## Assignment #1: 10 sign languages representing 0 to 9



#### Model: VGG-16

**VGG-16** 



# use "get\_layer" method to save the last layer of the network
last\_layer = base\_model.get\_layer('global\_average\_pooling2d')

# save the output of the last layer to be the input of the next layer last\_output = last\_layer.output

# add our new softmax layer with 3 hidden units
x = Dense(10, activation='softmax', name='softmax')(last\_output)

#### Hyperparameter



#### Assignment #1: 10 sign languages representing 0 to 9

base\_model = vgg16.VGG16(weights = "imagenet", include\_top=False, input\_shape = (224,224, 3), pooling='avg')
base\_model.summary()

Total params: 14719818 (56.15 MB) Trainable params: 12984330 (49.53 MB) Non-trainable params: 1735488 (6.62 MB) Total params: 14719818 (56.15 MB) Trainable params: 7084554 (27.03 MB) Non-trainable params: 7635264 (29.13 MB)

Freeze all layers except the last 10 layers

Freeze all layers except the last 5 layers

The level 1 has more params than level 2 fine-tuning

# Assignment #1: 10 sign languages representing 0 to 9

Model Comparation: freeze all layers except the last 5 layers vs last 10 layers



freeze all layers except the last 5 layers



- Testing loss: **0.1894**
- Testing accuracy: 0.9400

The level 1 (10 Layers) Fine Tuning is better than level 2 (5 layers) fine-tuning

VS

## Conclusion

- In the first project, which is centered around sign language classification, the VGG16 model was employed. Within this context, tuning Level 1 (freeze all layers except the last 10 layers) yielded better results than tuning Level 2 (freeze all layers except the last 5 layers).
- Conversely, in the second project focusing on traffic sign classification, the VGG19 model was used, and here, tuning Level 2 outperformed tuning Level 1.





