Grenze International Journal of Engineering and Technology, June Issue

Alzheimer's Disease Identification using Transfer Learning and Advanced Convolutional Neural Network Models

Samiksha Satpute[1], Mr. Chetan Puri[2] and Aman Waghmare[3]
[1-3]Datta Meghe Institute of Higher Education & Research, Department of Computer Science and Design Wardha, Maharashtra, India
Email: samikshasatpute04@gmail.com, chetanp.feat@dmimsu.edu, waghmareaman8080@gmail.com

***Abstract*—Alzheimer's disease (AD) is an important global health issue that primarily affects older people. As the neurodegenerative disease advances, only two of the physical and mental issues that can develop are memory loss and language loss. The early and precise identification of AD has drawn increasing attention in recent years. This work suggests a deep learning-based approach for categorizing pictures of both healthy and Alzheimer's-affected brains. Image categorization and ROI extraction are the two main components of the suggested approach. Another method for diagnosing AD or moderate cognitive impairment (MCI) is ROI extraction, which focuses on separating global brain areas, such the hippocampus, from the whole brain in an imaging or scan visualization. Later on, classification may be done using transfer learning and convolutional neural networks (CNN). Important details are removed before the CNN model recognizes the images. For classification, Transfer Learning makes use of pre-trained AlexNet features. Tests using the OASIS (Open Access Series of Imaging Studies) dataset show that the Transfer Learning method outperforms the CNN-based method in terms of accuracy (92.86%).**

***Index Terms*— area of interest extraction, image classification, deep learning, convolutional neural networks, Alzheimer's illness, AlexNet architecture, and transfer learning.**

I. INTRODUCTION

The field of medical imaging is becoming väry important for the modern health care as it enables diagnosis and therapy. Imaging techniques have become more effective and useful through advances in the field. Commonly used modalities include X-rays, radiography, ultrasound, and magnetic resonance imaging (MRI). Together, these unique aspects of each method provide a broad understanding of the body, including the brain. MRI is required to find abnormalities like cancers, blood clots, and other structural issues. Because brain-tissue interfaces have a high degree of contrast, MRI is particularly good at creating high-resolution images of the brain. It is also utilized for the diagnosis of diseases that affect different regions of the brain, such as Alzheimer’s disease (AD). It’s a complicated neurological disorder common in seniors, and is among the most common types of dementia. Common symptoms include memory loss, difficulty speaking and other problems that severely impair functioning in daily life.

Grenze ID: 01.GIJET.11.2.332_20

CNNs have resulted in impressive improvements in the accuracy of object classification for images in the last decade, and since then, they have the best performance among other CNN networks.
These methods have not outperformed manual feature extractors such as local binary patterns, covariance descriptors, and k-Nearest Neighbors. The ability of deep learning methods, particularly CNNs, to withstand rotational and scalar shifts makes them ideal for picture categorization applications. This research builds on recent advances by assessing the efficacy of two deep learning-based techniques for recognizing AD: CNNs and Transfer Learning models. The following is the structure of the paper: Following Section 2's examination of pertinent literature, Section 3's description of the recommended methodology, and Section 4's presentation of the experimental findings, the study concludes with closing remarks.

II. Related Works

Many of the current techniques for detecting AD rely on complex image processing and classification algorithms. The Gaussian Mixture Model (GMM), a dependable model for density prediction and addressing conventional classification problems, was employed by Nair and Mohan [7] for grey matter segmentation. They used Support Vector Machines (SVM) for classification and Partial Least Squares (PLS) for feature extraction. Ben Rabeh, Benzarti, and Amiri [8] introduced another notable segmentation technique based on the Level Set approach. In their classification approach, they had to compute distances based on four criteria, in order to determine the closest match to a new input image. The photos were then classified by Bayes theorem. To determine the area of interest (VOI) they employed a 3D mask, Mufidah, Wasito, Hanifah, and Faturrahman [9] employed voxel-based morphometry feature extraction approach. To classify the collected properties, they used a well-known deep learning prototype, i.e. Deep Belief Network (DBN). Devis, Prabha, and Sakthidasan [10] separated brain pictures into gray and white matter employing the Fuzzy CMeans approach. Using the Grey Level Co-occurrence Matrix (GLCM), which records the spatial correlations within the segmented tissues, they used second order statistical characteristics that are simple to classify.Using texture and form data from the GLCM methodology, Dalal and Raut [11] separated their methods into two sections: feature extraction and classification using an Artificial Neural Network (ANN). Angkoso, Purnama, and Purnomo [12] used voxel-based morphometry to divide the white matter, gray matter, and cerebrospinal fluid into three different brain tissues. They employed a backpropagation neural network for classification and the Kolmogorov-Smirnov distance for feature extraction. According to Song and colleagues [13], Convolutional Neural Networks (CNN), a type of deep learning architecture, have been used extensively in the identification of AD.

III. Proposed Method

Two main processes make up the suggested method: categorizing brain images and identifying regions of interest. As seen in Fig. 1, these stages work together to provide effective categorization.

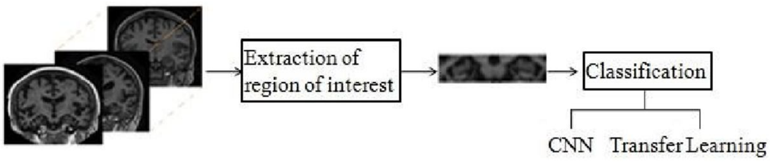

Fig 1. Overview of the Proposed Solution's Framework

A. Region of Interest Extraction

An essential component of image analysis in this study is the extraction of the area of interest (ROI). The technique entails splitting the brain MRI picture into a grid of 32 × 32 pixel square blocks for this purpose. Only those of these blocks that cover the hippocampal area of the brain—that is, blocks 43, 44, 45, and 46—are kept; the others are thrown away. This stage guarantees that only the pertinent brain regions are taken into account for further examination. Fig. 2 shows a graphic representation of the procedure.

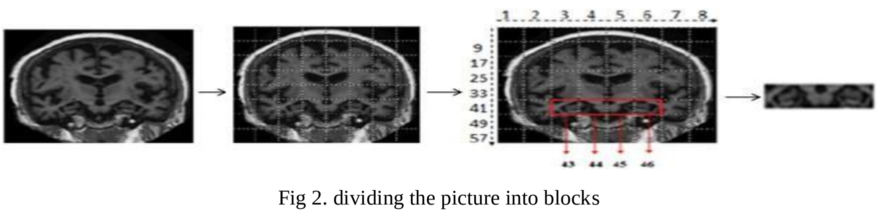

Fig 2. dividing the picture into blocks

The primary goal of ROI extraction is to derive a compact yet comprehensive representation of each image. This ensures the analysis is efficient while retaining critical features necessary for classification.

B. Classification

Image classification is the process wherein objects are classified into distinct categories according to a predetermined criterion. In this work, two categories considered in the classification challenge are images of Alzheimer's disease and normal brains. Following the extraction of ROIs, two methods are applied for classification: Convolutional Neural Networks (CNN) and Transfer Learning algorithms.

The comparative study evaluates and compares the various methods for image restoration from blocks for restoring, sometimes referred to as the multilayer perception, convolutional neural networks, CNNs, etc., which is itself an intricate multilayered architecture built upon the primitive version of neural networks. It comprises two main blocks: feature extraction and classification. Feature extraction happens within the first half of the CNN framework, where a sequence of convolutional filters are applied to the input image as it passes through the network, generating new representations known as feature maps or convolutional maps. Recognition and capturing of important features—like textures or edges—of the image itself are done through these filters.

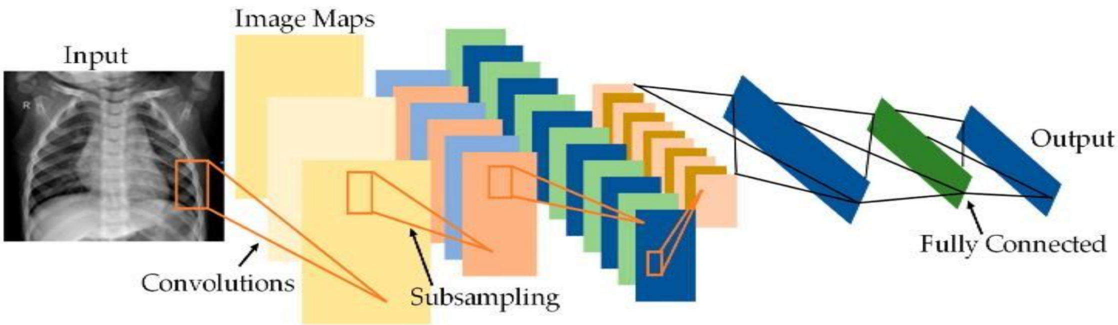

Fig. 3. CNN Architecture

Evolving heavily on the convolution layer to gain features from images, CNNs operate. It attaches an input image according to a sliding window approach to a filter (also termed kernel). While doing this, the process involves some computation that is simply called convolving, which, in essence, is matrix multiplication between the filter and the corresponding area of the image being processed. The filter is first applied at the top left corner of the image, and then the filter takes a step of stride distance across the image in the horizontal direction. After a single step, it again starts from the edge and proceeds to scan horizontally. This continues until the filter traverses the entire image. This particular operation is mostly concerned with enhancing certain features of the image like those of edges or textures or patterns for further processing and ultimately classification tasks.

Pooling layers reduce the spatial resolution of the image while preserving its important features. Max Pooling is one of the most widely used techniques, whereby the image is processed by selecting the maximum pixel value within a specified area that still retains the most dominant features of the image. This processes an image by moving a window, or filter, across the image surface, extracting the largest pixel value in that area for each window location. The result is a diminutive version of the original image that preserves the significant values of the original image while discarding the unimportant ones. In this way, it prevents overfitting while reducing the workload of computations. Figure 5 shows an instance of Max Pooling [17].

The Rectified Linear Unit (ReLU) layer is mainly responsible for enhancing the computational efficiency of the network. The signals between portions are modified by an activation function. The ReLU function converts all negative values to zero and retains positive values, ensuring the neurons produce only nonnegative outputs [16].

Flattening is an important step in transitioning from convolutional layers to fully connected layers. It converts the multi-dimensional matrix of image features into a single-dimensional vector. The network can analyze the retrieved features for categorization in later levels due to this vector's direct connection to the first fully connected layer.

The fully connected layers do the classification once the convolutional and pooling layers have collected the pertinent data. To enable a thorough feature analysis, each neuron in these layers is linked to every other neuron in the layer above it. The output from the fully connected layer is processed by the Softmax function, which then produces a probability distribution vector. The number of classes in the classification task determines the size of this vector, which displays the likelihood that the input image belongs to each class.

IV. Experimental Results

A. Dataset Description

Figure 2 shows the flowchart of our suggested technique, which is described in this part along with the subsequent steps. The DCNN and transfer learning models are used to classify tumors as either benign or malignant. We are putting out a DCNN model that makes use of a few more layers. Furthermore, we have tested a number of alternative transfer learning models, including AlexNet, ResNet, VGG-16, DenseNet, and MobileNet, on the same dataset.

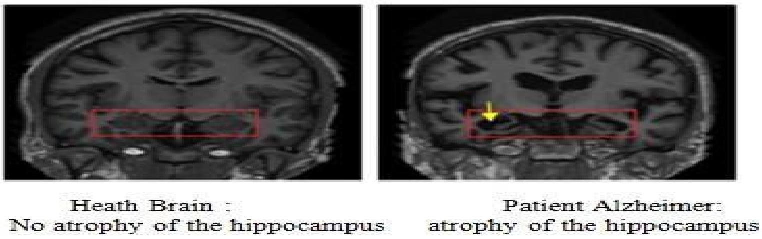

Fig 7. Brains with AD and normal brains are compared.

B. Results

Transfer Learning and CNN. As per the findings, the CNN model produced an accuracy of 88.10%, whereas Transfer Learning achieved an accuracy of 92.86%. This exemplifies the Transfer Learning concept whereby large knowledge is transferred from a pre-trained model (AlexNet) to a smaller dataset (OASIS). Such approaches increase classification accuracy, reduce training time, and minimize data need, allowing the creation of an accurate, efficient model. Table 1 presents the comparison between our proposed approach and some state-of-the-art methods. The proposed technique achieved the highest accuracy of 92.86%, indicating excellent classification ability.

Table I Performance Evaluation Table: Proposed Method vs. Other State-of-the-Art Approaches

Methods	Technique	Classification rate
Manzak and Çetinel [14]	Deep Neural Network (DNN)	67%
Martinez-Murciaet al. [15]	Convolutional	80%
Cortical Images with Inception [16]	Inception	81%
Our Proposed method	CNN	88.10%
Our Proposed method	Transfer Learning	92.86%

Table 1's comparison study demonstrates how much better our suggested strategy performed than previous strategies. Using Deep Neural Networks (DNN), Manzak and Çetinel [21] achieved an accuracy rate of 67%. The accuracy of 80% was reported by Martinez-Murcia et al. [22], who also used Convolutional Autoencoders (CAE). Using Inception networks, cortical image analysis achieved 81% accuracy [23]. Our method improved AlexNet's performance by utilizing Transfer Learning, which effectively transferred data from the pre-trained architecture.

The model's remarkable accuracy of 92.86% was attained by substituting a specially designed layer for binary classification (healthy vs. AD-affected brains) for the last fully linked layers. Furthermore, because of its strong feature extraction capabilities and classification using the Softmax function, the solo CNN model also performed well, with an accuracy of 88.10%.

V. Conclusion

In this work, we employed and evaluated two techniques for AD detection: convolutional neural networks (CNN) and transfer learning. The two main phases of the suggested approach were classification and region of interest extraction. The image was initially segmented to locate the hippocampal region of the brain. Both CNN and Transfer Learning methods were used for categorisation in the second stage. The outcomes showed that Transfer Learning outperformed CNN in terms of classification accuracy, demonstrating how well it uses pre-trained models for smaller datasets. Both strategies outperformed other cutting-edge techniques using comparable procedures, achieving high organization rates. We hope to expand the suggested method in further research to include the identification and examination of additional brain-related disorders, such brain tumours. Furthermore, we intend to investigate cutting-edge strategies, such deep quantisation, to optimise CNN by lowering the number of parameters while preserving strong performance; we may even integrate approaches like the Keep of Features paradigm

REFERENCES

[1] M. BALAMURUGAN, A. NANCY, and S. VIJAYKUMAR, "Diagnosing Alzheimer's Disease through Dimensionality Reduction Using a KNN Classifier," Biomedical Pharmacology Journal, vol. 10, pp. 1823-1830, 2017.

[2] "3D Face recognition using covariance based descriptors," Pattern identification Letters, vol. 78, pp. 1–7, 2016, W. Hariri, H. Tabia, N. Farah, A. Benouareth, and D. Declercq.

[3] "3D facial expression recognition using kernel methods on Riemannian manifold," vol. 64, pp. 25-32, 2017, by W. Hariri, H. Tabia, N. Farah, A. Benouareth, and D. Declercq.

[4] Alzheimer's disease diagnosis in magnetic resonance imaging (MR) images using statistical methods was presented by J. Nair and N. Mohan at the IEEE International Conference on Communication and Signal Processing in April 2017. The paper was published in volume 17, pages 1232-1235.

[5] "New Method of Classification to detect Alzheimer Disease," by A. Ben Rabeh, F. Benzarti, and H. Amiri, IEEE 14th International Conference on Computer Graphics, Imaging, and Visualization, vol. 17, pp. 111-116, 2017.

[6] "Structural MRI classification for Alzheimer's disease detection using deep belief network," vol. 17, pp. 37–42, 2017, R. Mufidah, I. Wasito, N. Hanifah, and M. Faturrahman.

[7] "Brain Hemisphere Analysis using Genetic Algorithm and Fuzzy Clustering in Alzheimer Disease," International Conference on Communication and Signal Processing, vol. 18, pp. 901-905, April 2018, D. Chitradevi, S. Prabha, and K. Sakhidasan.

[8] A. Raut and V. Dalal, "A Machine Learning-Based Method for Alzheimer's Disease Detection Using Hippocampus Analysis"

[9] IEEE International Conference on Computing Methodologies and Communication (ICCMC), vol. 17, pp. 236-242, 2017.

[10] C. Angkoso, I. Purnama and M. Purnomo, ”Analysis of Brain Tissue and Cerebrospinal Fluid Feature for Alzheimer’s disease Detection”, IEEE International Conference on Computer Engineering, Network and Intelligent Multimedia (CENIM), vol. 31, pp. 285-288, 2018.

[11] T. Song, S. Chowdhury, F. Yang, H.Jacobs, G. Fakhri, Q. Li, K. Johnson and J. Dutta, ”GRAPH CONVOLUTIONAL NEURAL NETWORKS FOR ALZHEIMER’S DISEASE CLASSIFICATION”, vol. 19, pp. 414417, April 2019.

[12] H. Padole, S. D. Joshi, T. K. Gandhi,”Early Detection of Alzheimer’s Disease using Graph Signal Processing on Neuroimaging Data”, 2nd European Conference on Electrical Engineering and Computer Science (EECS), vol.18, pp. 302-306, 2018.

[13] A. Kaya, A. Keceli, C. Catal, H. Yalic, H. Temucina and B. Tekinerdogan,””Analysis of transfer learning for deep neural network based plant classification models”, Computers and Electronics in Agriculture, vol. 158, pp. 20-29, March 2019.

[14] Y .Zhang, C. Pan, J. Sun and C.Tang, ”Multiple sclerosis identification by convolutional neural network with dropout and parametric ReLU”, Journal of Computational Science, vol. 28, pp. 1-10, September 2018.

[15] W. Shen and W. Wang, ”Node Identification in Wireless Network Based on Convolutional Neural Network”, IEEE 14th International Conference on Computational Intelligence and Security (CIS), vol. 31, pp. 238-241, 2018.

[16] C. Mazo, J. Bernal, M. Trujillo and E. Alegre, ”Transfer Learning for Classification of Cardiovascular Tissues in Histological Images”, Computer Methods and Programs in Biomedicine, vol. 18, pp. 1-20, 2018.

[17] A. Unnikrishnan, V. Sowmya and KP. Soman, ”Deep AlexNet with Reduced Number of Trainable Parameters for Satellite Image Classification”, Procedia Computer Science, vol. 143, pp. 931-938, 2018.