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Contents

Introduction

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that leads to cognitive decline and significant neuronal damage. It affects millions globally and is anticipated to rise sharply with aging populations, making early and accurate diagnosis crucial for effective intervention. Magnetic Resonance Imaging (MRI) has become an invaluable tool for detecting neurodegenerative changes associated with AD. However, conventional diagnostic methods face challenges such as data scarcity, class imbalances, and the need for interpretable AI systems to support clinical decisions. The integration of AI techniques such as Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) has shown promise in addressing these issues [1]–[3].

This analysis synthesizes findings from three studies that explore AI-driven approaches to enhance AD classification. These studies focus on using GANs for data augmentation, transfer learning for leveraging pre-trained models, and novel architectures like DEMxNET to improve classification accuracy and interpretability [1], [2], [3].

Literature Review

Deep learning methods, particularly CNNs, have been widely used in medical imaging for tasks such as object detection and disease classification. CNNs can extract hierarchical features from MRI scans, identifying critical biomarkers indicative of AD. However, their performance is often hindered by imbalanced and limited datasets [1], [3].

To overcome these challenges, GANs have been employed to augment datasets by generating synthetic images that closely mimic real-world data. This approach has been shown to significantly improve classification accuracy. For example, GAN-augmented MRI datasets trained with structural similarity metrics improved model performance compared to those without synthetic augmentation [1], [2].

Transfer learning models, such as VGG19, DenseNet201, and ResNet, have been fine-tuned for AD classification. These models, pre-trained on large datasets like ImageNet, leverage existing knowledge to reduce training time and improve accuracy. Methods like SMOTE have also been used to address dataset imbalances, ensuring robust model training [3].

Explainability in AI is increasingly emphasized, as clinicians need to understand model decisions. Tools like LIME (Local Interpretable Model-Agnostic Explanations) provide insights into how AI models classify MRI scans, making them more transparent and acceptable for clinical use [3].

Methodology

The studies utilized diverse datasets and AI architectures to enhance AD classification:

Dataset Sources:

MRI scans were obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI), the Australian Imaging, Biomarker & Lifestyle Flagship Study of Ageing (AIBL), the National Alzheimer's Coordinating Center (NACC), and a Kaggle repository. The Kaggle dataset contained 6400 images divided into four categories: Non-Demented (ND), Very Mild Demented (VMD), Mild Demented (MD), and Moderate Demented (MOD) [2], [3].

Data Preprocessing:

Techniques included resizing images, normalizing pixel values, and applying SMOTE to balance class distributions. GANs were used to generate synthetic images, evaluated using metrics like Signal-to-Noise Ratio (SNR) and Natural Image Quality Evaluator (NIQE) [2], [3].

Models and Techniques:

GANs

GANs generated synthetic MRI images, enriching datasets to address data scarcity. These models used Fully Convolutional Networks (FCNs) for binary classification tasks [2].

CNNs

Novel architectures like DEMxNET employed separable convolution blocks and dense layers to enhance feature extraction and classification. The DEMxNET model focused on classifying AD into its stages with high accuracy [1], [3].

Transfer Learning

Models such as VGG19, Xception, and DenseNet201 were fine-tuned for AD stage classification. These models used pre-trained weights to leverage existing knowledge and improve performance [3].

Results

GAN-enhanced datasets significantly improved model accuracy. For example, GAN-generated 3T* images improved the area under the curve (AUC) from 0.907 to 0.932 on the ADNI dataset compared to models trained on original 1.5T images [2]. The DEMxNET model achieved the highest accuracy of **99.79%**, outperforming nine state-of-the-art transfer learning models. It also addressed class imbalances effectively through SMOTE [3].

Transfer learning models demonstrated high performance, with DenseNet201 and VGG19 achieving accuracies of 96.35% and 97%, respectively, on the Kaggle dataset [3]. These findings underscore the potential of GANs, CNNs, and transfer learning in improving AD classification.

Discussion

The studies collectively highlight the transformative role of AI in AD diagnosis. GANs effectively addressed data scarcity by generating high-quality synthetic images, significantly improving model metrics. CNN architectures like DEMxNET demonstrated superior accuracy and robustness, emphasizing the importance of customized models for medical imaging [1], [2], [3].

Explainability emerged as a critical component, with tools like LIME enhancing model transparency. This fosters trust among clinicians and paves the way for wider adoption of AI in clinical settings. Despite these advancements, challenges like generalization to multi-cohort datasets and avoidance of overfitting require further exploration [3].

Conclusion

The reviewed studies highlight the efficacy of integrating GANs, CNNs, and transfer learning for [3]architectures like DEMxNET offer state-of-the-art performance. Future work should focus on optimizing synthetic data quality, exploring multi-cohort validation, and advancing interpretability frameworks to bridge the gap between AI research and clinical practice [1], [2], [3].

References

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