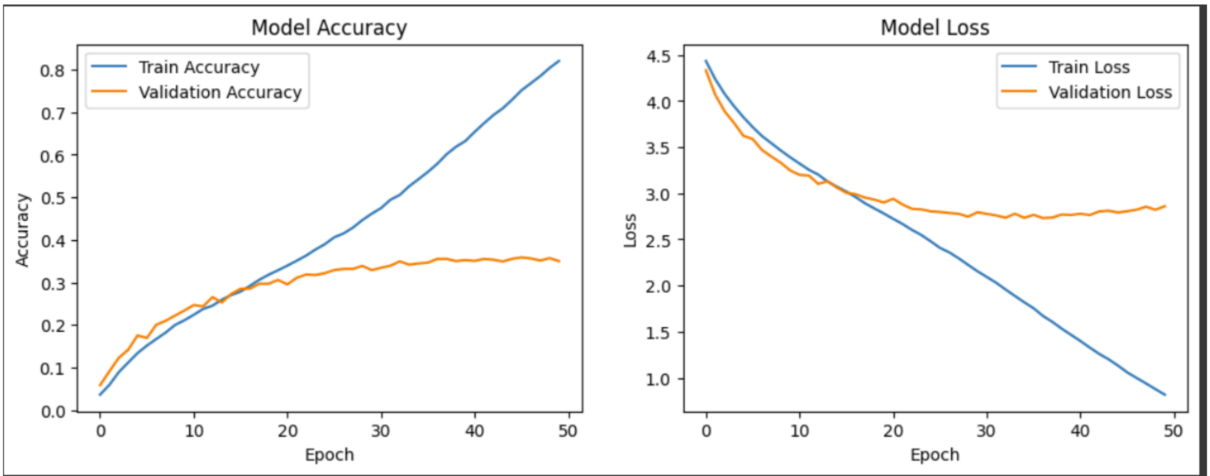
Assignment 4

Exercise 1

3.




```
313/313 - 4s - 13ms/step - accuracy: 0.3603 - loss: 2.8037
Test Accuracy: 0.3603000044822693
Test Loss: 2.8037221431732178
```

Training/Validation Accuracy and Loss Plot:

Training Accuracy: The accuracy improves across the epochs, starting from around 5% and reaching above 80%. This indicates that the model is learning effectively during training.

Training Loss: The loss decreases progressively, suggesting that the model is minimizing errors as it is trained.

Validation Accuracy: The validation accuracy increases quickly at the start but then it slows down. During the last epochs, it reaches a point (around 36%) where it does not improve any more than it already has and it stays approximately the same for the remaining epochs.

Validation Loss: The validation loss decreases quickly at the start but then it slows down. After around the 30th epoch, it reaches a point (around 2.8) where it does not decrease any more than it already has and stays approximately the same (maybe even a little worse) for the rest of the epochs.

4.

```
Classification Report:
              precision    recall  f1-score   support

    accuracy                           0.36     10000
   macro avg       0.38      0.36      0.36     10000
weighted avg       0.38      0.36      0.36     10000
```

<u>Classification Report</u>

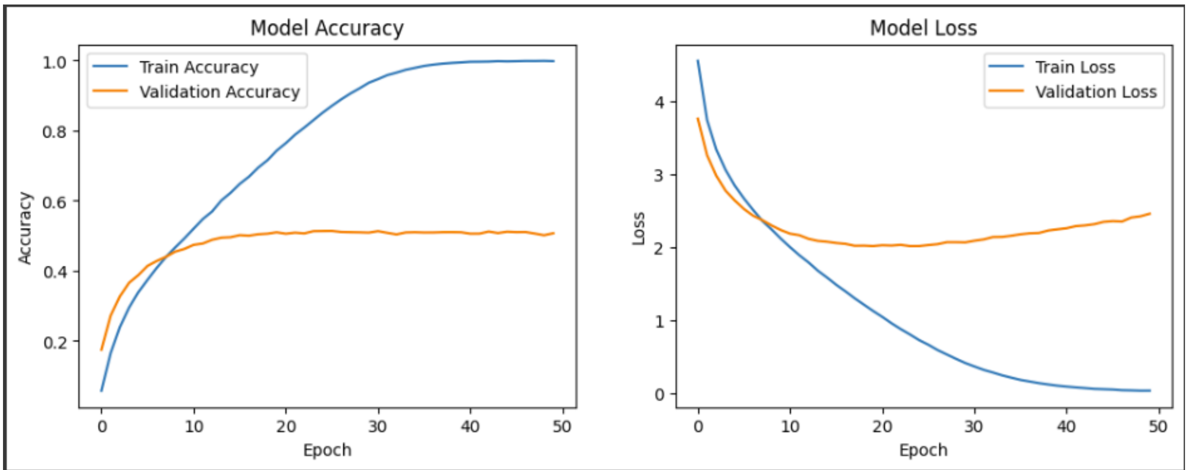
<u>Overall Accuracy:</u> The model achieved an accuracy of 0.36, indicating that 36% of the predictions were correct.

<u>Precision, Recall, and F1-Score:</u> The precision (avg) is at around 0.38, and the recall and f1-score (avg) are around 0.36.

<u>Support:</u> Each category has a support value of 10000, meaning the model was tested on 10000 instances per category.

<u>Exercise 2</u>

4.




```
313/313 - 2s - 8ms/step - accuracy: 0.5116 - loss: 2.4108
Test Accuracy: 0.5116000175476074
Test Loss: 2.410801887512207
```

<u>Training/Validation Accuracy and Loss Plot:</u>

<u>Training Accuracy:</u> The accuracy improves across the epochs, starting from around 5% and reaching above 95%. This indicates that the model is learning effectively during training.

<u>Training Loss:</u> The loss decreases progressively, suggesting that the model is minimizing errors as it is trained.

<u>Validation Accuracy:</u> The validation accuracy increases quickly at the start but then it slows down. After approximately the 20th epoch, it reaches a point (around 51%) where it does not improve any more than it already has and it stays approximately the same for the remaining epochs.

Validation Loss: The validation loss decreases quickly at the start but then it slows down. At around the 20th epoch, it reaches it best point (around 2.4) and then it slowly increases for the rest of the epochs.

5.

```
Classification Report:
              precision    recall  f1-score   support
```

```
    accuracy                           0.51     10000
   macro avg       0.53      0.51      0.51     10000
weighted avg       0.53      0.51      0.51     10000
```

Classification Report

Overall Accuracy: The model achieved an accuracy of 0.51, indicating that 51% of the predictions were correct.

Precision, Recall, and F1-Score: The precision (avg) is at around 0.53, and the recall and f1-score (avg) are around 0.51.

Support: Each category has a support value of 10000, meaning the model was tested on 10000 instances per category.

The improved test accuracy and the rest improved metrics of from the classification report show an improvement of this pre-trained model's (trained on ImageNet) performance in comparison to the previous model which was not pre-trained.

There are a lot of benefits when it comes to transfer learning, and they are:

1. Reduced Training Time

With transfer learning, we can start with a model pre-trained on a related task, which already has useful patterns and features learned.

2. Improved Performance with Limited Data

Transfer learning is highly beneficial when there's limited labeled data available for the target task. By leveraging knowledge from a larger, related dataset, models can achieve better performance, even when working with small, domain-specific datasets.

3. Higher Model Accuracy

Models that use transfer learning tend to achieve higher accuracy than those trained from scratch, especially in situations where the target task has similar characteristics to the original training data. This is because transfer learning leverages previously learned features that are often more robust than what would be learned from a small target dataset alone.

4. Adaptability Across Domains

Transfer learning enables easier adaptation of models across different domains. For instance, a model trained on natural image datasets can be adapted to medical imaging, as basic visual features (like edges, textures) are often useful across various types of image data.

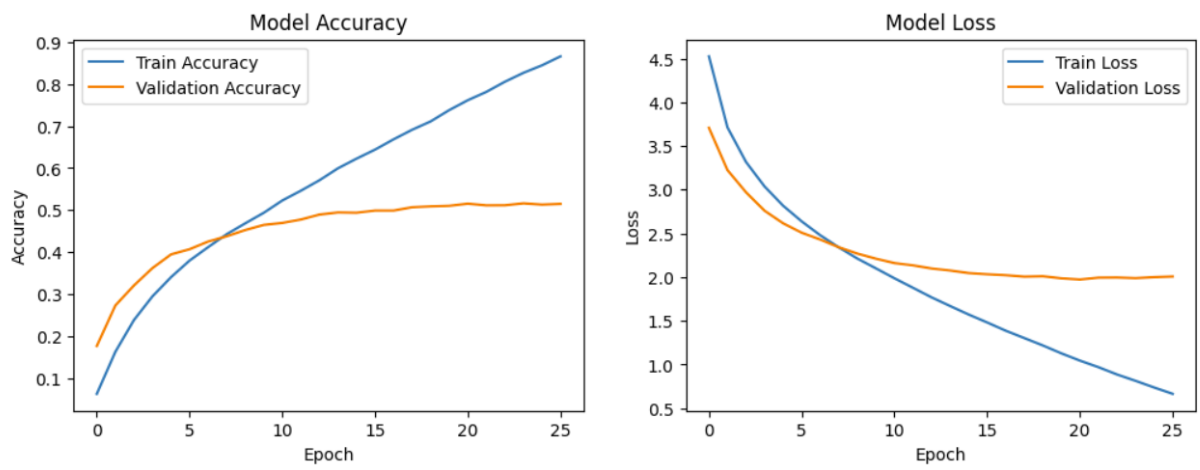
6. Scalable and Customizable

Transfer learning provides flexibility for creating customized models. By fine-tuning specific layers or parts of a network, practitioners can adjust models to different levels of specificity, making it a scalable approach that can cater to a variety of tasks.

The effect of these benefits can be seen when we compare the performance of the pre-trained model in exercise 2 to the model which was not pre-trained in exercise 1.

Exercise 3

3.




```
313/313 - 4s - 11ms/step - accuracy: 0.5265 - loss: 1.9407
Test Accuracy: 0.5264999866485596
Test Loss: 1.9407347440719604
```

Training/Validation Accuracy and Loss Plot:

Training Accuracy: The accuracy improves across the epochs, starting from around 5% and reaching above 85%. This indicates that the model is learning effectively during training.

Training Loss: The loss decreases progressively, suggesting that the model is minimizing errors as it is trained.

Validation Accuracy: The validation accuracy increases quickly at the start but then it slows down, reaching the best point of around 53% by the end of the model training.

Validation Loss: The validation loss decreases quickly at the start but then it slows down, reaching its best point of around 1.94 by the end of the training.

Classification Report:

	precision	recall	f1-score	support
accuracy			0.53	10000
macro avg	0.53	0.53	0.52	10000
weighted avg	0.53	0.53	0.52	10000

Classification Report

Overall Accuracy: The model achieved an accuracy of 0.53, indicating that 53% of the predictions were correct.

Precision, Recall, and F1-Score: The precision and recall (avg) is at around 0.53, and the f1-score (avg) are around 0.52.

Support: Each category has a support value of 10000, meaning the model was tested on 10000 instances per category.

The final test accuracy is 0.53, which is an improvement compared to the final test accuracy of the previous model that did not use early stopping, which was 0.51. An improvement can also be seen in the final test loss, as the final test loss for this model was 1.94, and for the previous model 2.41. The number of epochs completed with early stopping was 26, whereas without early stopping the number of epochs was 50. So early stopping saved 24 epochs and improved the models performance by stopping at its optimal point.

5.

Purpose of Early Stopping

The main purpose of early stopping is to detect the point at which a model's performance on the validation set stops improving and might start degrading due to overfitting. By stopping training early, we save computational resources and maintain the model's ability to generalize well to new data.

Benefits of Early Stopping

1. **Prevents Overfitting**: It stops training before the model starts fitting noise in the training data, which helps maintain generalization.
2. **Saves Time and Resources**: By stopping early, it reduces unnecessary training time and computational costs.
3. **Automated Model Optimization**: It allows the model to find an optimal stopping point without manual intervention, making it a practical tool in deep learning workflows.

These benefits can be seen in our case when we compare our model that uses early stopping with the model that does not. As we have already seen, early stopping saved 24 epochs and also improved the models performance by stopping at its optimal point, also preventing overfitting.