Gesture Recognition from Upgrad's video dataset

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We have tried quite a few approaches to tackle this problem and have split them into 4 logical chunks. We have summarized our findings of various trials in a table at the end of each section. We have played with Conv2D + GRU, a custom Conv3D network, optical flow followed by a custom Conv3D network & finally an approach from a paper titled, Quo Vadis. Let's go over them one by one:

Approach 1: Extracting features using a pretrained CNN model(inception) followed by GRUs for classification:

In this approach we can use a pre-trained network like Inceptionv3 or VGG to extract meaningful features from each frame of the video. These feature for each frame from the video are feed into RNN as sequence of the features.

For this approach we have written a custom generator which will give a batch of videos containing features for each frame using InceptionV3 pretrained model.

These batch are input to the RNN model containing the following layers

1. GRU layer with 16 features
2. Dense layer with 32 features and relu activation
3. Dense layer with 5 features and softmax activation

Below are the mentioned experiments done the above model:

Experiment Number	Conv3D	Result	Decision + Explanation
1	**RCNN**	**Throws Generator error**	**Started with initial one GRU Layer with 16 features and 5 features softmax dense layer**
2	**RCNN**	**Throws Input shape error**	**Fixed issues with generator**
3	**RCNN**	**Accuracy: 0.70**	**Fixed issue with generator to get the desired input shape for the model**

4	**RCNN**	**Accuracy: 0.60**	**Added another GRU layer with double the feature from previous layer**
5	**RCNN**	**Accuracy: 0.72**	**Removed the GRU as it did not improve the accuracy**
6	**RCNN**	**Accuracy: 0.65**	**Added another GRU layer with half the feature from previous layer**
7	**RCNN**	**Accuracy: 0.70**	**Removed the GRU as it did not improve the accuracy**
8	**RCNN**	**Accuracy: 0.71**	**Add 30% dropout after dense layer which is after Conv3D layers**
9	**RCNN**	**Accuracy: 0.82**	**Added a Dense Layer with 32 features**
10	**RCNN**	**Accuracy: 0.72**	**Added Cropping to all frames of a video in generator**
11	**RCNN**	**Accuracy: 0.81**	**Removed Cropping as it did not seem to improve accuracy**
12	**RCNN**	**Accuracy: 0.68**	**Added masking to video which did not have 1:1 aspect ratio**
13	**RCNN**	**Accuracy: 0.82**	**Removed the masking as it had no effect**

Approach 2: A custom Conv3D network:

In this approach we can have used a custom Conv3D network with the features increasing with layers with relu activation and 3x3x3 filter size.

For this approach we have written a custom generator which will give a batch of videos containing frames which have been resized to (244,244,3) and normalized by dividing each pixel by 255.

After playing around with various architectures, the following network seems to be the best performer

1. Conv3D layer with 16 features
2. Max Pooling layer
3. Conv3D layer with double the features from the previous layer
4. Max Pooling layer

5. Conv3D layer with double the features from the previous layer
6. Max Pooling layer
7. Conv3D layer with double the features from the previous layer
8. Max Pooling layer
9. Flatten layer
10. Dense layer with 216 & 128 neurons and relu activation
11. Dense layer with 5 neurons and softmax activation

Below are the mentioned experiments done the above model:

Experiment Number	Conv3D	Result	Decision + Explanation
1	**Conv3D**	**Throws Generator error**	**Started with initial one Conv3D layer with a 3x3x3 filter 16 features and 5 features softmax dense layer**
2	**Conv3D**	**Throws Input shape error**	**Fixed issues with generator**
3	**Conv3D**	**Accuracy: 0.42**	**Fixed issue with generator to get the desired input shape for the model**
4	**Conv3D**	**Accuracy: 0.57**	**Added another Conv3D layer with double the feature from previous layer and MaxPolling3D**
5	**Conv3D**	**Accuracy: 0.61**	**Added Dense layer with double the features from the previous layer**
6	**Conv3D**	**Accuracy: 0.65**	**Added another Conv3D layer with double the feature from previous layer and MaxPolling3D**
7	**Conv3D**	**Accuracy: 0.70**	**Added another Conv3D layer with double the feature from previous layer and MaxPolling3D**

8	**Conv3D**	**Accuracy: 0.75**	**Added another Conv3D layer with double the feature from previous layer and MaxPolling3D**
9	**Conv3D**	**Accuracy: 0.79**	**Added another Conv3D layer with double the feature from previous layer**
10	**Conv3D**	**Accuracy: 0.78**	**Added another Conv3D layer with double the feature from previous layer**
11	**Conv3D**	**Accuracy: 0.74**	**Added another Conv3D layer with double the feature from previous layer**
12	**Conv3D**	**Accuracy: 0.70**	**Added another Conv3D layer with double the feature from previous layer**
13	**Conv3D**	**Accuracy: 0.80**	**Removed the last 3 Conv3D layers as it did not seem to improve the accuracy and lead to overfitting the model**
14	**Conv3D**	**Accuracy: 0.84**	**Added a Flatten layer after the Conv3D Layers**
15	**Conv3D**	**Accuracy: 0.84**	**Add 20% dropout after dense layer which is after Conv3D layers**
16	**Conv3D**	**Accuracy: 0.83**	**Increased the dropout to 40%**
17	**Conv3D**	**Accuracy: 0.75**	**Added Cropping to all frames of a video in generator**
18	**Conv3D**	**Accuracy: 0.85**	**Removed Cropping as it did not seem to improve accuracy**
19	**Conv3D**	**Accuracy: 0.70**	**Added masking to video which did not have 1:1 aspect ratio**
20	**Conv3D**	**Accuracy: 0.84**	**Removed the masking as it had no effect**

21	**Conv3D**	**Accuracy: 0.87**	**Number of neurons in dense layer = 128**
22	**Conv3D**	**Accuracy: 0.9**	**Number of neurons = 128, normalization = min Max, where Max = 90 percentile and min = 10percentile**

We tried two more approaches and in both we compute optical flow on each frame of the video and feed that to a 3D Convolution network. But before we jump into the actual implementation, let's look at what OF is and how flow vectors are obtained mathematically.

Optical Flow:

When you are looking at motion in videos, optical flow should be considered. It is defined as the apparent motion of individual pixels on the image plane. It often serves as a good approximation of the true physical motion projected onto the image plane. Most methods that compute optical flow assume that the color/intensity of a pixel is invariant under the displacement from one video frame to the next. Optical flow provides a concise description of both the regions of the image undergoing motion and the velocity of motion.

So, we are mainly interested in looking at the intensity variation between two frames. A voxel at location (x,y,t) with intensity I(x,y,t) has moved to Δx , Δy & Δt . Following the brightness constancy constraint:

$$I(x, y, t) = I(x + \Delta x, y + \Delta y, t + \Delta t)$$

Assuming the movement to be small, the image constraint at I(x,y,t)} with Taylor series can be developed to get:

$$I(x + \Delta x, y + \Delta y, t + \Delta t) = I(x, y, t) + \frac{\partial I}{\partial x}\Delta x + \frac{\delta I}{\delta y}\Delta y + \frac{\delta I}{\delta t}\Delta t$$

We only keep the first order terms and ignore everything else.

Dividing by Δt , we get:

$$\frac{\partial I}{\partial x}\frac{\Delta x}{\Delta t} + \frac{\partial I}{\partial y}\frac{\Delta y}{\Delta t} + \frac{\partial I}{\partial t}\frac{\Delta t}{\Delta t} = 0$$

or:

$\frac{\partial I}{\partial x} V_x + \frac{\partial I}{\partial y} V_y + \frac{\partial I}{\partial t} = 0$, where Vx, Vy are the components of the velocity or optical flow of $I(x, y, t)$, while $\frac{\delta I}{\delta x}$, $\frac{\delta I}{\delta y}$ & $\frac{\delta I}{\delta t}$ are the derivatives of the image at (x, y, t) in the corresponding directions. Writing it succinctly as follows:

$$I_x V_x + I_y V_y = -I_t$$

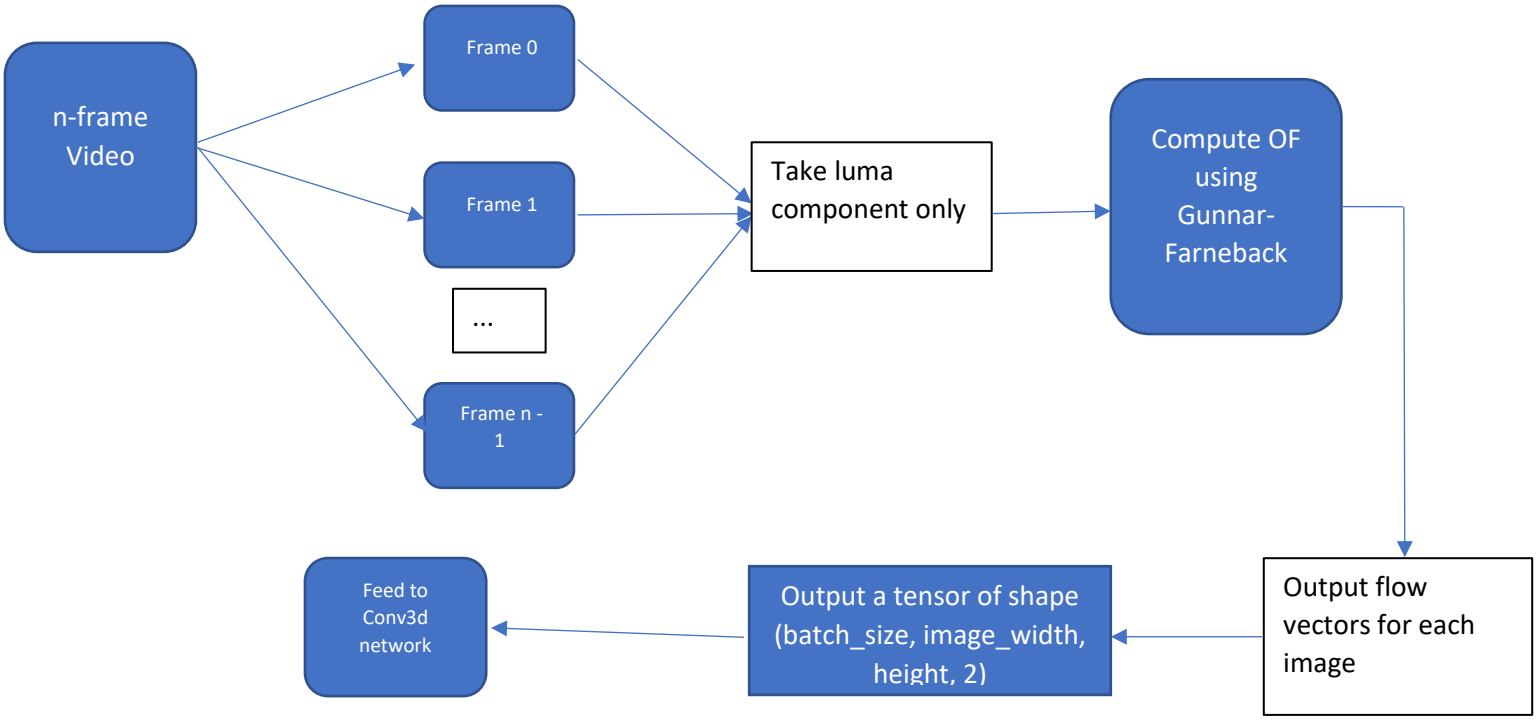
Or $\nabla I . V = -I_t$

There are various ways to solve the above problem. OpenCV has two ways implemented: Lucas-Kanade, which computes sparse OF and the Gunnar-Farneback OF which computes dense OF i.e., a flow vector is obtained for every pixel of the image. So, for a (224, 224) image, the output will be (224, 224, 2).

We went with dense OF in our implementation. There is also a new improved method of computing optical flow viz. the Semi-global matching OF proposed by Heiko Hirschmüller. Though we have not tried it, we have reserved this as a future scope.

Approach 3: Optical flow followed by Conv3D network

The flow of the generator code for this approach is as follows:



With this approach alone, the best accuracy we were able to obtain was 94%(validation) & 93%(training) on the dataset given by Upgrad.

Approach 4: Quo Vadis, Action Recognition:

In 2017, a seminal paper was released by Joao Carreira & Andrew Zisserman which talks about how to tackle action classification while looking at some of the popular datasets like UCF-101, HMDB-51 & the Kinetics Human Action Video dataset. They introduced a new Two-stream Inflated 3D ConvNet(I3D) that is based on 2D ConvNet inflation: filters and pooling kernels of very deep image classification ConvNets are expanded into 3D, making it possible to learn seamless spatio-temporal feature extractors from video while leveraging successful ImageNet architecture designs and even their parameters.

I3D builds upon state-of-the-art image classification architectures but inflates their filters and pooling kernels (and optionally their parameters) into 3D, leading to very deep, naturally spatiotemporal classifiers.

Here are the various architectures considered in the paper:

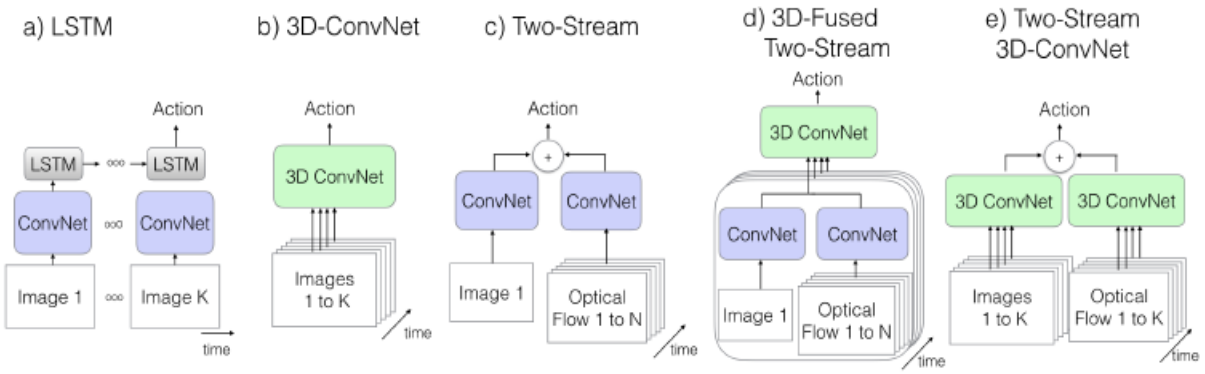
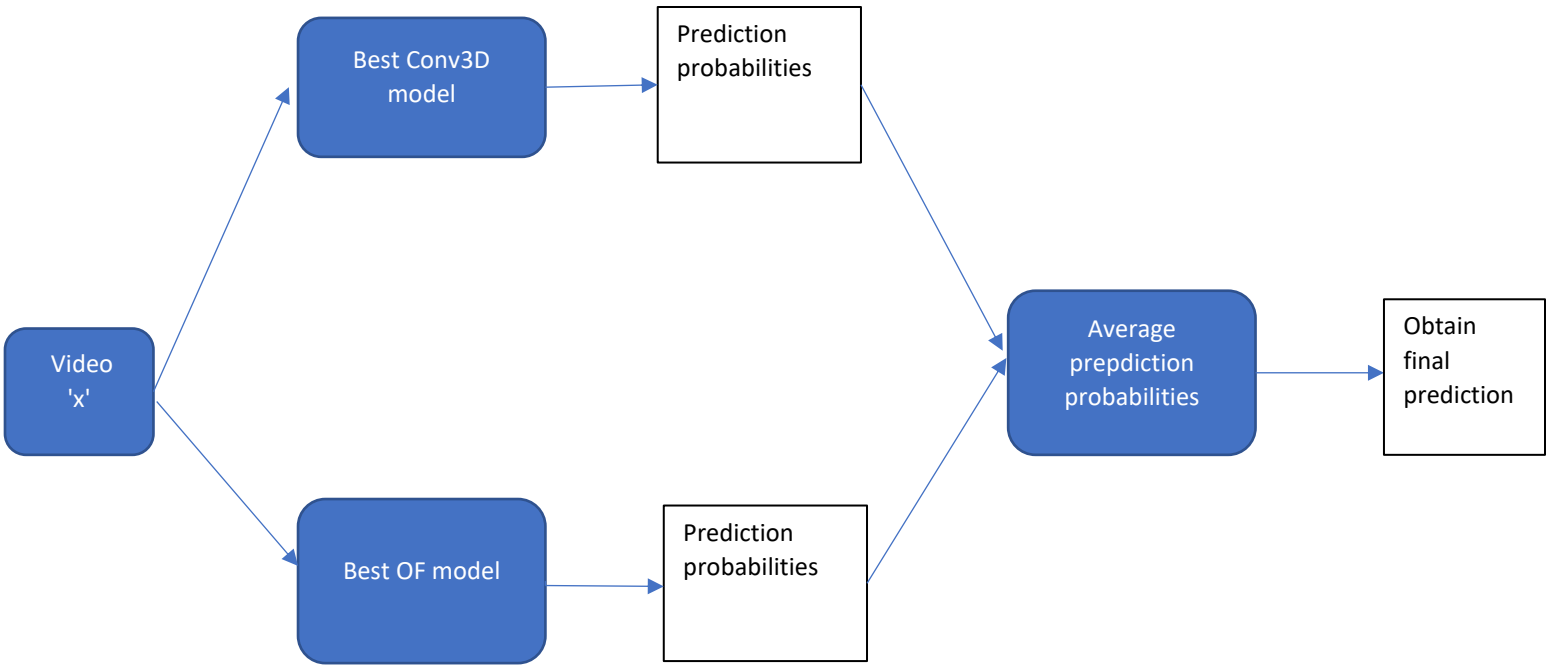


Figure 2. Video architectures considered in this paper. K stands for the total number of frames in a video, whereas N stands for a subset of neighboring frames of the video.

Of the 5 shown above, the last one is their novelty i.e., expand the 2d conv from the existing two-stream architecture shown in c) to a 3D Conv. While a 3D ConvNet should be able to learn motion features from RGB inputs directly, it still performs pure feedforward computation, whereas optical flow algorithms are in some sense recurrent (e.g., they perform iterative optimization for the flow fields)

In our implementation, we trained the two models separately and cached their respective best models. Finally, on the validation data, we averaged the prediction probabilities from both the models and obtained the result. It can be summarized with a diagram as follows:



With the added complexity, the final accuracy obtained was 93%(validation). We feel that with the current implementation, the added complexity does not seem to be worth the hassle. Perhaps, if we could tweak our approach slightly and build upon this method, the results could be different. This will be bookmarked as another area of improvement in the future.

Conclusion:

We have tried many approaches to solve of problem of gesture recognition from videos. We initially started working with Upgrad's sample generator but later ditched it for custom generators by inheriting from keras.utils.Sequence as it fit well with our design philosophy which can be seen in our notebook.

From a model deployment standpoint, we see that a custom conv3d network with minMax normalization gives us 90% on validation data early on before it starts overfitting. If we do a div by 255 normalization instead, we get a stable 87% accuracy on validation data & training accuracy is 93.2%. By incorporating optical flow into the mix, we get a solid 94% accuracy on validation and a 93% on training accuracy. By trying Quo Vadis, the accuracy on validation data is 93%. It does not seem like the added complexity is adding any value with the current implementation.

After trying out all experiments, we have chosen the model obtained detailed in the section, *Approach 3: Optical flow followed by Conv3D network*. To recall, this model first calculates the flow vector of each pixel in a frame and feeds it to a custom conv3d network whose architecture is described in detail in *Approach 2: A custom Conv3D network.* Metrics obtained: 93% training accuracy and 94% validation accuracy.

References:

[1] arXiv:1705.07750: Quo Vadis, Action Recognition? A New Model and the Kinetics Dataset, Joao Carreira, Andrew Zisserman

[2] Optical flow: https://www.sciencedirect.com/topics/engineering/optical-flow , Industrial Ventilation Design Guidebook, 2001