Deep Learning Course Project- Gesture Recognition

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Problem Statement

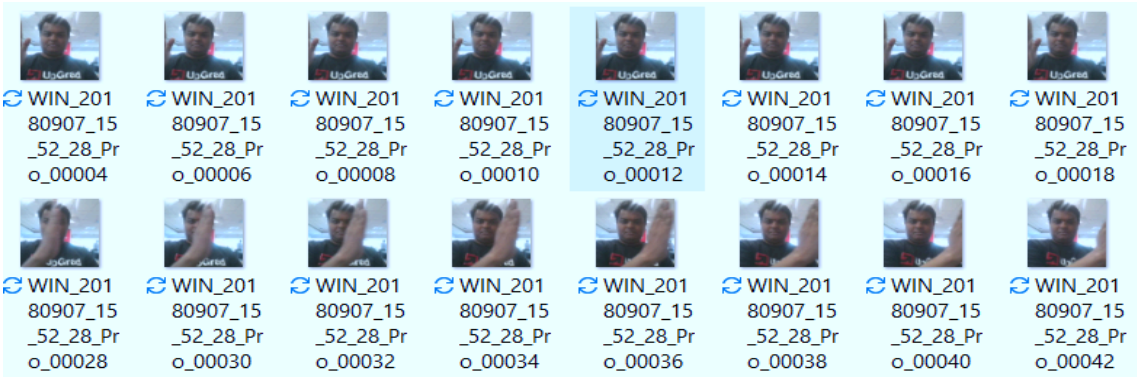
As a data scientist at a home electronics company which manufactures state of the art smart televisions. We want to develop a cool feature in the smart-TV that can recognise five different gestures performed by the user which will help users control the TV without using a remote.

- Thumbs up : Increase the volume.
- Thumbs down : Decrease the volume.
- Left swipe : Jump backwards 10 seconds.
- Right swipe : Jump forward 10 seconds.
- Stop : Pause the movie.

Here's the data:https://drive.google.com/uc?id=1ehyrYBQ5rbQQe6yL4XbLWe3FMvuVUGiL

Understanding the Dataset

The training data consists of a few hundred videos categorized into one of the five classes. Each video (typically 2-3 seconds long) is divided into a **sequence of 30 frames (images)**. These videos have been recorded by various people performing one of the five gestures in front of a webcam - similar to what the smart TV will use.



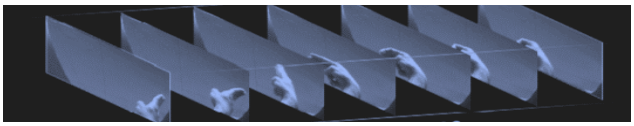
Objective

Our task is to train different models on the 'train' folder to predict the action performed in each sequence or video and which performs well on the 'val' folder as well. The final test folder for evaluation is withheld - final model's performance will be tested on the 'test' set.

Two types of architectures suggested for analyzing videos using deep learning:

1. **3D Convolutional Neural Networks (Conv3D)**

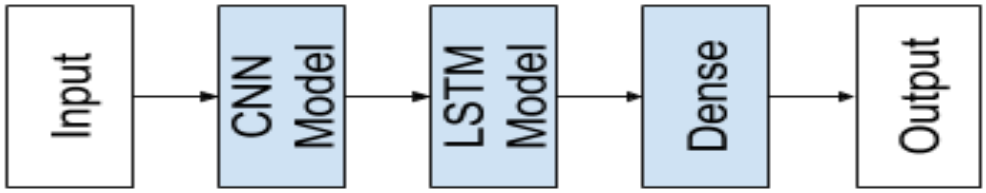
3D convolutions are a natural extension to the 2D convolutions you are already familiar with. Just like in 2D conv, you move the filter in two directions (*x* and *y*), in 3D conv, you move the filter in three directions (*x*, *y* and *z*). In this case, the input to a 3D conv is a video (which is a sequence of 30 RGB images). If we assume that the shape of each image is *100 x 100 x 3*, for example, the video becomes a 4D tensor of shape *100 x 100 x 3 x 30* which can be written as *(100 x 100 x 30) x 3* where *3* is the number of channels. Hence, deriving the analogy from 2D convolutions where a 2D kernel/filter (a square filter) is represented as *(f x f) x c* where *f* is filter size and *c* is the number of channels, a 3D kernel/filter (a *'cubic'* filter) is represented as *(f x f x f) x c* (here *c = 3* since the input images have three channels). This cubic filter will now *'3D-convolve'* on each of the three channels of the *(100 x 100 x 30)* tensor



30 frames….

2. **CNN + RNN architecture**

The *conv2D* network will extract a feature vector for each image, and a sequence of these feature vectors is then fed to an RNN-based network. The output of the RNN is a regular softmax (for a classification problem such as this one).

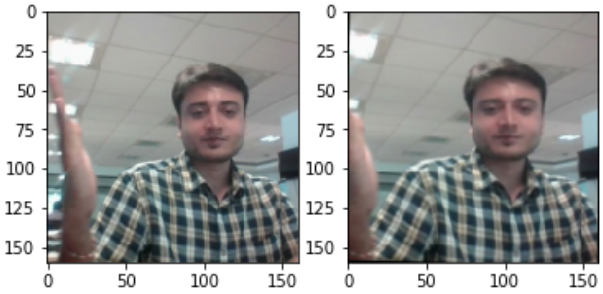


Data Generator

This is one of the most important parts of the code. In the generator, we are going to pre-process the images as we have images of 2 different dimensions (*360 x 360* and *120 x 160*) as well as create a batch of video frames. The generator should be able to take a batch of videos as input without any error. Steps like cropping, resizing and normalization should be performed successfully.

Data Pre-processing

- ***Resizing* and *cropping* of the images.** This was mainly done to ensure that the NN only recognizes the gestures effectively rather than focusing on the other background noise present in the image.
- ***Normalization* of the images.** Normalizing the RGB values of an image can at times be a simple and effective way to get rid of distortions caused by lights and shadows in an image.
- At the later stages for improving the model's accuracy, we have also made use of ***data augmentation***, where we have ***slightly rotated*** the pre-processed images of the gestures in order to bring in more data for the model to train on and to make it more generalizable in nature as sometimes the positioning of the hand won't necessarily be within the camera frame always.



CAUTION: It was taken into consideration that we don't rotate images to a greater extent as this would change the meaning of the gestures completely ☺ !!

NN Architecture development and training

- Experimented with different model configurations and hyper-parameters and various iterations and combinations of batch sizes, image dimensions, filter sizes, padding and stride length were experimented with. We also played around with different learning rates and *ReduceLROnPlateau* was used to decrease the learning rate if the monitored metrics (*val_loss*) remained unchanged in between epochs.
- We experimented with *SGD()* and *Adam()* optimizers but went forward with *Adam()* as it led to improvement in model's accuracy by rectifying high variance in the model's parameters. We were unsupportive of experimenting with *Adagrad()* and *Adadelta()* due to the limited computational capacity as these take a lot of time to converge because of their dynamic learning rate functionalities.
- We also made use of *Batch Normalization*, *pooling* and *dropout layers* when our model started to overfit, this could be easily witnessed when our model started giving poor validation accuracy in spite of having good training accuracy.
- *Early stopping* was used to put a halt at the training process when the *val_loss* would start to saturate / model's performance would stop improving.

Model Type	Result	Decision	Parameters
Conv3D frames_to_sample=30, batch_size=20, num_epochs=2	categorical_accuracy: 0.6244 val_categorical_accuracy: 0.1900	As we see from the above experiments image resolution and number of frames in sequence have more impact on training time than batch_size. We can consider the Batch Size around 15-40. We will change the resoulution 160*160, 120*120 according the model performance	Total Params: 687813
Conv3D frames_to_sample=30, batch_size=15, num_epochs=2	categorical_accuracy: 0.6893 val_categorical_accuracy: 0.1800		Total Params: 1736389
Conv3D frames_to_sample=16, batch_size=40, num_epochs=2	categorical_accuracy: 0.5897 val_categorical_accuracy: 0.2000		Total Params: 1117061

Further suggestions for improvement:

- **Using Transfer Learning**: Using a pre-trained *ResNet50/ResNet152/Inception V3* to identify the initial feature vectors and passing them further to a *RNN* for sequence information before finally passing it to a softmax layer for classification of gestures. (This was attempted but other pre-trained models couldn't be tested due to lack of time and disk space in the nimblebox.ai platform.)
- **Using GRU:** A *GRU* model in place of *LSTM* appears to be a good choice. Trainable Parameters of a *GRU* are far less than that of a *LSTM*. Therefore would have resulted in faster computations. However, its effect on the validation accuracies could be checked to determine if it is actually a good alternative over LSTM.
- **Deeper Understanding of Data:** The video clips where recorded in different backgrounds, lightings, persons and different cameras where used. Further exploration on the available images could give some more information about them and bring more diversity in the dataset. This added information can be exploited in favor inside the generator function adding more stability and accuracy to model.
- **Tuning hyperparameters:** Experimenting with other combinations of hyperparameters like, activation functions (*ReLU, Leaky ReLU, mish, tanh, sigmoid*), other optimizers like *Adagrad()* and *Adadelta()* can further help develop better and more accurate models. Experimenting with other combinations of hyperparameters like the *filter size, paddings, stride_length, batch_normalization, dropouts* etc. can further help improve performance.