In [1]:
```
import numpy as np
import pandas as pd
import sklearn
import matplotlib.pyplot as plt
import seaborn as sns

## Data Processing
import os
from tqdm import tqdm
from PIL import Image
import cv2
```

Checking out Each Class & Respective Image Size in that Class

Based off dataset description, most of the images should be (512,512)

In [2]:
```
train_dir = "/global/scratch/users/kraj21/Training/"
classes = [label for label in os.listdir(train_dir) if label.isalnum()]
classes
```

Out[2]:
```
['pituitary', 'meningioma', 'glioma', 'notumor']
```

Pituitary Image Size class

In [3]:
```
# Pituitary class has 97% of images are 512 by 512
count = 0
num_images = len(os.listdir(train_dir + classes[0])) # number of files in folde
for img_path in os.listdir(train_dir + classes[0]): # for all image file paths
    image = cv2.imread(train_dir + classes[0] + '/' + img_path,
                       cv2.IMREAD_GRAYSCALE)
    if image.shape == (512,512):
        count += 1
print("Number of images of (512,512):", count / num_images)
print("Number of images:", num_images)
```

```
Number of images of (512,512): 0.9732326698695951
Number of images: 1457
```

Meningioma Image Class Sizes

In [4]:
```
count = 0
num_images = len(os.listdir(train_dir + classes[1])) # number of files in folde
for img_path in os.listdir(train_dir + classes[1]): # for all image file paths
    image = cv2.imread(train_dir + classes[1] + '/' + img_path,
                       cv2.IMREAD_GRAYSCALE)
    if image.shape == (512,512):
        count += 1
print("Number of images of (512,512):", count / num_images)
print("Number of images:", num_images)
```

```
Number of images of (512,512): 0.8954443614637789
Number of images: 1339
```

Glioma Image Sizes Class

In [5]:
```
count = 0
num_images = len(os.listdir(train_dir + classes[2])) # number of files in folde
for img_path in os.listdir(train_dir + classes[2]): # for all image file paths
    image = cv2.imread(train_dir + classes[2] + '/' + img_path,
                       cv2.IMREAD_GRAYSCALE)
    if image.shape == (512,512):
        count += 1
print("Number of images of (512,512):", count / num_images)
print("Number of images:", num_images)
```

```
Number of images of (512,512): 1.0
Number of images: 1321
```

No Tumor Image Sizes Class

In [6]:
```
count = 0
num_images = len(os.listdir(train_dir + classes[3])) # number of files in folde
for img_path in os.listdir(train_dir + classes[3]): # for all image file paths
    image = cv2.imread(train_dir + classes[3] + '/' + img_path,
                       cv2.IMREAD_GRAYSCALE)
    if image.shape == (512,512):
        count += 1
print("Number of images of (512,512):", count / num_images)
print("Number of images:", num_images)
```

```
Number of images of (512,512): 0.010658307210031349
Number of images: 1595
```

All tumor affiliated classes are mostly 512 by 512 images, but the no tumor class is randomly sized

MRI Image Processing:

1. Convert all images to grayscale
2. Apply a binary mask to identify the largest contour or the brain MRI image from the background
3. Identify MRI ROI and crop to it
4. Resize all MRI ROI to (256, 256) since (512,512) is too much for GPU to handle and does not provide as much value for training the model

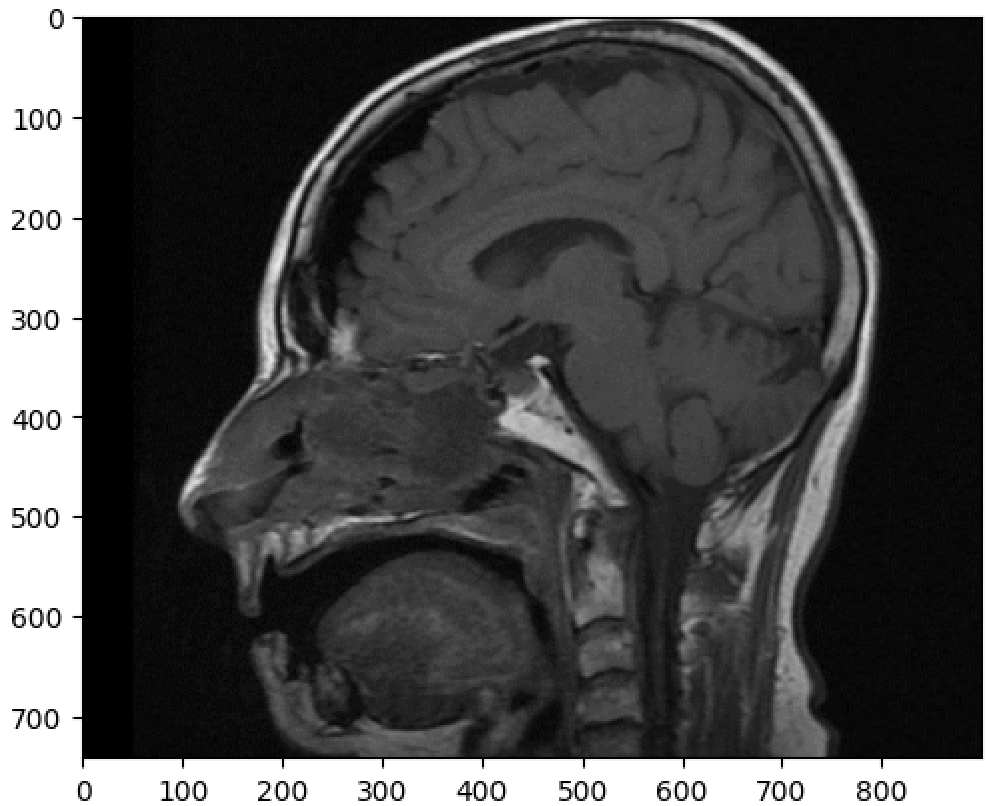
Dataset appears to have MRI scans in different orientations; introducing inherent data variation and hopefully boosting model generalizability

Trialing Dataprocessing Process on 1 Image

In [7]:
```
### Reading in original image
samp_path_img = train_dir + "pituitary/Tr-pi_0044.jpg"
og_image = cv2.imread(samp_path_img, cv2.IMREAD_ANYCOLOR)
print(og_image.shape)
```

```
(741, 900, 3)
```

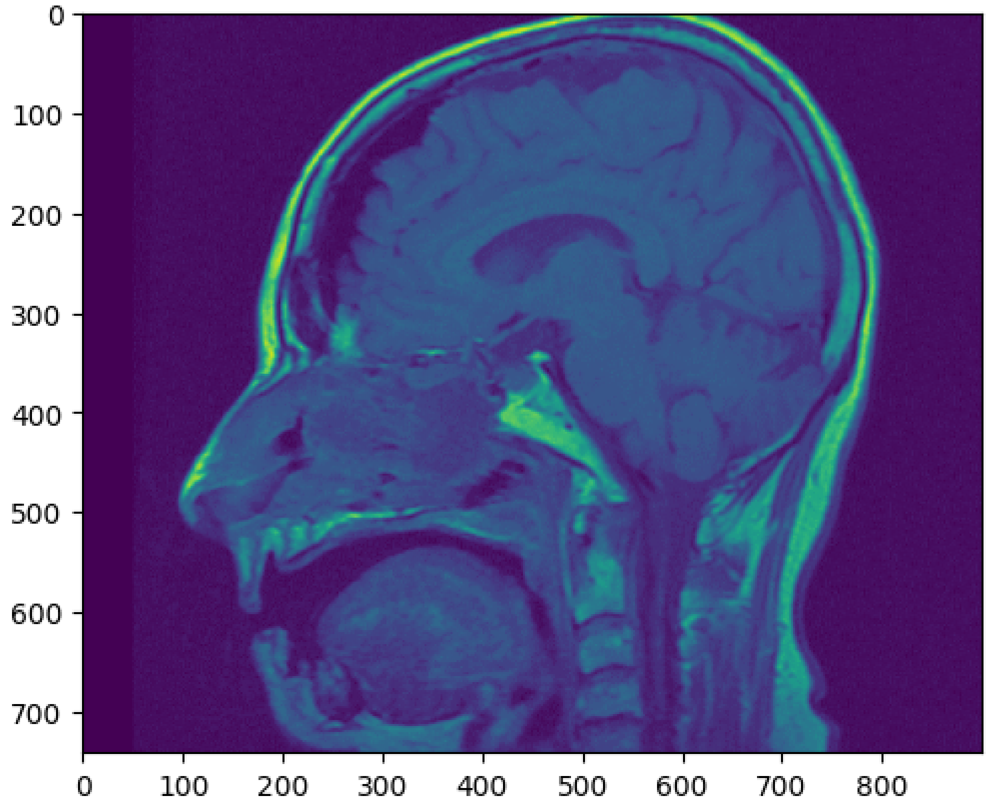
In [8]:
```
plt.imshow(og_image);
```



In [9]:
```
### Reading in grayscale image
samp_path_img = train_dir + "pituitary/Tr-pi_0044.jpg"
gr_image = cv2.imread(samp_path_img, cv2.IMREAD_GRAYSCALE)
print(gr_image.shape)
```

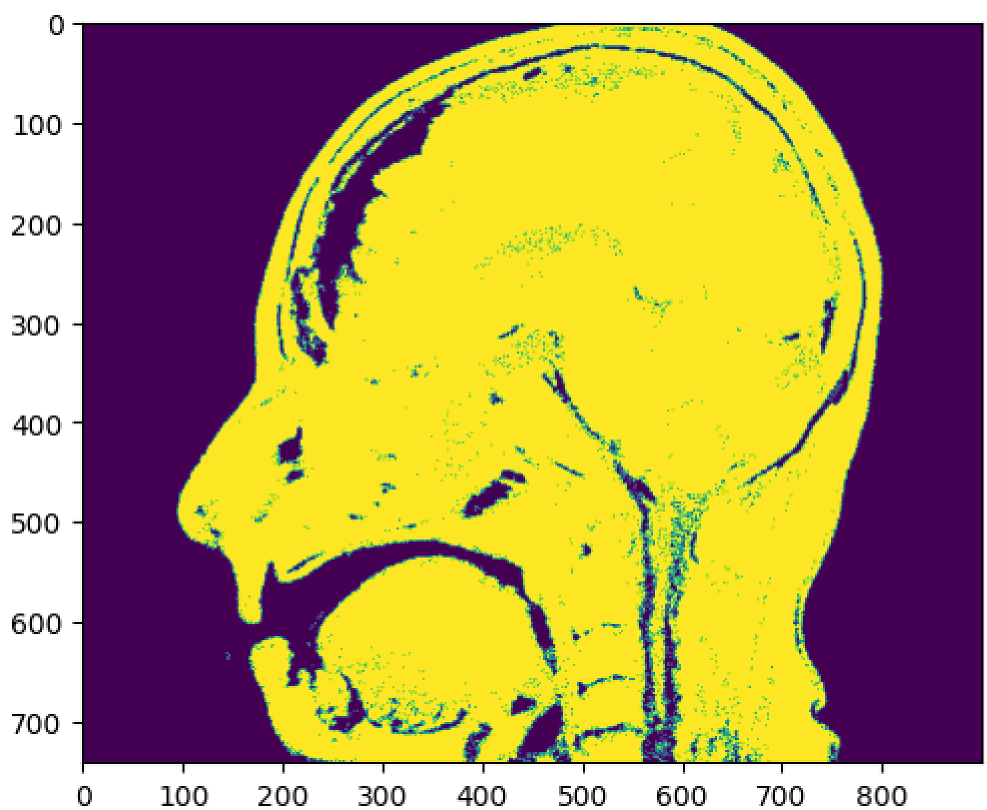
```
(741, 900)
```

In [11]:
```
plt.imshow(gr_image);
```

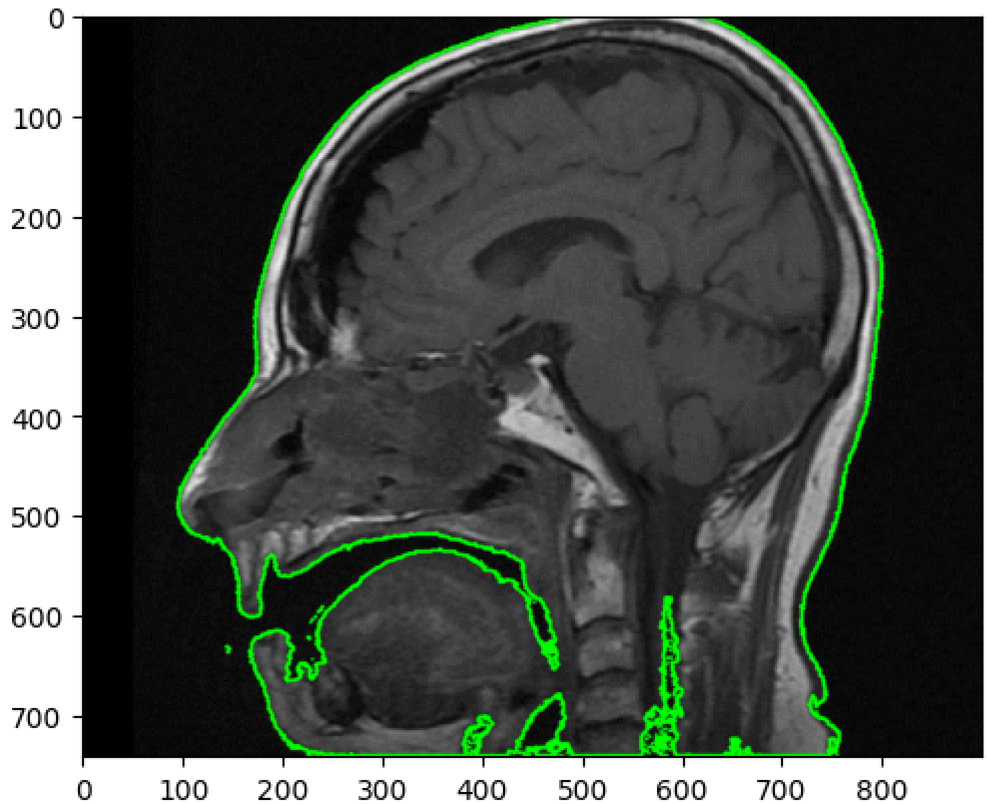


In [12]:
```
# Creating binary mask to identify contours or bounded areas in image
ret, thresh = cv2.threshold(gr_image, 30, 255, cv2.THRESH_BINARY)
# Lowering threshold allows more points to go through
# but makes it easier to fully construct contours by open cv
```

In [13]:
```
plt.imshow(thresh);
```



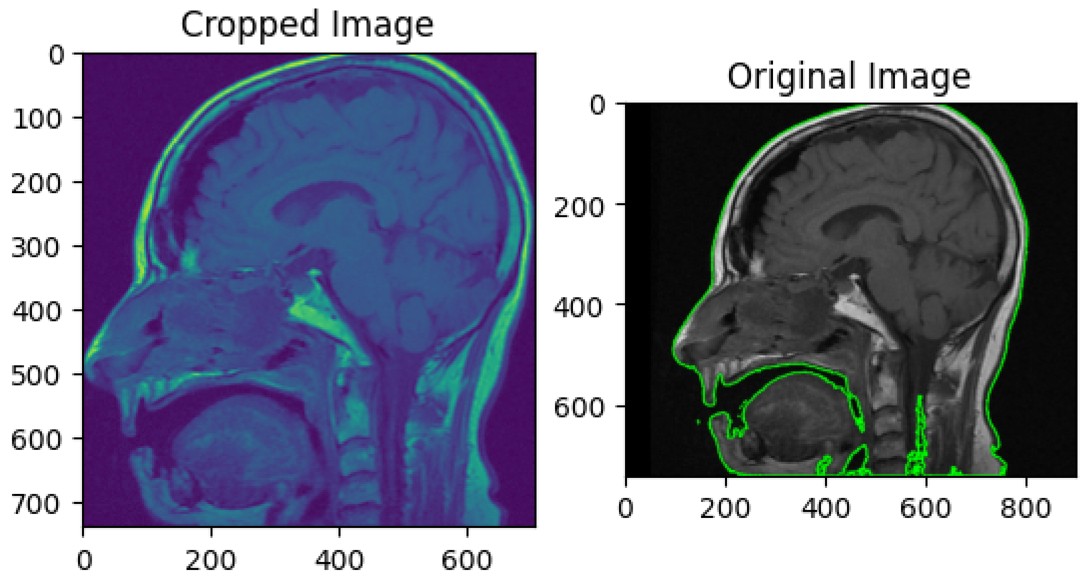
In [15]:
```
image = cv2.imread(samp_path_img, cv2.IMREAD_ANYCOLOR)
# Storing all contours evident in the mask
contours, hierarchy = cv2.findContours(image=thresh, mode=cv2.RETR_EXTERNAL,
                                       method=cv2.CHAIN_APPROX_SIMPLE)

# drawing largest contour on the original image
image_copy = og_image.copy()
cv2.drawContours(image=image, contours=contours, contourIdx=-1, color=(0, 255,
                 thickness=2, lineType=cv2.LINE_AA)
plt.imshow(image);
```



In [16]:
```
c = max(contours, key = cv2.contourArea) # Storing the largest contour or ROI
                                         # as identified by contour area
c_2d = np.squeeze(c) # Displays the points defining the contour as x and y coor
```

In [17]:
```
# Getting extrema points of largest contour
bottom_y = np.max(c_2d[:,1])
top_y = np.min(c_2d[:,1])
left_x = np.min(c_2d[:,0])
right_x = np.max(c_2d[:,0])
```

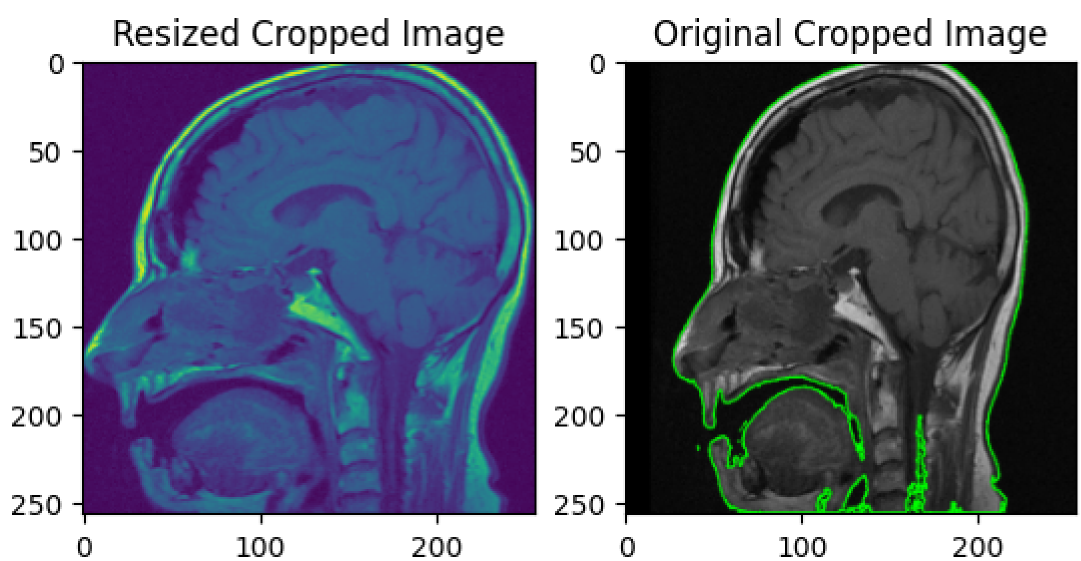
In [18]:
```
# Showing cropped image
temp = gr_image[top_y :bottom_y, left_x : right_x]
# Showing both images side by side
fig, (ax1,ax2) = plt.subplots(1,2)
ax1.imshow(temp)
ax1.set_title("Cropped Image")
ax2.imshow(og_image);
ax2.set_title("Original Image");
```



Resizing Both Cropped & Original image

In [19]:
```
# Resized image after cropping
resized = cv2.resize(temp, (256,256), interpolation = cv2.INTER_AREA)
# Resized image with no cropping
og_resized = cv2.resize(image, (256,256), interpolation = cv2.INTER_AREA)
```

In [20]:
```
# Showing both images side by side
fig, (ax1,ax2) = plt.subplots(1,2)
ax1.imshow(resized)
ax1.set_title("Resized Cropped Image")
ax2.imshow(og_resized);
ax2.set_title("Original Cropped Image");
```



Finalized Code for Generating X_train & Y_train datasets via Established Data processing pipeline

In [21]:
```
def generate_train_test(file_path):
    ind = 0
    # Defining arrays to store labels & images. Dict to note which class
    # corresponds with which value
    y_labels = np.array([])
    num_imgs = sum([len(os.listdir(file_path + cla)) for cla in classes])
    all_imgs = np.ndarray((num_imgs, 256, 256))
    dict_classes = {}
    # Filling the arrays and dict
    # Running process used for prior image for all images now
    for tm_class in range(len(classes)):
        for img_path in os.listdir(file_path + classes[tm_class] + '/'):
            img_arr = cv2.imread(file_path + classes[tm_class] + '/' + img_path
                                 cv2.IMREAD_GRAYSCALE)
            ret, thresh = cv2.threshold(img_arr, 30, 255, cv2.THRESH_BINARY)
            contours, hierarchy = cv2.findContours(image=thresh, mode=cv2.RETR_
                                                   method=cv2.CHAIN_APPROX_SIMP
            largest_contour = max(contours, key = cv2.contourArea)
            largest_contour = np.squeeze(largest_contour)
            # Finding points defining largest contour
            bottom_y = np.max(largest_contour[:,1])
            top_y = np.min(largest_contour[:,1])
            left_x = np.min(largest_contour[:,0])
            right_x = np.max(largest_contour[:,0])
            # Cropping image based on these points
            cropped_img = img_arr[top_y :bottom_y, left_x : right_x]
            # Resizing image to smaller size while maintaining aspect ratio
            resized_img = cv2.resize(cropped_img, (256,256),
                                     interpolation = cv2.INTER_AREA)
            all_imgs[ind] = resized_img
            y_labels = np.append(y_labels, tm_class)
            ind +=1
        dict_classes[classes[tm_class]] = tm_class
    return all_imgs, y_labels, dict_classes
```

In [22]:
```
X_train, train_y, dict_train = generate_train_test(train_dir)
print(X_train.shape)
dict_train
```

```
(5712, 256, 256)
```

Out[22]:
```
{'pituitary': 0, 'meningioma': 1, 'glioma': 2, 'notumor': 3}
```

In [23]:
```
test_dir = '/global/scratch/users/kraj21/Testing/'
X_test, test_y, dict_test = generate_train_test(test_dir)
print(X_test.shape)
dict_test
```

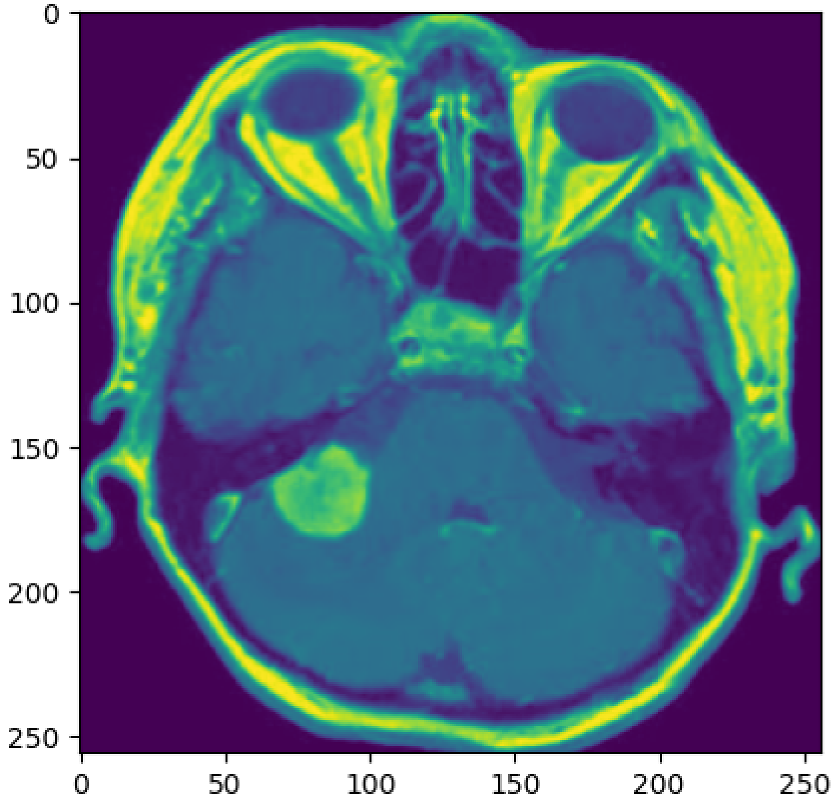
```
(1311, 256, 256)
```

Out[23]:
```
{'pituitary': 0, 'meningioma': 1, 'glioma': 2, 'notumor': 3}
```

In [24]:
```
# Trialing data transform function
fnc_reshape = lambda x: x.reshape(x.shape[0], 1 , x.shape[1], x.shape[2])
reshaped_X_train = fnc_reshape(X_train)
reshaped_X_train.shape
```

Out[24]:
```
(5712, 1, 256, 256)
```

In [27]:
```
# Seeing how a random cropped image looks like
import random
rand_val = random.randint(0, len(test_y))
plt.imshow(X_test[rand_val]);
```



Defining Training and Validation Class

In [28]:
```
from functools import wraps
from time import time

def timing(f):
    @wraps(f)
    def wrap(*args, **kw):
        ts = time()
        result = f(*args, **kw)
        te = time()
        print('func:%r  took: %2.4f sec' % (f.__name__,  te-ts))
        return result
    return wrap
```

In [29]:
```
from torch.optim import SGD, Adam
import torch
from torch import nn
import torch.nn.functional as F
import random
from tqdm import tqdm
import math
from sklearn.model_selection import train_test_split

def create_chunks(complete_list, chunk_size=None, num_chunks=None):
    '''
```

```
    Cut a list into multiple chunks, each having chunk_size
    (the last chunk might be less than chunk_size)
    or having a total of num_chunk chunks
    '''
    chunks = []
    if num_chunks is None:
        num_chunks = math.ceil(len(complete_list) / chunk_size)
    elif chunk_size is None:
        chunk_size = math.ceil(len(complete_list) / num_chunks)
    for i in range(num_chunks):
        chunks.append(complete_list[i * chunk_size: (i + 1) * chunk_size])
    return chunks

class Trainer():
    def __init__(self, model, optimizer_type, learning_rate, epoch, batch_size,
                 input_transform=lambda x: x.reshape(x.shape[0], 1, x.shape[1],
                                                    x.shape[2])):
        """ The class for training the model
        model: nn.Module
            A pytorch model
        optimizer_type: 'adam' or 'sgd'
        learning_rate: float
        epoch: int
        batch_size: int
        input_transform: func
            transforming input. Can do reshape here
        """
        self.model = model
        if optimizer_type == "sgd":
            self.optimizer = SGD(model.parameters(), learning_rate,momentum=0.9
        elif optimizer_type == "adam":
            self.optimizer = Adam(model.parameters(), learning_rate)

        self.epoch = epoch
        self.batch_size = batch_size
        self.input_transform = input_transform


    @timing
    def train(self, inputs, outputs, val_inputs, val_outputs,early_stop=False,l
              silent=False, tens_logger = None):
        """ train self.model with specified arguments
        inputs: np.array, The shape of input_transform(input) should be (ndata,
        outputs: np.array shape (ndata,)
        val_inputs: np.array, The shape of input_transform(val_input)
                    should be (ndata,nfeatures)
        val_outputs: np.array shape (ndata,)
        early_stop: bool
        l2: bool
        silent: bool. Controls whether or not to print the train
                      and val error during training

        @return
        a dictionary of arrays with train and val losses and accuracies
        """
        ### convert data to tensor of correct shape and type here ###
        # Conversion of input arrays to correct shape
        train_input = self.input_transform(inputs)
        #val_inputs = self.input_transform(val_inputs)
```

```
        # Conversion of arrays to tensors
        inputs = torch.tensor(train_input, dtype= torch.float).cuda()
        outputs = torch.tensor(outputs, dtype = torch.int64).cuda()

        losses = []
        accuracies = []
        val_losses = []
        val_accuracies = []
        weights = self.model.state_dict()
        lowest_val_loss = np.inf

        # Training over self.epoch or the Number of passes over entire dataset
        for n_epoch in tqdm(range(self.epoch), leave=False):
            self.model.train()
            batch_indices = list(range(inputs.shape[0]))
            random.shuffle(batch_indices)
            batch_indices = create_chunks(batch_indices, chunk_size=self.batch_
            epoch_loss = 0
            epoch_acc = 0
            # Training over every batch of 16 images
            for batch in batch_indices:
                batch_importance = len(batch) / len(outputs)
                batch_input = inputs[batch]
                batch_output = outputs[batch]
                ### make prediction and compute loss with loss function
                ### of your choice on this batch ###
                batch_predictions = self.model(batch_input)
                loss = nn.CrossEntropyLoss()(batch_predictions, batch_output)
                if l2:
                    ### Compute the loss with L2 regularization ###
                    # Square and sum each entry in each of the arrays and then
                    loss = loss + 1e-5 * sum([(wei ** 2).sum() for wei in
                                              self.model.parameters()])
                self.optimizer.zero_grad()
                loss.backward()
                self.optimizer.step()
                ### Compute epoch_loss and epoch_acc
                epoch_loss += loss.detach().item() * batch_importance
                acc = sum(torch.argmax(batch_predictions, dim = 1) == batch_out
                epoch_acc += acc.detach().item() * batch_importance
            val_loss, val_acc = self.evaluate(val_inputs, val_outputs, print_ac
            if n_epoch % 10 ==0 and not silent:
                print("Epoch %d/%d - Loss: %.3f - Acc: %.3f" % (n_epoch + 1, se
                print("              Val_loss: %.3f - Val_acc: %.3f" %
                      (val_loss, val_acc))
            losses.append(epoch_loss)
            accuracies.append(epoch_acc)
            val_losses.append(val_loss)
            val_accuracies.append(val_acc)
            if early_stop:
                if val_loss < lowest_val_loss:
                    lowest_val_loss = val_loss
                    weights = self.model.state_dict()
            if tens_logger is not None:
                tens_logger.add_scalar("losses", epoch_loss, n_epoch + 1)
                tens_logger.add_scalar("accuracies", epoch_acc, n_epoch + 1)
                tens_logger.add_scalar("val_losses", val_loss, n_epoch + 1)
                tens_logger.add_scalar("val_accuracies", val_acc, n_epoch + 1)
        if early_stop:
            self.model.load_state_dict(weights)
```

```
        return {"losses": losses, "accuracies": accuracies, "val_losses": val_l
                "val_accuracies": val_accuracies, "model": self.model}

    def evaluate(self, inputs, outputs, print_acc=True, val = True):
        """ evaluate model on provided input and output
        inputs: np.array, The shape of input_transform(input) should be (ndata,
        outputs: np.array shape (ndata,)
        print_acc: bool

        @return
        losses: float
        acc: float
        """
        inputs = self.input_transform(inputs)
        tensor_inp = torch.tensor(inputs, dtype = torch.float).cuda()
        tensor_out = torch.tensor(outputs, dtype = torch.int64).cuda()
        with torch.no_grad():
            if val == True:
                preds = self.model(tensor_inp)
                losses = nn.CrossEntropyLoss()(preds, tensor_out)
                losses = losses.item()
                acc = (sum(torch.argmax(preds, axis= 1) == tensor_out) / len(te
                if print_acc:
                    print("Accuracy: %.3f" % acc)
                return losses, acc
            else:
                pred_probs = self.model(tensor_inp)
                pred_labels = torch.argmax(pred_probs, axis= 1)
                acc = (sum(torch.argmax(pred_probs, axis= 1) == tensor_out) / l
                print("Test Accuracy: %.3f" % acc)
                return pred_labels,pred_probs
```

```
/global/home/users/kraj21/.conda/envs/ml_life/lib/python3.8/site-packages/tqd
m/auto.py:21: TqdmWarning: IProgress not found. Please update jupyter and ipyw
idgets. See https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

Model Definition

In [30]:

```
import torch
from torch import nn
class CNN(nn.Module):
    def __init__(self):
        super(CNN, self).__init__()
        self.conv = nn.ModuleList([nn.Conv2d(in_channels= 1, out_channels= 7,
                                             kernel_size = 5, stride = 1, paddi
                                   nn.Conv2d(in_channels= 7, out_channels= 12,
                                             kernel_size = 3, stride = 1, paddi
        self.bn = nn.ModuleList([nn.BatchNorm2d(7), nn.BatchNorm2d(12)])
        self.fc = nn.ModuleList([nn.Linear(3072, 4)])
        self.pooling = nn.AvgPool2d(kernel_size = 4)
        self.activation = nn.ReLU()

    def forward(self, x):
        for i in range(2):
```

```
            x = self.pooling(self.activation(self.bn[i](self.conv[i](x))))
        x = nn.Flatten() (x)
        x = self.fc[0](x)
        return x
```

In [31]:

```
from torchsummary import summary
model = CNN()
# Input is the (number of channels, image height, image width) if input is 2d
s = summary(model, (1,256,256))
```

```
==============================================================================
============
Layer (type:depth-idx)                   Output Shape              Param #
==============================================================================
============
├─ModuleList: 1                          []                        --
|    └─Conv2d: 2-1                       [-1, 7, 256, 256]         182
├─ModuleList: 1                          []                        --
|    └─BatchNorm2d: 2-2                  [-1, 7, 256, 256]         14
├─ReLU: 1-1                              [-1, 7, 256, 256]         --
├─AvgPool2d: 1-2                         [-1, 7, 64, 64]           --
├─ModuleList: 1                          []                        --
|    └─Conv2d: 2-3                       [-1, 12, 64, 64]          768
├─ModuleList: 1                          []                        --
|    └─BatchNorm2d: 2-4                  [-1, 12, 64, 64]          24
├─ReLU: 1-3                              [-1, 12, 64, 64]          --
├─AvgPool2d: 1-4                         [-1, 12, 16, 16]          --
├─ModuleList: 1                          []                        --
|    └─Linear: 2-5                       [-1, 4]                   12,292
==============================================================================
============
Total params: 13,280
Trainable params: 13,280
Non-trainable params: 0
Total mult-adds (M): 14.58
==============================================================================
============
Input size (MB): 0.25
Forward/backward pass size (MB): 7.75
Params size (MB): 0.05
Estimated Total Size (MB): 8.05
==============================================================================
============
```

In [32]:

```
from torch.utils.tensorboard import SummaryWriter
cnn_logger = SummaryWriter(log_dir = 'CNN_MRI_256_5712')
cnn_logger.flush()
```

Model Training via Cross Validation:

In [33]:

```
# Defining dataframe to store results from 3 fold testing on various versions o
train_res = pd.read_csv('4_29_230PM', index_col = 0)
train_res
```

Out[33]:

	epochs	batch_size	LR	avg_train_acc	avg_val_acc	L2	num_layers	num_filters	kern
0	28	16	0.001	0.983894	0.911590	True	2	7 & 12	
1	28	16	0.001	0.981968	0.902836	True	2	5 & 10	
2	28	16	0.001	0.979779	0.906688	True	2	5 & 10	
3	28	16	0.001	0.985732	0.908438	True	2	5 & 10	
4	28	16	0.001	0.983456	0.907038	True	2	5 & 10	
5	28	16	0.001	0.982230	0.911415	True	2	5 & 10	
6	24	16	0.001	0.981968	0.909139	True	2	5 & 10	
7	24	16	0.001	0.984681	0.909839	True	2	7 & 12	
8	24	16	0.001	0.991246	0.910889	True	2	10 & 15	
9	24	16	0.001	0.976891	0.904762	True	3	5 & 8 & 12	
10	24	16	0.001	0.972514	0.904237	True	3	5 & 8 & 12	
11	24	16	0.001	0.980917	0.908789	True	2	7 & 12	
12	24	16	0.001	0.982405	0.902836	True	2	5 & 10	
13	24	32	0.001	0.977241	0.905287	True	2	5 & 10	
14	24	32	0.001	0.977766	0.903011	True	2	7 & 12	
15	27	16	0.001	0.984156	0.904937	True	2	7 & 12	
16	27	16	0.001	0.982668	0.910889	True	2	7 & 12	
17	27	16	0.001	0.984769	0.914741	True	2	7 & 12	
18	27	16	0.001	0.985294	0.913691	True	2	7 & 12	
19	27	16	0.001	0.984156	0.918943	True	2	7 & 12	

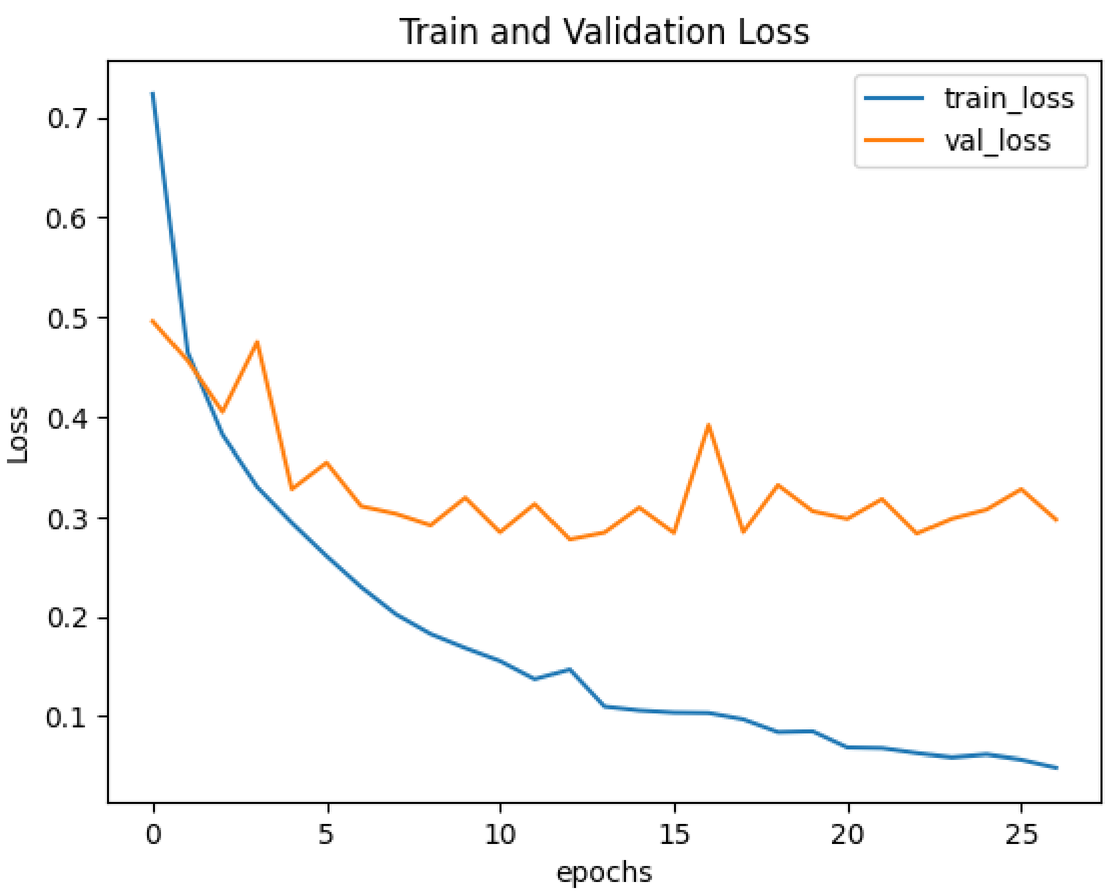
In [34]:

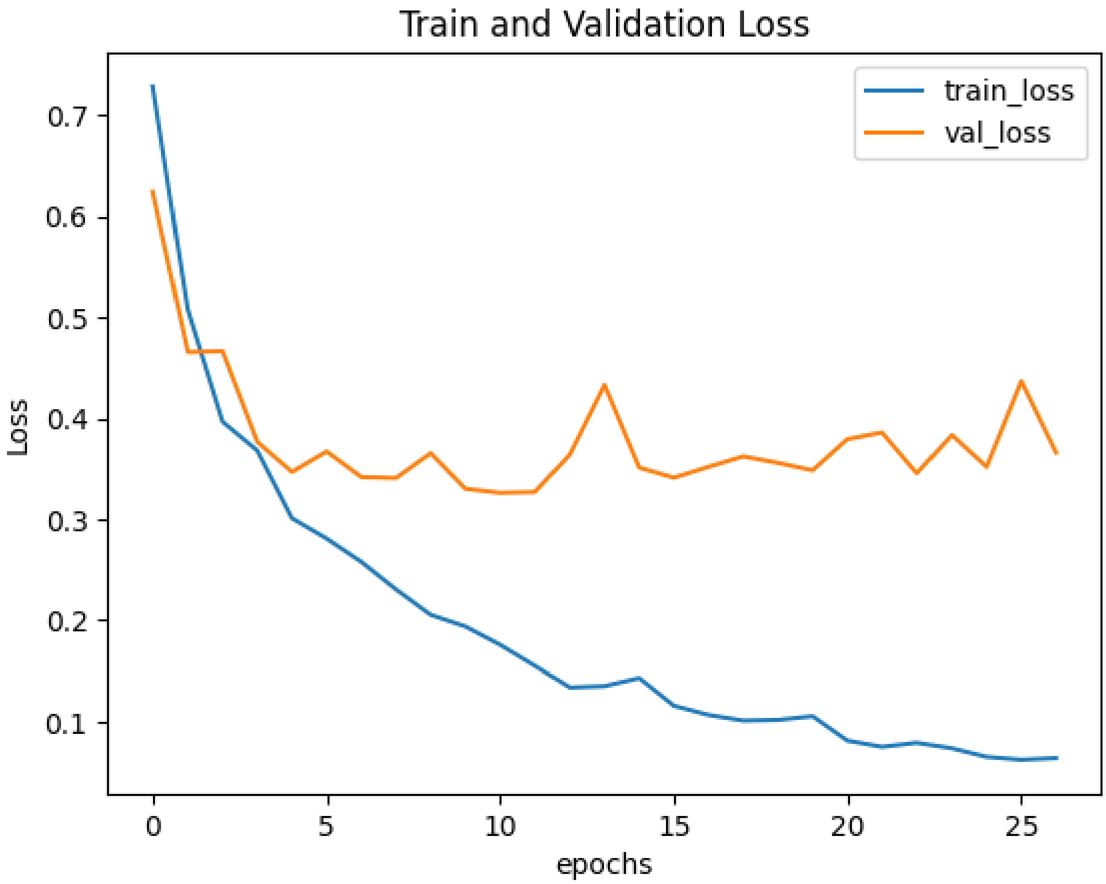
```
from sklearn.model_selection import KFold
kfold = KFold(n_splits= 3, shuffle = True)
# Initializing lists to store values for reporting mean acc and for confusion m
train_acc = []
all_test_pred_labels = []
val_acc = []
# Defining parameters tested in this iteration
epochs = 27
batchsize = 16
lr = 1e-3
l2 = True
num_layers = 2
num_filters =  "7 & 12"
kernel_sizes = "5 & 3"
for train_ind, test_ind in kfold.split(X_train, train_y):
        trainfold_X = X_train[train_ind]
        trainfold_y = train_y[train_ind]
        valfold_x = X_train[test_ind]
        valfold_y = train_y[test_ind]
        cnn = CNN().cuda()
        mlp_trainer = Trainer(cnn, 'adam', 1e-3, epoch= epochs, batch_size= bat
        train_val_dict = mlp_trainer.train(trainfold_X, trainfold_y, valfold_x,
                                    valfold_y, early_stop= True, l2= l2,
```

```
        # Filling train and validation accuracies
        train_acc.append(train_val_dict['accuracies'][-1])
        val_acc.append(max(train_val_dict['val_accuracies']))
        # Plotting Training & Validation Loss
        plt.figure()
        plt.plot(train_val_dict['losses'])
        plt.plot(train_val_dict['val_losses'])
        plt.legend(['train_loss', 'val_loss'])
        plt.title("Train and Validation Loss")
        plt.ylabel('Loss')
        plt.xlabel('epochs');
print('Average train accuracy:', np.mean(train_acc))
print('Average validation accuracy:', np.mean(val_acc))
train_res.loc[len(train_res.index)] = [epochs, batchsize, lr, np.mean(train_acc
                                       np.mean(val_acc), l2,num_layers, num_fil
                                       kernel_sizes]
```

```
  4%|▌         | 1/27 [00:09<04:08,  9.55s/it]
Epoch 1/27 - Loss: 0.707 - Acc: 0.728
              Val_loss: 0.516 - Val_acc: 0.808
 41%|████      | 11/27 [01:43<02:29,  9.37s/it]
Epoch 11/27 - Loss: 0.140 - Acc: 0.959
              Val_loss: 0.334 - Val_acc: 0.891
 78%|███████▊  | 21/27 [03:17<00:56,  9.47s/it]
Epoch 21/27 - Loss: 0.084 - Acc: 0.974
              Val_loss: 0.365 - Val_acc: 0.910

func:'train'  took: 254.9683 sec
  4%|▌         | 1/27 [00:09<04:04,  9.41s/it]
Epoch 1/27 - Loss: 0.724 - Acc: 0.716
              Val_loss: 0.496 - Val_acc: 0.808
 41%|████      | 11/27 [01:44<02:31,  9.48s/it]
Epoch 11/27 - Loss: 0.156 - Acc: 0.945
              Val_loss: 0.285 - Val_acc: 0.905
 78%|███████▊  | 21/27 [03:19<00:56,  9.45s/it]
Epoch 21/27 - Loss: 0.069 - Acc: 0.981
              Val_loss: 0.298 - Val_acc: 0.908

func:'train'  took: 256.5309 sec
  4%|▌         | 1/27 [00:09<04:07,  9.50s/it]
Epoch 1/27 - Loss: 0.729 - Acc: 0.713
              Val_loss: 0.624 - Val_acc: 0.760
 41%|████      | 11/27 [01:44<02:31,  9.49s/it]
Epoch 11/27 - Loss: 0.176 - Acc: 0.941
              Val_loss: 0.326 - Val_acc: 0.898
 78%|███████▊  | 21/27 [03:19<00:56,  9.47s/it]
Epoch 21/27 - Loss: 0.081 - Acc: 0.976
              Val_loss: 0.379 - Val_acc: 0.905

func:'train'  took: 256.7277 sec
Average train accuracy: 0.984331232492995
Average validation accuracy: 0.9145658612251282
```


Train and Validation Loss
train_loss
val_loss
Loss
epochs
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
5
10
15
20
25


Train and Validation Loss
train_loss
val_loss
Loss
epochs
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
5
10
15
20
25



In [35]:
```
train_res
```

Out [35]:

	epochs	batch_size	LR	avg_train_acc	avg_val_acc	L2	num_layers	num_filters	kerr
0	28	16	0.001	0.983894	0.911590	True	2	7 & 12	
1	28	16	0.001	0.981968	0.902836	True	2	5 & 10	
2	28	16	0.001	0.979779	0.906688	True	2	5 & 10	
3	28	16	0.001	0.985732	0.908438	True	2	5 & 10	
4	28	16	0.001	0.983456	0.907038	True	2	5 & 10	
5	28	16	0.001	0.982230	0.911415	True	2	5 & 10	
6	24	16	0.001	0.981968	0.909139	True	2	5 & 10	
7	24	16	0.001	0.984681	0.909839	True	2	7 & 12	
8	24	16	0.001	0.991246	0.910889	True	2	10 & 15	
9	24	16	0.001	0.976891	0.904762	True	3	5 & 8 & 12	
10	24	16	0.001	0.972514	0.904237	True	3	5 & 8 & 12	
11	24	16	0.001	0.980917	0.908789	True	2	7 & 12	
12	24	16	0.001	0.982405	0.902836	True	2	5 & 10	
13	24	32	0.001	0.977241	0.905287	True	2	5 & 10	
14	24	32	0.001	0.977766	0.903011	True	2	7 & 12	
15	27	16	0.001	0.984156	0.904937	True	2	7 & 12	
16	27	16	0.001	0.982668	0.910889	True	2	7 & 12	
17	27	16	0.001	0.984769	0.914741	True	2	7 & 12	
18	27	16	0.001	0.985294	0.913691	True	2	7 & 12	
19	27	16	0.001	0.984156	0.918943	True	2	7 & 12	
20	27	16	0.001	0.984331	0.914566	True	2	7 & 12	

In [44]:

```
train_res.sort_values(by = 'avg_val_acc', ascending= False).head()
```

Out[44]:

	epochs	batch_size	LR	avg_train_acc	avg_val_acc	L2	num_layers	num_filters	kerr
19	27	16	0.001	0.984156	0.918943	True	2	7 & 12	
17	27	16	0.001	0.984769	0.914741	True	2	7 & 12	
20	27	16	0.001	0.984331	0.914566	True	2	7 & 12	
18	27	16	0.001	0.985294	0.913691	True	2	7 & 12	
0	28	16	0.001	0.983894	0.911590	True	2	7 & 12	

Final Model Accuracy

In [38]:

```
test_pred_labels, model_outputs = mlp_trainer.evaluate(X_test, test_y, print_ac
```

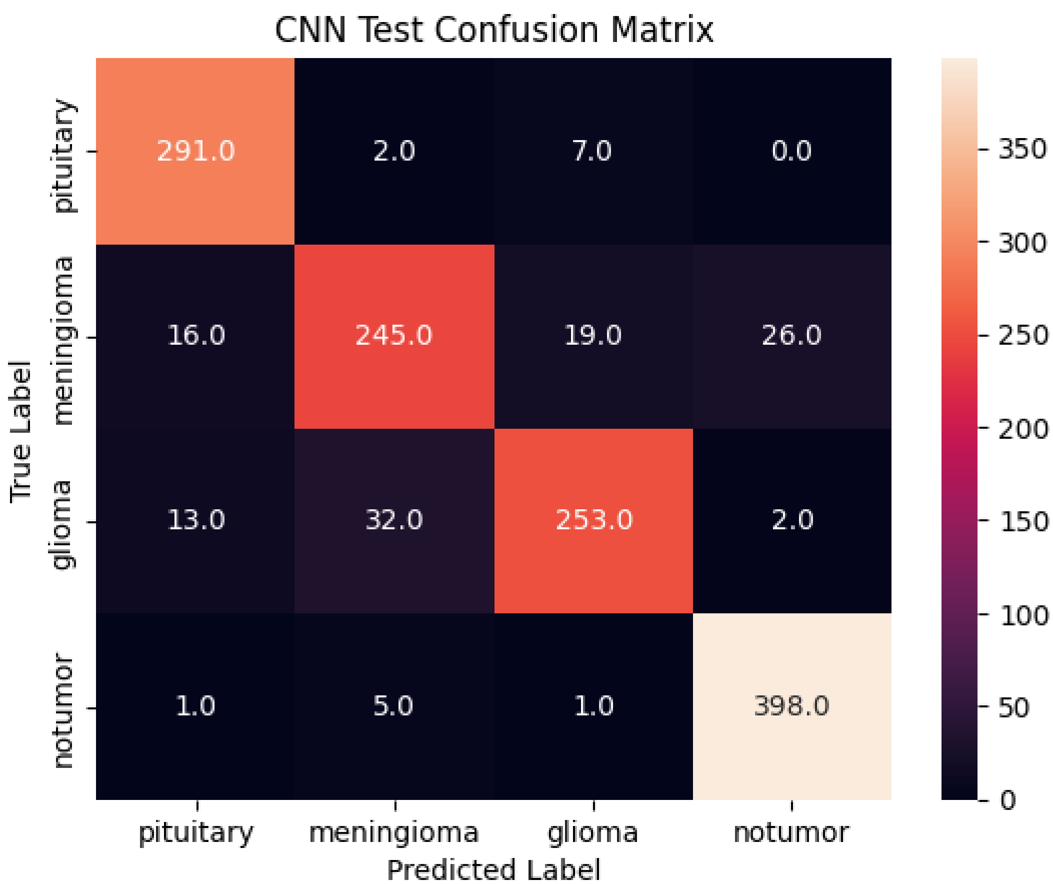
```
Test Accuracy: 0.905
```

Classification Metrics for Final Model

In [39]:
```
from sklearn.metrics import confusion_matrix
model_conf = confusion_matrix(y_pred= test_pred_labels.cpu().numpy(),
                              y_true= test_y, labels= [0,1,2,3])
model_conf
```

Out[39]:
```
array([[291,   2,   7,   0],
       [ 16, 245,  19,  26],
       [ 13,  32, 253,   2],
       [  1,   5,   1, 398]])
```

In [40]:
```
ax = sns.heatmap(model_conf,annot = True, fmt=".1f", xticklabels= dict_test.key
                 yticklabels= dict_test.keys())
ax.set_title("CNN Test Confusion Matrix");
ax.set_xlabel("Predicted Label")
ax.set_ylabel("True Label");
```



In [41]:
```
from sklearn.metrics import classification_report
print(classification_report(test_y, test_pred_labels.cpu().numpy(),
                            target_names=dict_test.keys()))
```

```
              precision    recall  f1-score   support

   pituitary       0.91      0.97      0.94       300
  meningioma       0.86      0.80      0.83       306
      glioma       0.90      0.84      0.87       300
     notumor       0.93      0.98      0.96       405

    accuracy                           0.91      1311
   macro avg       0.90      0.90      0.90      1311
weighted avg       0.90      0.91      0.90      1311
```

Aside: Potential Extension -> Highlighting Images that are Potentially Misclassified

The core idea is that the model is never going to be a hundred percent accurate and may sometimes predict 2 classes with slight differences in the respective probabilities for the tumor type of an image. In this scenario, the slight difference is the 2 highest probabilities that the model has predicted the tumor type to be are within 10% of each other. This state will be defined as the model is unsure of the true class of the tumor type of the MRI image. If this occurs, the model will store the indicies of the images it is unsure that it correctly classified for the radiologist to verify in a further analysis.

Steps:

1. Storing the probabilities used to generate the predicted labels
2. Determine the 2 highest probabilities for each image
3. If difference between the 2 images is less than 0.1, store the indices
4. Return indices of images that the model is unsure of

In [42]:

```
def unsure_image(model_output):
    probs = nn.Softmax(dim = 1)(model_output).cpu().numpy()
    largest_2_probs = np.sort(probs)[:, -2:]
    unsure_ind = np.squeeze(np.diff(largest_2_probs) < 0.10).nonzero()[0]
    return unsure_ind
```

In [43]:

```
uns_inds = unsure_image(model_output= model_outputs)
uns_inds
```

Out[43]:

```
array([  10,   30,   70,  140,  366,  373,  420,  442,  513,  622,  651,
        666,  703,  726,  739,  838,  856, 1208])
```