Gender-Based Age Estimation using Quantified Brain Asymmetry

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April 2, 2019

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1 Introduction

In this term project, we would like to revisit the problem of estimation of human age from quantified brain asymmetry in MR images. Specifically, we would like to combine the existing model of age estimation [1] with a classification model which will first learn to categorize the samples as *male* or *female* and then we can develop separate regression models for the male and female samples for the age estimation, after doing feature selection.

The reason for following such an approach is that we believe that for accurate estimation of human ages from quantified asymmetry of brain in MR images, we need to account the factor of gender in the subjects. The core of this belief arises from the fact that male and female brain have structural differences[2], which might lead to different asymmetry of the brain in both the genders. This might result in having different features for learning the regression model for age estimation. Therefore, we should train different regression models for age estimation of male and female subjects.

Problem Statement Train a classifier model which would categorize subjects into two categories as *male* or *female*. Based on the separate categories, train a regression model based on quantified asymmetry of human brain for each category for estimation of age.

1.1 Goals

We hope to answer the following question after completion of this project:

- Is the age estimate of human subjects significantly affected by the gender of the subject?
- Do male and female brain have different asymmetry?

2 Related Work

Estimation of human age from MR images of brain is a very common approach. Most of the approaches have to goal to identify anomalies in the structure of brain for the early detection of neurodegenerative diseases like Alzheimer's disease (AD) or Parkinson's disease(PD).

2.1 Related Work on the dataset area

There are many related work using MR images of brain; some of which has the objective of age estimation and most of them don't. Popular works using MR images of brain are [3], [4] which deals with segmentation of MR images of brain.

2.2 Related work on the Pattern Recognition Approach

In Pattern Recognition Approach, a recent work where estimation of age is done by brain MRI images using deep learning [5]. Another approach of age estimation uses local brain features for T1-weighted images[6].

3 Data

The dataset we will use for our purpose is the *Normal Aging Dataset*. The summary of the dataset is given below:

Total Subjects	Males	Females	Total Features	No. of Classes
198	98	100	55,000,000	3

Table 1: Summary of the Normal Aging Dataset

In addition to this, ages of each subject has also been provided in the dataset.

4 Methods

In this section, we will describe how our project shall span out, including the steps we are planning to take.

4.1 Steps to achieve the goal

- Step 1: **Label the Data** The data needs to be labelled as to whether it is *male* or *female*. There are separate folders for this, so to do the labelling we just need to check the folder it is in and then provide a label and store into a different directory. Estimate Time: 4 days.

- Step 2: **Train a Classifier** We would like a train a classifier(choice not decided yet) on the given selected 1000 ranked features and store the predicted samples for creation of labelled data. Estimate Time: 4 days

- Step 3: **Feature Selection and Training** On the 1000 highest ranked features given to us, we would use forward selection to select features for our regression model to estimate the age of the subjects for both male and female categories separately. Estimate Time: 6 days

- **Estimate the Age and Compare with the Original Problem Model** We shall report the testing and validation accuracy and compare our results with the original estimation model which does not account for gender. Estimate Time: 5 days

4.2 Alternatives if failure of primary methods

If our primary methods of action fail, then we will revert back to the original problem of age-estimation without any gender influence, which just requires to train a regression model.

5 Quantitative Validation Method

For the initial classification into males and females, we are using the classification accuracy to determine the effectiveness of our model. For the regression models, we shall use the minimization of squared error between actual and predicted ages. This is given by:

$$E(w) = \frac{1}{2}\sum_{1}^{N}(y(x,w) - t_n)^2 \tag{1}$$

In (1), N is the number of samples in each case and t_n is the actual age of the subject.

6 Expected outcome

The hypothesis regarding the project will be that if the preparation and pre-processing of the data goes well, then there will be good results which would answer the question of whether the age estimation method should depend on gender or not.

7 An estimated timetable for each step

Table 2: A Simple weekly timetable for the project.

Week	Info
Week 1 (4/2–4/6):	Working on Step 1
Week 2 (4/9–4/13):	Completing Step 1 and looking at 2
Week 3 (4/14–4/20):	Step 3
Week 4 (4/23–4/27):	Step 4 and Project Due!

References

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