Summary

In this project, a new convolutional neural network will be created with computer vision challenges , keeping in mind. The dataset is a portion of the "Dog-vs-Cats" dataset that is accessible on Kaggle. Making an effective model is significantly difficult due to the limited amount of data provided. Convolutional neural networks, or "convnets," are a well-known deep learning model with a proven track record of performance in computer vision tasks. Their extraordinary ability to recognize and learn the spatial patterns found in images is what sets them apart from other systems.They are especially well suited for applications like picture identification, object detection, and segmentation because of this property. It is firmly believed that the "convnet" model can still produce satisfactory results despite the limitations imposed by the small amount of accessible data. This assurance is based on "convnets'" capacity to learn from small datasets and generalize well by identifying and recognizing pertinent visual features. Using the small dataset, the model is trained; it is then improved using transfer learning strategies, and its performance is evaluated using appropriate assessment criteria. The objective is to build a convolutional neural network that can identify photos from the "Dog-vs-Cats" dataset accurately and efficiently using a small quantity of training data. With a compressed size of 543MB, the Cats-vs-Dogs dataset has 25,000 photos that are equally split between dogs and cats. I downloaded and unzipped the dataset to produce a new one that had three subsets.1000 samples from each class make up the training set, 500 samples make up the validation set, and 500 samples make up the test set.The neural network's capacity needs to be increased because of the higher image size and the difficulty of the current challenge.This was accomplished by adding one extra level to the Conv2D + MaxPooling2D architecture. This will shrink the feature maps in order to prevent them from being too large when they reach the Flatten layer, in addition to enhancing network bandwidth. The size of the photographs is originally 150x150. Despite the fact that the input size chosen is somewhat arbitrary, it is appropriate for the current problem.

Steps for processing the image

• Transform the JPEG content into RGB pixel grids by decoding it.

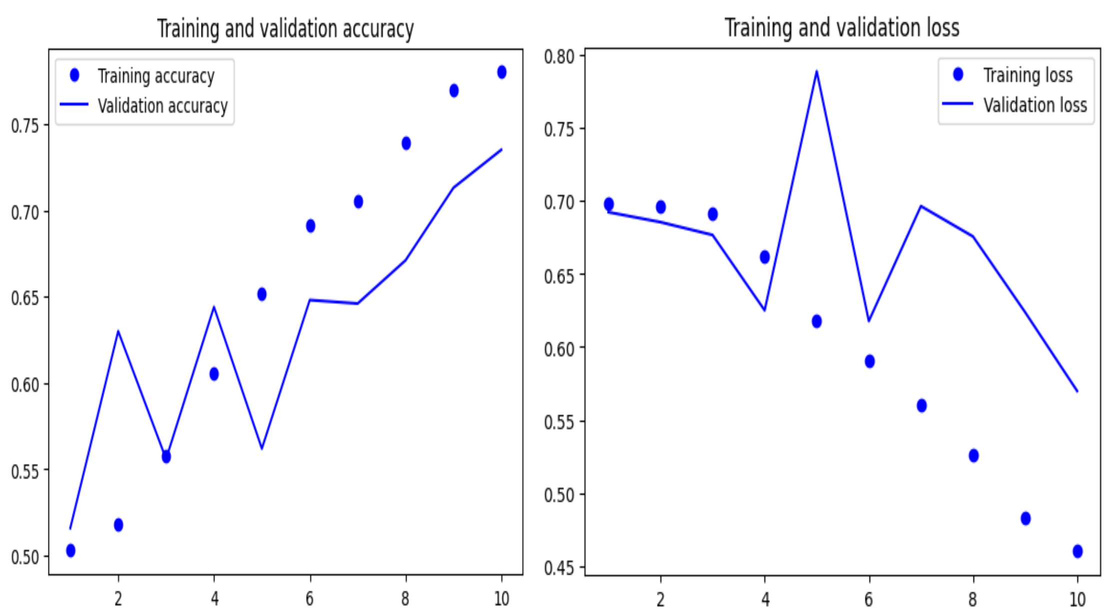
• Create floating-point tensors from these grids.

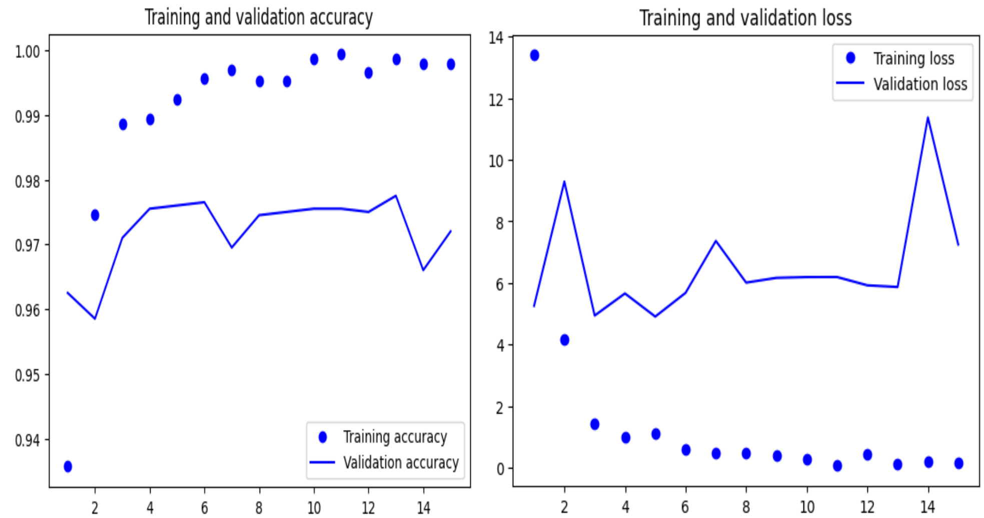
• To make sure the input values are within a range that is good for neural networks, this is done.

Techniques for data augmentation can be employed to improve the model's accuracy. When working with small datasets, data augmentation is a technique that enables accurate results. By using random transformations, it includes producing additional data from the available training examples. This method makes sure the model is exposed to a variety of images during training, which improves the model's capacity to generalize successfully.

A pre-trained network can be used as a general model and its features can be used for a wide range of computer vision applications if the original dataset was large and diverse. One of deep learning's main advantages over other machine learning methods is its capacity to transfer learnt characteristics across various tasks.

The results are as following





The findings demonstrate that models that regularly underwent data augmentation during training were unable to outperform those trained without it. By increasing the training set or decreasing the size of the validation set, the model's accuracy is further improved. When I compared the pre-trained model with and without data augmentation, I discovered Neither the model's accuracy nor its validation accuracy was raised. Usually, pre-trained models perform better overall than models developed from scratch, especially when training data.