# Self-Supervised SimCLR

## Selecting Model

Since training contrastive loss requires heavy computing and cannot be done on a single GPU stream, I imported SimCLR embeddings. As classifier I framed a 3 layered fully connected neural network and trained it by inputting the embeddings obtained after passing the images through the ResNet50 model.

## Training the model

Since we only need to train a simple classifier, overfitting isn’t much of an issue and can be easily avoided using image augmentations and dropout layers. Putting a dropout layer before the first Dense layer helps prevent overdependence on any of the 2048 features in the output of the ResNet50 model. Furthermore only 8 epochs are enough to obtain an optimum accuracy and minimum loss without overfitting on the train set.

# Auto Augmentation

Previous models on all datasets have almost exclusively used manual image augmentation which takes experience on data manipulation.

In SimCLR we have to apply two data augmentations on each image and calculate the loss based on the embeddings. Thus, choosing the right augmentation is going to be very important, choosing two augmentations that are very similar will lead to no learning as the embeddings generated will be inherently similar. At the same time, we do not want augmentations which will lead to starkly different embeddings as it will lead to a very vague and generalised final result. Therefore, in SimCLR if implemented properly auto augmentation can help increase the accuracy by a significant margin.

For datasets like MNIST or OCR detection purposes, image augmentations like image ratio manipulation, stretching and compressing will be very useful while colour shifts wont affect the efficiency much

On the other hand, image datasets which are used to classify objects and animals like ImageNet, stretching and compression should be restricted to a very small extent while augmentation should focus more on colour shifts and random cropping. Colour shift will prevent the algorithm from focussing on a given colour while cropping will prevent the algorithm from focussing on a specific feature of a given object/animal.

By training an automated image augmentation, we can make the algorithm itself determine which augmentation will help create the greatest increasing in the accuracy.

Augmentation will depend not only on the image subject but also image composition. Darkening an already dark image will lead to featureless images which will lead to no learning. This is an avenue where automated generator will give an advantage over manual augmentation