Gender-Based Age Estimation using Quantified Brain Asymmetry

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Term Project Presentation
CSE 583 Pattern Recognition & Machine Learning

Overview

- **Motivation**

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- Problem Statement

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- Tools and Techniques (including specific roadblocks and assumptions)

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- Conclusion and Major Takeaways

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- Seek answer to the question whether male and female brain have different asymmetry?

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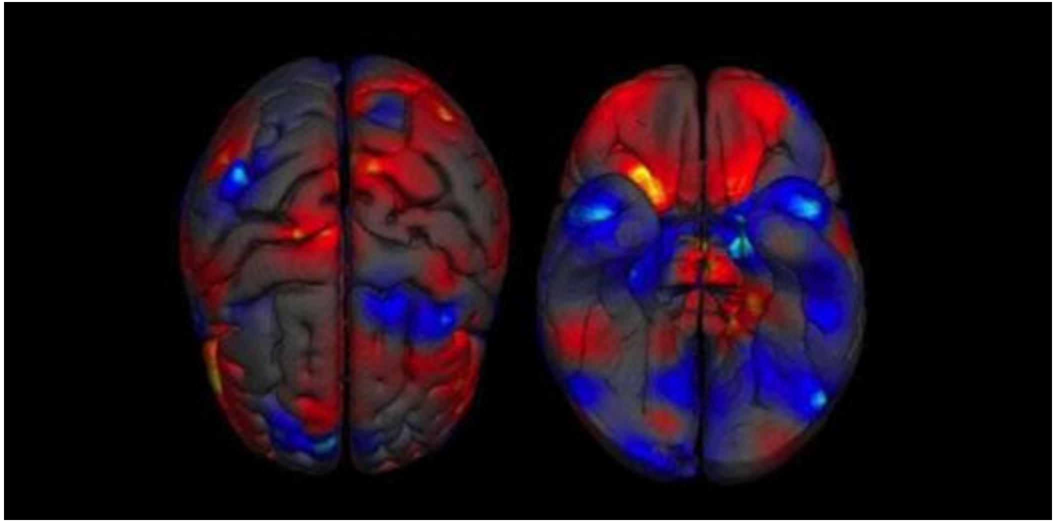

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- Our hypothesis is that differences in anatomical structure should also cause difference in brain asymmetry.
- As a result, the features for regression model for age estimation might change depending on gender.

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- Compare with the original regression model which predicts age for all subjects (gender-neutral model)

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- Predesigned Matlab modules to get ages of the subjects

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- Combination of the respective train-test split in both the cases of males and females

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- Used reverse-feature selection to remove the unnecessary features

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Average Test Accuracy (Classification Rate)	Average Test Standard Deviation
0.9543	0.032

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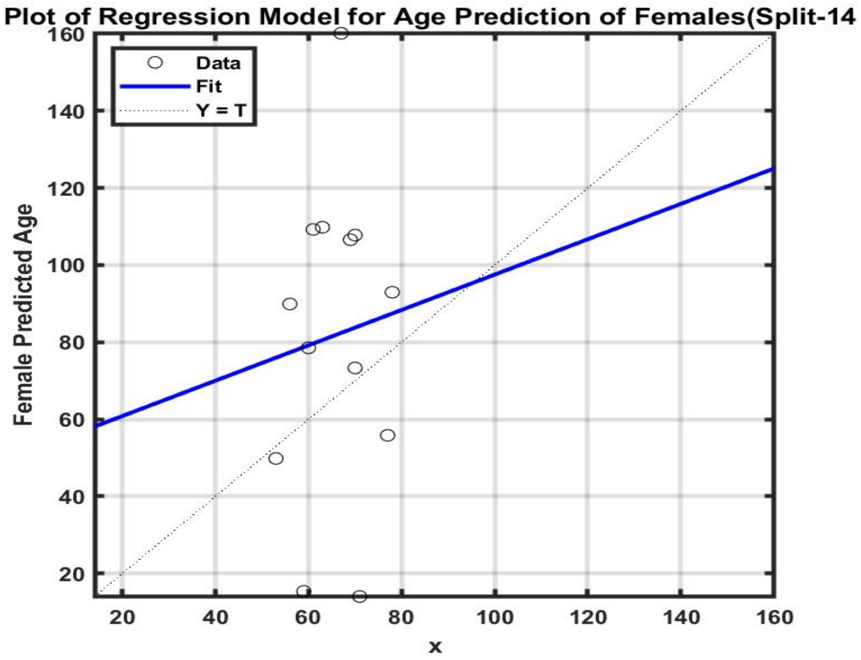
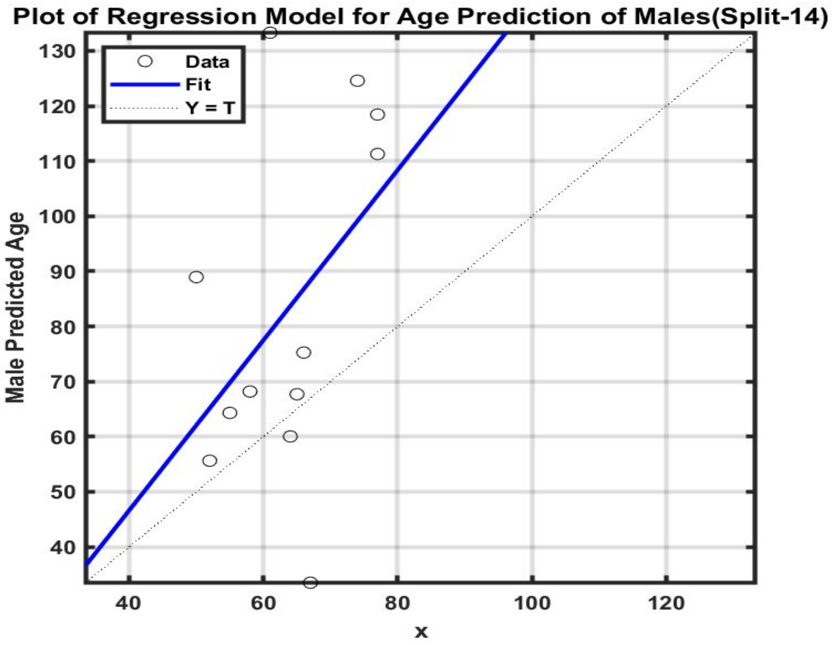
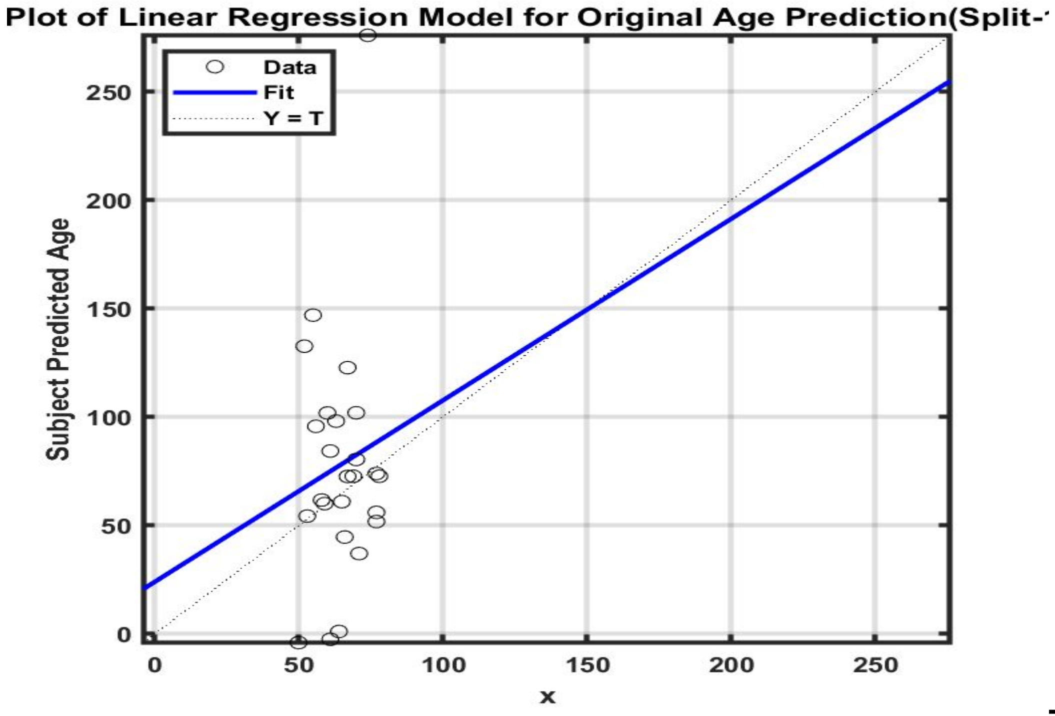
- Reconstructed the original feature set for training the regression model (N x 1001)

Plots for Regression Models





Plots for Original Regression Models



Related Works (State of Art)

- Estimating the age of healthy subjects from T1-weighted MRI scans using kernel methods: Exploring the influence of various parameters (Franke,Zeigler, et al ,2010)

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- An age estimation method using brain local features for T1-weighted images (Kondo, et al 2015)

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- There are 248 features out of the 1000 features which can perfectly distinguish the gender of the subject (different asymmetry of male and female brains)

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- There are 248 features out of the 1000 features which can perfectly distinguish the gender of the subject (different asymmetry of male and female brains)
- There is substantial difference between the output of original regression model and the separate regression models (gender should influence age estimation)