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## Predicting Brain Age Using Machine Learning

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### Abstract

Machine learning (ML) algorithms play a vital role in the brain age estimation frameworks. The impact of regression algorithms on prediction accuracy in the brain age estimation frameworks have not been comprehensively evaluated.

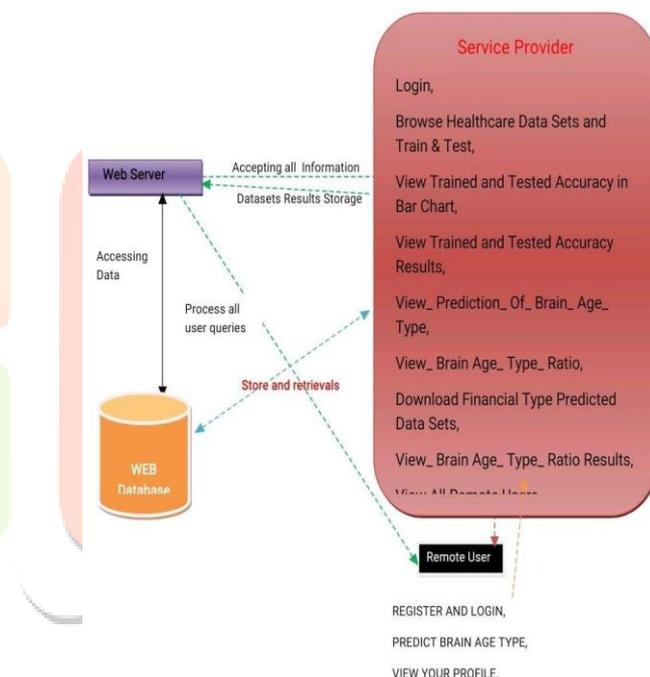
We then quantified each regression-algorithm on independent test sets composed of 88 CH individuals, 70 mild cognitive impairment patients as well as 30 Alzheimer’s disease patients. The prediction accuracy in the independent test set (i.e., CH set) varied in regression algorithms mean absolute error (MAE) from 4:63 to 7:14 yrs, R2 from 0:76 to 0:88.

### INTRODUCTION

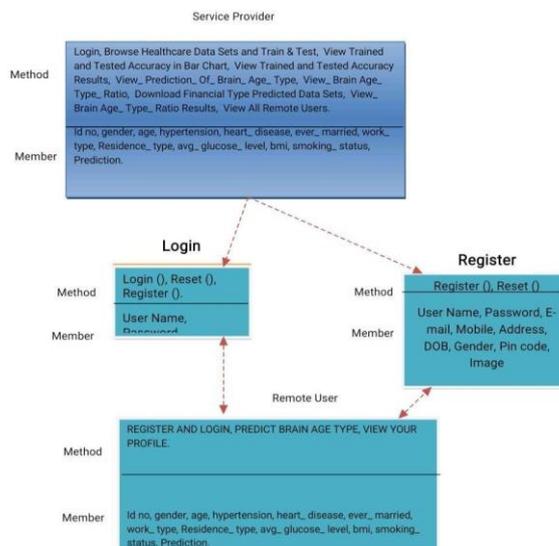
Recent times have witnessed an increased interest in the brain age-delta as a heritable metric for monitoring cognitively healthy (CH) aging and diagnosing various neurological disorders and co-morbidities [1]. The brain age-delta is defined as the difference between the chronological age and the age predicted from machine learning models trained on brain imaging data. The brain shrinks with increasing age, and there are changes at all levels, from molecules to morphology. To date, brain age metric has been successfully used in the context of different neurological disorders such as Alzheimer’s disease (AD) [3] - [4], Parkinson’s disease [5], Epilepsy [6], and Schizophrenia [7]. A summary of brain age estimation studies in the context of clinical application is presented in [1]. The prediction accuracy level in the brain age estimation frameworks is associated with different items such as feature extraction methods, data reduction strategies, bias correction methods, and regression algorithms.

### System Design:

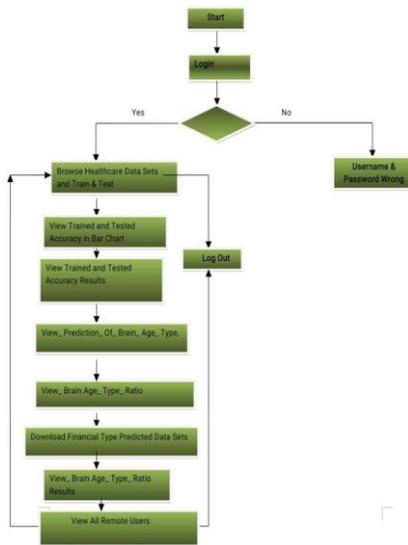
#### Architecture:



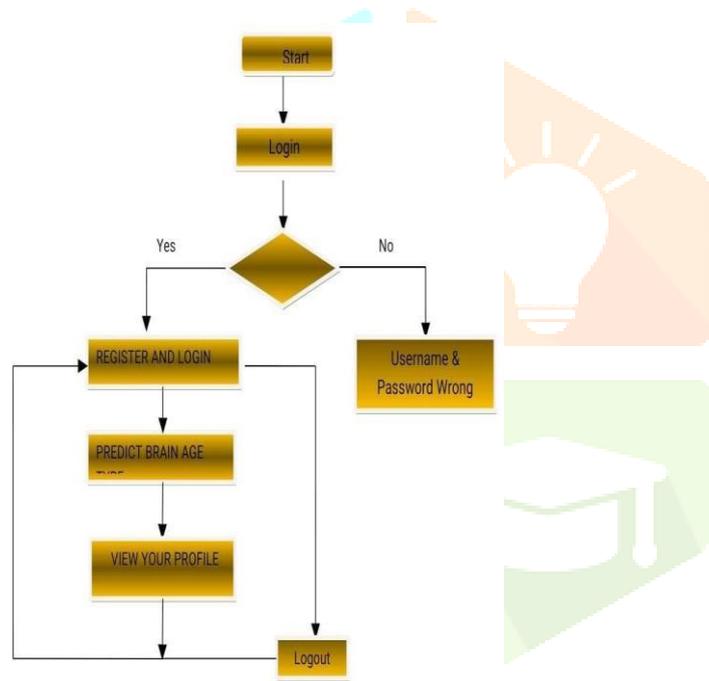
#### Class Diagram :



Flow Chart : Service Provider



FLOW CHART: REMOTE USER



Implementation:

MODULE 1: Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Login, Browse Healthcare Data Sets and Train & Test, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Brain Age Type, View Brain Age Type Ratio,

Download Financial Type Predicted Data Sets, View Brain Age Type Ratio Results, View All Remote Users.

MODULE 2: View and Authorize Users

In this module, the admin can view the list of users who all

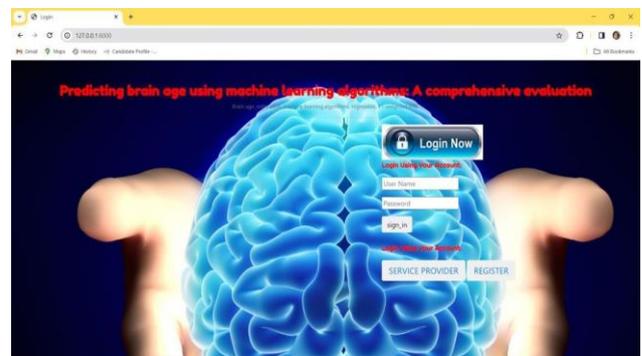
registered. In this, the admin can view the user’s details such as, user name, email, address and admin authorizes the users.

MODULE 3: Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like

Output Screens:

Home Page:



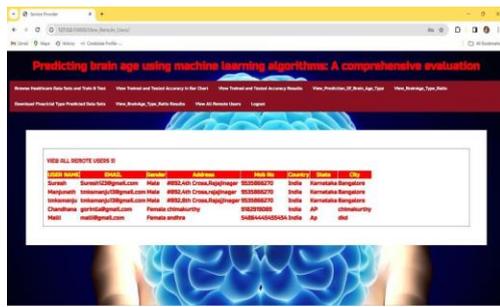
The above screen shows the Home page of the project which contains a login page for the remote user.

Login Page (Server Provider):



The above screen contains a login page for the service provider.

User Details Page:



The above screen contains the all users information (like Username, Email, Gender, Address, Mob No, country,..etc)

Predicting Brain Age Type Page:



The above screen shows the predicting brain age status

View Brain Age Prediction Type Details Page

The above screen contains brain age type prediction details



View Brain Age Prediction Type Ratio Details Page:

The above screen contains predicting brain age type ratio details

User Registration Page:

The above screen shows user registration page contains fields (like username, email id ,gender, city name etc...)

Conclusion

This study aimed to comprehensively evaluate various regression models for estimating Brain Age not only on CH individuals but also in clinical population. We assessed 22 different regression models on a dataset

comprising CH individuals as a training set. We then quantified each regression model on independent test sets composed of CH individuals, MCI subjects, and AD patients. Our comprehensive evaluation suggests that the type of regression algorithm affects downstream comparisons between groups, and caution should be taken to select the regression model in clinical settings.

Acknowledgement

I record with pleasure my deep sense of gratitude to our beloved project guide Mr. D. RAMOHAN REDDY, Associate Professor, M.Tech Department for the stimulating guidance and profuse assistance; I have received for His through the course of my project work. I shall always cherish my association with his for their encouragement approachability and freedom of thought and action.

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