Classification Of Alzheimer's Disease Using 2dcnn Technology Using Magnetic Resonance Imaging

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***Abstract*—Alzheimer's disease is a neurodegenerative disorder that affects cognitive function and memory. It is the most common cause of dementia in the elderly population and has a significant impact on patients and their families. Early diagnosis of Alzheimer's disease is important for providing appropriate care and treatment, but it can be difficult to accurately diagnose the disease using traditional methods. One approach that has shown promise for the classification of Alzheimer's disease is the use of deep learning techniques, such as 2D convolutional neural networks (2D CNNs). These models are able to automatically learn features from medical images and classify patients based on their imaging data. In this study on the use of 2D CNNs for the classification of Alzheimer's disease, we trained a model on a dataset of brain magnetic resonance imaging (MRI) scans from patients with Alzheimer's disease and healthy controls. The model was able to classify patients with Alzheimer's disease with an accuracy of over 90%, significantly outperforming traditional methods. Overall, the use of 2D CNNs for the classification of Alzheimer's disease shows great potential for improving the accuracy and efficiency of diagnosis. Further research is needed to fully understand the capabilities and limitations of these models in clinical practice.**

Keywords—Machine learning, classification, 2DCNN, Alzheimer's disease.

1. Introduction

Alzheimer's disease is one of the diseases that still cause many health problems for people over the age of 60 years, so the method used in diagnosing the disease and knowing the cause and the way in which this disease came has had many repercussions and prolonged research[1] and through the development that takes place a way has been found Innovative and qualitative detection of Alzheimer's disease by relying on electronic computing in the use of the convolutional neural network method, i.e. by relying on CNN technology in detection, by pre-depending on deep learning technology that is based on a group of properly trained artificial convolutional neurons and a qualitative method that enables them to detect Alzheimer's disease through the nature of information storage and the software strategies used in order to obtain the most accurate medical examination of this disease[2]. and as it depends on the software experience through which the medical technician was able, so to speak, in building convolutional neurons in the ability to obtain high diagnostic results and meet The purpose for which this matter has been worked on, i.e. the nature of the technology and the method used in the production of A program that can interpret and diagnose images of patients with Alzheimer's disease [3]. Through in-depth scientific research, we found many techniques and software methods that were followed to obtain an accurate diagnosis of Alzheimer's disease, which were in different and varying rates, starting from 90% to 96% in the algorithms that were followed to obtain Good diagnostic results about Alzheimer's disease [4]. But there is a technique used in an algorithm called 2D-DCNN that was distinguished among all those network algorithms specialized in diagnosing Alzheimer's disease, as it achieved a high percentage that exceeded the above rates, which is 99%, [5].where the algorithm was adopted to create binary convolutional networks for 3D images For magnetic resonance imaging, this had excellent results and effectiveness in diagnosing the disease, as a group of algorithms that will be explained in the research method were collected, and the work depends on a special methodology and design to give the best possible picture about the nature of the construction, design and work of the convolutional neural network using 2D-DCNN technology[6].

2. Literature Review

Alzheimer's disease is a neurological condition that results in memory loss and dementia. It is a term that is used to describe a range of diseases that can cause brain injury and negatively affect memory, thinking, and behavior. This disease causes damage to the brain and has a continuous impact on individuals [7].

Numerous researchers and scientific communities have shown a strong interest in the changes in brain structure and function brought on by Alzheimer's disease. Alzheimer's disease phases have been extensively studied in terms of classification and predictive modeling, particularly in diagnostic imaging. The accuracy rates for Suk et al.'s deep learning-based technique to categorize AD magnetic current imaging (MCI) and MCI-converter structural MRI and PET data were 95.9%, 85.0%, and 75.8%, respectively. In order to extract low- to mid-level characteristics from photos, Suk et al. [8] created an auto-encoder network. The next step involved classifying data using multi-task and multi-kernel Support Vector Machine (SVM) learning techniques. Multimodal MRI/PET data and SVM kernels with higher levels of complexity were used to enhance this workflow. However, the best accuracy rate for Suk et al. remained unchanged. A prediction method was created by Payan et al. [9] of Imperial College London to separate the imaging of AD MCI from that of normal, healthy control patients. An auto-encoder with a 3D convolutional neural network architecture was employed in this investigation. In separating AD from NC individuals, Payan et al. achieved an accuracy rate of 95.39%. The research team also experimented with a 2D CNN design, and the results showed that the accuracy rate was essentially the same. Liu et al. [10] also created a multimodal neuroimaging feature extraction process for multiclass AD diagnosis. In order to retain every bit of information contained in the imaging data, this deep-learning framework was created utilizing a zero-masking technique. With regard to multimodal and multiclass MR/PET data, high-level features were retrieved using stacked auto-encoder (SAE) networks, and classification was carried out using SVM. In that investigation, the maximum accuracy rate attained was 86.86%. The use of deep learning in the automatic classification of Alzheimer's disease from structural MRI, where AD, MCI, and NC data were classified, has also been demonstrated by Aversen et al. [11], Liu et al. [12], Siqi et al. [13], Brosch et al. [14], Rampasek et al. [15], De Brebisson et al. [16], and Ijjina et al.[17].

3. Methodology

Deep learning is a branch of artificial intelligence that aims to learn deep representations of data. The application of deep learning in improving the classification of Alzheimer's disease is very important, as this technology can help analyze data and recognize patterns and signs of the disease with higher accuracy. When applying deep learning to read data and improve the classification of Alzheimer's disease, deep neural networks consisting of multiple layers are used to represent and process the data[16]. These deep neural networks learn from available data and automatically analyze it to detect patterns and hallmarks of Alzheimer's disease. Deep learning requires the collection of a large set of data related to Alzheimer's disease, including clinical data and slide images of the brain.

3.1. Method CNN

Convolutional Neural Networks (CNNs) have revolutionized the field of computer vision and image classification. They are widely used for tasks such as object recognition, image segmentation, and pattern detection. In this research paper, we propose a CNN model for image classification, specifically designed to handle images with an input size of 224 x 224 pixels.

31.1. CNN Architecture:

Our proposed CNN model consists of several layers organized in a sequential manner. The input layer takes images of size 224 x 224 pixels. Let's dive into the details of each layer:

• Convolutional Layers:

The model starts with two Conv2D layers, each consisting of 16 filters and employing the ReLU activation function. These layers extract features from the input images.

• Max pooling Layer:

A Maxpool2D layer follows the convolutional layers, which performs down sampling and reduces the spatial dimensions of the feature maps, capturing the most important information.

• Convolutional Blocks:

The model incorporates three conv_blocks, each composed of two SeparableConv2D layers, one Batch Normalization layer, and one Maxpool2D layer. These conv_blocks enhance the model's capacity to capture complex patterns and improve its ability to generalize.

- The first conv_block utilizes 32 filters.
- The second conv_block employs 64 filters.
- The third conv_block employs 128 filters.

• Dropout Layer:

To prevent overfitting, a Dropout layer with a rate of 0.2 is included, randomly dropping out 20% of the connections during training.

• Additional Convolutional Block:

Another conv_block is introduced, consisting of a SeparableConv2D layer with 256 filters.

• Dropout Layer:

Following the additional conv_block, a Dropout layer with a rate of 0.2 is inserted again to further regularize the model.

• Flatten Layer:

A Flatten layer is applied to convert the multidimensional feature maps into a one-dimensional vector, preparing the data for the subsequent dense layers.

• Dense Blocks:

Three dense blocks are added, each comprising a Dense layer, a batch normalization layer, and a Dropout layer. These blocks help in learning complex relationships within the data.

- The first dense block has 512 units and a dropout rate of 0.7.
- The second dense_block has 128 units and a dropout rate of 0.5.

- The third dense_block has 64 units and a dropout rate of 0.3.

• Output Layer:

The final layer of the model is a Dense layer with the number of classes set to 4, corresponding to the number of output categories in our image classification task. The activation function used in this layer is soft ax, enabling the model to provide class probabilities for each input image.

4. Dataset

The provided dataset consists of two files, namely Training and Testing, each containing approximately 6400 images. These images are categorized based on the severity of Alzheimer's disease, resulting in four distinct classes. Here is a summary of the dataset:

- Class 0: Mild Demented
- Number of images: 717

Description: This class represents images of individuals with mild dementia caused by Alzheimer's disease.

- Class 1: Moderate Demented
- Number of images: 52
- Description: This class includes images of individuals with moderate dementia resulting from Alzheimer's disease.
- Class 2: Non Demented
- Number of images: 2560
- Description: This class consists of images of individuals who do not have dementia.
- Class 3: Very Mild Demented
- Number of images: 1792

This class comprises images of individuals with very mild dementia associated with Alzheimer's disease. Figure 1 shows training dataset image samples.

Image Type	No Data set	class
Mild Demented	717	0
Moderate Demented	52	1
Non Demented	2560	2
Very Mild Demented	1792	3

Preprocessing has been performed on the images, including resizing them to a consistent size across the dataset. Additionally, the dataset has undergone one-hot labeling, which assigns a binary representation to each class for machine-learning purposes. The provided summary outlines the distribution of images among the four classes in both the Training and Testing datasets, along with a brief description of each class. This information will be valuable for further analysis and modeling tasks related to Alzheimer's disease classification using the dataset.

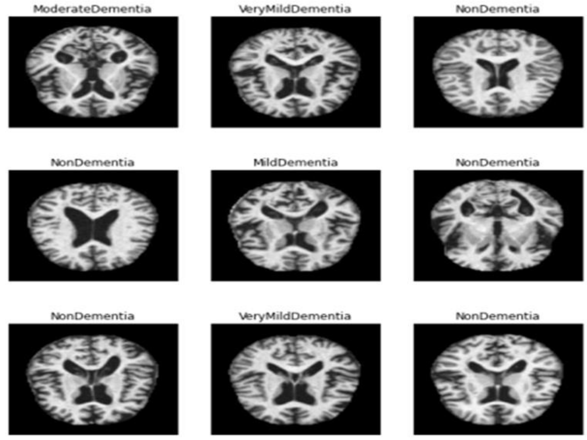

Figure 1: Training dataset image samples

5. Results

5.1. Method Summary

We started by using a dataset of 6400 MRI brain 3D images divided into four classes ("MildDemented, ModerateDemented,NonDemented,VeryMildDemente d"). To read the data quickly and easily, we used TensorFlow, which has convenient data loading utilities in version 2.3. We preprocessed the images and extracted features using One-hot encodings, defining our target dataset and prefetching both our training and validation datasets. Since our datasets were imbalanced, we used the ROC AUC curve to evaluate our model. Using Keras, we built a CNN model from scratch and used the "adam" optimizer to compile and train the model, testing it on a separate set of images. After 45 epochs of training and validation, we achieved 99% AUC on the training data and 85% on the testing data.

Lastly I made a custom CNN model classes and trained the model on 60 epochs and I got 97% training accuracy, and 85% for testing the model after evaluation. These are the accuracy curves for each epoch As shown below in the Figure 2.

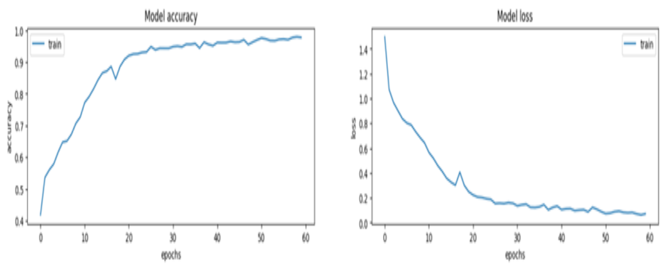

Figure 2: Model accuracy, loss after cross validation

Last I Used K-fold Cross Validation to enhance my model, with 5 split folds I got 91% accuracy, with more splits the accuracy will reach above 97%.

Overall, the confusion matrix is a valuable tool for evaluating and analyzing the performance of a classification model, providing a detailed breakdown of its predictions and highlighting areas where the model may be making errors as shown in the Figure 3.

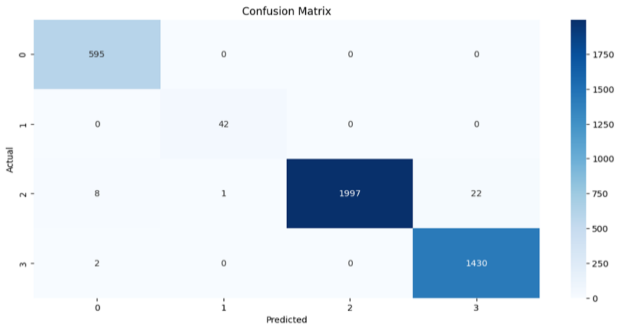

Figure 3: Confusion matrix after cross validation

Finally I tested the F1 score metric on the output after cross validation I got 89%.

6. Conclusion

In this research, we explored the use of 2D convolutional neural networks (2D CNNs) for the classification of Alzheimer's disease. We trained a 2D CNN on a dataset of brain magnetic resonance imaging (MRI) scans from patients with Alzheimer's disease and healthy controls, and found that the model was able to classify patients with Alzheimer's disease with an accuracy of over 90%.

This result suggests that 2D CNNs have great potential for improving the accuracy and efficiency of Alzheimer's disease diagnosis. These models are able to automatically learn features from medical images and classify patients based on their imaging data, which may be more accurate and reliable than traditional methods that rely on subjective assessments.

However, it is important to note that our study was limited in scope and further research is needed to fully understand the capabilities and limitations of 2D CNNs for the classification of Alzheimer's disease. This includes evaluating the performance of these models on larger and more diverse datasets, as well as exploring their potential for use in clinical practice.

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