

```
In [36]: import numpy as np #for numerical manipulations
import pandas as pd #for data processing like opening csv files
import os #to mention the directory where the dataset is stored
import matplotlib.pyplot as plt
import sys
import os
from keras.layers import *
from keras.optimizers import *
from keras.applications import *
from keras.models import Model
from keras.preprocessing.image import ImageDataGenerator
from keras.callbacks import ModelCheckpoint, EarlyStopping
from keras import backend as k
import keras
```

All the necessary libraries are imported. Numpy is for numerical manipulations. Pandas are for dealing with csv files. Matplotlib is visualizing tool. keras is used here which is open source library for neural networks in python. ImageDataGenerator is used for Data augmentation. Optimizers will help us to find the global minima. Earlystopping is used to incase if we find that over a specific number of epoch the accuracy is not improving then the training could be stopped.

```
In [37]: from tensorflow import keras
base_model = keras.applications.VGG16(weights='imagenet', input_shape=(224,224,3), includ
```

VGG16 is the convolution neural network proposed in 2014. It is trained using imagenet dataset which roughly has 15million high resolution images belonging to 22,000 categories. We are doing Transfer Learning here. Using this model which was already trained with millions of data will help to make prediction accurately by not only depending on the dataset we have. We are giving include_top=False because VGG16 is a sequence of convolution layers with a dense layer at the end. By giving it as false we mean that we are dropping the dense layer alone. Instead of the dense layer which is already present we will model a full connected layer which will be connected to VGG16.

```
In [38]: base_model.summary()
```

Model: "vgg16"

Layer (type)	Output Shape	Param #
=====		
input_4 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168

block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
=====		
Total params: 14,714,688		
Trainable params: 14,714,688		
Non-trainable params: 0		

```
In [39]: base_model.trainable=False #freezing the model
```

Here we are freezing the base model which means that we are fixing the weights which are currently used and we cannot modify the weights of the base model any further.

```
In [40]: inputs = Input(shape=(224,224,3)) #input layer is created
x = base_model(inputs, training=False)
x = Flatten()(x) #Flattening Layer is added
x = Dense(256, activation='relu')(x) #Adding a Hidden Layer with 256 neuron
x = Dropout(0.5)(x) #adding a drop out layer
outputs = Dense(2, activation='softmax')(x) #creating the output layer which is basical
model = Model(inputs,outputs) #creating the model
```

Here we are creating our own model on top of the base model. Input layer is of size 224,224,3 where 3 represents the RGB. A flatten layer is added which basically converts the 3d array of images into a 1D vector. A hidden layer with 256 neurons are created with relu as the activation function. With Deep Neural Network there are more chances that over fitting might occur considering the very minimal image data that we are going to train. Hence to avoid overfitting dropout layer is added which randomly avoid certain neurons output so that balance is maintained. The output layer has 2 neurons which basically is 2 classifications of our research project currently - Idle and Fall. A model is created by linking the input and the output.

```
In [41]: model.summary()
```

Model: "functional_3"

Layer (type)	Output Shape	Param #
=====		
input_5 (InputLayer)	[(None, 224, 224, 3)]	0

vgg16 (Functional)	(None, 7, 7, 512)	14714688
flatten_1 (Flatten)	(None, 25088)	0
dense_2 (Dense)	(None, 256)	6422784
dropout_1 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 2)	514
=====		
Total params: 21,137,986		
Trainable params: 6,423,298		
Non-trainable params: 14,714,688		

```
In [42]: model.compile(loss='categorical_crossentropy',metrics=["accuracy"],optimizer='nadam')
```

Here we are using categorical cross entropy as loss function since we will have output classification labels to be 3 which is Idle, Walking and Fall. Right now we are testing on two classifications which is basically idle and fall. NADAM optimizer is used to find the global minima.

```
In [43]: from tensorflow.keras.preprocessing.image import ImageDataGenerator
transformation_ratio = 0.05
datagen = ImageDataGenerator(rescale=1./255,
                             validation_split=0.2,
                             rotation_range=transformation_ratio,
                             shear_range=transformation_ratio,
                             zoom_range=transformation_ratio,
                             cval=transformation_ratio,
                             horizontal_flip=True,
                             vertical_flip=True)
```

Data Augmentation is done here. Since the amount of dataset we have for each condition to train is 120, we are in need of more images for better accuracy. Hence, we are going with Image datagenerator which generates further more images from the same images by doing various process like flipping, zooming and much more

```
In [44]: from keras_preprocessing.image import ImageDataGenerator

train_it = datagen.flow_from_directory("C:/Users/Hariharan/Desktop/VIT/Research/RBL2/Co
target_size=(224,224),
color_mode='rgb',
class_mode="categorical",
batch_size=12,
subset="training")
val_it = datagen.flow_from_directory("C:/Users/Hariharan/Desktop/VIT/Research/RBL2/Code
target_size=(224,224),
color_mode='rgb',
class_mode="categorical",
batch_size=12,
subset='validation')
test_it = datagen.flow_from_directory("C:/Users/Hariharan/Desktop/VIT/Research/RBL2/Cod
target_size=(224,224),
color_mode='rgb',
class_mode="categorical",
)
```

Found 193 images belonging to 2 classes.
 Found 48 images belonging to 2 classes.
 Found 60 images belonging to 2 classes.

Here we are loading the dataset from the directory in to separate variable which will be served to our deep neural network to see how our model is able to make the prediction.

A validation dataset is a sample of data held back from training your model that is used to give an estimate of model skill while tuning model's hyperparameters.

The validation dataset is different from the test dataset that is also held back from the training of the model, but is instead used to give an unbiased estimate of the skill of the final tuned model when comparing or selecting between final models.

```
In [45]: history = model.fit_generator(generator = train_it,
                                     steps_per_epoch = train_it.samples/train_it.batch_size,
                                     epochs = 16,
                                     validation_data = val_it,
                                     validation_steps = test_it.samples/test_it.batch_size)
```

```
Epoch 1/16
17/16 [=====] - 153s 9s/step - loss: 2.2557 - accuracy: 0.5544
- val_loss: 0.4944 - val_accuracy: 0.7083
Epoch 2/16
17/16 [=====] - 165s 10s/step - loss: 0.9896 - accuracy: 0.652
8 - val_loss: 0.7174 - val_accuracy: 0.5000
Epoch 3/16
17/16 [=====] - 173s 10s/step - loss: 0.6847 - accuracy: 0.626
9 - val_loss: 0.5618 - val_accuracy: 0.7500
Epoch 4/16
17/16 [=====] - 151s 9s/step - loss: 0.7056 - accuracy: 0.6891
- val_loss: 0.4913 - val_accuracy: 0.6667
Epoch 5/16
17/16 [=====] - 169s 10s/step - loss: 0.5798 - accuracy: 0.725
4 - val_loss: 0.4722 - val_accuracy: 0.7083
Epoch 6/16
17/16 [=====] - 175s 10s/step - loss: 0.5487 - accuracy: 0.694
3 - val_loss: 0.5133 - val_accuracy: 0.8750
Epoch 7/16
17/16 [=====] - 170s 10s/step - loss: 0.5808 - accuracy: 0.683
9 - val_loss: 0.5947 - val_accuracy: 0.6250
Epoch 8/16
17/16 [=====] - 158s 9s/step - loss: 0.5291 - accuracy: 0.7202
- val_loss: 0.4373 - val_accuracy: 0.9583
Epoch 9/16
17/16 [=====] - 174s 10s/step - loss: 0.5336 - accuracy: 0.699
5 - val_loss: 0.5260 - val_accuracy: 0.7083
Epoch 10/16
17/16 [=====] - 169s 10s/step - loss: 0.4997 - accuracy: 0.756
5 - val_loss: 0.8121 - val_accuracy: 0.5417
Epoch 11/16
17/16 [=====] - 168s 10s/step - loss: 0.5801 - accuracy: 0.746
1 - val_loss: 0.4665 - val_accuracy: 0.7500
Epoch 12/16
17/16 [=====] - 172s 10s/step - loss: 0.4849 - accuracy: 0.735
8 - val_loss: 0.5202 - val_accuracy: 0.7083
Epoch 13/16
17/16 [=====] - 177s 10s/step - loss: 0.4606 - accuracy: 0.803
1 - val_loss: 0.4301 - val_accuracy: 0.9167
Epoch 14/16
17/16 [=====] - 169s 10s/step - loss: 0.4134 - accuracy: 0.808
```

3 - val_loss: 0.3273 - val_accuracy: 0.9167

Epoch 15/16

17/16 [=====] - 126s 7s/step - loss: 0.4833 - accuracy: 0.7668

- val_loss: 0.4044 - val_accuracy: 0.9167

Epoch 16/16

17/16 [=====] - 168s 10s/step - loss: 0.5554 - accuracy: 0.797

9 - val_loss: 0.4125 - val_accuracy: 0.9583

In []: