Journal Publication of International Research for Engineering and Management (JOIREM)
Volume: 04 Issue: 5 | may-2026
ISSN (O) 3107-6696

AI POWERED VISION INTO THE BRAIN'S MICROSTRUCTURE

Gowthami H V[1], Hamsa M[2], Khushi K S[3], Monica S[4], Mr.Mallesh H L[5]

Student, Dept of AIML, Sri Siddhartha Academy of Higher Education (SSIT), Tumakuru, Karnataka, India[1,2,3,4],
Assistant Professor, Dept of AIML, Sri Siddhartha Academy of Higher Education (SSIT), Tumakuru, Karnataka, India[5]

---***---

Abstract - Accurate diagnosis of neurological disorders requires detailed analysis of brain microstructure, particularly white matter integrity. Manual interpretation of Magnetic Resonance Imaging (MRI) and Diffusion Tensor Imaging (DTI) scans is often time-consuming and susceptible to human error. This paper presents an AI-powered framework for automated brain microstructure analysis using Fractional Anisotropy (FA) values, image processing techniques, and deep learning models. The proposed system integrates MRI preprocessing, segmentation, tractography visualization, and disease classification into a unified diagnostic platform. Convolutional Neural Networks (CNN) and Random Forest classifiers are employed to identify abnormalities associated with neurological disorders such as Alzheimer's disease, Parkinson's disease, and brain tumors. Additionally, deterministic tractography is used to visualize defective neural fiber pathways in 3D, while an AI chatbot module provides basic clinical guidance and user interaction. The system is implemented using React.js, Node.js, and RESTful APIs to ensure scalability and efficient communication between modules. Experimental results demonstrate that the framework improves diagnostic efficiency, enhances visualization of brain abnormalities, and reduces the workload of radiologists. The proposed approach supports early detection, clinical decision-making, and future advancements in AI-assisted neuroimaging systems.

Keywords: Magnetic Resonance Imaging (MRI), Diffusion Tensor Imaging (DTI), Fractional Anisotropy (FA), Convolutional Neural Network (CNN), Random Forest, Tractography, Brain Micro structure, Deep Learning, Neuroimaging.

1. INTRODUCTION

The human brain is one of the most complex organs in the human body and is responsible for controlling cognitive functions, memory, emotions, movement, and communication. It mainly consists of gray matter and white matter, where white matter plays an important role in transmitting neural signals between different regions of the brain. Any damage or abnormality in white matter structure may lead to serious neurological and psychiatric disorders such as Alzheimer's disease, Parkinson's disease, multiple sclerosis, schizophrenia, and traumatic brain injuries. Therefore, accurate and early detection of abnormalities in brain microstructure is highly important for effective diagnosis, treatment planning, and monitoring of neurological disorders.

Magnetic Resonance Imaging (MRI) is a widely used non-invasive imaging technique that provides high-resolution images of brain tissues without exposing patients to harmful radiation. In recent years, Diffusion Tensor Imaging (DTI), an advanced form of MRI, has gained significant importance in neuroimaging because it allows the analysis of water molecule diffusion within brain tissues. DTI helps in studying white matter fiber tracts and understanding the structural connectivity of the brain. One of the key parameters derived from DTI is Fractional Anisotropy (FA), which measures the directional movement of water molecules within white matter pathways. Higher FA values indicate healthy and organized neural fibers, while lower FA values may indicate tissue damage, demyelination, or degeneration caused by neurological diseases.

Manual analysis of MRI and DTI scans is a difficult and time-consuming process that depends heavily on the experience of radiologists and medical experts. With the increasing volume of neuroimaging data, manual interpretation may also lead to inconsistencies and human errors. These limitations create the need for intelligent automated systems capable of analyzing medical images more efficiently and accurately. Recent advancements in Artificial Intelligence (AI), machine learning, and deep learning have shown promising results in medical image analysis, especially in disease detection and classification tasks.

Deep learning techniques, particularly Convolutional Neural Networks (CNN), are highly effective in extracting important features from medical images and performing classification with improved accuracy. Machine learning algorithms such as Random Forest classifiers further enhance prediction performance by combining multiple decision trees to produce reliable outputs. By integrating AI techniques with MRI and DTI analysis, it becomes possible to detect subtle abnormalities in brain micro structure that may not be easily identified through manual observation.

This project proposes an AI-powered framework for analyzing brain microstructure using MRI and DTI imaging techniques. The system integrates image preprocessing, segmentation, Fractional Anisotropy extraction, tractography visualization, and AI-based disease classification into a single platform. The proposed framework is designed to detect neurological disorders such as Alzheimer's disease, Parkinson's disease, and brain tumors. The system also includes a chatbot module that assists users by providing basic information related to brain diseases and imaging results.

The framework uses tractography techniques to visualize neural fiber pathways in three dimensions, helping doctors and researchers better understand structural abnormalities in white matter regions. By combining quantitative FA analysis with advanced AI algorithms, the proposed system aims to improve diagnostic accuracy, reduce the workload of radiologists, and support early detection of neurological diseases. The project contributes to the growing field of AI-assisted healthcare and provides a scalable and clinically relevant solution for future neuroimaging applications.

2. PROBLEM STATEMENT

Neurological disorders such as Alzheimer's disease, Parkinson's disease, and brain tumors require accurate and early diagnosis for effective treatment and disease management. Traditional analysis of brain MRI scans is mainly performed manually by radiologists and medical experts, which is often time-consuming, labor-intensive, and prone to human error. Detecting abnormalities in brain structure through manual observation becomes difficult when dealing with large amounts of imaging data.

Existing diagnostic methods often lack automation, intelligent analysis, and efficient visualization techniques, which may result in delayed diagnosis and reduced accuracy. Small structural changes associated with Alzheimer’s disease, Parkinson’s disease, and brain tumors may not always be easily identified during manual examination. In addition, the increasing number of patients and limited availability of neurological specialists create challenges in providing timely and reliable diagnosis.

Although Artificial Intelligence and deep learning techniques have shown promising results in medical image analysis, there is still a need for an integrated system that combines MRI preprocessing, image segmentation, disease classification, and tractography visualization within a single platform. Therefore, the main problem addressed in this project is the development of an AI-powered automated framework capable of analyzing brain MRI images, detecting abnormalities related to Alzheimer’s disease, Parkinson’s disease, and brain tumors, and improving the accuracy, efficiency, and reliability of neurological diagnosis while reducing the workload of healthcare professionals.

3. LITERATURE REVIEW

Pierpaoli et al., in “Diffusion Tensor Imaging of the Human Brain” (1996), introduced Diffusion Tensor Imaging (DTI) for analyzing white matter integrity using Fractional Anisotropy (FA). The study showed that reduced FA values are associated with fiber degeneration and tissue abnormalities. The authors also emphasized preprocessing techniques such as motion correction and skull stripping for accurate FA computation. This work forms the foundation for FA-based analysis used in the proposed project.[1]

Smith et al., in “Tract-Based Spatial Statistics (TBSS)” (2006), proposed a framework for comparing FA values across multiple subjects. The study introduced preprocessing and voxel-wise analysis techniques for identifying abnormalities in white matter regions. The concepts of normalization and comparison are useful for improving the reliability of the proposed system.[2]

Mori et al., in “Three-Dimensional Tracking of Axonal Projections” (1999), presented one of the earliest tractography techniques for reconstructing white matter pathways. The study demonstrated that neural fiber tracts can be visualized non-invasively using diffusion imaging. This work supports the tractography visualization module used in the proposed framework.[3]

Alexander et al., in “An Evaluation of Noise and Artifacts in Diffusion MRI” (2001), investigated the effect of motion artifacts and noise on FA accuracy. The authors proposed correction and filtering methods to improve MRI image quality. This research supports the preprocessing and denoising stages implemented in the project.[4]

Zhang et al., in “Segmentation of Brain MR Images Through a Hidden Markov Random Field Model” (2001), proposed a robust MRI segmentation technique for separating white matter, gray matter, and cerebrospinal fluid regions. The study improved segmentation accuracy in noisy MRI images and supports the segmentation stage of the proposed system.[5]

Prakash et al., in “Automated Detection of Alzheimer’s Disease Using DTI Metrics and Machine Learning” (2014), used FA and tract-based features with Support Vector Machine (SVM) and Random Forest classifiers for disease detection. The study achieved high classification accuracy and demonstrated the effectiveness of machine learning in neurological disorder prediction. This work supports the AI-based classification module of the project.[6]

Liu et al., in “Deep Learning for Brain MRI Analysis: A Survey” (2020), reviewed deep learning techniques such as CNNs and U-Net for MRI segmentation and anomaly detection. The study highlighted the effectiveness of deep learning in medical image analysis and supports the use of CNN models in the proposed framework.[7]

Reuter et al., in “Automated Longitudinal MRI Analysis with FreeSurfer” (2012), developed an automated MRI analysis pipeline for monitoring disease progression over time. The study demonstrated that automated analysis improves consistency and reliability in repeated MRI scans. This research highlights the importance of automation in MRI-based diagnostic systems.[8]

Tournier et al., in “Diffusion MRI and the Fiber Orientation Distribution Function” (2007), introduced advanced methods for analyzing crossing fibers in white matter regions using spherical deconvolution techniques. The study improved the accuracy of fiber orientation analysis and enhanced white matter visualization. This work is useful for improving tractography and FA-based brain analysis in the proposed project.[9[

Zhang and Laidlaw, in “Visualizing Brain Microstructure Using Diffusion Tensor MRI” (2005), proposed color-coded FA visualization techniques for better interpretation of white matter abnormalities. The study improved the understanding of brain microstructure and assisted radiologists in identifying damaged regions. This work supports the visualization module used in the proposed framework.[10]

Le Bihan, in “Looking into the Functional Architecture of the Brain with Diffusion MRI” (2003), explained the relationship between diffusion imaging and brain functionality. The study showed that FA changes are strongly associated with neurological impairments and disease progression. This research highlights the clinical importance of FA-based analysis in neurological diagnosis.[11]

Basser et al., in “Microstructural and Physiological Features of Tissues Revealed by Diffusion Tensor MRI” (2000), explained how DTI captures tissue microstructure and introduced principal diffusion directions for tractography. The study demonstrated that white matter abnormalities can be quantified using FA and other diffusion metrics. This work provides theoretical support for the FA computation methods used in the project.[12]

Chen et al., in “Applications of Generative Artificial Intelligence in Brain MRI Image Analysis” (2024), reviewed the role of generative AI models in MRI preprocessing, segmentation, and disease analysis. The study highlighted how AI improves image quality and diagnostic performance in neuroimaging systems. This work supports the integration of AI techniques in the proposed framework.[13]

Ma et al., in “Deep Learning with Diffusion MRI as In Vivo Microscope Reveals Sex-Related Brain Microstructure” (2024), used deep learning models to identify structural differences in brain tissues. The research demonstrated the capability of AI models in extracting complex imaging features from MRI scans. This study supports the use of deep learning in brain microstructure analysis.[14]

Guo et al., in “A Review on Deep Learning MRI Reconstruction without Fully Sampled k-Space Data” (2023), discussed deep learning techniques for improving MRI reconstruction and reducing scan time. The study highlighted the importance of AI in enhancing image quality and supporting efficient MRI analysis. This research is relevant to the preprocessing stage of the proposed system.[15]

4.METHODOLOGY

The methodology of the proposed system is designed to provide a systematic and intelligent approach for analyzing brain MRI images and detecting abnormalities in brain microstructure. The framework integrates image preprocessing, FA map generation, tractography visualization, machine learning classification, and chatbot interaction into a single automated pipeline. Each stage of the methodology contributes to improving diagnostic accuracy, reducing manual effort, and supporting early detection of neurological disorders such as Alzheimer’s disease, Parkinson’s disease, and brain tumors.

The process begins when the user uploads a brain MRI image into the system through the application interface. The uploaded image is first checked to determine whether it is in NIfTI format, which is a standard format commonly used for storing neuroimaging data. If the image is not in NIfTI format, the system automatically converts it into the required format to ensure compatibility with further processing stages.

After format verification and conversion, preprocessing operations are performed on the MRI image. Medical images often contain unwanted noise, distortions, intensity variations, and non-brain tissues that may affect analysis accuracy. To improve image quality, preprocessing techniques such as denoising, normalization, skull stripping, and motion correction are applied. These operations help generate cleaner and more reliable MRI data for further analysis.

Following preprocessing, K-Means clustering is applied for image segmentation. The segmentation process separates important brain regions, especially white matter structures, from other tissues. This helps the system focus on regions that are more relevant for detecting abnormalities. Segmentation improves precision and reduces unnecessary information during feature extraction and classification.

Once segmentation is completed, the system generates Diffusion Tensor Imaging (DTI) and Fractional Anisotropy (FA) maps. FA maps are used to analyze the directional movement of water molecules within white matter fibers. Healthy white matter structures generally show high FA values, whereas damaged or abnormal tissues show reduced anisotropy. The generated FA maps provide important quantitative information about brain microstructure and neural connectivity.

The methodology also includes deterministic fiber tractography visualization. This process reconstructs white matter fiber pathways and displays neural tracts in two-dimensional and three-dimensional forms. Tractography helps identify disruptions in connectivity and highlights damaged regions within the brain. The system also measures the severity of abnormalities based on FA variations and structural changes observed in white matter regions.

After feature extraction from MRI images and FA maps, machine learning and deep learning models are applied for disease classification. The proposed system uses Convolutional Neural Networks (CNN) and Random Forest classifiers because of their effectiveness in medical image analysis. CNN models learn spatial and structural features from MRI images, while Random Forest improves classification reliability through ensemble learning. These models classify brain conditions into normal and abnormal categories and identify disorders such as Alzheimer’s disease, Parkinson’s disease, and brain tumors.

Journal Publication of International Research for Engineering and Management (JOIREM)
Volume: 04 Issue: 5 | may-2026
ISSN (O) 3107-6696

A threshold stopping criterion is implemented within the classification stage to improve system efficiency. The process continues until the required classification confidence or accuracy threshold is achieved. This ensures stable and reliable prediction performance during abnormality detection.

The methodology further includes a chatbot interaction module integrated with Natural Language Processing (NLP) models. Users can enter symptoms or queries related to neurological disorders and MRI analysis. The chatbot processes the input using NLP techniques and provides simplified responses, explanations, and guidance based on the MRI analysis results. This feature improves user interaction and makes the system more accessible to both medical and non-medical users.

Finally, the system displays the MRI analysis results along with chatbot responses through the application interface. Abnormal regions are highlighted visually, and tractography outputs are presented to assist clinicians in understanding the detected abnormalities. The methodology combines preprocessing, segmentation, FA analysis, tractography, machine learning, visualization, and chatbot interaction into a complete AI-powered framework for intelligent brain microstructure analysis and neurological disorder detection.

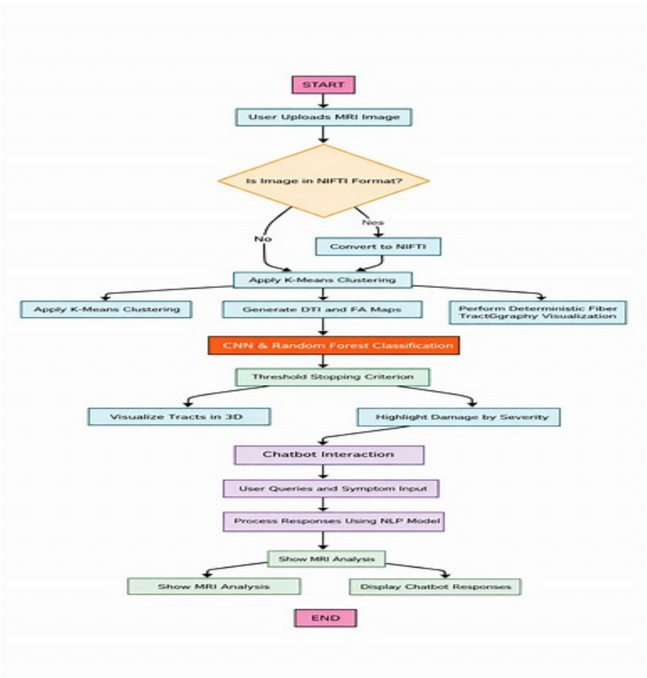

Figure 4.1: Block Diagram

5. IMPLEMENTATION

5.1 Data Collection

The implementation process begins with the collection of brain MRI datasets from publicly available medical imaging sources and clinical databases. The dataset includes normal and abnormal MRI scans related to neurological disorders such as Alzheimer's disease, Parkinson's disease, and brain tumors. The collected MRI images are stored digitally and organized according to disease categories for efficient processing and model training.

5.2 MRI Image Upload and Format Conversion

Users upload MRI images through the application interface. The uploaded images are checked to determine whether they are in NIfTI format, which is commonly used in neuroimaging applications. If the images are not in the required format, the system automatically converts them into NIfTI format to maintain compatibility with the processing pipeline.

5.3. Image Preprocessing

Preprocessing is performed to improve MRI image quality and remove unwanted distortions. Medical images often contain noise, motion artifacts, and intensity variations that can affect analysis accuracy. Therefore, preprocessing techniques such as denoising, skull stripping, normalization, motion correction, and registration are applied. These operations generate clean and standardized MRI images suitable for further analysis.

5.4. Image Segmentation Using K-Means Clustering

K-Means clustering algorithms are implemented for segmenting MRI images and isolating white matter regions from other tissues such as gray matter and cerebrospinal fluid. Segmentation helps the system focus specifically on relevant white matter structures and improves the accuracy of abnormality detection.

5.5 DTI and FA Map Generation

After segmentation, the system generates Diffusion Tensor Imaging (DTI) and Fractional Anisotropy (FA) maps. FA maps analyze the directional movement of water molecules within white matter fibers. Healthy neural pathways generally show higher FA values, while damaged or abnormal tissues exhibit lower FA values. These maps provide quantitative information about brain microstructure and connectivity.

5.6. Feature Extraction

Feature extraction techniques are applied to obtain meaningful numerical information from MRI images and FA maps. Features such as FA values, intensity levels, texture information, structural patterns, and white matter characteristics are extracted and converted into numerical representations. These features are later used for classification by machine learning models.

5.7. Machine Learning and Deep Learning Classification

The classification stage is implemented using Convolutional Neural Networks (CNN) and Random Forest classifiers. CNN models learn spatial and structural features from MRI images, while Random Forest improves classification accuracy using ensemble learning techniques. The models classify MRI scans

Volume: 04 Issue: 5 | may-2026
ISSN (O) 3107-6696

into normal and abnormal categories and identify disorders such as Alzheimer's disease, Parkinson's disease, and brain tumors.

5.8. Threshold Stopping Criterion

A threshold stopping criterion is implemented to improve prediction efficiency and model stability. The classification process continues until the required confidence level or prediction accuracy is achieved. This ensures reliable and stable diagnostic outputs.

5.9. Tractography Visualization

The system implements deterministic fiber tractography techniques for reconstructing white matter pathways. Neural fiber tracts are visualized in two-dimensional and three-dimensional forms. Damaged or abnormal regions are highlighted based on severity levels, helping clinicians understand connectivity disruptions more effectively.

5.10. Chatbot Integration

The system includes a chatbot module developed using Natural Language Processing (NLP) techniques and Hugging Face models. Users can enter symptoms or queries related to neurological disorders and MRI analysis. The chatbot processes the input and provides simplified explanations, guidance, and MRI-related responses.

6.RESULT

The developed Brainalyze system was successfully implemented as a full-stack AI-powered application for analyzing brain MRI images and detecting neurological abnormalities. The system integrates React.js frontend modules, Node.js backend services, machine learning models, tractography visualization, and chatbot interaction into a single intelligent framework. The results obtained from the implemented modules demonstrate that the proposed system can effectively process MRI images, classify neurological disorders, visualize white matter abnormalities, and assist users through AI-based interaction.

A. Brainalyze Application Dashboard

The Brainalyze dashboard acts as the central interface of the application and provides access to all major modules including Alzheimer's Disease Prediction, Parkinson's Disease Detection, Brain Tumor Prediction, Tractography Visualization, NeuroBot Chat Assistant, and Blog sections. The dashboard is designed using a card-based layout for easy navigation and user interaction.

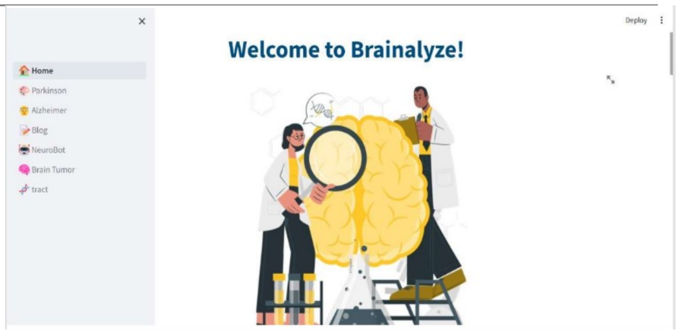

Fig 6.1: Dashboard of the Brainalyze application.

B. Alzheimer's Disease Prediction Interface

The Alzheimer's Disease Prediction module allows users to upload MRI images using a drag-and-drop feature. After image upload, preprocessing and classification are performed automatically using CNN and Random Forest algorithms. The system then displays the uploaded MRI image along with the prediction result.

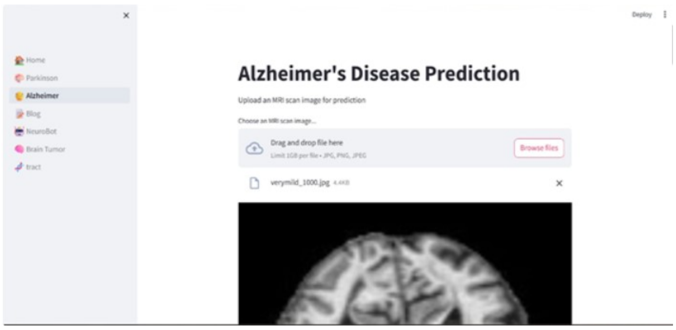

Fig 6.2 Alzheimer's Disease Prediction

C. NeuroBot Chat Assistant Interface

NeuroBot is an AI-powered chatbot integrated into the Brainalyze application to provide assistance related to neurological disorders and MRI analysis. Users can enter symptoms or queries, and the chatbot generates responses using NLP models and Hugging Face technologies.

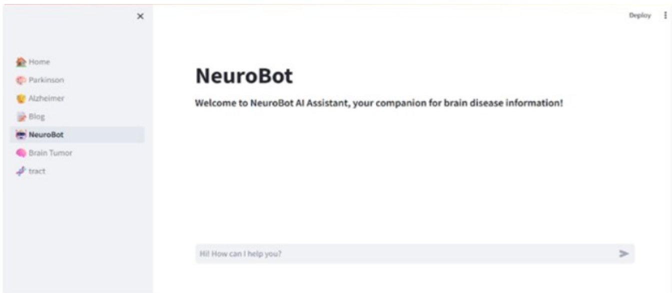

Fig 6.3 NeuroBot Chat Assistant

D. Brain Tumor Prediction Interface

The Brain Tumor Prediction module enables users to upload MRI images for tumor analysis and classification. The uploaded image undergoes preprocessing and feature extraction before being analyzed using CNN and Random Forest models. The system displays the uploaded image together with the prediction result and disease-related information.

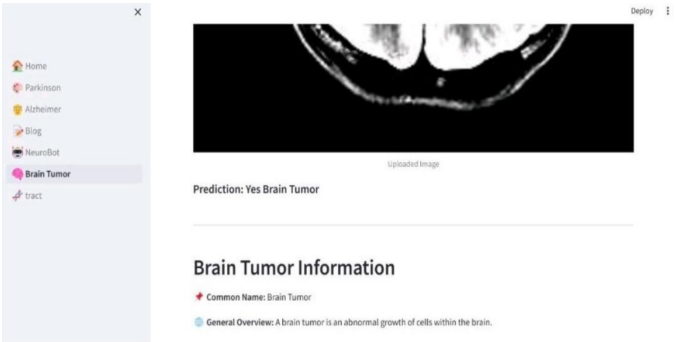

Fig 6.4 Brain Tumor Prediction

E. Tractography Visualization

The tractography visualization module generates graphical representations of white matter connectivity and Fractional Anisotropy (FA) analysis. The visualizations help identify structural abnormalities and changes in neural connectivity within the brain.

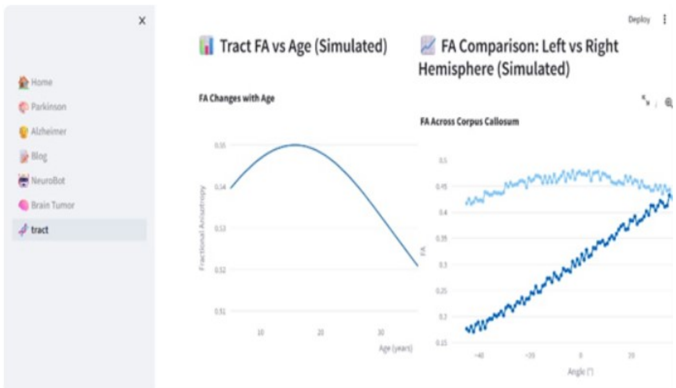

Fig 6.5 tractography visualization module of the Brainalyze system.

7.CONCLUSION

The proposed Brainalyze system successfully demonstrates the application of Artificial Intelligence and medical imaging techniques for intelligent brain microstructure analysis and neurological disorder detection. The system integrates MRI image processing, preprocessing, segmentation, Fractional Anisotropy (FA) analysis, tractography visualization, machine learning classification, and chatbot interaction into a unified diagnostic framework. By combining these technologies, the project provides an automated and efficient solution for analyzing abnormalities in brain structures and white matter regions.

The implemented system effectively processes MRI images and identifies abnormalities associated with Alzheimer's disease, Parkinson's disease, and brain tumors. The use of Convolutional Neural Networks (CNN) and Random Forest classifiers improves prediction accuracy and enables intelligent classification of neurological conditions. In addition, tractography visualization and FA analysis provide meaningful insights into white matter connectivity and structural changes within the brain.

The Brainalyze application also enhances user interaction through an AI-powered NeuroBot chatbot that provides simplified explanations and guidance related to MRI analysis and neurological disorders. The integration of frontend technologies such as React.js and backend technologies such as Node.js and Express.js ensures smooth communication between system modules and provides an interactive user experience.

Overall, the project demonstrates that AI-powered medical imaging systems can support early diagnosis, improve diagnostic efficiency, reduce manual workload for healthcare professionals, and enhance visualization of brain abnormalities. The proposed framework contributes to the advancement of intelligent healthcare systems and provides a scalable foundation for future research in brain MRI analysis and neurological disease detection.

8. REFERENCES

[1]. Gholami, A. B. H., et al. (2024). Artificial intelligence for diffusion MRI-based tissue microstructure estimation in the human brain: an overview. NeuroImage.

[2]. Li, Y., Fan, G., & Sun, Z. (2024). Deep learning enables accurate brain tissue microstructure analysis based on clinically feasible diffusion magnetic resonance imaging. Medical Image Analysis, 91: 103006.

[3]. Neher, A., et al. (2024). Deep learning microstructure estimation of developing brains from clinically feasible diffusion magnetic resonance imaging. NeuroImage, 285: 120463.

[4]. Chen, S., et al. (2024). Applications of Generative Artificial Intelligence in Brain MRI Image Analysis: A Review. Brain Science Advances, 10(1): 1-15.

[5]. Ma, Z., et al. (2024). Deep learning with diffusion MRI as in vivo microscope reveals sex-related brain microstructure. Communications Biology, 7(1): 1-13.

[6]. Li, T., & Tang, T. (2024). A Diffusion Model for Anatomically Consistent Brain MRI Synthesis. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1-10.

[7]. Kamran, M., et al. (2023). The role of generative adversarial networks in brain MRI: a scoping review. European Radiology Experimental, 7(1): 1-17.

[8]. Guo, H., et al. (2023). A review on deep learning MRI reconstruction without fully sampled k-space data. Magnetic Resonance Imaging, 99: 1-10.

[9]. Valentini, M. B., et al. (2023). Deep learning prediction of diffusion MRI data with microstructure-aware loss functions. Medical Image Analysis, 83: 102652.

[10]. Jelescu, I. O., & Leemans, A. (2023). Imaging brain microstructure with diffusion MRI. Physics in Medicine &

Biology, 68(1): 1-32.
[11]. Dertkigil, I. F., et al. (2023). Deep learning for accelerated and robust MRI reconstruction. Magnetic Resonance Imaging, 97: 110-120.
[12]. Liao, Y., et al. (2023). Mapping tissue microstructure of brain white matter in vivo in health and disease using diffusion MRI. NeuroImage, 268: 119859.
[13]. Kazerouni, A., et al. (2023). From 2D to 3D, Deep Learning-based Shape Reconstruction in Medical Imaging: A Systematic Review. Medical Image Analysis, 86: 102830.
[14]. Chen, G., et al. (2023). Application of artificial intelligence-based magnetic resonance imaging in cerebral small vessel disease: a comprehensive review. Journal of Medical Imaging and Radiation Oncology, 67(1): 1-15.
[15]. Lu, J., et al. (2023). Generative AI for brain image computing and brain network computing: a systematic review. Journal of Medical Imaging, 10(1): 01090

Journal Publication of International Research for Engineering and Management (JOIREM)
Volume: 04 Issue: 5 | may-2026
ISSN (O) 3107-6696