CO416 - Machine Learning for Imaging

Coursework 2 - Age regression from brain MRI

Predicting age from a brain MRI scan can have diagnostic value for a number of diseases that cause structural changes and damage to the brain. Discrepancy between the predicted, biological age and the real, chronological age of a patient might indicate the presence of disease and abnormal changes to the brain. For this we need an accurate predictor of brain age which may be learned from a set of healthy reference subjects. The objective for the coursework is to implement two different supervised learning approaches for age regression from brain MRI. Data from 600 healthy subjects will be provided. Each approach will require a processing pipeline with different components that you will need to implement using methods that were discussed in the lectures and tutorials. There are dedicated sections in the Jupyter notebook for each approach which contain some detailed instructions, hints and notes.

You may find useful ideas and implementations in the tutorial notebooks. Make sure to add documentation to your code. Markers will find it easier to understand your reasoning when sufficiently detailed comments are provided in your implementations.

Read the descriptions and provided code cells carefully and look out for the cells marked with 'TASK'.

Getting started and familiarise ourselves with the data

The following cells provide some helper functions to load the data, and provide some overview and visualisation of the statistics over the population of 600 subjects. Let's start by loading the meta data, that is the data containing information about the subject IDs, their age, and gender.

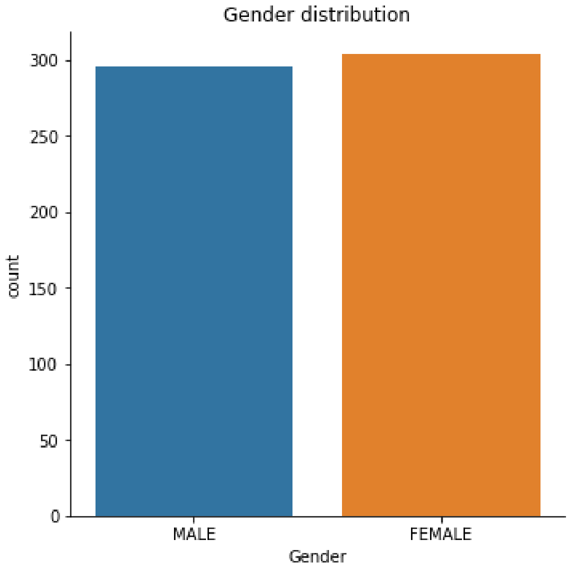
In [2]:
```
# Read the meta data using pandas
import pandas as pd

data_dir = "./data/brain/"

meta_data = pd.read_csv(data_dir + 'meta/clean_participant_data.csv')
meta_data.head() # show the first five data entries
```

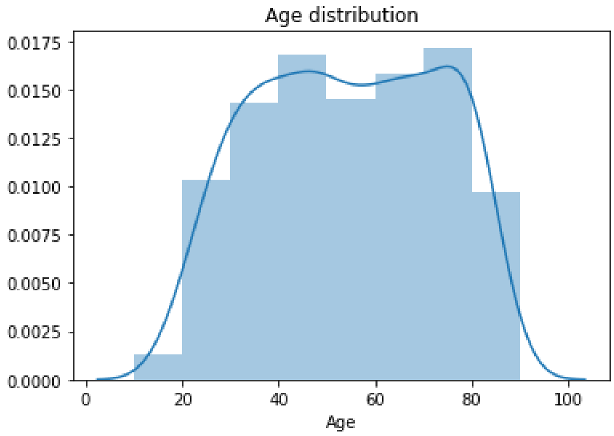
Out[2]:

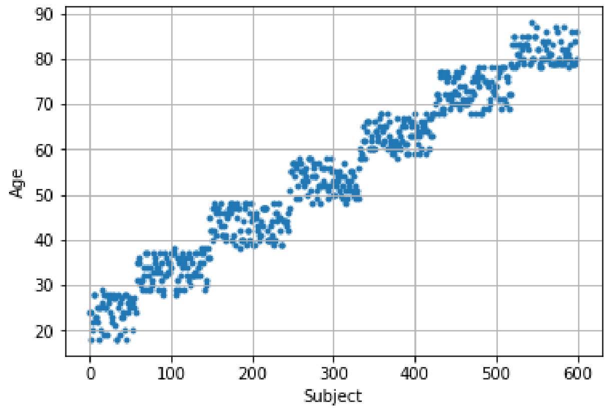
	ID	age	gender_code	gender_text
0	CC110033	24	1	MALE
1	CC110037	18	1	MALE
2	CC110045	24	2	FEMALE
3	CC110056	22	2	FEMALE
4	CC110062	20	1	MALE

Let's have a look at some population statistics.

In [3]:
```
%matplotlib inline

import matplotlib.pyplot as plt
import seaborn as sns

sns.catplot(x="gender_text", data=meta_data, kind="count")
plt.title('Gender distribution')
plt.xlabel('Gender')
plt.show()

sns.distplot(meta_data['age'], bins=[10,20,30,40,50,60,70,80,90])
plt.title('Age distribution')
plt.xlabel('Age')
plt.show()

plt.scatter(range(len(meta_data['age'])),meta_data['age'], marker='.')
plt.grid()
plt.xlabel('Subject')
plt.ylabel('Age')
plt.show()
```







Set up a simple medical image viewer and import SimpleITK

In [4]:
```
import numpy as np
import SimpleITK as sitk
import matplotlib.pyplot as plt

from ipywidgets import interact, fixed
from IPython.display import display

from utils.image_viewer import display_image

from sklearn import metrics
```

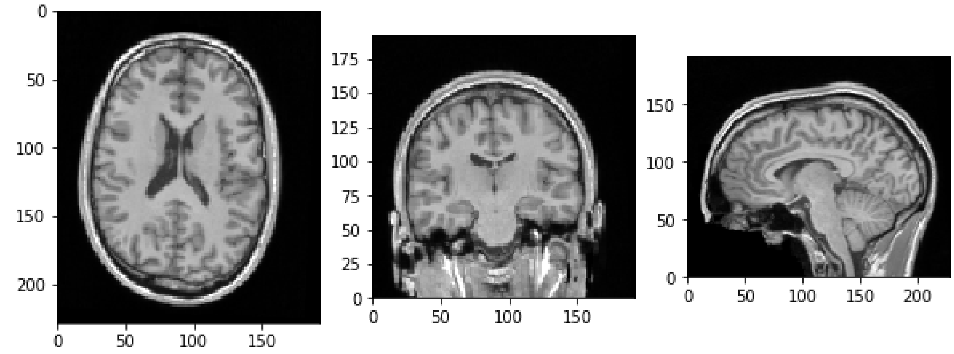
Imaging data

Let's check out the imaging data that is available for each subject. This cell also shows how to retrieve data given a particular subject ID from the meta data.

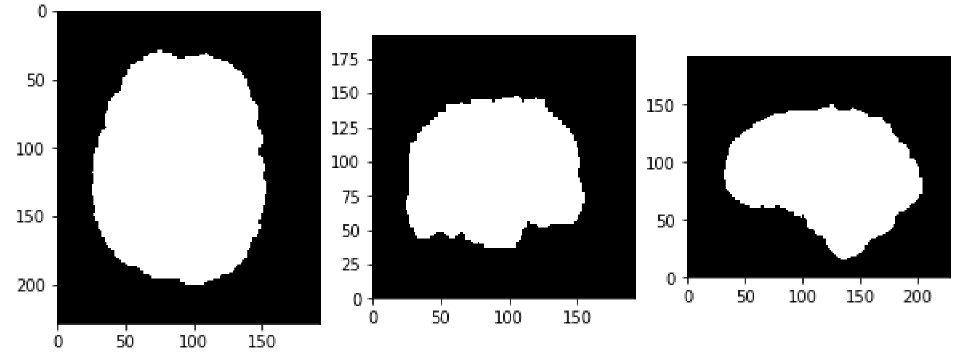
In [5]:
```
import glob

# Subject with index 0
ID = meta_data['ID'][0]
age = meta_data['age'][0]

# Data folders
image_dir = data_dir + 'images/'
image_filenames = glob.glob(image_dir + '*.nii.gz')

mask_dir = data_dir + 'masks/'
mask_filenames = glob.glob(mask_dir + '*.nii.gz')

greymatter_dir = data_dir + 'greymatter/'
greymatter_filenames = glob.glob(greymatter_dir + '*.nii.gz')


image_filename = [f for f in image_filenames if ID in f][0]
img = sitk.ReadImage(image_filename)

mask_filename = [f for f in mask_filenames if ID in f][0]
msk = sitk.ReadImage(mask_filename)

greymatter_filename = [f for f in greymatter_filenames if ID in f][0]
gm = sitk.ReadImage(greymatter_filename)

print('Imaging data of subject ' + ID + ' with age ' + str(age))

print('\nMR Image (used in part A)')
display_image(img, window=400, level=200)

print('Brain mask (used in part A)')
display_image(msk)

print('Spatially normalised grey matter maps (used in part B)')
display_image(gm)
```

```
Imaging data of subject CC110033 with age 24
```

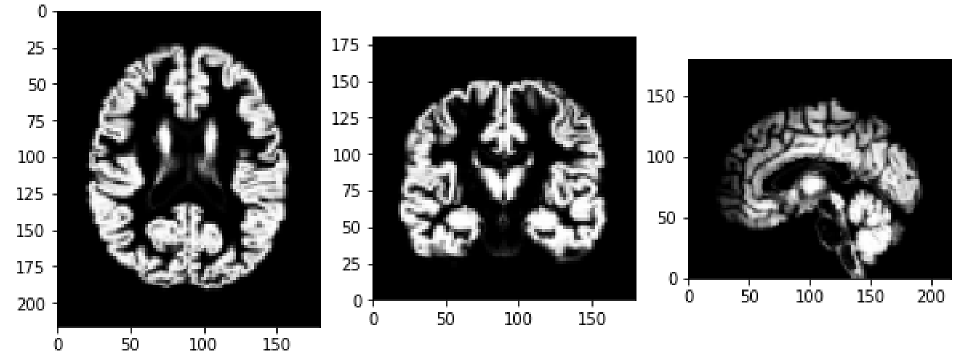
```
MR Image (used in part A)
```



```
Brain mask (used in part A)
```



```
Spatially normalised grey matter maps (used in part B)
```



Part A: Volume-based regression using brain structure segmentation

The first approach aims to regress the age of a subject using the volumes of brain tissues as features. The structures include grey matter (GM), white matter (WM), and cerebrospinal fluid (CSF). It is known that with increasing age the ventricles enlarge (filled with CSF), while it is assumed that grey and white matter volume may decrease over time. However, as overall brain volume varies across individuals, taking the absolute volumes of tissues might not be predictive. Instead, relative volumes need to be computed as the ratios between each tissue volume and overall brain volume. To this end, a four-class (GM, WM, CSF, and background) brain segmentation needs to be implemented and applied to the 600 brain scans. Brain masks are provided which have been generated with a state-of-the-art neuroimaging brain extraction tool.

Different regression techniques should be explored, and it might be beneficial to investigate what the best set of features is for this task. Are all volume features equally useful, or is it even better to combine some of them and create new features. How does a simple linear regression perform compared to a model with higher order polynomials? Do you need regularisation? How about other regression methods such as regression trees or neural networks? The accuracy of different methods should be evaluated using two-fold cross-validation, and average age prediction accuracy should be compared and reported appropriately.

Note: For part A, only the MR images and the brain masks should be used from the imaging data. The spatially normalised grey matter maps are used in part B only. If you struggle with task A-1, you can continue with A-2 using the provided reference segmentations in subfolder `segs_refs` .

TASK A-1: Brain tissue segmentation

Implement a CNN model for brain tissue segmentation which can provide segmentations of GM, WM, and CSF. For this task (and only for this task), we provide a separate dataset of 52 subjects which are split into 47 images for training and 5 for validation. The template code below has the data handling and main training routines already implemented, so you can focus on implementing a suitable CNN model. A simple model is provided, but this won't perform very well.

Once your model is trained and you are happy with the results on the validation data you should apply it to the 600 test images. We provide reference segmentations in a subfolder `segs_refs` for all subjects. Calculate Dice similarity coefficients per tissue when comparing your predicted segmentations for the 600 test images to the reference segmentations. Summarise the statistics of the 600 Dice scores for each tissue class in [box-and-whisker-plots (https://matplotlib.org/api/_as_gen/matplotlib.pyplot.boxplot.html)](https://matplotlib.org/api/_as_gen/matplotlib.pyplot.boxplot.html).

Note: Implementing a full-fledged machine learning pipeline with training and testing procedures in Jupyter notebooks is a bit cumbersome and a pain to debug. Also, running bigger training tasks can be unstable. The code below should work as is on your VM. However, if you want to get a bit more serious about implementing an advanced CNN approach for image segmentation, you may want to move code into separate Python scripts and run them from the terminal.

Imports

In [6]:
```
import os
import torch
import torch.nn as nn
import torch.nn.functional as F
from utils.data_helper import ImageSegmentationDataset
```

Check that the GPU is up and running

In [7]:
```
cuda_dev = '0' #GPU device 0 (can be changed if multiple GPUs are available)

use_cuda = torch.cuda.is_available()
device = torch.device("cuda:" + cuda_dev if use_cuda else "cpu")

print('Device: ' + str(device))
if use_cuda:
    print('GPU: ' + str(torch.cuda.get_device_name(int(cuda_dev))))
```

```
Device: cuda:0
GPU: Tesla K80
```

Config and hyper-parameters

Here we set some default hyper-parameters and a starting configuration for the image resolution and others.

This needs to be revisited to optimise these values. In particular, you may want to run your final model on higher resolution images.

In [8]:
```
rnd_seed = 42 #fixed random seed

# img_size = [128, 128, 128]
img_size = [64, 64, 64]
img_spacing = [3, 3, 3]

num_epochs = 100
learning_rate = 0.001
batch_size = 4
val_interval = 10

num_classes = 4

out_dir = './output'

# Create output directory
if not os.path.exists(out_dir):
    os.makedirs(out_dir)
```

Loading and pre-processing of training and validation data

We apply some standard pre-processing on the data such as intensity normalization (zero mean unit variance) and downsampling according to the configuration above.

We provide a 'debug' csv file pointing to just a few images for training. Replace this with the full training dataset when you train your full model.

In [9]:
```
# USE THIS FOR TRAINING ON ALL 47 SUBJECTS
train_data = data_dir + 'train/csv/train.csv'

# USE THIS FOR DEBUGGING WITH JUST 2 SUBJECTS
# train_data = data_dir + 'train/csv/train_debug.csv'

val_data = data_dir + 'train/csv/val.csv'

print('LOADING TRAINING DATA...')
dataset_train = ImageSegmentationDataset(train_data, img_spacing, img_size)
dataloader_train = torch.utils.data.DataLoader(dataset_train, batch_size=batch_size, shuffl
e=True)

print('\nLOADING VALIDATION DATA...')
dataset_val = ImageSegmentationDataset(val_data, img_spacing, img_size)
dataloader_val = torch.utils.data.DataLoader(dataset_val, batch_size=1, shuffle=False)
```

```
LOADING TRAINING DATA...
+ reading image msub-CC110319_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110319.nii.gz
+ reading mask sub-CC110319_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120208_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120208.nii.gz
+ reading mask sub-CC120208_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120462_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120462.nii.gz
+ reading mask sub-CC120462_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC121144_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC121144.nii.gz
+ reading mask sub-CC121144_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC122405_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC122405.nii.gz
+ reading mask sub-CC122405_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC210422_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC210422.nii.gz
+ reading mask sub-CC210422_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC220203_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC220203.nii.gz
+ reading mask sub-CC220203_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC220518_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC220518.nii.gz
+ reading mask sub-CC220518_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC221220_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC221220.nii.gz
+ reading mask sub-CC221220_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC221595_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC221595.nii.gz
+ reading mask sub-CC221595_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC222120_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC222120.nii.gz
+ reading mask sub-CC222120_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC222956_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC222956.nii.gz
+ reading mask sub-CC222956_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC310203_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC310203.nii.gz
+ reading mask sub-CC310203_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC310407_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC310407.nii.gz
+ reading mask sub-CC310407_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC320089_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC320089.nii.gz
+ reading mask sub-CC320089_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC320336_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC320336.nii.gz
+ reading mask sub-CC320336_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC320574_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC320574.nii.gz
+ reading mask sub-CC320574_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC321069_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC321069.nii.gz
+ reading mask sub-CC321069_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC321428_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC321428.nii.gz
+ reading mask sub-CC321428_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC321899_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC321899.nii.gz
+ reading mask sub-CC321899_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC410113_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC410113.nii.gz
+ reading mask sub-CC410113_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC410243_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC410243.nii.gz
+ reading mask sub-CC410243_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC410432_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC410432.nii.gz
+ reading mask sub-CC410432_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC420137_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC420137.nii.gz
+ reading mask sub-CC420137_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC420202_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC420202.nii.gz
+ reading mask sub-CC420202_T1w_rigid_to_mni_brain_mask.nii.gz
```

```
+ reading image msub-CC420286_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC420286.nii.gz
+ reading mask sub-CC420286_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC420888_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC420888.nii.gz
+ reading mask sub-CC420888_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC510226_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC510226.nii.gz
+ reading mask sub-CC510226_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC510329_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC510329.nii.gz
+ reading mask sub-CC510329_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC510474_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC510474.nii.gz
+ reading mask sub-CC510474_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC520002_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC520002.nii.gz
+ reading mask sub-CC520002_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC520134_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC520134.nii.gz
+ reading mask sub-CC520134_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC520253_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC520253.nii.gz
+ reading mask sub-CC520253_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC520503_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC520503.nii.gz
+ reading mask sub-CC520503_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC520775_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC520775.nii.gz
+ reading mask sub-CC520775_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC610288_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC610288.nii.gz
+ reading mask sub-CC610288_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC610575_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC610575.nii.gz
+ reading mask sub-CC610575_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC620073_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC620073.nii.gz
+ reading mask sub-CC620073_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC620262_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC620262.nii.gz
+ reading mask sub-CC620262_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC620444_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC620444.nii.gz
+ reading mask sub-CC620444_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC620557_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC620557.nii.gz
+ reading mask sub-CC620557_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC620821_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC620821.nii.gz
+ reading mask sub-CC620821_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC621642_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC621642.nii.gz
+ reading mask sub-CC621642_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC710416_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC710416.nii.gz
+ reading mask sub-CC710416_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC720103_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC720103.nii.gz
+ reading mask sub-CC720103_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC720511_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC720511.nii.gz
+ reading mask sub-CC720511_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721291_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721291.nii.gz
+ reading mask sub-CC721291_T1w_rigid_to_mni_brain_mask.nii.gz

LOADING VALIDATION DATA...
+ reading image msub-CC220901_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC220901.nii.gz
+ reading mask sub-CC220901_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC320698_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC320698.nii.gz
+ reading mask sub-CC320698_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC420454_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC420454.nii.gz
+ reading mask sub-CC420454_T1w_rigid_to_mni_brain_mask.nii.gz
```

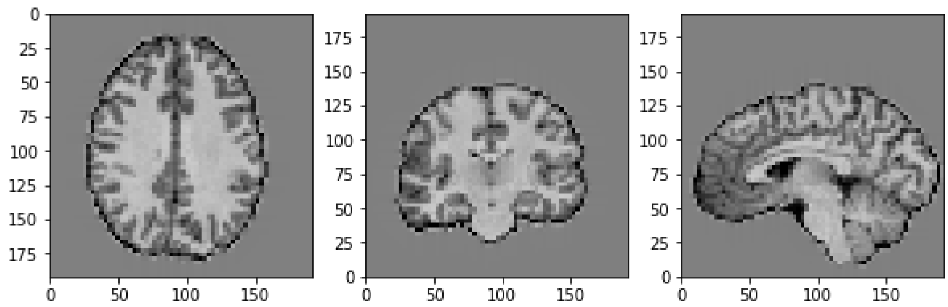
```
+ reading image msub-CC610058_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC610058.nii.gz
+ reading mask sub-CC610058_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC710679_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC710679.nii.gz
+ reading mask sub-CC710679_T1w_rigid_to_mni_brain_mask.nii.gz
```

Visualise training example

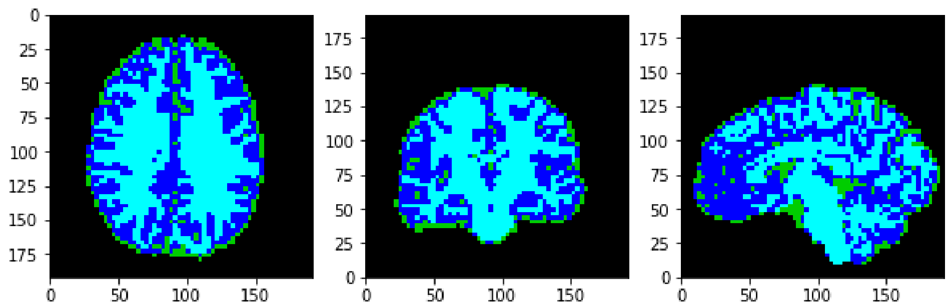
Just to check how a training image looks like after pre-processing.

In [10]:
```
sample = dataset_train.get_sample(0)
img_name = dataset_train.get_img_name(0)
seg_name = dataset_train.get_seg_name(0)
print('Image: ' + img_name)
display_image(sample['img'], window=5, level=0)
print('Segmentation: ' + seg_name)
display_image(sitk.LabelToRGB(sample['seg']))
print('Mask')
display_image(sample['msk'])
```

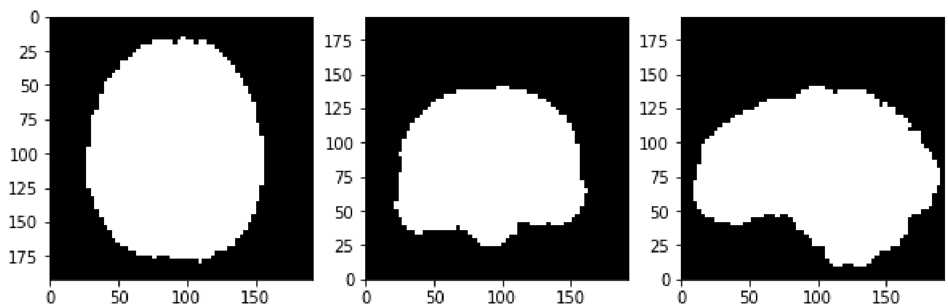
```
Image: msub-CC110319_T1w_rigid_to_mni.nii.gz
```



```
Segmentation: CC110319.nii.gz
```



```
Mask
```



The Model

This is the **key part of task A-1** where you have to design a suitable CNN model for brain segmentation. The simple model provided below works to some degree (it let's you run through the upcoming cells), but it will not perform very well. Use what you learned in the lectures to come up with a good architecture. Start with a simple, shallow model and only increase complexity (e.g., number of layers) if needed.

In [11]:
```
class SimpleNet3D(nn.Module):

    def __init__(self, num_classes):
        super(SimpleNet3D, self).__init__()
        self.num_classes = num_classes
        self.conv1 = nn.Conv3d(1, 18, kernel_size=3, padding=1)
        self.conv2 = nn.Conv3d(18, 36, kernel_size=3, padding=1)
        self.conv3 = nn.Conv3d(36, 54, kernel_size=3, padding=1)
        self.conv4 = nn.Conv3d(54, 27, kernel_size=1)
        self.conv5 = nn.Conv3d(27, num_classes, kernel_size=1)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        x = F.relu(self.conv2(x))
        x = F.relu(self.conv3(x))
        x = F.relu(self.conv4(x))
        x = self.conv5(x)
        return F.softmax(x, dim=1)
```

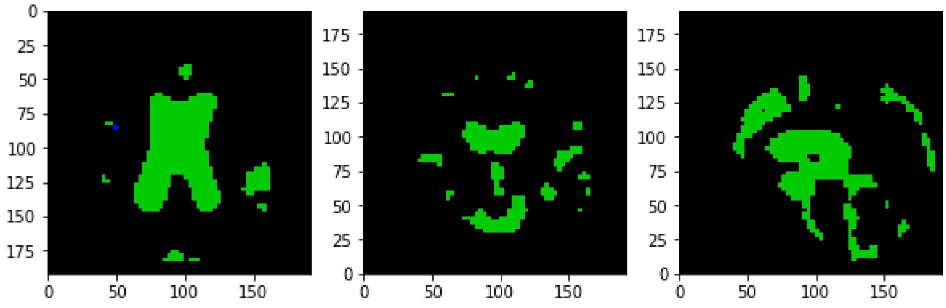
TRAINING

Below is an implementation of a full training procedure including a loop for intermediate evaluation of the model on the validation data. Feel free to modify this procedure. For example, in addition to the loss you may want to monitor precision, recall and Dice scores (or others).

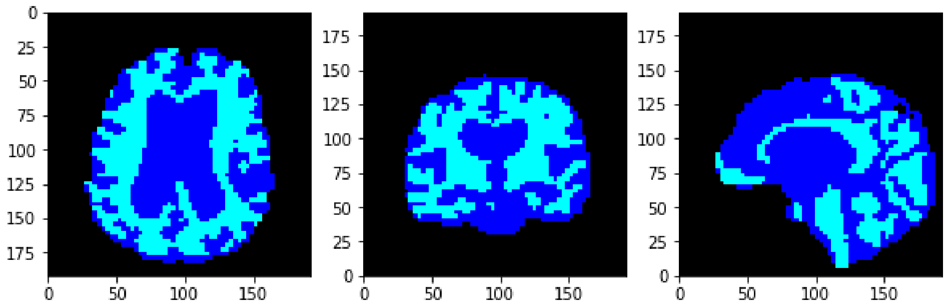
In [111]:
```
import time
model_dir = os.path.join(out_dir, 'model')
if not os.path.exists(model_dir):
    os.makedirs(model_dir)

torch.manual_seed(rnd_seed) #fix random seed

model = SimpleNet3D(num_classes=num_classes).to(device)
model.train()

optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)

loss_train_log = []
loss_val_log = []
epoch_val_log = []
start = time.time()

print('START TRAINING...')
for epoch in range(1, num_epochs + 1):

    # Training
    for batch_idx, batch_samples in enumerate(dataloader_train):
        img, seg = batch_samples['img'].to(device), batch_samples['seg'].to(device)
        optimizer.zero_grad()
        prd = model(img)
        prd_flat = prd.view(prd.size(0), prd.size(1), -1)
        seg_flat = seg.view(seg.size(0), seg.size(1), -1)
        loss = F.cross_entropy(prd_flat, seg_flat.squeeze(1))
        loss.backward()
        optimizer.step()

    loss_train_log.append(loss.item())

    print('+ TRAINING \tEpoch: {} \tLoss: {:.6f}'.format(epoch, loss.item()))

    # Validation
    if epoch == 1 or epoch % val_interval == 0:
        loss_val = 0
        sum_pts = 0
        d_score = 0
        idx_test = 0
        with torch.no_grad():
            for data_sample in dataloader_val:
                img, seg = data_sample['img'].to(device), data_sample['seg'].to(device)
                prd = model(img)
                prd_flat = prd.view(prd.size(0), prd.size(1), -1)
                seg_flat = seg.view(seg.size(0), seg.size(1), -1)
                loss_val += F.cross_entropy(prd_flat, seg_flat.squeeze(1), reduction='sum')
.item()
                sum_pts += seg_flat.size(2)

                sample = dataset_val.get_sample(idx_test)
                prd = torch.argmax(prd, dim=1)
                prediction = sitk.GetImageFromArray(prd.cpu().squeeze().numpy().astype(np.u
int8))
                prediction.CopyInformation(sample['seg'])
                segmentation = sitk.GetImageFromArray(seg.cpu().squeeze().numpy().astype(np
.uint8))
                segmentation.CopyInformation(sample['seg'])
                overlap_measures_filter = sitk.LabelOverlapMeasuresImageFilter()
                overlap_measures_filter.Execute(prediction, segmentation)
                d_score += overlap_measures_filter.GetDiceCoefficient()


                idx_test += 1


        loss_val /= sum_pts
        avg_d_score = d_score / idx_test

        loss_val_log.append(loss_val)
        epoch_val_log.append(epoch)

        print('--------------------------------------------------')
        print('+ VALIDATE \tEpoch: {} \tLoss: {:.6f} \tTime: {:6f}'.format(epoch, loss_val,
 time.time()-start))
```

```
        print('DSC\t' + str(avg_d_score))
        display_image(sitk.LabelToRGB(prediction))
        print('--------------------------------------------------')

torch.save(model.state_dict(), os.path.join(model_dir, 'model.pt'))

print('\nFinished TRAINING.')

plt.plot(range(1, num_epochs + 1), loss_train_log, c='r', label='train')
plt.plot(epoch_val_log, loss_val_log, c='b', label='val')
plt.legend(loc='upper right')
plt.xlabel('epoch')
plt.ylabel('loss')
plt.show()
```

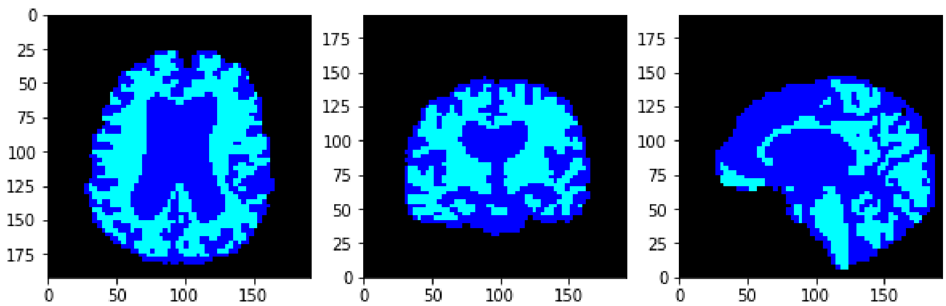
```
START TRAINING...
+ TRAINING      Epoch: 1        Loss: 1.229930
--------------------------------------------------
+ VALIDATE      Epoch: 1        Loss: 1.188562  Time: 17.173074
DSC     0.1887462948551526
```



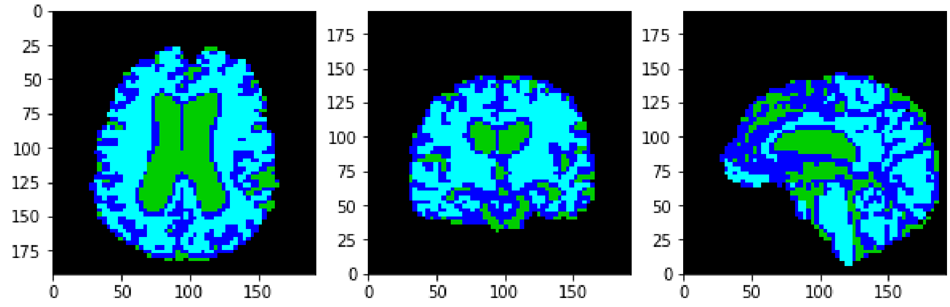
```
--------------------------------------------------
+ TRAINING      Epoch: 2        Loss: 0.872511
+ TRAINING      Epoch: 3        Loss: 0.842169
+ TRAINING      Epoch: 4        Loss: 0.840396
+ TRAINING      Epoch: 5        Loss: 0.835717
+ TRAINING      Epoch: 6        Loss: 0.826876
+ TRAINING      Epoch: 7        Loss: 0.825030
+ TRAINING      Epoch: 8        Loss: 0.818294
+ TRAINING      Epoch: 9        Loss: 0.822773
+ TRAINING      Epoch: 10       Loss: 0.811307
--------------------------------------------------
+ VALIDATE      Epoch: 10       Loss: 0.822223  Time: 169.954166
DSC     0.6690933765608478
```



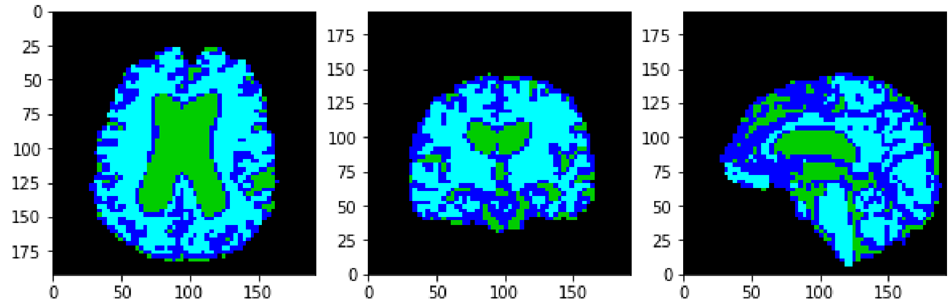
```
--------------------------------------------------
+ TRAINING      Epoch: 11       Loss: 0.812752
+ TRAINING      Epoch: 12       Loss: 0.810590
+ TRAINING      Epoch: 13       Loss: 0.813111
+ TRAINING      Epoch: 14       Loss: 0.810729
+ TRAINING      Epoch: 15       Loss: 0.807958
+ TRAINING      Epoch: 16       Loss: 0.806675
+ TRAINING      Epoch: 17       Loss: 0.806372
+ TRAINING      Epoch: 18       Loss: 0.798685
+ TRAINING      Epoch: 19       Loss: 0.815937
+ TRAINING      Epoch: 20       Loss: 0.806181
--------------------------------------------------
+ VALIDATE      Epoch: 20       Loss: 0.811789  Time: 341.255172
DSC     0.7111856768458671
```



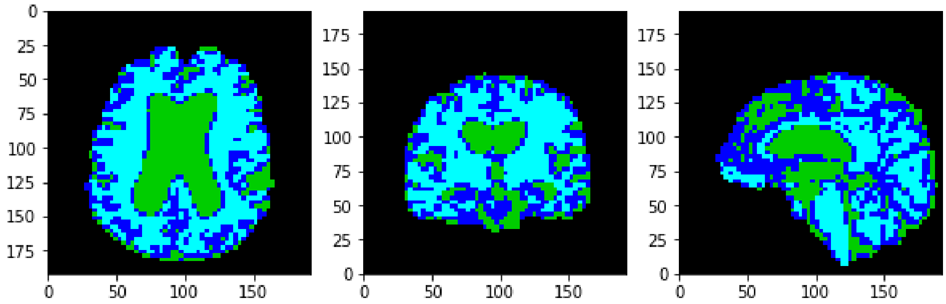
```
--------------------------------------------------
+ TRAINING      Epoch: 21       Loss: 0.796506
+ TRAINING      Epoch: 22       Loss: 0.797091
+ TRAINING      Epoch: 23       Loss: 0.805497
+ TRAINING      Epoch: 24       Loss: 0.798363
+ TRAINING      Epoch: 25       Loss: 0.800462
+ TRAINING      Epoch: 26       Loss: 0.792722
+ TRAINING      Epoch: 27       Loss: 0.792261
+ TRAINING      Epoch: 28       Loss: 0.786099
+ TRAINING      Epoch: 29       Loss: 0.782417
+ TRAINING      Epoch: 30       Loss: 0.782994
--------------------------------------------------
+ VALIDATE      Epoch: 30       Loss: 0.784902   Time: 512.661394
DSC     0.8326115842562446
```



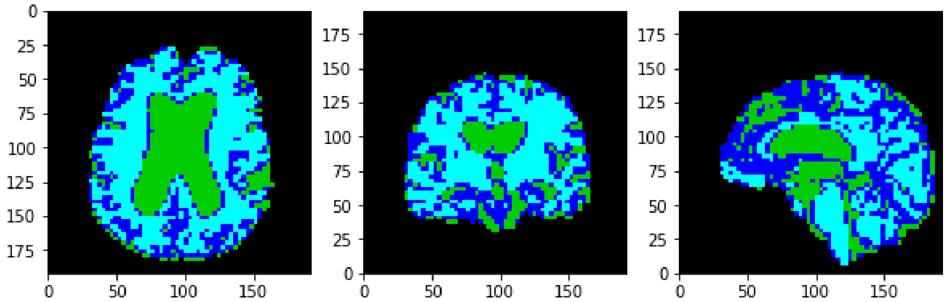
```
--------------------------------------------------
+ TRAINING      Epoch: 31       Loss: 0.778088
+ TRAINING      Epoch: 32       Loss: 0.777878
+ TRAINING      Epoch: 33       Loss: 0.775787
+ TRAINING      Epoch: 34       Loss: 0.778423
+ TRAINING      Epoch: 35       Loss: 0.779409
+ TRAINING      Epoch: 36       Loss: 0.778551
+ TRAINING      Epoch: 37       Loss: 0.778065
+ TRAINING      Epoch: 38       Loss: 0.775737
+ TRAINING      Epoch: 39       Loss: 0.775506
+ TRAINING      Epoch: 40       Loss: 0.775027
--------------------------------------------------
+ VALIDATE      Epoch: 40       Loss: 0.780995   Time: 683.919609
DSC     0.843789210978465
```



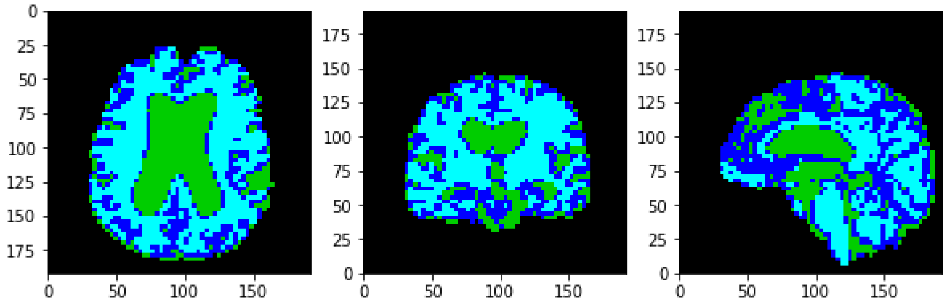
```
--------------------------------------------------
+ TRAINING      Epoch: 41       Loss: 0.775712
+ TRAINING      Epoch: 42       Loss: 0.774946
+ TRAINING      Epoch: 43       Loss: 0.774344
+ TRAINING      Epoch: 44       Loss: 0.772837
+ TRAINING      Epoch: 45       Loss: 0.771259
+ TRAINING      Epoch: 46       Loss: 0.775367
+ TRAINING      Epoch: 47       Loss: 0.772607
+ TRAINING      Epoch: 48       Loss: 0.772896
+ TRAINING      Epoch: 49       Loss: 0.775150
+ TRAINING      Epoch: 50       Loss: 0.772654
--------------------------------------------------
+ VALIDATE      Epoch: 50       Loss: 0.775896   Time: 855.386376
DSC     0.8666671000440388
```



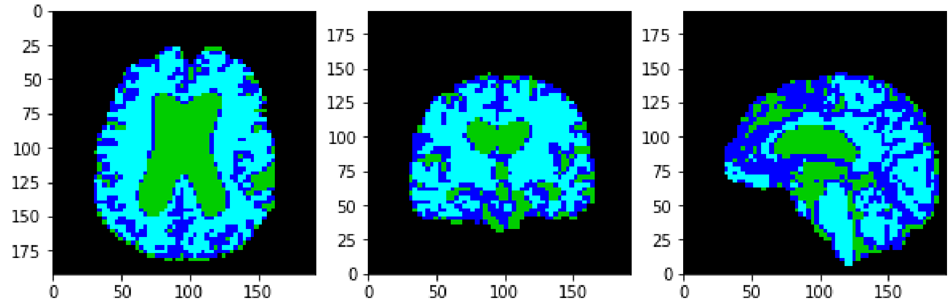
```
-------------------------------------------------
+ TRAINING       Epoch: 51       Loss: 0.771759
+ TRAINING       Epoch: 52       Loss: 0.774002
+ TRAINING       Epoch: 53       Loss: 0.771399
+ TRAINING       Epoch: 54       Loss: 0.774904
+ TRAINING       Epoch: 55       Loss: 0.776264
+ TRAINING       Epoch: 56       Loss: 0.774715
+ TRAINING       Epoch: 57       Loss: 0.774725
+ TRAINING       Epoch: 58       Loss: 0.771668
+ TRAINING       Epoch: 59       Loss: 0.775373
+ TRAINING       Epoch: 60       Loss: 0.774977
-------------------------------------------------
+ VALIDATE       Epoch: 60       Loss: 0.774848   Time: 1026.475206
DSC      0.8699170200200124
```



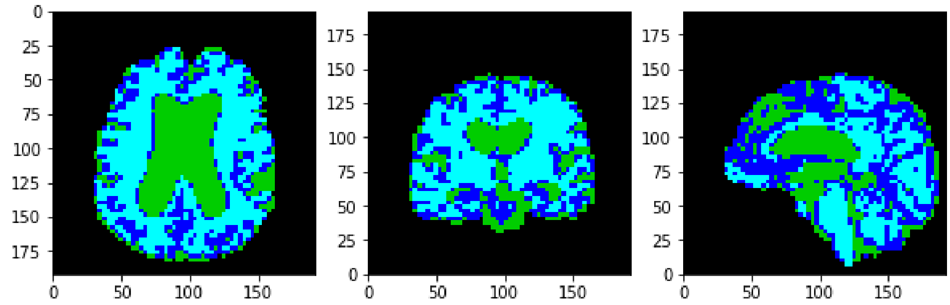
```
-------------------------------------------------
+ TRAINING       Epoch: 61       Loss: 0.772892
+ TRAINING       Epoch: 62       Loss: 0.772741
+ TRAINING       Epoch: 63       Loss: 0.771755
+ TRAINING       Epoch: 64       Loss: 0.773381
+ TRAINING       Epoch: 65       Loss: 0.772918
+ TRAINING       Epoch: 66       Loss: 0.773151
+ TRAINING       Epoch: 67       Loss: 0.770131
+ TRAINING       Epoch: 68       Loss: 0.769743
+ TRAINING       Epoch: 69       Loss: 0.769737
+ TRAINING       Epoch: 70       Loss: 0.772247
-------------------------------------------------
+ VALIDATE       Epoch: 70       Loss: 0.773459   Time: 1197.649762
DSC      0.8752786140693299
```



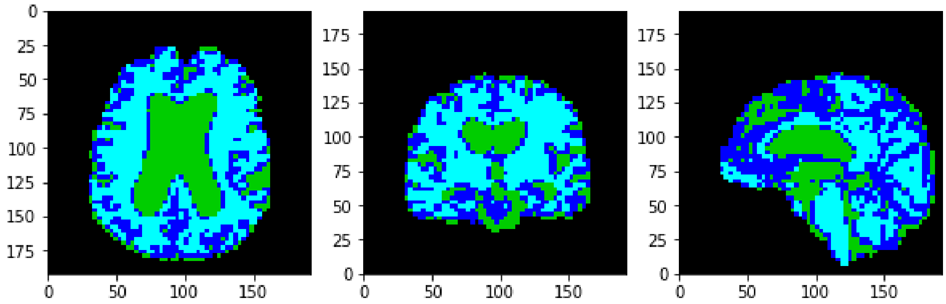
```
--------------------------------------------------
+ TRAINING      Epoch: 71       Loss: 0.771197
+ TRAINING      Epoch: 72       Loss: 0.772430
+ TRAINING      Epoch: 73       Loss: 0.770703
+ TRAINING      Epoch: 74       Loss: 0.771834
+ TRAINING      Epoch: 75       Loss: 0.772284
+ TRAINING      Epoch: 76       Loss: 0.769083
+ TRAINING      Epoch: 77       Loss: 0.769516
+ TRAINING      Epoch: 78       Loss: 0.772671
+ TRAINING      Epoch: 79       Loss: 0.766728
+ TRAINING      Epoch: 80       Loss: 0.770979
--------------------------------------------------
+ VALIDATE      Epoch: 80       Loss: 0.774888   Time: 1368.662950
DSC     0.8670126212420385
```



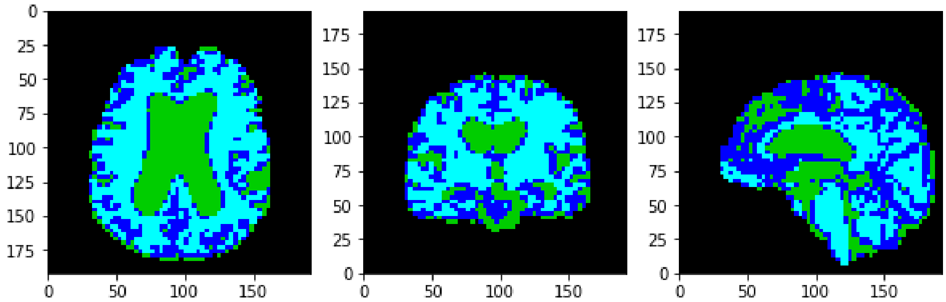
```
--------------------------------------------------
+ TRAINING      Epoch: 81       Loss: 0.769058
+ TRAINING      Epoch: 82       Loss: 0.772520
+ TRAINING      Epoch: 83       Loss: 0.770833
+ TRAINING      Epoch: 84       Loss: 0.771484
+ TRAINING      Epoch: 85       Loss: 0.772005
+ TRAINING      Epoch: 86       Loss: 0.771688
+ TRAINING      Epoch: 87       Loss: 0.772027
+ TRAINING      Epoch: 88       Loss: 0.772998
+ TRAINING      Epoch: 89       Loss: 0.767728
+ TRAINING      Epoch: 90       Loss: 0.770848
--------------------------------------------------
+ VALIDATE      Epoch: 90       Loss: 0.772492   Time: 1539.648258
DSC     0.8783727346337494
```



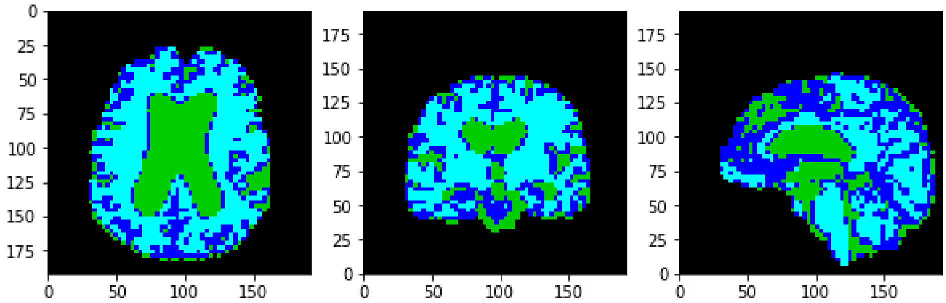
```
--------------------------------------------------
+ TRAINING      Epoch: 91       Loss: 0.770269
+ TRAINING      Epoch: 92       Loss: 0.767729
+ TRAINING      Epoch: 93       Loss: 0.773504
+ TRAINING      Epoch: 94       Loss: 0.771511
+ TRAINING      Epoch: 95       Loss: 0.769213
+ TRAINING      Epoch: 96       Loss: 0.769578
+ TRAINING      Epoch: 97       Loss: 0.769886
+ TRAINING      Epoch: 98       Loss: 0.769751
+ TRAINING      Epoch: 99       Loss: 0.769543
+ TRAINING      Epoch: 100      Loss: 0.771080
--------------------------------------------------
+ VALIDATE      Epoch: 100      Loss: 0.771996   Time: 1710.607319
DSC     0.8799650087972035
```



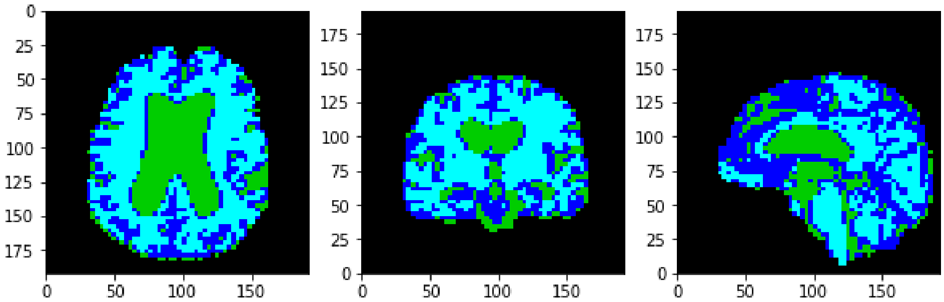
```
-------------------------------------------------
+ TRAINING      Epoch: 101      Loss: 0.770115
+ TRAINING      Epoch: 102      Loss: 0.771149
+ TRAINING      Epoch: 103      Loss: 0.771908
+ TRAINING      Epoch: 104      Loss: 0.767554
+ TRAINING      Epoch: 105      Loss: 0.770689
+ TRAINING      Epoch: 106      Loss: 0.767444
+ TRAINING      Epoch: 107      Loss: 0.768819
+ TRAINING      Epoch: 108      Loss: 0.771110
+ TRAINING      Epoch: 109      Loss: 0.770796
+ TRAINING      Epoch: 110      Loss: 0.769088
-------------------------------------------------
+ VALIDATE      Epoch: 110      Loss: 0.771498   Time: 1881.578091
DSC     0.8819830090494056
```



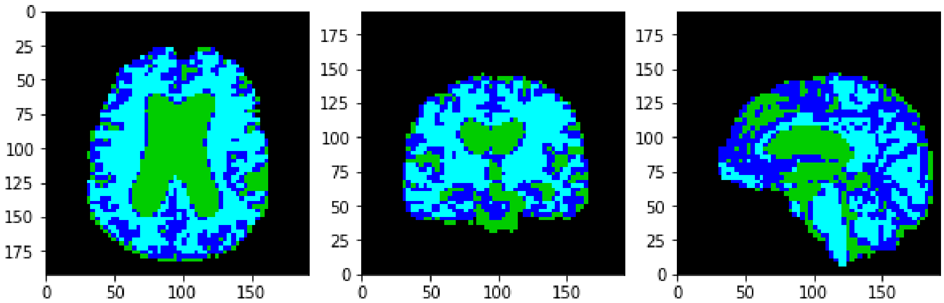
```
-------------------------------------------------
+ TRAINING      Epoch: 111      Loss: 0.768812
+ TRAINING      Epoch: 112      Loss: 0.770404
+ TRAINING      Epoch: 113      Loss: 0.769139
+ TRAINING      Epoch: 114      Loss: 0.769357
+ TRAINING      Epoch: 115      Loss: 0.769062
+ TRAINING      Epoch: 116      Loss: 0.769941
+ TRAINING      Epoch: 117      Loss: 0.772174
+ TRAINING      Epoch: 118      Loss: 0.770011
+ TRAINING      Epoch: 119      Loss: 0.770329
+ TRAINING      Epoch: 120      Loss: 0.770906
-------------------------------------------------
+ VALIDATE      Epoch: 120      Loss: 0.771479   Time: 2052.370511
DSC     0.8816012955991898
```



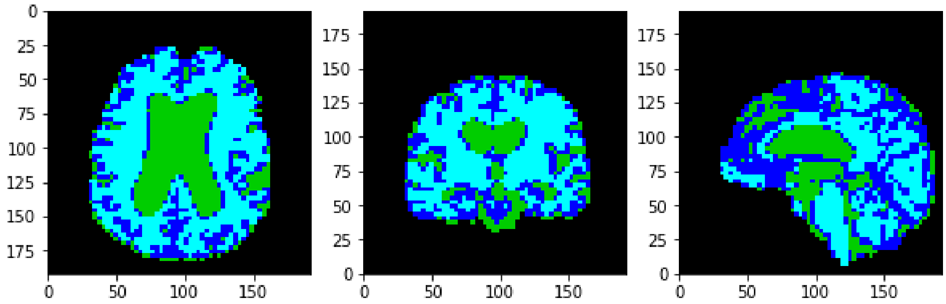
```
--------------------------------------------------
+ TRAINING      Epoch: 121      Loss: 0.770975
+ TRAINING      Epoch: 122      Loss: 0.771567
+ TRAINING      Epoch: 123      Loss: 0.768481
+ TRAINING      Epoch: 124      Loss: 0.769649
+ TRAINING      Epoch: 125      Loss: 0.770674
+ TRAINING      Epoch: 126      Loss: 0.768200
+ TRAINING      Epoch: 127      Loss: 0.770872
+ TRAINING      Epoch: 128      Loss: 0.769193
+ TRAINING      Epoch: 129      Loss: 0.770875
+ TRAINING      Epoch: 130      Loss: 0.770110
--------------------------------------------------
+ VALIDATE      Epoch: 130      Loss: 0.772345  Time: 2223.210756
DSC     0.876893519300918
```



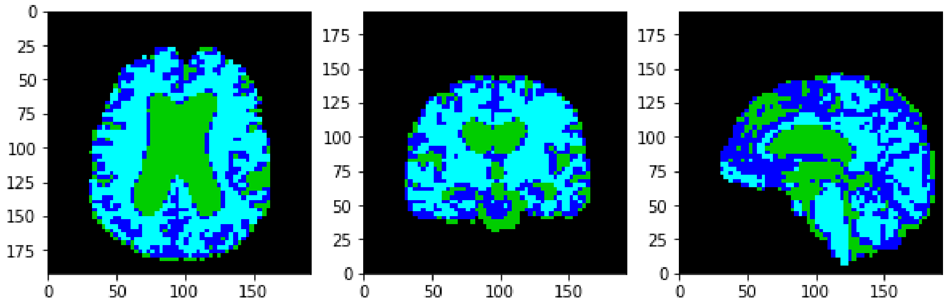

```
--------------------------------------------------
+ TRAINING      Epoch: 131      Loss: 0.767041
+ TRAINING      Epoch: 132      Loss: 0.767716
+ TRAINING      Epoch: 133      Loss: 0.765535
+ TRAINING      Epoch: 134      Loss: 0.768821
+ TRAINING      Epoch: 135      Loss: 0.767818
+ TRAINING      Epoch: 136      Loss: 0.770124
+ TRAINING      Epoch: 137      Loss: 0.770144
+ TRAINING      Epoch: 138      Loss: 0.768336
+ TRAINING      Epoch: 139      Loss: 0.769318
+ TRAINING      Epoch: 140      Loss: 0.772699
--------------------------------------------------
+ VALIDATE      Epoch: 140      Loss: 0.770821  Time: 2394.158781
DSC     0.8838418023208021
```



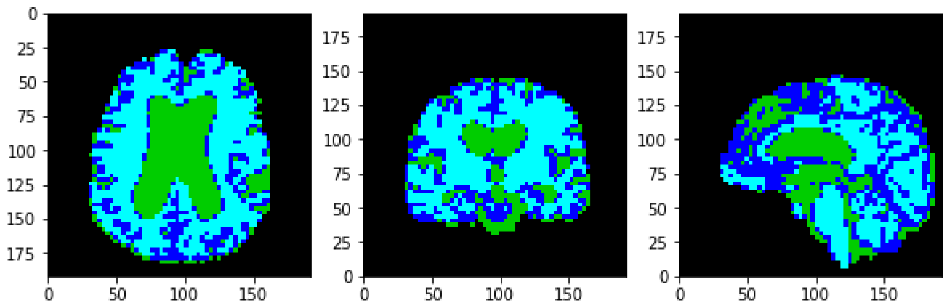

```
--------------------------------------------------
+ TRAINING      Epoch: 141      Loss: 0.768998
+ TRAINING      Epoch: 142      Loss: 0.769562
+ TRAINING      Epoch: 143      Loss: 0.772746
+ TRAINING      Epoch: 144      Loss: 0.768379
+ TRAINING      Epoch: 145      Loss: 0.770333
+ TRAINING      Epoch: 146      Loss: 0.767623
+ TRAINING      Epoch: 147      Loss: 0.766394
+ TRAINING      Epoch: 148      Loss: 0.768516
+ TRAINING      Epoch: 149      Loss: 0.768519
+ TRAINING      Epoch: 150      Loss: 0.769720
--------------------------------------------------
+ VALIDATE      Epoch: 150      Loss: 0.771633  Time: 2564.771925
DSC     0.8792097028675402
```



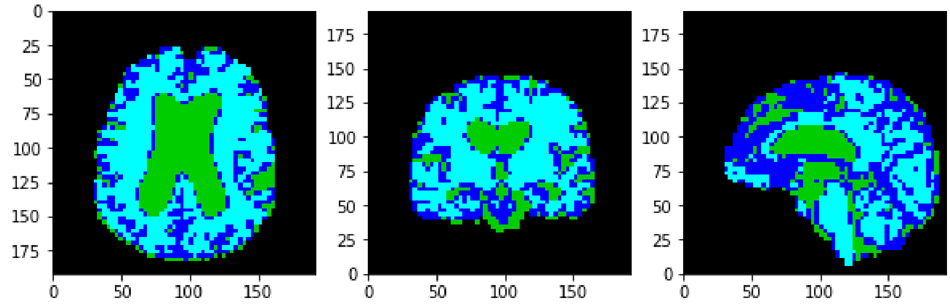
```
-------------------------------------------------
+ TRAINING      Epoch: 151      Loss: 0.766170
+ TRAINING      Epoch: 152      Loss: 0.768105
+ TRAINING      Epoch: 153      Loss: 0.768837
+ TRAINING      Epoch: 154      Loss: 0.768510
+ TRAINING      Epoch: 155      Loss: 0.768573
+ TRAINING      Epoch: 156      Loss: 0.769333
+ TRAINING      Epoch: 157      Loss: 0.766485
+ TRAINING      Epoch: 158      Loss: 0.768792
+ TRAINING      Epoch: 159      Loss: 0.767608
+ TRAINING      Epoch: 160      Loss: 0.768400
-------------------------------------------------
+ VALIDATE      Epoch: 160      Loss: 0.770493   Time: 2735.291732
DSC     0.884857556454618
```



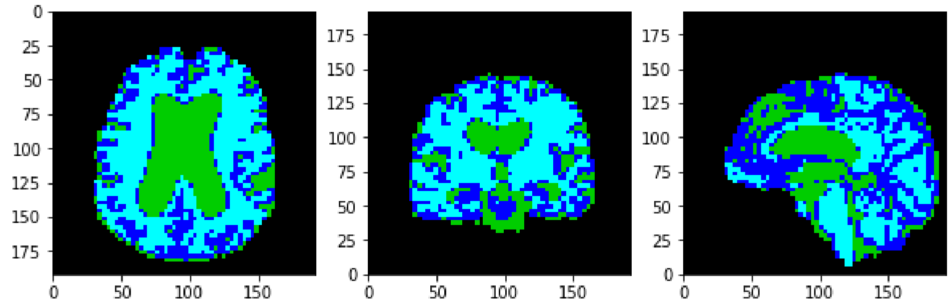
```
-------------------------------------------------
+ TRAINING      Epoch: 161      Loss: 0.769935
+ TRAINING      Epoch: 162      Loss: 0.768230
+ TRAINING      Epoch: 163      Loss: 0.765899
+ TRAINING      Epoch: 164      Loss: 0.768474
+ TRAINING      Epoch: 165      Loss: 0.767675
+ TRAINING      Epoch: 166      Loss: 0.768505
+ TRAINING      Epoch: 167      Loss: 0.769228
+ TRAINING      Epoch: 168      Loss: 0.770220
+ TRAINING      Epoch: 169      Loss: 0.767345
+ TRAINING      Epoch: 170      Loss: 0.767782
-------------------------------------------------
+ VALIDATE      Epoch: 170      Loss: 0.771067   Time: 2906.120534
DSC     0.8817688272490628
```



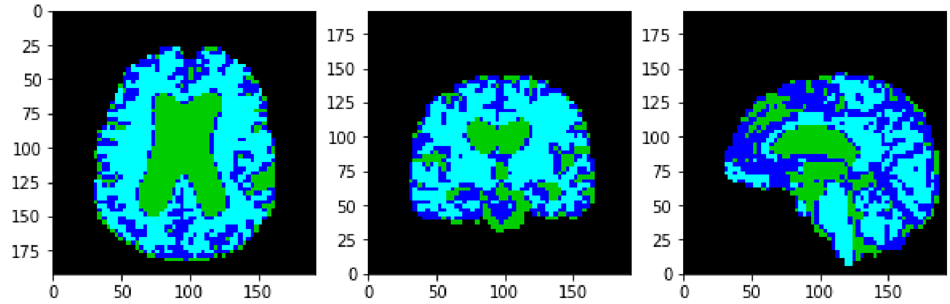
```
--------------------------------------------------
+ TRAINING       Epoch: 171       Loss: 0.766861
+ TRAINING       Epoch: 172       Loss: 0.767854
+ TRAINING       Epoch: 173       Loss: 0.768519
+ TRAINING       Epoch: 174       Loss: 0.767926
+ TRAINING       Epoch: 175       Loss: 0.767215
+ TRAINING       Epoch: 176       Loss: 0.767925
+ TRAINING       Epoch: 177       Loss: 0.769906
+ TRAINING       Epoch: 178       Loss: 0.769573
+ TRAINING       Epoch: 179       Loss: 0.768355
+ TRAINING       Epoch: 180       Loss: 0.767083
--------------------------------------------------
+ VALIDATE       Epoch: 180       Loss: 0.772978   Time: 3076.771561
DSC      0.8725254628185196
```



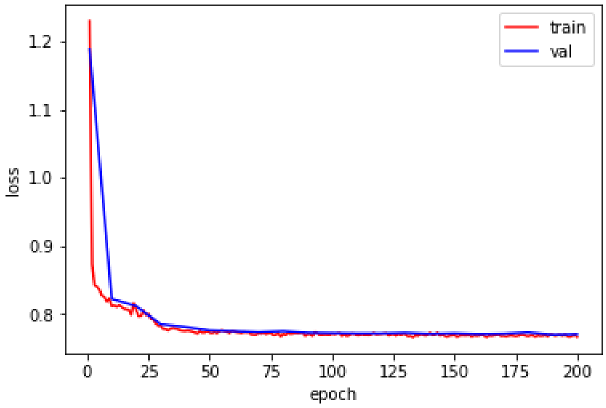

```
--------------------------------------------------
+ TRAINING       Epoch: 181       Loss: 0.768874
+ TRAINING       Epoch: 182       Loss: 0.768547
+ TRAINING       Epoch: 183       Loss: 0.766467
+ TRAINING       Epoch: 184       Loss: 0.768465
+ TRAINING       Epoch: 185       Loss: 0.767521
+ TRAINING       Epoch: 186       Loss: 0.767862
+ TRAINING       Epoch: 187       Loss: 0.769083
+ TRAINING       Epoch: 188       Loss: 0.766840
+ TRAINING       Epoch: 189       Loss: 0.769694
+ TRAINING       Epoch: 190       Loss: 0.769671
--------------------------------------------------
+ VALIDATE       Epoch: 190       Loss: 0.769571   Time: 3247.322600
DSC      0.8884704776655381
```




```
--------------------------------------------------
+ TRAINING       Epoch: 191       Loss: 0.767787
+ TRAINING       Epoch: 192       Loss: 0.768885
+ TRAINING       Epoch: 193       Loss: 0.769389
+ TRAINING       Epoch: 194       Loss: 0.767913
+ TRAINING       Epoch: 195       Loss: 0.769795
+ TRAINING       Epoch: 196       Loss: 0.766930
+ TRAINING       Epoch: 197       Loss: 0.766452
+ TRAINING       Epoch: 198       Loss: 0.767506
+ TRAINING       Epoch: 199       Loss: 0.769548
+ TRAINING       Epoch: 200       Loss: 0.766161
--------------------------------------------------
+ VALIDATE       Epoch: 200       Loss: 0.770328   Time: 3418.236503
DSC      0.8845790670330633
```




```
--------------------------------------------------
Finished TRAINING.
```



Loading and pre-processing of testing data

Now that we have trained a model, the next cells are about applying that model to our test dataset. Before testing on the full 600 subjects, you may want to initially just test on the 5 validation subjects.

In [12]:
```
# USE THIS FOR TESTING ON THE 600 SUBJECTS
test_data = data_dir + 'csv/test.csv'

# USE THIS FOR TESTING ON THE 5 VALIDATION SUBJECTS
# test_data = data_dir + 'train/csv/val.csv'

print('LOADING TESTING DATA...')
dataset_test = ImageSegmentationDataset(test_data, img_spacing, img_size)
dataloader_test = torch.utils.data.DataLoader(dataset_test, batch_size=1, shuffle=False)
```

```
LOADING TESTING DATA...
+ reading image msub-CC110033_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110033.nii.gz
+ reading mask sub-CC110033_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC110037_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110037.nii.gz
+ reading mask sub-CC110037_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC110045_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110045.nii.gz
+ reading mask sub-CC110045_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC110056_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110056.nii.gz
+ reading mask sub-CC110056_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC110062_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110062.nii.gz
+ reading mask sub-CC110062_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC110069_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110069.nii.gz
+ reading mask sub-CC110069_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC110087_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110087.nii.gz
+ reading mask sub-CC110087_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC110098_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110098.nii.gz
+ reading mask sub-CC110098_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC110101_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110101.nii.gz
+ reading mask sub-CC110101_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC110126_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110126.nii.gz
+ reading mask sub-CC110126_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC110174_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110174.nii.gz
+ reading mask sub-CC110174_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC110182_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110182.nii.gz
+ reading mask sub-CC110182_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC110187_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110187.nii.gz
+ reading mask sub-CC110187_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC110411_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110411.nii.gz
+ reading mask sub-CC110411_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC110606_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC110606.nii.gz
+ reading mask sub-CC110606_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC112141_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC112141.nii.gz
+ reading mask sub-CC112141_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120008_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120008.nii.gz
+ reading mask sub-CC120008_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120049_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120049.nii.gz
+ reading mask sub-CC120049_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120061_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120061.nii.gz
+ reading mask sub-CC120061_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120065_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120065.nii.gz
+ reading mask sub-CC120065_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120120_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120120.nii.gz
+ reading mask sub-CC120120_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120123_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120123.nii.gz
+ reading mask sub-CC120123_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120166_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120166.nii.gz
+ reading mask sub-CC120166_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120182_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120182.nii.gz
+ reading mask sub-CC120182_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120218_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120218.nii.gz
+ reading mask sub-CC120218_T1w_rigid_to_mni_brain_mask.nii.gz
```

```
+ reading image msub-CC120234_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120234.nii.gz
+ reading mask sub-CC120234_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120264_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120264.nii.gz
+ reading mask sub-CC120264_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120276_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120276.nii.gz
+ reading mask sub-CC120276_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120286_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120286.nii.gz
+ reading mask sub-CC120286_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120309_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120309.nii.gz
+ reading mask sub-CC120309_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120313_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120313.nii.gz
+ reading mask sub-CC120313_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120319_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120319.nii.gz
+ reading mask sub-CC120319_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120347_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120347.nii.gz
+ reading mask sub-CC120347_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120376_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120376.nii.gz
+ reading mask sub-CC120376_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120409_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120409.nii.gz
+ reading mask sub-CC120409_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120469_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120469.nii.gz
+ reading mask sub-CC120469_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120470_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120470.nii.gz
+ reading mask sub-CC120470_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120550_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120550.nii.gz
+ reading mask sub-CC120550_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120640_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120640.nii.gz
+ reading mask sub-CC120640_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120727_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120727.nii.gz
+ reading mask sub-CC120727_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120764_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120764.nii.gz
+ reading mask sub-CC120764_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120795_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120795.nii.gz
+ reading mask sub-CC120795_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120816_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120816.nii.gz
+ reading mask sub-CC120816_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC120987_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC120987.nii.gz
+ reading mask sub-CC120987_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC121106_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC121106.nii.gz
+ reading mask sub-CC121106_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC121111_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC121111.nii.gz
+ reading mask sub-CC121111_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC121158_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC121158.nii.gz
+ reading mask sub-CC121158_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC121194_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC121194.nii.gz
+ reading mask sub-CC121194_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC121200_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC121200.nii.gz
+ reading mask sub-CC121200_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC121317_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC121317.nii.gz
+ reading mask sub-CC121317_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC121397_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC121397.nii.gz
```

```
+ reading image msub-CC720622_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC720622.nii.gz
+ reading mask sub-CC720622_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC720646_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC720646.nii.gz
+ reading mask sub-CC720646_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC720670_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC720670.nii.gz
+ reading mask sub-CC720670_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC720685_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC720685.nii.gz
+ reading mask sub-CC720685_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC720941_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC720941.nii.gz
+ reading mask sub-CC720941_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC720986_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC720986.nii.gz
+ reading mask sub-CC720986_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721052_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721052.nii.gz
+ reading mask sub-CC721052_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721107_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721107.nii.gz
+ reading mask sub-CC721107_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721114_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721114.nii.gz
+ reading mask sub-CC721114_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721224_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721224.nii.gz
+ reading mask sub-CC721224_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721292_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721292.nii.gz
+ reading mask sub-CC721292_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721374_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721374.nii.gz
+ reading mask sub-CC721374_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721377_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721377.nii.gz
+ reading mask sub-CC721377_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721392_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721392.nii.gz
+ reading mask sub-CC721392_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721418_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721418.nii.gz
+ reading mask sub-CC721418_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721434_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721434.nii.gz
+ reading mask sub-CC721434_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721504_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721504.nii.gz
+ reading mask sub-CC721504_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721519_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721519.nii.gz
+ reading mask sub-CC721519_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721532_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721532.nii.gz
+ reading mask sub-CC721532_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721585_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721585.nii.gz
+ reading mask sub-CC721585_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721618_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721618.nii.gz
+ reading mask sub-CC721618_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721648_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721648.nii.gz
+ reading mask sub-CC721648_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721704_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721704.nii.gz
+ reading mask sub-CC721704_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721707_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721707.nii.gz
+ reading mask sub-CC721707_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721729_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721729.nii.gz
+ reading mask sub-CC721729_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721888_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721888.nii.gz
```

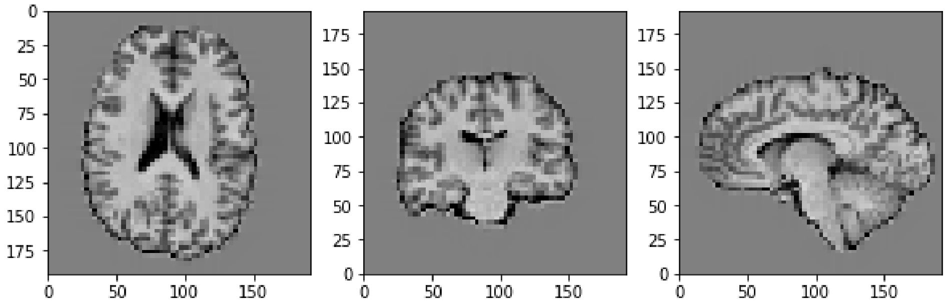
```
+ reading mask sub-CC721888_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721891_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721891.nii.gz
+ reading mask sub-CC721891_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC721894_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC721894.nii.gz
+ reading mask sub-CC721894_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC722216_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC722216.nii.gz
+ reading mask sub-CC722216_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC722421_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC722421.nii.gz
+ reading mask sub-CC722421_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC722536_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC722536.nii.gz
+ reading mask sub-CC722536_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC722542_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC722542.nii.gz
+ reading mask sub-CC722542_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC722651_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC722651.nii.gz
+ reading mask sub-CC722651_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC722891_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC722891.nii.gz
+ reading mask sub-CC722891_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC723197_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC723197.nii.gz
+ reading mask sub-CC723197_T1w_rigid_to_mni_brain_mask.nii.gz
+ reading image msub-CC723395_T1w_rigid_to_mni.nii.gz
+ reading segmentation CC723395.nii.gz
+ reading mask sub-CC723395_T1w_rigid_to_mni_brain_mask.nii.gz
```

Visualise testing example

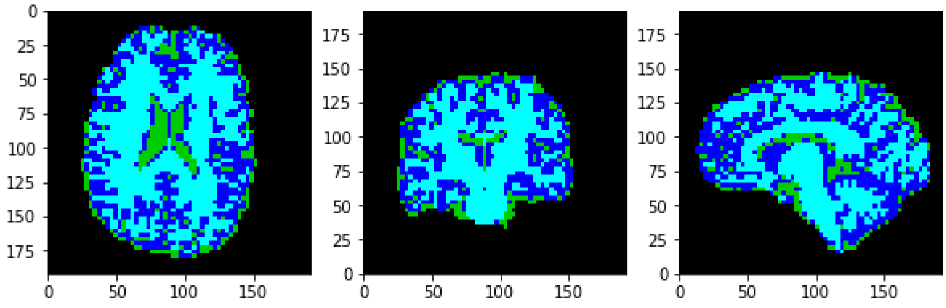
Just to check how a testing image looks like after pre-processing.

In [13]:
```
sample = dataset_test.get_sample(0)
img_name = dataset_test.get_img_name(0)
seg_name = dataset_test.get_seg_name(0)
print('Image: ' + img_name)
display_image(sample['img'], window=5, level=0)
print('Segmentation: ' + seg_name)
display_image(sitk.LabelToRGB(sample['seg']))
print('Mask')
display_image(sample['msk'])
```

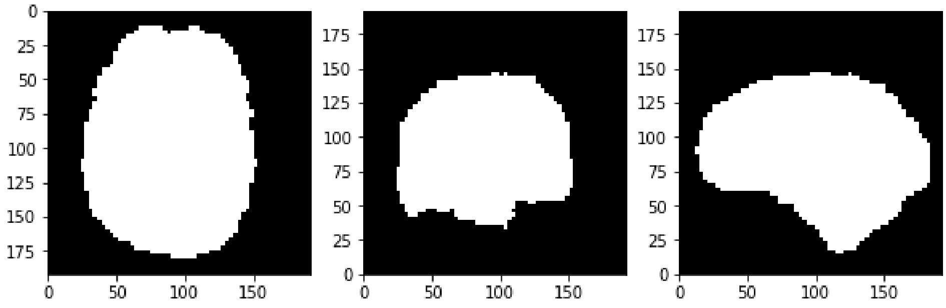
```
Image: msub-CC110033_T1w_rigid_to_mni.nii.gz
```



```
Segmentation: CC110033.nii.gz
```



```
Mask
```



TESTING

Below is an implementation of a full testing procedure that saves the segmentations in an output folder. Feel free to modify this procedure.

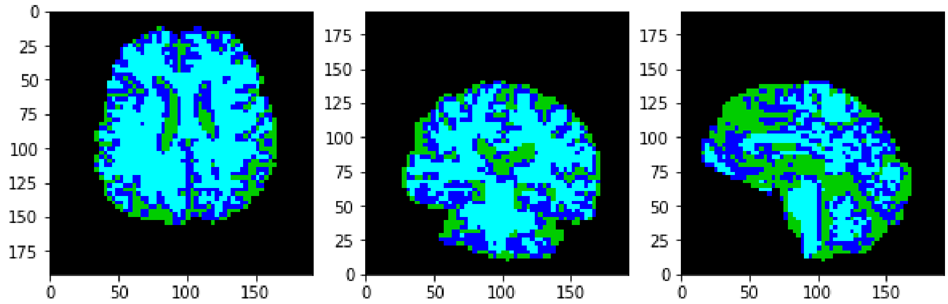
You will need to add the calculations of Dice scores (and possibly others) to evaluate the segmentation performance.

In [92]:

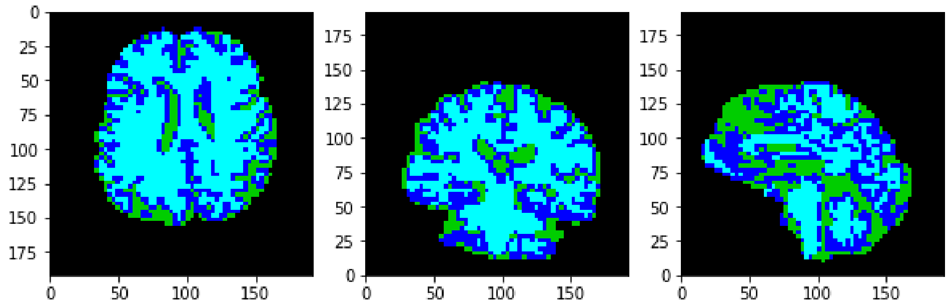
```
pred_dir = os.path.join(out_dir, 'pred')
if not os.path.exists(pred_dir):
    os.makedirs(pred_dir)

# model = SimpleNet3D(num_classes=num_classes)
# model.load_state_dict(torch.load(os.path.join(model_dir, 'model.pt')))
model.to(device)
model.eval()

print('START TESTING...')

loss_test = 0
sum_pts = 0
idx_test = 0
d_score = 0
skd_score = 0
with torch.no_grad():
    for data_sample in dataloader_test:
        img, seg = data_sample['img'].to(device), data_sample['seg'].to(device)
        prd = model(img)
        prd_flat = prd.view(prd.size(0), prd.size(1), -1)
        seg_flat = seg.view(seg.size(0), seg.size(1), -1)
        loss_test += F.cross_entropy(prd_flat, seg_flat.squeeze(1), reduction='sum').item()
        sum_pts += seg_flat.size(2)

        prd = torch.argmax(prd, dim=1)
        # Dice Score

        prd_d = prd.view(prd.size()[0], -1)
        seg_d = seg.view(seg.size()[0], -1)
        skd_score += metrics.f1_score(seg_d.cpu().squeeze(), prd_d.cpu().squeeze(), average
='weighted')

        sample = dataset_test.get_sample(idx_test)
        name = dataset_test.get_seg_name(idx_test)
        prediction = sitk.GetImageFromArray(prd.cpu().squeeze().numpy().astype(np.uint8))

        # Dice Score
        prediction.CopyInformation(sample['seg'])
        segmentation = sitk.GetImageFromArray(seg.cpu().squeeze().numpy().astype(np.uint8))
        segmentation.CopyInformation(sample['seg'])
        overlap_measures_filter = sitk.LabelOverlapMeasuresImageFilter()
        overlap_measures_filter.Execute(prediction, segmentation)
        d_score += overlap_measures_filter.GetDiceCoefficient()

        sitk.WriteImage(prediction, os.path.join(pred_dir, name))

        idx_test += 1
        if (idx_test % 40 == 0):
            print('+ TESTING: \tIdx: {}'.format(idx_test))

loss_test /= sum_pts
avg_d_score = d_score / idx_test
avg_skd_score = skd_score.item() / idx_test

print('+ TESTING \tLoss: {:.6f}, \tAvg Dice Score: {:.6f}, \tAvg f1 Score : {:.6f}'.format(
loss_test, avg_d_score, avg_skd_score))

# Show last testing sample as an example
print('\n\nReference segmentation')
display_image(sitk.LabelToRGB(sample['seg']))
print('Predicted segmentation')
display_image(sitk.LabelToRGB(prediction))

print('\nFinished TESTING.')
```

```
START TESTING...
+ TESTING:       Idx: 40
+ TESTING:       Idx: 80
+ TESTING:       Idx: 120
+ TESTING:       Idx: 160
+ TESTING:       Idx: 200
+ TESTING:       Idx: 240
+ TESTING:       Idx: 280
+ TESTING:       Idx: 320
+ TESTING:       Idx: 360
+ TESTING:       Idx: 400
+ TESTING:       Idx: 440
+ TESTING:       Idx: 480
+ TESTING:       Idx: 520
+ TESTING:       Idx: 560
+ TESTING:       Idx: 600
+ TESTING        Loss: 0.767359,         Avg Dice Score: 0.887529,       Avg f1 Score : 0.9
75770
```

Reference segmentation



Predicted segmentation



Finished TESTING.

In [91]:
```
# Use this block to save or load models
# a1_model_loc = 'A_1_model.pt'
# torch.save(model.state_dict(), a1_model_loc)
# model = SimpleNet3D(num_classes=num_classes)
# model.load_state_dict(torch.load(a1_model_loc, map_location=device))
```

TASK A-2: Feature calculation

Start by calculating the three absolute tissue volumes for each subject. Plot the volumes against the subjects' ages. Taking the absolute volumes of tissues as features, however, might not be predictive. Instead, relative volumes need to be computed as the ratios between each tissue volume and overall brain volume. But you might also want to explore using different combinations or even polynomial features.

Implement a function that constructs a big matrix X with a row for each subject and features across the columns. Start with just calculating three simple features of relative tissue volumes for GM, WM and CSF, and compare these to the absolute volumes plotted above.

Note: If you are struggling with the previous task on image segmentation, or if you prefer to work on this and the following tasks first, you can continue here using the provided reference segmentations which can be found in a subfolder `segs_refs` .

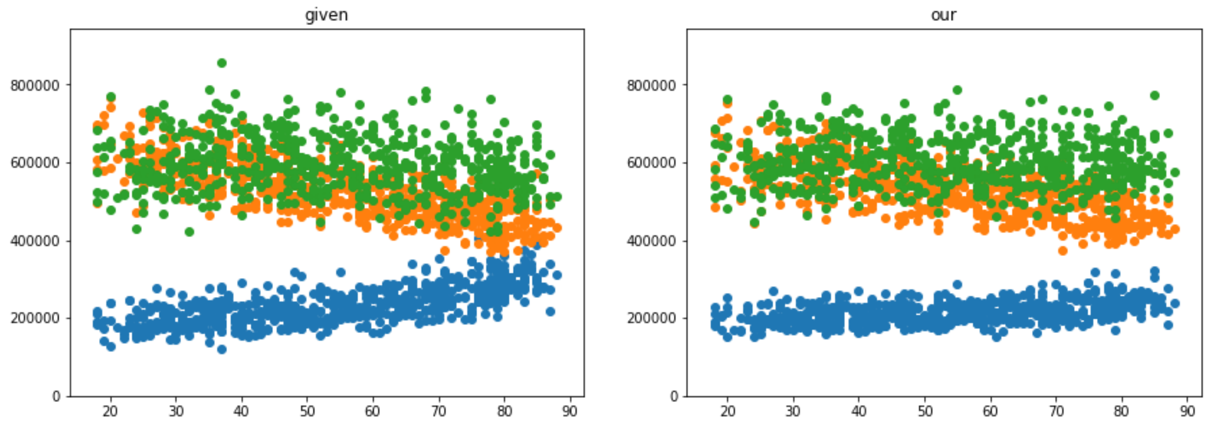
In [93]:
```
## CALCULATE ABSOLUTE TISSUE VOLUMES

import os
from utils.data_helper import resample_image
import collections

# USE THIS TO RUN THE CALCULATIONS ON YOUR SEGMENTATONS
# seg_dir = './output/pred/'

# USE THIS TO RUN THE CALCULATIONS ON OUR REFERENCE SEGMENTATIONS
seg_dir = data_dir + './segs_refs/'

vols_given = np.zeros((3,meta_data['ID'].count()))
for i in range(meta_data['ID'].count()):
########################################
# ADD YOUR CODE HERE
########################################
    if (i % 50 == 0):
        print("Loading given:\t{}".format(i))
    ID = meta_data['ID'][i]
    seg = sitk.ReadImage(seg_dir+ID+'.nii.gz')
    seg=resample_image(seg,img_spacing,img_size, is_label=True)
    seg_array = sitk.GetArrayFromImage(seg)
    seg_transformed = seg_array.flatten().squeeze()
    freq = collections.Counter(seg_transformed)

    x, y, z = seg.GetSpacing()
    vols_given[:,i] = freq[1]*x*y*z, freq[2]*x*y*z, freq[3]*x*y*z

seg_dir = './output/pred/'
vols_our = np.zeros((3,meta_data['ID'].count()))
for i in range(meta_data['ID'].count()):
########################################
# ADD YOUR CODE HERE
########################################
    if (i % 50 == 0):
        print("Loading our:\t{}".format(i))
    ID = meta_data['ID'][i]
    seg = sitk.ReadImage(seg_dir+ID+'.nii.gz')
    seg=resample_image(seg,img_spacing,img_size, is_label=True)
    seg_array = sitk.GetArrayFromImage(seg)
    seg_transformed = seg_array.flatten().squeeze()
    freq = collections.Counter(seg_transformed)

    x, y, z = seg.GetSpacing()
    vols_our[:,i] = freq[1]*x*y*z, freq[2]*x*y*z, freq[3]*x*y*z
```

```
Loading given:  0
Loading given:  50
Loading given:  100
Loading given:  150
Loading given:  200
Loading given:  250
Loading given:  300
Loading given:  350
Loading given:  400
Loading given:  450
Loading given:  500
Loading given:  550
Loading our:    0
Loading our:    50
Loading our:    100
Loading our:    150
Loading our:    200
Loading our:    250
Loading our:    300
Loading our:    350
Loading our:    400
Loading our:    450
Loading our:    500
Loading our:    550
```

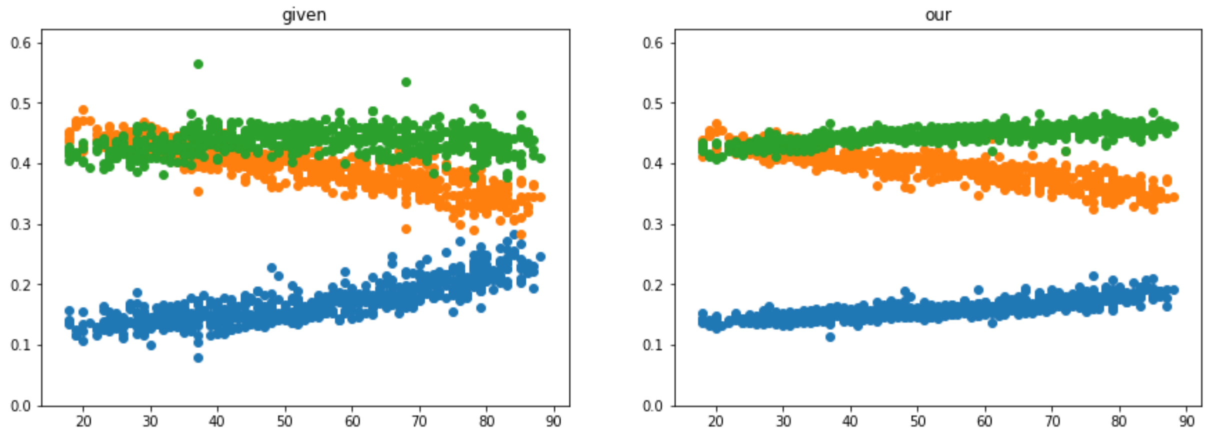
Plot features versus age.

In [96]:

```
########################################
# ADD YOUR CODE HERE
########################################
age = meta_data['age']
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 5))
height = np.max(vols_given) if np.max(vols_given) \
    >= np.max(vols_our) else np.max(vols_our)
height *= 1.1
ax1.scatter(age, vols_given[0, :])
ax1.scatter(age, vols_given[1, :])
ax1.scatter(age, vols_given[2, :])
ax1.set_ybound(0,height)
ax1.set_title("given")
ax2.scatter(age, vols_our[0, :])
ax2.scatter(age, vols_our[1, :])
ax2.scatter(age, vols_our[2, :])
ax2.set_ybound(0,height)
ax2.set_title("our")
plt.show()
```



In [97]:
```
## CALCULATE RELATIVE TISSUE VOLUMES

########################################
# ADD YOUR CODE HERE
########################################
vols_given_normalised = vols_given / (vols_given[0,:]+vols_given[1,:]+vols_given[2,:])
vols_normalised = vols_our / (vols_our[0,:]+vols_our[1,:]+vols_our[2,:])
height = np.max(vols_given_normalised) if np.max(vols_given_normalised) \
        >= np.max(vols_normalised) else np.max(vols_normalised)
height *= 1.1
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 5))
ax1.scatter(age, vols_given_normalised[0, :])
ax1.scatter(age, vols_given_normalised[1, :])
ax1.scatter(age, vols_given_normalised[2, :])
ax1.set_ybound(0,height)
ax1.set_title("given")
ax2.scatter(age, vols_normalised[0, :])
ax2.scatter(age, vols_normalised[1, :])
ax2.scatter(age, vols_normalised[2, :])
ax2.set_ybound(0,height)
ax2.set_title("our")
plt.show()
```



In [98]:
```
X = vols_normalised.T
y = meta_data['age'].values.reshape(-1,1)

print(X.shape)
print(y.shape)
```

```
(600, 3)
(600, 1)
```

TASK A-3: Age regression and cross-validation

Experiment with different regression methods from the [scikit-learn toolkit (http://scikit-learn.org/stable/supervised_learning.html#supervised-learning)](http://scikit-learn.org/stable/supervised_learning.html#supervised-learning). Remember to construct the output vectur y containing the age for each of the subjects.

Evaluate the methods using two-fold [cross-validation (http://scikit-learn.org/stable/modules/cross_validation.html#cross-validation)](http://scikit-learn.org/stable/modules/cross_validation.html#cross-validation) where the dataset of 600 subjects is split into two equally sized sets (X_1, y_1) and (X_2, y_2) which are used for training and testing in an alternating way (so each set is used as $(X_{\text{train}}, y_{\text{train}})$ and $(X_{\text{test}}, y_{\text{test}})$ exactly once).

Try using at least three different regression methods, and generate a plot allows easy comparison of the performance of the three methods. Useful [error metrics (https://scikit-learn.org/stable/modules/model_evaluation.html#regression-metrics)](https://scikit-learn.org/stable/modules/model_evaluation.html#regression-metrics) to report include mean absolute error and r2 score. You might also want to plot the real vs predicted ages.

Note: These [scikit-learn examples (https://scikit-learn.org/stable/auto_examples/)](https://scikit-learn.org/stable/auto_examples/) might serve as an inspiration.

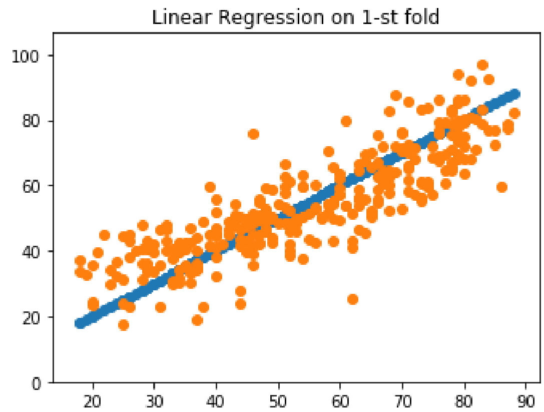
Hint: Be careful how you split the dataset into two folds. Take into account the data characteristics shown at the top of the notebook.

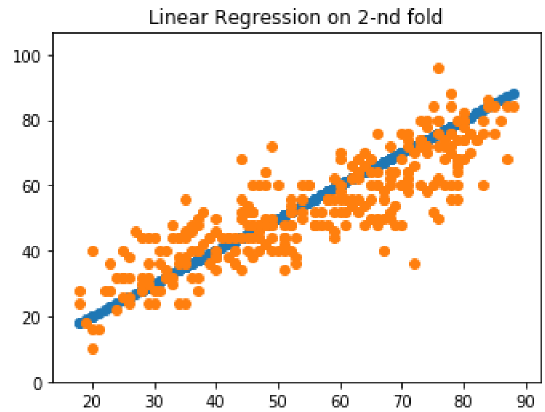
In [99]:
```
def display_pred(preds, y, info=None):
    preds = np.array(preds)
    height = np.max(preds) if np.max(preds) >= np.max(y) else np.max(y)
    height *= 1.1
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))

    ax1.scatter(y, y)
    ax1.scatter(y, preds[0,:])
    ax1.set_ybound(0,height)

    ax2.scatter(y, y)
    ax2.scatter(y, preds[1,:])
    ax2.set_ybound(0,height)

    if info != None:
        ax1.set_title(info + " on 1-st fold")
        ax2.set_title(info + " on 2-nd fold")

    plt.show()
```

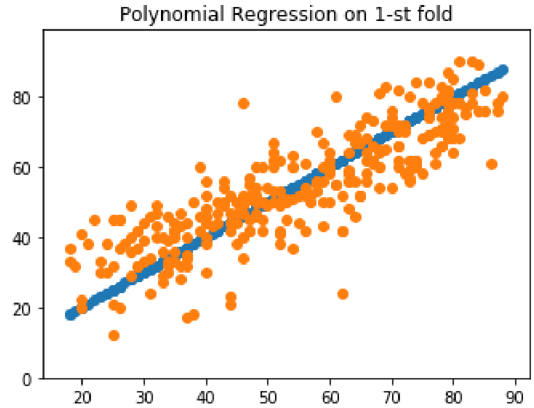
In [100]:

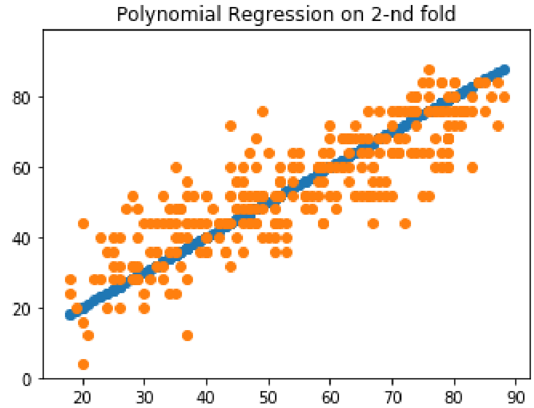
```
########################################
# ADD YOUR CODE HERE
########################################
from sklearn.model_selection import KFold
from sklearn import linear_model
from sklearn.preprocessing import PolynomialFeatures
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_absolute_error, r2_score
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.linear_model import BayesianRidge

y = y.squeeze()

linear_preds = []
poly_preds = []
knn_preds = []
ridge_preds =[]
kf = KFold(n_splits=2, random_state = rnd_seed, shuffle=True)
for train, test in kf.split(X):
    X_train, X_test = X[train], X[test]
    y_train, y_test = y[train], y[test]
    #print(X_train.shape)

    # Linear Regression
    reg = linear_model.LinearRegression(normalize=True)
    reg.fit(X_train, y_train)
    linear_pred = reg.predict(X_test)
    linear_preds.append(linear_pred)
    mae = mean_absolute_error(y_test, linear_pred)
    r2 = r2_score(y_test, linear_pred)
    print("Linear Regression:\tmae={:.6f}\tr2={:.6f}".format(mae, r2))

    # Polynomial Regression
    poly = PolynomialFeatures(degree=2)
    X_train_poly = poly.fit_transform(X_train)
    X_test_poly = poly.fit_transform(X_test)

    clf = linear_model.LinearRegression(normalize=True)
    clf.fit(X_train_poly, y_train)
    pred = clf.predict(X_test_poly)
    poly_preds.append(pred)
    mae = mean_absolute_error(y_test, pred)
    r2 = r2_score(y_test, pred)
    print("Poly Regression:\tmae={:.6f}\tr2={:.6f}".format(mae, r2))

    # KNN Regression
    knn = KNeighborsRegressor(n_neighbors=4, algorithm='auto')
    knn.fit(X_train, y_train)
    pred = knn.predict(X_test)
    knn_preds.append(pred)
    mae = mean_absolute_error(y_test, pred)
    r2 = r2_score(y_test, pred)
    print("KNNeighbour Regression:\tmae={:.6f}\tr2={:.6f}".format(mae, r2))

    # Bayesian Ridge Regression
    br = BayesianRidge(normalize=True)
    br.fit(X_train, y_train)
    pred = br.predict(X_test)
    ridge_preds.append(pred)
    mae = mean_absolute_error(y_test, pred)
    r2 = r2_score(y_test, pred)
    print("Ridge Regression:\tmae={:.6f}\tr2={:.6f}".format(mae, r2))

    print()

display_pred(linear_preds, y_test, info="Linear Regression")
display_pred(poly_preds, y_test, info="Polynomial Regression")
display_pred(knn_preds, y_test, info="KNeighbour Regression")
display_pred(ridge_preds, y_test, info="Ridge Regression")
```

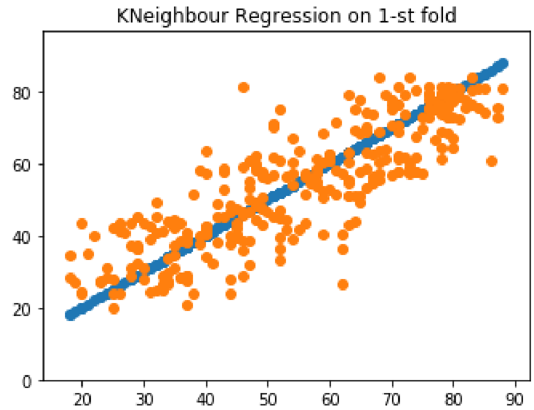
```
Linear Regression:       mae=7.813750    r2=0.748598
Poly Regression:         mae=7.736667    r2=0.751389
KNNeighbour Regression: mae=7.839167    r2=0.730045
Ridge Regression:        mae=7.830806    r2=0.747908

Linear Regression:       mae=7.216667    r2=0.734137
Poly Regression:         mae=7.310000    r2=0.731111
KNNeighbour Regression: mae=7.636667    r2=0.694060
Ridge Regression:        mae=7.087022    r2=0.742334
```

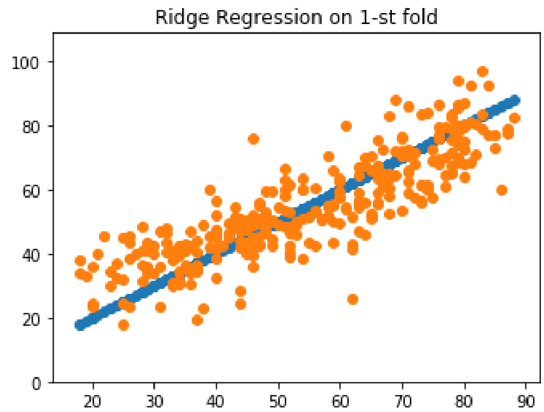


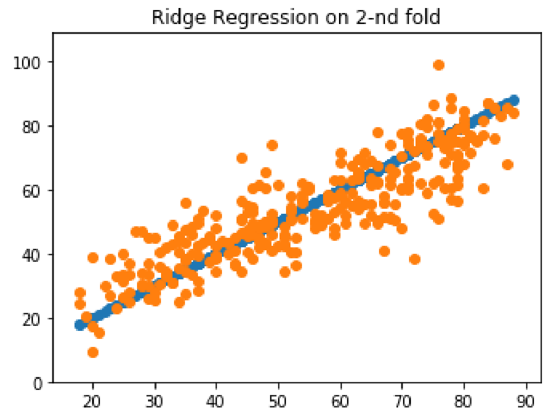












Part B: Image-based regression using grey matter maps

The second approach will make use of grey matter maps that have been already extracted from the MRI scans and aligned to a common reference space to obtain spatially normalised maps. For this, we have used an advanced, state-of-the-art neuroimaging toolkit, called SPM12. The reference space corresponds to the commonly used MNI atlas as seen in the lecture on image segmentation.

Because these grey matter maps are spatially normalised (ie., registered), voxel locations across images from different subjects roughly correspond to the same anatomical locations. This means that each voxel location in the grey matter maps can be treated as an individual feature. Because those maps are quite large at their full resolution there would be a very large number of features to deal with (more than 850,000). A dimensionality reduction using PCA may need to be performed before training a suitable regressor on the low-dimensional feature representation obtained with PCA. It might also be beneficial to apply some pre-processing (downsampling, smoothing, etc.) before running PCA, which should be explored. The implemented pipeline should be evaluated using two-fold cross-validation using the same data splits as in part A, so the two different approaches can be directly compared in terms average age prediction accuracy.

Note: For part B, only the spatially normalised grey matter maps should be used.

TASK B-1: Pre-processing

Before running PCA to reduce the dimensionality of the feature space for grey matter maps, it might be beneficial to run some pre-processing on the maps. In voxel-based analysis where each voxel location is a feature, it is common to apply some smoothing beforehand. This is to reduce noise and to compensate for errors of the spatial normalisation that had been applied to the maps.

Because the maps are quite large, it might also be worthwile to explore whether downsampling could be performed even before PCA. This would further reduce the dimensionality, and might be even needed in the case where PCA on the orignial resolution runs into memory issues. You may want to consider other ways of pre-processing and you can find insipiration in the notebook on medical image computing `MLI-MIC-Summary.ipynb` .

Implement a function that performs suitable pre-processing on each grey matter map.

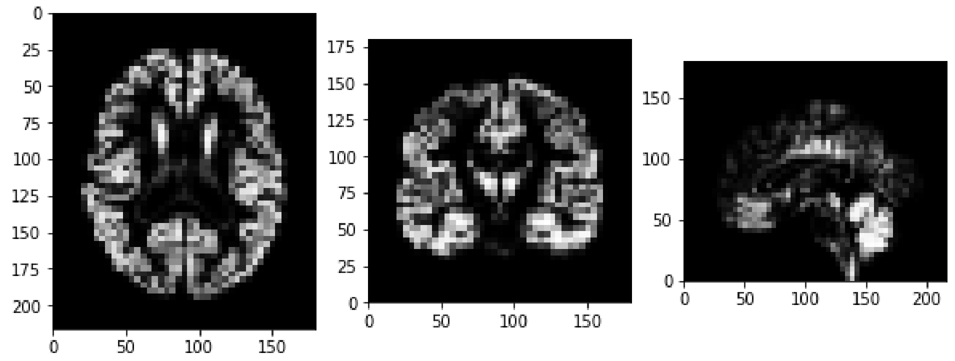
Hint: You may want to save the pre-processed maps using `sitk.WriteImage` to avoid recomputation each time you run the notebook.

In [85]:
```
########################################
# ADD YOUR CODE HERE
########################################

# Pre-processing
# Gaussian smoothing and downsampling

# USE THIS TO RUN THE CALCULATIONS ON OUR REFERENCE SEGMENTATIONS
grey_dir = data_dir + './greymatter/'

def downsample(img, factor=2):
    smoothed = sitk.DiscreteGaussian(img, (.5 * factor) ** 2)
    return smoothed[::factor, ::factor, ::factor]

# img_size = [64, 64, 64]

write_image = True
grey_out = os.path.join(out_dir, 'grey')
if not os.path.exists(grey_out):
    os.makedirs(grey_out)

img_data = []
for i in range(meta_data['ID'].count()):
# for i in range(50):
    ID = meta_data['ID'][i]
    file_name = ID +  '.nii.gz'
    if (i % 50 == 0):
        print("Loading: \t{}".format(i))
    if write_image:
        #seg = sitk.ReadImage(seg_dir+ID+'.nii.gz')
        #seg=resample_image(seg,img_spacing,img_size)
        img = sitk.Cast(sitk.ReadImage(grey_dir+'wc1sub-'+ID+'_T1w_rigid_to_mni.nii.gz'), s
itk.sitkFloat32) #wc1sub-CC110033_T1w_rigid_to_mni.nii.gz
        img_size = [np.min(img.GetSize()).item()]*3
        #          print(img.GetSize(), "original")
#          display_image(img)

        # Resample the image
#          img = resample_image(img, out_spacing = img_spacing, out_size = img_size, is_labe
l=True)
#          print(img.GetSize(), "resampled")
#          display_image(img)
        # Gaussian smoothing
#          img_downsample = downsample(img_resample, factor=2)
        factor = 2
#          img = sitk.DiscreteGaussian(img, (.5 * factor) ** 2)
#          img = img[::factor, ::factor, ::factor]
        img = downsample(img, factor)
        img_size = img.GetSize()
#          img_gauss = sitk.DiscreteGaussian(img_resample, 1)
#          print("gaussian-ed")
#          display_image(img_gauss)
#          img_down_1 = downsample(img_gauss)
#          print(img.GetSize(), "down-sampled")
#          display_image(img)
        #print(os.path.join(out_dir, file_name))
        sitk.WriteImage(img, os.path.join(grey_out, file_name))

    else:
        img = sitk.ReadImage(os.path.join(grey_out, file_name))
        img_size = img.GetSize()

    img_array = sitk.GetArrayFromImage(img) # Convert the SimpleITK image to a NumPy array

    img_transformed = img_array.flatten().squeeze()
    img_data.append(img_transformed)

img_data = np.array(img_data)
print("Loading finished. Loaded data size is: {}".format(img_data.shape))
```

```
Loading:        0
Loading:        50
Loading:        100
Loading:        150
Loading:        200
Loading:        250
Loading:        300
Loading:        350
Loading:        400
Loading:        450
Loading:        500
Loading:        550
Loading finished. Loaded data size is: (600, 109350)
```

In [86]:
```
X = img_data #PRE-PROCESSED IMAGE DATA
y = meta_data['age'].values.reshape(-1,1)

print(img_size)
print(X.shape)
print(y.shape)

display_image(img)
```

```
(45, 54, 45)
(600, 109350)
(600, 1)
```



TASK B-2: Dimensionality reduction

Implement dimensionality reduction for grey matter maps using [scitkit-learn's PCA (http://scikit-learn.org/stable/modules/decomposition.html#pca)](http://scikit-learn.org/stable/modules/decomposition.html#pca). PCA has an option to set the percentage of variance to be preserved (by setting the parameter `n_components` to a value between 0 and 1). The number of principal modes, that is the new dimensionality of the data, is then automatically determined. Try initially to preserve 95% of the variance (`n_components=0.95`).

Note: When dimensionality reduction is used as pre-processing step for supervised learning, as in this case, it is important that PCA is fitted to the training data only, but then applied to both the training and testing data. So make sure your implementation consists of two separate steps, 1) fitting the PCA model to X_{train} (using the `fit` function), and 2) applying dimensionality reduction to X_{train} and X_{test} using the `transform` function.

In [87]:
```
########################################
# ADD YOUR CODE HERE
########################################

from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.5, random_state = r
nd_seed)

pca = PCA(n_components = 0.95, random_state=rnd_seed)
print("fitting train set")
pca.fit(X_train)
print("transforming train set")
X_train_transformed = pca.transform(X_train)

print("transforming test set")
X_test_transformed = pca.transform(X_test)

# print("evaluating train")
# print(pca.score(X_train)) # 0.95 -9110.579
# print("evaluating test")
# print(pca.score(X_test)) # 0.95 -9238.559
```

```
fitting train set
transforming train set
transforming test set
```

TASK B-3: Age regression and cross-validation

Experiment with different regression methods from the [scikit-learn toolkit (http://scikit-learn.org/stable/supervised_learning.html#supervised-learning)](http://scikit-learn.org/stable/supervised_learning.html#supervised-learning). Evaluate the methods using two-fold [cross-validation (http://scikit-learn.org/stable/modules/cross_validation.html#cross-validation)](http://scikit-learn.org/stable/modules/cross_validation.html#cross-validation) in the same way as for your approach in Part A so results can be directly compared. Generate the similar plots.

Try using at least three different regression methods.

Hint: Remember, when you use cross-validation where you swap training and testing sets in each fold, you need to fit PCA to the training set of each fold.

In [88]:

```
#########################################
# ADD YOUR CODE HERE
#########################################
y = y.squeeze()

# X, y = shuffle(X, y)

linear_preds = []
poly_preds = []
knn_preds = []
ridge_preds =[]

kf = KFold(n_splits=2, random_state = rnd_seed, shuffle=True)
#rkf = RepeatedKFold(n_splits=2, n_repeats=1, random_state=rnd_seed)
for train, test in kf.split(X):
    X_train, X_test, y_train, y_test = X[train], X[test], y[train], y[test]

    pca = PCA(n_components = 0.95) # 0.95 linear mae 15.28473323363056
    pca.fit(X_train)
    X_train_transformed = pca.transform(X_train)
    X_test_transformed = pca.transform(X_test)

    # Linear Regression
    reg = linear_model.LinearRegression()
    reg.fit(X_train_transformed, y_train)
    linear_pred = reg.predict(X_test_transformed)
    linear_preds.append(linear_pred)
    mae = mean_absolute_error(y_test, linear_pred)
    r2 = r2_score(y_test, linear_pred)
    print("Linear Regression:\tmae={:.6f}\tr2={:.6f}".format(mae, r2))

    # Polynomial Regression
    poly = PolynomialFeatures(degree=2)
    X_train_poly = poly.fit_transform(X_train_transformed)
    X_test_poly = poly.fit_transform(X_test_transformed)

    clf = linear_model.LinearRegression()
    clf.fit(X_train_poly, y_train)
    pred = clf.predict(X_test_poly)
    poly_preds.append(pred)
    mae = mean_absolute_error(y_test, pred)
    r2 = r2_score(y_test, pred)
    print("Poly Regression:\tmae={:.6f}\tr2={:.6f}".format(mae, r2))

    # KNN Regression
    knn = KNeighborsRegressor(n_neighbors=4, algorithm='auto')
    knn.fit(X_train_transformed, y_train)
    pred = knn.predict(X_test_transformed)
    knn_preds.append(pred)
    mae = mean_absolute_error(y_test, pred)
    r2 = r2_score(y_test, pred)
    print("KNNeighbour Regression:\tmae={:.6f}\tr2={:.6f}".format(mae, r2))

    # Bayesian Ridge Regression
    br = BayesianRidge(normalize=True)
    br.fit(X_train_transformed, y_train)
    pred = br.predict(X_test_transformed)
    ridge_preds.append(pred)
    mae = mean_absolute_error(y_test, pred)
    r2 = r2_score(y_test, pred)
    print("Ridge Regression:\tmae={:.6f}\tr2={:.6f}".format(mae, r2))

    print()

display_pred(linear_preds, y_test, info="Linear Regression")
display_pred(poly_preds, y_test, info="Polynomial Regression")
display_pred(knn_preds, y_test, info="KNeighbour Regression")
display_pred(ridge_preds, y_test, info="Ridge Regression")
```

```
Linear Regression:       mae=5.744854     r2=0.857178
Poly Regression:         mae=13.689005    r2=0.310770
KNNeighbour Regression:  mae=7.550833     r2=0.757745
Ridge Regression:        mae=5.968928     r2=0.849762

Linear Regression:       mae=5.372419     r2=0.868518
Poly Regression:         mae=12.710742    r2=0.345545
KNNeighbour Regression:  mae=7.653333     r2=0.726163
Ridge Regression:        mae=5.499683     r2=0.862488
```