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Personalized Alzheimer's Disease Progression Prediction with Machine Learning

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Abstract:- One of the most prevalent diseases in the world is Alzheimer's (AD). It is a neurological condition that can lead to cognitive decline and memory loss. Both the senior population and the prevalence of diseases affecting them have dramatically increased in recent years. It is critical to categorize the progression of Alzheimer's disease. Alzheimer's disease (AD) is a complicated neurological ailment that progresses in different ways for each individual. In this study, we present a novel approach to personalised Alzheimer's disease progression prediction using machine learning techniques. Our goal is to create a model that can forecast the stage of the condition for specific individuals and classify them into one of four categories: Normal, Mild, Average, or Critical. Our method uses Convolutional Neural Networks (CNN) to extract characteristics from various MRI scans, capturing complex patterns in Alzheimer's progression. The CNN is extensively trained on a diverse dataset. Traditional classifiers such as Support Vector Machines (SVM) and Decision Trees supplement the CNN, improving the classification process. Furthermore, ensemble learning, specifically majority voting, harmonises predictions from CNN, SVM, and Decision Trees, increasing accuracy by using their individual strengths to predict Alzheimer's disease development.

Keywords:- *Convolutional Neural Networks (CNNs), Decision Trees, Image Preprocessing, Machine Learning, Support Vector Machine (SVM), Ensemble Learning.*

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurological disorder characterised by cognitive decline, memory loss, and reduced everyday function. It is a huge global health concern, with millions of people afflicted by its crippling effects. AD appears in several stages, ranging from the early Normal stage to the Mild and Average stages to the advanced Critical stage, each with its own set of clinical characteristics and problems. This variability in course highlights the importance of personalised approaches to understanding and forecasting the disease's trajectory.

Existing solutions for Alzheimer's progression prediction often face challenges in capturing the intricate nuances of individualized disease trajectories. Conventional methods may lack the granularity required for personalized assessments. Some approaches rely on clinical evaluations, while others utilize basic machine learning models. However, the complexities inherent in Alzheimer's progression demand more sophisticated techniques capable of handling diverse and detailed datasets, such as those derived from MRI images.

In response to the various problems provided by Alzheimer's Disease (AD), our research calls for a novel and personalised strategy to disease progression prediction that makes use of machine learning. At the heart of our methodology is the Convolutional Neural Network (CNN), a powerful tool precisely created to thoroughly analyze MRI pictures. This CNN captures not just fine details, but also subtle patterns that indicate the progression of Alzheimer's disease. To improve the model's discernment, we incorporate classic machine learning classifiers like Support Vector Machines (SVM) and Decision Trees into our system. This combination seeks to leverage the characteristics of both deep learning and classical approaches, resulting in a more robust and nuanced categorization process.

Furthermore, our methodology provides an ensemble learning paradigm that uses a majority vote strategy to align predictions from different models. This synergistic integration aims to improve the predictive accuracy of Alzheimer's disease development. By combining insights from CNN, SVM, and Decision Trees, our model develops a thorough grasp of the intricate interplay between numerous aspects in MRI images, resulting in more precise and informed predictions. The overarching goal of our research is to achieve substantial advances in personalised medicine. Through the development of this nuanced predictive tool, we hope to provide clinicians and researchers with a powerful tool for unravelling the

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intricate trajectories of Alzheimer's disease at an individualized level, thereby improving our understanding and prediction capabilities for this complex neurodegenerative disorder.

II. MACHINE LEARNING

Machine Learning (ML) is a key field of artificial intelligence that allows computers to learn and make informed decisions from data patterns without the need for explicit programming. ML algorithms and models use data insights to improve performance and anticipate future outcomes. This technology has a wide range of applications, including image identification, natural language processing, recommendation systems, and even self-driving cars, which drives innovation across multiple industries. Machine learning is an extremely important field in today's digital world, serving as the foundation for data-driven decision-making and automation.

Machine Learning technology has proven useful in providing an immeasurable platform in the medical industry, allowing health care issues to be treated effortlessly and quickly. Disease Prediction is a machine learning-based system that largely operates depending on the symptoms provided by the user. The disease is predicted using algorithms that compare datasets to the user's symptoms.

CNNA Convolutional Neural Network (CNN) is a deep learning method developed primarily for image processing and recognition. Compared to other classification models, CNNs require less preprocessing since they can learn hierarchical feature representations from raw input images. They excel in assigning priority to diverse objects and attributes in images using convolutional layers, which use filters to discover local patterns.

CNN connectivity patterns are modelled after the visual cortex in the human brain, where neurons respond to specific regions or receptive fields in visual space. This architecture enables CNNs to accurately detect spatial relationships and patterns in images. CNNs learn progressively complicated features by stacking many convolutional and pooling layers, resulting in high accuracy in tasks such as image classification, object detection, and segmentation.Three Layers of CNN

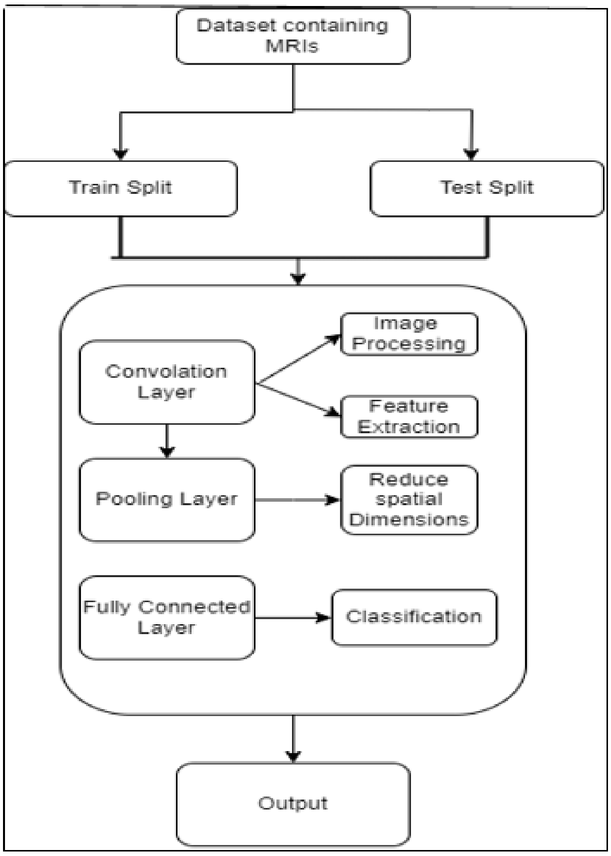

Fig 1 CNN

Convolutional Layer: In a typical neural network each input neuron is connected to the next hidden layer. In CNN, only a small region of the input layer neurons connects to the neuron hidden layer.

Pooling Layer: The pooling layer is used to reduce the dimensionality of the feature map. There will be multiple activation & pooling layers inside the hidden layer of the CNN.

Fully-Connected layer: Fully Connected Layers form the last few layers in the network. The input to the fully connected layer is the output from the final Pooling or Convolutional Layer, which is flattened and then fed into the fully connected layer.

➢ *Alzheimer's Disease Progression Stages:*

- *Normal*:

Individuals at this stage have typical cognitive function, with no obvious evidence of memory loss or impairment. There are no significant disruptions in regular activities or routines.The normal stage serves as a benchmark for illness progression assessments.

- *Mild Cognitive Impairment (MCI):*

Individuals in the MCI stage experience cognitive decline that exceeds what is typical for their age. Memory lapses become more noticeable, disrupting regular activities. MCI is classified as an intermediate stage between normal ageing and more severe cognitive loss.

- *Moderate or Average Alzheimers:*

During this stage, cognitive impairment accelerates significantly. Memory loss worsens, affecting both present and old memories. Individuals may struggle to solve problems, make decisions, and complete ordinary tasks. Behavioral and personality changes may occur.

- *Severe Alzheimers:*

Individuals in the severe stage exhibit considerable cognitive impairment. Memory loss is widespread, with people frequently failing to recognize close family members or recall major life events. Communication skills degrade, and people may need help with daily tasks like eating and bathing. This stage marks a considerable deterioration in cognitive and functional ability.

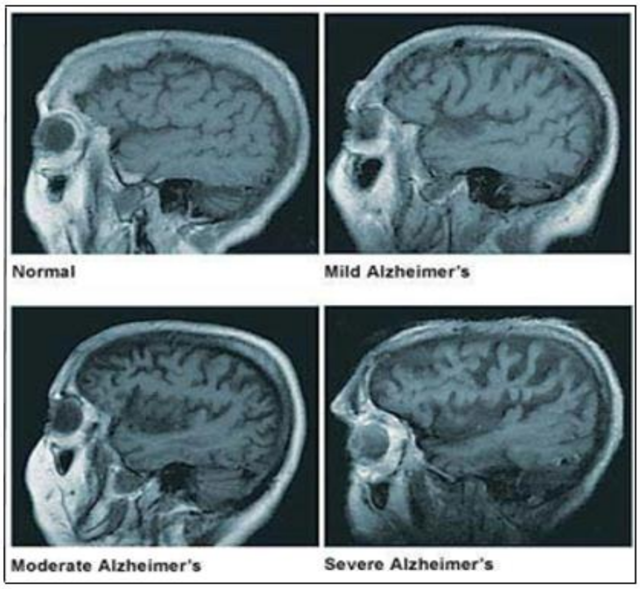

Fig 2 Stages

III. CLASSIFICATION MODELS

SVM Support Vector Machines (SVM) are an important component of our Alzheimer's disease progression prediction model, complementing the capabilities of Convolutional Neural Networks (CNN). SVM is capable of detecting complicated patterns in MRI images, making it an effective classifier for categorizing individuals into different Alzheimer's stages. SVM captures both linear and nonlinear correlations in our dataset by utilizing a varied range of kernels, including linear, polynomial, and radial basis function (RBF). The training method entails optimizing hyperparameters such as the regularization parameter (C) and kernel-specific parameters, with performance measured using conventional metrics such as accuracy, precision, recall, and F1-score. The interpretability of SVM findings, as well as their valuable contributions to the ensemble learning process, improve our model's overall prediction accuracy.

Decision Trees play an important part in our Alzheimer's disease progression prediction model by identifying complicated interactions within MRI data. Decision Trees, when used as a standalone classifier, make the classification process more understandable and transparent. The model's tree structure, which is established by feature importance and branching criteria, helps us comprehend crucial indications of Alzheimer's progression. Decision Trees play an important role in the ensemble learning technique, working with Convolutional Neural Networks (CNN) and Support Vector Machines (SVM). Their forecasts are smoothly merged using majority voting, increasing the resilience of our model. Performance evaluation criteria, such as accuracy and contributions to overall ensemble accuracy, highlight the significance of Decision Trees in our holistic approach to personalised Alzheimer's disease progression prediction.

IV. LITERATURE SURVEY

J. Neelaveni and M. S. G. Devasana, "Alzheimer Disease Prediction using Machine Learning Algorithms," 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2020, pp. 101-104, doi: 10.1109/ICACCS48705.2020.9074248.

Abstract: Alzheimer disease is the one amongst neurodegenerative disorders. Though the symptoms are benign initially, they become more severe over time. Alzheimer's disease is a prevalent sort of dementia. This disease is challenging one because there is no treatment for the disease. Diagnosis of the disease is done but that too at the later stage only. Thus, if the disease is predicted earlier, the progression or the symptoms of the disease can be slow down. This paper uses machine learning algorithms to predict the Alzheimer disease using psychological parameters like age, number of visits, MMSE and education.

Shi J, Zheng X, Li Y, Zhang Q, Ying S. Multimodal Neuroimaging Feature Learning with Multimodal Stacked Deep Polynomial Networks for Diagnosis of Alzheimer's Disease. IEEE J Biomed Health Inform. 2018 Jan;22(1):173-183. doi: 10.1109/JBHI.2017.2655720. Epub 2017 Jan 19. PMID: 28113353.

Fan, Zhao & Xu, Fanyu & Qi, Xuedan & Li, Cai & Yao, Lili. (2020). Classification of Alzheimer's disease based on brain MRI and machine learning. Neural Computing and Applications. 32. 10.1007/s00521-019-04495-0. Alzheimer's disease (AD) is one of the most common diseases in the world. It is a neurodegenerative disease that can cause cognitive impairment and memory deterioration. In recent years, the number of the elderly population is increasing, and the incidence of elderly diseases has increased significantly. The most representative of these diseases is Alzheimer's disease. According to some data, the average survival time of Alzheimer's disease patients is only 5.5 years, which is the "fourth killer" that endangers the health of the elderly after cardiovascular diseases, cerebrovascular diseases and cancer. According to conservative estimates of the International Federation of Alzheimer's Diseases, the number of Alzheimer's disease patients worldwide will increase to 75.62 million by 2030; by 2050, the number of patients will reach 135.46 million. Therefore, it is urgent to classify the course of Alzheimer's disease. In this paper, support vector machine (SVM) model method is used to classify and predict different disease processes of Alzheimer's disease based on structural brain magnetic resonance imaging (MRI) imaging data, so as to help the auxiliary diagnosis of the disease. In this paper, the extracted MRI data and the SVM model are combined to obtain more accurate classification prediction results. The accuracy of classification and prediction is the best. According to the predicted results, the data characteristics related to diseases can be determined, which can provide a basis for clinical and basic research, etiology and pathological changes.

Morshedul Bari Antor, A. H. M. Shafayet Jamil, Maliha Mamtaz, Mohammad Monirujjaman Khan, Sultan Aljahdali, Manjit Kaur, Parminder Singh, Mehedi Masud, "A Comparative Analysis of Machine Learning Algorithms to Predict Alzheimer's Disease", Journal of Healthcare Engineering, vol. 2021, Article ID 9917919, 12 pages, 2021.

Parnetti, L., Chipi, E., Salvadori, N. et al. Prevalence and risk of progression of preclinical Alzheimer's disease stages: a systematic review and meta-analysis. Alz Res Therapy 11, 7 (2019).https://doi.org/10.1186/s13195-018-0459-7.

Wang M, Zhang D, Shen D, Liu M. Multi-task exclusive relationship learning for alzheimer's disease progression prediction with longitudinal data. Med Image Anal. 2019 Apr;53:111-122. doi: 10.1016/j.media.2019.01.007. Epub 2019 Jan 30. PMID: 30763830; PMCID: PMC6397780.

Sun, BL., Li, WW., Zhu, C. et al. Clinical Research on Alzheimer's Disease: Progress and Perspectives. Neurosci. Bull. 34, 1111–1118 (2018). https://doi.org/10.1007/s12264-018-0249-z

Doody, R.S., Pavlik, V., Massman, P. et al. Predicting progression of Alzheimer's disease. Alz Res Therapy 2, 2 (2010).https://doi.org/10.1186/alzrt25

Counts, S.E., Ikonomovic, M.D., Mercado, N. et al. Biomarkers for the Early Detection and Progression of Alzheimer's Disease. Neurotherapeutics 14, 35–53 (2017). https://doi.org/10.1007/s13311-016-0481-z.

V. PROPOSED SYSTEM

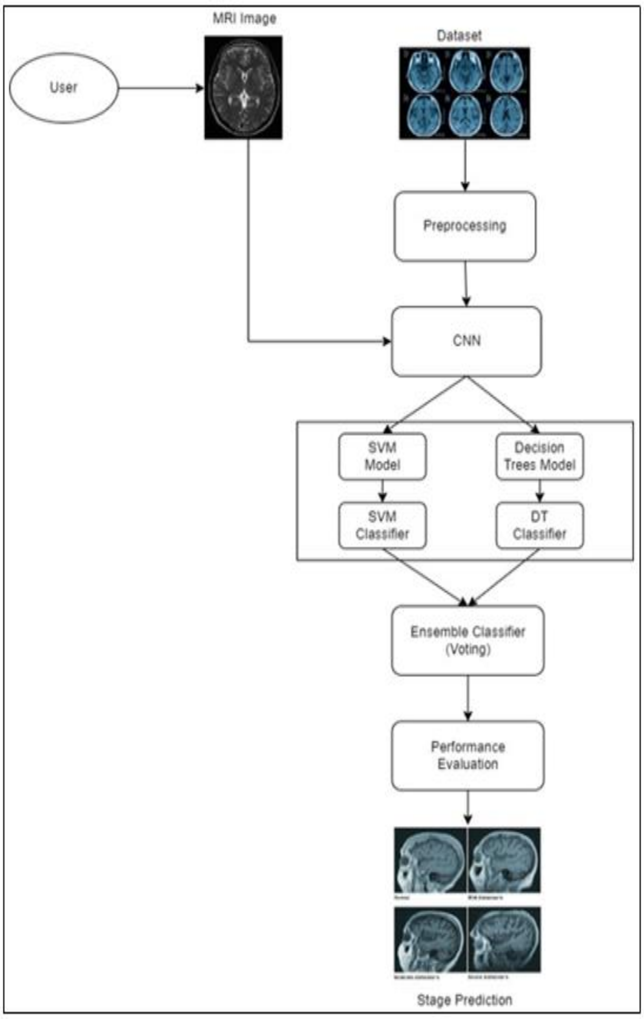

Fig 2 Proposed System

- Step 1: Data Collection and Preparation: Gather datasets from various sources such as, Kaggle, ImageNet, and Open Images for training, validation, and testing the model. Criteria for dataset selection should include a high-quality MRI Image, distinct presentation of the features of the MRI image, and overall image quality. Split the dataset into training and testing sets, with a common ratio like 80% for training and 20% for testing.

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- Step 2: Data Preprocessing: Label datasets, ensuring bounding boxes for CNN compatibility. Reshape images to uniform dimensions (e.g., 600 x 600 pixels) using tools like labelImg. Train the CNN Model by using the training dataset to automatically extract the hierarchical features from the input MRI image. Layers in the CNN will extract the low-level features(edges,textures) to high-level features(patterns,shapes).
- Step 3: Classification using SVM and Decision Trees : 3.1: Feature Reduction : Use the features extracted from the CNN as a starting point and then apply the dimensionality reduction techniques like Principle Component Analysis(PCA) before feeding the features into the SVM and Decision Trees Classifiers. 3.2: Classification: 3.2.1:SVM : Utilized the reduced features as input for SVM classification.3.2.2: Decision Trees : Can be directly use the features or can use the reduced features.
- Step 4: Ensembling Methods (Voting): The classified results from each of those classifiers will be given as input to majority voting algorithms and aggregate the results. The results of majority voting algorithm will be used to performance evaluation of the model.Ensemble Model Output: Ensemble_Output = Majority_Voting(SVM_Output,DT_Output)
- Step 5: Stage Prediction :5.1: Performance Evaluation: Evaluate the performance of the ensemble model using the metrics such as the accuracy, precision, recall, F1-Score.

$$Accuracy = \frac{TP+TN+FP+FN}{TP+TN}$$

$$Precision = \frac{TP}{TP+FP}$$

$$Recall = \frac{TP}{TP+FN}$$

$$F1score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

- ✓ True Positive (TP): Instances that are positive and are correctly classified as positive.
- ✓ True Negative (TN): Instances that are negative and are correctly classified as negative.
- ✓ False Positive (FP): Instances that are negative but are incorrectly classified as positive.
- ✓ False Negative (FN): Instances that are positive but are incorrectly classified as negative.

- 5.2: Alzheimers Stage Prediction : Predict the stage of the Alzheimers Disease based on the performance evaluation result.

VI. CONCLUSION

The project, "Personalized Alzheimer's Disease Progression Prediction Using Machine Learning" is a pioneering effort aimed at addressing a critical need in the healthcare domain. Alzheimer's disease is a growing global health concern, and early intervention is key to improving patient outcomes and advancing research in the field. This project combines cutting-edge technologies with a patient-centered approach to provide personalized predictions regarding the progression of Alzheimer's disease. The core of this project involves leveraging machine learning algorithms, including Convolutional Neural Networks (CNNs), Support Vector Machines (SVM), and decision trees, to analyze patient-specific data. This data includes MRI scans, clinical information, demographic details, and potential biomarker data. The algorithms process this information to make individualized predictions about the patient's disease progression, including identifying the disease stage and assessing the risk of further advancement. Efficiency and optimization are central to the project, ensuring that the algorithms are computationally efficient and that the predictions are both accurate and timely. Data security and privacy measures are also a priority, safeguarding sensitive patient information. A user-friendly web application serves as the interface for both healthcare professionals and patients. It allows for seamless data input, interaction, and visualization of predictions. The project's outcomes include not only personalized predictions but also actionable recommendations for treatment and clinical monitoring. By providing healthcare professionals and patients with valuable insights into the disease's progression, this project empowers them to make informed decisions, plan for the future, and potentially slow the disease's advance.

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REFERENCES

[1]. Zhao Fan1, Fanyu Xu2, Xuedan Qi3, Cai Li4, Lili (2020) Classification of Alzheimer's disease based on brain MRI and machine learning.
[2]. J. Neelaveni, M.S. Geetha Devasana (2019). Alzheimer disease Prediction using machine learning algorithms.
[3]. Morshedul Bari Antor, A. H. M. Shafayet Jamil, Manjit Kaur, Parminder Singh, (2020) A Comparative Analysis of Machine Learning Algorithms to Predict Alzheimer's Disease.
[4]. C. Kavitha1, Vinodhini Mani, S. R. Srividhya1, Osamah Ibrahim Khalaf and Carlos Andrés Tavera Romero (2020) Early-Stage Alzheimer's Disease Prediction Using Machine Learning Models.

[5]. Yudong Zhang, Shuihua Wang, and Zhengchao Dong (2019) Classification of Alzheimer Disease Based on Structural Magnetic Resonance Imaging by Kernel Support Vector Machine Decision Tree.

[6]. Shi, X. Zheng, Y. Li, Q. Zhang, S. Ying (2020) Multimodal neuroimaging feature learning with multimodal stacked deep polynomial networks for diagnosis of Alzheimer's disease

[7]. Ruoxuan Cuia, Manhua Liu, Informatics in Medicine Unlocked, 2019. RNN-based longitudinal analysis for diagnosis of Alzheimer's disease.

[8]. D. Chitradevi, S. Prabha Hindustan Institute of Technology and Science, India 2022 Analysis of brain subregions using optimization techniques and deep learning method in Alzheimer disease.

[9]. Weiner MW, Veitch DP, Aisen PS, Beckett LA, Cairns NJ, et al. (2012) The Alzheimer's Disease Neuroimaging Initiative: a review of papers published since its inception. Alzheimers Dement 8: S1–68.

[10]. Davatzikos C, Fan Y, Wu X, Shen D, Resnick SM (2008) Detection of prodromal Alzheimer's disease via pattern classification of magnetic resonance imaging. Neurobiol Aging 29:514–523.

[11]. Vemuri P, Gunter JL, Senjem ML, Whitwell JL, Kantarci K, et al. (2008) Alzheimer's disease diagnosis in individual subjects using structural MR images: validation studies. Neuroimage 39: 1186–1197.

[12]. Llano DA, Laforet G, Devanarayan V, Alzheimer's Disease Neuroimaging I (2011) Derivation of a new ADAS-cog composite using tree-based multivariate analysis: prediction of conversion from mild cognitive impairment to Alzheimer disease. Alzheimer Dis Assoc Disord 25: 73–84.

[13]. Casanova R, Whitlow CT, Wagner B, Williamson J, Shumaker SA, et al. (2011) High dimensional classification of structural MRI Alzheimer's disease data based on large scale regularization. Frontiers of Neuroscience in Neuroinformatics 5.

[14]. Kloppel S, Stonnington CM, Chu C, Draganski B, Scahill RI, et al. (2008) Automatic classification of MR scans in Alzheimer's disease. Brain 131: 681– 689.

[15]. Cuingnet R, Gerardin E, Tessieras J, Auzias G, Lehericy S, et al. (2011) Automatic classification of patients with Alzheimer's disease from structural MRI: a comparison of ten methods using the ADNI database. Neuroimage 56: 766–781.

[16]. Casanova R, Hsu F-C, Espeland MA (2012) Classification of structural MRI images in Alzheimer's disease from the perspective of ill-posed problems. PLOS One 7.

[17]. Petersen RC, Aisen PS, Beckett LA, Donohue MC, Gamst AC, et al. (20010) Alzheimer's Disease Neuroimaging Initiative (ADNI). Clinical characterization. Neurology 74: 201–209.

[18]. Jack CR Jr, Bernstein MA, Fox NC, Thompson P, Alexander G, et al. (2008) The Alzheimer's Disease Neuroimaging Initiative (ADNI): MRI methods. J Magn Reson Imaging 27: 685–691.

[19]. Zhang D, Wang Y, Zhou L, Yuan H, Shen D, et al. (2011) Multimodal classification of Alzheimer's disease and mild cognitive impairment. Neuroimage 55: 856–867.

[20]. Chu C, Hsu AL, Chou KH, Bandettini P, Lin C, et al. (2012) Does feature selection improve classification accuracy? Impact of sample size and feature selection on classification using anatomical magnetic resonance images. Neuroimage 60: 59–70.

[21]. Biffi A, Anderson CD, Desikan RS, Sabuncu M, Cortellini L, et al. Genetic variation and neuroimaging measures in Alzheimer disease. Arch Neurol 67: 677–685.

[22]. Teipel SJ, Born C, Ewers M, Bokde AL, Reiser MF, et al. (2007) Multivariate deformation-based analysis of brain atrophy to predict Alzheimer's disease in mild cognitive impairment. Neuroimage 38: 13–24.

[23]. Liu J, Huang S, Nowinski WL (2009) Automatic segmentation of the human brain ventricles from MR images by knowledge-based region growing and trimming. Neuroinformatics 7: 131–146.

[24]. Black SE, Moffat SD, Yu DC, Parker J, Stanchev P, et al. (2000) Callosal atrophy correlates with temporal lobe volume and mental status in Alzheimer's disease. Can J Neurol Sci 27: 204–209.

[25]. Di Paola M, Spalletta G, Caltagirone C In vivo structural neuroanatomy of corpus callosum in Alzheimer's disease and mild cognitive impairment using different MRI techniques: a review. J Alzheimers Dis 20: 67–95.

[26]. Canu E, Frisoni GB, Agosta F, Pievani M, Bonetti M, et al. (2012) Early and late onset Alzheimer's disease patients have distinct patterns of white matter damage. Neurobiology of Aging 33: 1020–1023.

[27]. R. N. Kalaria, G. E. Maestre, R. Arizaga et al., "Alzheimer's disease and vascular dementia in developing countries: prevalence, management, and risk factors," Ae Lancet Neurology, vol. 7, no. 9, pp. 812–826, 2008.

[28]. M. C. Bou, C. Minguillon, N. Gramunt, and J. L. Molinuevo, ´ "Alzheimer's disease prevention: from risk factors to early intervention," Alzheimer's Research & Aerapy, vol. 9, p. 71, 2017.

[29]. Prajapati R, Khatri U, Kwon GR. "An efficient deep neural network binary classifier for alzheimer's disease classification," In: International Conference on Artificial Intelligence in Information and Communication (ICAIIC). (2021), p. 231–234.

[30]. Williams., Jennifer A, Weakley A, Cook MS, Edgecombe DJ. "Machine learning techniques for diagnostic differentiation of mild cognitive impairment and dementia," In Workshops at the Twenty-Seventh AAAI Conference on Artificial Intelligence. (2018), pp. 71–6.