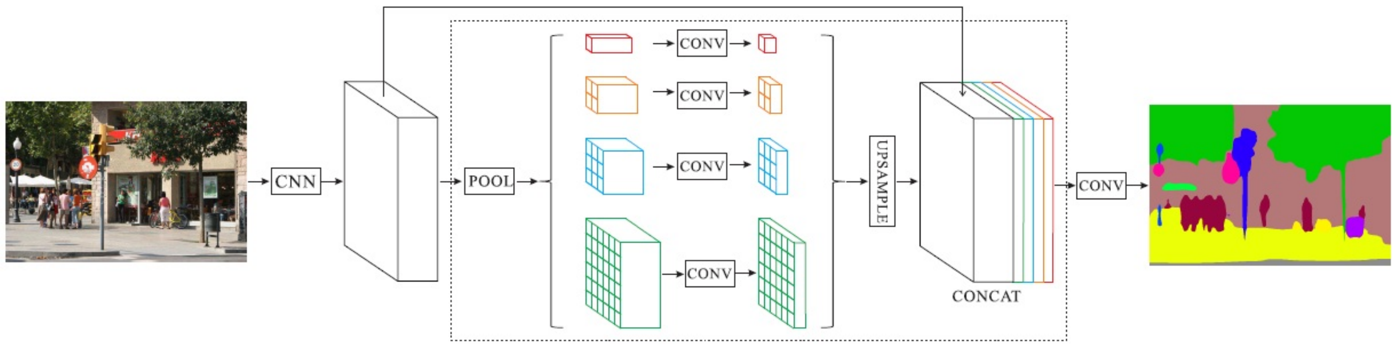
Pyramid Scene Parsing Network for Semantic Segmentation

- **Pyramid scene parsing network(PSPNet) takes into account the global context of the image to predict the local level predictions hence gives better performance when compared to other state of the art networks**
- **Scene parsing is based on semantic segmentation, Where the goal is to assign each pixel in the image a category label where Scene parsing provides a complete understanding of the scene.**
- **The Pyramid Scene Parsing Network(Pspnet) consists of a pyramid pooling module as an effective global context prior which represents global context information and also considers sub-region context which is helpful for accurate prediction.**
  For more information please refer the paper [Pyramid Scene Parsing Network](#) and its summary [here](#)
- **The pspnet is described in below image as below**
  (a) Input image (b) Feature map (c) Pyramid pooling module (d) Final Prediction



****Implementation Overview:****

```
(a)Input image:
    (i) This is the input image with some resolution
(b)Feature map:
    (i) Feature map can be obtained by using Restnet with dilated convolutions aka atrous convoluti
on which is the
        same as Deep_lab network strategy.
    (ii) The final output size of the feature map should be ⅛ size of the input image
(c)Pyramid parsing module:
    (i) Global average pooling and Sub average pooling is applied to feature maps to get different
sub-region
        representations as Sub-regions: Red:1x1, Orange:2x2, Blue:3x3, Green:6x6.
    (ii) 1x1 convolution is applied to reduce the context of feature map to 1/number of the subregi
on that is ¼.
    (iii) Upsampling is performed on subregions to get the size same as original feature map and fi
nally, all
          feature maps are concatenated to get the final feature representation, which carries both
local
          and global context information.
(d) Final Prediction: The final representation is fed into a convolution layer to get the final pre
diction.
```

Importing required Modules

In [ ]:

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import backend as K
from numpy import asarray,zeros,moveaxis
from tensorflow.keras.initializers import *
from tensorflow.keras.models import *
from tensorflow.keras.layers import *
from tensorflow.keras.callbacks import *
from tensorflow.keras.optimizers import *
import matplotlib.pyplot as plt
```

```
from sys import getsizeof
from keras.callbacks import TensorBoard
from tqdm import tqdm_notebook,tqdm
from sklearn.metrics import *
import os,sys,ntpath,fnmatch,shutil,cv2
import joblib,os.path,itertools,warnings
from keras.models import load_model
from scipy.sparse import csc_matrix
import numpy as np
import pandas as pd
from os import path
!pip install import_ipynb
from IPython.display import clear_output
from time import time
np.random.seed(0)
from google.colab import drive
drive.mount('/content/drive')
! cp -v "/content/drive/My Drive/IID_Files/Utility_Functions.ipynb" "/content"
! cp -v "/content/drive/My Drive/IID_Files/Final.ipynb" "/content"
! cp -v "/content/drive/My Drive/IID_Files/IID_Data_Prep_Utils.ipynb" "/content"
warnings.filterwarnings("ignore")
clear_output()
```

Importing Data Preparation Modules

In [ ]:

```
import import_ipynb
from Utility_Functions import *
from Final import *
from IID_Data_Prep_Utils import *
```

```
Checking Status:
------------------------------------------------------
1.Image Data Preparation     .. .. .. >>> |Done| <1/5>
2.Label Mask Preparation     .. .. .. >>> |Done| <2/5>
3.Data Shuffling             .. .. .. >>> |Done| <3/5>
4.Data Train_Test_Split      .. .. .. >>> |Done| <4/5>
5.Loading Final Data         .. .. .. >>> |Done| <5/5>
------------------------------------------------------

Gen RAM Free: 2.41 GB  - Used: 23.22 GB - Total : 25.51 GB - Util  91.02 %
GPU RAM Free: 15.9 GB  - Used: 0.0 GB - Total : 15.9 GB  - Util  0.0 %
```

General Utility Function for Prediction

In [ ]:

```
def predict_for(data_for_prediction, weights_save_path=False):

    """  General Function to perform prediction for the specified data split  """

    Mean_MIoU, Accuracy, cf_matrix=[], [], np.zeros((7,7))
    x, y = Load_For_Prediction(data_for_prediction)
    Model, Skip = Select_Model(weights_save_path), 2

    for d in tqdm_notebook(range(0,len(x),Skip)):

        if (d>=(len(x)-Skip)):
            plot,_,_=True,clear_output(),print("Total number of samples in {0} : {1}".format(data_for_pr
ediction,len(x)))
        else: plot=False

        Miou, cf_matrix, Accuracy=Function_2(x[d:d+Skip],y[d:d+Skip],Mean_MIoU,cf_matrix,Accuracy,Model,
plot,False,False,False)
    collected = gc.collect()

    return Miou, Accuracy, cf_matrix
```

Implementation of Pyramid Scene Parsing Network (PSPNET)

In [ ]:

```
def PSPNET(Input_shape, n_classes):

    """
    Function to build Pyramid Scene Parsing Network for Image Segmentation
    Input   : input_shape <Tuple>, n_classes <Int>
```

```
    Return : model """

    def Restnet50_Module(Input_layer, n_classes):

        """
        Function to Build RestNet for PSPNET Architecture to perform Image Segmentation
        Input  : Input_layer <keras.layer>, n_classes <Int>
        Return : Block5_3_ID <keras.layer> """

        def Restnet_Conv_Block(Block_Number,Name,Filters,Previous_layer,initialize="he_normal"):

            """
            Function to Build RestNet Convolution Blocks
            Input  : Block_Number <Int>, Name <String>, Filters <List>, Previous_layer <keras.layer>, ini
tialize <String>
            Return : Final_Conv <keras.layer> """

            # Defining strides values Based on Block_Number
            strides=(1,1) if Block_Number==2 else (2,2)

            # Defining Dilated Rate Based on Block_Number
            if (Block_Number==4):
                D_Rate=2
            elif (Block_Number==5):
                D_Rate=4
            else:
                D_Rate=1

            # Defining First Convolution layer with Batch Normalization for RestNet Convolution Block
            Convolution1 = tf.keras.layers.Conv2D(Filters[0],(1,1), strides=strides, name= Name+"Conv1",
activation = 'relu', kernel_initializer=initialize)(Previous_layer)
            Batch_norm1=tf.keras.layers.BatchNormalization()(Convolution1)

            # Defining Second Convolution layer with Batch Normalization for RestNet Convolution Block
            Convolution2 = tf.keras.layers.Conv2D(Filters[1],(3,3), dilation_rate=D_Rate, name= Name+"Co
nv2", padding='same', activation = 'relu', kernel_initializer=initialize)(Batch_norm1)
            Batch_norm2=tf.keras.layers.BatchNormalization()(Convolution2)

            # Defining Third Convolution layer with Batch Normalization for RestNet Convolution Block
            Convolution3 = tf.keras.layers.Conv2D(Filters[2],(1,1),name= Name+"Conv3", activation = None
, kernel_initializer=initialize)(Batch_norm2)
            Batch_norm3=tf.keras.layers.BatchNormalization()(Convolution3)

            # Defining Convolution layer with Batch Normalization for RestNet Convolution Block
            Layer_to_add = tf.keras.layers.Conv2D(Filters[2],(1,1), strides=strides, name= Name+"conv_pr
ep_add", activation = None, kernel_initializer=initialize)(Previous_layer)
            Layer_to_add=tf.keras.layers.BatchNormalization()(Layer_to_add)

            # Defining Skip Connection for RestNet Convolution Blocks
            Added_Layer=tf.keras.layers.add([Batch_norm3,Layer_to_add])
            Final_Conv=tf.keras.layers.Activation("relu")(Added_Layer)

            return Final_Conv

        def Restnet_Id_Block(Block_Number,Name,Filters,Previous_layer,initialize="he_normal"):

            """
            Function to Build RestNet Identity Blocks
            Input  : Block_Number <Int>, Name <String>, Filters <List>, Previous_layer <keras.layer>, ini
tialize <String>
            Return : Final_Conv1 <keras.layer>  """

            # Defining Dilated Rate Based on Block_Number
            if (Block_Number==4):
                D_Rate=2
            elif (Block_Number==5):
                D_Rate=4
            else:
                D_Rate=1

            # Defining First Convolution layer with Batch Normalization for RestNet Identity Block

            Convolution1 = tf.keras.layers.Conv2D(Filters[0], (1,1), name= Name+"Conv1", activation = 'r
elu', kernel_initializer=initialize)(Previous_layer)
            Batch_norm1=tf.keras.layers.BatchNormalization()(Convolution1)

            # Defining Second Convolution layer with Batch Normalization for RestNet Identity Block
            Convolution2 = tf.keras.layers.Conv2D(Filters[1], (3,3), dilation_rate=D_Rate, name= Name+"C
onv2", padding='same', activation = 'relu', kernel_initializer=initialize)(Batch_norm1)
            Batch_norm2=tf.keras.layers.BatchNormalization()(Convolution2)

            # Defining Third Convolution layer with Batch Normalization for RestNet Identity Block
            Convolution3 = tf.keras.layers.Conv2D(Filters[2], (1,1), name= Name+"Conv3", activation = No
```

```
ne, kernel_initializer=initialize)(Batch_norm2)
            Batch_norm3=tf.keras.layers.BatchNormalization()(Convolution3)

            # Defining Skip Connection for RestNet Identity Block
            Added_Layer=tf.keras.layers.add([Batch_norm3,Previous_layer])
            Final_Conv1=tf.keras.layers.Activation("relu")(Added_Layer)

            return Final_Conv1

        # Building RestNet Block-1
        Block_1_Conv = tf.keras.layers.Conv2D(64,(7,7),strides=(2,2),name= "Block1_Conv1", activation = 
'relu', padding='same', kernel_initializer="he_normal")(Input_layer)
        Block_1_Batch_norm1=tf.keras.layers.BatchNormalization(name="Block1_Conv1_BN")(Block_1_Conv)
        Block_1_MaxPool = tf.keras.layers.MaxPooling2D(pool_size=(3,3),strides=(2,2), name="Block1_Maxpoo
l1", padding='same')(Block_1_Batch_norm1)

        # Building RestNet Block-2
        Block2_1_con= Restnet_Conv_Block(2, "Block2.1_CONV_", [16,16,64], Block_1_MaxPool)
        Block2_2_ID= Restnet_Id_Block( 2,  "Block2.2_ID_",    [16,16,64], Block2_1_con)
        Block2_3_ID= Restnet_Id_Block( 2,  "Block2.3_ID_",    [16,16,64], Block2_2_ID)

        # Building RestNet Block-3
        Block3_1_con= Restnet_Conv_Block(3, "Block3.1_CONV_", [32,32,128], Block2_3_ID)
        Block3_2_ID= Restnet_Id_Block( 3,   "Block3.2_ID_",   [32,32,128], Block3_1_con)
        Block3_3_ID= Restnet_Id_Block( 3,   "Block3.3_ID_",   [32,32,128], Block3_2_ID)
        Block3_4_ID= Restnet_Id_Block( 3,   "Block3.4_ID_",   [32,32,128], Block3_3_ID)

        # Building RestNet Block-4
        Block4_1_con= Restnet_Conv_Block(4, "Block4.1_CONV_", [64,64,256], Block3_4_ID)
        Block4_2_ID= Restnet_Id_Block( 4,   "Block4.2_ID_",   [64,64,256], Block4_1_con)
        Block4_3_ID= Restnet_Id_Block( 4,   "Block4.3_ID_",   [64,64,256], Block4_2_ID)
        Block4_4_ID= Restnet_Id_Block( 4,   "Block4.4_ID_",   [64,64,256], Block4_3_ID)
        Block4_5_ID= Restnet_Id_Block( 4,   "Block4.5_ID_",   [64,64,256], Block4_4_ID)
        Block4_6_ID= Restnet_Id_Block( 4,   "Block4.6_ID_",   [64,64,256], Block4_5_ID)

        # Building RestNet Block-5
        Block5_1_con= Restnet_Conv_Block(5, "Block5.1_CONV_", [128,128,512], Block4_6_ID)
        Block5_2_ID= Restnet_Id_Block( 5,   "Block5.2_ID_",   [128,128,512], Block5_1_con)
        Block5_3_ID= Restnet_Id_Block( 5,   "Block5.3_ID_",   [128,128,512], Block5_2_ID)

        return Block5_3_ID

    def Pyramid_Module(Rest50_Layer):

        """  Function to Build Pyramid Pooling Module  """

        def Feature_Sub_Map(Sub_block, Pool_size, Previous_layer, filters=128):

            """
            Fuction to build Parallel Sub-pooling Operations of Pyramid Pooling Module
            Input  : Sub_block <Int>, Pool_size <Tuple>, Previous_layer <keras.layer>, Filters <Int>
            Return : Retn_Sub <keras.layer>  """

            # Defining Sub-pooling operation Based on Sub_block Number
            if Sub_block == "RED":
                Pool_size = (Previous_layer.shape[1],Previous_layer.shape[2])
                Sub_pool = tf.keras.layers.GlobalAveragePooling2D(name= Sub_block+'_GL_POOL')(Previous_l
ayer)
                Sub_pool = tf.keras.layers.Reshape((1,1,Previous_layer.shape[3]))(Sub_pool)
            else:
                Sub_pool = tf.keras.layers.AveragePooling2D(pool_size=Pool_size,name= Sub_block+'_AVG_PO
OL')(Previous_layer)

            # Defining Convolution layer with Batch Normalization for Pyramid Pooling Module
            Conv_sub = tf.keras.layers.Convolution2D(filters=filters,kernel_size=(1,1),name= Sub_block+'
Conv1_1')(Sub_pool)
            Conv_sub=tf.keras.layers.BatchNormalization()(Conv_sub)
            Retn_Sub = tf.keras.layers.UpSampling2D(size=Pool_size, name=Sub_block+'Up_sample',interpolat
ion='bilinear')(Conv_sub)

            return Retn_Sub

        # UpSampling Features to some sensible Size
        Rest50_Layer = UpSampling2D(size=(4,4),interpolation='bilinear',name='Size_Adjust_samp')(Rest50_L
ayer)
        Rest50_Layer=tf.keras.layers.ZeroPadding2D((2,0),name='up_Size_Adjust_pad')(Rest50_Layer)

        # building Pyramid Pooling Module with Sub-pooling
        Red_Map= Feature_Sub_Map(    "RED",    (1,1), Rest50_Layer)
        Orange_Map= Feature_Sub_Map("ORANGE", (2,2), Rest50_Layer)
        Blue_Map= Feature_Sub_Map(   "BLUE",   (3,3), Rest50_Layer)
        Green_Map= Feature_Sub_Map(  "GREEN", (6,6), Rest50_Layer)
```

```
        # Concatenating of all Parallel Sub-pooling layers to get concatenated features
        Global_Concat= tf.keras.layers.concatenate([Rest50_Layer, Green_Map, Blue_Map, Orange_Map, Red_Ma
p])

        # UpSampling Pyramid Pooling Features to Orginal size of Network input
        UpSampling = tf.keras.layers.UpSampling2D(size=(6,8),interpolation='bilinear',name='en_Size_Adjus
t_samp')(Global_Concat)
        Convolution1 = tf.keras.layers.Conv2D(64, (5,5),name= "Conv1", activation = 'relu', padding="sam
e",kernel_initializer="he_normal")(ZeroPadding2D((12,0))(UpSampling))
        Convolution1=tf.keras.layers.BatchNormalization()(Convolution1)

        # Final Convolution layer with number of classes as filter size followed by softmax Layer
        Convolution2 = tf.keras.layers.Conv2D(7, (3,3),name= "Conv2",activation = 'relu', padding="same"
,kernel_initializer="he_normal")(Convolution1)
        Output=Activation('softmax', name="Softmax")(Convolution2)

        return Output

    # Defining input layer of PSPNET
    Input_layer = tf.keras.layers.Input(shape=Input_shape)

    # Invoking Restnet50_Module() for Restnet50
    Rest50_Layer = Restnet50_Module(Input_layer, n_classes)

    # Invoking Pyramid_Module() for Pyramid pooling Module
    Output = Pyramid_Module(Rest50_Layer)

    # Defining Model with Input and Output Layer
    PSPNET_Model = Model(Input_layer, Output)

    return PSPNET_Model

# Invoking PSPNET() to get PSPNET Model
Input_shape, n_classes = (240, 480,3), 7
Pspnet_Model=PSPNET(Input_shape, n_classes)
```

Training Pspnet Model

In [ ]:

```
# Get current Time
start_time = time()

# Defining Batch size and epoch
batch_size, epochs = 8, 30

# Defining tensorboard to store Training Information and filepath to store PSPNET model
tensorboard, filepath = TensorBoard(log_dir=root+"logs/pspnet_{}".format(str(time())[5:10])), root+"/Pspn
et.best.hdf5"

# Defining steps_per_epoch and validation_steps for Training
steps_per_epoch, validation_steps = int((len(train_img_files1)+len(train_img_files2))/batch_size), int((l
en(val_img_files1)+len(val_img_files2))/batch_size)

# Compile PSPNET Model
Pspnet_Model.compile(optimizer = tf.keras.optimizers.Adam(), loss = 'categorical_crossentropy',metrics =
['accuracy',miou])

# Defining EarlyStopping with patience=3 and monitor='val_miou'
es = EarlyStopping(monitor='val_miou', mode='max', verbose=1, patience=3)

# Defining ModelCheckpoint with monitor as 'val_miou'
checkpoint = ModelCheckpoint(filepath, monitor='val_miou', verbose=2, save_best_only=True, mode='max')

# Defining ReduceLROnPlateau to reduce learning rate with patience=2
learning_rate_reduction = ReduceLROnPlateau(monitor='val_miou', patience=2, verbose=2, factor=0.2, min_lr
=0.0005)

# Fit PSPNET Model to start training
history = Pspnet_Model.fit_generator(train_batch_generator(batch_size,epochs), steps_per_epoch=steps_per_
epoch, epochs=epochs, verbose=1, validation_data=val_batch_generator(batch_size,epochs),
                             validation_steps=validation_steps, callbacks=[learning_rate_reduction,checkp
oint,es,tensorboard])

# Printing Time taken for Training
print("--- %s seconds ---" % (time() - start_time))
```

```
WARNING:tensorflow:From <ipython-input-7-807d9ad5d018>:10: Model.fit_generator (from tensorflow.python.ker
as.engine.training) is deprecated and will be removed in a future version.
Instructions for updating:
Please use Model.fit, which supports generators.
Epoch 1/50
```

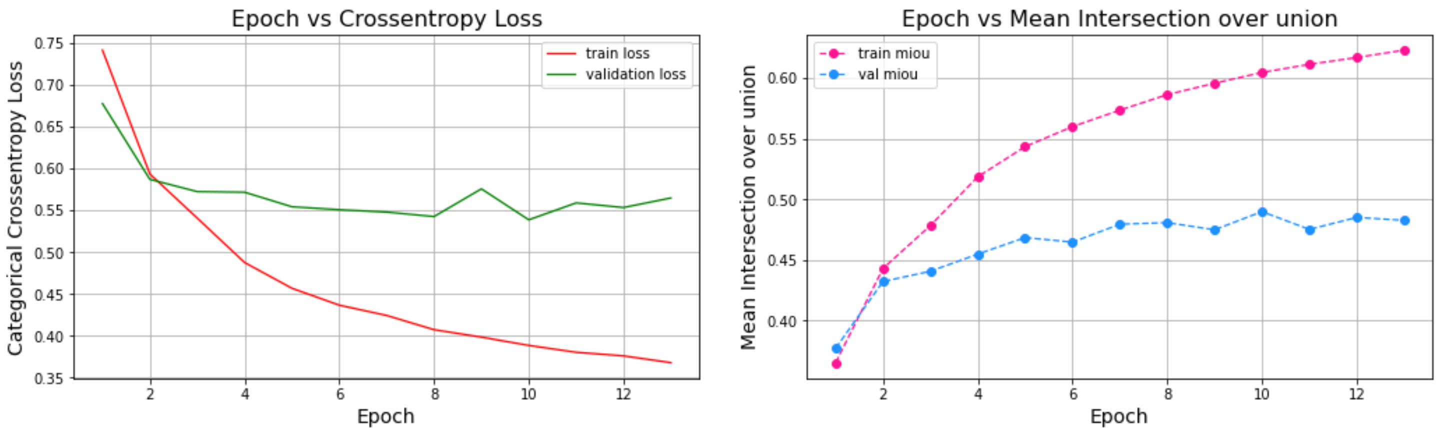
```
Epoch 1/50
   1/1753 [..............................] - ETA: 0s - loss: 1.9719 - accuracy: 0.1705 - miou: 0.0737WARNI
NG:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/summary_ops_v2.py:1277: st
op (from tensorflow.python.eager.profiler) is deprecated and will be removed after 2020-07-01.
Instructions for updating:
use `tf.profiler.experimental.stop` instead.
1753/1753 [==============================] - ETA: 0s - loss: 0.7414 - accuracy: 0.7208 - miou: 0.3652
Epoch 00001: val_miou improved from -inf to 0.37707, saving model to /content/drive/My Drive/Pspnet.best.h
df5
1753/1753 [==============================] - 6250s 4s/step - loss: 0.7414 - accuracy: 0.7208 - miou: 0.365
2 - val_loss: 0.6776 - val_accuracy: 0.7379 - val_miou: 0.3771
Epoch 2/50
1753/1753 [==============================] - ETA: 0s - loss: 0.5934 - accuracy: 0.7675 - miou: 0.4429
Epoch 00002: val_miou improved from 0.37707 to 0.43206, saving model to /content/drive/My Drive/Pspnet.bes
t.hdf5
1753/1753 [==============================] - 2064s 1s/step - loss: 0.5934 - accuracy: 0.7675 - miou: 0.442
9 - val_loss: 0.5870 - val_accuracy: 0.7648 - val_miou: 0.4321
Epoch 3/50
1753/1753 [==============================] - ETA: 0s - loss: 0.5407 - accuracy: 0.7865 - miou: 0.4783
Epoch 00003: ReduceLROnPlateau reducing learning rate to 0.0005.

Epoch 00003: val_miou improved from 0.43206 to 0.44064, saving model to /content/drive/My Drive/Pspnet.bes
t.hdf5
1753/1753 [==============================] - 2073s 1s/step - loss: 0.5407 - accuracy: 0.7865 - miou: 0.478
3 - val_loss: 0.5723 - val_accuracy: 0.7724 - val_miou: 0.4406
Epoch 4/50
1753/1753 [==============================] - ETA: 0s - loss: 0.4876 - accuracy: 0.8062 - miou: 0.5185
Epoch 00004: val_miou improved from 0.44064 to 0.45474, saving model to /content/drive/My Drive/Pspnet.bes
t.hdf5
1753/1753 [==============================] - 2071s 1s/step - loss: 0.4876 - accuracy: 0.8062 - miou: 0.518
5 - val_loss: 0.5716 - val_accuracy: 0.7719 - val_miou: 0.4547
Epoch 5/50
1753/1753 [==============================] - ETA: 0s - loss: 0.4568 - accuracy: 0.8187 - miou: 0.5434
Epoch 00005: ReduceLROnPlateau reducing learning rate to 0.0005.

Epoch 00005: val_miou improved from 0.45474 to 0.46841, saving model to /content/drive/My Drive/Pspnet.bes
t.hdf5
1753/1753 [==============================] - 2067s 1s/step - loss: 0.4568 - accuracy: 0.8187 - miou: 0.543
4 - val_loss: 0.5542 - val_accuracy: 0.7823 - val_miou: 0.4684
Epoch 6/50
1753/1753 [==============================] - ETA: 0s - loss: 0.4366 - accuracy: 0.8271 - miou: 0.5599
Epoch 00006: val_miou did not improve from 0.46841
1753/1753 [==============================] - 2064s 1s/step - loss: 0.4366 - accuracy: 0.8271 - miou: 0.559
9 - val_loss: 0.5507 - val_accuracy: 0.7862 - val_miou: 0.4646
Epoch 7/50
1753/1753 [==============================] - ETA: 0s - loss: 0.4243 - accuracy: 0.8321 - miou: 0.5735
Epoch 00007: ReduceLROnPlateau reducing learning rate to 0.0005.

Epoch 00007: val_miou improved from 0.46841 to 0.47942, saving model to /content/drive/My Drive/Pspnet.bes
t.hdf5
1753/1753 [==============================] - 2065s 1s/step - loss: 0.4243 - accuracy: 0.8321 - miou: 0.573
5 - val_loss: 0.5478 - val_accuracy: 0.7926 - val_miou: 0.4794
Epoch 8/50
1753/1753 [==============================] - ETA: 0s - loss: 0.4073 - accuracy: 0.8390 - miou: 0.5863
Epoch 00008: val_miou improved from 0.47942 to 0.48073, saving model to /content/drive/My Drive/Pspnet.bes
t.hdf5
1753/1753 [==============================] - 2068s 1s/step - loss: 0.4073 - accuracy: 0.8390 - miou: 0.586
3 - val_loss: 0.5425 - val_accuracy: 0.7944 - val_miou: 0.4807
Epoch 9/50
1753/1753 [==============================] - ETA: 0s - loss: 0.3984 - accuracy: 0.8424 - miou: 0.5957
Epoch 00009: ReduceLROnPlateau reducing learning rate to 0.0005.

Epoch 00009: val_miou did not improve from 0.48073
1753/1753 [==============================] - 2067s 1s/step - loss: 0.3984 - accuracy: 0.8424 - miou: 0.595
7 - val_loss: 0.5756 - val_accuracy: 0.7897 - val_miou: 0.4748
Epoch 10/50
1753/1753 [==============================] - ETA: 0s - loss: 0.3885 - accuracy: 0.8462 - miou: 0.6046
Epoch 00010: val_miou improved from 0.48073 to 0.48985, saving model to /content/drive/My Drive/Pspnet.bes
t.hdf5
1753/1753 [==============================] - 2073s 1s/step - loss: 0.3885 - accuracy: 0.8462 - miou: 0.604
6 - val_loss: 0.5386 - val_accuracy: 0.7951 - val_miou: 0.4898
Epoch 11/50
1753/1753 [==============================] - ETA: 0s - loss: 0.3803 - accuracy: 0.8496 - miou: 0.6113
Epoch 00011: ReduceLROnPlateau reducing learning rate to 0.0005.

Epoch 00011: val_miou did not improve from 0.48985
1753/1753 [==============================] - 2075s 1s/step - loss: 0.3803 - accuracy: 0.8496 - miou: 0.611
3 - val_loss: 0.5588 - val_accuracy: 0.7931 - val_miou: 0.4751
Epoch 12/50
1753/1753 [==============================] - ETA: 0s - loss: 0.3760 - accuracy: 0.8510 - miou: 0.6169
Epoch 00012: val_miou did not improve from 0.48985
1753/1753 [==============================] - 2077s 1s/step - loss: 0.3760 - accuracy: 0.8510 - miou: 0.616
9 - val_loss: 0.5533 - val_accuracy: 0.7945 - val_miou: 0.4850
Epoch 13/50
```

```
1753/1753 [==============================] - ETA: 0s - loss: 0.3679 - accuracy: 0.8543 - miou: 0.6230
Epoch 00013: ReduceLROnPlateau reducing learning rate to 0.0005.

Epoch 00013: val_miou did not improve from 0.48985
1753/1753 [==============================] - 2073s 1s/step - loss: 0.3679 - accuracy: 0.8543 - miou: 0.623
0 - val_loss: 0.5647 - val_accuracy: 0.7952 - val_miou: 0.4826
Epoch 00013: early stopping
--- 31121.242070913315 seconds ---
```

Pspnet Training Results

In [ ]:

```
# training_result
plot_training_result(history)
```



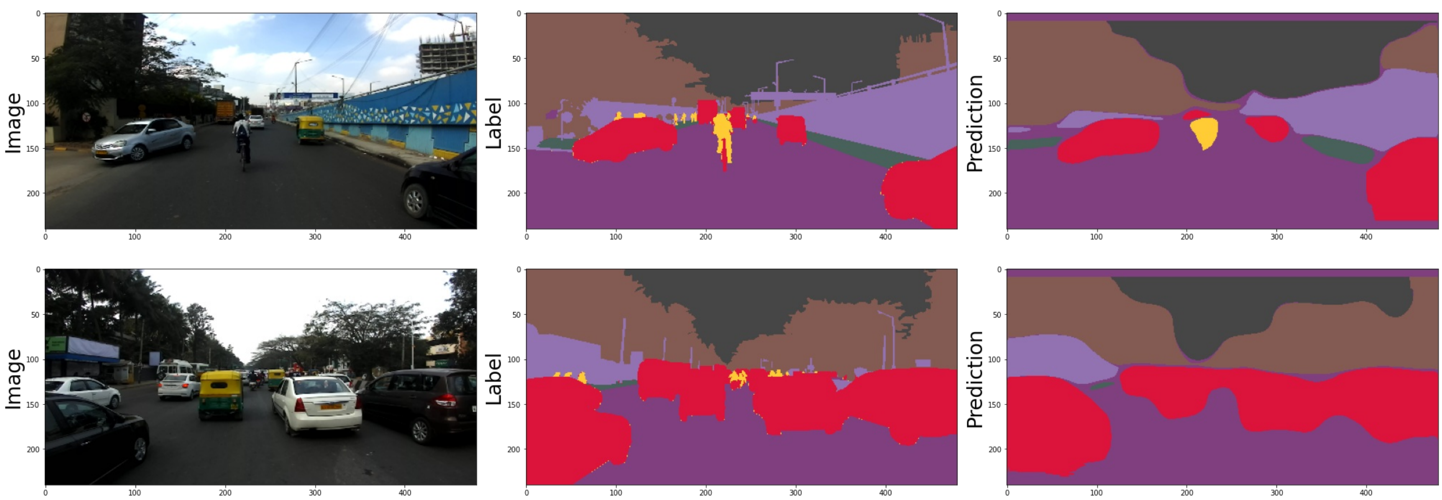
- **The Lowest value of Validation Categorical Crossentopy is 0.4898 which is at epoch-10 as above in the Graph.**
- **The Best Value of Validation Mean Intersection Over Union is 0.5386 which is at epoch-10 as above in the Graph.**
- **Keras callback ModelCheckpoint is used to save the best Model during Training to avoid overfitting.**

Pspnet Prediction on Train Data

In [ ]:

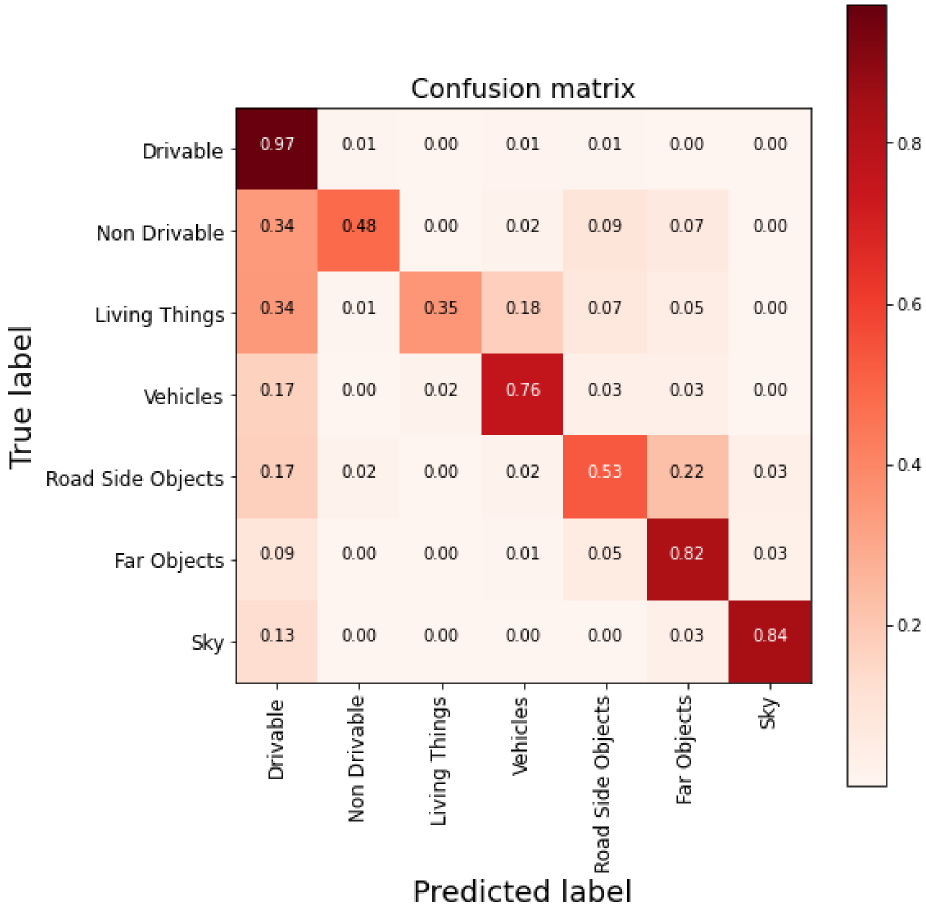
```
# Train Prediction
Miou, Accuracy, cf_matrix = predict_for("Train_data")
```

```
Total number of samples in Train_data : 10016

Few Segmentation Samples:>>>
```




```
Printing Results:>>

-----------------------
|      MIOU Score      |
-----------------------

   MIOU Score: 0.4612

-----------------------
|   Accuracy Score    |
```

```
------------------------

   Accuracy Score: 0.8225

------------------------
|  Confusion Matrix    |
------------------------
```

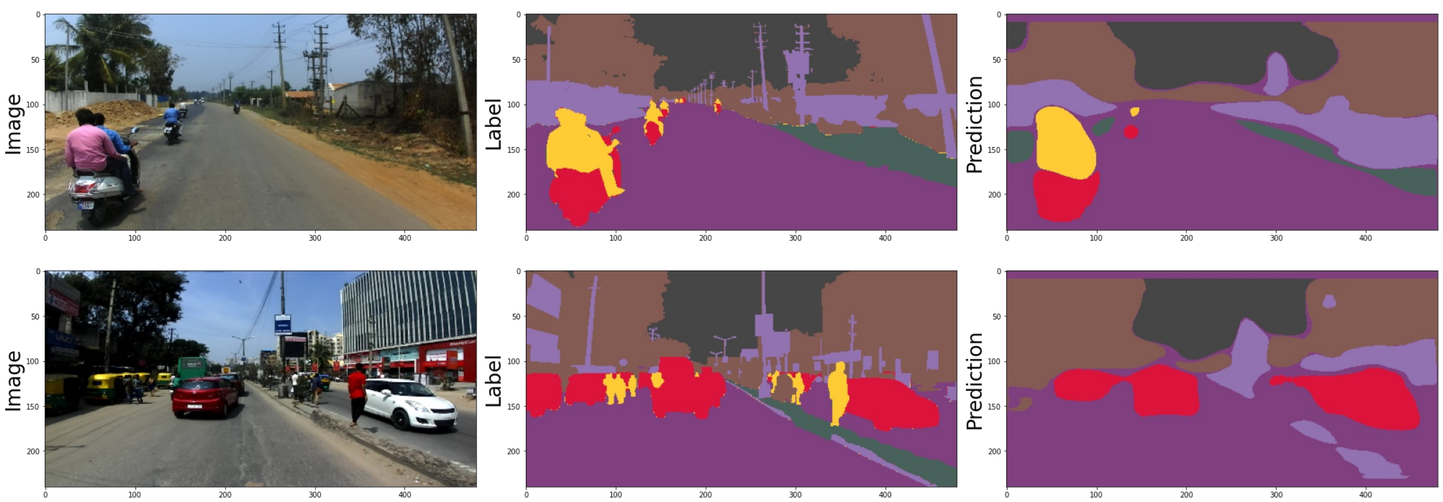


Pspnet Prediction on Validation Data

In [ ]:

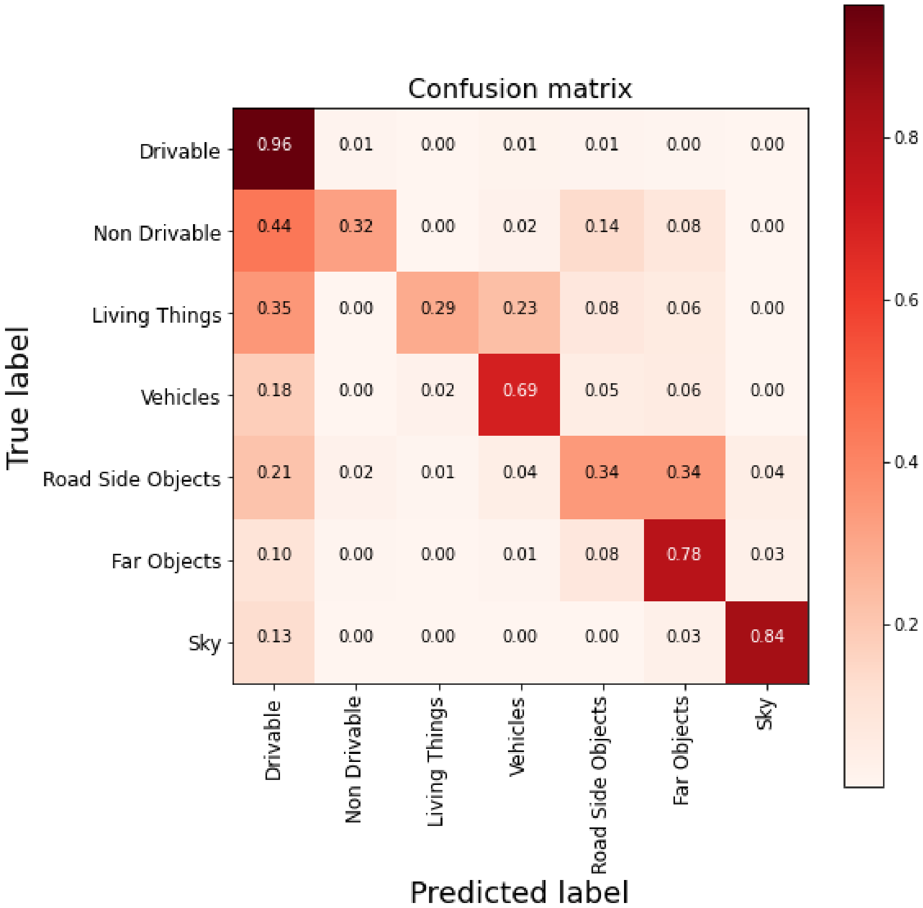
```
# Validation Prediction
Miou, Accuracy, cf_matrix = predict_for("Val_data")
```

```
Total number of samples in Val_data : 2036

Few Segmentation Samples:>>>
```




```
Printing Results:>>

------------------------
|      MIOU Score      |
------------------------
```

```
   MIOU Score: 0.4201

-----------------------
|   Accuracy Score    |
-----------------------

   Accuracy Score: 0.7796

-----------------------
|  Confusion Matrix    |
-----------------------
```

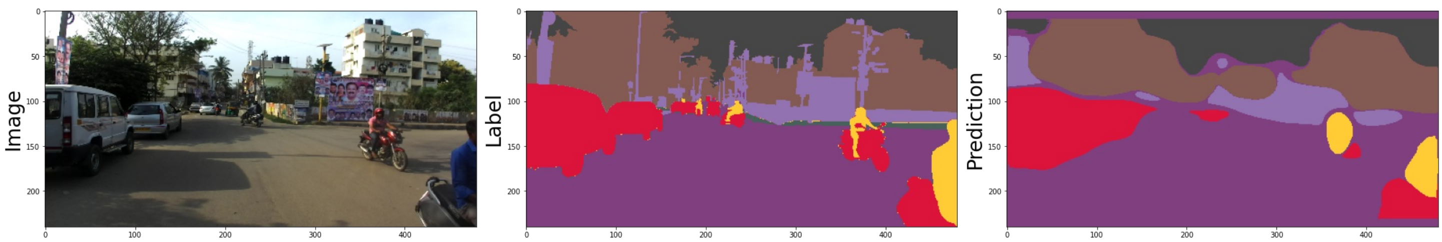


Pspnet Prediction on Test Data

In [ ]:

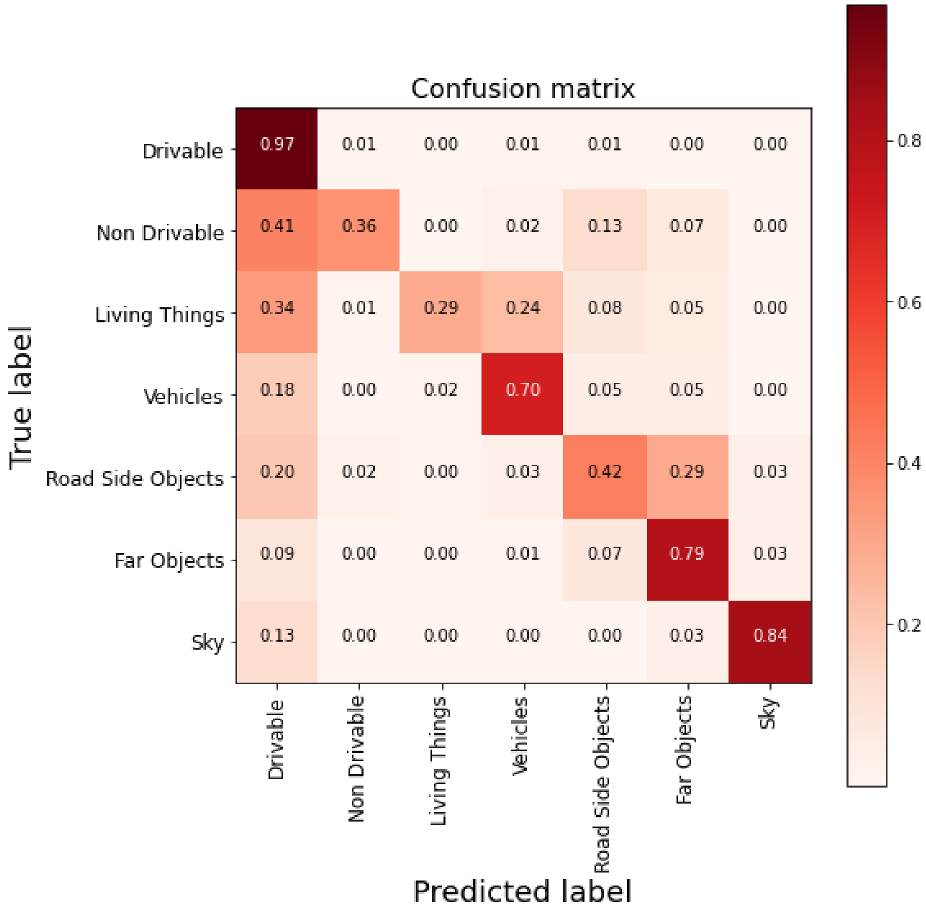
```python
# Test Prediction
Miou, Accuracy, cf_matrix = predict_for("Test_data")
```

```
Total number of samples in Test_data : 4011

Few Segmentation Samples:>>>
```




```
Printing Results:>>

-----------------------
|      MIOU Score      |
-----------------------

   MIOU Score: 0.4284

-----------------------
|   Accuracy Score    |
-----------------------

   Accuracy Score: 0.7041
```

```
   Accuracy Score: 0.7941

-----------------------
|  Confusion Matrix   |
-----------------------
```



Pretty Tabel

In [ ]:

```
# https://ptable.readthedocs.io/en/latest/tutorial.html
print("\n\t      Performance Table")
from prettytable import PrettyTable
T = PrettyTable()
T.field_names = ["PspNet","MIOU", "Accuracy"]
T.add_row(["Train ","0.4612","0.8225"])
T.add_row([" ---------- ","----------","----------"])
T.add_row(["Validation ","0.4201","0.7796"])
T.add_row([" ---------- ","----------","----------"])
T.add_row(["Test ","0.4284","0.7941"])
print(T)
```

```
	      Performance Table
+--------------+------------+------------+
|    PspNet    |    MIOU    |  Accuracy  |
+--------------+------------+------------+
|    Train     |   0.4612   |   0.8225   |
|  ----------  | ---------- | ---------- |
|  Validation  |   0.4201   |   0.7796   |
|  ----------  | ---------- | ---------- |
|     Test     |   0.4284   |   0.7941   |
+--------------+------------+------------+
```

****Conclusion:****

- **PspNet is an effective network for complex scene understanding with a global pyramid pooling that provides contextual information.**
- **PspNet has misclassified many of the labels due to fewer Filters used while training because of limited availability of hardware.**
- **PspNet architecture achieves relatively lower performance on Image segmentation when compared to other segmentation models.**
- **More performance can be obtained by training Models with data in high resolution with more powerful hardware resources**