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PREDICTING BRAIN AGE USING MACHINE LEARNING ALGORITHMS A COMPREHENSIVE EVALUATION

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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. Here, we sought to assess the efficiency of different regression algorithms on brain age estimation. To this end, we built a brain age estimation framework based on a large set of cognitively healthy (CH) individuals (N = 788) as a training set followed by different regression algorithms (22 different algorithms in total). 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. Our experimental results demonstrate that the prediction accuracy in brain age frameworks is affected by regression algorithms, indicating that advanced machine learning algorithms can lead to more accurate brain age predictions in clinical settings.

Keywords: MAE, CH, Alzheimer, N, ML.

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I. 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. A brain age-delta equal to zero indicates a 'healthy aging trajectory', whereas a large brain age-delta is indicative of an 'accelerative cognitive aging', pointing to a higher risk of age related neurological diseases or abnormal brain changes for a given age [2]. 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. In the context of feature extraction, various neuroimaging modalities such as anatomical MRI [1], [8], [9], functional MRI [10], fluoride oxy glucose positron emission tomography imaging [3], and diffusion tensor imaging [10] can be used to extract the brain imaging features after respective preprocessing stage. Among different neuroimaging modalities, anatomical MRI is the most frequently used in brain age studies because of its widespread availability, excellent spatial resolution, and good tissue contrast. When the number of extracted features is larger than the number of samples, a data reduction technique, such as principal component analysis (PCA), can be used for avoiding the curse of dimensionality [5]. In the

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prediction stage, a supervised learning technique (i.e., regression algorithm) is used to predict the brain age values for the given input data.

The prediction model in a brain age estimation framework is vital to accurately predict the brain age values for clinical applications. The most widely used regression algorithms include Gaussian process regression [11] - [12], and support vector regression [4], [6], [8]. While considering the regression algorithm for brain age estimation, the following points should be considered:

_ The algorithm should be accurate and sensitive to various data points in the training data. Generally, the performance of such models is measured on the basis of Mean Absolute Error (MAE) between the predicted age and the chronological age.

_ The chosen algorithm should be able to draw a relation between naturally occurring variation, such as that caused by genetic factors. Many aspects of brain aging and susceptibility to age-related brain disease are thought to be under genetic influence. Hence, the model should be capable to "learn" these variations.

_ The algorithm should be able to produce reliable results across different datasets and patient groups.

To date, few brain age studies have addressed the effects of regression algorithms on prediction accuracy in the brain age estimation frameworks [4], [13]. For instance, Valizadeh and peers [13] investigated six statistical regression algorithms (random forest, multiple linear regression, neural network, ridge regression, k-nearest neighborhood, and support vector machine) on brain age prediction results based on brain anatomical measurements (e.g. thicknesses, volumes, and cortical surfaces) among CH individuals. They reported the best results based on Neural Network and Support Vector Machine (SVM) based algorithms (R2 = 0:84) over the entire dataset. The most significant issue raised in [13] was that the effects of

different regression algorithms should be assessed at the clinical level (i.e., testing on clinical populations). In order to address this issue, we conducted this study to comprehensively assess the brain age prediction results followed by various salient regression techniques (22 different algorithms in total) not only on CH individuals but also in the clinical population (i.e.,the context of neurodegeneration, such as that due to AD). We also adjudge the best performing regression technique for this task, and discuss future works needed in this direction.

II.EXISTING SYSTEM:

Recent publications have shown that training supervised regression methods on MRI brain imaging can be used to predict the brain age of an individual with high precision. We can use these predictions to detect diseases associated with abnormal brain ageing where the predicted age does not match the chronological age. In an existing system, the system develops a convolutional neural network to predict brain age accurately. The architecture of the model is a simplified adaptation of the VGG architecture. The network is trained on healthy grey-matter segmented images and applied to clinical T1-weighted MRIs. The model is trained on a publicly available healthy dataset and applied to a clinical dataset consisting of Schizophrenia, Parkinson's Disease, and Post-Traumatic Stress Disorder patients. We demonstrated bias in brain age prediction, and we corrected it to improve the reliability of the results. Our BrainAge model obtained a mean absolute error (MAE) of 4.03 years and 0.96 R2 on the healthy dataset after correcting the bias. We used transfer learning to apply the BrainAge model to the clinical data and compared the brain age delta (predicted age – chronological age) for each condition. The results were not statistically significant $p<=0.5$ meaning that the brain age delta does not indicate abnormal brain ageing in this instance.

Disadvantages

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The system is not implemented Regression Algorithms in which the user can get less accuracy on datasets.

The prediction accuracy level in the brain age estimation frameworks is not associated with different items such as feature extraction methods, data reduction strategies, bias correction methods, and regression algorithms.

III.PROPOSED SYSTEM:

The prediction model in a brain age estimation framework is vital to accurately predict the brain age values for clinical applications. The most widely used regression algorithms include Gaussian process regression, and support vector regression. While considering the regression algorithm for brain age estimation, the following points should be considered:

_ The algorithm should be accurate and sensitive to various data points in the training data. Generally, the performance of such models is measured on the basis of Mean Absolute Error (MAE) between the predicted age and the chronological age.

_ The chosen algorithm should be able to draw a relation between naturally occurring variation, such as that caused by genetic factors. Many aspects of brain aging and

susceptibility to age-related brain disease are thought to be under genetic influence. Hence, the model should be capable to "learn" these variations.

_ The algorithm should be able to produce reliable results across different datasets and patient groups.

Advantages

- The k-Nearest Neighbors algorithm is essentially non-parametric classification method, which was later expanded for regression. Under this algorithm, the closest 'k' samples from the dataset are taken with respect to the object under consideration.

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- Ridge regression is a model tuning method that is used to analyze the data that suffers from multi-collinearity.

IV.MODULES

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.

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.

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 register and login, predict brain age type, view your profile.

Fig.1. Login page.

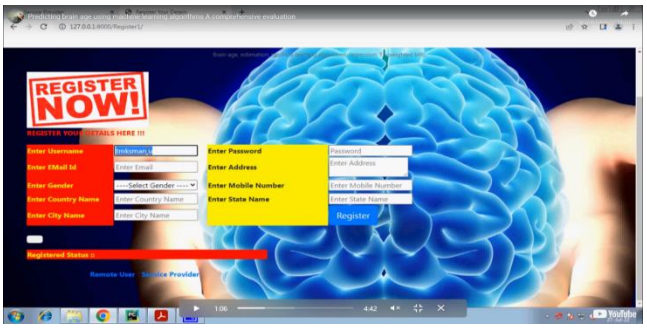

Fig.2. Register page.

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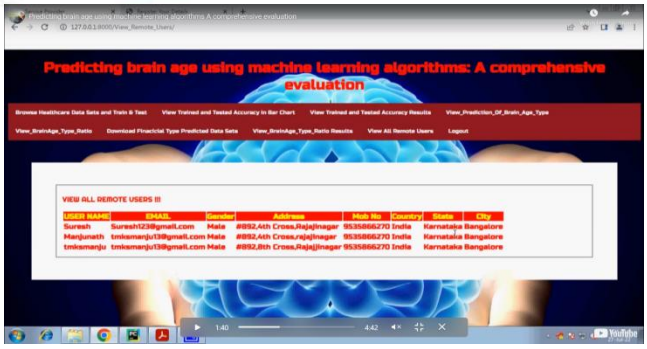

Fig.3. Users name.

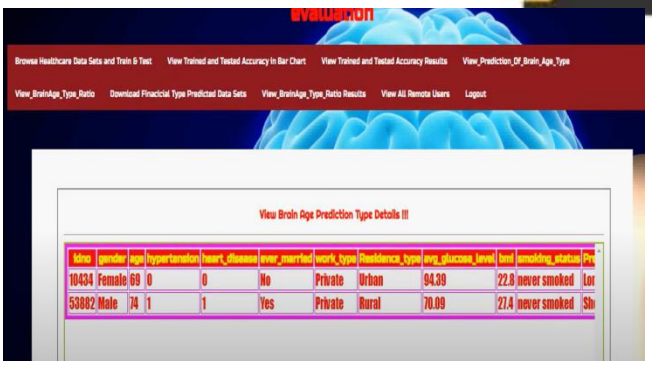

Fig.6. Complete data evaluation.

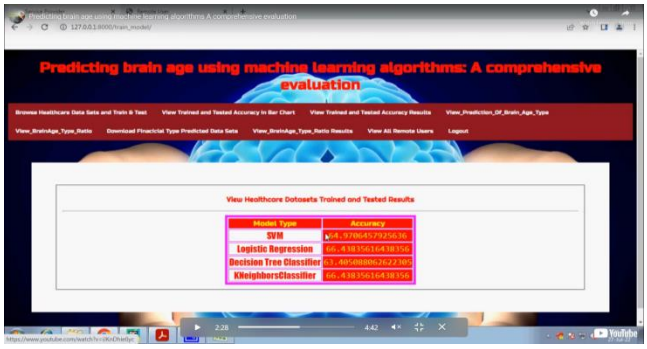

Fig.4. SVM and different modules accuracy.

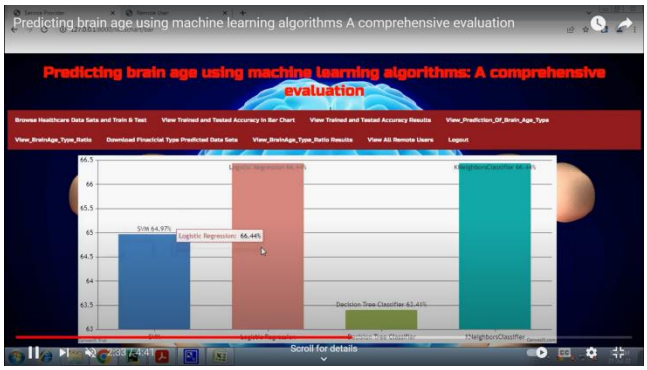

Fig.5. graph data with respective of time.

V.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.

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