**Transfer learning**

Transfer learning is a machine learning technique that involves applying knowledge gained from one task to another related task in order to speed up the learning process, improve model accuracy, and enhance generalization performance. In traditional machine learning, training a new model often requires a large amount of data and computing resources. However, obtaining such resources can be difficult in practice, leading to high costs and training difficulties. Transfer learning can help overcome this challenge by leveraging existing models and data. There are three types of transfer learning:

1. Parameter-based transfer learning: uses the parameters of a pre-trained model as a starting point for the new model, accelerating the learning process.
2. Feature-based transfer learning: uses the learned features from a pre-trained model in a new model to improve generalization performance.
3. Model-based transfer learning: uses the entire pre-trained model in a new model to improve accuracy and generalization performance.

Transfer learning has several advantages, including:

1. It reduces training time and costs by utilizing existing models and data.
2. It enhances model accuracy and generalization performance, reducing overfitting and underfitting issues.
3. It solves the problem of data sparsity by using existing data to improve learning performance. In other words,transfer learning is well suited to small sample data, which is the case we are going to use in this article.

**Data Augmentation**

Data augmentation is a technique of generating new data by applying various transformations to the existing dataset. The goal is to increase the diversity and quantity of data, which can improve the performance and robustness of machine learning models. The common data augmentation methods we use are as follows.

1. Flipping: horizontally or vertically flipping images to create new ones. This method is often used in image classification, object detection, and other related tasks.
2. Cropping: cropping images into different sizes and positions to create new ones. This method is often used in image classification and object detection.
3. Scaling: scaling images by a certain ratio to create new ones. This method is often used in image classification and object detection.

In addition to the methods we use, common methods include rotation, translation, noise addition, contrast or colour adjustment, etc.

**Result and Evaluation**

1. **Evaluation Indicators**

**Test accuracy**: The proportion of correctly classified samples in the test set.

Test accuracy = (Number of Correct Predictions) / (Total Number of Predictions)

**Test recall:** The proportion of true positive samples among all samples that belong to a certain class.

Test Recall = (Number of True Positives) / (Number of True Positives + Number of False Negatives)

**Test loss:** The average loss of the model on the test set. During model training, we optimize the model by minimizing the loss function.

**Test precision**: The proportion of true positive samples among all samples that are predicted to belong to a certain class.

Test Precision = (Number of True Positives) / (Number of True Positives + Number of False Positives)

**F1 score**: A commonly used performance metric that combines both precision and recall into a single score. It is the harmonic mean of precision and recall, and it ranges from 0 to 1, with a higher score indicating better performance.

F1 score = 2 \* (Precision \* Recall) / (Precision + Recall)

1. **Test Results**