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Research Article

An Introspective Study on Attention-Based Transfer Learning in CNNs for Alzheimer's Disease Detection

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ABSTRACT

Introduction: Deep learning (DL) algorithms have demonstrated remarkable advancements in the field of medical image analysis, particularly in the classification of Alzheimer's Disease (AD). Despite these advancements, a significant challenge remains in acquiring the extensively annotated image datasets required to effectively train DL models. Attention mechanisms have emerged as powerful tools in DL, enabling models to prioritize critical regions within data and extract essential features. This focus not only enhances training efficiency but also improves overall classification performance. In this study, convolutional neural networks (CNNs) are utilized as the foundational architecture for AD classification tasks. To further enhance their performance, the Convolutional Block Attention Module (CBAM) is integrated into the CNN framework. CBAM is a lightweight and versatile attention mechanism that can be easily incorporated into any CNN architecture with minimal computational cost. By emphasizing important spatial and channel-wise features, CBAM significantly improves the feature extraction capability of CNNs. Building on this concept, an enhanced version of CBAM, referred to as enCBAM, is proposed. EnCBAM optimizes the generation of output feature maps, further improving the discriminative power of CNN architectures. In this work, the pre-trained VGG-16 network is employed as the base CNN model. When combined with enCBAM, the resulting architecture, referred to as EnCNN, achieves a substantial boost in classification performance. Specifically, EnCNN attains an impressive classification accuracy of 95.06%, outperforming its standalone counterpart and demonstrating the effectiveness of the enhanced attention mechanism.

Keywords: Deep learning, Alzheimer's disease, CBAM, Attention, MRI..

INTRODUCTION

Neurological disorders are increasingly reported among the elderly, with Alzheimer's disease being one of the most common. India, currently the most populous country in the world, had a population of 1.43 billion as of August 2023, according to Worldometer's analysis of the latest United Nations data [1]. With its rapidly growing population, India is projected to reach 319 million elderly individuals by 2050, comprising nearly 20% of its total population [2]. By that time, 15.4% of the global population will be aged 60 or older. India's life expectancy has also seen a significant rise, increasing from 42.9 years in 1960 to 70.4 years in 2020 [3]. Aging is the most significant and well-established risk factor for dementia [4], suggesting a potential surge in dementia cases in India in the coming decades. To effectively address this challenge, a robust national assessment of dementia prevalence is crucial. In light of limited nationwide studies, the Alzheimer's and Related Disorders Society of India [5] has provided estimates based on the World Alzheimer Report 2015 [6] for South Asia. These projections highlight the urgent need to understand the extent of the dementia burden in India to inform public health strategies and policy-making.

The pathophysiological mechanisms underlying Alzheimer's disease continue to be elusive, despite significant advancements in research. Research indicates that the accumulation of tau proteins and amyloid-beta (Aβ) substances in brain tissue plays a critical role in the development of Alzheimer's disease. This buildup disrupts neuronal activity, leads to neuronal death, causes brain tissue shrinkage, and triggers inflammatory responses. These pathological processes contribute to the progressive cognitive and functional decline observed in individuals with the disease [7]. Patients with Alzheimer's disease (AD) display significant heterogeneity in brain imaging and cognitive function. Variations in the regional distribution of brain atrophy contribute to this imaging diversity [8]. Clinical investigations have identified multiple subtypes of Alzheimer's disease (AD), with each subtype exhibiting distinct patterns of brain degeneration [9], [10]. Between normal controls (NC), mild cognitive impairment (MCI), and Alzheimer's disease (AD), studies have shown that MCI often progresses to AD if left untreated or without intervention [11], [12].

MRI is a critical biomarker for diagnosing Alzheimer's disease (AD), providing clinicians with an essential tool for assessment. By analyzing MRI images, doctors can determine the extent of brain shrinkage in AD patients and gain insights into how the disease progresses. However, managing long and complex MRI scans poses challenges for healthcare professionals. As a result, there is a growing interest in computer-aided diagnosis of AD using MRI to enhance diagnostic accuracy [16].

Over the past two decades, traditional machine learning techniques, involving manual feature extraction, have played a crucial role in broad-scale AD diagnosis, often outperforming even highly skilled medical professionals. Many studies have tackled this issue using various deep learning approaches, with Convolutional Neural Networks (CNNs) being the most widely used model for AD classification. Other approaches, such as U-Net, Y-Net, and W-Nets, have also been explored. Many models employ transfer learning, utilizing pre-trained CNNs to extract essential features. Popular transfer learning models include AlexNet, MobileNet, ResNet, and VGG-16.

According to studies by [21] and Thayumanasamy et al. [27], CNNs offer superior adaptability and generalization for AD classification when compared to traditional machine learning techniques. The ability of pre-trained networks to reduce the training burden inspired the proposed model, which is computationally cost-effective and significantly enhances performance.

The structure of the paper is as follows: Section II reviews prior work in this area. Section III outlines the proposed methodology. Section IV details the experimental settings. Results and discussions are presented in Section V, with the conclusion in Section VI.

RELATED WORKS

In [17], voxel-based machine learning approaches were used to extract basic features from medical images, which were then input into a classifier. F. Previtali et al. [18] introduced a method for deriving traits from patients' brain MRI data, which involved identifying brain regions most likely associated with Alzheimer's disease using prior knowledge. After extracting spatial information about the affected regions and their distinct patterns in the brain, the data was fed into a Support Vector Machine (SVM) classifier. In contrast, the Region-of-Interest (ROI)-based technique segmented the MRI image into multiple regions, using specific features to describe each one. Li et al. [19] illustrated this approach by predicting the progression of mild cognitive impairment through MRI-based segmentation of the hippocampus. Zhang et al. [20] proposed a local block-based technique, segmenting MRI scans into smaller blocks using texture data from MRI slices to identify Alzheimer's disease.

Zhu et al. developed a 3D U-shaped deep network, HA-ResUNet, inspired by the attention mechanism found in human visual systems [28]. This model incorporates both channel and spatial attention mechanisms and is based on ResNet. HA-ResUNet can autonomously assign attention during model training, enhancing its performance. Zhang and his team [29] created two CNN designs using 2D segments from various MRI and PET scans, combining the results with Mini-Mental State Examination (MMSE) and Clinical Dementia Rating (CDR) scores to classify individuals into categories such as cognitively normal (CN), mild cognitive impairment (MCI), and Alzheimer's disease (AD). However, using only a single MRI or PET slice to characterize the entire scan is insufficient, as the affected regions may not be consistently visible across all 2D slices.

To address this, Aderghal et al. [30] improved network classification performance by using pre-trained networks on multi-modal brain imaging. Abdelaziz et al. [31] developed a system that jointly identifies Alzheimer's disease by combining high-level information from multiple modalities, such as genetic and neural scan data, using a convolutional neural network. Altay et al. [32] proposed a deep learning architecture to predict preclinical Alzheimer's disease.

Based on the literature review above, the following gaps have been identified:

- Some deep learning models, such as Recurrent Neural Networks (RNNs), have inherent sequential processing limitations and cannot process all features (spatial and temporal) simultaneously [33-34].
- RNNs struggle to capture long-range local features within MRI images.
- Many CNN variants are prone to overfitting, particularly when using relatively small datasets.

The proposed methodology in the next section addresses these research gaps.

1 Proposed Methodology

The various steps of proposed method are depicted in Fig 1. Initially input MRI images are given and the pre-processing of images is done. Features are extracted using pre-trained Convolutional Neural Networks (CNNs). CBAM is used to handle temporal dependencies of features. Features extracted are fed to the classifier and output is attained. that had been pre-trained were used to complete the ImageNet classification job. Initially, these networks were taught to categorize items into 1,000 different groups. As a consequence, all levels from

these networks were accepted by us, with the exception of the FC layers. In- stead, It is replaced with our own set of FC layers that were customized for our particular dataset, which has two classes: AD and CN (cognitively normal), and include elements like flattening, dense layer, global average pooling, softmax, etc.

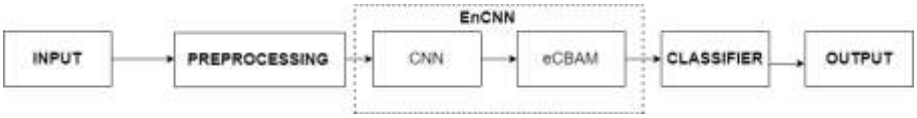


Fig. 1. Proposed workflow pipeline.

Input: Structural MRI images were given as input.

Preprocessing In the pre-processing stage, skull removal, intensity normalizationtion, and registration of brain slices are done.

Feature Extraction using Enhanced Convolutional block attention module (eCBAM). Woo et al. [41] introduced CBAM, a structurally effective solution that lever-ages the combined power of spatial and channel-wise attention processes first put forth by Chen et al. (2017), to address this problem. The spatial attention mech- anism successfully hones down on relevant information by highlighting specific regions with high perceptual value. The channel-wise attention strategy shownin fig 3, on the other hand, gives channels weights based on how important theyare, highlighting the significance of the more significant ones. The architecturaldetails of both modules are shown in Fig. 2.

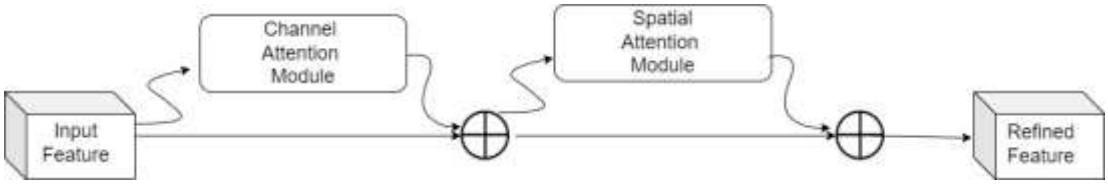


Fig. 2. enCBAM Block

The spatial dimensions of the input feature map are diminished by utilizinga combination of maximum and average polling. While the global max poolinglayer gathers particular image features and directs more precise channel-wise attention, the global average pooling layer combines all spatial information. In-put feature map F and its scaling elements are given for element wise multipli-cation operation. It has given output as a channel-enhanced feature map. By concentrating more on particular areas of the feature map than the channel at-tention module, the spatial attention module completes the latter. The channel-enhanced feature map is split into two 2D feature maps along the channel axisand uses maximum and average pooling to compute the spatial attention module shown in fig 4. Then, a conventional convolutional layer is used to convolution-ally combine these 2D feature maps. Each element in the channel-enhanced mapis element-wise multiplied with the matching spatial weight produced from thespatial attention map to produce the CBAM's final output.

To focus on "what" and "where," respectively, CBAM successfully uses both channel and spatial attention mechanisms. Due to its dual focus, CBAM are better suited to find the data which are central to both spatial and channle dimension which will increase the efficiency of the feature extraction process. CBAM was merged with the CNNs feature map to showcase the increased effec-tiveness of CBAM to produce more unique features and therefore boosting the performance of CNNs.

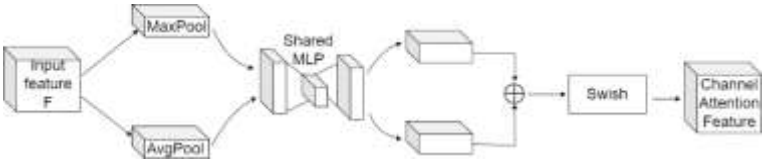


Fig. 3. Channel attention module

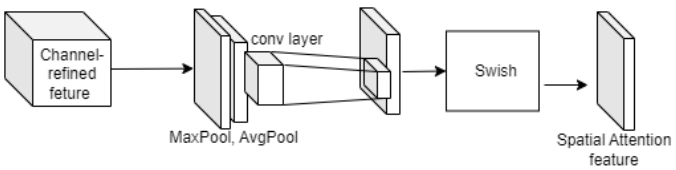


Fig. 4. Spatial attention module

The FC layers were then applied in a similar way as that of models whichare pre-trained.

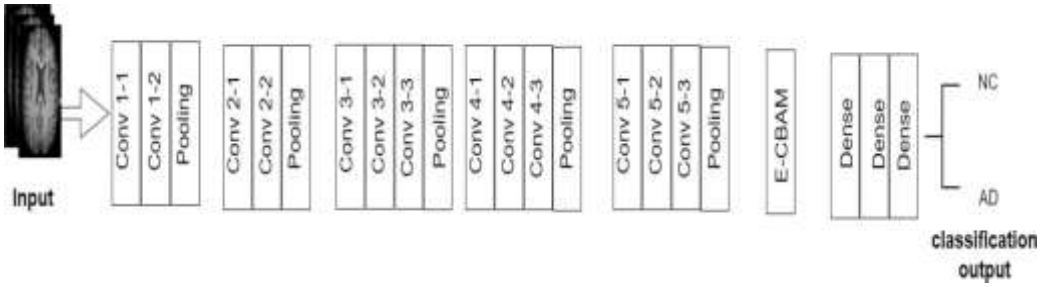


Fig. 5. Proposed architecture EnCNN

An overview of EnCNN (pre-trained VGG-16+enCBAM) architectures is shownin Figure 5. The extraction of more precise characteristics relied heavily on this CBAM integration.

EXPERIMENTAL SETUP

The experiment was carried out on a multicore i7 processor having 16 GB RAM and a GPU100 as an accelerator. GPU100 with CUDA support is faster and makes thetraining process seamless**.**

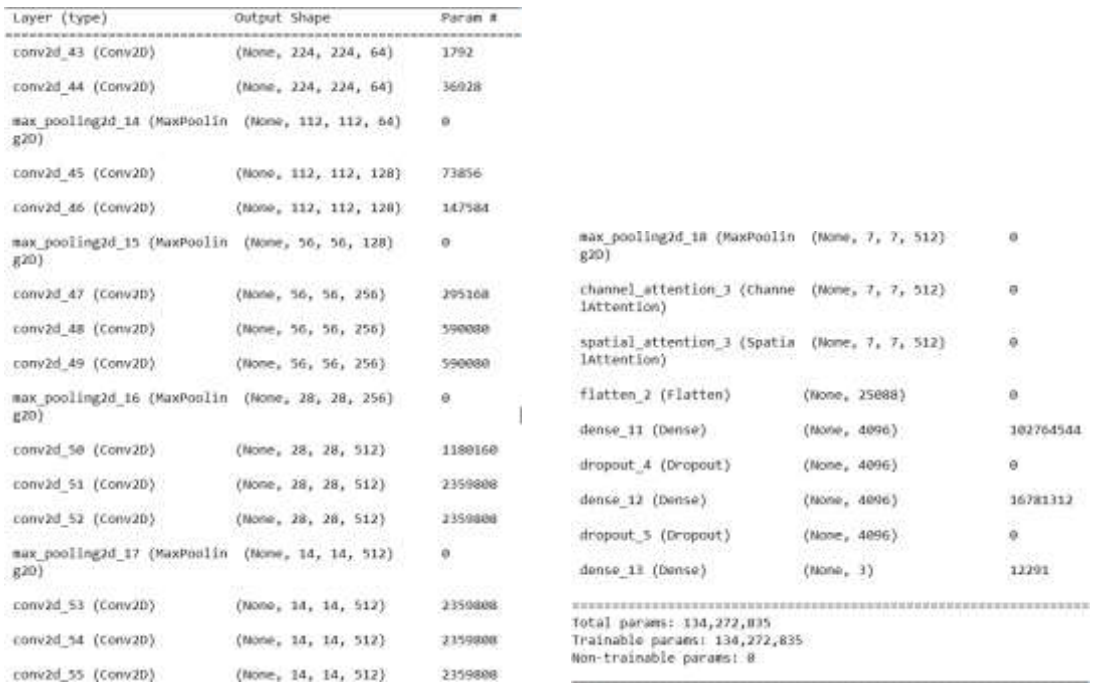
1.1 Dataset

In this experiment, the dataset is utilized from the ADNI database, which may be accessed at http://adni.loni.usc.edu. In these study, T1 MRI images from thecategories AD and NC were the only ones used for classification. Table I provides the glimpse of the dataset. Each patient had an average of 3.5 scans performedat various times, as shown in Table 1. This study consists of a total of 2964 images of 831 healthy controls and 1492 images of 418 patients with Alzheimer'sdisease (AD). In a 4:1 ratio, the training and validation sets were split. In our experiments, we fed completely three-dimensional samples with dimensions of121 145 121 into our suggested model pipeline.

The MRI scans were obtained at different stages of the Alzheimer's DiseaseNeuroimaging Initiative (ADNI), which caused changes in the acquisition techniques. This is a crucial first point to make. Spatial normalization must be usedbecause of the discrepancies in spatial resolution and slice thickness that resultfrom these variances across the obtained MRI scans. FMRIB Software Library (FSL) is the spatial normalization tool, and MNI152 is the registration template.

Table 1. The ADNI Dataset

class	Number of Subjects	Images
AD	418	1492
CN	831	2964



Layer (type)	Output Shape	Param #
conv2d_43 (Conv2D)	(None, 224, 224, 64)	1792
conv2d_44 (Conv2D)	(None, 224, 224, 64)	36928
max_pooling2d_14 (MaxPooling2D)	(None, 112, 112, 64)	0
conv2d_45 (Conv2D)	(None, 112, 112, 128)	73856
conv2d_46 (Conv2D)	(None, 112, 112, 128)	147584
max_pooling2d_15 (MaxPooling2D)	(None, 56, 56, 128)	0
conv2d_47 (Conv2D)	(None, 56, 56, 256)	295168
conv2d_48 (Conv2D)	(None, 56, 56, 256)	590080
conv2d_49 (Conv2D)	(None, 56, 56, 256)	590080
max_pooling2d_16 (MaxPooling2D)	(None, 28, 28, 256)	0
conv2d_50 (Conv2D)	(None, 28, 28, 512)	1180160
conv2d_51 (Conv2D)	(None, 28, 28, 512)	2359808
conv2d_52 (Conv2D)	(None, 28, 28, 512)	2359808
max_pooling2d_17 (MaxPooling2D)	(None, 14, 14, 512)	0
conv2d_53 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_54 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_55 (Conv2D)	(None, 14, 14, 512)	2359808
max_pooling2d_18 (MaxPooling2D)	(None, 7, 7, 512)	0
channel_attention_3 (ChannelAttention)	(None, 7, 7, 512)	0
spatial_attention_3 (SpatialAttention)	(None, 7, 7, 512)	0
flatten_2 (Flatten)	(None, 25088)	0
dense_11 (Dense)	(None, 4096)	102764544
dropout_4 (Dropout)	(None, 4096)	0
dense_12 (Dense)	(None, 4096)	16781312
dropout_5 (Dropout)	(None, 4096)	0
dense_13 (Dense)	(None, 3)	12291

Total params: 134,272,835
Trainable params: 134,272,835
Non-trainable params: 0

Fig. 6. EnCNN Architecture summary

RESULTS AND DISCUSSIONS

The binary classification task—differentiating AD from CN, was tested in this study. We separated the dataset in such a way that 70% for training, 15% for validation, and 15% for testing, all of which were randomly sampled, for each ofthis binary classification. To improve the data, we randomly rotated theimage slices between -15 and 15 degrees.

We trained the model for 150 epochs with the parameter learning rate set to 0.0001 for the binary classification task between AD and CN. We used the SGDoptimizer for each of the three training problems. We used 80 slices per MRI picture and 2 MRI sample batches to work around GPU restrictions. Grad-CAM is used to visualize the important regions shown in Fig. 9. Our proposed system outperforms other systems by achieving 95.06% accuracy. Age and Mini-Mental State Examination (MMSE) scores were taken using Expectation and SD values. The general cognitive status was evaluated using the MMSE.

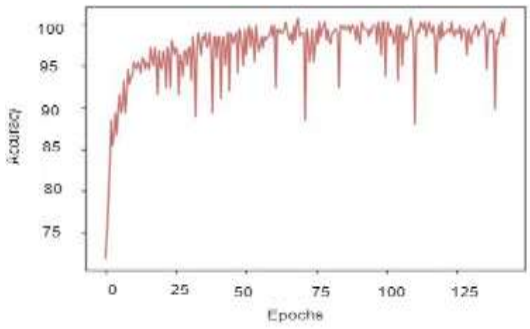


Fig. 7. AD vs CN validation accuracy

The validation accuracy and validation loss charts for EnCNN in the binaryclassification tasks is given in Fig 7 and Fig 8. As it is visible from the graph in Fig 7, accuracy stabilizes as the number of epochs increases. In Fig 8, the loss is

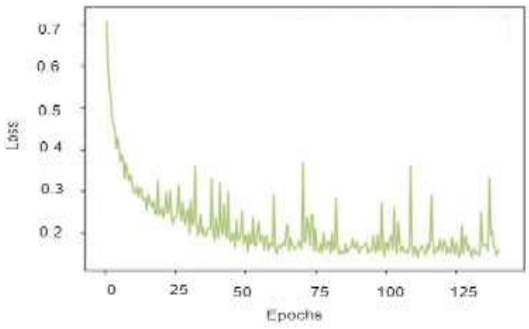


Fig. 8. AD vs CN validation loss

reduced from 0.7 in the initial epoch to 0.2 in the 125th epoch. The visualizationof the localization of brain atrophy of AD is given in Fig 9. The atrophy attentionsare attained using the Grad-CAM.

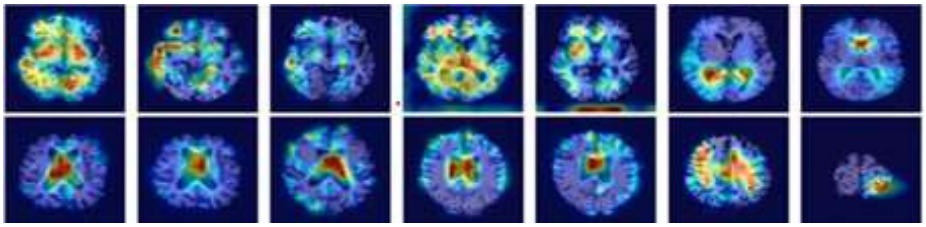


Fig. 9. Grad-CAM visualization results

Table II gives a comparative analysis of the current technique with the existing works.

Table 2. The Comparative results of various models

Approach	Methods	Accuracy(%)
Safiullin et al. [45]	3D CNN	87.00
Masoumzadeh et al. [43]	Transformer	88.20
Lao H et al. [46]	3D CNN+SVM	92.0

Liang G et al.[44]	3D CNN+Transformer	91.34
G.R. Sánchez et al.[32]	3D CNN	85.23
Recurrent Attention [33]	3D CNN+RNN	88.84
Proposed	3D CNN+Attention block(enCBAM)	95.06

CONCLUSIONS

For the pairwise classification of Cognitive Normal (CN) and Alzheimer's Disease (AD), the EnCNN model integrates Convolutional Neural Networks (CNN) with Attention modules. This approach begins by extracting low-level planar features from 2D MRI slices using a VGGNet-16-based CNN. These features are further refined through the Enhanced Convolutional Block Attention Module (enCBAM), which employs the Swish activation function within CBAM to optimize local planar characteristics. This mechanism enhances the focus on local spatial details, improving the integration of these features. Unlike traditional methods that treat all MRI planes equally, experiments demonstrate that EnCNN excels at capturing the properties of neighboring planes in 3D MRI images. This capability enables the model to detect localized mild brain atrophy with higher precision, enhancing its ability to differentiate between CN and AD.

This study leverages 2D CNNs to extract detailed features from MRI slices and incorporates Attention mechanisms to achieve a more granular representation of MRI features, resulting in improved classification performance. Additionally, the research aims to utilize genomics data from patients with Mild Cognitive Impairment (MCI) to predict disease progression, which is of significant clinical importance. Future work will focus on exploring the genomics-related aspects of Alzheimer's Disease, with the goal of achieving even more accurate classification and prediction outcomes.

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