

# Age Regression from Brain MRI

Group: 41

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## 1 Summary

In this coursework, we are given some brain MRI scans, and we want to develop age regression models using 3 different approaches. The 3 approaches are: regression on CNN brain segmentation, regression on pre-processed grey matter map and regression on brain images using CNN-based model. The performance metrics are MAE and  $r^2$  for age regression, and dice score for segmentation. Linear Regression after pre-processing has the best performance, with MAE of 5.77 and  $r^2$  of 0.88. **Due to the page limit, we cannot include all implementation details, please refer to our notebook.**

## 2 Part A

### 2.1 Task A-1: Brain tissue segmentation

Our neural network is constructed and modified based on U-Net. It consists of a contracting path and an expansive path. The contracting path contains several blocks of  $3 \times 3 \times 3$  convolutions, ReLU activation and  $2 \times 2 \times 2$  max poolings with stride 2. The expansive path contains several upsampling blocks. The final layer is a  $1 \times 1 \times 1$  convolution to output segmentation. **After training, the segmentation reaches a dice score of 0.894 and MSE loss of 0.071.**

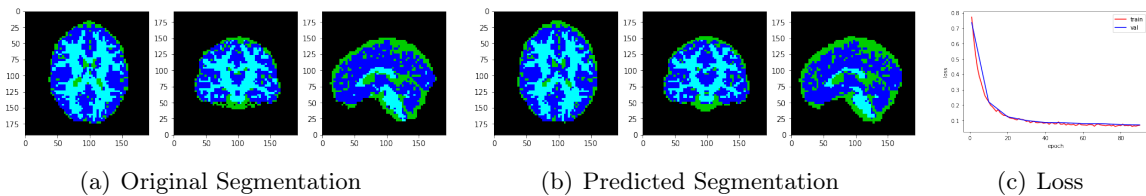


Figure 1: CNN Segmentation Result

### 2.2 Task A-2: Feature Calculation (Using Reference Segmentation)

In the 3D array converted from the segmentation image, each voxel is assigned a label: 0-background, 1-CSF, 2-GM and 3-WM. In the unnormalised calculation, the plot illustrates the absolute number of voxels. Whereas in the normalised calculation, the plot shows the ratio of each part to the total number of voxels. Ratio calculation will omit background voxels so that future calculation are more efficient.

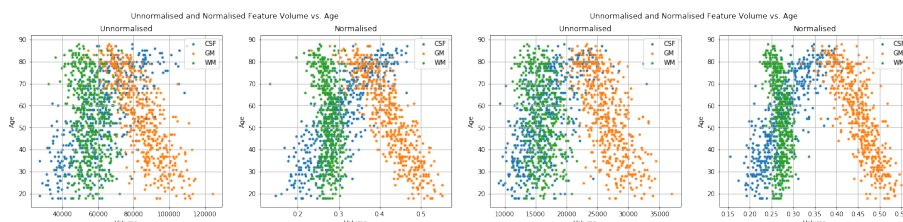


Figure 2: Unnormalised and Normalised Feature Volume vs. Age (Left-Reference, Right-Prediction)

### 2.3 Task A-3: Age regression and cross-validation (Using Reference Segmentation)

The age regression was implemented using 4 approaches: Linear Regression, Lasso Lars Regression, K Neighbor Regression, Bayesian Ridge Regression. Cross-validation is applied to each method to obtain an averaged test accuracy (MAE). The dataset is split into two folds for cross-validation, where the models are trained using the two folds once each, and the other fold serves as validation set. During each fold, the test dataset is used to calculate test accuracy, and the average accuracy is calculated for each regression model. **Referring to table 1 in the results section and plot below, we believe that Linear Regression and Bayesian Ridge Regression with the lowest MAEs of 7.2, perform the best in this part.**

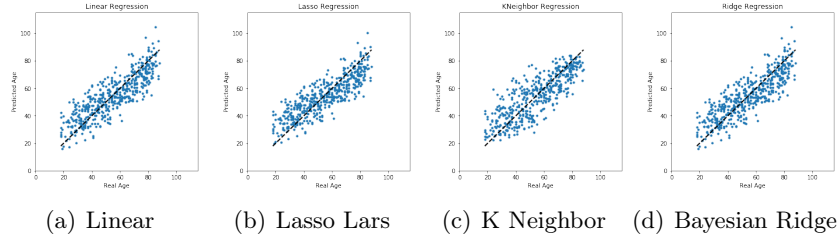


Figure 3: Regression Plot for Each Regression Model (Using Reference Segmentation)

## 3 Part B

The pre-processing includes smoothing using `DiscreteGaussian` with kernel size 1 and `resampling` to reduce the image size from (90,108,90) to (64,64,64), with `img_spacing = (3,3,3)`.

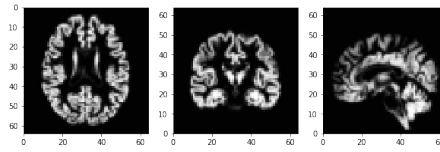


Figure 4: Visualization of Smoothing and Resampling Pre-processing

The second part is PCA and age regression using Linear Regression, Lasso Lars Regression, K Neighbor Regression, Bayesian Ridge Regression methods. We use the flattened training images to fit the PCA, then it transforms flattened training and testing images. With `n_components=0.95`, we reduce the number of dimensions from  $64 * 64 * 64 = 262144$  to around 400. Transformed training images are used to train the regressions models and the models predict brain age for the testing images. The predictions are checked against ground-truth to calculate MAE and  $r^2$ , which are the performance metrics. **Referring to table 1 in the results section, the Linear Regression model has the best performance, with MAE of 5.77 and  $r^2$  of 0.88.**

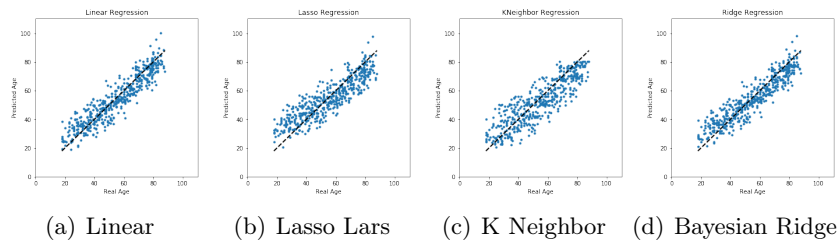


Figure 5: Regression Plot for Each Regression Model

## 4 Part C

We used the same smoothing and resampling pre-processing methods as in part B. **DiscreteGaussian** is used to smooth the image with kernel size 1 and **resampling** reduces the image size from (90, 108, 90) to (64, 64, 64). The age regression neural network has three conv3D layers, each followed by BatchNorm3d and MaxPooling3d. After the convolution layers, we added two fully connected layers and one output layer. The activation function for hidden layers is ReLU. Detailed (hyper)parameters can be found in the code. The losses and result are shown below (model with lowest MAE in the cross-validation):

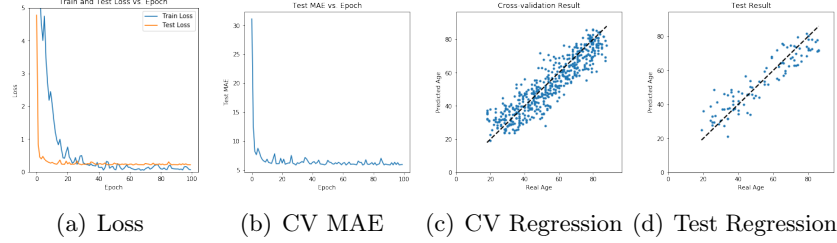


Figure 6: Cross-Validation Result

## 5 Age Regression Results

Below is the table with test set regression results for all parts. **Note that for the first 4 columns, the first value is the result from Part A using reference segmentation, second is from Part A using predicted segmentation, and third is from Part B.**

$A_{ref}, A_{pred}, B$	Linear	Lasso Lars	K Neighbor	Bayesian Ridge	CNN-based
MAE	7.20, 8.32, 5.77	7.54, 8.69, 7.16	7.52, 8.39, 7.50	7.20, 8.33, 6.07	6.23
$r^2$	0.78, 0.73, 0.88	0.76, 0.71, 0.79	0.73, 0.70, 0.78	0.78, 0.73, 0.86	0.85

Table 1: MAE and  $r^2$  Error for Each Regression Model

For part C, we noticed that the CNN-based method is somewhat unstable, because sometimes it would start with a very high loss, and the loss doesn't decrease during the training, which is caused by the parameter initialization. We tried many fixes such as Kaiming initialization, smaller learning rate, etc., but the problem still exists. Whereas the other two approaches are very stable and give very similar results every time. Thus, although sometimes the CNN-based method can achieve test MAE of below 5.5, we prefer the Linear Regression with pre-processing. Below is combined validation set regression result from the two folds for each part (reference segmentation used for part A). Linear Regression is used to represent the performance of Part A and B.

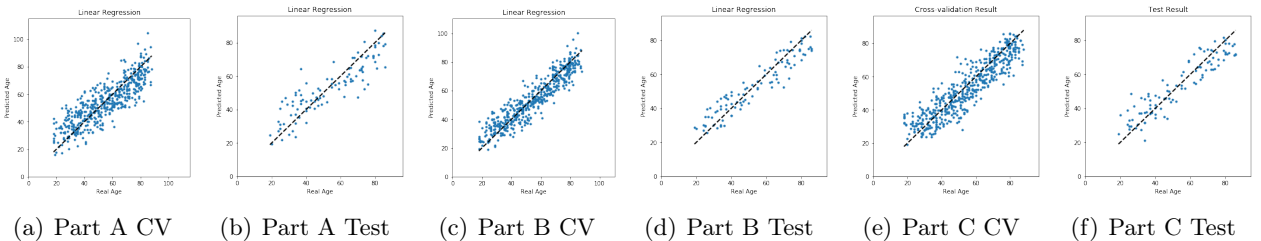


Figure 7: Validation and Test Set Regression Plot