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1 Detecting Tumors in MRI Brain Scans using Convolutional Neural Networks

1.0.1 This notebook contains the code necessary to load and classify MRI images as containing a brain tumor or being tumor-free.

The process is as follows:

- Section 1.1
- Section 2
- Section 3
- Section 5
- Section 6
- Section 7
- Section 8
- Section 9

1.1 Imports

```
import libraries/packages
import numpy as np
import os
import cv2
import matplotlib.pyplot as plt
import seaborn as sns

from keras.preprocessing.image import ImageDataGenerator
from keras.models import Sequential
from keras.layers import Dense, Conv2D, MaxPool2D, Flatten, Dropout,

BatchNormalization
from keras.callbacks import ReduceLROnPlateau
from sklearn.metrics import classification_report, confusion_matrix
from skimage.segmentation import mark_boundaries
import math
import lime.lime_image as li
```

```
[3]: # import custom functions
import sys
```

```
sys.path.append('../../src')
from data_functions import *
```

2 Get Image Paths

2.0.1 Custom function returns all image files within given directory

```
[4]: # get paths from base directory
base_dir = 'D:/MRI_data/Kaggle'
absent_paths, present_paths = get_img_paths(base_dir)
```

2.0.2 Split Paths into Train, Validation, and Test sets with sklearn train_test_split

```
[5]: # define train size for data set
     train_size = 0.8 # eighty percent
     test size = 0.15 # fifteen percent
     val_size = 0.05 # five percent
     # calculate test size for second split
     test_size2 = test_size/(1-train_size)
     # split absent paths into train and test
     absent_train, absent_test = train_test_split(absent_paths,__
     →train_size=train_size, random_state=2021)
     # split absent test paths into test and validation
     absent_test, absent_val = train_test_split(absent_test, train_size=test_size2,_u
     →random_state=2021)
     # split present paths into train and test
     present_train, present_test = train_test_split(present_paths,_
     →train_size=train_size, random_state=2021)
     # split present paths into test and val
     present_test, present_val = train_test_split(present_test,__
     →train_size=test_size2, random_state=2021)
```

```
[6]: # combine train and test and validation lists (respectively)
    train = absent_train
    train.extend(present_train)

test = absent_test
    test.extend(present_test)

val = absent_val
```

```
val.extend(present_val)
```

3 Load Image Data

3.0.1 Custom function loads data given path and class specified

```
[7]: # load image data
train_img_data = get_data(train)

val_img_data = get_data(val)

test_img_data = get_data(test)
```

4 Remove Duplicates

4.0.1 Custom function compares each image and removes duplicates. This is necessary for correctly fitting the model.

```
[8]: # remove duplicates from each set
unique_train_img, train_duplicate = remove_duplicates(train_img_data)
unique_val_img, val_duplicate = remove_duplicates(val_img_data)
unique_test_img, test_duplicate = remove_duplicates(test_img_data)
```

4.0.2 View samples of scans with and without tumors present

```
[]: labels = ['Tumor Absent', 'Tumor Present']

# create figure hold images
fig, ax = plt.subplots(1,2, figsize=(10,5))
ax = ax.flatten()

# plot image data from first [1] train image data (tumor-free brain)
ax[0].imshow(unique_train_img[100][0], cmap='gray')
ax[0].set_title(labels[unique_train_img[100][1]])
ax[0].axis('off')

# plot image data from last [-1] train image data (tumor patient brain)
ax[1].imshow(unique_train_img[-22][0], cmap='gray')
ax[1].set_title(labels[unique_train_img[-22][1]])
ax[1].axis('off')

# save figure
plt.savefig("../figures/scan_comparison.jpg", transparent=True)
```

5 Reshape Image Data

```
[]: # separate image data and identifiers
     x_train = []
     y_train = []
     x_val = []
     y_val = []
     x_test = []
     y_test = []
     for data, label, _ in unique_train_img:
         x_train.append(data)
         y_train.append(label)
     for data, label, _ in unique_val_img:
         x_val.append(data)
         y_val.append(label)
     for data, label, _ in unique_test_img:
         x_test.append(data)
         y_test.append(label)
[]: # scale data and convert to np.array for efficiency
     x_train = np.array(x_train)/255
     x_test = np.array(x_test)/255
     x_val = np.array(x_val)/255
[]: img_size = 150
     # resize data for deep learning
     x_train = x_train.reshape(-1, img_size, img_size, 3)
     x_test = x_test.reshape(-1, img_size, img_size, 3)
```

6 ImageDataGenerator

x_val = x_val.reshape(-1, img_size, img_size, 3)

```
featurewise_std_normalization=False,
samplewise_std_normalization=False,
zca_whitening=False,
rotation_range=30,
zoom_range=0.25,
width_shift_range=0.2,
height_shift_range=0.2,
horizontal_flip=True,
vertical flip=False)
```

Build Model

```
[]: metrics = ['Recall', 'accuracy']
    →patience=2, verbose=1, factor=0.3, min_lr=10**-9)
    learning_rate_reduction_acc = ReduceLROnPlateau(monitor='val accuracy',__
     →patience=2, verbose=1, factor=0.3, min_lr=10**-9)
    model= Sequential()
    model.add(Conv2D(32, (3,3), strides =1, padding = 'same', activation = 'relu', __
     \rightarrowinput_shape = (150,150,3)))
    model.add(MaxPool2D((2,2), strides=2, padding='same'))
    model.add(Conv2D(64, (2,2), strides =1, padding ='same', activation='relu'))
    model.add(Dropout(0.15))
    model.add(MaxPool2D((2,2), strides=2, padding='same'))
    model.add(Conv2D(64, (3,3), strides =1, padding ='same', activation='relu'))
    model.add(Dropout(0.2))
    model.add(MaxPool2D((2,2), strides=2, padding='same'))
    model.add(Conv2D(64, (3,3), strides =1, padding ='same', activation='selu'))
    model.add(Flatten())
    model.add(Dense(units=128, activation='relu'))
    model.add(Dropout(0.1))
    model.add(Dense(units=1, activation='sigmoid'))
    model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=metrics)
    model.summary()
    model_history = model.fit(datagen.flow(x_train, y_train), epochs=epochs,_
     →validation_data=datagen.flow(x_val, y_val),
```

```
[15]: epochs = 12
       →callbacks=[learning_rate_reduction_loss, learning_rate_reduction_acc])
```

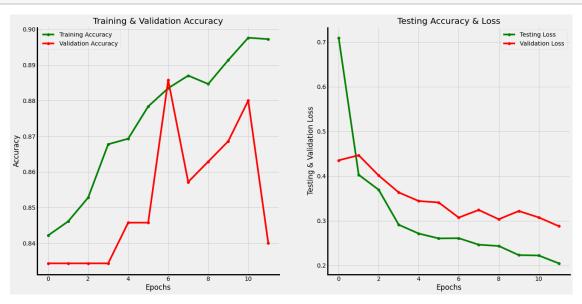
```
Epoch 1/12
```

```
0.9748 - accuracy: 0.8421 - val_loss: 0.4352 - val_recall: 1.0000 -
val_accuracy: 0.8343
Epoch 2/12
0.9794 - accuracy: 0.8461 - val loss: 0.4465 - val recall: 1.0000 -
val_accuracy: 0.8343
Epoch 3/12
- accuracy: 0.8528
Epoch 00003: ReduceLROnPlateau reducing learning rate to 0.0003000000142492354.
0.9826 - accuracy: 0.8528 - val_loss: 0.4012 - val_recall: 1.0000 -
val_accuracy: 0.8343
Epoch 4/12
0.9739 - accuracy: 0.8677 - val_loss: 0.3633 - val_recall: 0.9452 -
val_accuracy: 0.8343
Epoch 5/12
0.9441 - accuracy: 0.8693 - val_loss: 0.3440 - val_recall: 0.9726 -
val_accuracy: 0.8457
Epoch 6/12
0.9432 - accuracy: 0.8783 - val_loss: 0.3408 - val_recall: 0.9247 -
val_accuracy: 0.8457
Epoch 7/12
0.9487 - accuracy: 0.8835 - val_loss: 0.3070 - val_recall: 0.9726 -
val_accuracy: 0.8857
Epoch 8/12
0.9510 - accuracy: 0.8870 - val_loss: 0.3240 - val_recall: 0.9589 -
val_accuracy: 0.8571
Epoch 9/12
- accuracy: 0.8846
Epoch 00009: ReduceLROnPlateau reducing learning rate to 9.000000427477062e-05.
0.9500 - accuracy: 0.8846 - val_loss: 0.3032 - val_recall: 0.9384 -
val_accuracy: 0.8629
Epoch 10/12
80/80 [============ ] - 67s 834ms/step - loss: 0.2230 - recall:
0.9473 - accuracy: 0.8913 - val_loss: 0.3216 - val_recall: 0.9110 -
val_accuracy: 0.8686
Epoch 11/12
- accuracy: 0.8976
Epoch 00011: ReduceLROnPlateau reducing learning rate to 2.700000040931627e-05.
```

8 Visualize Model Performance

8.0.1 Display changes in accuracy by epoch to help understand model learning progress

[16]: plot_metrics(model.history, filename='final')



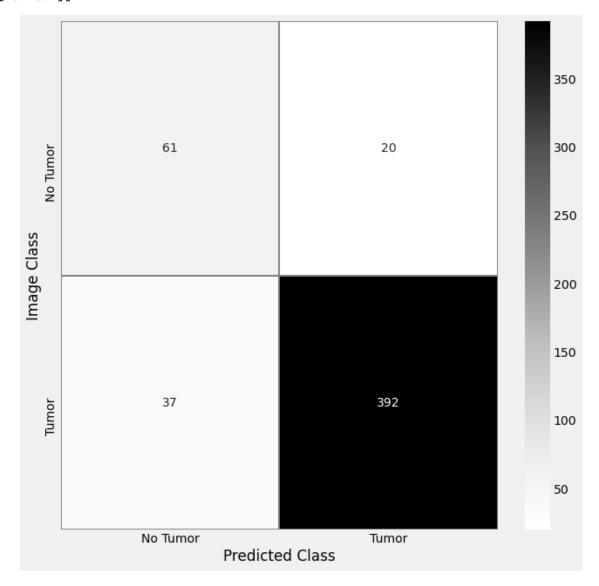
8.0.2 Create a confusion matrix representing the model's corect and incorrect predictions

[17]: plot_confusion_matrix(model, x_test, y_test, filename='final')

	precision	recall	f1-score	support
No Tumor	0.62	0.75	0.68	81
Tumor	0.95	0.91	0.93	429
accuracy			0.89	510
macro avg	0.79	0.83	0.81	510

weighted avg 0.90 0.89 0.89 510

[[61 20] [37 392]]



9 Analyze Model Performance

9.0.1 Get all image classifications and compare to predictions. Store for use in identifying error types.

```
[18]: # get model predictions
      predictions = (model.predict(x_test) > 0.5).astype('int32')
      # identify image classifications
      good_preds0 = []
      good_preds1 = []
      type_1 = []
      type_2 = []
      for i in range(len(y_test)):
          if y_test[i] == predictions[i]:
              if y_test[i] == 0:
                  good_preds0.append(i)
              else:
                  good_preds1.append(i)
          elif y_test[i] == 1:
              type_1.append(i)
          else:
              type_2.append(i)
      good_preds0 = np.array(good_preds0)
      good_preds1 = np.array(good_preds1)
      type_1 = np.array(type_1)
      type_2 = np.array(type_2)
```

9.1 TIME for LIME

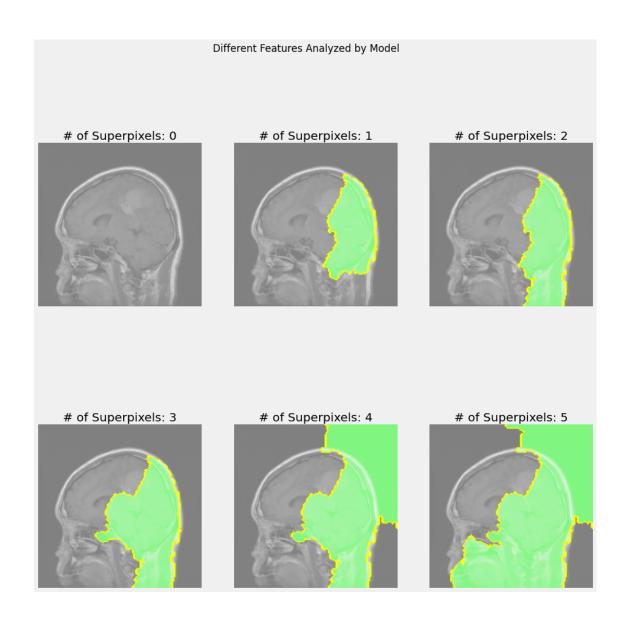
9.1.1 Use LIME techniques to visualize model's analysis of images

```
[19]: # analyze correctly identified image
lime_image(model, x_test[good_preds1[2]], min_superpixels=0, max_superpixels=6,___
filename='tumor_correct[2]')

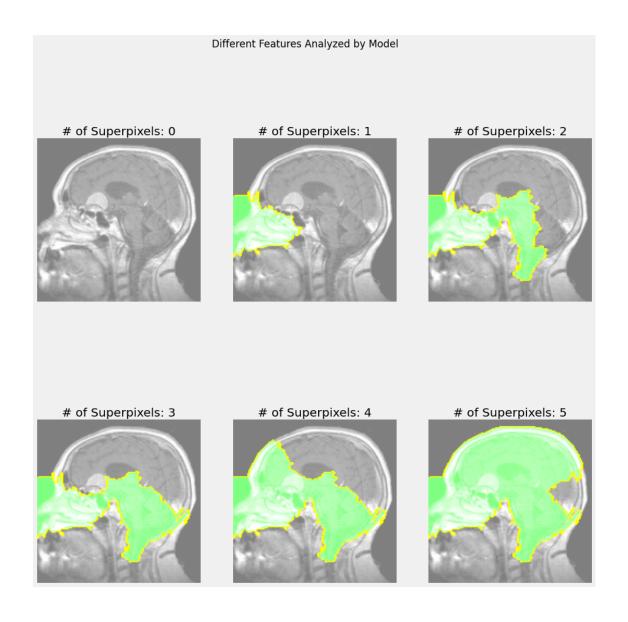
rows: 2 columns: 3
len(ax) = 2
m_end: 3 n_end: 0

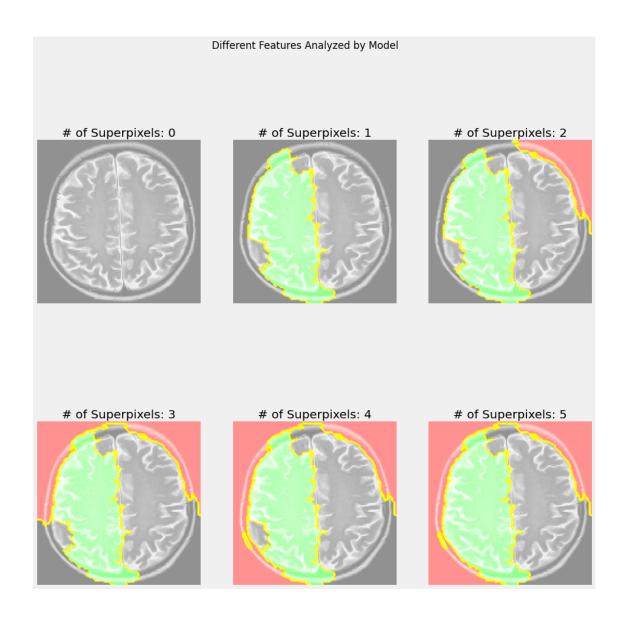
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value=''))))
```

```
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
```

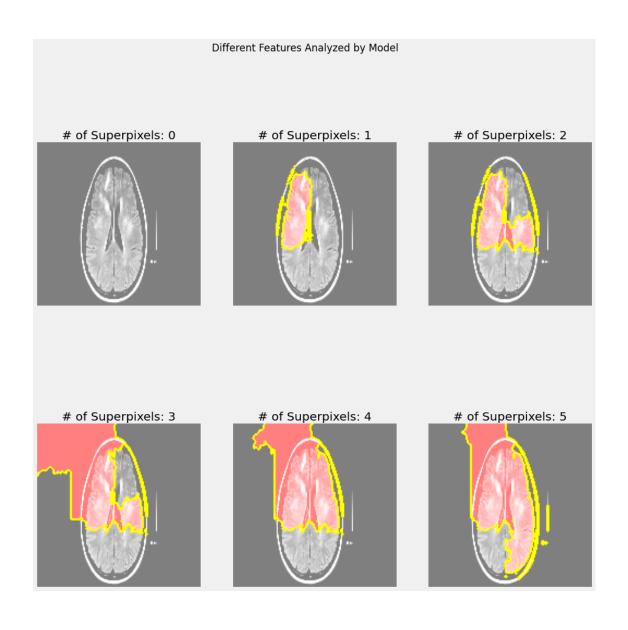


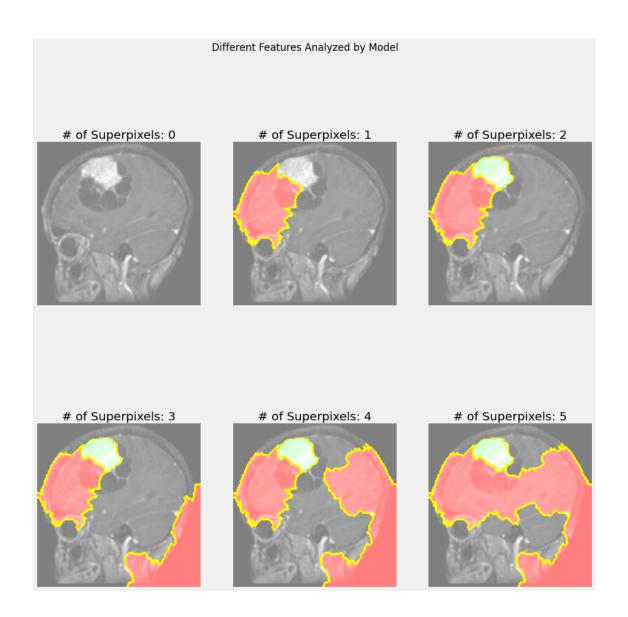
```
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
```



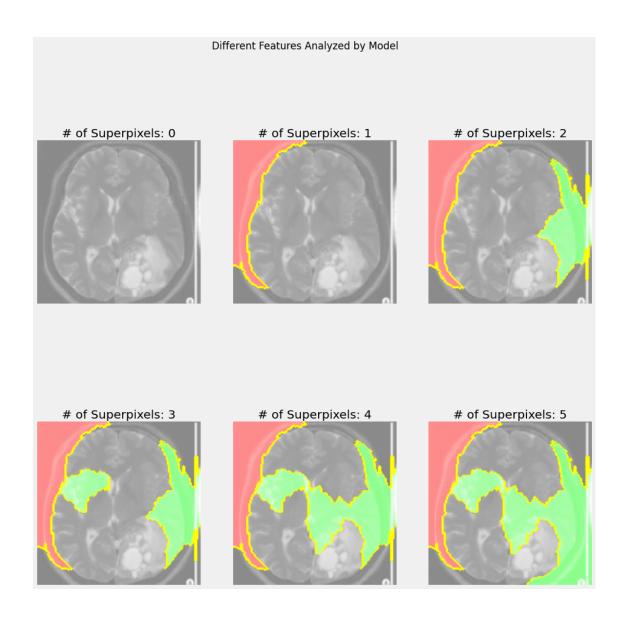


```
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
```





```
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
```

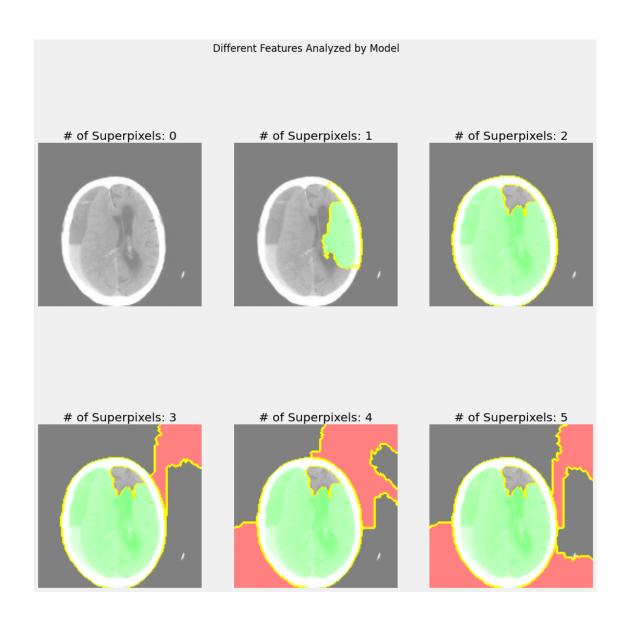


```
[25]: lime_image(model, x_test[type_2[0]], min_superpixels=0, max_superpixels=6,u
-filename='type_2_error[0]')

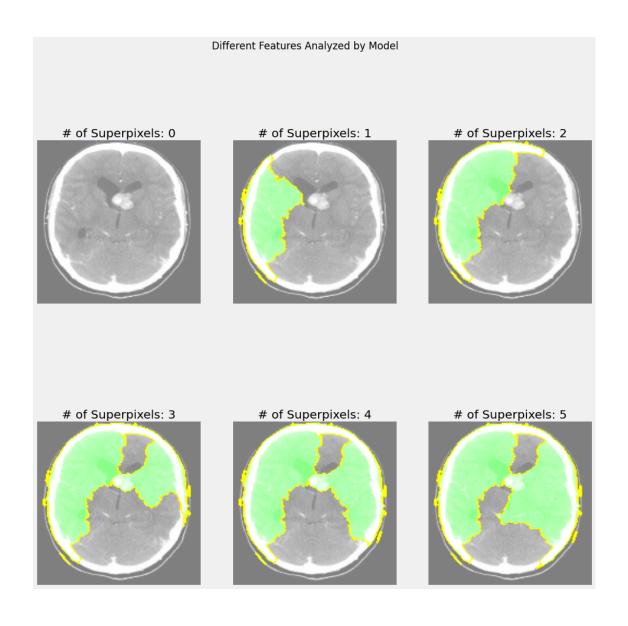
rows: 2 columns: 3
len(ax) = 2
m_end: 3 n_end: 0

HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))

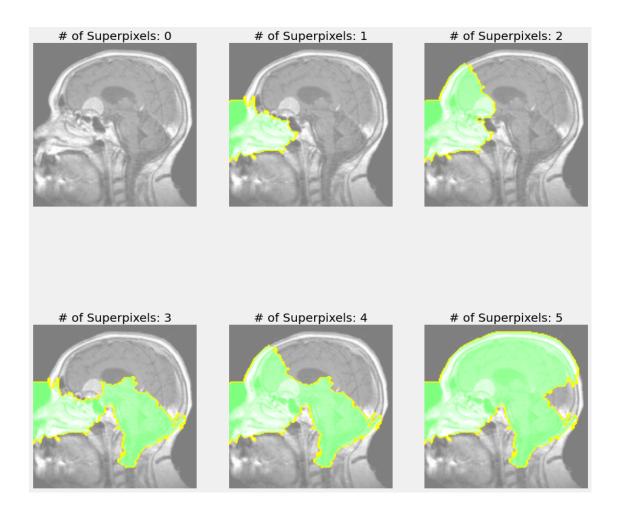
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
```



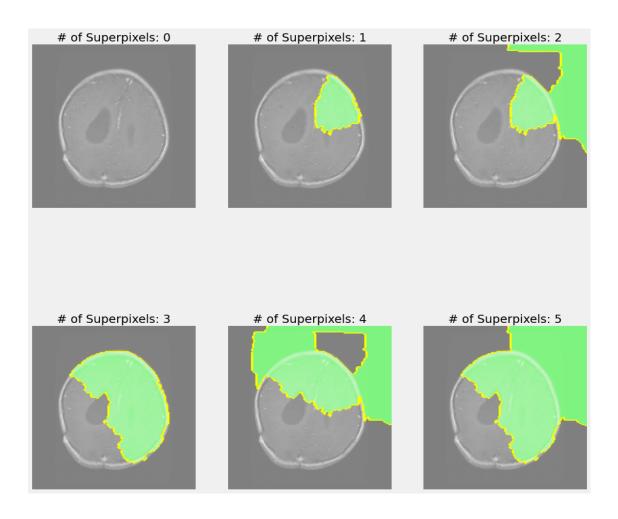
```
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
```



HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))



```
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
```

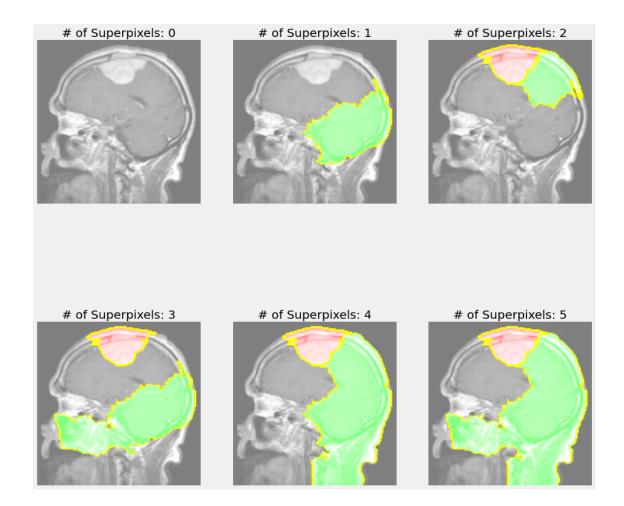


```
[32]: # analyze correctly identified image
num = 50
lime_image(model, x_test[good_preds1[num]], min_superpixels=0,__

--max_superpixels=6, filename=f'tumor_correct[{num}]', suptitle=None)
```

```
rows: 2 columns: 3
len(ax) = 2
m_end: 3 n_end: 0
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))

HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=1000.0), HTML(value='')))
```



[]: