Lab 6 Deep Learning: Reflections on transfer learning

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In this lab two approaches were built to solving the boat data classification problem, this was done by utilising a pretrained ResNet50 network. Firstly, the classification head of the network was modified and then fine-tuned. Fine-tuning the CNN allowed for a higher training accuracy overall than the default, model without fine-tuning. The method of fine-tuning was to unfreeze layers with the model to adapt more of its features to the specific data set. There must be a balance between frozen and unfrozen layers, as unfreezing too many with allow the model to overfit to the dataset. Firstly, all layers are frozen except the final fully connected layer. The results of this model, seen in Table I, will provide a base score to compare the fine-tuned models. The model has 4 layers with a final fully connected layer, the model is fine-tuned by unfreezing layer 4 with the results seen in Table II. As the results from this model were an improvement on the default model, layers 3 and 4 are unfrozen seen in Table III.

Metric	Value
Precision	0.72
Recall	0.74
F1-Score	0.72

TABLE I
WEIGHTED AVERAGE METRICS OF DEFAULT MODEL

Metric	Value
Precision	0.82
Recall	0.83
F1-Score	0.83

TABLE II
WEIGHTED AVERAGE METRICS OF MODEL WITH UNFROZEN LAYER 4

Metric	Value
Precision	0.87
Recall	0.87
F1-Score	0.87

TABLE III
WEIGHTED AVERAGE METRICS OF MODEL WITH UNFROZEN LAYER 3 AND 4

With the success of the accuracy of unfreezing layers, layers 2,3 and 4 are unfrozen. However, the learning rate is reduced to stop the data from overfitting while allowing for the model to adapt to the specific dataset. The ConvNet weights provide good performance and therefore lowering the learning rate will not distort them too quickly. The results are seen in Table IV.

Next, the model is attempted to be fine-tuned through the gradual unfreezing of layers. The fully connected layer will only be trained and then gradually the pretrained layers starting at layer 4 will be unfrozen while continuing training. By gradually unfreezing layers, it allows the model to adjust to the newly added fully connected layer before fine-tuning the existing features. This didn't work as well as previous models by Table V. Therefore the highest accuracy was seen by unfreezing layers 3 and 4 in Table III. Now a Support Vector Machine is trained to learn the boat classes using the features extracted by the ResNet50. A classification report was printed out, and the results are shown as weighted average metrics in Table VI.

Metric	Value
Precision	0.83
Recall	0.84
F1-Score	0.83

TABLE IV
WEIGHTED AVERAGE METRICS OF MODEL WITH ALL UNFROZEN LAYERS.

Metric	Value
Precision	0.71
Recall	0.74
F1-Score	0.71

TABLE V
WEIGHTED AVERAGE METRICS OF MODEL WITH GRADUAL UNFREEZING OF LAYERS

Metric	Value
Precision	0.92
Recall	0.92
F1-Score	0.92

TABLE VI
WEIGHTED AVERAGE METRICS OF SVM MODEL

From the results, it is shown that the SVM classifier using the features extracted outperformed any of the fine-tuned ResNet models. The precision, Recall and F1-Score were all higher. In addition, the speed of training the SVM classifier was a lot faster in comparison to training the data on 100 epochs. The SVM classifier can handle high-dimensional data and can be effective with feature representations, this makes SVM suited to a small dataset or limited resources. Whereas, the fine-tuned ResNet can learn dataset-specific features that could have been missed by the pre-trained model.

In reality, fine-tuning has the capability of achieving higher accuracy but at the cost of a longer training time and is ideal for larger datasets where the new task is substantially different from the original dataset.