

OcularCNN-Improvements

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import pandas as pd
import random
import numpy as np
```

```

import random
import numpy as np

theFile = pd.read_csv("../data/full_df.csv")
theFile

In [1]:

```

	Patient ID	Patient Age	Patient Sex	Left-Fundus	Right-Fundus	Left-Diagnostic Keywords	Right-Diagnostic Keywords	N	D	G	C	A	H	M	O	filepath	labels	
	0	61	69	Female	0_left.jpg	0_right.jpg	cataract	normal fundus	0	0	0	1	0	0	0	0	./input/ocular-disease-recognition-odir5/ODL...	[N]
	1	1	57	Male	1_left.jpg	1_right.jpg	normal fundus	normal fundus	1	0	0	0	0	0	0	0	./input/ocular-disease-recognition-odir5/ODL...	[N]
	2	2	42	Male	2_left.jpg	2_right.jpg	laser spot, moderate non proliferative retinopathy	moderate non proliferative retinopathy	0	1	0	0	0	0	0	1	./input/ocular-disease-recognition-odir5/ODL...	[D]
	3	4	53	Male	4_left.jpg	4_right.jpg	macular epiretinal membrane	mild nonproliferative retinopathy	0	1	0	0	0	0	0	1	./input/ocular-disease-recognition-odir5/ODL...	[D]
	4	5	50	Female	5_left.jpg	5_right.jpg	moderate non proliferative retinopathy	moderate non proliferative retinopathy	0	1	0	0	0	0	0	0	./input/ocular-disease-recognition-odir5/ODL...	[D]
	
	6387	4686	63	Male	4686_left.jpg	4686_right.jpg	severe retinopathy	proliferative retinopathy	0	1	0	0	0	0	0	0	./input/ocular-disease-recognition-odir5/ODL...	[D]
	6388	4688	42	Male	4688_left.jpg	4688_right.jpg	moderate non proliferative retinopathy	moderate non proliferative retinopathy	0	1	0	0	0	0	0	0	./input/ocular-disease-recognition-odir5/ODL...	[D]
	6389	4689	54	Male	4689_left.jpg	4689_right.jpg	mild nonproliferative retinopathy	mild normal fundus	0	1	0	0	0	0	0	0	./input/ocular-disease-recognition-odir5/ODL...	[D]
	6390	4690	57	Male	4690_left.jpg	4690_right.jpg	mild nonproliferative retinopathy	mild normal fundus	0	1	0	0	0	0	0	0	./input/ocular-disease-recognition-odir5/ODL...	[D]
	6391	4784	58	Male	4784_left.jpg	4784_right.jpg	hypertensive retinopathy, age-related macular d...	hypertensive retinopathy, age-related macular d...	0	0	0	0	1	1	0	0	./input/ocular-disease-recognition-odir5/ODL...	[H]

6392 rows x 19 columns

```

In [2]:
theFile.drop(np.linspace(1, 3194, 3193, dtype = int), inplace = True )
catract = target.loc[target['Left-Diagnostic Keywords'] == 'catract'] | (theFile['Left-Diagnostic Keywords'] == 'normal fundus')
target = theFile.loc[(theFile['Left-Diagnostic Keywords'] == 'catract') | (theFile['Left-Diagnostic Keywords'] == 'normal fundus')]

In [3]:
print(len(target.loc[target['Left-Diagnostic Keywords'] == 'catract']))
print(len(target.loc[target['Left-Diagnostic Keywords'] == 'normal fundus']))

151
1433

In [4]:
#As shown above, there are much more normal fundus entries than cataract
#lets sample the normal fundus to get equivalent numbers of each class
catract = target.loc[target['Left-Diagnostic Keywords'] == 'catract']
normal = normal.sample(135)
frames = [catract, normal]
target = pd.concat(frames)

#now shuffle these randomly
# shuffle the DataFrame rows
target = target.sample(frac = 1)

In [5]:
pictures = target[['filename']]

In [6]:
target

Out[6]:

```

	Patient ID	Patient Age	Patient Sex	Left-Fundus	Right-Fundus	Left-Diagnostic Keywords	Right-Diagnostic Keywords	N	D	G	C	A	H	M	O	filepath	labels	
	458	990	41	Female	990_left.jpg	990_right.jpg	normal fundus	macular epiretinal membrane	0	0	0	0	0	0	0	1	./input/ocular-disease-recognition-odir5/ODL...	[N]
	6232	4496	53	Female	4496_left.jpg	4496_right.jpg	normal fundus	mild nonproliferative retinopathy	0	1	0	0	0	0	0	0	./input/ocular-disease-recognition-odir5/ODL...	[N]
	4132	1113	56	Female	1113_left.jpg	1113_right.jpg	normal fundus	mild nonproliferative retinopathy	0	1	0	0	0	0	0	0	./input/ocular-disease-recognition-odir5/ODL...	[N]
	4805	2432	45	Female	2432_left.jpg	2432_right.jpg	normal fundus	normal fundus	1	0	0	0	0	0	0	0	./input/ocular-disease-recognition-odir5/ODL...	[N]
	4588	2123	47	Male	2123_left.jpg	2123_right.jpg	catract	refractive media opacity	0	0	0	1	0	0	0	1	./input/ocular-disease-recognition-odir5/ODL...	[C]
	
	5080	2740	55	Male	2740_left.jpg	2740_right.jpg	normal fundus	normal fundus	1	0	0	0	0	0	0	0	./input/ocular-disease-recognition-odir5/ODL...	[N]
	4574	2109	82	Male	2109_left.jpg	2109_right.jpg	catract	catract	0	0	0	1	0	0	0	0	./input/ocular-disease-recognition-odir5/ODL...	[C]
	4585	2120	72	Female	2120_left.jpg	2120_right.jpg	catract	catract	0	0	0	1	0	0	0	0	./input/ocular-disease-recognition-odir5/ODL...	[C]
	5245	2916																


```
[17]: actual_pics = np.array(actual_pics)
      classifications = np.array(classifications)
      actual_pics.astype('float32')/255.0

#shuffle & false events data split being different everytime
X_train, X_test, y_train, y_test = train_test_split(actual_pics, classifications, test_size=0.2, shuffle
e = False)

#split test into validate and test, again making sure the data is always the same for consistency
X_train, xt, y_train, yt = train_test_split(X_train, y_train, test_size=0.1, shuffle = True)

In [18]: #begin NN
import logging
logging.basicConfig()
import tensorflow as tf

In [19]: import numpy
len(actual_pics[2][0])

Out[19]: 224

In [20]: print(X_train.shape)
         y_train.shape

(194, 224, 224, 3)

Out[20]: (194, 2)

In [21]: # convert to numpy arrays
x = np.array(X_train)
y = np.array(y_train)

X_test = np.array(X_test)
y_test = np.array(y_test)

xt = np.array(xt)
yt = np.array(yt)

In [22]: from tensorflow.keras import datasets, layers, models
import matplotlib.pyplot as plt
from tensorflow.keras.layers import Dropout
from keras.layers.advanced_activations import LeakyReLU

model = models.Sequential()
model.add(layers.Conv2D(32, (3,3), activation = 'linear', input_shape=(img_res, img_res, 3)))
model.add(layers.Conv2D(128, (3,3), activation = 'linear'))
model.add(layers.MaxPooling2D((2,2)))
model.add(Dropout(0.25))
model.add(layers.Conv2D(128, (3,3), activation = 'linear'))
model.add(layers.Conv2D(128, (3,3), activation = 'linear'))
model.add(layers.MaxPooling2D(pool_size=(2, 2),padding='same'))
model.add(layers.Flatten())
model.add(layers.Dense(128, activation = 'sigmoid'))
model.add(layers.Dense(2, activation='softmax'))

model.summary()
from tensorflow import keras
opt = keras.optimizers.Adam( learning_rate=0.00001)

#early stopping stuff
# simple early stopping
from keras.callbacks import EarlyStopping
es = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=20, min_delta=0.01)

model.compile(loss='binary_crossentropy', optimizer=opt, metrics=['accuracy'])

Model: "sequential"

Layer (type)                Output Shape                Param #
-----
conv2d (Conv2D)              (None, 222, 222, 32)       896
leaky_re_lu (LeakyReLU)      (None, 222, 222, 32)       0
max_pooling2d (MaxPooling2D) (None, 111, 111, 32)       0
dropout (Dropout)            (None, 111, 111, 32)       0
conv2d_1 (Conv2D)            (None, 109, 109, 128)      36992
leaky_re_lu_1 (LeakyReLU)    (None, 109, 109, 128)      0
max_pooling2d_1 (MaxPooling2 (None, 54, 54, 128)       0
dropout_1 (Dropout)          (None, 54, 54, 128)       0
conv2d_2 (Conv2D)            (None, 52, 52, 128)      147584
leaky_re_lu_2 (LeakyReLU)    (None, 52, 52, 128)       0
max_pooling2d_2 (MaxPooling2 (None, 26, 26, 128)       0
flatten (Flatten)            (None, 86528)              0
dense (Dense)                (None, 128)                11075712
dense_1 (Dense)              (None, 2)                  258
=====
Total params: 11,261,442
Trainable params: 11,261,442
Non-trainable params: 0

In [23]: print(np.size(x))
         print(np.shape(x))
         print(np.size(y))
         print(np.shape(y))

2920432
(194, 224, 224, 3)
398
(194, 2)

In [24]: #this stores the fitting information
#put in our own data for the images and labelling stuff

history = model.fit(x, y, epochs = 10, validation_data = (xt, yt), callbacks = [es])

#dont forget to keep training until your accuracy becomes bad

Epoch 1/10
45 - val_accuracy: 0.5000
Epoch 2/10
7/7 [=====] - 13s 2s/step - loss: 0.7005 - accuracy: 0.5379 - val_loss: 0.68
47 - val_accuracy: 0.5000
Epoch 3/10
7/7 [=====] - 14s 2s/step - loss: 0.6844 - accuracy: 0.5163 - val_loss: 0.67
84 - val_accuracy: 0.5909
Epoch 4/10
7/7 [=====] - 14s 2s/step - loss: 0.6737 - accuracy: 0.6050 - val_loss: 0.67
69 - val_accuracy: 0.6364
Epoch 5/10
7/7 [=====] - 14s 2s/step - loss: 0.6700 - accuracy: 0.6041 - val_loss: 0.67
08 - val_accuracy: 0.6364
Epoch 6/10
7/7 [=====] - 13s 2s/step - loss: 0.6632 - accuracy: 0.6111 - val_loss: 0.67
27 - val_accuracy: 0.5909
Epoch 7/10
7/7 [=====] - 14s 2s/step - loss: 0.6718 - accuracy: 0.6098 - val_loss: 0.66
75 - val_accuracy: 0.7273
Epoch 8/10
7/7 [=====] - 13s 2s/step - loss: 0.6511 - accuracy: 0.6498 - val_loss: 0.66
88 - val_accuracy: 0.6818
Epoch 9/10
7/7 [=====] - 13s 2s/step - loss: 0.6641 - accuracy: 0.5980 - val_loss: 0.67
22 - val_accuracy: 0.7273
Epoch 10/10
7/7 [=====] - 14s 2s/step - loss: 0.6652 - accuracy: 0.5865 - val_loss: 0.66
55 - val_accuracy: 0.6364

In [25]: # Plot the change in accuracy and validation accuracy as a function of epochs

plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label='val_accuracy')
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.ylim(0, 1)
plt.legend(loc='lower right')

Out[25]: <matplotlib.legend.Legend at 0x7f93354ead50>

Accuracy
0.8
0.6
0.4
0.2
0.0
0 2 4 6 8
Epoch
accuracy
val_accuracy

In [26]: performance = model.evaluate(X_test, y_test, verbose=1)

2/2 [=====] - 1s 453ms/step - loss: 0.6503 - accuracy: 0.6667

In [27]: y_pred = model.predict(X_test)
         print(y_pred)

[[0.5788577 0.42113228]
 [0.97771764 0.0228238]
 [0.95908943 0.0409306 ]
 [0.50531015 0.49466082]
 [0.68056893 0.31943107]
 [0.5151514 0.48484862]
 [0.5131143 0.48686866]
 [0.5827789 0.4172211 ]
 [0.58487195 0.4151281 ]
 [0.5860251 0.4039748 ]
 [0.60610163 0.3938983 ]
 [0.5258783 0.47412172]
 [0.536712 0.46328804]
 [0.5292513 0.4707467 ]
 [0.5387855 0.46121445]
 [0.5465227 0.45347735]
 [0.53974645 0.6602535 ]
 [0.5355231 0.46447688]
 [0.58430666 0.41569328]
 [0.5782865 0.42217132]
 [0.735031 0.26479888]
 [0.6021158 0.39788422]
 [0.5793134 0.4206867 ]
 [0.49606153 0.50393644]
 [0.58762383 0.4123762 ]
 [0.6887743 0.31122577]
 [0.5857127 0.4342873 ]
 [0.45948133 0.54051864]
 [0.6057914 0.39420864]
 [0.4469654 0.55343455]
 [0.60244924 0.39758073]
 [0.5704854 0.4295314 ]
 [0.6301627 0.3698373 ]
 [0.4920884 0.5079116 ]
 [0.4035052 0.5964948 ]
 [0.56033206 0.43966797]
 [0.5877249 0.41227505]
 [0.56641195 0.43353805]
 [0.40571567 0.59428436]
 [0.48935604 0.5106439 ]
 [0.52726574 0.47373326]
 [0.3934633 0.60653675]
 [0.48530552 0.5146944 ]
 [0.49864906 0.5047655 ]
 [0.60464644 0.39535362]
 [0.5187622 0.48123786]
 [0.5898149 0.41018507]
 [0.6578592 0.34541083]
 [0.5853153 0.41468465]
 [0.5554536 0.44454637]
 [0.58864906 0.40115097]
 [0.5957013 0.40429872]
 [0.5611944 0.43880558]
 [0.6112777 0.3887223 ]]
```