Neural Networks
Project Submission
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## 1. Topic:

I have built a CNN network that when inputted with an human image tries to classify it to one of the 8 age categories: (0-2. 4-6, 8-13, 15-20, 25-32, 38-43, 48-53, 60+).

### Reference Paper:

https://talhassner.github.io/home/projects/cnn\_agegender/CVPR2015\_CNN\_AgeGenderEstimation.pdf

#### 2. Dataset:

I used Aligned images of Adience Dataset. It had total 17423 images with labels. All these images are colored and I have reshaped them to 227 X 227 while inputting to my CNN. But the dataset is very noisy i.e., there are many blurred images, images captured under very bad lighting conditions and some pictures even had more than 1 person in them. Also the small dataset was one of the bottlenecks for not building a deeper neural network which leads to overfitting.

http://www.cslab.openu.ac.il/download/

## 2.a Data-Preprocessing:

I created one more dataset by running face detection algorithm on all the images and extracting only facial portion from images. If any extracted image had 2 faces, I have chosen the face that is most dominant in that image and then resized all the images to 227 X 227. If there is an image which is so blurred or tilted in such a way that face detection is difficult then I have kept the original image as it is.

### 3. Implementation Details:

I trained the network from scratch using the CNN model as stated below. After 40 epochs with 0.001 learning rate and decay rate ( $10^{\text{A}}$ -5) with SGD optimizer it has attained an accuracy of 42.8 %  $\pm$  3.

Now I loaded this trained model and fine tuned it using the cropped face images (i.e., which are obtained by running face detection algorithms on original images) with all other parameters being kept same. After 40 epochs this model has attained an accuracy  $43.2 \pm 4$  with highest observed 47.12 %.

This increment can be attributed to using facial crop images as face plays a major role in determining a person's age and also most of these facial images get rid of disturbing background thus leading to better learning of our neural network. One notable point here is even the cropped face images still had these blurred Images.

### 3.1 Model Architecture:

It is a sequential model with 3 convd\_blocks. There are 3 convolution layers each followed by max pool layer and then batch normalization layers. After the convolution part, I have added 2 dense layers with a 0.5% dropout and then final output layer. For all layers I have used "relu" activation except for the output layer where softmax activation is being used.

```
#MODEL ARCHITECTURE
def baseModel():
       model = Sequential()
       model.add(layers.Conv2D(96, (7, 7), activation='relu', input_shape=(227, 227, 3), kernel_initializer=initializers.random_normal(stddev=0.01)))
       model.add(layers.MaxPooling2D((3, 3), strides=(2,2)))
       model.add(BatchNormalization())
       model.add(layers.Conv2D(256, (5, 5), activation='relu', kernel_initializer=initializers.random_normal(stddev=0.01)))
       model.add(layers.MaxPooling2D((3, 3), strides=(2,2) ))
       model.add(BatchNormalization())
       model.add(layers.Conv2D(384, (3, 3), activation='relu', kernel initializer=initializers.random normal(stddev=0.01)))
       model.add(layers.MaxPooling2D((3, 3)))
       model.add(layers.Flatten())
       model.add(layers.Dense(512, activation='relu', kernel initializer=initializers.random normal(stddev=0.01)))
       model.add(Dropout(0.5))
       model.add(layers.Dense(256, activation='relu', kernel initializer=initializers.random normal(stddev=0.01)))
       model.add(Dropout(0.5))
       model.add(layers.Dense(8, activation='softmax'))
       return model
```

All the layer weights are random initialized with zero mean Gaussian distribution and standard deviation of 0.01.

First Convolution layer used 96 filters of size 7 X 7 and stride (2,2) Second Convolution layer has 256 filters of size 5 X 5 with stride (2,2) Third Convolution layer has 384 filters of size 3 X 3

# Model.summary:

Layer (type)	Output	Shape	Param #
conv2d_1 (Conv2D)	(None,	221, 221, 96)	14208
max_pooling2d_1 (MaxPooling2	(None,	110, 110, 96)	0
batch_normalization_1 (Batch	(None,	110, 110, 96)	384
conv2d_2 (Conv2D)	(None,	106, 106, 256)	614656
max_pooling2d_2 (MaxPooling2	(None,	52, 52, 256)	0
batch_normalization_2 (Batch	(None,	52, 52, 256)	1024
conv2d_3 (Conv2D)	(None,	50, 50, 384)	885120
max_pooling2d_3 (MaxPooling2	(None,	16, 16, 384)	0
flatten_1 (Flatten)	(None,	98304)	0
dense_1 (Dense)	(None,	512)	50332160
dropout_1 (Dropout)	(None,	512)	0
dense_2 (Dense)	(None,	256)	131328
dropout_2 (Dropout)	(None,	256)	0
dense_3 (Dense)	(None,	8)	2056
======================================	=====		=======

My total data is tentatively divided into 11000 train images, 2500 test Images and 3500 Validation Images

# 3.2 Input: Shape of Tensor

X\_Train shape (11000, 227, 227) X\_Test shape (2500, 227, 227)

# 3.3 Output: Shape of Tensor

Y\_Train shape (11000,) Y\_Test shape (2500,)

## 3.4 Shape of Output tensor for each layer:

First Convolution layer: (96, 221, 221)
Max\_pooling layer: (96, 110, 110)
Batch\_normalization(96,110,110)

First Convolution layer: (256, 106, 106)

Max\_pooling layer: (256, 52, 52) Batch\_normalization(256,52,52)

First Convolution layer: (384, 50, 50) Max\_pooling layer: (384, 16, 16)

Flatten Layer: 98304 First Dense Layer: 512 Second Dense Layer: 256

## 4. HyperParameters

## 4.1 Various HyperParameters Tried:

Batch Size 32, 50, 64 Epochs 10 - 40 Learning Rates 0.01, 0.001, 0.0001

## 4.2 Optimal Parameters Found:

Batch Size: 50 Epochs 40

Learning rate: 0.001

Optimizer = Stochastic Gradient Descent

Learning rate = started with 0.001 with decay of (10 ^ -5)

#### 5. Code:

It has 2 parts. One is Neural network code and other is for face detection and creation of cropped face images from a given Image.

```
crop+align+15.txt
                                                                                                                                                      *8class model.py
from keras.preprocessing.image import ImageDataGenerator
from keras.models import Sequential, Model, load_model
from keras import layers
from keras.layers import Dropout, Flatten, Dense, Input
from keras import applications
from keras.applications.vgg16 import VGG16
from keras.layers import Conv2D, Convolution2D, MaxPooling2D, ZeroPadding2D
from keras.optimizers import RMSprop, SGD, Adam
import numpy as np
import os
from keras.layers.normalization import BatchNormalization
from keras.callbacks import ModelCheckpoint
from keras import initializers
#MODEL ARCHITECTURE
def baseModel():
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        model.add(layers.Conv2D(96, (7, 7), activation='relu', input_shape=(227, 227, 3), kernel_initializer=initializers.random_normal(stddev=0.01)))
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        model.add(layers.Dense(256, activation='relu', kernel initializer=initializers.random normal(stddev=0.01)))
        model.add(Dropout(0.5))
        model.add(layers.Dense(8, activation='softmax'))
        return model
#GENERATING IMAGE DATA GENERATORS
def baseModelDataGen(trainData, validData, testData):
       batchSize = 50
        train_datagen = ImageDataGenerator(rescale=1./255, width_shift_range=0.2,height_shift_range=0.2,shear_range=0.2,zoom_range=0.2,horizontal_flip=True_fill_mode='nearest')
        train_generator = train_datagen.flow_from_directory(trainData, target_size = (227, 227), batch_size = batchSize, class_mode = "categorical", shuffle = True)
        valid datagen = ImageDataGenerator(rescale=1./255, width_shift_range=0.2,height_shift_range=0.2,shear_range=0.2,zoom_range=0.2,horizontal_flip=True,fill_mode='nearest')
        valid_generator = valid_datagen.flow_from_directory(validData, target_size = (227, 227), batch_size = batchSize, class_mode = "categorical", shuffle = True)
        test_datagen = ImageDataGenerator(rescale=1./255, width_shift_range=0.2,height_shift_range=0.2,shear_range=0.2,horizontal_flip=True,fill_mode='nearest')
        test_generator = test_datagen.flow_from_directory(testData,target_size = (227, 227), batch_size = 1, class_mode = "categorical", shuffle = True)
        return (train generator, valid generator, test generator)
#TRAINING AND TESTING THE MODEL
def baseTrain(trainData, validData, testData):
                and - or notewall
```

```
crop+align+15.txt
                                                                                                                                                                                     *8class_model.py
          Moder.aduqrayers.bense(200, accrvacion= rero , kerner_iniciarizer=iniciarizers.random_normai(scudev=0.01)))
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          test_generator = test_datagen.flow_from_directory(testData,target_size = (227, 227), batch_size = 1, class_mode = "categorical", shuffle = True)
          return (train generator, valid generator, test generator)
#TRAINING AND TESTING THE MODEL
def baseTrain(trainData, validData, testData):
                   cwd = os.getcwd()
                   rainlen = sum(len(files) for _, _, files in os.walk(trainData))
validLen = sum(len(files) for _, _, files in os.walk(validData))
testLen = sum(len(files) for _, _, files in os.walk(testData))
                   batch_size = 50
                   myModel = load_model(cwd+'/hdf/cropped_aligned_40.h5')
                   train_generator, valid_generator, test_generator = baseModelDataGen(trainData, validData, testData)
                   test_acc = myModel.evaluate_generator(test_generator, int(np.ceil(testLen/batch_size)))
                   print("test", test_acc[0], test_acc[1])
myModel.compile(optimizer=SGD(\r=0.001, decay = 1e-5),\loss='categorical_crossentropy',metrics=['accuracy'])
callbacks = [ModelCheckpoint(filepath=cwd + '/call' + '/saved-model-{epoch:02d}-{val_acc:.2f}.hdf5', verbose=1, save_best_only=False, save_weights_only=False, period=3
                   history = myModel.fit_generator(train_generator,
                        steps_per_epoch = int(np.ceil(trainLen/batch_size)),
                        epochs=40,
                        validation_data=valid_generator,
                        validation_steps= int(np.ceil(validLen/batch_size)),
                   myModel.save(cwd + '/hdf' +'/cropped aligned 41.h5')
                   test_acc = myModel.evaluate_generator(test_generator, int(np.ceil(testLen/batch_size)))
                   print("test details", test_acc[0], test_acc[1])
trainData = cwd + '/data/age_train'
validData = cwd + '/data/age_valid'
testData = cwd + '/data/age_test'
```

baseTrain(trainData, validData, testData)

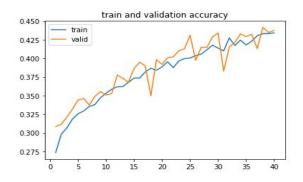
```
In [1]: import bz2
                   import os
                   from urllib.request import urlopen
                   def download_landmarks(dst_file):
                           url = 'http://dlib.net/files/shape_predictor_68_face_landmarks.dat.bz2'
decompressor = bz2.Bz2Decompressor()
                           with urlopen(url) as src, open(dst_file, 'wb') as dst:
                                    data = src.read(1024)
                                    while len(data) > 0:
                                            dst.write(decompressor.decompress(data))
data = src.read(1024)
                   dst dir = 'models'
                   dst_file = os.path.join(dst_dir, 'landmarks.dat')
                   if not os.path.exists(dst_file):
                           os.makedirs(dst dir)
                           download landmarks(dst file)
In [80]: import cv2
                   import numpy as np
                   TEMPLATE = np.float32([
                           PLATE = np.TtOat32[
(0.0792396913815, 0.339223741112), (0.0829219487236, 0.456955367943),
(0.0967927109165, 0.575648016728), (0.122141515615, 0.691921601066),
(0.168687863544, 0.800341263616), (0.239789390707, 0.895732504778),
(0.325662452515, 0.977068762493), (0.422318282013, 1.04329000149),
                           (0.53177882668, 1.6688371126), (0.641296298653, 1.6381924167), (0.738105872266, 0.972268833998), (0.824444363295, 0.839624682279), (0.894792677532, 0.792494155836), (0.939395486253, 0.681546643421), (0.96111933829, 0.562238253072), (0.979579841181, 0.441758925744),
                            (0.971193274221, 0.322118743967), (0.163846223133, 0.249151738053),
                            (0.21780354657, 0.204255863861), (0.291299351124, 0.192367318323),
                           (0.367460241458, 0.203582210627), (0.4392945113, 0.233135599851), (0.586445962425, 0.228141644834), (0.660152671635, 0.195923841854), (0.737466449096, 0.182360984545), (0.813236546239, 0.192828009114), (0.8707571886, 0.235293377042), (0.51534533827, 0.31863546193),
                            (0.516221448289, 0.396200446263), (0.517118861835, 0.473797687758),
                           (0.51816430343, 0.553157797772), (0.433701156035, 0.64054457668), (0.51816430343, 0.553157797772), (0.433701156035, 0.604054457668), (0.475501237769, 0.62976344024), (0.520712933176, 0.634268222208), (0.565874114041, 0.618796581487), (0.607054002672, 0.60157671656), (0.252418718401, 0.331052263829), (0.298663015648, 0.302646354002), (0.355749724218, 0.303020650651), (0.403718978315, 0.33867711083), (0.352507175597, 0.349987615384), (0.296791759886, 0.350478978225),
```

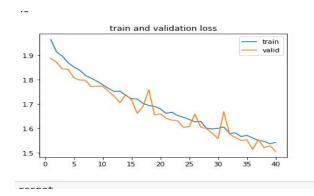
```
return None
        def findLandmarks(self, rgbImg, bb):
            assert rgbImg is not None
            assert bb is not None
            points = self.predictor(rgbImg, bb)
            return list(map(lambda p: (p.x, p.y), points.parts()))
        def align(self, imgDim, rgbImg, bb=None,
                  landmarks=None, landmarkIndices=INNER EYES AND BOTTOM LIP,
                  skipMulti=False):
            assert imgDim is not None
            assert rgbImg is not None
            assert landmarkIndices is not None
            if bb is None:
                bb = self.getLargestFaceBoundingBox(rgbImg, skipMulti)
                if bb is None:
                    return
            if landmarks is None:
                landmarks = self.findLandmarks(rgbImg, bb)
            npLandmarks = np.float32(landmarks)
            npLandmarkIndices = np.array(landmarkIndices)
            H = cv2.getAffineTransform(npLandmarks[npLandmarkIndices],
                                        imgDim * MINMAX TEMPLATE[npLandmarkIndices])
            thumbnail = cv2.warpAffine(rgbImg, H, (imgDim, imgDim))
            return thumbnail
2]: import cv2
    import matplotlib.pyplot as plt
    import matplotlib.patches as patches
    import glob
    import shutil
    #from AlignDlib import *
    #from align import AlignDlib
    %matplotlib inline
```

```
import matplotlib.patches as patches
import glob
import shutil
#from AlignDlib import *
#from align import AlignDlib
%matplotlib inline
def load image(path):
    img = cv2.imread(path, 1)
    # OpenCV loads images with color channels
    # in BGR order. So we need to reverse them
    return img[...,::-1]
# Initialize the OpenFace face alignment utility
#print("hello")
alignment = AlignDlib('models/landmarks.dat')
# Load an image of Jacques Chirac
#jc orig = load image(metadata[2].image path())
cwd = os.getcwd()
#imageFolders = [x[0] \text{ for } x \text{ in os.walk(cwd } + '/aligned')]
imageFolders = os.listdir(cwd + '/aligned')
newDir = cwd+'/cropped'
if os.path.exists(newDir):
    shutil.rmtree(newDir)
os.mkdir(newDir)
#print(imageFolders)
for folder in imageFolders:
    #subDir = folder.replace('aligned', 'cropped')\
    newDir = cwd + '/cropped/' + folder
oldDir = cwd + '/aligned/' + folder
    os.mkdir(newDir)
    pa = oldDir + '/*'
    for filename in glob.glob(pa):
        #print(filename)
        img = cv2.imread(filename)
        bb = alignment.getLargestFaceBoundingBox(img)
        cropped = alignment.align(227, img, bb, landmarkIndices=AlignDlib.OUTER_EYES_AND_NOSE)
        imgName = filename.replace('aligned', 'cropped')
        if bb == None:
            cropped = img
        #print(imgName)
        cv2.imwrite(imgName, cropped)
```

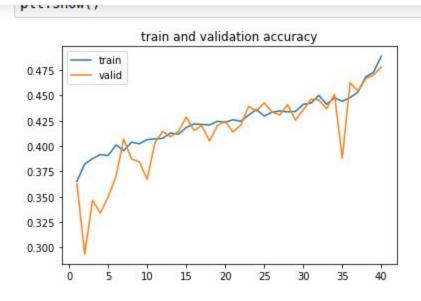
# Accuracy Plots for validation and train data:

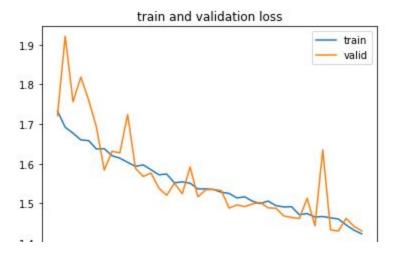
# 1. Base Model





# 2. Model preloaded with base and trained on cropped Images





```
Epoch 1/40
                 179s 516ms/step
                                         loss: 1.7331
                                                             acc: 0.3651
                                                                                val loss: 1.7211
                                                                                                          val acc: 0.3626
                                                                                val_loss: 1.9214
val_loss: 1.7562
val_loss: 1.8184
Epoch 2/40
Epoch 3/40
                 176s 507ms/step
176s 506ms/step
                                                             acc: 0.3823
                                         loss: 1.6918
                                                                                                          val_acc: 0.2935
                                                                                                          val_acc: 0.3463
                                          loss: 1.6771
                                                             acc: 0.3875
Epoch 4/40
                        507ms/step
                                                                                                          val_acc: 0.3338
                 176s
                                          loss: 1.6601
                                                             acc: 0.3916
                                                                                val_loss: 1.7603
val_loss: 1.6924
val_loss: 1.5839
Epoch 5/40
Epoch 6/40
                                                                                                         val_acc: 0.3498
val_acc: 0.3698
                 173s 500ms/step
174s 502ms/step
                                                             acc: 0.3905
                                         loss: 1.6583
                                          loss: 1.6371
                                                             acc: 0.4010
Epoch 7/40
                 174s 501ms/step
                                                                                                          val_acc: 0.4069
                                          loss: 1.6380
                                                             acc: 0.3956
Epoch 8/40
Epoch 9/40
                 174s 502ms/step
175s 504ms/step
                                                                                val_loss: 1.6312
val_loss: 1.6273
val_loss: 1.7241
                                                                                                         val_acc: 0.3872
val_acc: 0.3843
val_acc: 0.3672
                                         loss: 1.6201
                                                             acc: 0.4038
                                         loss: 1.6140
                                                             acc: 0.4022
Epoch 10/40
                  174s 502ms/step
                                           loss: 1.6035
                                                            - acc: 0.4063
                  171s 492ms/step
174s 500ms/step
                                                              acc: 0.4070
acc: 0.4076
Epoch 11/40
Epoch 12/40
                                                                                 val_loss:
val_loss:
                                                                                                           val_acc: 0.4034
val_acc: 0.4144
                                           loss: 1.5933
                                                                                               1.5885
                                           loss: 1.5971
                                                                                              1.5680
Epoch 13/40
                   173s 499ms/step
                                           loss: 1.5846
                                                               acc: 0.4129
                                                                                 val loss: 1.5765
                                                                                                           val acc: 0.4092
                                                                                 val_loss:
val_loss:
Epoch 14/40
Epoch 15/40
                  175s 503ms/step
178s 514ms/step
                                                                                                           val_acc: 0.4144
val_acc: 0.4284
                                           loss: 1.5722
                                                              acc: 0.4116
                                                                                               1.5385
                                           loss: 1.5739
                                                              acc: 0.4183
                                                                                               1.5203
Epoch 16/40
                         505ms/step
                                           loss: 1.5518
                                                               acc: 0.4217
                                                                                  val loss:
                                                                                               1.5509
                                                                                                           val acc: 0.4153
                   175s
Epoch 17/40
Epoch 18/40
                  175s 505ms/step
175s 503ms/step
                                                               acc: 0.4213
acc: 0.4208
                                                                                 val_loss:
val_loss:
                                                                                                           val_acc: 0.4202
val_acc: 0.4049
                                           loss: 1.5542
                                                                                               1.5240
                                           loss: 1.5509
                                                                                 val
                                                                                               1.5918
                   176s
Epoch 19/40
                         508ms/step
                                           loss: 1.5365
                                                               acc: 0.4244
                                                                                 val_loss:
                                                                                               1.5165
                                                                                                           val_acc: 0.4202
Epoch 20/40
Epoch 21/40
                  175s 503ms/step
174s 502ms/step
                                                                                 val_loss:
val_loss:
                                                                                                           val_acc: 0.4243
val_acc: 0.4139
                                           loss: 1.5366
                                                               acc: 0.4235
                                                                                               1.5343
                                           loss: 1.5350
                                                               acc: 0.4259
                                                                                               1.5350
Epoch 22/40
                   175s
                         503ms/step
                                           loss: 1.5280
                                                               acc: 0.4245
                                                                                  val_loss:
                                                                                               1.5323
                                                                                                           val_acc: 0.4205
Epoch 23/40
Epoch 24/40
                  174s 502ms/step
176s 507ms/step
                                                                                 val_loss:
val_loss:
                                                                                                           val_acc: 0.4391
val_acc: 0.4345
                                           loss: 1.5251
                                                               acc: 0.4305
                                                                                               1.4880
                                           loss: 1.5137
                                                               acc: 0.4361
                                                                                               1.4961
Epoch 25/40
                   174s
                         501ms/step
                                           loss: 1.5165
                                                               acc: 0.4296
                                                                                  val_loss:
                                                                                               1.4918
                                                                                                           val_acc: 0.4426
Epoch 26/40
Epoch 27/40
                         508ms/step
504ms/step
                                                                                 val_loss:
val_loss:
                                                                                                           val_acc: 0.4336
val_acc: 0.4307
                  176s
                                           loss: 1.5054
                                                               acc: 0.4333
                                                                                               1.4985
                                           loss: 1.4994
                                                               acc: 0.4346
                   175s
                                                                                               1.5023
Epoch 28/40
                   175s
                         505ms/step
                                           loss: 1.5059
                                                               acc: 0.4337
                                                                                  val_loss:
                                                                                               1.4887
                                                                                                           val_acc: 0.4408
Epoch 29/40
Epoch 30/40
                  176s 507ms/step
176s 507ms/step
                                                                                 val_loss:
val loss:
                                                                                                           val_acc: 0.4255
val_acc: 0.4356
                                           loss: 1.4943
                                                               acc: 0.4341
                                                                                               1.4878
                                           loss: 1.4910
                                                               acc: 0.4411
                                                                                               1.4686
Epoch 31/40
                   177s
                         509ms/step
                                           loss: 1.4916
                                                               acc: 0.4424
                                                                                 val_loss:
                                                                                               1.4644
                                                                                                           val_acc: 0.4461
                  174s 501ms/step
175s 506ms/step
                                                                                 val_loss:
val loss:
                                                                                                           val_acc: 0.4455
val_acc: 0.4368
Epoch 32/40
                                           loss: 1.4714
                                                               acc: 0.4500
                                                                                               1.4619
Epoch 33/40
                                           loss: 1.4743
                                                               acc: 0.4411
                                                                                               1.5129
Epoch 34/40
                   173s 497ms/step
                                           loss: 1.4657
                                                               acc: 0.4476
                                                                                  val_loss:
                                                                                               1.4436
                                                                                                           val_acc: 0.4510
Epoch 35/40
Epoch 36/40
                  176s 507ms/step
175s 505ms/step
                                                                                                           val_acc: 0.3881
val_acc: 0.4626
                                                               acc: 0.4441
                                                                                 val_loss:
val loss:
                                           loss: 1.4668
                                                                                               1.6351
                                           loss: 1.4635
                                                               acc: 0.4478
                                                                                               1.4332
Epoch 37/40
                                                               acc: 0.4531
                  175s 505ms/step
                                           loss: 1.4605
                                                                                 val_loss:
                                                                                               1.4304
                                                                                                           val_acc: 0.4542
                                                                                                           val_acc: 0.4664
val_acc: 0.4702
Epoch 38/40
                  174s 501ms/step
                                           loss: 1.4456
                                                              acc: 0.4682
                                                                                 val_loss: 1.4622
val_loss: 1.4422
Epoch 39/40
                  175s 505ms/step
                                          loss: 1.4324
                                                              acc: 0.4728
               - 173s 498ms/step - loss: 1.4230 - acc: 0.4886
Epoch 40/40
                                                                                 val loss: 1.4305
                                                                                                           val acc: 0.4779
  test details', 1.5034706606262032, 0.47128735632183906)
```

## 6. Training and Testing performance:

#### Base Model:

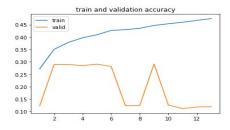
Train Data: 48.86 Valid Data: 47.79 Test Data: 47.1

Model	Train	Valid	Test
Base Model	45.42	43.73	44.9
PreTrained with Facial Images	48.86	47.79	47.1

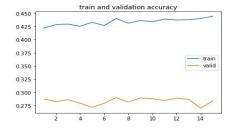
## 7. Other Tried Approaches:

I even tried resnet-50 where I first freezed resnet layers and trained only top two dense layers with 512 and 256 nodes and it started overfitting around 7th epoch. Later I unfreezed all the layers and tried to finetune it using with adience dataset, train accuracy kept on increasing but validation accuracy was hovering around 28%. One of the main reasons that we can't use more deeper networks is smaller dataset. I even experimented with VGG16 for 4 classes during previous submission but even that didn't work out.

### a. Resnet Model with lower layers freezed:



## b. Resnet Model with all layers Unfreezed



## **Instructions for Running:**

### Dependencies:

Python 3: Running CNN
Python 2.7: Running Tkinter

Tkinter

numpy

Keras

Pillow

Numpy

Pathlib

cv2

dlib

gensim

cmake

#### Run:

After cloning the repository from github (assuming you maintained same relative folder structure)

- 1. Python Base.py: For running base model
- 2. Python preTrained.py: For running pretrained model
- 3. GUI.py: For running GUI
- 4. faceRecog.ipynb: For creating cropped face images

### Demo link:

https://drive.google.com/file/d/12ZEh4d3bdHRrlWx4McgDqdc7HXPAFDpB/view

#### Github Link:

### **Entire code Base**

https://github.com/Manvitha-K/Age-Prediction-Neural-Project

#### **GDrive Link:**

For loading the trained model: These models should be downloaded to /hdf folders.

https://drive.google.com/open?id=1M-H2zl1u6GkV8ozDYNb3 GdErs9utgav

## **Updated Report:**

As per suggestion, I tried heatmaps(class activation maps). I have randomly picked images from various classes and tried heatmaps on top of those and observation is my current CNN model is triggered by face, especially eyes part. It is not focussing on any background or some disturbing ailment.

What I have written in this report is not my baseline model. My baseline model was only categorizing these images into 4 types which I have submitted in project4 submission. My improved model had 2 parts. Face detection and 8 classifier CNN.

**First Part:** Implementing the face detection algorithm for finding faces and then using these detected faces for training CNN.

**Second part:** CNN (3 Convolution blocks) for 8 class classification (0-2. 4-6, 8-13, 15-20, 25-32, 38-43, 48-53, 60+). I trained this model from scratch and after 40 epochs with 0.001 learning rate and decay rate (10^-5) with SGD optimizer it has attained an accuracy of **42.8** % ± **3.** Now I loaded this trained model and fine tuned it using the cropped face images (i.e., which are obtained by running face detection algorithms on original images) with all other parameters being kept same. After 40 epochs this model has attained an accuracy **43.2** ± **4** with highest observed **47.12** %.

The lower accuracy mentioned in the above section can be attributed to the difficulty of age classification problem unlike imagenet classification where we have many objects and different features are used for distinguishing them whereas here entire classification is based on the facial features. The publication which I took as baseline had only accuracy of 44% whereas my model was able to achieve 47%. My model is also focussing on the right parameters which is clearly evident from the heatmaps.

Attached heatmap images and corresponding code has been pushed to github.

