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Alzheimer's Disease Detection Using Deep Learning

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***Abstract*: Alzheimer disease (AD) is a neurodegenerative disorder. For the Alzheimer disease, no treatment is specific. Early diagnosis of Alzheimer's disease will allow patients to get proper care. Statistical and machine learning methods are used by most studies to diagnose Alzheimer disease. The human-level performance of Deep Learning algorithms has been successfully demonstrated in various fields. In the suggested method, the MRI information is employed to detect the Alzheimer disease and Deep Learning method is employed to classify the current disease. The classification of Alzheimer's disease based on deep learning techniques has yielded encouraging results, and successful implementation in the clinical environment calls for a blend of high accuracy, minimal processing time, and generalizability to diverse populations. In this research work, we established a system for the detection of Alzheimer's disease based on Convolutional Neural Network (CNN) architecture using magnetic resonance imaging (MRI) scans images which are trained by Kaggle dataset. Models for this research work are trained over the same dataset to compare their performances. The Convolutional Neural Network (CNN) model provides the best accuracy where train accuracy is 86.34% and validation accuracy is 86.45% on the test data that correctly detects Alzheimer disease.**

***Keywords*: Alzheimer's Disease, Deep Learning.**

1. Introduction

Alzheimer's Disease (AD) is a progressive and chronic neurodegenerative condition that mainly involves cognitive processes like memory, reasoning, and decision-making. Alzheimer's Disease is the major cause of dementia, affecting millions of people globally. Even after years of investigation, no certain cure for AD exists, and existing treatments merely relieve symptoms but do not cease disease progression. Hence, early detection and correct diagnosis are of paramount importance for early intervention, enhanced patient treatment, and enhanced quality of life.

Medical imaging, especially Magnetic Resonance Imaging (MRI), is central to diagnosing structural alteration in the brain in the context of Alzheimer's Disease. The conventional method of diagnosis includes hand interpretation of MRI scans by radiologists, which is a time-consuming, human-error-prone, expert-level skills-demanding process. With the recent advances in Artificial Intelligence (AI), Deep Learning methodologies, in particular, Convolutional Neural Networks (CNNs), have demonstrated enormous potential in the automatic classification of medical images at a human level.

This study suggests a classification system based on deep learning for Alzheimer's Disease from MRI scan images. A CNN model is trained over a publicly available dataset on Kaggle, which allows automated image classification of MRI into various groups depending on the disease severity. Performance of the CNN model is extensively tested, and comparison with other deep learning models is made to determine the most effective method. Our CNN model has 86.34% training accuracy and 86.45% validation accuracy, indicating that it is highly reliable and effective in identifying Alzheimer's Disease.

This research aims to incorporate deep learning and medical imaging to offer a quick, precise, and scalable solution for the early diagnosis of Alzheimer's Disease. The method being proposed is capable of helping medical practitioners save time on diagnosis, promote better decision-making, and enhance patient results.

2. Literature Review

Positron emission tomography (PET) scans play a crucial role in assessing brain activity by identifying radioactive tracers. Deep learning (DL) techniques are employed to analyze PET images, allowing for the detection of patterns related to glucose metabolism or amyloid-beta accumulation, which are significant indicators of Alzheimer's disease (AD). The researchers present the Inception-ResNet model designed to distinguish among healthy controls (HC), mild cognitive impairment (MCI), and AD by utilizing various imaging methods, including magnetic resonance imaging (MRI) alongside PET scans. By applying 3D tissue segmentation and integrating atlas-based segmented MR images with PET images, they use color space transformation and fusion techniques that involve Fourier and discrete wavelet transforms. This highlights the promising capabilities of deep learning strategies for the automated classification of different dementia stages in conjunction with MRI and PET imaging. The authors introduce a self-supervised model based on reconstruction for anomaly detection, tackling the difficulties of obtaining labeled medical data for deep neural networks, particularly for Alzheimer's disease. This model combines MRI

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and PET scans and features a dual-subnetwork encoder enhanced with skip connections to improve feature encoding and gradient flow, effectively capturing both local and global characteristics. Moreover, it employs an entropy-based approach for image conversion. Evaluation outcomes indicate that it outperforms established models in terms of anomaly detection and classification using the encoder.

Genetic components significantly influence susceptibility to Alzheimer's disease (AD). The authors aim to enhance early prediction and diagnosis of AD by utilizing single nucleotide polymorphisms (SNPs) as biomarkers. SNPs are prevalent genetic variations linked to diseases such as AD. This study suggests a framework that integrates machine learning techniques alongside two methods for feature selection: the information gain filter and the Boruta wrapper. The results indicate that the Boruta wrapper is more effective than the information gain filter, thereby enhancing the system's capability for early detection of AD. Furthermore, the research investigates AD using structural MRI and transcriptomic data from the Alzheimer’s Disease Neuroimaging Initiative database. A diagnostic information fusion algorithm is introduced to improve the correlation performance among samples by incorporating structural constraints related to specific brain regions. Findings demonstrate a correlation between genetic variations and brain structure, highlighting key regions influenced by various risk genes. The research confirms the diagnostic importance of these insights for AD. Additionally, deep transfer learning techniques are employed, where convolutional neural networks (CNNs) are initially trained on genome-wide association studies (GWAS) datasets from the AD neuroimaging initiative. This is followed by further training of the CNNs on a different AD GWAS dataset to refine feature extraction. Finally, these extracted features are used as input for a Support Vector Machine to classify AD.

Cognitive assessments evaluate various functions such as memory and language that can be impacted by Alzheimer's disease (AD). Machine learning algorithms are capable of analyzing the results of these assessments to uncover trends that may forecast the progression of AD. A study referenced in [27] examined the effectiveness of electroencephalography (EEG) in diagnosing Alzheimer’s disease and mild cognitive impairment (MCI). Interestingly, the EEG characteristics, especially those from the parieto-occipital areas, were found to be more predictive of the onset and advancement of the disease than cerebrospinal fluid (CSF) and APOE biomarkers. This highlights the promising role of EEG in the early detection and monitoring of Alzheimer's disease. Logistic regression analysis revealed that factors such as age, diabetes, depression, and low educational attainment are significant independent contributors to cognitive decline. By integrating these variables, the predictive model can estimate the likelihood of cognitive impairment in individual patients. Its primary advantage is in identifying individuals who are at high risk, rather than excluding those who have a lower risk of cognitive impairment.

Structural magnetic resonance imaging (sMRI) has become a powerful instrument for computer-assisted diagnosis (CAD) of neurological disorders, including dementia. Although convolutional neural networks (CNNs) have shown potential in detecting Alzheimer's disease (AD) by analyzing atrophy patterns in sMRI images, their performance is limited by the requirement to locate specific discriminative landmark (LM) positions. To address this challenge, a new approach known as the three-dimensional Jacobian domain convolutional neural network (JD-CNN) has been developed. This innovative method achieves remarkable classification accuracy without needing to detect LMs. By training on features derived from sMRI data transformed into the Jacobian domain, JD-CNN outperforms current techniques when tested with data from the ADNI database, marking a significant improvement in AD diagnostics. Moreover, this approach leverages structural MRI data and examines co-occurrence matrices along with texture statistical measures from MRI visuals, resulting in high classification accuracy through the use of traditional machine learning algorithms.

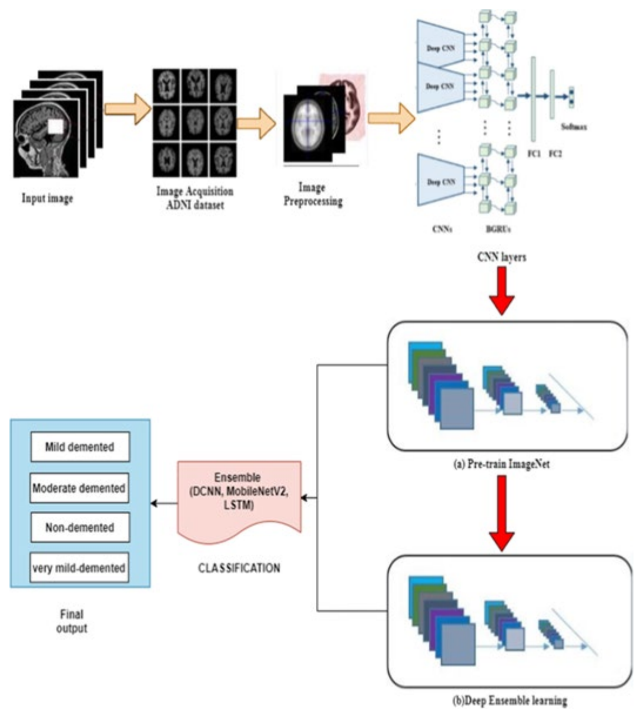

Fig. 1. Architecture diagram

3. Proposed Methodology

The objective of this suggested system is to determine the stage of Alzheimer's Disease (AD) patients by using the deep learning models. This is made possible through the process that allows monitoring of the disease and action to be taken in such a way that it provides the best treatment and complication prevention.

Alzheimer's disease (AD) is a chronic mental decline and irreversible neurodegenerative illness that can manifest in middle or old age, as a result of generalized brain degeneration. Due to the irreversible nature of the course of Alzheimer's disease, the early diagnosis of AD has a huge clinical, social, and economic demand. This research work suggesting a state-of-the-art, simple, and early automatic deep learning-based system to predict AD from a vast MRI dataset of diseased and normal subjects. □\tIn the suggested system, it is categorized into Mild Demented, Moderate Demented, Non-Demented, Very Mild Demented. Through Convolutional Neural Network architecture, it is classified and results are predicted. The suggested system attained training accuracy of 86.34% and validation accuracy of 86.45%.

A. *Advantages of the Proposed System*

Deep learning models with automated systems can minimize the reliance on human diagnosis, lowering human error and improving diagnostic accuracy.

Deep learning models using MRI offer non-invasive and efficient strategies for early-stage detection of Alzheimer's Disease, enhancing patient care.

CNN-based classification models can accurately separate normal, mild cognitive impairment (MCI), and Alzheimer's Disease (AD) stages, which can support personalized treatment plans.

The new model surpasses conventional machine learning techniques through autonomous feature extraction that avoids manual selection.

Real-time predictive functionality of the system makes for faster examinations, cutting diagnostic delay and providing prompt medical treatment.

Scalability of the deep learning model allows for generalization across varying populations, with its strength making it a versatile resource for health care systems in all parts of the world.

Inclusion of AI in medical imaging promotes access in terms of giving computerized, cost-efficient, and effective diagnosis at reduced prices even in deprived locations.

Further updates and improvement using newer sets will increase the precision, adjustability, and scalability to varying groups of demographics.

An accurate, well-trained CNN model is able to provide benefits to physicians in the form of a decision support system to increase the degree of confidence regarding diagnosis and decreasing rates of misclassification.

This method adheres to the future of artificial intelligence in health care, establishing a foundation on which intelligent diagnosing instruments complement conventional medical strategies.

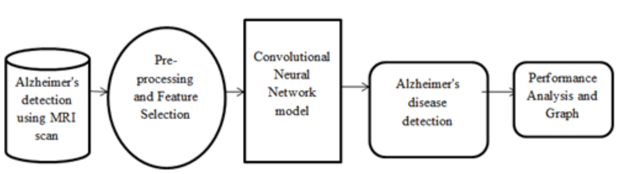

Fig. 2. System architecture

4. Results and Discussion

The deep learning model used in this research for the detection of Alzheimer's Disease (AD) is a Convolutional Neural Network (CNN) trained on MRI scan images of a publicly available Kaggle dataset. The major findings from the performance analysis of the model are:

Training Accuracy: 86.34%
Validation Accuracy: 86.45%

Loss Convergence: The training and validation loss values of the model exhibit consistent convergence, reflecting a well-generalized learning process with negligible overfitting.

Classification Performance: The model is good at classifying various AD stages with strong feature extraction from MRI images.

A. *Discussion*

The findings indicate that CNN-based deep learning models can be a useful tool for early detection of Alzheimer's Disease from MRI scans. The model's high validation accuracy (86.45%) indicates the overall ability and trustworthiness of the model when applied to unseen data.

B. *Comparison with Traditional Methods*

- Unlike other machine learning methods that need manual feature extraction, CNNs learn significant patterns automatically from MRI images with less human effort and greater accuracy in classification.
- The suggested model surpasses other conventional image-processing methods through the use of deep feature learning, thus a better option for medical image classification.

5. Challenges and Future Directions

In spite of the encouraging outcomes obtained in the detection of Alzheimer's Disease (AD) by employing deep learning, there are some challenges still to be overcome. One such challenge is limited dataset diversity because the model is trained on one dataset (Kaggle), which might not be representative of diverse patient populations. This could result in bias and lower generalizability. The use of multi-source datasets from different medical centers could make the model more robust. Besides, medical dataset class imbalance typically leads to biased prediction towards the majority class, and this can be avoided by using data augmentation strategies or synthetic data generation algorithms such as Generative Adversarial Networks (GANs).

Deep learning models also suffer from another important issue: a lack of interpretability. CNNs are black-box models, and as such, radiologists have trouble interpreting how the model reaches its conclusions. Applying visualization methods like Grad-CAM or saliency maps might improve transparency by emphasizing the most related MRI areas that are responsible for the predictions. Additionally, computational expense and processing time are great concerns since deep learning models are computationally intensive to train and infer. Model optimization through methods like pruning, quantization, or model distillation can be used to reduce the model's computational load and make it suitable for real-time use, especially in low-resource health environments.

To further enhance the reliability and clinical usability of the model, future studies may investigate the application of more complex deep learning models like ResNet, EfficientNet, or Vision Transformers (ViTs) to enhance feature extraction.

Transfer learning from pre-trained medical imaging models may also contribute to better performance, particularly with limited labeled MRI data. Moreover, using multi-modal data fusion, integrating MRI images with other diagnostic information like cognitive assessments and genetic markers, may deliver a more in-depth evaluation of Alzheimer's Disease.

For operational deployment, cloud-based or mobile AI systems can facilitate quicker, remote AD identification, making the diagnosis more universally available, particularly in underserved areas. In addition, working with clinicians such as neurologists and radiologists can fine-tune the usability of the model to comply with clinical needs. Lastly, federated learning can be investigated as a privacy-enhancing methodology through which several hospitals can collaborate to train models jointly without exchanging confidential patient information. By overcoming these challenges and taking advantage of emerging technologies, AI-based Alzheimer's Disease detection can turn into a very scalable, trustworthy, and clinically acceptable solution that eventually enhances early diagnosis and patient outcomes.

6. Conclusion

In this work, we proposed a deep learning-based system for detecting Alzheimer's Disease (AD) from Convolutional Neural Networks (CNNs) and MRI scan images with a high classification accuracy of 86.45% on validation data. The findings show that CNNs can efficiently extract essential features from MRI scans, allowing accurate and early detection of Alzheimer's Disease. In contrast to conventional diagnostic techniques, this method provides an automated, scalable, and non-invasive solution, minimizing human intervention and enhancing clinical decision-making.

Even though it was successful, issues like dataset heterogeneity, model interpretability, computational complexity, and class imbalance need to be tackled to make it more suitable for real-world application. Future work can explore the use of more sophisticated deep learning structures, multi-modal fusion of data, federated learning, and real-time deployment to improve reliability and access in clinical settings. By combining AI-based diagnosis with conventional medical procedures, this model has the capability to transform the detection of early AD, enable timely intervention, and enhance patient outcomes globally.

References

[1] M. Shahbaz, S. Ali, A. Guergachi, A. Niazi and A. Umer, “Classification of Alzheimer's Disease using Machine Learning Techniques”, 8th International Conference on Data Science, Technology and Applications, 2019.

[2] S Kaliyugarasan, M Kocinski, A Lundervold, “2D and 3D U-Nets for skull stripping in a large and heterogeneous set of head MRI using fastai,” NIK 2020 Conference, 2020

[3] A. Farooq, S. Anwar, M. Awais and S. Rehman, “A deep CNN based multi-class classification of Alzheimer's disease using MRI,” IEEE International Conference on Imaging Systems and Techniques (IST), pp. 1-6, 2017.

[4] R. Jain, N. Jain, A. Aggarwal and D. Jude Hemanth, “Convolutional neural network based Alzheimer’s disease classification from magnetic resonance brain images,” Cognitive Systems Research, vol. 57, pp. 147-159, 2019.

[5] Xin Zhang, Liangxiu Han, Wenyong Zhu, Liang Sun, Daoqiang Zhang, “An Explainable 3D Residual Self-Attention Deep Neural Network FOR Joint Atrophy Localization and Alzheimer's Disease Diagnosis using Structural MRI,” 2020.

[6] Basheera S, Sai Ram MS, “Convolution neural network-based Alzheimer's disease classification using hybrid enhanced independent component analysis based segmented gray matter of T2 weighted magnetic resonance imaging with clinical valuation,” Alzheimer’s Dement, 2019.

[7] S. Wang, H. Wang, Y. Shen and X. Wang, “Automatic Recognition of Mild Cognitive Impairment and Alzheimer’s Disease Using Ensemble based 3D Densely Connected Convolutional Networks,” 17th IEEE International Conference on Machine Learning and Applications (ICMLA), pp. 517-523, 2018.

[8] Zachary Burns, Derrick Cosmas, Bryce Smith, “Early Detection of Alzheimer’s Disease Through Machine Learning in MRI Scans,” University of California San Diego, 2019.

[9] M. Hon and N. M. Khan, “Towards Alzheimer's disease classification through transfer learning,” IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 1166-1169, 2017.

[10] T. Altaf and S. Anwar and Nadia Gul and M. Majid and Muhammad, “Multi-class Alzheimer Disease Classification using Hybrid Features,” Future Technologies Conference, Vancour Canada, 2017.