International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 05 | May - 2023 Impact Factor: 8.176 ISSN: 2582-3930

BRAIN AGE PREDICTION USINGMACHINE LEARNING

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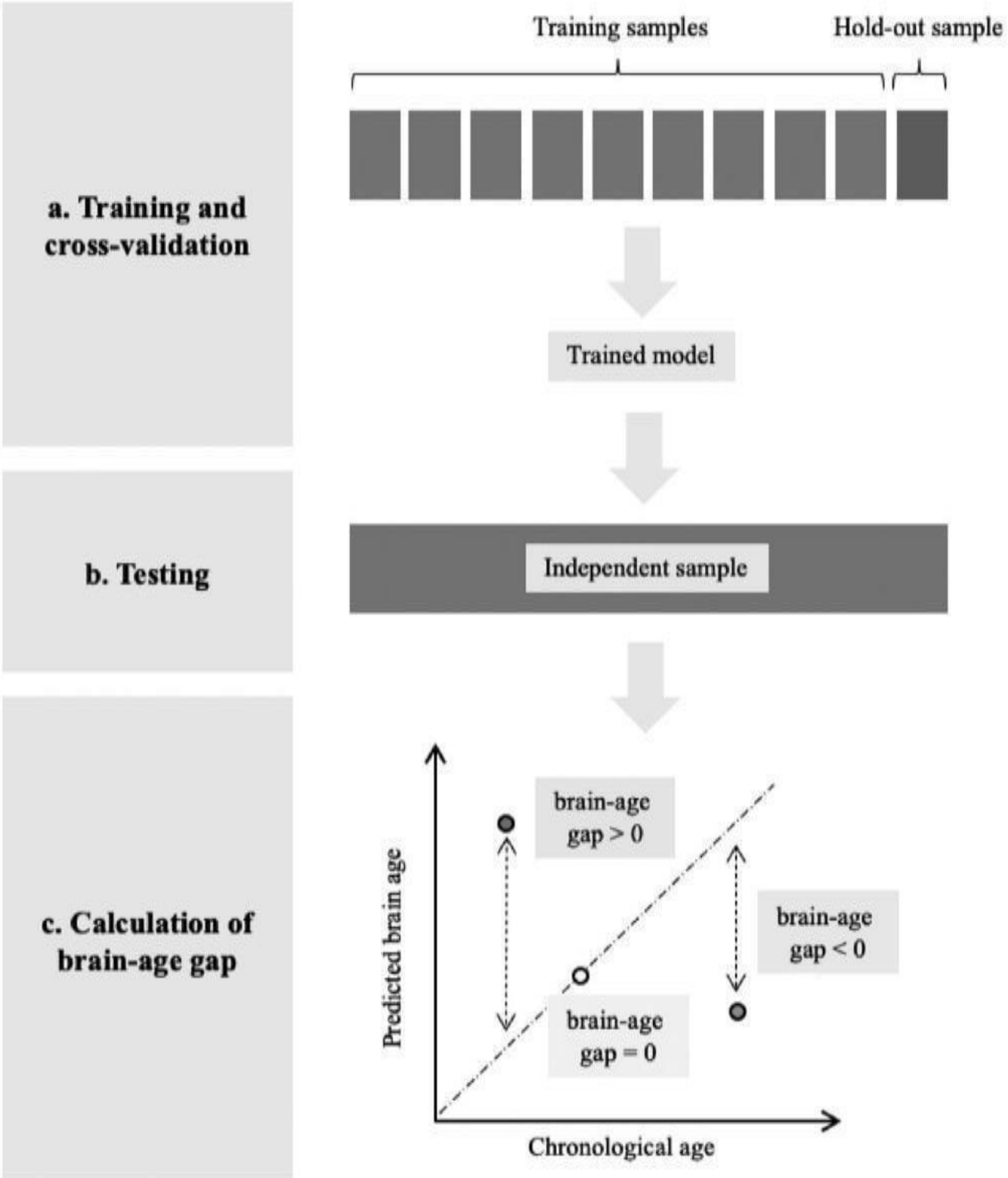
ABSTRACT: Aging is the process of getting older but when we discuss about ageing the main theme to know about the chronological age and biological age. Chronological age is the time that has passed from an individual's birth. Biological age is the aging occurs moderately accumulating damage to various tissues and cells. There is a connection between chronological age and biological age. In addition to biological aging it is a concept of normal ageing and abnormal ageing i.e., experiencing abnormal ageing or ageing faster. Aging has a impact on the brain and with increasing age it can cause degenerative disease like Alzheimer's disease. The effects of age on the brain or any abnormal activities in brain can be detected by some parameters like (gender, age factor, stress level, based on smoking, BMI, glucose). There are many methods in predict the brain age, by extracting the values from resources like (MRI and CT scan). Convolutional neural networks and Machine learning are the methods that are popular in computer vision. The prediction accuracy level in the brain age estimation frameworks is associated with different Machine learning algorithms such as Decision Tree, SVC (Support Vector Classifier), Passive Aggressive, Adaboost Classifier.

KEYWORDS: Aging, Chronological Age, SVC, Decision Tree, Passive Aggressive, Adaboost Classifier.

I INTRODUCTION

Ageing and its associated health conditions present a major challenge to individuals and societies worldwide. To address this challenge, increasing effortsare being made towards the early detection of age-related diseases with the ultimateaim of preventing or delaying their progression. The effects of ageing on the brain can be measured through an approach known as brain age prediction, which builds on the well-established relationship between age and neuroanatomy across the lifespan. The past decade has seen an exponential increase in studies on brain age. The majority of these involve the application of machine learning methods tostructured text data format in the form of excel sheets. Machine learning models learn patterns from data and then use these patterns to make predictions about new data. A key advantage of these methods over traditional statistics is that it is possible to make inferences at individual level rather than at group level, thereby increasing the potential for clinical translation. Brain age prediction studies commonly build machine learning algorithms using text data retrieved from the MRI and CT scans from healthy controls. This normative model is then applied to new subjects to assess to what extent their neuroanatomy deviatesfrom the norm and estimate brain abnormalities, resulting in their predicted brain age.

The main outcome measure in brain age prediction is the difference between an individual's predicted age and their chronological age, which is referred to as 'brain-age gap' in the present review. Studies of clinical groups typically estimate the mean brain- age gap across all patients and then either compare it to the meanbrain-age gap of a control group or to zero, where predicted and chronological age areequal. A positive brain-age gap means that the individual's predicted brain age was higher than their actual age, which is sometimes referred to as 'accelerated' or 'premature' ageing. A negative brain-age gap implies a lower predicted brain age, occasionally referred to as 'delayed' ageing. However, further research into the neurobiological mechanisms of brain ageing is needed to assess to what extent the terminology of 'accelerated' or 'delayed' ageing is warranted. In contrast, studies of healthy people typically assess the accuracyof a -age gaps across subjects. Where applicable, therefore, this review will report a study's results as mean brain- age gap (+/- X years) or MAE (MAE Xyears). Research suggests that an individual's brain-age gap can be understood as a marker of brain health. The validity of brain age as an ageing biomarkeris supported by the evidence that brain- age


a. Training and cross-validation
Training samples
Hold-out sample
Trained model
b. Testing
Independent sample
c. Calculation of brain-age gap
Predicted brain age
brain-age gap > 0
brain-age gap < 0
brain-age gap = 0
Chronological age

gap is significantly correlated with other measures of ageing, such as decline in cognitive function, weaker grip strength, and walking speed. This indicates clear potential for clinical translation. In this state-of-the-art review our aim to introduce the reader to the field of brain age prediction and highlight its clinical potential Our aim is not to present an exhaustive account of the literature but to explain the most common methodological approaches to brain age prediction and discuss five promising clinical applications and possible next steps, with reference to the most recent studies. As the vast majority of published studies on brain age prediction using text data, we focus on findings from this modality.

II DATASET DESCRIPTION

The dataset was taken from an open-source repository Kaggle and also collected manually. The dataset containsnearly 50,000 public datasets of healthy and diseased individuals of various age groups and different genders.

III PROPOSED MODEL

Here, we aimed to compare the performance of the machine learning models used to estimate brain age using brain morphological measures derived from the resources like structural magnetic resonance imaging scans and CT scans. We evaluated 27 machine learning models, applied to three independent datasets from the Human Connectome Project (HCP, n = 1113, age range 22–37), the Cambridge Centre for Ageing and Neuroscience (Cam- CAN, n = 601, age range 18–88), and the Information extraction from Images (IXI, n = 567, age range 19–86). Performance was assessed within each sample using cross-validation and an unseen test set. The models achieved mean absolute errors of 2.75–3.12, 7.08–10.50, and 8.04–9.86 years, as well as Pearson's correlation coefficients of 0.11–0.42, 0.64–0.85, and 0.63–0.79 between predicted brain age and chronological age for the HCP, Cam-CAN, and IXI samples, respectively. We found a substantial difference in performance between models trained on the same data type, indicating that the choice of model yields considerable variation in brain-predicted age. 24 Furthermore, in three datasets, regularized linear regression algorithms achieved similar performance to nonlinear and ensemble algorithms. Our results suggest that regularized linear algorithms are as effective as nonlinear and ensemble algorithms for brain age prediction, while significantly reducing computational costs. Our findings can serve as a starting point and quantitative reference for future efforts at improving brain age

prediction using machine learning models applied to brain morphometric data.

IV RELATED WORK

In recent years there has been tremendous research done on Brain age prediction. With the help of a literature survey we, realized the basic steps in Brainage prediction are:

A) Predictive Analysis :

Predictive analysis in brain age prediction typically involves the following steps:

- **Data preprocessing module:**

This module can be used to preprocessbrain imaging data, including text normalization, registration, and segmentation. Preprocessing can help to improve the quality of the data and reduce noise, which can improve the accuracy of age prediction.

- **Feature extraction module:**

This module can be used to extract features from the brain text parameters, such as gray matter volume, white matter integrity, and cortical thickness. These features can be used as inputs to machine learning models.

- **Model selection module:**

This module can be used to select the best machine learning model for the task of age prediction. Different models, such as linear regression, support vector machines, and neural networks, can be tested and compared to determine the best performingmodel.

- **Model tuning module:**

This module can be used to optimize the hyperparameters of the machine learning model, such as learning rate, regularization, and number of hidden layers. Model tuning can help to improve the performance of the model on the validation set.

- **Model evaluation module:**

This module can be used to evaluate the performance of the machine learning model on a test set. Metrics such as mean absolute error, mean squared error, and correlation coefficient can be used to assess the accuracy of age prediction.

- **Prediction:**

Once the model is trained and validated, it can be used to predict the age of new individuals based on their brain text parameters and other factors.

B) Age over sex variance :

Age over sex variance in the relationship between brain text data and age, depending on whether the individual is male or female. In other words, the relationship between brain features and age may vary between males and females, which can affect the accuracy of age prediction. Research has shown that there are some brain imaging

features that exhibit sex differences, such as gray matter volume, white matter integrity, and cortical thickness. For example, some studies have shown that males tend to have larger overall brain volume than females, while females tend to have greater gray matter density in certain regions of the brain.

Therefore, when building a predictive model for brain age prediction, it is important to take into account the potential sex differences in brain text features. This can be done by including sex as a covariate in the model, or by building separate models for males and females. Some studies have reported that including sex as a covariate can improve the accuracy of age prediction, particularly in datasets with a large number of male and female subjects. Other studies have reported that building separate models for males and females can result in better accuracy, particularly when the sex differences in brain imaging features are large. In summary, taking into account the potential sex differences in brain text features is important for accurate brain age prediction. This can be achieved by including sex as a covariate in the model, or by building separate models for males and females.

C) Brain age estimation :

- **Data preprocessing**:

Brain text data is preprocessed to remove noise and artifacts, and to normalize the data so that it is comparable across individuals.

- **Feature extraction:**

Features are extracted from the brain text data, such as measures of brain volume, thickness, and connectivity.

- **Model selection:**

Different machine learning algorithms are compared and tested to determine which algorithm works best for estimating brain age from brain text data.

- **Model training:**

The chosen machine learning algorithm is trained on a set of brain imaging data with known chronological ages, to learn the relationship between brain features and age.

- **Model evaluation:**

The performance of the model is evaluatedon a separate test set of brain text data with known chronological ages, to assess its accuracy and generalization ability.

- **Brain age estimation:**

Once the model is trained and validated, it can be used to estimate the brain age of new individuals based on their brain text data.

V METHODOLOGY & APPROACH

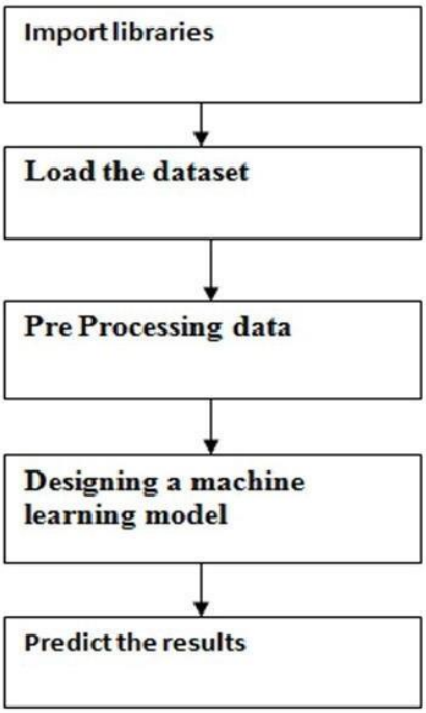
In this project we aimed to improve the accuracy by using the following algorithms.

- **PASSIVE AGGRESSIVE CLASSIFIER**
- **DECISION TREE**
- **SUPPORT VECTOR CLASSIFIER**
- **ADABOOST CLASSIFIER**

By using the above algorithms we have got better accuracy than the existing system by executing the following steps.

- **LOAD DATASET**
- **SPLIT DATASET**
- **TRAIN DATASET**
- **TEST DATASET**
- **PREDICT THE RESULT**

Load dataset using pandas read_csv() method. Here we will read the excel sheet data and store into a variable. After loading the dataset, Split the dataset to two types. One is train dataset and another is test dataset. Here we will remove missing values from the dataset. After splitting the data, Train dataset will train our dataset using fit method. 80% of data from dataset we used for training the algorithm. After training the dataset, Test dataset will test the dataset using appropriate algorithms. 20% of data from dataset we used for testing the algorithm. After testing the dataset, Predict() method will predict the results.



VI 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.

VII FUTURE ENHANCEMENT

For the future work, models will be improvised for not only predict the brain age but also detect the different kinds of brain diseases in early stages by using MRI and CT scan's for all age groups. Different methods for extracting more features will be explored and other famous methods of regression will be employed for this regression task. Our comprehensive evaluation suggests that the type of regression algorithm affects downstream comparisons between group- s caution should be taken to select the regression model in clinical settings. Our proposed system provides an accuracy of 94%, by using any other algorithms and models the accuracy can be improved in future.

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