In [3]:
```
# general package imports
import os
import sys
import random
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import auc, roc_curve, log_loss, roc_auc_score, auc, roc_

import warnings
warnings.simplefilter('ignore')
```

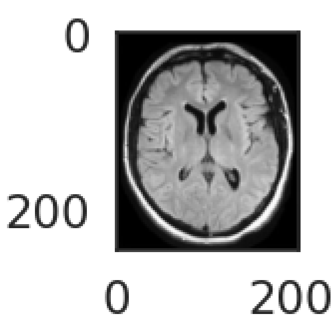
In [4]:
```
# image imports
from matplotlib.image import imread
```

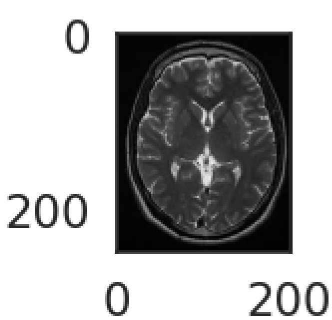
In [5]:
```
# cnn imports
import cv2
import keras
import tensorflow as tf
from keras.models import Sequential
from keras.layers import Conv2D,Activation,MaxPooling2D,Dense,Flatten,Dropout
```

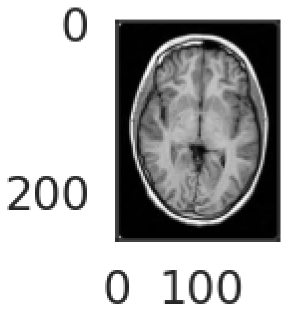
In [6]:
```
sns.set(font_scale=1.5)
sns.set_style('white')
```

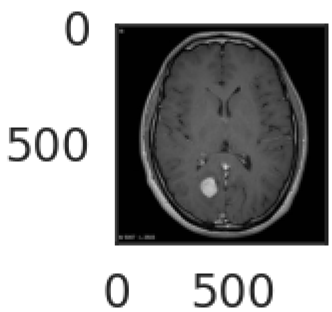
In [7]:
```
# control reproducibility with random seeds
seed_value = 1

np.random.seed(seed_value)
random.seed(seed_value)
tf.random.set_seed(seed_value)
```

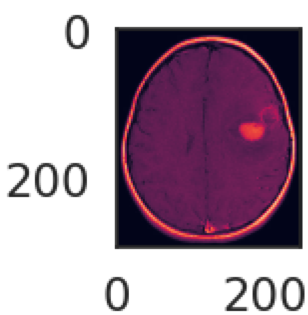
In [8]:
```
# define location of dataset
folder_no = 'brain_tumor_dataset/no'
folder_yes = 'brain_tumor_dataset/yes'

i = 0

for filepath, gt in zip([folder_no,folder_yes],[0,1]):

    # plot first few images
    for f in os.listdir(filepath)[0:3]:

        i = i+1

        # define subplot
        plt.subplot(330 + 1 + i)

        # define filename
        filename = filepath + '/' + f

        # load image pixels
        image = imread(filename)

        # plot raw pixel data
        plt.imshow(image)

        # show the figure
        plt.show()
```

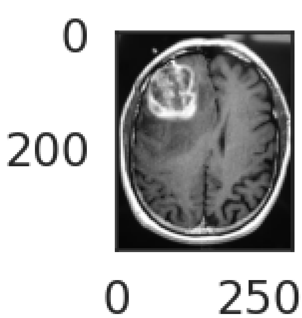




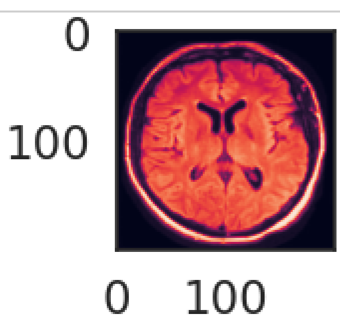

0
200
0
100

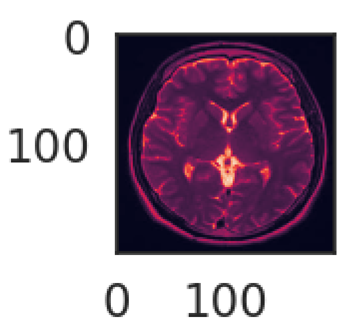

0
500
0
500


0
200
0
200


0
200
0
250

In [10]:
```
# define location of dataset
folder_no = 'brain_tumor_dataset/no'
folder_yes = 'brain_tumor_dataset/yes'

i = 0

for filepath, gt in zip([folder_no,folder_yes],[0,1]):

    # plot first few images
    for f in os.listdir(filepath)[0:3]:

        i = i+1

        # define subplot
        plt.subplot(330 + 1 + i)

        # define filename
        filename = filepath + '/' + f

        # load image pixels
        image = imread(filename)

        # resize into standard size for all images
        resized_image = cv2.resize(image,dsize=(200,200))

        # in case of grayscale images
        if len(np.shape(resized_image)) > 2:

            # convert the image from COLOR_BGR2GRAY
            resized_image = cv2.cvtColor(resized_image, cv2.COLOR_BGR2GRAY)

        # plot raw pixel data
        plt.imshow(resized_image)

        # show the figure
        plt.show()
```





In [11]:
```
# Read images into array
filepath = 'brain_tumor_dataset/'

images, labels, filenames = [], [], []

for gt in ['yes','no']:

    filepath_gt = filepath + gt

    for f in os.listdir(filepath_gt):

        filename = filepath_gt + '/' + f

        if '._' not in filename: # metadata files created by macos

            # Load image
            photo = tf.keras.utils.load_img(path=filename,target_size=(200, 20

            # Load image pixels
            image = imread(filename)
            resized_image = cv2.resize(image,dsize=(200,200))

            # in case of grayscale images
            if len(np.shape(resized_image)) > 2:
                # convert the image from COLOR_BGR2GRAY
                resized_image = cv2.cvtColor(resized_image, cv2.COLOR_BGR2GRAY

            # store to array
            images.append(resized_image)
            filenames.append(filename)

            if gt=='yes':
                label = 1
                labels.append(label)
            elif gt=='no':
                label = 0
                labels.append(label)
```

In [12]:
```
# Split into train/test sets (stratify by GT)
gtFr = pd.DataFrame(labels).rename(columns={0:'gt'}).reset_index(drop=False).r
gtFr['filename'] = filenames

# split into training and testing sets, stratifying by gt for equal representa
trainFr, testFr = train_test_split(gtFr, test_size=0.2, stratify=gtFr['gt'])

# store training/testing indices
trainFr['set'] = 'train'
testFr['set'] = 'test'

gtFr2 = pd.concat([trainFr,testFr],axis=0)
gtFr2.set_index(['filename']).to_csv('base_model_train_test.csv')
```

In [13]:
```
# Load and reformat training data
files_train = []
X_train = []
y_train = []

for idx, row in trainFr.iterrows():
    # load image pixels
    image = imread(row['filename'])

    # resize image to standard 200x200
    resized_image = cv2.resize(image,dsize=(200,200))

    # in case of grayscale images
    if len(np.shape(resized_image)) > 2:
        # convert the image from COLOR_BGR2GRAY
        resized_image = cv2.cvtColor(resized_image, cv2.COLOR_BGR2GRAY)

    # store to array
    X_train.append(resized_image)
    y_train.append(row['gt'])
    files_train.append(row['filename'])

# reshape data to fit model
X_train = np.array(X_train).reshape(len(trainFr),200,200,1)
y_train = np.array(y_train)
```

In [14]:
```
# Load and reformat testing data
files_test = []
X_test = []
y_test = []

for idx, row in testFr.iterrows():
    # load image pixels
    image = imread(row['filename'])

    # resize image to standard 200x200
    resized_image = cv2.resize(image,dsize=(200,200))

    # in case of grayscale images
    if len(np.shape(resized_image)) > 2:
        # convert the image from COLOR_BGR2GRAY
        resized_image = cv2.cvtColor(resized_image, cv2.COLOR_BGR2GRAY)

    # store to array
    X_test.append(resized_image)
    y_test.append(row['gt'])
    files_test.append(row['filename'])

# reshape data to fit model
X_test = np.array(X_test).reshape(len(testFr),200,200,1)
y_test = np.array(y_test)
```

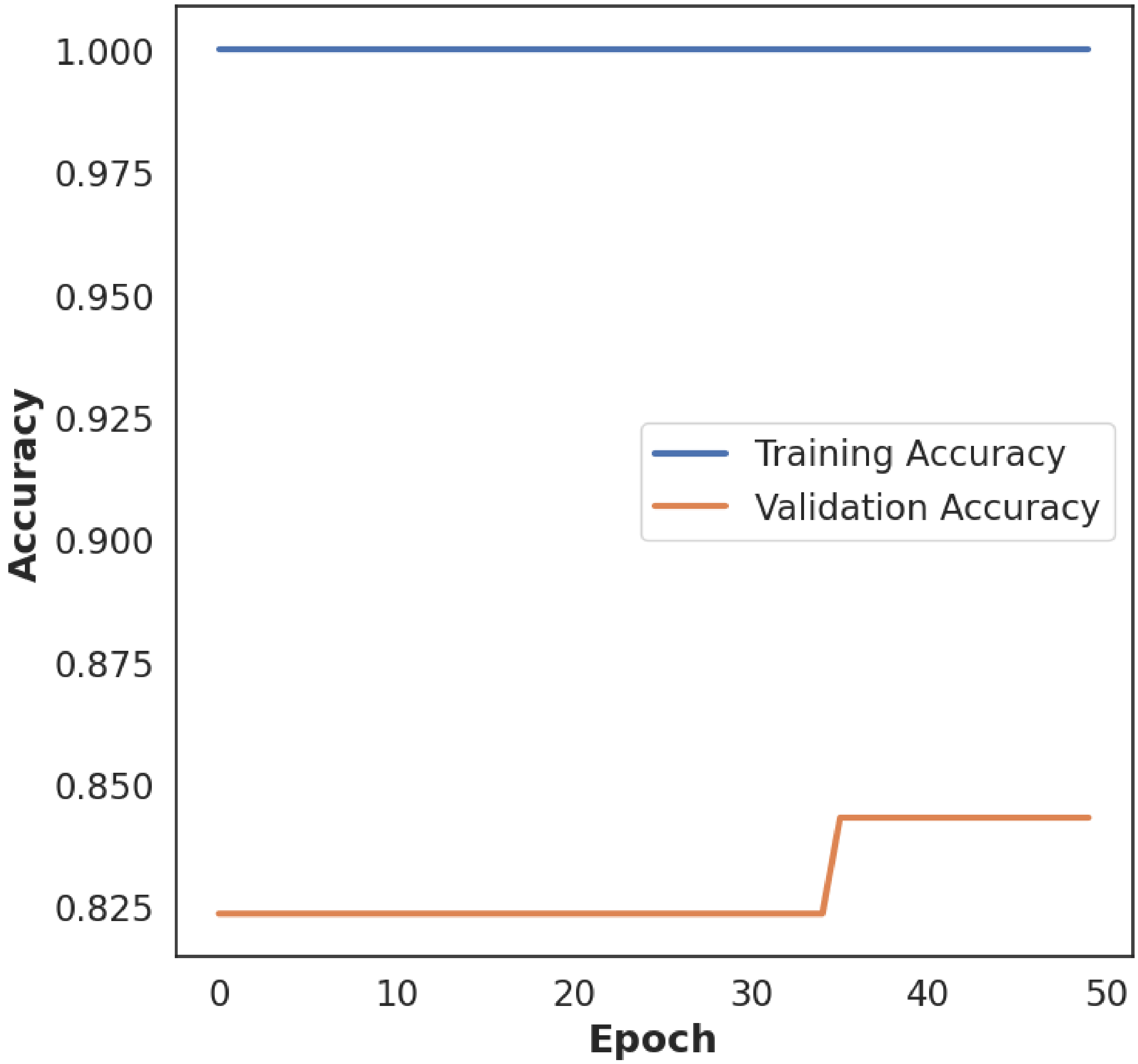
In [15]:
```
# Build, compile, and train CNN
# create model
model = Sequential()

# add convolutional layer
model.add(Conv2D(64, kernel_size=3, activation='relu', input_shape=(200,200,1)

# add max pooling layer
model.add(MaxPooling2D(pool_size=(2, 2)))

# add another convolutional layer
model.add(Conv2D(32, kernel_size=3, activation='relu'))

# add another max pooling layer
model.add(MaxPooling2D(pool_size=(2, 2)))

# flatten output (connect convolutional layers and dense layers)
model.add(Flatten())

# add a dense layer with 128 neurons and ReLU activation
model.add(Dense(128, activation='relu'))

# add dense layer
model.add(Dense(1, activation='sigmoid'))

# compile model using accuracy to measure model performance
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy
```

In [18]:
```
# Plot the training and validation accuracy against number of epochs
history = model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs

fig, ax = plt.subplots(1,1,figsize=(8,8))

ax.plot(history.history['accuracy'], label='Training Accuracy',lw=3)
ax.plot(history.history['val_accuracy'], label='Validation Accuracy',lw=3)
ax.set_xlabel('Epoch',weight='bold')
ax.set_ylabel('Accuracy',weight='bold')
ax.legend()

plt.savefig('accuracy_over_epochs.png')
plt.show()
```

```
Epoch 1/50
7/7 [==============================] - 1s 81ms/step - loss: 2.9874e-05 - acc
uracy: 1.0000 - val_loss: 2.0274 - val_accuracy: 0.8235
Epoch 2/50
7/7 [==============================] - 0s 57ms/step - loss: 2.8300e-05 - acc
uracy: 1.0000 - val_loss: 2.0328 - val_accuracy: 0.8235
Epoch 3/50
7/7 [==============================] - 0s 56ms/step - loss: 2.6593e-05 - acc
uracy: 1.0000 - val_loss: 2.0363 - val_accuracy: 0.8235
Epoch 4/50
7/7 [==============================] - 0s 56ms/step - loss: 2.5291e-05 - acc
uracy: 1.0000 - val_loss: 2.0404 - val_accuracy: 0.8235
Epoch 5/50
7/7 [==============================] - 0s 58ms/step - loss: 2.4229e-05 - acc
uracy: 1.0000 - val_loss: 2.0455 - val_accuracy: 0.8235
Epoch 6/50
7/7 [==============================] - 0s 42ms/step - loss: 2.3070e-05 - acc
uracy: 1.0000 - val_loss: 2.0493 - val_accuracy: 0.8235
Epoch 7/50
7/7 [==============================] - 0s 42ms/step - loss: 2.2042e-05 - acc
uracy: 1.0000 - val_loss: 2.0535 - val_accuracy: 0.8235
Epoch 8/50
7/7 [==============================] - 0s 42ms/step - loss: 2.1162e-05 - acc
uracy: 1.0000 - val_loss: 2.0580 - val_accuracy: 0.8235
Epoch 9/50
7/7 [==============================] - 0s 42ms/step - loss: 2.0268e-05 - acc
uracy: 1.0000 - val_loss: 2.0612 - val_accuracy: 0.8235
Epoch 10/50
7/7 [==============================] - 0s 42ms/step - loss: 1.9445e-05 - acc
uracy: 1.0000 - val_loss: 2.0642 - val_accuracy: 0.8235
Epoch 11/50
7/7 [==============================] - 0s 42ms/step - loss: 1.8618e-05 - acc
uracy: 1.0000 - val_loss: 2.0669 - val_accuracy: 0.8235
Epoch 12/50
7/7 [==============================] - 0s 46ms/step - loss: 1.7857e-05 - acc
uracy: 1.0000 - val_loss: 2.0718 - val_accuracy: 0.8235
Epoch 13/50
7/7 [==============================] - 0s 52ms/step - loss: 1.7153e-05 - acc
uracy: 1.0000 - val_loss: 2.0752 - val_accuracy: 0.8235
Epoch 14/50
7/7 [==============================] - 0s 54ms/step - loss: 1.6466e-05 - acc
uracy: 1.0000 - val_loss: 2.0790 - val_accuracy: 0.8235
Epoch 15/50
7/7 [==============================] - 0s 53ms/step - loss: 1.5734e-05 - acc
uracy: 1.0000 - val_loss: 2.0804 - val_accuracy: 0.8235
Epoch 16/50
7/7 [==============================] - 0s 49ms/step - loss: 1.5168e-05 - acc
uracy: 1.0000 - val_loss: 2.0829 - val_accuracy: 0.8235
Epoch 17/50
7/7 [==============================] - 0s 46ms/step - loss: 1.4652e-05 - acc
uracy: 1.0000 - val_loss: 2.0846 - val_accuracy: 0.8235
Epoch 18/50
7/7 [==============================] - 0s 55ms/step - loss: 1.4135e-05 - acc
uracy: 1.0000 - val_loss: 2.0883 - val_accuracy: 0.8235
Epoch 19/50
7/7 [==============================] - 0s 43ms/step - loss: 1.3634e-05 - acc
uracy: 1.0000 - val_loss: 2.0900 - val_accuracy: 0.8235
```

```
Epoch 20/50
7/7 [==============================] - 0s 43ms/step - loss: 1.3142e-05 - acc
uracy: 1.0000 - val_loss: 2.0921 - val_accuracy: 0.8235
Epoch 21/50
7/7 [==============================] - 0s 49ms/step - loss: 1.2746e-05 - acc
uracy: 1.0000 - val_loss: 2.0942 - val_accuracy: 0.8235
Epoch 22/50
7/7 [==============================] - 0s 42ms/step - loss: 1.2262e-05 - acc
uracy: 1.0000 - val_loss: 2.0970 - val_accuracy: 0.8235
Epoch 23/50
7/7 [==============================] - 0s 42ms/step - loss: 1.1892e-05 - acc
uracy: 1.0000 - val_loss: 2.0990 - val_accuracy: 0.8235
Epoch 24/50
7/7 [==============================] - 0s 43ms/step - loss: 1.1517e-05 - acc
uracy: 1.0000 - val_loss: 2.1015 - val_accuracy: 0.8235
Epoch 25/50
7/7 [==============================] - 0s 42ms/step - loss: 1.1147e-05 - acc
uracy: 1.0000 - val_loss: 2.1035 - val_accuracy: 0.8235
Epoch 26/50
7/7 [==============================] - 0s 42ms/step - loss: 1.0755e-05 - acc
uracy: 1.0000 - val_loss: 2.1047 - val_accuracy: 0.8235
Epoch 27/50
7/7 [==============================] - 0s 42ms/step - loss: 1.0489e-05 - acc
uracy: 1.0000 - val_loss: 2.1061 - val_accuracy: 0.8235
Epoch 28/50
7/7 [==============================] - 0s 42ms/step - loss: 1.0080e-05 - acc
uracy: 1.0000 - val_loss: 2.1057 - val_accuracy: 0.8235
Epoch 29/50
7/7 [==============================] - 0s 42ms/step - loss: 9.8038e-06 - acc
uracy: 1.0000 - val_loss: 2.1080 - val_accuracy: 0.8235
Epoch 30/50
7/7 [==============================] - 0s 42ms/step - loss: 9.3509e-06 - acc
uracy: 1.0000 - val_loss: 2.1100 - val_accuracy: 0.8235
Epoch 31/50
7/7 [==============================] - 0s 42ms/step - loss: 9.0754e-06 - acc
uracy: 1.0000 - val_loss: 2.1126 - val_accuracy: 0.8235
Epoch 32/50
7/7 [==============================] - 0s 42ms/step - loss: 8.7631e-06 - acc
uracy: 1.0000 - val_loss: 2.1156 - val_accuracy: 0.8235
Epoch 33/50
7/7 [==============================] - 0s 42ms/step - loss: 8.5165e-06 - acc
uracy: 1.0000 - val_loss: 2.1176 - val_accuracy: 0.8235
Epoch 34/50
7/7 [==============================] - 0s 43ms/step - loss: 8.2297e-06 - acc
uracy: 1.0000 - val_loss: 2.1202 - val_accuracy: 0.8235
Epoch 35/50
7/7 [==============================] - 0s 42ms/step - loss: 8.0183e-06 - acc
uracy: 1.0000 - val_loss: 2.1228 - val_accuracy: 0.8235
Epoch 36/50
7/7 [==============================] - 0s 43ms/step - loss: 7.7930e-06 - acc
uracy: 1.0000 - val_loss: 2.1245 - val_accuracy: 0.8431
Epoch 37/50
7/7 [==============================] - 0s 44ms/step - loss: 7.5632e-06 - acc
uracy: 1.0000 - val_loss: 2.1267 - val_accuracy: 0.8431
Epoch 38/50
7/7 [==============================] - 0s 43ms/step - loss: 7.3909e-06 - acc
uracy: 1.0000 - val_loss: 2.1294 - val_accuracy: 0.8431
```

```
Epoch 39/50
7/7 [==============================] - 0s 42ms/step - loss: 7.1729e-06 - acc
uracy: 1.0000 - val_loss: 2.1307 - val_accuracy: 0.8431
Epoch 40/50
7/7 [==============================] - 0s 42ms/step - loss: 6.9902e-06 - acc
uracy: 1.0000 - val_loss: 2.1328 - val_accuracy: 0.8431
Epoch 41/50
7/7 [==============================] - 0s 42ms/step - loss: 6.8055e-06 - acc
uracy: 1.0000 - val_loss: 2.1338 - val_accuracy: 0.8431
Epoch 42/50
7/7 [==============================] - 0s 43ms/step - loss: 6.6667e-06 - acc
uracy: 1.0000 - val_loss: 2.1357 - val_accuracy: 0.8431
Epoch 43/50
7/7 [==============================] - 0s 43ms/step - loss: 6.4661e-06 - acc
uracy: 1.0000 - val_loss: 2.1375 - val_accuracy: 0.8431
Epoch 44/50
7/7 [==============================] - 0s 42ms/step - loss: 6.3312e-06 - acc
uracy: 1.0000 - val_loss: 2.1392 - val_accuracy: 0.8431
Epoch 45/50
7/7 [==============================] - 0s 42ms/step - loss: 6.1632e-06 - acc
uracy: 1.0000 - val_loss: 2.1404 - val_accuracy: 0.8431
Epoch 46/50
7/7 [==============================] - 0s 42ms/step - loss: 6.0267e-06 - acc
uracy: 1.0000 - val_loss: 2.1426 - val_accuracy: 0.8431
Epoch 47/50
7/7 [==============================] - 0s 43ms/step - loss: 5.8575e-06 - acc
uracy: 1.0000 - val_loss: 2.1454 - val_accuracy: 0.8431
Epoch 48/50
7/7 [==============================] - 0s 44ms/step - loss: 5.7279e-06 - acc
uracy: 1.0000 - val_loss: 2.1489 - val_accuracy: 0.8431
Epoch 49/50
7/7 [==============================] - 0s 43ms/step - loss: 5.5935e-06 - acc
uracy: 1.0000 - val_loss: 2.1504 - val_accuracy: 0.8431
Epoch 50/50
7/7 [==============================] - 0s 43ms/step - loss: 5.4576e-06 - acc
uracy: 1.0000 - val_loss: 2.1526 - val_accuracy: 0.8431
```



In [19]:
```
# make predictions
predictions = model.predict(X_test)

# store as probabilities
probabilities = [p[0] for p in predictions]
testFr['pred'] = probabilities
```

```
2/2 [==============================] - 0s 11ms/step
```

In [21]:
```
testFr.set_index(['pID']).to_csv('base_model_predictions.csv')
```

In [24]:
```
# Evaluate results
dataPos = testFr[testFr['gt']==1]['pred'].values
dataNeg = testFr[testFr['gt']==0]['pred'].values
dataAll = np.concatenate((dataPos, dataNeg))
lblArr = np.zeros(len(dataAll), dtype=bool)
lblArr[0:len(dataPos)] = True

fpr, tpr, thresholds = roc_curve(lblArr, dataAll, pos_label=True)
roc_auc = auc(fpr, tpr)

# invert comparison if (ROC<0.5) required
if roc_auc<0.5:
    lblArr = ~lblArr
    fpr, tpr, thresholds = roc_curve(lblArr, dataAll, pos_label=True)
    roc_auc = auc(fpr, tpr)
    print('inverting labels')

print('ROC AUC: {:0.2f}'.format(roc_auc))

# calculate best cut-off based on distance to top corner of ROC curve
distArr = np.sqrt(np.power(fpr, 2) + np.power((1 - tpr), 2))
cutoffIdx = np.argsort(distArr)[0]
cutoffTh = thresholds[cutoffIdx]

print('Cutoff threshold that maximizes sens/spec: {:0.2f}'.format(cutoffTh))

lblOut = dataAll >= cutoffTh

acc = accuracy_score(lblArr, lblOut)
print('Accuracy: {:0.2f}'.format(acc))

sens = tpr[cutoffIdx]
print('Sensitivity: {:0.2f}'.format(sens))

spec = 1 - fpr[cutoffIdx]
print('Specificity: {:0.2f}'.format(spec))

kappa = cohen_kappa_score(lblOut, lblArr)
print('Cohen kappa score: {:0.2f}'.format(kappa))
```

```
ROC AUC: 0.90
Cutoff threshold that maximizes sens/spec: 0.99
Accuracy: 0.86
Sensitivity: 0.81
Specificity: 0.95
Cohen kappa score: 0.72
```

In [26]:
```
fig, ax = plt.subplots(1,1,figsize=(8,8))

sns.boxplot(y=testFr['pred'],x=testFr['gt'],palette=['blue','red'])
ax.set_xticklabels(['No','Yes'])
ax.set_xlabel('Presence of brain tumor',weight='bold')
ax.set_ylabel('CNN prediction',weight='bold')
ax.axhline(cutoffTh,lw=3,linestyle='--',color='black',label='Cutoff Threshold'
ax.set_title('Model prediction results',weight='bold')
ax.legend(loc=4)

plt.savefig('cnn_prediction_boxplot_by_gt.png')
plt.show()
```