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Emergence of Transfer Learning towards Specific Identification of Alzheimer's Disease – A Prospective Approach

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***Abstract*— Worldwide, millions of senior citizens are suffering from Alzheimer disease abbreviated as AD, a well-versed form of dementia. AD is featured by amnesia, intellectual disability, and difficulty with consciousness. DL and ML models are undoubtedly explored to identify AD related patterns on large dimensional neuroimaging data but they need global optimization and are suffering from overfitting issue that might yield dissatisfactory result in testing data set. DL overcomes the issue by convolution of input image with kernel but any sudden change in the MRI image or human manipulation, limited pre-processing of the images can mislead CNN in achieving highly accurate detection. Transfer Learning (TL) has proved itself in AD diagnosis by utilizing pre-trained models on large data sets to guide novice model in a new neuroimaging dataset. This review provides an inclusive glimpse of TL implication in classification, identification including the conversion of AD. Keeping in view, we have assessed the strengths and limitations of TL in improvising diagnostic accuracy even with limited data. The uniqueness of the present review is the incorporation of explainable AI in TL based AD diagnosis system. Finally, it can be claimed that the review will guide the new re-searchers in the area of TL induced neurodegenerative disease detection.**

Keywords*— *AD, ML, CNN, Transfer Learning, Explainable AI, Neuroimaging, MRI, PET

I. INTRODUCTION

Worldwide, millions of senior citizens are suffering from Alzheimer disease abbreviated as AD, a well-versed form of dementia. Presently, no disease-modifying treatment is available. As of 2022, nonetheless around 60 million people around the globe are symptomized with AD or supplementary forms dementias. Around 60–70% of dementia cases are treated as AD [1]. AD is featured by unexpected symptoms like memory loss, sharp decline in intellectual ability etc. thereby creating a burden on patients' caretakers and society. Generally speaking, dementia spectrum is partitioned by NC, MCI, and AD. The key concept in identifying AD is to detect MCI, an intermediate state between AD and NC. MCI is symptomized by substantial amnesia, leading to hypomnesia. MCI is suspicious in terms of daily activity management but shows a sharp decline in cognitive abilities. Therefore, proper detection of MCI/AD is important, and the classification of MCI and AD is highly needed for the optimum treatment of dementia. Moreover, early detection and medication of MCI can inhibit the progression to AD. The transformation of MCI to AD engraves more than classification, with very nearly 35% of patients with MCI being vulnerable to AD within 3 to 5 years [2]. Thus, quick and accurate multidimensional detection of AD is highly sought by medical practitioners. Unfortunately, conventional medical diagnosis systems are bottlenecked by the limited knowledge of doctors and nurses. Computer-enabled diagnosis offers automatic classification and prediction of AD. There are several open-source databases for AD [3,4] among which ADNI [5], AIBL, OASIS, J-ADNI [6,7] are the well-known and commonly used database. Imaging technologies have proven to be the best method for identifying the evolution of AD. MRI (Fig. 1) as well as Positron Emission Tomography (PET)-these two imaging technologies are established techniques for identifying AD, as these two imaging technologies are associated with biomarkers such as amyloid-beta and tau proteins. Currently, MRI-related software such as Statistical Parametric Mapping (SPM) and Freesurfer are freely available and widely used by researchers to identify AD. However, Computer-Aided Software still lacks the accuracy needed to detect the conversion of pMCI from sMCI. DL and ML models have been extensively explored to identify AD-related patterns in large neuroimaging datasets. Shallow ML models like SVM and RF are employed, but they face issues with global optimization that do not fit the problem well. On the other hand, ANN is used for local optimization. In advanced ANN forms, deep ML models such as CNN and RNN are extensively used to accurately identify AD from neuroimaging data. DL models inherently include feature extraction steps within the learning model itself. Ensemble methods are also a competitive tool for detecting AD, though they face challenges such as overfitting and underfitting of data [8]. On the contrary, transfer learning (TL), a DL approach, effectively addresses the problem of insufficient labelled neuroimaging data, advancing the detection of AD accurately. By using pre-trained features, a smaller amount of data is needed, drastically cutting down computation time to train the model for a new task. TL further fine-tunes the pre-

demented MRI images are received with more than 90% validation accuracy. Although TL provides less computation time along with handling less amount of data, still there is a scarcity in clear understanding and reasoning of this AI based AD detection. In this regard, Explainable AI (XAI) models such as GradCAM, L1, G1, P1, M1 are added to provide a transparent and strong administered AD detection system. Thus, the incorporation of explain-able AI in TL based AD diagnosis system enhance the confidence, adoption and reliable outcomes. Conclusively, it can be claimed that the review will guide the new researchers in the area of TL induced neurodegenerative disease detection.

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