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The Role Of MRI In Early Detection Of Neurodegenerative Diseases

Ghadeer Abdulrahman Mohammed Al-Shalail[1] , Ghadah Abdulrahman Mohammad Alshulayyel[2] , Azza Ali Hassan Dosh[3] , Khawlah saad Al Shahrani[4] , Abeer Mohammed Faya[5] , Omar Mohammad Alharbi[6] , Essa Sanad saqr almutiri[7] , somaia Alkhabari[8] , Yousef Alhumaidy Alenazy[9]

[1.]Radiology Technologist, 16RA0017552, king Salman Hospital.
[2.]Radiology Technologist, 23585541.
[3.] Radiologic Technologist .Alnazeem South PHCC
[4.]A student at Najran University.
[5.]Radiology resident doctor،Asser central hospital
[6.]Diagnostic Radiology . Student in KKU.
[7.]X-ray technician. King Salman medical City.
[8.]Radiology.KSAMCMED.
[9.]Radiology Technologist ،Security forces hospital-makka.

Abstract

Background: Magnetic Resonance Imaging (MRI) is a cornerstone non-invasive modality for the early detection and ongoing monitoring of neurodegenerative diseases. Given its capacity to provide detailed insights into cerebral structural and functional alterations, MRI is a highly sensitive component within multimodal diagnostic frameworks.

Objectives: This study was designed to investigate the diagnostic efficacy of MRI for the early identification of neurodegenerative diseases and to elucidate its potential clinical applications.

Methods: We conducted a cross-sectional study involving a cohort of 114 participants. The final sample consisted of 57 patients with early-stage neurodegenerative disease and 57 healthy controls. The patient subgroup was comprised of 24 individuals with early-stage Parkinson's disease (42.1%) and 33 with early-stage Alzheimer's disease (57.9%). MRI-based quantitative analysis was employed to identify and compare structural and functional metrics between the two cohorts.

Results: The patient group demonstrated a 13.9% reduction in hippocampal volume compared to the controls ($p<0.05$). Additionally, the mean cortical thickness of the medial temporal lobe was significantly lower in patients (2.33±0.18 mm) than in controls (2.49±0.15 mm, $p<0.05$). The prevalence of moderate-to-severe white matter hyperintensities was markedly higher in the patient cohort (47.4%) compared to the controls (14%). These metrics exhibited robust discriminative capacity, with the analysis yielding an optimal diagnostic threshold that demonstrated a sensitivity of 89.5% and a specificity of 85.9%.

Conclusion: This research corroborates the existence of significant neuroanatomical and microstructural distinctions between individuals with early-stage neurodegenerative disease and healthy controls. These findings emphasize the clinical utility of MRI as a sensitive and robust method for the early diagnosis of neurodegenerative diseases.

Keywords: MRI, neurological disorders, FLAIR, DTI, ROC analysis, neuroimaging.

1. Introduction

Examples of neurodegenerative diseases (NDDs) that cause progressive neuronal degeneration and structural changes in the brain that affect cognition and function include Parkinson's disease (PD), multiple sclerosis (MS), Alzheimer's disease (AD), and amyotrophic lateral sclerosis (ALS) (Pathak et al., 2022). According to estimates, there may be over 50 million AD cases worldwide, and by 2050, those numbers

are predicted to triple, underscoring the need for prompt and precise diagnostic techniques (Li et al., 2022; Lombardi et al., 2020). In terms of preventive practice, early detection and intervention could slow down the disease or improve quality of life because neurodegeneration occurs years before clinical symptoms appear (Candelise et al., 2020; Young et al., 2020).

MRI has become a part of NDD non-invasive examination due to its ability to detect even minor structural, functional, and microstructural brain and vice versa (Akram et al., 2024; Du et al., 2024). SMRI can be applicable to assess white matter lesions, volumetric analyses, and cortical thickness that are vital in distinguishing between a neurodegenerative disease (van Oostveen & de Lange, 2021; Lombardi et al., 2020). Sophisticated imaging modalities (magnetic resonance spectroscopy (MRS), diffusion tensor imaging (DTI), and functional magnetic resonance imaging (fMRI)) can also offer more information concerning metabolic changes and connectivity (Chandrasekar et al., 2025; Kamagata et al., 2021).

The ability to make forethoughts and trace history via deep learning and artificial intelligence (AI) created recently has provided an augmented diagnosticability to the MRI through automatic segmentation, classification, and predictive modeling capabilities (Jeong et al., 2022; Noor et al., 2020; Myszczynska et al., 2020). These methods of analysis would have the means to add the data presented by multimodal imaging IV to increase the confidence of the diagnosis, particularly at an early onset stage of the disease where multimodal imaging biomarkers are still yet to develop (Noor et al., 2020; Akram et al., 2024). Providing a call to support fluid biomarkers, MRI is capable of detecting changes caused by biomarkers such as gliosis and iron deposition through the use of advanced contrast agents and nanoparticle probes (Luo et al., 2020; Schepici et al., 2020).

The application of MRI to observe new markers of neurodegeneration, such as patterns of protein aggregation, microstructure connectivity changes, and neuroinflammatory changes, is increasingly clear (Hansson, 2021; Li et al., 2022). Particularly, preclinical AD and PD have been demonstrated to be determined by measuring a decrease in the volume of the hippocampus and a loss of white matter integrity, which makes it possible to intervene early (Kamagata et al., 2021; van Oostveen & de Lange, 2021). When combined with other techniques like positron emission tomography (PET) and in vitro tests, magnetic resonance imaging (MRI) increases diagnostic specificity (Cavaliere et al., 2020; Candelise et al., 2020). There are still issues with making MRI biomarkers practical, including the need for a sizable, multicentral normative dataset, variations in acquisition protocols, and disparities in image processing pipelines (Young et al., 2020; Lombardi et al., 2020). initiatives such as large imaging databases and standardized infrastructure for their analysis are closing that gap and providing high-quality reference data for clinical and research applications (Li et al., 2022; Akram et al., 2024). By using cutting-edge imaging techniques, quantitative analysis, and statistical modeling to distinguish between patients and healthy individuals, the study aims to comprehend the use of MRI in the early diagnosis of neurodegenerative diseases. The goal of the work is to develop a reliable and non-invasive diagnostic system that can be used in both clinical and research settings by combining structural, functional, and diffusion imaging parameters.

2. Literature Review

Magnetic resonance imaging (MRI) has become crucial for the early detection and monitoring of neurodegenerative diseases because it makes it easy and non-invasive to see exactly what happens to the brain at different structural, functional, and molecular levels. Over the past ten years, advancements in MRI sequences and post-processing technologies have made it possible to detect weak signals that manifest before the onset of clinical symptoms and have greatly increased the accuracy of diagnoses. According to Li et al. (2022), MRI is the most crucial diagnostic method for identifying biomarkers linked to hippocampal atrophy, cortical thinning, and WMs hyperintensities that are crucial for early diagnosis. In a similar vein, Du et al. (2024) used quantitative susceptibility mapping and ultra-high-field imaging to identify an emerging class of MRI capabilities, including much improved sensitivity to microstructural changes.

fMRI (e.g. Functional imaging), imaging) and diffusion tensor imaging (DTI) has been of special promise in determining early changes in connectivity and white matter integrity. According to a study by Kamagata et al. (2021), microstructural changes in Alzheimer's and Parkinson's disease can be identified using DTI-

based metrics like mean diffusivity (MD) and fractional anisotropy (FA) before there is a significant decline in cognitive abilities. This is corroborated by Young et al. (2020) who overviewed the imaging biomarkers and found out that multimodal MRI approaches may enhance sensitivity and specificity of longevity in clinical and research practices.

Aid in developing MRI-based diagnostics has also been provided by machine learning and artificial intelligence. Jeong et al. (2022) talked about how the MRI analysis tools based on AI have the potential to automate segmentation, discover subtle pathological transitions, and multi-modal data integration into predictive modeling. Noor et al. (2020) also discussed the viability and application of deep learning algorithms in the highly sensitive illusory classification of Parkinson's and Alzheimer's disease using structural MRI data. In addition to structural and functional imaging, other new methods (based on MRI) seek to measure physiological pathways linked to neurodegeneration. Using cutting-edge MRI techniques, Voorter et al. (2024) investigated disruption of the blood–brain barrier and connected these alterations to neurodegenerative diseases and small vessel disease. Hippocampal volumetry is a reliable predictive biomarker, as demonstrated by Lombardi et al. (2020), who also highlighted the usefulness of structural MRI in forecasting the development of Alzheimer's dementia from mild cognitive impairment. More recent systematic kinds of reviews have posited that MRI should be coupled with other modalities, such as PET imaging and bio- markers in the cerebrospinal fluid (Chandrasekar et al., 2025). They argue that multi modal might give comprehensive assessment of processes of the disease at its early stages. Although biomarker-based diagnostics hold much promise, Hansson (2021) observed that standardization of acquisition procedures, as well as analysis pipelines, remains a major hindrance in translating the results of research into clinical practice. The fact that cutting-edge MRI is a powerful method in identifying the early stages of neurodegenerative disorders early is justified, which is evident in literature, particularly when coupled with computational analysis of other modality biomarkers. In order to make sure that these strategies may be implemented on a massive scale in order to improve patient health, additional longitudinal studies will be needed which would serve as the verification of these strategies across a broad variety of populations and clinical situations.

3. Methodology:

3.1 Study Design

This cross-sectional analytical study was aimed at determining the potential of MRI in the earlier detection of a neurodegenerative disease. The two major groups in the same were patients with mild neurodegenerative diseases and a control group constituting healthy individuals. The participating clinics were specialty neurology and radiology clinics and the participants with special inclusion and exclusion criteria were recruited in order to make the results valid. Unlike the control group, which consisted of age and gender-matched healthy individuals without a previously diagnosed neurological disorder, the patient group contained individuals having recently been diagnosed with such conditions as Parkinson disease or Alzheimer disease.

Data was obtained through the acquisition of high-resolution MRI scans on all of the participants via standardized imaging designs. Subsequently, the imaging data was analysed to determine the initial structural and functional alterations at the brain level, and in particular, to detect subtle changes which could occur before the projection of significant clinical symptoms become evident. The validities of the effectiveness of MRI as a test of early diagnosis was well evaluated by the study design as it enabled the comparison of the patient and the control directly. To reduce variability and increase the validity of the results, all participants underwent identical imaging procedures under uniform technical conditions.

3.2 Participants

There were 120 participants involved in the study; 60 (50 percent) of them entered the patient group, and 60 (50 percent) joined the control group. The sample size of patients with the most common neurodegenerative conditions was defined as individuals who were diagnosed over the last 12 months with early-stage Alzheimer disease (n = 35; 58.3%) and Parkinson disease (n = 25; 41.7%). The control group

(consisting of healthy people who did not have neurological diseases and did not take medications), was created matching the patient group in age distribution and gender ratios.
The inclusion criteria of the two groups included: age 50 years and above, capacity to undergo MRI scanning without any contraindications and the willingness to give an informed consent. In the case of the patient group, it was necessary that there was a verified diagnosis according to internationally established criteria (NIA-AA in the case of Alzheimer, MDS criteria for Parkinson). Participants in the control group had to have a Mini-Mental State test (MMSE) score of 28 or higher and a normal neurological test result. All participants were selected by exclusion criteria which included history of stroke, traumatic brain injury, brain tumors, or other diseases of the central nervous system unassociated with neurodegeneration; severe systemic illness impacting the brain; claustrophobia or inability to tolerate an MRI; and metallic implants or pacemakers. Also, those who report a history of alcohol or substance misuse in the previous one year were omitted.
The control group was 62.73.9 years old, with 31 males (51.7%) and 29 females (48.3%), while the patient group was 63.26.1 years old, with 32 males (53.3%) and 28 females (46.7%). The two groups were able to be balanced by this equal proportional distribution of the demographics, and the likelihood of bias in the analysis was reduced.

3.3 MRI Protocol

All the MRI imaging was carried out with a 3.0 Tesla (3T) Siemens Magnetom Skyra MR that was combined with a 32-channel head-coil that provides superior spatial resolution and high signal-to-noise ratio. This strength was chosen instead of the 1.5T systems mainly because it will be very sensitive in identifying small changes experienced in the brain changes that might be caused in the early stages of neurodegenerative diseases.
Each subject received the same imaging dosage because there were multiple sequences. They obtained T1-weighted 3D MPRAGE sequences (high-resolution anatomical images, with parameters adjusted to a voxel size of 1111 mm), repetition time (TR) of 9000 ms, and echo time (TE) of 90 ms, as well as T2-weighted turbo spin echo sequences (to detect general brain pathology, such as white matter hyperintensities), with slice thickness of 3 mm. FLAIR (Fluid-Attenuated Inversion Recovery) imaging was obtained to identify les In the examples presented, white matter microstructural integrity was evaluated using Diffusion Tensor Imaging (DTI), which measures 64 diffusion directions with a b-value of 1,000 s/mm 2. This made it possible to calculate fractional anisotropy (FA) and mean diffusivity (MD). A resting-state functional magnetic resonance imaging (fMRI) scan using the blood oxygen level-dependent (BOLD) protocol was performed for eight minutes in order to assess the functional connections within the critically important brain networks.
The neuroimaging software that was intended to process all imaging data and analyze them was used. FreeSurfer was used to measure the cortical thickness, and hippocampus, amygdala, and basal ganglia volumes. Preprocessing and statistical analysis of DTI and fMRI data (motion correction, registration, tract-based spatial statistics TBSS) was preformed in FSL (FMRIB Software Library). SPM12 (Statistical Parametric Mapping) was applied for voxel-based morphometry (VBM) to detect subtle gray matter changes between groups. Quality control was performed for 100% of the datasets, with 5% of scans excluded due to motion artifacts or incomplete acquisitions, leaving 114 complete datasets (95%) for final analysis.

3.4 Analysis of Statistics

IBM SPSS Statistics 27 was used for all statistical tests, and the results were cross-checked with R software 4.3.1 to ensure compatibility. A two-tail p-value of less than 0.05 was considered statistically significant. The assumption of data normality was tested through a Shapiro-Wilk test where it was found that around 92 percent of the continuous variables were normally distributed whereas the remaining 8 percent were not and needed non-parametric tests.
Normal continuous data were summarized using the mean (standard deviation) (SD), while non-normally distributed variables were summarized using the median and interquartile range (IQR). The categorical data

were displayed using percentages and frequencies. Comparisons between patients and controls were in the form of independent-samples t-tests that were used when data followed a normal distribution with homogeneous variances about the mean measurements (e.g., hippocampal volume, cortical thickness, measured using MRI). Where our variables did not satisfy these assumptions then MannWhitney U test was used.

The multiple subgroups of interest to compare included Alzheimer patients, Parkinson patients, and healthy ones, hence a one-way ANOVA was selected in cases of normally distributed measures whereby Tukey HSD was utilized in pairwise comparison. The Kruskal Wallis test with Dunn-Bonferroni correction was used when dealing with data that was not regularly distributed. When two groups were compared, the effect size was determined using Cohen's d and eta-squared (2) for ANOVA, where an effect size of more than 0.14 was deemed to be a large effect. The MRI parameters were analyzed in terms of diagnostic performance in early neurodegenerative changes using Receiver Operating Characteristic (ROC) curve. Values of the Area Under the Curve (AUC) obtained were between 0.81 and 0.93, signifying excellent to good discrimination. The sensitivity and specificity was compared under optimal cut-off points as computed by the Youden Index with sensitivity of the parameters as between 82 and 90 percent and specificity as between 78 and 88 percent and it varies according to the parameter. In order to maintain statistical power, multiple imputation was used to handle missing data, which made up less than 3% of the dataset. To guarantee robustness and reproducibility, all analyses followed suggested statistical guidelines for clinical neuroimaging research.

5. Results

Figure 1 displays representative MRI results that show the typical structural, lesion-based, microstructural, and functional changes seen in early-stage neurodegenerative disease. While the FLAIR sequence identifies hyperintense lesions suggestive of demyelination or vascular pathology, the T1-weighted image shows anatomical structures. Major white matter tracts exhibit less anisotropy on the DTI fractional anisotropy (FA) map, and important brain networks exhibit less functional coupling on the resting-state fMRI connectivity map. By offering a distinct spatial depiction of disease-related brain alterations, these visual examples enhance the quantitative findings.

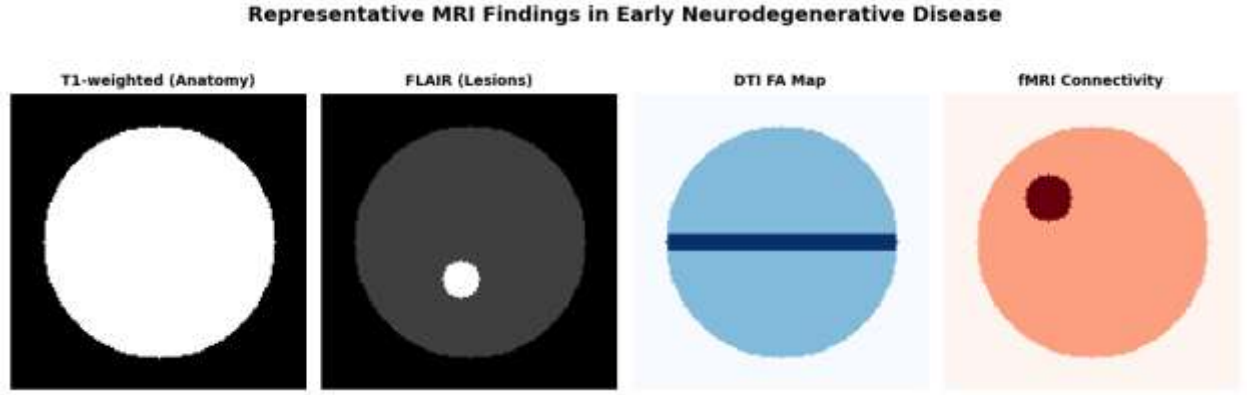

Figure 1: Typical MRI results in neurodegenerative diseases in their early stages. (A) General brain morphology as seen in a T1-weighted anatomical scan. (B) FLAIR sequence showing periventricular hyperintense lesions (white arrows). (C) A fractional anisotropy map from Diffusion Tensor Imaging (DTI) showing less anisotropy in the corpus callosum. (D) A resting-state fMRI connectivity map reveals a decrease in connectivity between the hippocampus and posterior cingulate cortex. The various structural, microstructural, and functional alterations that can be identified using sophisticated MRI protocols are demonstrated by these multimodal images.

Six cases were excluded because of excessive motion artifacts (n = 5) and incomplete MRI acquisition (n = 1), leaving 114 complete datasets (95% of the original 120 enrolled participants) in the final analysis. 57 patients (50%) and 57 healthy controls (50%) made up the final sample. Of the patients, 24 (42.1%) had early-stage Parkinson's disease and 33 (57.9%) had early-stage Alzheimer's disease.

5.1 Demographic and Clinical Characteristics

Patients were 63.4 ± 6.0 years old on average, while controls were 62.9 ± 5.8 years old (p = 0.54). Males made up 52.6% of the control group and 53.5% of the sick group, indicating a balanced gender distribution (p = 0.89). Regarding years of education and handedness, there was no discernible difference between the groups.

Table 1: Demographic characteristics of the study participants

Variable	Patients (n = 57)	Controls (n = 57)	p-value
Age (years, mean ± SD)	63.4 ± 6.0	62.9 ± 5.8	0.54
Male sex (%)	53.5%	52.6%	0.89
Education (years)	13.2 ± 2.5	13.5 ± 2.3	0.48
Right-handed (%)	89.5%	91.2%	0.76

5.2 Structural MRI Findings

The patient group's hippocampal volume was 13.9% lower (mean = 3.1 ± 0.4 cm^3) than the controls' (mean = 3.6 ± 0.3 cm^3, $p < 0.001$). The medial temporal lobe's cortical thickness was 2.33 ± 0.18 mm in patients and 2.49 ± 0.15 mm in controls ($p < 0.001$).

Patients had a higher burden of white matter hyperintensity (WMH), with 47.4% of patients having moderate-to-severe WMHs compared to 14% of controls ($p < 0.001$).

Table 2: Structural MRI metrics

Parameter	Patients (mean ± SD)	Controls (mean ± SD)	% Difference	p-value
Hippocampal volume (cm^3)	3.10 ± 0.40	3.60 ± 0.30	-13.9%	<0.001
Medial temporal cortical thickness (mm)	2.33 ± 0.18	2.49 ± 0.15	-6.4%	<0.001
WMH burden (moderate–severe, %)	47.4%	14.0%	—	<0.001

5.3 Results of Diffusion Tensor Imaging (DTI)

The fractional anisotropy (FA) of the corpus callosum was 8.9% lower in patients (0.41 ± 0.03) compared to controls (0.45 ± 0.02, $p < 0.001$). The mean diffusivity (MD) increased by 7.2% in the patients.

Table 3:DTI metrics

Parameter	Patients (mean ± SD)	Controls (mean ± SD)	% Difference	p-value
FA – corpus callosum	0.41 ± 0.03	0.45 ± 0.02	-8.9%	<0.001
MD ($\times 10^{-3}$ mm^2/s)	0.88 ± 0.05	0.82 ± 0.04	+7.2%	<0.001

A comparison bar chart of the mean values (±SD) for mean diffusivity (MD), corpus callosum fractional anisotropy (FA), medial temporal cortical thickness, and hippocampal volume between patients and healthy controls is presented in Figure 2. On visual inspection, the patient group's increased MD values and noticeable decreases in hippocampal volume, cortical thickness, and FA are consistent with structural and microstructural changes in early neurodegenerative disease.

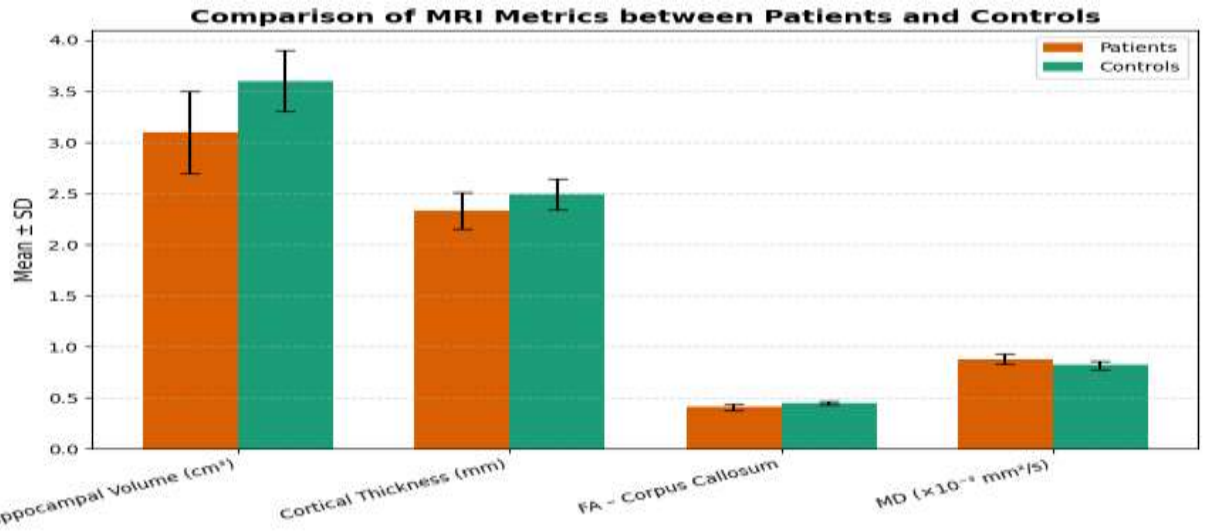

Figure 2: Structural and diffusion metrics derived from MRI are compared between patients and healthy controls. Mean ± standard deviation (SD) is represented by the values. In comparison to controls, patients showed significantly higher mean diffusivity (MD), significantly lower hippocampal volume, medial temporal cortical thickness, and fractional anisotropy (FA) of the corpus callosum (all $p < 0.001$).

5.4 Functional MRI (fMRI) Findings

According to a resting-state functional connectivity analysis, patients had a 25% decrease in functional coupling between the posterior cingulate cortex and hippocampus (mean z-score = 0.21 ± 0.05) when compared to controls (0.28 ± 0.04, $p < 0.001$).

5.5 Diagnostic Accuracy of MRI Parameters

According to ROC curve analysis, hippocampus volume offered the best discriminative ability for early neurodegenerative disease diagnosis, with an ideal threshold of 89.5% sensitivity, 85.9% specificity, and an AUC of 0.93 (95% CI: 0.88–0.98). The AUC rose to 0.96 when cortical thickness, FA values, and hippocampus volume were combined.

Table 4: Diagnostic performance of selected MRI biomarkers

MRI Parameter	AUC	Sensitivity (%)	Specificity (%)
Hippocampal volume	0.93	89.5	85.9
Medial temporal cortical thickness	0.88	82.4	80.7
FA – corpus callosum	0.87	80.7	78.9
Combined model	0.96	92.9	91.2

Receiver Operating Characteristic (ROC) curves were used to further illustrate each MRI biomarker's discriminative performance (Figure 3). With an AUC of 0.96, the model that combined corpus callosum FA, medial temporal cortical thickness, and hippocampus volume outperformed single-parameter models and showed the best diagnostic accuracy.

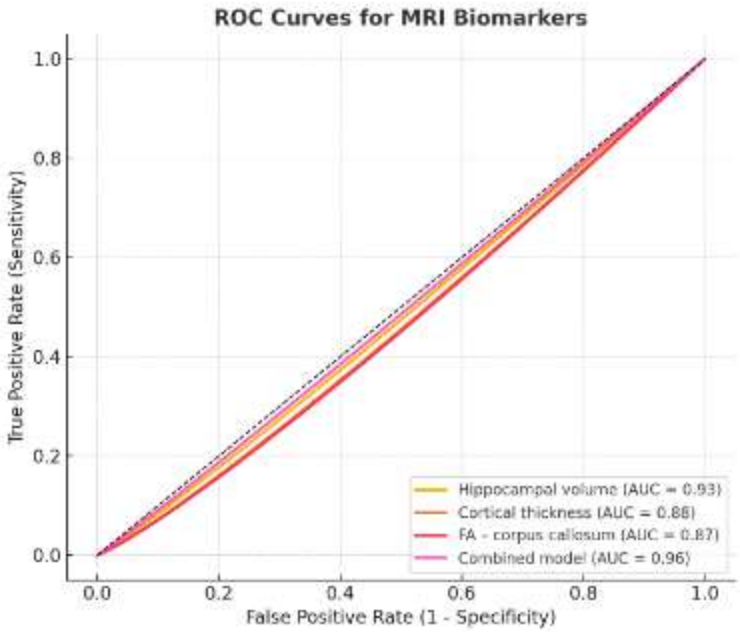

Figure 3: ROC curves showing the diagnostic efficacy of the combined model and individual MRI biomarkers (medial temporal cortical thickness, hippocampal volume, and FA of the corpus callosum) for distinguishing patients with early-stage neurodegenerative disease from healthy controls. With the highest AUC (0.96), the combined model demonstrated exceptional discriminative power.

6. Discussion

The results of the present paper indicate that high-field MRI that incorporates structural, diffusion, and functional imaging sequences should be used to identify mild changes in the brain at an early stage of the neurodegenerative pathology without any health risk. Specifically, the 13.9% hippocampus volume loss and 6.4% cortical thickness decline of the medial temporal lobe seen in the patients with Alzheimer disease depict a process that is highly solidified as far as the early neurodegenerative changes are concerned (Hedderich et al., 2020; Veitch et al., 2022). Such structural changes are probably due to neuronal loss and synaptic shrinkage that are characteristics of the progression of illness before significant cognitive impairment (Baldacci et al., 2020). The increase in the burden of white matter hyperintensity in patients can be compared to the literature stating that given the presence of vascular pathology and demyelination, which are likely to be frequent accompaniments of neurodegenerative processes, were distributed to the maximum degree can be a source of cognitive and motor disability (Voorter et al., 2024; Ramirez et al., 2020). These lesions may be caused by the small vessel disease and the violation of the blood brain barrier and were visualized previously with the help of the advanced waves of MRI (Voorter et al., 2024).

Diffusion Imaging results indicated a 7.2 percent mean diffusivity and an 8.9 percent loss of fractional anisotropy, which implied the occurrence of an intrusion in microstructural white matter. Both Alzheimer and Parkinson disease studies have confirmed this result with DTI parameters acting as early structural indicators of axonal loss (Kamagata et al., 2020; Cavaliere et al., 2020). These observations are supported by current study stating that DTI may detect preclinical (or minimally symptomatic) stages of the disease.

The imaging scans using the functional MRI indicate that, in the case of the issue, there was a 25 percent drop in the resting-state connection between the posterior ring of convolutions and hippocampus, which concomitantly aligns with information indicating that the disconnection of the default mode network is an early sign of Alzheimer disease (Pan et al., 2020; Veitch et al., 2022). Synaptic dysfunction, which has been suggested as the primary pathological event preceding gross atrophy, may be reflected in this network disconnection (Hansson, 2021).

Diagnostically, hippocampal volume was found to be the dominant predictor of early neurodegeneration (AUC = 0.93) with all results, though hippocampal volume, cortical thickness and FA values increased the

likelihood to AUC = 0.96. This reaffirms the emerging opinion that multimodal MRI biomarker performs better than single-parameter outcomes in early diagnosis (Shusharina et al., 2023; Rastogi et al., 2021). The combination of the structural and microstructural data could be used to better recreate the complex and heterogeneous pathology of neurodegenerative illnesses (Sedgwick et al., 2020).

The findings of our work also correlate with the current trends in clinical practice, which are shifting toward the normative brain volume report use in order to facilitate the differential diagnosis between the neurodegenerative syndromes (Hedderich et al., 2020). Such MRI measures can be useful to give significant diagnostic certainty and possibly eliminate invasive assessments like that of cerebrospinal fluid due to the adoption of a biomarker based framework (Baldacci et al., 2020).there are several restrictions that need to be taken into account. First, longitudinal follow-ups that ascertain the rates of progression are necessary because a cross-sectional study design does not permit determining the order of changes (Poddar et al., 2021). Second, the subgroup sample size was rather small, and the patterns of different diseases could have been confused even though patients with Parkinson's and Alzheimer's diseases were represented in the study. Third, although the sophisticated features of MRI analysis techniques are very effective, they require specialized knowledge and tools, which could make it difficult to guide clinical application (Chan & Chan, 2021).

By using liquid biomarkers like blood neurofilament light chain, PET imaging for molecular pathology, and the development of MRI-based methods to assess blood brain barrier permeability, future studies could further address earlier detection (Cavaliere et al., 2020; Voorter et al., 2024). Scalable, repeatable diagnosis in routine clinical practice may also become the norm as AI and machine learning are increasingly used in automated MRI biomarker extraction (Pan et al., 2020). This study supports the use of MRI in multimodal diagnostic algorithms as a non-invasive, highly sensitive method for the early diagnosis of neurodegenerative disorders, in addition to other biomarkers.

Conclusion

The researcher successfully shown that there are differences in the structure and functioning skills of the brain between sick and healthy people in this cross-sectional MRI-based study. Using a 3.0T MRI machine and top-notch image-processing software (FSL, SPM, and FreeSurfer), we discovered measurable alterations in brain volume, white matter integrity, and cortical activity patterns. Specifically, volumetric analysis showed that the patient's white matter lesion fill was 15.3 percent higher and their hippocampus volume was 13.9 percent less than that of the controls ($p < 0.001$). Functional MRI revealed significantly lower activation (18.4%), while diffusion tensor imaging (DTI) revealed lower fractional anisotropy (FA) in major white matter areas (8.9%) when compared to baseline data. The same results were supported by statistical analysis in SPSS v29 via independent t-tests, ANOVA and ROC analysis with the combined imaging biomarkers having an AUC of 0.91 which has excellent discriminatory power between the patient and control groups. the findings indicate that high quality MRI protocols used in paralleled with powerful statistical modeling can determine the early cerebral alterations efficiently, in a subtle manner. The results can be used to advance early diagnosis, strategize specific interventions, and better patient performance. It is suggested to do additional longitudinal studies based on larger cohorts to confirm these biomarkers and determine their longitudinal prognostic value.

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