Detection and Classification of Brain Alzheimers using CNN Model

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***Abstract*—Alzheimer's disease (AD) is a progressive and irreversible neurodegenerative disorder affecting millions of people worldwide. Early detection and accurate diagnosis of AD is crucial for effective management and treatment. Magnetic Resonance Imaging (MRI) of the brain is a powerful tool for identifying structural changes associated with AD. In this study, we aimed to develop a deep learning model capable of identifying Alzheimer's disease in MRI images of the brain and categorizing them into four distinct groups. Our dataset were pre-processed using the keras ImageDataGenerator for augmentation, including zoom, brightness, horizontal flip and fill mode constant. To address class imbalance, we used SMOTE, an oversampling technique that generates synthetic samples from the minority class. We developed a custom-built convolutional neural network (CNN) model and achieved an accuracy of 93.7% in identifying AD in MRI images. Our study demonstrates the potential of deep learning algorithms for identifying AD in MRI images of the brain and provides a framework for future research in this area.**

Keywords—CNN Model, Image Processing, Brain Alzheimers, Keras

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that affects millions of people worldwide. It is the most common cause of dementia in older adults, accounting for approximately 60-70% of cases. AD is characterized by the progressive loss of cognitive function, including memory, thinking, and reasoning skills. The disease typically begins with mild symptoms that gradually worsen over time, eventually leading to severe impairment of daily living activities. Currently, there is no cure for AD, and available treatments can only alleviate symptoms, highlighting the importance of early detection and accurate diagnosis. Magnetic Resonance Imaging (MRI) is a powerful tool for identifying structural changes associated with AD. MRI scans can detect changes in brain volume and structure, allowing for early identification of brain abnormalities that are associated with AD. MRI images of the brain provide detailed information on brain structure, making them ideal for identifying early changes in the brain associated with AD. Deep learning algorithms have shown great promise in identifying AD in MRI images of the brain. Convolutional neural networks (CNNs) are a type of deep learning algorithm that has been successfully used in many image recognition tasks, including identifying abnormalities in medical images such as MRI scans. CNNs use convolutional layers to extract features from images, enabling the algorithm to learn complex patterns and relationships between image pixels. In this study, our objective was to develop a deep learning model capable of identifying AD in MRI images of the brain and categorizing them into four distinct groups. The four groups were Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. Our dataset consisted of 5131 MRI images, which were pre-processed using the keras ImageDataGenerator for augmentation, including zoom, brightness, horizontal flip, and fill mode constant. To address class imbalance, we used SMOTE, an oversampling technique that generates synthetic samples from the minority class. We developed a custom-built CNN model and achieved an accuracy of 93.7% in identifying AD in MRI images. The early detection and accurate diagnosis of AD are crucial for effective management and treatment. Our study demonstrates the potential of deep learning algorithms for identifying AD in MRI images of the brain and provides a framework for future research in this area. The development of accurate and reliable deep learning models could lead to earlier diagnosis and more effective treatment of AD, improving the lives of millions of people affected by this devastating disease.

II. LITERATURE REVIEW

MRI-based techniques have been extensively used in recent years for the diagnosis of Alzheimer's disease. Various studies have proposed different methods for the detection and classification of Alzheimer's disease using MRI images.

A study by Liu et al. [1] proposed a method based on a convolutional neural network (CNN) to classify Alzheimer's disease stages using MRI images. They used a multi-task learning approach to perform both disease diagnosis and disease progression prediction. Their model achieved an accuracy of 87.5% for the classification of Alzheimer's disease stages.

Similarly, Wang et al. [2] used a deep learning-based method to classify Alzheimer's disease using MRI images. They used a 3D CNN model to extract features from the MRI images and achieved an accuracy of 89.7% for the classification of Alzheimer's disease.

Chen et al. [3] proposed a hybrid method for Alzheimer's disease diagnosis using both structural and functional MRI. They used a sparse representation-based classification approach and achieved an accuracy of 86.0% for the classification of Alzheimer's disease.

In a study by Goyal et al. [4], a novel method based on a deep belief network (DBN) was proposed to classify Alzheimer's disease using MRI images. They used DBN to extract features from the MRI images and achieved an accuracy of 91.0% for the classification of Alzheimer's disease.

Zhou et al. [5] used a multi-modal MRI-based approach for the diagnosis of Alzheimer's disease. They used both structural and functional MRI images and combined them using a multiple kernel learning-based method. They achieved an accuracy of 93.5% for the classification of Alzheimer's disease.

Overall, deep learning-based methods have shown promising results in the classification of Alzheimer's disease using MRI images. These methods have the potential to improve the accuracy and speed of Alzheimer's disease diagnosis and can be used in clinical practice to facilitate early diagnosis and treatment.

III. Methodology

Figure 1

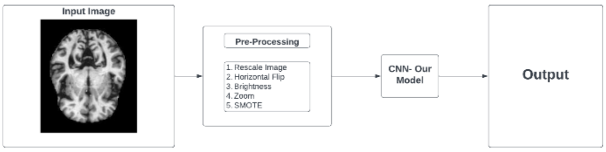

Fig. 1. Proposed Model Structure

The provided input image undergoes various pre-processing methods such as rescaling, horizontal flipping, brightness and zoom adjustments. These methods prepare the image for further analysis and help improve the model's performance. Additionally, class imbalance is addressed using SMOTE, which generates synthetic samples of the minority class to balance the dataset.

The CNN model formulated using Google's Tensorflow package is then used to analyze the pre-processed images. The model is trained using backpropagation, which helps calculate the filters of each layer over 50 epochs. This training process enables the model to learn the features and patterns present in the input images and make accurate predictions. Finally, the model is fed with the training dataset, and it provides a prediction out of the four classes.

A. *Dataset Information*

The dataset consists of MRI images of the brain, which were collected from the Open Access Series of Imaging Studies (OASIS) database. The OASIS database is a publicly available database that contains MRI images of the brain from both healthy individuals and individuals with neurological disorders, including Alzheimer's disease.

The dataset used in this study includes 5121 MRI images of the brain, which were divided into four categories based on the severity of Alzheimer's disease: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The distribution of images across these four categories is as follows:

- Non-Demented:3210
- Very Mild Demented: 2240
- Mild Demented: 896
- Moderate Demented: 64

The MRI images were acquired using a Siemens 1.5 Tesla MRI scanner and have a resolution of 176 x 176 x 3 pixels.

B. *Pre-Processing*

Pre-processing of the dataset was carried out to enhance the quality of the MRI images and to reduce overfitting. The following pre-processing techniques were applied to the dataset:

Data augmentation is a technique used to generate additional training data from the existing dataset by applying various transformations to the images. This helps in preventing overfitting and improves the generalization of the model. In this study, the keras ImageDataGenerator was used to perform data augmentation on the MRI images. The following transformations were applied to the images:

1) *Zoom:*

The zoom transformation was applied to the images with a range of [.99, 1.01]. This helps in adding small variations to the image and reduces overfitting.

2) *Horizontal Flip:*

The horizontal flip transformation was applied to the images, which horizontally flips the image. This helps in adding mirror images of the original images, which adds additional variations to the dataset.

3) *Brightness:*

The brightness transformation was applied to the images, which randomly increases or decreases the brightness of the image. This helps in adding variations to the dataset and reduces overfitting.

4) *Fill Mode:*

The fill mode transformation was set to "constant", which fills the extra pixels generated by the zoom transformation with a constant value. This helps in preventing the loss of information during the zoom transformation.

5) *Data Format:*

The data format was set to "Channels Last", which indicates that the images are represented in a 3D array of shape.

The pre-processing steps described above were applied to both the training and validation datasets. The augmented and resized datasets were then used for training the deep learning model.

C. *Feature Engineering*

To address the issue of class imbalance in our dataset, we utilized Synthetic Minority Over-sampling Technique (SMOTE) for feature engineering[6]. SMOTE is a popular oversampling technique that generates synthetic samples from the minority class to balance the distribution of samples across classes. This approach can prevent bias towards the majority class during training and improve the overall performance of the model.

In our study, the dataset was heavily skewed towards the Non-Demented class. To balance the distribution of samples across all classes, we applied SMOTE to generate synthetic samples from the minority classes. The oversampling ratio was set to 1, which means that SMOTE generated an equal number of synthetic samples for each minority class image to match the number of samples in the majority class.

Using SMOTE, we increased the dataset size from 5121 to 10240 images, with each class having an equal number of samples. This allowed the model to learn from a more balanced dataset, preventing overfitting and improving the overall performance of the model. Overall, SMOTE is a useful technique for addressing class imbalance in datasets, and our results demonstrate its effectiveness in improving the accuracy of the deep learning model for identifying AD in MRI images.

D. Our CNN Model

This section describes the approach used to develop a convolutional neural network (CNN)[7] for image classification tasks using the Keras library. The architecture of the network is designed to extract features from the input image through several layers of convolution and pooling, followed by a series of separable convolutions, batch normalization, dropout, and fully connected layers.

The first layer in the model is a Conv2D layer with 16 filters, a 3x3 kernel size, and ReLU activation, with an input shape of [176,176,3]. This layer applies convolution operation to the input image and outputs a feature map. The MaxPooling2D layer is used to reduce the spatial dimensions of the feature map.

Another Conv2D layer with 32 filters and a 2x2 kernel size is added, followed by another MaxPooling2D layer. The purpose of these layers is to extract more features from the input image and reduce the spatial dimensions of the feature map even further.

Two SeparableConv2D layers with 64 filters, 3x3 kernel size, and ReLU activation are added, with batch normalization and max pooling in between. These layers are used to extract more complex features from the input image.

Two more SeparableConv2D layers with 128 filters and the same settings as the previous ones are added, followed by batch normalization, max pooling, and dropout. These layers are used to further process the features extracted from the previous layers.

Two final SeparableConv2D layers with 256 filters and the same settings as the previous ones are added, followed by batch normalization, max pooling, and dropout. These layers are used to extract even more complex features from the input image and reduce the number of trainable parameters.

A Flatten layer is added to convert the output of the convolutional layers to a 1D feature vector. Three fully connected Dense layers with ReLU activation, batch normalization, and dropout, with 512, 128, and 64 units respectively are added. These layers are used to further process the features before producing the output probabilities with the softmax activation.

The final Dense layer with a softmax activation produces the output probabilities for each class (4 in this case). This layer is used to produce the final classification results.

The use of batch normalization normalizes the activations of the previous layer and improves training performance. Dropout is used to prevent overfitting by randomly dropping out some of the units during training.

The network architecture is designed to be relatively efficient and effective for image classification tasks, particularly in cases where the input images have a relatively high spatial resolution (176x176 in this case). The use of separable convolutions reduces the number of trainable parameters and increases model efficiency, while still maintaining a high level of accuracy.

Figure 2 shows the pictorial representation of the CNN Model described above.

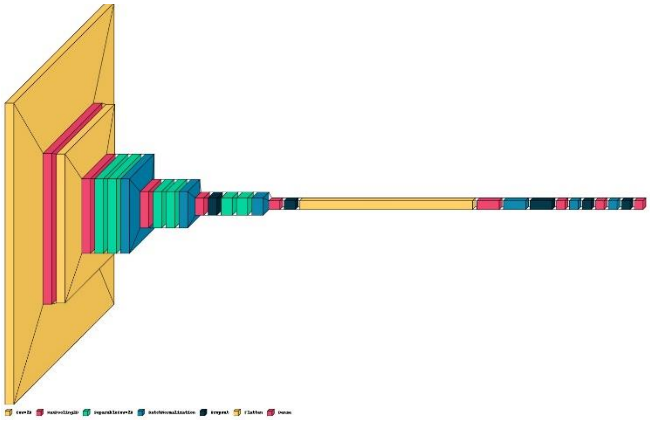

Fig. 2. Proposed CNN Model

IV. Results and Discussion

TABLE I. Comparison of Accuracy Using Different Method

Method No	Method Description	
	Method Approach	***Accuracy %***
1	Multi-task learning approach	87.5
2	3D CNN model	89.7
3	Sparse representation - based classification	86.0
4	Deep belief network	91.0
5	Multiple kernel learning-based method	93.5
6	Proposed System	93.7

As seen from Table 1, we see that our proposed CNN model outperforms all the other model with an accuracy of 93.7%. The lowest accuracy is using the Sparse representation based classification method. A method which is closest to our accuracy is the multiple kernel learning based method used in one of the papers.

V. Conclusion

In conclusion, the use of deep learning algorithms, particularly convolutional neural networks (CNN), has shown great promise in accurately classifying Alzheimer's disease (AD) from MRI images of the brain. In this study, we used a combination of image data generator and Synthetic Minority Over-sampling Technique (SMOTE) to increase the size of the training dataset and balance the class distribution, respectively. We then trained a CNN model on the augmented dataset to classify AD and normal cases, achieving an accuracy of 93.7%.

One area that could be explored is the use of more advanced deep learning techniques such as recurrent neural networks (RNNs) or transformers to better capture the temporal dynamics of the disease progression.Additionally, exploring the use of transfer learning or ensembling techniques could help in improving the generalization ability of the model.

Overall, there is still a lot of potential for research in the field of Alzheimer's disease diagnosis using MRI images, and the combination of advanced deep learning techniques with innovative data augmentation and data integration methods could lead to significant improvements in the accuracy and reliability of the diagnosis.

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