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AI based Detection of Mild Cognitive Impairment (MCI)

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***Abstract*—Mild Cognitive Impairment (MCI) is an early stage of cognitive decline that has a potential for developing into dementia, including Alzheimer's disease (AD). Early and timely MCI detection is important in ensuring timely intervention and management. In this study, the use of multiple biomarkers and sophisticated machine learning (ML) methods for proper detection of MCI is investigated. Multimodal biomarkers such as cognitive test scores e.g., Mini Mental State Examination (MMSE) and other demographic factors were used to support diagnostic performance. Feature extraction and selection methods were employed in order to obtain the most informative biomarkers. The results enhance the accuracy of MCI detection and achieve state-of-the-art performance. Models such as Gradient Boosting provides improved balance and more applicable performance than other models such as Logistic Regression, XGBoost and Decision Trees This research presents the possibility of multimodal biomarkers with ML to construct solid, non-invasive methods for early detection of MCI, opening doors for personalized therapeutic interventions.**

***Keywords*— MCI, Gradient Boosting, SVM, Decision tree, Logistic Regression, MMSE, OASIS.**

I. INTRODUCTION

Worldwide, millions have MCI which presents a huge challenge to patients, families, health care providers and the economy [1]. In 2022, an estimated 55 million individuals had MCI and this figure is likely to reach 78 million in 2030. This growth is primarily attributed to the increase in life expectancy and developments in diagnostic technologies.

According to projections, the total economic impact of MCI in 2022 was $1.3 trillion, but this amount is predicted to reach $2.8 trillion by 2030. MCI is becoming increasingly common and as it develops, it leads to more severe illness, which is contributing to higher expenses for healthcare, caregiving and long-term care services. These problems pose a threat that can only be resolved with appropriate funding in prevention, early intervention and novel approaches [2]. Physiologically, MCI has negative effects with respect to cognitive functions as well as the quality of life and independence [3]. Approximately 15 % of individuals aged 60 and above live with MCI reside in the world [4], and approximately 12–20 % of them progress to dementia annually [5]. Thus, timely detection of early phase dementia among MCI patients is important as these patients are reversible so that further cognitive decline can be delayed [4,7]. But if the patients develop into dementia, treatments are limited [7]. So, one of the greatest emphasis in dementia study and treatment is to be able to successfully and efficiently identified whether a patient of MCI would eventually develop dementia or not [5,8]. Detection of dementia is normally based on multimodal information such as cognitive exams, MRI and PET scans, and other biomarkers.

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Despite the wealth of information provided by these sources, studies have revealed that over 18% of dementia patients in the US receive the wrong diagnosis and treatment for another illness. This demonstrates the challenges in accurately diagnosing dementia. To reduce such errors, better diagnostic techniques must be used[9]. In recent years, AI and ML have become more and more important in the early detection and management of many illnesses. The creation of machines, systems, or software to carry out tasks that would typically need human intelligence is the focus of artificial intelligence (AI), a broad field of computer science. ML, a branch of AI, is concerned with developing statistical models and algorithms that enable computers to learn to do a particular task more effectively by seeing data without explicit programming[10–12]. Early identification of cognitive alterations in individuals with MCI by computer-aided image analysis is a prodromal phase of AD dementia. The evolution of medical imaging technology with computational capability has opened doors to novel techniques employed for detection of neurocognitive disorders to avoid cognitive impairment [13]. This study is planned into the sections as section 2 presents the associated work under study. The section 3, presents the methodology which is proposed to detect MCI through the MMSE. The section 4 presents the discussion on the results obtained and finally through section 5, conclusion remarks with the future scope.

II. Related Work

MCI is often mistreated in primary care due to barriers in cognitive performance evaluation. A global panel of experts has observed the need for large-scale cognitive screening focused on individuals with concerns about their cognition, so as to improve timely identification and management. In light of growing cases of AD, innovative approaches are warranted to minimize healthcare burdens, as anticipation of the authorization of disease-modifying therapies is emerging. Urgent integration of infrastructure, resources, and equipment in primary care is necessary to optimize the patient journey and support a widespread cognitive evaluation [14]. Apps, wearable's, and digital tools offer passive monitoring and interactive assessments for MCI detection, allowing self-administrated or caregiver-assisted evaluations outside of clinical environments. This is bound to overcome several barriers associated with primary care. Where test validation and user experience remains challenges, their solution could make large-scale self-assessed screening in cognitive areas feasible [15]. During non-acute office visits, 300 participants aged 65 to 89 who did not have a diagnosis of cognitive problems were recruited for the study. Each of the two participating PCP offices saw 100 consecutive eligible patients. One office asked informants about cognitive changes using the SAGE test. After 60 days, chart reviews were conducted, and group outcomes were compared using one-way ANOVA and Fisher exact tests [16]. In [17] it was a study that sought to assess cognitive performance in rehabilitation inpatients with SCI acquired recently employing the MoCA, examine relations between patient and MoCA score, and contrast MoCA and the cognitive factor of the USER. In [18] The study found a significant difference in the severity of CI between patients with no DR, non-proliferative diabetic retinopathy (NPDR), and proliferative diabetic retinopathy (PDR) ($p < 0.001$), and an association between CI and the severity of DR. The rates of severe and moderate CI were higher in the PDR group. On the MMSE and MoCA tests, DR grades and CI severity were negatively correlated ($r = -0.522$, $p < 0.001$; $r = -0.540$, $p < 0.001$). Eleven trials involving 1,569 MCI patients who were monitored for dementia conversion were included in this analysis. Eight studies examined AD dementia, and four examined the contribution of baseline MMSE scores to conversion to all-cause dementia. One study looked at conversion to vascular dementia and MMSE. The baseline MMSE's sensitivity and specificity for conversion to dementia ranged from 23% to 76% and 40% to 94%, respectively [19].

III. Prediction Model for MCI Detection

A. Architecture of the proposed model

In the proposed architecture which is shown in Fig 1, a model learns data using a machine learning algorithm and classifies data into normal and MCI based on the biomarkers such as MMSE score.

B. The Dataset

The Open Access Series of Imaging Studies (OASIS) is a popular publicly accessible dataset for magnetic resonance imaging (MRI) utilized in MCI research analysis. 100 persons over 60 with a clinical diagnosis of very mild to moderate AD make up the dataset, which includes 416 right-handed men and women between the ages of 18 and 96. Three to four T1-weighted MRI images from a single imaging session are included in each subject's collection, and each one has a high contrast-to-noise ratio that supports a variety of analytical techniques, including completely automated computational analysis. Additionally provided is a reliability dataset of 20 individuals without dementia who were photographed again within 90 days. The information supports research on whole-brain and total intracranial volumes, enabling comparisons between AD and normal aging[20].

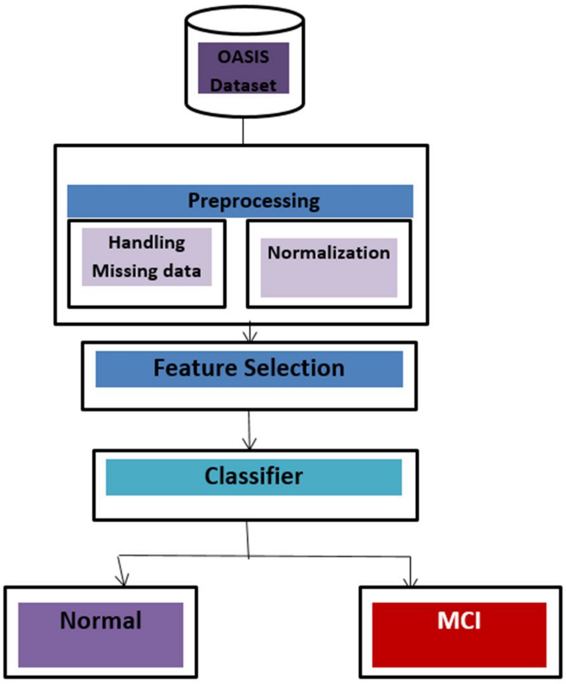

Figure 1

C. Preprocessing

Data preprocessing is the removal of certain unwanted or inaccuracy records from a record set, table or even database by the detection and correction process. The process helps to identify the incomplete, erroneous, inaccuracy or irrelevant part of the data and then replace, modify or delete the data. The process entails finding out invalid, incomplete, irrelevant or corrupt data in a record set, table, or database and either correcting or deleting the information. The missing values in the data tend to come from patients who failed to understand the test properly during clinical follow up. Data normalization converts values within different ranges into values having the same range such that an attribute with a higher range of values is not allowed to be given a higher weight than that of a lower range of attributes. For numeric data, there are four methods used for normalizing data: first, to map the range to 0 through 1; second is to have a value in between −1 through 1; third is to calculate the mean and variance of the feature and fourthly is to normalize the data by using the log value. In the case of categorical data, neural network-based algorithms and statistical algorithms among ML algorithms cannot handle categorical data, so they are translated to binary data or one-hot encoding. For instance, in the context of one-hot encoding, if there are three categorical data then they are translated to a form like (100), (010), (001). The maximum-minimum normalization technique is applied to the numerical data and one-hot encoding to the categorical data among various techniques. Equation 1 illustrates the maximum-minimum normalization formula.

$$\text{Normalization Value } (d) = \frac{origin\ Value - oldMin}{oldMax - oldMin}$$

D. Feature Selection

Feature selection is a process of obtaining the most suitable features from data with some specific pattern and can be utilized for eliminating unsuitable data, redundancy elimination and finding out which features make a high accuracy model. While developing a model, one should write minimum features so that one can decrease the number of features by feature selection. In this research, feature selection is performed by chi square and information gain. The chi-square test is a test applied when one is working with categories, relations or variables and it is helpful while working with categorical variables like the regional and political inclinations, In two general contexts, the chi-square test might be applied. The first is as a test of fitness that tests if observed data follows some expected distribution. As a test of independence, it can also be used to determine whether two random variables are independent of one another. Independence means that there is no cause or effect relationship between them. The following Equation 2 indicates the chi-square feature selection.

$$\text{chi square} = \frac{(observed - expected)^2}{expected}$$

E. Classifier

Finding a feature-label mapping from labeled training data is the goal of supervised learning. Every instance comes with a label that is used to identify trends and make predictions about future, unobserved instances. Data preparation, which involves cleaning and changing features to facilitate learning, is one of the most crucial labeling techniques. Feature engineering plays a major role in identifying important factors that improve the quality of the model. Second, methods like cross-validation are used to confirm that the model will work with data that hasn't been seen before. Thirdly, models such as Neural Networks (NN), Support Vector Machines (SVC), and decision trees are used to learn from the labeled data.

Logistic Regression

Logistic regression is a probabilistic model used when the dependent variable has a binomial outcome. It is a statistical technique to forecast the likelihood of an occurrence from a linear combination of independent variables [21]. This establishes a tangible relationship between the independent and dependent variables, which can be utilized to make future predictions. In contrast to linear regression, logistic regression is chiefly employed for prediction and classification purposes, primarily when input data match to categorical outcomes

Support Vector Machine

SVM is a machine learning technique used to analyze data in order to find patterns, mostly in regression and classification. To categorize invisible data, SVM creates a binary linear classification model with a defined boundary. SVM is utilized for both linear and nonlinear scenarios, and it aims to maximize this boundary to deliver the best classification. The kernel trick is a potent technique used in the nonlinear classification scenario to project data to a higher-dimensional feature space [22].

Decision Tree

One machine learning technique that can be used for both regression and classification is the decision tree. A decision tree is a decision model that divides data into subsets according to feature values, creating a tree to represent decisions and their possible consequences. While leaf nodes in the tree reflect an outcome or a label, internal nodes in the tree represent feature decisions. The feature that best divides the data is repeatedly selected to create the tree, typically based on information gain or Gini impurity. Decision trees are easy to understand and effectively handle both continuous and categorical data [23].

Gradient Boosting

One machine learning method for classification and regression issues is gradient boosting. To build a powerful predictive model, the model combines a number of weak learners, usually decision trees, in succession. By focusing on residual errors, or the difference between the expected and actual values, the new tree corrects the errors of the previous trees. By minimizing the loss function, the gradient descent optimization approach is used to train the model. It is quite predictive, but if overfitting is not well controlled, it could be very sensitive [24].

XGBoost

The gradient boosting algorithm, which is optimized for speed and performance, is upgraded in XGBoost. By adding methods like regularization (L1 and L2), effective management of missing data, and parallelization for quicker calculation, it improves on the conventional gradient boosting. Sequentially, XGBoost constructs an ensemble of decision trees, each of which fixes the mistakes of the one before it. It is a popular among machine learning contests due to its great application in real-world situations and its ability to scale very widely while producing good accuracy on enormous datasets[25].

IV. Results and Discussions

This section discusses the early detection of MCI based on the results of machine learning algorithms such as logistic regression, random forest, SVM, and XGboost. These algorithms are then compared to see which is more accurate in identifying MCI. In order to statistically assess and compare learning algorithms, cross-validation divides the data into two parts. The model is trained using one half of the data (the training set), and it is tested using the other half. Such sets must typically be spaced out throughout the course of following rounds so that each piece of data can be confirmed by the data that comes after it. K-fold cross-validation, the most popular type of cross-validation, gives the norm altered in certain situations or when cross-validation is repeated. On this account, the accuracy of these criteria: precision, recall, and F-measure in detecting MCI is shown.

$$precision = \frac{TP}{TP + FP} \tag{3}$$

$$recall = \frac{TP}{TP + FN} \tag{4}$$

$$F - measure = 2 \times \frac{precision \times recall}{precision + recall} \tag{5}$$

TP (True Positives) is equal to the number of samples that have been correctly identified as positive. Similarly, FP (False Positives) is equal to the number of samples that have been incorrectly identified as positive, and FN (False Negative) is equal to the number of samples that have been incorrectly identified as negative.

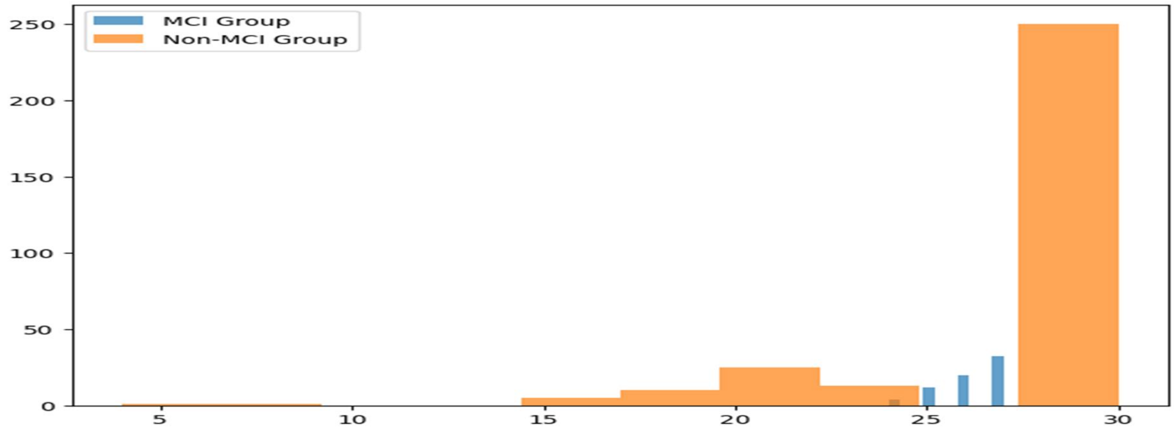

Figure 1 Distribution of MMSE scores for MCI and Non-MCI Groups

The Figure 1 clearly differentiates the two groups, providing an indication that MMSE or similar cognitive assessment tools are effective in distinguishing individuals with MCI from those without. It also emphasizes the concentration of scores at the extremes for Non-MCI participants versus the spread observed for MCI participants.

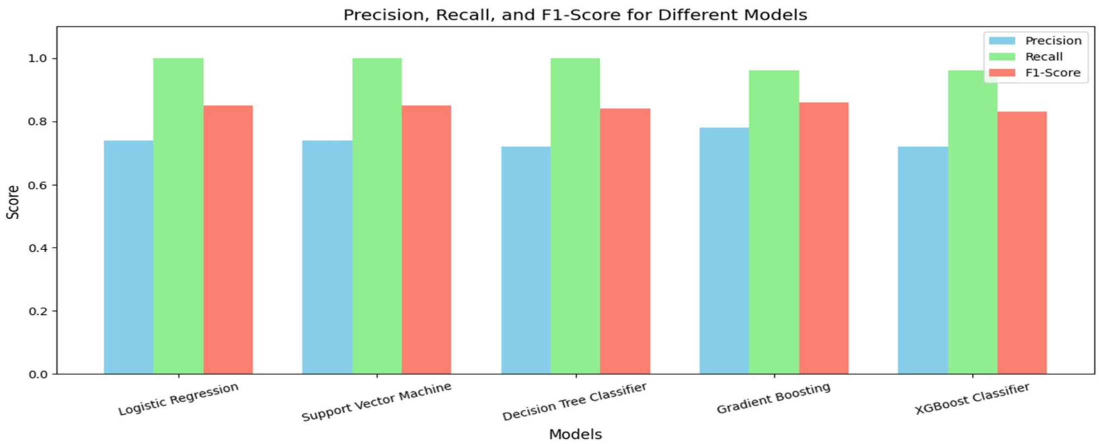

Figure 2 The classification report for Non-MCI patients

The Figure 2 shows the Precision, Recall and F1-Score for five classification models: Logistic Regression, SVM, Decision Tree, Gradient Boosting, and XGBoost and highlights the performance differences across the models, allowing for clear identification of strengths and weaknesses.

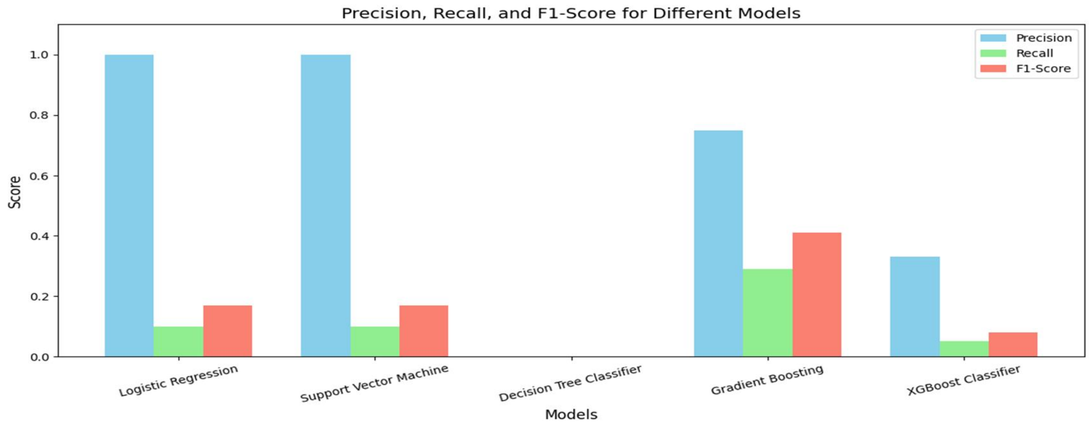

Figure 3 The classification report for MCI patients

The Figure 3 shows the comparison which underscores the importance of considering Precision, Recall and F1-Score together when evaluating model performance. The models like Logistic Regression and SVM excel at predicting specific positives, their inability to generalize reduces their overall utility. Models like Gradient Boosting offer better balance and more practical performance.

V. Conclusion

The frequency of MCI rises along with the number of young patients with MCI as the number of seniors rises as a result of societal aging. Since the number of older people is expected to increase in the next decades, primary care physicians will need to be proficient in identifying and treating MCI and cognitive decline because both conditions have serious repercussions for the patient and their family. By developing a system of criteria to identify patients with MCI and diagnose MCI at an early stage in a timely, reliable, and cost-effective manner, the proposed model can streamline the process of interpreting test findings and improve current clinical practice. In the future, a model that can more precisely predict MCI based on the patient's lifestyle or disease data will be developed with the goal of improving precision.

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