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A novel convolutional neural network architecture for Alzheimer's disease classification using magnetic resonance imaging data

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ABSTRACT

Accurate categorization of Alzheimer's disease is crucial for medical diagnosis and the development of therapeutic strategies. Deep learning models have shown significant potential in this endeavor; however, they often encounter difficulties due to the intricate and varied characteristics of Alzheimer's disease. To address this difficulty, we suggest a new and innovative architecture for Alzheimer's disease classification using magnetic resonance data. This design is named Res-BRNet and combines deep residual and boundary-based convolutional neural networks (CNNs). Res-BRNet utilizes a methodical fusion of boundary-focused procedures within adapted spatial and residual blocks. The spatial blocks retrieve information relating to uniformity, diversity, and boundaries of Alzheimer's disease, although the residual blocks successfully capture texture differences at both local and global levels. We conducted a performance assessment of Res-BRNet. The Res-BRNet surpassed conventional CNN models, with outstanding levels of accuracy (99.22%). The findings indicate that Res-BRNet has promise as a tool for classifying Alzheimer's disease, with the ability to enhance the precision and effectiveness of clinical diagnosis and treatment planning

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1. INTRODUCTION

Alzheimer's disease (AD) is an ever-increasing threat in the world, proving the need to diagnose it and differentiate it from other similar conditions. The present therapeutic diagnosis depends on the expert reading of radiologists, which is considered erroneous because they are human beings. There is growing evidence on the application of deep learning in early AD diagnosis [1]. AD, a neurological illness, has become more common and is today the fourth leading cause of mortality in industrialized nations [2], [3]. The primary symptoms of Alzheimer's disease are memory loss and cognitive decline, which occur due to the degeneration and death of neurons associated with memory in the brain. Mild cognitive impairment (MCI) is a state that lies between normal brain function and AD [4]. Over time, Alzheimer's disease progresses from the first stage of moderate cognitive impairment (MCI) to dementia. Studies indicate that individuals with MCI have a 10% to 15% annual risk of developing Alzheimer's disease [2].

Early identification of persons with MCI may hinder or delay the progression from the MCI stage to Alzheimer’s disease. Patients in the intermediate phases of MCI exhibit subtle alterations in the configuration of their cerebral lesions [5]. The most recent research suggests that early moderate cognitive impairment (EMCI) is seen in the early stages of MCI. Conversely, late mild cognitive impairment (LMCI) or progressive mild cognitive impairment (PMCI) is characterized by a steady worsening of symptoms over time [6]. As symptoms advance and transition from one stage to the next, medical professionals exercise more caution. Researchers may face challenges when trying to discern variations in specific symptoms across different populations. Positron emission tomography (PET), magnetic resonance imaging (MRI), and computed tomography (CT) are distinct medical imaging methods that provide standardized testing formats and essential images for experimental operations in the area of medicine [7].

MRI is widely recognized as a very efficient and secure technology for detecting many conditions, including brain tumors, neurological illnesses, spinal cord injuries and abnormalities, and liver diseases [8]–[10]. The exceptional sensitivity of this technique enables early detection of diseases, hence enhancing its versatility [11]–[14]. The distinct attributes of various MRI sequences may be advantageous for a range of medical conditions. This study presents a novel approach for classifying Alzheimer’s disease in MRI images using a convolutional neural network (CNN). The Res-BRNet, a novel CNN architecture, is proposed as a suitable choice for classifying Alzheimer’s disease. We evaluated the predictive performance of the novel strategy on the experimental dataset and compared it to other state-of-the-art CNNs and traditional approaches.

Contributions to the planned work: The Res-BRNet is an innovative architecture that combines deep residual and regional convolutional neural networks. It is specifically built to classify Alzheimer’s disease. The Res-BRNet employs a fusion of spatial and residual blocks to accurately capture complex patterns linked to Alzheimer’s disease in brain MRIs. This strategy improves the precision of the classification model for Alzheimer’s disease. Res-BRNet used spatial connections and textural variations derived from MRI images of patients diagnosed with Alzheimer’s disease. The use of regional and boundary-based techniques in a predetermined order inside different spatial and residual blocks made this possible. The Res-BRNet convolutional neural network incorporates residual and spatial blocks to enhance differentiation and generalization. The ability to extract both boundary-driven properties and abstract patterns is a feature of spatial blocks. The remaining blocks at the target level also get information on both local and global changes in the texture of Alzheimer’s disease.

The sections are arranged in the following order: The “related work” section presents the latest studies on the early identification of Alzheimer’s disease. The “method” section provides a detailed explanation of the recommended approach for diagnosing AD. The “discussion” section thoroughly examines the experimental results, including extensive explanations and comparisons to previous studies. The “conclusion” section offers a succinct overview of our final discoveries

2. RELATED WORK

Lately, there has been a notable surge in the use of deep learning techniques to categorize Alzheimer’s disease by examining data from several brain imaging modalities. Multiple studies have shown that CNNs may be enhanced to classify Alzheimer’s disease by using sample data obtained from different imaging modalities. The researchers in reference [15] developed a technique for predicting the conversion of MCI using domain transfer learning. The researchers used several techniques, including target and auxiliary domain data samples. They attained a prediction accuracy of 79.40% by using experimental methodologies in domain transfer learning. The author of the paper [16] proposes a robust and efficient deep-learning method that leverages MRI and PET modalities. To enhance their ability to categorize, they used a dropout methodology. In addition, researchers used the multitask learning methodology of the deep learning framework to assess the disparities between models with and without dropouts. The dropout method yielded experimental findings that demonstrated a 5.9% improvement.

A different research study [17] used a SegNet-based deep learning approach to identify the specific local brain morphological traits that are essential for identifying Alzheimer’s disease. The researchers found that using a deep learning approach with a pre-trained model significantly enhanced the performance of the classifier. Meanwhile, Çelebi and Emiroğlu [18] used morphometric images acquired using tensor-based morphometry (TBM) preprocessing of MRI data. Their study used the deep, compact block-based Xception architecturebased deep learning method, yielding a significant degree of precision in detecting early-stage Alzheimer’s disease. However, this study did not directly address issues related to dataset unpredictability, overfitting, and the challenges associated with extracting image characteristics from TBM.

Baglat *et al.* [19] constructed hybrid machine learning models using support vector machines (SVM), random forests, and logistic regression to detect Alzheimer’s disease. Their models used MRI patient pictures derived from the OASIS dataset. Fu’adah *et al.* [20] constructed a classification model using a CNN that was built upon the architecture of AlexNet. They attained a 95% accuracy rate by using a collection of MRI pictures linked to Alzheimer's disease. Murugan *et al.* [21] devised a CNN model specifically tailored to detect and categorize instances of Alzheimer's disease. Their proposed model consisted of two convolutional layers, one max-pooling layer, and four dementia network blocks. When evaluated using the ADNI MRI imaging dataset, it attained a precision of 95.23%. Rallabandi *et al.* [22] devised a method that employs the ADNI database to identify and categorize Alzheimer's disease in elderly individuals with intact cognitive function. Their model achieved a 75% accuracy rate.

To improve the accuracy of finding Alzheimer's disease, this model uses weight randomization, deep feature concatenation, and gradient-weighted class activation mapping. Bamber and Vishvakarma [23] developed a CNN to classify Alzheimer's disease in medical image patches. CNN used a superficial convolutional layer and achieved a precision rate of 98%. The modified InceptionV3 model created by [24] was very good at putting brain MRIs into groups that showed the different stages of Alzheimer's disease. It surpassed conventional methods, achieving a test accuracy of 98.67%. Some of the latest works have shown how TBM integrated with deep learning can identify volumes of differences in AD by measuring tissue volumes of certain parts of the brain such as the hippocampus and temporal lobe with an accuracy rate of up to 93% [25]. Using ResNet-18 for feature extraction and with combined IMPA-MSVM AD classification accuracy of up to 98.43% was obtained using the ADNI dataset [26].

3. METHOD

This paper introduces an innovative deep residual and regional CNN architecture for the automated classification of Alzheimer's disease based on MRI data. Several well-known performance metrics are used to test how well the proposed classification method works, and the results are compared to those of existing CNNs. An increase in the number of training examples in the experimental setup may lead to improved generalization. Figure 1 presents a succinct and thorough representation of the recognized classification method for Alzheimer's disease.

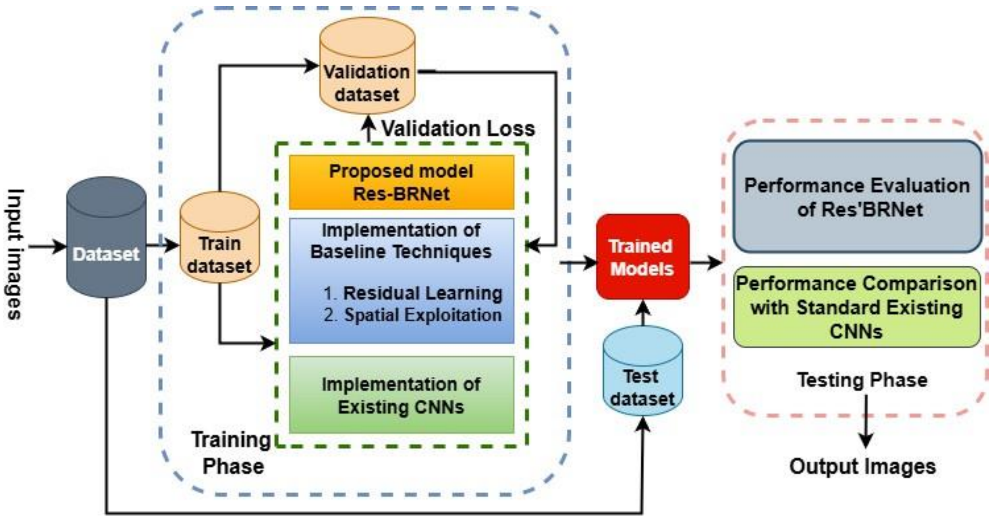

Figure 1. The detailed architecture of the suggested approach for classifying for Alzheimer's disease associated with Alzheimer's disease

3.1. The dataset

This work used datasets from reputable organizations such as Kaggle, ADNI37, and OASIS38, which are accessible for research and instructional purposes. The MRI ADNI dataset comprises the MRI scans used in this investigation. The ADNI dataset includes individuals diagnosed with Alzheimer's disease, MCI, and healthy controls. The ADNI collection includes genetic data, cognitive assessments, blood and CSF biomarkers, MRI and PET scans, and clinical information.

3.2. Development of deep Res-BRNet categorization

For this investigation, we used CNNs to acquire knowledge about the MRI patterns associated with Alzheimer's disease. The capacity of CNNs to acquire knowledge about image features and patterns serves as a driving force for their use in tasks such as classification and identification. CNNs are widely used to extract features and categorize data, mostly due to their learning capacity. Our study presented Res-BRNet, CNN architecture that utilizes boundary and region-based techniques to accurately detect Alzheimer's disease in brain MRI data. The proposed methodology extracts information about Alzheimer's disease patterns directly from MRI scans, covering the entire process. The final classifications are performed using the last fully connected layers and SoftMax-based operations of the recommended CNNs. Conventional image processing techniques [27], [28] had an impact on the design of Res-BRNet. Adding convolution operators to the proposed framework improves the performance of region and boundary-based operators so that patterns of Alzheimer's disease can be captured more accurately. Figure 2 illustrates how we use spatial and residual blocks as initial components to demonstrate the role of area uniformity and boundary-related factors in helping CNNs detect patterns

Compared to spatial block learning, residual learning lets the algorithm take into account small changes in texture and contrast, get around the problem of vanishing gradients, and improve the learned feature maps and algorithm convergence. The Res-BRNet architecture comprises an initial set of three spatial blocks, followed by four residual blocks. Each spatial block comprises batch normalization, ReLU, and a single convolution layer. The ReLU function serves as an activation function, whereas the convolution layer exploits patterns related to Alzheimer's illness. After each spatial block, a max-pooling or average-pooling operation is performed to assess the area's uniformity and identify Alzheimer's disease features connected to boundaries.

Residual learning allows the model to solve the vanishing gradient problem, account for minor changes in texture and contrast, and enhance feature map representation and convergence during training as compared to spatial block learning. Conventional plain convolutional blocks and residual blocks differ mostly in Figure 2. Figure 2(a) specifically displays the architecture of a plain convolutional block in which consecutive inputs are successively routed through convolutional and activation layers devoid of shortcut connections. By means of skip connections that enable gradients to go straight to earlier layers, Figure 2(b) shows the structure of a residual block, therefore enabling deeper network training and improving feature extraction capacity for Alzheimer's-related patterns.

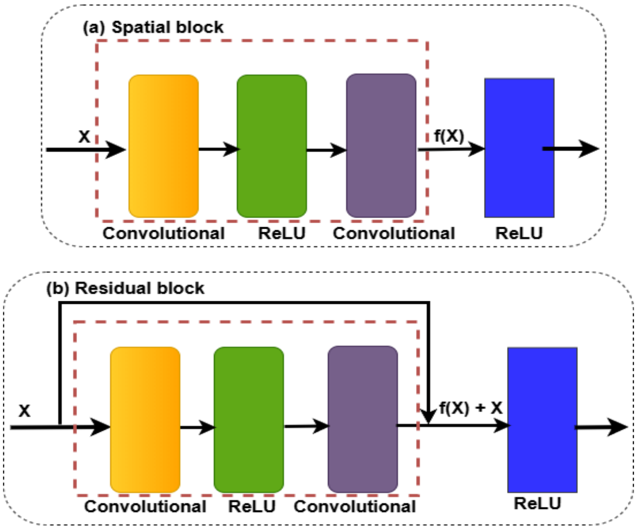

Figure 2. The difference in the process of (a) plain and (b) residual blocks

4. RESULT AND DISCUSSION

This paper proposes using a CNN system to accurately identify people with Alzheimer's disease based on MRI scans. We conducted tests to evaluate the proposed approach empirically. An overall evaluation of Alzheimer's MRI classification is conducted by comparing the performances with a state-of-the-art model. The Res-BRNet model in this work was trained with a learning rate of 0.001, with a batch size of 32, and it was trained for 50 epochs. The latter used the Adam optimizer and cross-entropy loss. To avoid the case of overfitting for the layers with a fully connected nature, a dropout rate of 0.3 was implemented.

4.1. Analysis of Performance with a state-of-the-art model

The proposed Res-BRNet model has been quantitatively compared with the earlier studies that are summarized in Table 1. From the table, we can see that Res-BRNet has a better performance in identifying specific patterns associated with MRI for Alzheimer's disease classification tasks. This superiority is assessed by means of standard performance indicators, such as accuracy, precision, recall, and F1-score. Thus, compared to the basic ResNet structure, enough reasons exist to explain why the Res-BRNet model gains higher performance in architectural design. The model uses high-level convolutional operations that supersede feature extraction in that it takes into consideration local and global spatial hierarchies of the input MRI images.

Table 1. A performance gain of the developed Res-BRNet compared to a state-of-the-art model

Authors	Methodology	Accuracy
[17]	VGGNet	96.08%
[29]	3D CNN	93.00%
[21]	CNN	95.23%
[23]	CNN	98%
[24]	Inception V3 (Finetuning)	98.68%
Proposed work	Res-BRNet	99.22%

More specifically, Res-BRNet includes a residual connection that solves the vanishing gradient issue and enables the authors to realize deeper networks. In addition to this, the consistent integration of batch normalization layers makes the training process more stable and faster. Other important improvements include the determination of a well-balanced hyperparameter including the learning rate, the batch size and the dropout factors which minimize overfitting and increase the generality of the model. Furthermore, methods such as augmenting data helped achieve the goal of being invariant to variability in the MRI datasets, which was also highly effective.

The following results are obtained as indicated in Table 1, the proposed Res-BRNet which is a breakthrough achieves an accuracy of 99.22% out comping other methods. This result strengthens the model's ability to extract discriminative features related to MRI scans of AD as well as amplifies its effectiveness as a reliable diagnostic tool for Alzheimer's disease. Figure 3 shows brain magnetic resonance images that juxtapose the anticipated classes with the actual classes derived from the test data. As shown in Figure 3, the CNN that was created exhibits a smooth and rapid convergence toward its ideal value. The likely causes of misdiagnosis include low contrast, uneven sample patterns, and variable light fluctuations. CNN are used to enhance the generalization and resilience of test samples.

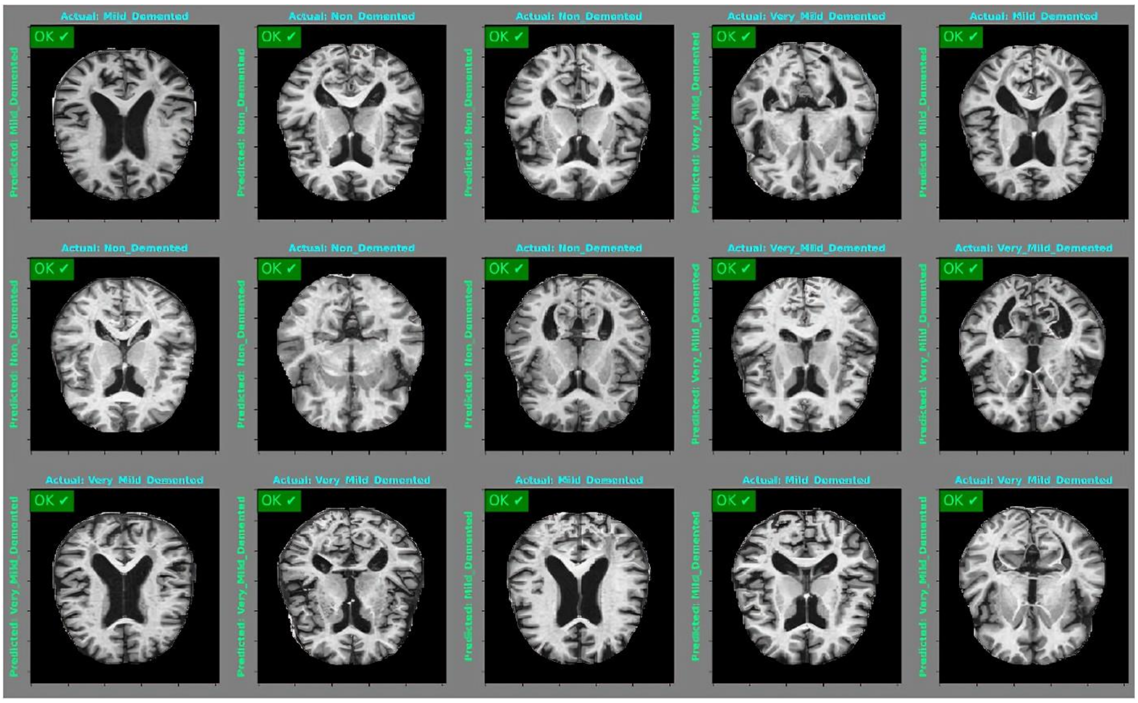

Figure 3. Examining whether the predicted label matched the real label or not

5. CONCLUSION

Early detection of Alzheimer's disease is essential for patient recovery. Consequently, a novel tailored deep CNN model is created in this study to categorize brain MRI data associated with Alzheimer's disease. The created Res-BRNet's regional and boundary operators are useful for teaching discriminative characteristics to the suggested model. The Res-BRNet that was made also uses spatial and residual ideas to get feature maps with a lot of different kinds of information. This makes it easier to understand the homogeneity, textural variation, and structural patterns that are linked to Alzheimer's disease. Using the current deep CNN models, the build system's performance is examined. The suggested Res-BRNet performs better than current CNN designs, according to the experiment findings, suggesting an increase in accuracy. The suggested method will probably make it easier for medical practitioners to identify Alzheimer's disease in the brain.

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AUTHOR CONTRIBUTIONS STATEMENT

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Suhaila Abuowaida	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The data that support the findings of this study are openly available from the Alzheimer's Disease Neuroimaging Initiative (ADNI) at *https://adni.loni.usc.edu*, the OASIS Brain Project at *https://www.oasis-brains.org*, and Kaggle at *https://www.kaggle.com*. These datasets include MRI scans, cognitive assessments, genetic data, and related clinical information and are accessible for research and instructional purposes.

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