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ASSESSING BRAIN-AGE PREDICTION THROUGHCOMPREHENSIVE EVALUATION USING MACHINE LEARNING ALGORITHM

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ABSTRACT-
Machine learning (ML) algorithms play a crucial role in brain-age estimation systems, yet a comprehensive evaluation of their impact on prediction accuracy remainsunexplored. In this study, we aimed to evaluate the effectiveness of various regression algorithms for brain-age estimation. Our methodology involved constructing a brain-age estimation framework using a large training set of cognitively healthy (CH) individuals (N = 788)and testing 22 different regression algorithms. We then assessed each algorithm on independent test sets consisting of 88 CH individuals, 70 mild cognitive impairment patients, and 30 Alzheimer's disease patients. The prediction accuracy in the independent test set (CH set) showed variations across regression algorithms, with mean absolute error (MAE) ranging from 4.63 to 7.14 years and R2 from 0.76 to 0.88. The Quadratic Support Vector Regression algorithm achieved the highest accuracy (MAE = 4.63 years, R2 = 0.88; 95% CI = [-1.26; 1.42]), while the Binary Decision Tree algorithm demonstrated the lowest accuracy (MAE = 7.14 years, R2 = 0.76; 95% CI = [-1.50; 2.62]). Our experimentalresults highlight the impact of regression algorithms on prediction accuracy in brain-ageestimation frameworks, indicating that advanced machine learning algorithms have thepotential to improve precision in clinical settings.

Keywords:
Brain-agee, Machine Learning, Regression Algorithms

I. INTRODUCTION

Brain-agee estimation, a method utilizing machine learning (ML) algorithms, holds promise for assessing brain health and detecting neurological disorders. ML algorithms have been extensively employed in this domain, yet there remains a gap in understanding the comprehensive impact of regression algorithms on prediction accuracy. In this study, we aimed to address this gap by evaluating the efficacy of various regression algorithms [1] for brain-agee estimation. Our investigation involved constructing a robust brain- agee estimation framework utilizing a sizable training dataset of cognitively healthy (CH) individuals and testing a diverse set of 22 regression algorithms [2]. The evaluation was conducted on independent test sets comprising CH individuals, mild cognitive impairment patients, and Alzheimer's disease patients. By analyzing the performance metrics such as mean absolute error (MAE) and R2 [3], we aimed to discern the influence of regression algorithms on prediction accuracy and identify the most effective approach for precise brain-agee estimation. This research endeavors to shed light on the role of regression algorithms in enhancing the accuracy of brain-agee estimation models [4], thus potentially facilitating more accurate diagnoses and interventions in clinical settings.

II. LITERARURE SURVEY

This literature review delves into the realm of brain-agee estimation, concentrating on the extensive assessment of regression algorithms and their implications for predictive precision in both the context of cognitively healthy aging and clinical applications. Various MRI contribute to feature extraction, with anatomical MRI commonly employed due to its accessibility and superior spatial resolution. The selection of regressionalgorithms, such as Gaussian process regression and support vector regression, significantly influences predictive accuracy, necessitating algorithms that showcase precision, sensitivity, and adaptability across diverse datasets. This review underscores the vital role of regression algorithms in clinical applications, emphasizing theirimportance in accurately estimating brain-agee in diverse neurological disorders. Although some studies have explored the impact of regression algorithms on brain-agee prediction accuracy, particularly in cognitively healthy individuals, there exists a noticeable void in evaluating these algorithms within clinical populations. To address this lacuna, future research should concentrate on comprehensive assessments utilizing varied regression techniques, encompassing diverse patient groups and refining methodologies to enhance predictive efficacy in neurological diagnostics and research.

III. PROBLEM STATEMENTEXISTING SYSTEM:

When it pertains to brain-agee estimation, the most widespread strategy uses machine learning algorithms to forecast an individual's neural age viaevaluation of neuroimaging data. The term "brain-agee-delta," which refers to the variance between the age anticipated in these machine learning models and their real age, has begun to receive more attention recently. This measure is useful in gauging healthy aging and diagnosing neurological disorders. A "healthy aging trajectory" is indicated by a brain-agee-delta of zero, but a large variance points to a "accelerated cognitive aging" and raises the prospect of age-related illnesses.

Neuroimaging modalities play a crucial role in the existing system, with various techniques such as anatomical MRI, contributing to the extraction of features from brain imaging data. Anatomical MRI, owing to its common accessibility, towering spatial ruling, and first-rate tissue disparity, is frequently employed in brain-agee studies. Additionally, data reduction techniques, including principal component analysis (PCA), are applied to manage the challenges associated with a large number of extracted features.

The choice of regression algorithms is pivotal in the existing system, with GPR and SVR being commonly use for their effectiveness in capturing complex relationships within the data. These regression algorithms are crucial in predicting brain-agee values during the training stage.

The existing system has demonstrated promisingresults particularly in clinical populations. A few studies have investigated this aspect, highlighting the importance of assessing these algorithms at the clinical level to ensure their efficacy and reliability across different datasets and patient groups.

In summary, the existing system utilizes machine learning algorithms, neuroimaging modalities, and regression techniques for brain-agee estimation, showing potential for applications in monitoring healthy aging and diagnosing neurological disorders. Ongoing research seeks to refine and enhance these methods, particularly in the contextof clinical populations, to improve predictive accuracy and broaden the scope of applications in neurological diagnostics and research.

PROPOSED SYSTEM:

In our proposed system, we aim to integrate and evaluate the k-Nearest Neighbors (k-NN) algorithm and Ridge regression method as integral components of the brain-agee estimation framework. The k-NN algorithm, renowned for its non-parametric classification capabilities, will beexplored for its potential application in regression tasks within our brain-agee prediction model. By leveraging the proximity-based nature of k-NN, we anticipate capturing intricate relationships within the brain imaging data for more nuanced and accurate age predictions.

Additionally, we propose the incorporation of Ridge regression as a model tuning method to address potential multi-collinearity issues within the brain-agee estimation dataset. Ridge regression's ability to handle correlated features will contribute to mitigating potential challengesarising from complex

interactions within the neuroimaging data. This inclusion aligns with our goal of improving the efficiency and robustness of the brain-age prediction model.
The proposed system will involve an iterative process of training and testing, using a diverse and comprehensive dataset that includes cognitively healthy individuals as well as a broader representation of clinical populations. We plan to assess the predictive accuracy of the k-NN algorithm and Ridge regression in comparison to other regression methods, emphasizing theireffectiveness in capturing both local and global relationships within the brain-agee data.
Furthermore, the proposed system will explore various hyperparameter configurations for both algorithms to optimize their performance.Regularized tuning of the k-NN algorithm and fine-tuning of the Ridge regression parameters will be conducted to achieve an optimal balance between accuracy and generalizability.
Through rigorous experimentation and validationon independent test sets, including diverse clinical groups, we anticipate demonstrating the effectiveness of integrating k-Nearest Neighbors and Ridge regression within the brain-agee estimation framework. This proposed system aims to contribute to the refinement of regression algorithms, paving the way for other accurate and reliable brain-age predictions, particularly in irrefutable setting.

ADVANTAGES:
Enhanced Predictive Accuracy: The integration of the k-Nearest Neighbors (k-NN) algorithm and Ridge regression in the proposed system is expected to lead to improved predictive accuracyfor brain-agee estimation. By leveraging k-NN's ability to capture intricate relationships and Ridge regression's capacity to handle multi-collinearity,the proposed system aims to provide more nuanced and precise age predictions.
Robust Handling of Multi-Collinearity: Ridge regression, as a model tuning method, addresses the challenge of multi-collinearity often present in brain-agee estimation datasets. Its regularization technique ensures stability in the presence of correlated features, contributing to a more robust and reliable prediction model.
Adaptability to Diverse Data: The proposed system advocates for an iterative approach, allowing the adaptation and evaluation of the k-NN algorithm and Ridge regression across diverse datasets. This adaptability ensures that the model is capable of generalizing well to different populations, including cognitively healthy individuals and those with various neurological conditions.
Incorporation of Local and Global Relationships: The k-NN algorithm, known for its non-parametric nature, excels at capturing local relationships withinthe data, complementing Ridge regression's ability to capture global patterns. The combined strengths of these algorithms supply to a added all-inclusive perceptive of the intricate structures within brain imaging data.
Optimized Hyperparameter Configurations: The proposed system involves a systematic exploration of hyperparameter configurations for both algorithms, ensuring optimal settings for improved performance. This optimization process contributes to the fine-tuning of the model, striking a balance between accuracy and generalizability.
Iterative Model Refinement: Through an iterative training and testing process, the proposed system allows for continuous refinement of the brain-agee estimation model. This iterative approach includes experimenting with various algorithmic configurations, contributing to the ongoing enhancement of the model's effectiveness andadaptability.
Applicability in Clinical Settings: By assessing the proposed system on diverse clinical populations, the advantages extend to its applicability in real- world clinical settings. This ensures that the refined model is not only accurate but also clinically relevant for the untimely revealing and monitoring of neurological disorders.
In summary, the proposed system's advantages lie in its commitment to enhancing predictiveaccuracy, addressing multi-collinearity challenges, adapting to diverse datasets, incorporating local and global relationships, optimizing hyperparameter configurations, and iteratively refining the model for

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practical use in clinical settings.

IV. RESULTS & DISCUSSION

The system is structured to facilitate seamless interactions among different entities. One module is designed for service providers, offering functionalities such as secure login, healthcare dataset exploration, training and testing operations, and visual representation of accuracy results. Service providers can also download predicted datasets, analyze brain-agee type predictions, and view the ratio of predicted brain-agee types. Another module focuses on user management and authorization, allowing administrators to oversee user registrations, access user details, and authorize users. The third module caters to remote users, guiding them through registration and login processes before enabling brain-agee typeprediction and profile management. Collectively,these modules form an integrated platform, providing efficient data management, user oversight, and interactive features for brain-agee estimation and related tasks.

V. RESULT FOR PROPOSED SYSTEM

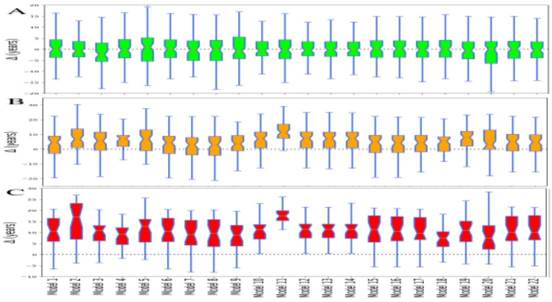

Fig.1. Models Comparison

Fig. 1: The box-plots showing the brain-age delta followed by different regression algorithms on independent test sets. A) CH individuals, B) MCI patients, and C) AD patients. Model 1 = Linear SVR, Model 2 = Quadratic SVR, Model 3 = Gaussian SVR, Model 4 = Ensemble Trees (Bag) , Model 5 = Ensemble Trees (LSBoost), Model 6 = Linear Regression, Model 7 = Lasso Regression, Model 8 = Ridge Regression, Model 9 = Binary Decision Tree, Model 10 = Gaussian Regression (Kernel-Exponential), Model 11 = Gaussian Regression (Kernel-Squared Exponential), Model 12 = Gaussian Regression (Kernel-Matern32), Model 13 = Gaussian Regression (Kernel-Matern52), Model 14 = Gaussian Regression (Kernel-Rational-Quadratic), Model 15 = ETSVR (Kernel - Linear), Model 16 = Kernel Ridge Regression (Kernel-Linear), Model 17 = Nystrom Kernel Ridge Regression, Model 18 = DNNE, Model 19 = kNN (Weighted Mean), Model 20 = Neural Network (NN), Model 21 = RKNNWTSVR, Model 22 = LTSVR.

S.No	Regression Model	MAE (Years)	RMSE (Years)	Mean brain age-delta (Years)	95 % CI Values	R^2 Score
1.	Linear SVR	5.40	6.92	0	[-0.48 , 0.48]	0.88
2.	Quadratic SVR	5.36	6.84	0	[-0.48 , 0.48]	0.89
3.	Gaussian SVR	3.04	4.45	0	[-0.31 , 0.31]	0.95
4.	Ensemble Trees (Bag)	5.48	7.16	0	[-0.50 , 0.50]	0.88
5.	Ensemble Trees (LSBoost)	6.71	8.62	0	[-0.60 , 0.60]	0.84
6.	Linear Regression	5.40	6.91	0	[-0.48 , 0.48]	0.89
7.	Lasso Regression	4.77	6.23	0	[-0.44 , 0.44]	0.91
8.	Ridge Regression	4.74	6.21	0	[-0.43 , 0.43]	0.91
9.	Binary Decision Tree	5.72	7.37	0	[-0.52 , 0.52]	0.88
10.	Gaussian Regression (Kernel - Exponential)	5.29	6.78	0	[-0.47 , 0.47]	0.89
11.	Gaussian Regression (Kernel - Squared Exponential)	7.54	9.43	0	[-0.66 , 0.66]	0.81
12.	Gaussian Regression (Kernel - Matern 32)	5.33	6.81	0	[-0.48 , 0.48]	0.89
13.	Gaussian Regression (Kernel - Matern 52)	5.34	6.82	0	[-0.48 , 0.48]	0.89
14.	Gaussian Regression (Kernel - Rational-Quadratic)	5.35	6.85	0	[-0.48 , 0.48]	0.89
15.	ETSVR (Kernel - Linear)	5.30	6.77	0	[-0.47 , 0.47]	0.89
16.	Kernel Ridge Regression (Kernel - Linear)	5.34	6.81	0	[-0.48 , 0.48]	0.89
17.	Nystrom Kernel Ridge Regression (Kernel - Linear)	5.37	6.84	0	[-0.48 , 0.48]	0.89
18.	DNNE	5.65	7.30	0	[-0.51 , 0.51]	0.88
19.	kNN (Weighted Mean)	5.41	7.01	0	[-0.49 , 0.49]	0.89
20.	Neural Network	6.65	8.88	0	[-0.62 , 0.62]	0.83
21.	RKNNWTSVR (Kernel - Linear)	5.45	6.93	0	[-0.48 , 0.48]	0.89
22.	LTSVR (Kernel - Linear)	5.33	6.77	0	[-0.47 , 0.47]	0.89

MAE: Mean Absolute Error, RMSE: Root Mean Square Error, R^2: Coefficient of Determination

Fig.2. Training Algorithms Summary

The outline of recital result base on diverse forecastalgorithms in the exercise set provides a detailed examination of how various regression algorithms perform in estimating brain-agee. In this comprehensive evaluation, the focus was on assessing the predictive accuracy of each algorithm by employing key metrics like mean absolute error (MAE) and R2 on a substantial training setcomprised of cognitively healthy individuals.

VI. CONCLUSION

In this study, our primary objective was to conduct a thorough assessment of diverse regression-models for the estimation of Brain-Age, extending our analysis beyond cognitively healthy (CH)

persons to include a clinical population. The evaluation involved the scrutiny of 22 distinct regression models, utilizing a dataset primarily composed of CH persons. Subsequently, we rigorously quantify the performance of each regression model on independent test sets, encompassing not only CH individuals but also subjects with MCI and patients diagnose with AD.
The outcomes of our comprehensive evaluation revealed that the choice of regression-algorithm significantly influence the precision and reliability of Brain-Age estimations, particularly when applied to different clinical groups. The impact of regression models on downstream comparisons between various groups was evident, emphasizing the need for careful consideration and selection of the appropriate regression model, especially in clinical settings. These findings underscore the importance of tailoring regression algorithms to the unique characteristics and complexities present in diverse populations, ensuring the robustness and applicability of Brain-agee estimation models in clinical contexts.

VII. FUTURE WORK:

The present study opens avenues for severalpromising directions in future research. Firstly, exploring additional regression models beyond the 22 considered in this study could provide a more exhaustive understanding of their performance in diverse datasets, including those with neurological disorders. Investigating the impact of hyperparameter tuning on the selected models may further optimize their predictive accuracy.
This would enhance the generalizability of the regression models, making them more applicable in real-world clinical scenarios. Incorporating longitudinal data and integrating multiple modalities, such as functional and structural neuroimaging, could offer a more comprehensive perspective on brain-ageing.
Additionally, exploring ensemble methods thatcombine the strengths of multiple regression models might lead to enhanced predictive capabilities. Investigating the interpretability of these models and their applicability in individualized predictions could also be a valuable avenue for future exploration. Lastly, as the field of machine learning and neuroimaging continues to advance, incorporating emerging techniques and methodologies, such as deep learning approaches, may present exciting opportunities for refining Brain-agee estimation models. These advancements could contribute tomore accurate predictions and improved clinical relevance, ultimately advancing our understanding of brain-ageing and age-relate neurological disorders.

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