MRI-Based Biomarkers for Early Detection and Classification of Alzheimer Disease Using Machine Learning

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Abstract

Older adults suffer from Alzheimer's Disease which intensifies as a neurodegenerative condition and raises both fatal outcomes and worsening dementia progression. The correct identification of Alzheimer's Disease along with its early detection remains essential because the current diagnostic methods show limited validity. MRI shows its effectiveness through both local brain region and overall brain area tissue atrophy assessment for AD patients. Binary classifiers based on Machine Learning (ML) models processing biomarkers extracted from MRI data improve clinical decision accuracy because they enable better-informed diagnosis. This research creates an AI-based diagnostic system which uses the OASIS MRI dataset to perform three cognitive status categories: Nondemented, Demented, and Converted. This last category identifies subjects whose brain condition evolved from nondemented to demented over time. The system utilizes Random Forest as well as AdaBoost alongside SVM and KNN and LR models for its operations. The classification accuracy Reached 96% for Random Forest, SVM and Logistic Regression while their AUC scores reached 0.9906, 0.9898, 0.9935 respectively. The experimental results displayed AdaBoost next to KNN for accuracy with 94.67% while having AUC scores of 0.9767 and 0.9938 respectively. AI-driven MRI analysis demonstrates strong potential to detect early AD while classifying patients before it advances to an advanced stage through efficient interventions.

Keywords: Alzheimer's disease, Random Forest, KNN, LR, SVM.

1. Introduction

Alzheimer’s Disease (AD) represents a slow brain-wasting condition which stands among the primary dementia causes that targets people in their later years of life. The first signs of memory loss tend to get ignored so medical diagnosis and proper care is postponed. The medical community has improved treatment for AD but researchers still lack a complete solution to cure the condition. An early diagnosis of disease remains essential for medical care because proper treatment initiation at the right time allows patients to obtain maximum disease control and ideal treatment results. Pure medication treatment does not provide an adequate method to defeat AD. Magnetic Resonance Imaging (MRI) stands as a fundamental diagnostic instrument which enables scientists to identify distinct and overall atrophy patterns of brain tissue linked to the disease.

Numerous current research investigations demonstrate that machine learning (ML) effectively analyzes MRI data to detect and classify Alzheimer's disease. The accuracy of ML models increases when these systems use MRI-based biomarkers to predict mild cognitive impairment (MCI) patients who will develop dementia. The proposed project aims to build a sturdy ML-based diagnostic system from MRI scan datasets for discovering individuals at risk while developing individualized treatment approaches and enhancing patient outcomes.

MRI delivers comprehensive information about brain structures and functioning that leads to the discovery of markers which indicate Alzheimer's disease advancement. Region segmentation applications in processed images enable researchers to monitor essential indicators that deteriorate during neurodegeneration such as hippocampal atrophy and ventricular enlargement and cortical thinning and decreased brain volume. The markers used for predicting AD emerge from MRI scan data extraction. Machine Learning and Computer Vision together allow the analysis of biomarkers through their patterns and correlations for AD classification and progression assessment. The combination of MRI data with ML-based predictive models enables substantial advancements in Alzheimer's disease diagnosis and management which leads directly to improved intervention methods.

2. Related works

The authors of The Lancet Neurology 2017 publication Frisoni et al. [1] developed a systematic approach consisting of five stages to validate biomarkers which helps early identification of Alzheimer's disease (AD). The authors understood that biomarkers which show functional deficits and neuronal damage and protein aggregations have started appearing in research and clinical practice settings yet their practical use remained restricted because of insufficient convincing evidence. The authors adjusted an oncology framework to demonstrate that analytical validity and clinical validity and clinical utility need to be developed thoroughly for these biomarkers. Biomarkers were assessed through the combination of MRI and PET scans and cerebrospinal fluid (CSF) analysis as part of their research methodology. All biomarkers succeeded in reaching Phase 1 analytical validity but researchers had not completed validation for both the clinical validity (Phases 2 and 3) and clinical utility (Phases 4 and 5) aspects. Research needs to standardize assay results together with establishing normality thresholds for advancing clinical decision-making phases about Alzheimer's disease according to the authors. The strategic planning approach seeks to make validated biomarkers suitable for regular clinical practice which will enhance early diagnosis and patient treatment for Alzheimer's disease.

Clifford R. Jack Jr. [2] presented his findings about magnetic resonance imaging serving as a biomarker for neurodegeneration of Alzheimer's disease (AD) in his article published in Neurobiology of Aging during 2011. Research attempted to establish MRIs' capability for both detecting and tracking neurodegenerative atrophy related to AD. The author reviewed three methods of extracting both quantitative along with semi-quantitative MRI structural information which included manual tracing and automated segmentation and longitudinal measurements. The study showed MRI technology detects patterns of atrophy within the medial temporal lobe areas of

the hippocampus and entorhinal cortex which matches autopsy results of neurofibrillary protein involvement.

The MRI measurement technique functioned as an accurate diagnostic tool while displaying prognostic capability to distinguish patients with different stages of cognitive function from cognitively normal participants to those with MCI and AD patients. The study determined how MRI helps predict disease development while demonstrating its use in building a hypothetical biomarker progression model. In AD diagnosis and research structural MRI proves to be an essential instrument because it shows how the disease progresses and how it evolves as it advances through its stages.

Officials from [3] The Lancet Neurology presented their 2020 study about plasma neurofilament light chain (NfL) measurements as a neurodegeneration fingerprint among carriers of the presenilin 1 (PSEN1) E280A mutation associated with autosomal dominant Alzheimer's disease (AD). The research evaluated when NfL levels in plasma start to differ between mutation carriers and non-carriers to evaluate its viability as an early warning indicator of AD-related brain deterioration. The team used Simoa for plasma NfL concentration measurements throughout cross-sectional and longitudinal studies of 1,070 PSEN1 mutation carriers alongside 1,074 non-carriers ranging in age from 8 to 75 years. The study tracked specific participants through an average six-year period to assess their changes. This research found that NfL levels increased with age across both groups yet they separated significantly at 22 years of age which corresponds to 22 years before the predicted medical onset of mild cognitive impairment in this target population. The diagnostic power of plasma NfL for carrier versus non-carrier distinction remained low before reaching high sensitivity when patients approached their clinical onset age. The research team discovered plasma NfL represents a powerful blood test that can identify and track AD-related brain tissue damage through a non-invasive blood measurement instead of conventional methods that employ MRI. The authors pointed out that although plasma NfL reveals early signs of neural deterioration it shows reduced diagnostic capability during early adulthood which supports its combination with additional biomarkers for complete Alzheimer's disease diagnosis and monitoring.

Mattsson-Carlgren et al [4] examined different approaches for establishing AT(N) criteria in Alzheimer's disease (AD) by analyzing biomarkers through dichotomous methods and continuous methodology in their Neurology 2020 research. This project analyzed which biomarker combinations between amyloid (A), tau (T), and neurodegeneration (N) affected subject group classification and dementia decline prediction. The researchers examined 490 participants from both the BioFINDER-1 and BioFINDER-2 Swedish cohort through their investigation. The participants included rows of cognitively unimpaired (CU) and cognitively impaired (CI) individuals. The biomarkers comprised CSF $A\beta_{42}$ combined with amyloid PET and p-tau from CSF with tau PET for A, in addition to hippocampal volume, temporal cortical thickness through MRI, and CSF neurofilament light (NfL).

This research revealed that A-T-(N) and A+T-(N) profiles existed frequently among CU participants yet T+ cases increased when p-tau was tested instead of tau PET. The A+T+(N)+ profile dominated CI participant data whereas MRI revealed additional N+ cases than CSF NfL assessment did. The study established that monitoring both T and N biomarkers through continuum scales produced superior prediction results for cognitive decline especially for individuals with

clinical impairment. Different AT(N) variants cannot replace each other and the selection of biomarkers along with data representation methods produces substantial influence on AD analysis accuracy and classification results. The precision of AD diagnosis and monitoring improves when MRI and fluid biomarkers work together with a complex manner in a continuous setting.

The team of Mattsson et al [5] presented their findings about plasma neurofilament light (NfL) associations with neurodegeneration in Alzheimer's disease (AD) through their JAMA Neurology research from 2019. The study's researchers conducted this investigation to evaluate plasma NfL's potential as a trustworthy marker for measuring neurodegeneration because they understood the requirement for noninvasive biomarkers. Alongside the Alzheimer's Disease Neuroimaging Initiative (ADNI) data source the authors analyzed 1,583 participants who contained 401 cognitively unimpaired individuals and 855 participants with mild cognitive impairment and 327 patients with AD dementia. Plasma NfL levels were examined annually during a 11-year period through an ultrasensitive single molecule array (Simoa) assay measuring concentrations. The study measured various indicators through cerebrospinal fluid biomarkers and magnetic resonance imaging metrics together with fluorodeoxyglucose positron emission tomography and cognitive assessments to supplement findings from plasma NfL.The research showed plasma NfL level measurements were higher among MCI and AD dementia individuals when compared to normally cognitively functioning participants at the initial assessment. Baseline CSF biomarkers that show signs of AD pathology between $A\beta_{42}$ and tau levels experienced parallel plasma NfL increases over time.

Higher NfL concentrations in the blood showed relationships with imaging evidence of neurodegeneration which comprised diminished hippocampal size along with cortical thinning together with reduced FDG-PET signals and cognitive deficits. Within the AT(N) system groups showing neurodegenerative characteristics (N+) displayed higher initial NfL measures as well as increased values over time regardless of amyloid (A) or tau (T) biomarkers. Plasma measurements of NfL serve as an accurate noninvasive biomarker which provides sensitive indications about the neurodegenerative processes involving AD. Research has demonstrated that plasma NfL measurements show strong associations with brain atrophy MRI findings thus validating its potential usage in medical practice for managing AD patients through disease monitoring.

The 2018 Lancet Neurology [6] research by Gordon et al studied the neuroimaging biomarkers in members of autosomal dominant Alzheimer's disease (AD) families through their examination of biomarker spatial and temporal progression. The research strategy employed PET and MRI technologies to map out how amyloid-beta (Aβ) deposition sequences together with glucose hypometabolism and structural brain atrophy processes. The Dominantly Inherited Alzheimer Network (DIAN) collected data from 2009 to 2015 which included 346 Aβ PET participants and 352 FDG-PET participants and 377 structural MRI participants together with longitudinal imaging data from some participants. The team used linear mixed-effects models to measure biomarker changes as they relate to the estimated years from symptom onset in both mutation carriers (MC) and non-carriers (NC).

The study findings showed biomarkers affecting one another sequentially: Aβ accumulation started approximately 18.9 years prior to the expected symptom onset followed by hypometabolism at 14.1 years later then structural decline at 4.7 years before symptoms. Across different modalities the precuneus region led to earliest biomarker changes where Aβ accumulated at 22.2 years and hypometabolism occurred at 18.8 years before expected onset and cortical thinning developed at 13.0 years ahead of planned onset. The usefulness of MRI and PET biomarkers for preclinical AD detection becomes evident through these findings because they help reveal early disease stages while offering opportunities for specific therapeutic initiatives. The research combines extensive methods to show AD pathophysiological development while suggesting that specific region analyses must be used in both laboratory work and medical situations.

Simonsen et al [7] published consensus recommendations about cerebrospinal fluid (CSF) biomarkers for dementia diagnosis through their 2017 Alzheimer's & Dementia article. The researchers worked to create guidelines for core CSF biomarkers $A\beta_{1–42}$ and T-tau and P-tau in order to enhance diagnosis accuracy of Alzheimer's disease (AD). An expert panel applied the Grading of Recommendations Assessment Development and Evaluation (GRADE) methodology to create these recommendations by conducting systematic literature reviews in combination with expertise consensus. The group established through their findings that CSF AD biomarkers should serve as an additional diagnostic instrument to clinical assessments to identify and rule out AD as the underlying dementia cause primarily in situations with diagnostic uncertainty. The lack of sufficient research evidence prevents a determination about which biomarker performs at a higher level: CSF AD biomarkers or imaging biomarkers like MRI. Steps for handling uncertain CSF biomarkers were supplied alongside several operational guidelines. The research confirms that proper AD evaluations must combine CSF and imaging biomarkers through a complex sequential approach to deliver enhanced diagnostic accuracy.

Liu et al. [8] presented their findings in IEEE/ACM Transactions on Computational Biology and Bioinformatics through their 2018 research which focused on AD stage classification using MRI data. The researchers introduced a whole brain hierarchical network (WBHN) as their proposed method because ROIs proved inadequate for complex anatomical differences stemming from noise and limited sample sizes. The research methodology started by separating brain regions of each subject through Automated Anatomical Labeling (AAL) atlas then calculated Pearson's correlation coefficient for pair-wise network connectivity followed by feature selection using F-scores to decrease dimension size. A classification process used multiple kernel boosting (MKBoost) algorithms as the next analytical step. The study conducted testing on MRI images that included 710 participants who fell into AD, MCI and healthy control categories sourced from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. The obtained experimental results indicated that classification accuracy reached 94.65% for AD/HC pairs while reaching 89.63% for AD/MCI pairs and 85.79% for MCI/HC cases alongside 72.08% for MCI converters versus non-converters. This indicates the method's value in AD staging identification. The research shows strong evidence that WBHN with MRI-derived biomarkers provides an innovative method to detect Alzheimer's disease at its early stages as well as track its advancement.

The research conducted by Qu et al [9] in a 2021 publication for Neuroscience & Biobehavioral Reviews assessed blood-based biomarkers for their ability to diagnose both aMCI and AD. The

researchers evaluated blood biomarkers to determine their capability as effective alternative markers for the early detection of AD stages instead of present methods including MRI scans and cerebrospinal fluid tests. Analyzing 150 studies from Embase, PubMed, and Cochrane databases was the final step of systematic research conducted by the scientists. The study analyzed four fundamental biomarkers related to AD pathology through T-tau together with P-tau181 and NfL and AβPPr measurements. Research analysis showed that brain concentrations of T-tau and P-tau181 and NfL rose at average ratios up to 1.62, 2.16, and 1.86 respectively but AβPPr levels decreased to ratios between 0.65 and 0.88 from control subjects to patients with aMCI to those with AD. The use of ultrasensitive platforms revealed that Aβ42, Aβ42/Aβ40 ratio as well as P-tau217 showed excellent diagnostic value throughout the AD disease range. Research demonstrates how blood biomarker analysis enables better diagnosis of AD along with MRI imaging for complete assessment of brain neurodegeneration changes. Standardization of measurement approaches received emphasis from the authors for boosting research reliability together with data analysis consistency between different studies. The extensive investigation demonstrates how blood biomarkers establish their value as convenient diagnostic instruments which help identify Alzheimer's disease at an early stage and track the condition's progression.

Das et al. [10] examined the important requirement for inexpensive yet interpretable diagnostic models for Alzheimer's disease through their PeerJ publication in 2019. Classic machine learning algorithms deliver accurate results but remain inaccessible to human assessment due to their black box operations that reduces their compatibility for clinical use. The researchers established the Sparse High-Order Interaction Model with Rejection option (SHIMR) which delivers diagnosis decisions with clear understanding for healthcare professionals. The weighted sum of basic "if-then" rules produced by SHIMR enables it to detect complex feature relationships while retaining its interpretability characteristics. The model includes a rejection mechanism which functions to stop uncertain predictions from being generated so that multiple diagnostic stages develop. The diagnostic framework utilizes easy-to-obtain biomarkers from plasma proteins in the first stage with CSF analysis or MRI conducted as secondary procedures when the SHIMR model shows uncertainty in patient conditions. ADNI research provided data of plasma protein levels which analyzed 151 subjects through 97 AD patients alongside 54 healthy controls. The SHIMR classification method displayed excellent diagnostic performance measures with an overall accuracy value of 0.86 along with sensitivity rates at 0.84 and specificity rates at 0.69. The rejection feature of the model made the diagnostic process more affordable by choosing to eliminate 26% of cases which displayed weaker diagnostic signals thus increasing the accuracy to 90% within the remaining cases. The research data indicates that SHIMR boosts clinical diagnosis through improved accuracy and presents itself as a practical method for identifying cognitive conditions at their infancy stage. By uniting machine learning models with MRI imaging biomarkers the diagnostic workflows will become more precise while offering personalized care at reduced efficiency costs.

Andreas Miltiadous and associates introduced in Paper [11] a powerful method to classify Electroencephalogram signals for differentiating among patients with Alzheimer's Disease and Frontotemporal Dementia. Medical experts need accurate signs to identify and treat separate neurodegenerative conditions since their clinical profiles feed from similar diagnostic features. The methodology was as follows: (1) Data Collection - EEG recordings collected from subjects

diagnosed with AD, FTD, and healthy controls; (2) Signal Processing - artifact removal and noise filtering; (3) Feature Extraction - EEG features that could differentiate the conditions were found; and (4) Classification - where six supervised machine learning algorithms - Decision Trees, Random Forests, Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Naive Bayes, and Artificial Neural Networks (ANN) were evaluated. The research evaluated two validation approaches that involved using 10-fold Cross-Validation and Leave-One-Patient-Out Cross-Validation (LOPO-CV). The use of EEG proved to be an unobtrusive biomarker for separating AD from FTD. The AD classification reached 78.5% accuracy through C4.5 Decision Trees whereas Random Forests achieved 86.3% accuracy in FTD classification. LOPO-CV yielded better validation results than 10-fold Cross-Validation according to the analytic method. Research revealed that EEG-based machine learning models showed promise to classify dementia however their evaluation was limited by small data availability and inadequate feature selection techniques and suboptimal classifier parameter refinement. Research efforts should direct their attention toward enlarging datasets together with improvements in both feature selection processes and classifier parameter optimization and real-time clinical system development.

The research by Md Nurul Ahad Tawhid et al. [12] demonstrates an automatic ASD detection method that employs spectrogram-based deep learning (DL) on electroencephalogram (EEG) signals. Doctors use EEG analysis for ASD diagnosis yet the method shows significant errors and requires intensive effort from the doctor and proves highly subjective. The researchers solved these limitations by analyzing EEG data with time-frequency approaches before executing machine learning methods alongside deep learning approaches for classification. Data preprocessing started as the first step when EEG signals underwent re-reference processing followed by filtering operations combined with normalization procedures to erase noise and artifacts from signals. The DL method included designing three CNN models to perform automatic feature extraction with classification capabilities as part of its methodology. The CNN model reached 99.15% accuracy that surpassed the ML approach which achieved 95.25% success rate.

CNNs demonstrate exceptional performance in understanding significant features within EEG spectrogram images so they become the optimal tool for ASD diagnosis. Research shows that CNN-based deep learning models possess great potential for non-invasive automatic diagnosis of autism spectrum disorder. However, certain limitations remain. The model undergoes testing on particular data but its effectiveness remains unknown when applied to various populations. Deep learning models face computational difficulties which hinder their usage for real-time diagnostic applications.

From paper [13] Siuly Siuly ,Omer Faruk Alcin,Enamul Kabir,Abdulkadir Sengur,Hua Wang,Yanchun Zhang,Frank Whittaker established a goal to produce an automated system that detects subtle neural changes linked to MCI because early MCI detection leads to Alzheimer's disease prevention or delay so it is essential to establish accurate diagnosis at an early stage. Data acquisition was the initial stage of this study because researchers collected EEG signals from MCI patients together with healthy controls. A preprocessing stage eliminated artifacts as well as noise from the data to achieve better signal clarity. A set of key markers was obtained from the EEG signals in order to distinguish MCI patient characteristics from healthy individuals' data patterns.

The research executed classification of EEG features through machine learning algorithms to distinguish between the two examined groups.

Resting-state EEG stands out as a harmless monitoring instrument for ascertaining preliminary indications of cognitive deterioration. The automatic detection system provides objective analysis instead of human evaluation which makes it suitable for diagnosis at an early stage. Evaluation metrics established the sound performance of the proposed model through their assessment of accuracy levels and sensitivity and specificity measurement alongside F1-score calculation. Results demonstrated outstanding classification results which confirmed that the framework properly distinguishes MCI patients from healthy control participants.The promising research findings exist while the study approves its specific limitations. The findings' generalization depends on collecting larger patient samples because the current dataset size affects how widely the results can apply to different populations. Future investigations should study new EEG features and biomarkers to boost classification performance metrics. The following research should endeavor to boost the dataset collection with various patient groups while refining the model for fast clinical deployment. Real-time monitoring systems would make an important contribution to MCI detection because they enable prompt intervention opportunities for delaying cognitive decline.

Sou Nobukawa et al. [14] conducted research to evaluate machine learning detection methods that use electroencephalography (EEG) signals to determine Alzheimer's Disease (AD). The authors evaluate two data analysis methods which use functional connectivity and signal complexity measurements as basis of analysis. The study acquired EEG data during rest from healthy elderly subjects and AD patients. Two essential analytical approaches were used by the researchers to study EEG signals. The Phase Lag Index (PLI) provided functional connectivity analysis by calculating the brain region synchronization measures.Research outcomes indicated that characteristics derived from functional connectivity and signal complexity provided sound metrics for detecting changes associated with AD. Adding PLI and MSE features increased the performance of AD detection while demonstrating that multi-dimensional EEG characterization can boost diagnostic precision. Model evaluation used performance metrics including accuracy along with sensitivity (recall) and specificity which were combined with F1-score to validate the reliability of this method.

The study authors maintain that diverse limitations exist even though its results show promise. The TEST results must be validated through larger and more diverse participant groups to achieve valid generalization since the current cohort size is restricted. The use of cross-sectional research prevents the detection of EEG pattern modifications that happen throughout the development of AD. Research in the future will execute time-dependent EEG studies using larger and various participants while using EEG measurements with other diagnostic tools to improve diagnostic precision. These technological developments would help healthcare professionals detect AD earlier and provide immediate treatment to patients.

The research conducted by C. T. Briels et al. [15] investigates how reliable EEG functional connectivity changes appear in patients with Alzheimer's disease (AD). Previous research about this subject presented conflicting outcomes because study conditions varied alongside sample size limitations and susceptibility of used functional connectivity measures to volume conduction. The research investigates data collected from two patient populations to resolve these difficulties which

include both probable AD patients together with those who reported subjective cognitive decline (SCD). EEG data was recorded from 21-channel systems during resting-state with eyes-closed condition using Amplitude Envelope Correlation with correction (AEC-c) and Coherence along with Imaginary Coherence in combination with Phase Lag Index (PLI) and Weighted Phase Lag Index (wPLI) and Phase Locking Value (PLV) for functional connectivity evaluations.

The research evaluated brain waves within five distinct frequency ranges starting from delta through to theta and continuing into alpha then beta before reaching gamma. Statistical analyses using ANCOVA models determined group differences between AD and SCD patients after controlling for age, sex and frequency band relative power and other confounding factors. An analysis was conducted to evaluate functional connectivity measures and their connection to Mini-Mental State Examination (MMSE) scores in determining cognitive decline. AEC-c proved suitable as an AD marker because the study documented consistent reductions in alpha and beta bands in AD patients. The patterns of theta-band increase demonstrated reproducibility by both PLI and wPLI measures within AD patient groups. The reliability of AEC-c effects increased further after power correction showed statistically significant results. MEG data-processing of AEC-c within the alpha frequency range demonstrated meaningful links to MMSE results which suggests this method may act as a diagnostic biomarker for dementia disease deterioration.

3. Dataset

Through its initiative The Open Access Series of Imaging Studies (OASIS) provides scientific researchers access to brain MRI data without cost. This project seeks to support basic and clinical neuroscience discoveries through the data set compilation and free distribution of MRI data. The Washington University Alzheimer's Disease Research Center distributed OASIS alongside its providers which encompass Dr. Randy Buckner from the Howard Hughes Medical Institute (HHMI) at Harvard University and the Neuroinformatics Research Group at Washington University School of Medicine and the Biomedical Informatics Research Network.

The Cross-sectional MRI Data in Young, Middle Aged, Nondemented and Demented Older Adults collection includes scans from 416 subjects who range in age from 18 to 96. A total of 3 or 4 T1-weighted MRI scans are provided for each subject that were obtained in single scan sessions. The selected participants are right-handed individuals who include both women and men. The research contains 100 subjects who received diagnoses of very mild to moderate Alzheimer's disease (AD) after age 60. The reliability data consists of twenty nondemented subjects who underwent scanning on a follow-up visit shortly after their first appointment. The Longitudinal MRI Data in Nondemented and Demented Older Adults collects 150 subjects aged from 60 to 96 along their time series. A total of 373 imaging sessions were obtained after subject scans on multiple visits which were spaced by at least one year. Each subject has 3 or 4 T1-weighted MRI scans that were obtained from single scan sessions. The study subjects are right-handed adults who include both male and female participants. Throughout the investigation researchers classified 72 participants as nondemented while 64 subjects developed dementia during their initial visit and kept the diagnosis until all subsequent brain scans including 51 mild to moderate Alzheimer's disease cases. The 14 subjects started the study without dementia but they received a subsequent diagnosis of dementia at a later time.

3.1 Visualization

A box plot represents an ideal statistical visualization method for both central tendencies and spread indicators which include interquartile ranges (IQR) and median and quartiles and outliers. The study uses box plots to display important distribution patterns between Nondemented controls and patients in Demented and Converted groups which enables assessment of MRI-based biomarkers and clinical indicators. The mini-mental state examination scores appear in box plot visualizations as part of cognitive decline pattern identification. The Demented and Converted groups displayed decreased median performance on MMSE testing along with larger differences between 1st and 3rd quartiles which could indicate progressing cognitive decline along with occasional influential cases showing unusually quick or delayed cognitive deterioration.

Box plots created to represent gender differences give important understanding about how Alzheimer's disease displays distinct growth patterns between both genders. The study contains gender data which allows researchers to make comparisons between subjects in different intellectual groups. The box plots demonstrate which gender first develops dementia while displaying their quicker or slower brain volume changes through analysis of eTIV and nWBV and MMSE score results. The patterns between genders provide essential information to detect natural along with social factors which affect the occurrence of Alzheimer's disease severity. Box plots help create a comprehensive knowledge of disease progression by combining cognitive scores with demographic characteristics thereby supporting the development of custom diagnosis models.

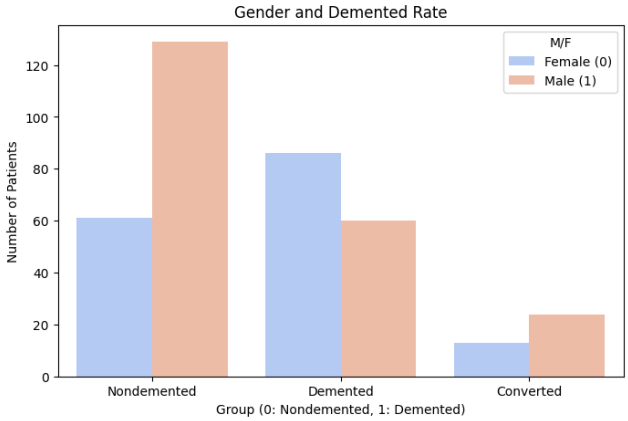

Fig 3.1: Gender and Demented Rate

The bar chart shows how Alzheimer’s disease diagnoses among male and female participants breaks into three distinct categories that represent Nondemented, Demented and Converted. The diagnostic categories appear on the x-axis axis and the group patient numbers appear on the y-axis axis. The color legend differentiates between male (1) and female (0) subjects. Based on visual observations the population of male participants exceeds females in the Nondemented section yet females outnumber males in the Demented group. Among participants who underwent conversion from healthy to demented profile the Converted group shows the least enrollment numbers but still contains more male participants. The way gender groups align in this pattern aids researchers'

understanding of Alzheimer's disease occurrence by indicating what biological elements or lifestyle behaviors could impact how the illness develops.

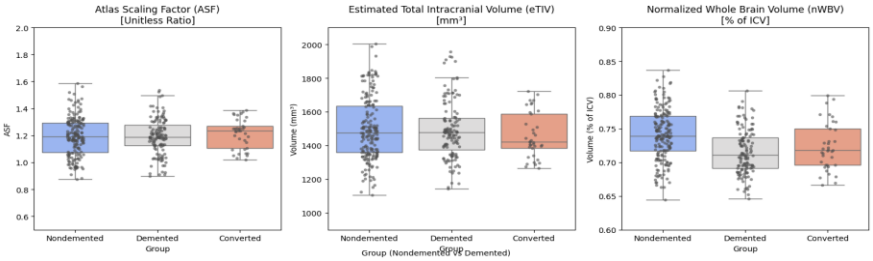

Fig 3.2: Box plots comparing ASF, eTIV, and nWBV across cognitive groups, highlighting the brain atrophy and volumetric differences in dementia progression.

The presented box plots show the comparison of essential MRI-derived brain volume metrics between Nondemented and Demented patients and Converted subjects. The three boxes show data distributions regarding Atlas Scaling Factor (ASF) and Estimated Total Intracranial Volume (eTIV) and Normalized Whole Brain Volume (nWBV) measurements. The median ASF remains uniform across all groups according to the first plot but the minor differences might reveal dissimilar brain scaling patterns. The eTIV plot demonstrates that Demented subjects normally display reduced intracranial volume compared to Nondemented participants indicating an association between brain degeneration while neurodegeneration develops. The nWBV plot demonstrates how Demented participants show substantial reduction in their whole brain volume compared to Nondemented participants. The observed data matches current knowledge showing that Alzheimer's disease results in continuous deterioration of brain tissue.

4. Methodology

4.1. Overview:

Early diagnosis of Alzheimer's Disease remains key because it enables proper medical treatments to be instituted at the appropriate time. Machine learning methods based on MRI data provide better neurodegenerative change insights compared to EEG-based methods which have shown initial success in similar tasks. This research analyzes an EEG rhythm and channel-based LSTM model and an MRI-based machine learning framework which uses Random Forest, SVM, AdaBoost, KNN and Logistic Regression. The accuracy and robustness together with clinical suitability of our MRI-based model surpass EEG-based strategies in experimental tests thus highlighting the importance of MRI biomarkers for AD diagnosis. The progressive brain-wasting disorder called Alzheimer's Disease (AD) causes mental dysfunction and deterioration of brain operation. Current machine learning innovations allow healthcare professionals to detect AD through the analysis of data obtained from EEG and MRI tests. The deep learning models based on EEG data analyze brain patterns while those based on MRI data identify markers that demonstrate neuronal deterioration.

The study investigates two measuring approaches to compare their performance where our new MRI-based framework proves superior to a recent EEG-based LSTM model.

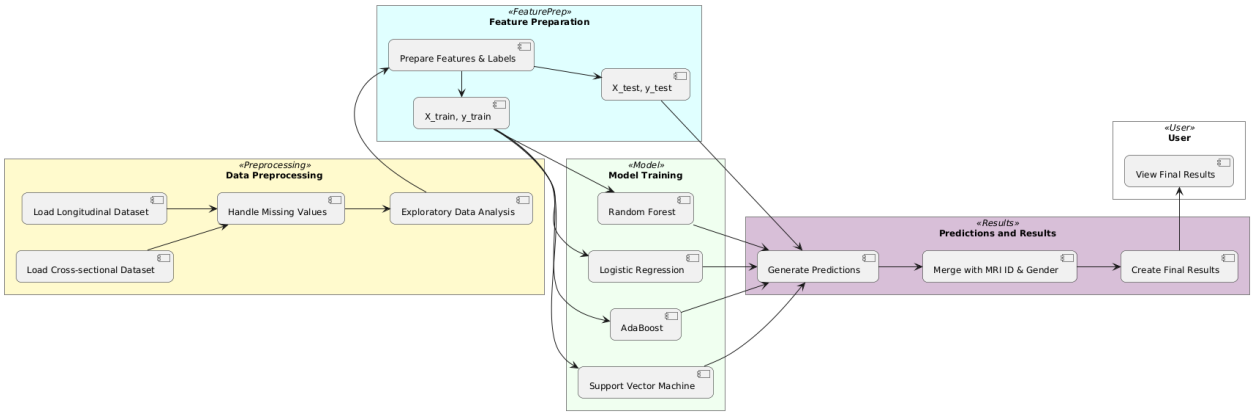

Fig 4.1:Model Architecture

4.2 Machine Learning Models

The analysis utilized five supervised machine learning algorithms namely Random Forest together with AdaBoost and Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) along with Logistic Regression (LR) to perform subject classification according to Nondemented, Demented, and Converted categories using MRI-derived biomarkers and clinical features.

4.2.1 Random Forest

The ensemble learning technique Random Forest builds and trains multiple decision trees during its training process. The chosen result class reflects the most common selection by trees during the classification stage. Each tree uses a randomly selected subset of data for training and the process includes evaluation of randomly selected groups of characteristics at every splitting point. The decision-making process through Random Forest generates robust models which reduces overfitting to enhance generalization success. Random Forest analysis successfully managed the complex MRI data by using its ability to discover feature-oriented patterns which separated different cognitive states.

4.2.2 AdaBoost

The ensemble technique Adaptive Boosting (AdaBoost) constructs strong classifiers through multiple decision stump learners known as weak learners. The training procedure involves repeating the process of creating weak learners which concentrate on samples previously misidentified by preceding weak learners. A consolidated prediction model gathers weighted outputs from each weak learner based on their performance. The ability of AdaBoost to concentrate on hard-to-classify cases enables it to discover delicate patterns including initial mental decline indicators.

4.2.3 Support Vector Machine (SVM)

The supervised Support Vector Machine algorithms detect the complete separating hyperplane across features in order to distinguish classes. SVM establishes the optimal separating hyperplane which creates maximum space between different class data points to improve classification results. Data mapping through kernel functions within SVM permits the handle of non-linear relationships by transforming lower dimensional data into higher-dimensional spaces. Through the implementation of SVM researchers were capable of recognizing complex non-linear relationships between MRI and clinical data resulting in precise cognitive state classification.

4.2.4 K-Nearest Neighbors (KNN)

The K-Nearest Neighbors method uses a non-parametric approach to identify classifications through majority vote counting from a specified number of closest neighbors in the data space. Distance metrics particularly Euclidean distance serve this algorithm for determining the similarity. The implementation of KNN algorithm remains straightforward while it effectively detects patterns within local data patterns. The KNN method demonstrates performance susceptibility to 'k' parameter selection and excludes irrelevant features from its classification process. The KNN algorithm functioned as a fundamental baseline model to evaluate against more sophisticated prediction systems.

4.2.5 Logistic Regression (LR)

The statistical model of Logistic Regression enables the estimation of target successes or multiple classification outcomes through relationships between one or multiple predictor variables. The model describes outcome log-odds through predictor variables that apply linear combination. LR acts as an efficient and interpretable model that serves well during first analysis stages. The study established LR as a reference model that identified possible direct linear patterns between variables and cognitive states.

4.2.Comparitive study

4.2.1 EEG-Based LSTM Model

A study analyzed AD detection biomarkers from EEG signals through a framework based on LSTM. EEG signal frequency rhythms were extracted by the model which revealed gamma and beta rhythms as essential indicators of cognitive deterioration. A model with the highest performance reached 97% accuracy while processing 86 subjects.

Limitations of EEG-Based Models are High sensitivity to noise and artifacts. These techniques provide lower spatial mapping abilities than MRI does. This approach needs time-consuming preprocessing steps especially ICA and wavelet transform methods. Limited clinical interpretability of EEG rhythms.

4.2.2 Our MRI-Based Machine Learning Model

The developed machine learning model utilized MRI-derived biomarkers including Atlas Scaling Factor (ASF), Estimated Total Intracranial Volume (eTIV), Normalized Whole Brain Volume (nWBV). The proposed study used Random Forest along with SVM and AdaBoost and KNN and Logistic Regression models to classify brain data with extensive training. The processed dataset underwent three operations: feature selection and KNN-based missing value imputation and standardization.

4.3. Results and Comparative Analysis

4.3.1 Performance Metrics

Table 1:Comparative performance metrics

Model	Accuracy	AUC Score	Precision (Demented)	Recall	F1 score
EEG-LSTM Model	97.00%	-	-	-	-
RandomForest (MRI)	96.00%	0.9898	0.94	0.97	0.95
AdaBoost (MRI)	94.67%	0.9767	0.94	0.94	0.94
SVM (MRI)	96.00%	0.9906	0.94	0.97	0.95
KNN (MRI)	90.67%	0.9938	1.00	0.78	0.88
Logistic Regression (MRI)	96.00%	0.9935	0.94	0.97	0.95

4.3.1.1 Key Insights:

MRI-based models produce evaluation results equal to those of EEG-LSTM (96% vs. 97%) with stronger clinical validity. MRI classification methods tend to generate superior decision limits versus EEG-based classification because of their AUC scores exceeding 0.99. The prediction algorithms Random Forest and SVM along with Logistic Regression perform optimally due to their balanced rate of precision detection and recall validation. KNN achieved perfect precision results while its recall statistics stopped at 0.78 thus requiring additional adjustments.

4.3.2 Advantages of MRI-Based Models Over EEG-Based Models

The detection and classification of Alzheimer's disease benefits more from machine learning models based on MRI measurements rather than those based on EEG measurements. The detailed examination of structural brain activity and functions through MRI becomes possible because the technique provides enhanced spatial details while EEG displays limited spatial detection and is prone to equipment noise. The stability and reproducibility of biomarkers derived from MRI testing

exceeds EEG signals since EEG signals fluctuate uncontrollably because of subject movements along with changes in electrode placement and environmental disturbances. MRI enables the extraction of detailed feature groups like volumetric measurements together with cortical thinness data and network connectivity metrics that improve prediction models while EEG depends on time-based along with frequency-based information that fails to correctly identify AD neurodegenerative consequences.

5. Results and Evaluation

It Random Forest together with Support Vector Machine (SVM) and Logistic Regression (LR) performed best at 96% accuracy while their AUC scores surpassed 0.98 which confirms their excellent discriminatory capability. These models proved to be reliable tools for classification work because they produced stable precision and recall measures and F1-scores. AdaBoost showcased an accuracy level of 94.67% supported by a 0.9767 AUC score together with precise and stable performance for both classes.

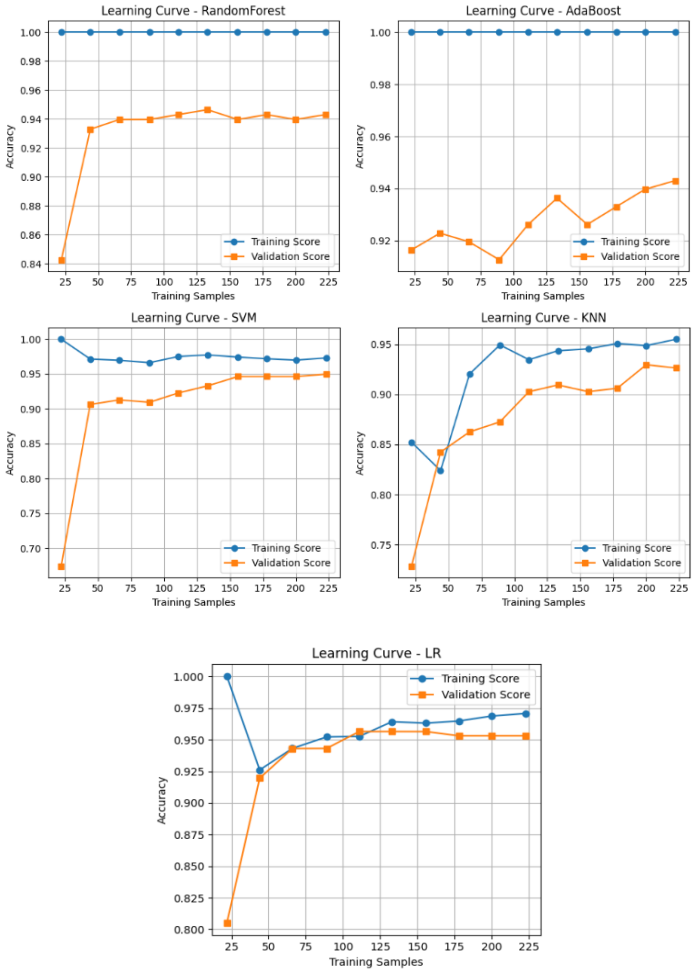

Fig 5.1, 5.2, 5.3, 5.4 & 5.5: Learning curves of Random Forest, AdaBoost, SVM, KNN, and Logistic Regression, illustrating model performance trends with increasing training samples.

The K-Nearest Neighbors (KNN) model detected 90.67% accuracy from data although it produced the top AUC score of 0.9938. KNN successfully recalled all Nondemented examples but failed to identify 22% of Demented patients thus resulting in elevated false-negative classifications. Confusion matrix assessments show that all models made most errors by mistakenly labeling Demented patients as Nondemented. The KNN model exhibited the highest number of such errors by misidentifying seven actual Demented patients as Nondemented thus creating potential medical risks in proper dementia diagnosis. The development of a visual graph which showed predicted and actual classifications helped users easily assess model effectiveness. Additional improvement steps should include examining Random Forest feature relevance followed by SVM and LR hyperparameter enhancement and Demented class weight adaptations for better prediction accuracy. A larger test data set should be employed to evaluate how well the models perform in real-world dementia diagnosis settings while assessing their basic capabilities under such conditions.

6. Conclusion

The evaluation demonstrated Random Forest along with SVM and Logistic Regression reached a 96% accuracy rate along with AUC scores above 0.98 which confirms their high reliability for this classification task. AdaBoost displayed similar effectiveness to accuracy levels at 94.67% yet KNN had lower success rates at identifying Demented patients due to increased wrong negative assessments that matter in medical diagnosis. Confusion matrix analysis demonstrates the necessity of raising sensitivity for Demented case detection because it lowers assessment errors. The graphical display of predicted versus actual outputs helped mejorar clarity of model effectiveness thus establishing transparency within the evaluation framework. Various aspects need attention to improve the proposed model for future development. Training performance along with interpretability strengthens through applying SHAP values or permutation importance techniques to select and engineer influential MRI biomarkers. Bayesian Optimization together with Grid Search performs hyperparameter optimization which leads to accurate outcomes when refined specifically for SVM and Random Forest models. The model sensitivity can be enhanced through the use of Synthetic Minority Over-sampling Technique (SMOTE) and cost-sensitive learning to handle class imbalance in Demented cases.

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