best training accuracy, the Base model had severe overfitting. Regularization helped Dropout avoid excessive overfitting and show greater generalization despite having reduced training accuracy. L2 regularization resulted in a notable decline in performance. Consequently, Dropout stands out as the best option among the three models because to its capacity to balance generalization and accuracy. This is true even though its accuracy in training and validation is lower.

Model 2: By increasing the training dataset to 1500

Increasing the training sample to 1500 while maintaining same validation and test sample sizes.

Model	Training Image count	Training Accuracy	Validation Accuracy	Testing Accuracy
Base	1000	0.97	0.73	0.72
Model 2	1500	0.97	0.77	0.72

Model with 1500 training image count:



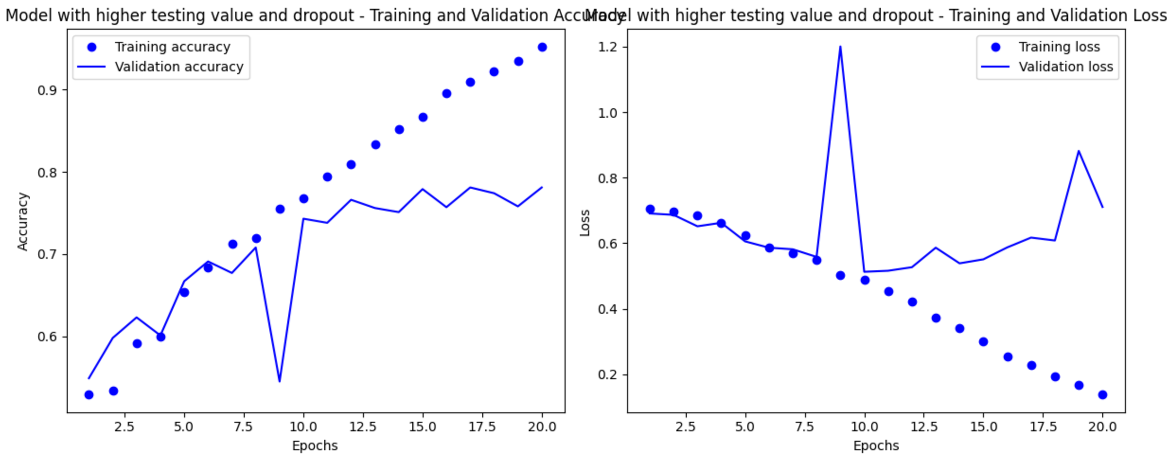
The model's accuracy on unseen test data stayed mostly unchanged despite the increased dataset, suggesting that the additional samples did not considerably improve generalization. This modest gain might be explained by the fact that the initial dataset size has already allowed the model's architecture to learn all of its features. It is also possible that the fresh samples were too close to the previous training set and did not provide enough variation to provide the model with much new information. These findings demonstrate that in order to achieve notable performance improvements and strong generalization capabilities in CNN-based image classification tasks, it is crucial to consider not only the quantity of training data but also model complexity and variety.

<u>Model 3: By increasing the training dataset to 2000</u>

Further more increasing the training sample by 500 i.e., model 3 has training sample of 2000.

Model	Training Image count	Training Accuracy	Validation Accuracy	Testing Accuracy
Base	1000	0.97	0.73	0.72
Model 2	1500	0.97	0.77	0.72
Model 3	2000	0.98	0.79	0.74

Model with 2000 training image count:



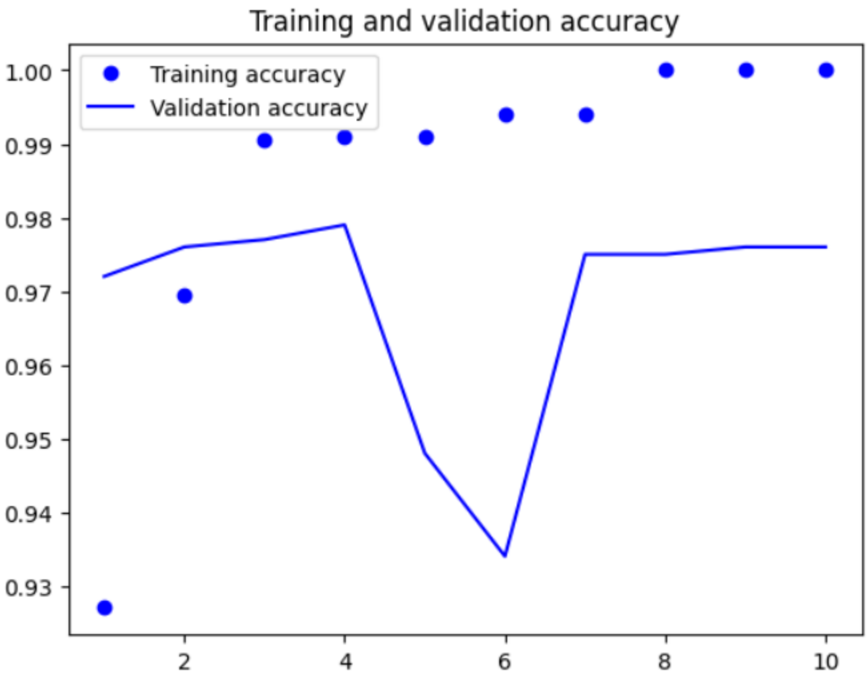
The advantages of using a larger training dataset are demonstrated by Model 3, which performs exceptionally well after being trained on 2000 photos. With the highest testing accuracy (0.74) and validation accuracy (0.79), it performs better than other models. This enhancement highlights how more training data improves model performance and generalization capabilities. The strong generalization demonstrated by Model 3's high validation accuracy suggests that it is less likely to overfit and is more likely to function well on fresh, untested data. Because of its higher accuracy and potential for generalization, Model 3 is the suggested option for this image categorization assignment.

Model 4: Pre-Trained Model

The model was trained using same sample size as in for step 3. Below are the results:

Model	Training Image count	Training Accuracy	Validation Accuracy	Testing Accuracy
Pre-Trained	Same as step 3	0.98	0.97	0.97

Pre-Trained Model:



With 2000 training samples, the pre-trained model has the highest accuracy (0.982). This result suggests that although pre-trained models function well with little data, their accuracy can be increased with additional samples, particularly for fine-tuning jobs. With training and validation accuracy closely matching, the pre-trained model showed little overfitting. This illustrates how long-lasting pre-trained models are at attaining high accuracy while reducing overfitting.

The pre-trained VGG16 model demonstrated a high accuracy of 0.974, continuously outperforming the from the other models because pre-trained models can leverage pre-existing feature representations to achieve outstanding performance with limited data, this demonstrates the advantage of transfer learning for small datasets. In conclusion, pre-trained model offers a notable performance advantage and ought to be preferred for small to moderate datasets.