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| **S. No** | **Title**  *(Name of the journal, author and publication details)* | **Methodology**  *(Provide a Summary of key studies and their findings)* | **Identification of gaps and limitations.**  *(Identify the limitations of the Research Paper)* |
| 1 | In 2021, Zhang, et al. [14] have suggested a CNN that is densely connected and has a connection-wise attention system to acquire the multi-level features of brain MRI for the purpose of classifying AD. | * Multi Modal deep learning. * Densely connected CNN with attention mechanism. * Multiple modalities were trained using separate con volutional neural networks. | * Limited exploration of drawbacks provided. * Integration of multiple modalities can increase computational complexity. |
| 2 | In 2016, Beheshti et al. [16] have established an automatic CAD system for AD classification using seven feature-ranking approaches and classification errors. | * Automatic CAD system. * The optimal fea ture size was chosen to minimize training phase classification error. Raw features from GM atrophy clusters extracted through VBM analysis were utilized, with SVM employed for classification after feature selection. | * Early diagnosis of AD using brain connectivity and clinical data. |
| 3 | In 2021, Ebrahimi, et al. [18] have presented the use of CNN on MRI to identify AD. | * CNNs for AD detection on MRI. * The accuracy of identifying Alzheimer’s disease on MRI scans was greatly increased by the use of 3D CNNs for voxel-based decisions combined with transfer learn ing from 2D images. * Expanding transfer learning from 2 to 3D MRI scans. | * Training 3D CNNs from scratch performed poorly on MRI dataset. |
| 4 | In 2019, Maqsood et al. [17] have used an effective, automated Alzheimer’s classifcation system formulated using transfer learning, addressing binary and multi-class tasks (stage detection). | * Automated system with transfer learning. * Classification using transfer learning with fine tuned AlexNet. | * Need to analyze accuracy by fine-tuning all convolutional layer. |
| 5 | Ju et al. 2017. | * Deep learning with brain network and clinical text. * Early diagnosis of AD using brain connectivity and clinical data. | * Need for evaluation on larger datasets. |
| 6 | Shi et al. | * Functional magnetic resonance imaging (fMRI) classification of AD symptoms. * Recognizing AD patients through FC. | * Lack of evaluation on a more diverse dataset. |
| 7 | An et al. | * Improving AD classification accuracy with deep learning algorithms. * Deep ensemble learning framework. | * Potential sensitivity to small dataset size. |
| 8 | Castro et al. | * Deep learning. * Utilize deep learning techniques for automated AD diagnosis | * Data availability and interpretability challenges in complex deep learning systems for medical diagnosis |
| 9 | Bi X, Wang H (2019). | * Deep Learning. * EEG spectral images using deep learning. | * Ethical constraints in conducting invasive procedures or experimental treatment. |
| 10 | Ju R, Hu C, Zhou P, Li Q (2019). | * Early diagnosis of Alzheimer’s disease based on resting-state brain networks and deep learning. | * Difficulty in integrating findings from diverse methodologies and disciplines. |
| 11 | Deng J, Nie W, Zhang Y (2020) | * The identification of Alzheimer’s disease using functional connectivity between activity voxels in resting-state fMRI data. | * Recruitment challenges, especially in advanced stages of the disease. |
| 12 | van de Mortel, L. A., Thomas, R. M., & van Wingen, G. A. (2021). Grey matter loss at different stages of cognitive decline: A role for the thalamus in developing Alzheimer’s disease. Journal of Alzheimer’s Disease, 83(2), 705–720. | * Montreal Cognitive Assessment (MoCA). * Another common test that evaluates similar cognitive domains but is considered more sensitive in detecting mild cognitive impairment (MCI). | * small or homogeneous sample sizes can limit the generalizability of the findings. |
| 13 | Thung, K.-H., Wee, C.-Y., Yap, P.-T., & Shen, D. (2016). Identifica tion of progressive mild cognitive impairment patients using incomplete longitudinal MRI scans. Brain Structure & Func tion, 221(8), 3979–3995. | * Cognitive Testing. * Regular cognitive assessments help track changes over time | * High attrition rates in long-term studies due to the severity of the disease or death of participants. |
| 14 | Valverde, J. M., Imani, V., Abdollahzadeh, A., De Feo, R., Prakash, M., Ciszek, R., et al. (2021). Transfer learning in magnetic resonance brain imaging: A systematic review. Journal of Imaging, 7(4), 66. | * Predictive Modeling. | * Challenges in obtaining informed consent, especially from individuals with cognitive impairments. |
| 15 | Yamanakkanavar, N., Choi, J. Y., & Lee, B. (2020). MRI segmentation and classification of human brain using deep learning for diag nosis of Alzheimer’s disease: A survey. Sensors, 20(11), 3243 | * Positron Emission Tomography (PET). | * Differences in dosages, duration of treatment, and patient adherence can affect study outcomes. |



**Literature survey – Students should refer to 15-20 research papers from reputed journals and prepare a literature survey in the following format**