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Classifying Alzheimer's disease based on a convolutional neural network with MRI images

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Abstract

Alzheimer's disease is a significant disease that negatively affects daily life and reduces the quality of human life. Dementia and Alzheimer's disease occur as the loss of neurons or a decrease in the relationship between neurons. So far, no effective drug has been found in diagnosing this disease. For this reason, it has become essential for individuals to diagnose the disease early and to detect the disease before it progresses. However, early diagnosis of the disease is challenging. The disease can be diagnosed after significant and irreversible effects on humans occur. A lot of research has been done worldwide for early disease diagnosis. Deep learning algorithms have become essential in diagnosing this disease. Significant progress has been made in diagnosing the disease with models created using deep learning algorithms. This study used a sequential model, conv2D, maxPooling2D, and dense layers to diagnose and classify. According to the dataset from Kaggle, a 4-class dataset has been used in this study to diagnose Alzheimer's disease. According to the Alzheimer's MRI dataset, the disease has been classified as nondemented, moderate demented, mild demented, and very mild demented, respectively.
The proposed model has been trained using CNN. The number of layers and dropout rate have been used as performance metrics. In our study, activation Leaky ReLU was used. The SMOTE technique has been used to oversample the available data. This study's classification results will help experts make the right decisions. With F1Score, accuracy, recall, and precision values, 96.35% success was achieved in the CNN model. Different CNN methods can be used to advance these studies.

Keywords

MRI imaging, Convolutional neural network, Alzheimer's disease recognition, SMOTE technique, deep learning model

1. Introduction

Alzheimer's disease is one of today's most important health problems. Alzheimer's disease causes cognitive decline and memory loss with the deformation of brain cells.

The disease causes irreversible damage to brain cells, and its advanced stages result in death. People with the disease have beta-amyloid plaques in the brain. The life expectancy of people with Alzheimer's disease varies between 3-10 years. This life expectancy varies according to the age at which the disease occurs, and life expectancy decreases with increasing age [1].

In the initial phase, it only manifests itself with simple forgetfulness. As time passes, the patient forgets the events in his recent past and may even become unable to recognize family, and it only manifests itself with simple forgetfulness. As time passes, the patient forgets the events in his recent past and may even become unable to recognize family members or relatives. Patients in more advanced stages of the disease have difficulty meeting their basic needs and need care despite the fact Alzheimer's disease is known as a common ailment in the elderly because there are individuals at a young age who suffer from this disease [2].

Alzheimer's disease is incurable. Therefore it is vital to take precautions together with early diagnosis. Models or systems created with deep learning algorithms are used for early diagnosis. The most important of these diagnostic systems is artificial intelligence applications. Computer vision is the most important artificial intelligence sub-research area in health. One of the most important reasons for this is the constantly developing medical imaging systems. Magnetic resonance imaging (MRI), X-rays, and computed tomography (CT) are the most common medical methods to detect Alzheimer's disease. Therefore, including computer vision applications in healthcare systems is a significant issue.

Machine learning is a system that produces results based on the data it receives in the face of new situations by using and learning the information from the registered dataset of the computers. The sub-learning cluster of machine learning is deep learning [3]. Deep learning is a multi-layered structure similar to a neural network in the human brain. Basic network structures are widely seen in deep learning [4]. Structures such as CNN, among the basic network structures in deep learning, are widely seen [5]. CNN is an algorithm that takes images as input and filters them with the values it learns and detects or classifies the features in the images [6]. In this article, the classification of MRI images is provided utilizing deep learning and CNN basic network methods. The results of this classification it is aimed to divide Alzheimer's disease into 4 different categories.

2. Materials and Methods

The inputs or materials we will use often appear as irregular structures. These are called irregular data structures in machine learning—the number of observations in another. Machine learning aims to reduce errors without class distinction. This situation presents some problems today. Techniques such as decision trees or logistic regression can be used for classification in machine learning, but these techniques are suitable for the majority class. In this case, machine learning prefers to ignore the minority class. Mainly for this reason, the minority class can be misclassified to a large extent. To be more precise, if there is an unbalanced data distribution in our dataset, our model neglects the minority class. This causes them not to remember or remember less of the data in the minority.

2.1. MRI Dataset

The dataset of this study has been obtained from the KAGGLE website. It has been studied on a dataset of 4 classes with dimensions (176x208) and 6400 images. An example from the dataset is given below in Figure 1.

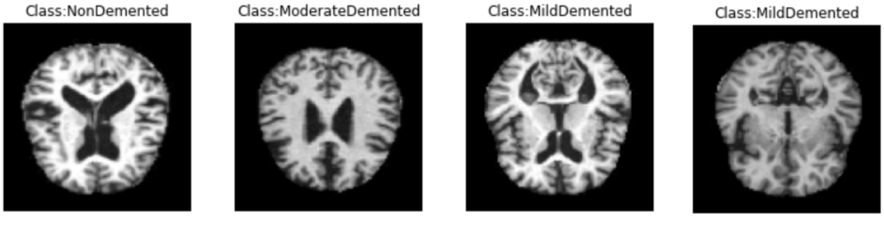

Figure 1. Alzheimer's Dataset classification

2.2. Data Preprocessing

The SMOTE (Synthetic Minority Oversampling Technique) algorithm is used to obtain the correct distribution in the unbalanced data class. It is associated with unbalanced data when performing the SMOTE technique. Since data to be classified is scarce, the SMOTE technique is used. For example, it increases the number of rare data. So that the minority data in the dataset is increased in a balanced way but these data are not the same as the rare data. There are k nearest neighbors to this data. One of its k nearest neighbors is selected, and after a sample is selected from the minority data, a synthetic sample is obtained between the two. The synthetic sample in the sample space is combined with the line segment.

2.3. The Proposed CNN Model

Convolutional Neural Network is a type of Multi-Layer Perceptron. The visual center of animals inspires CNN to create a forward-looking neural network. In Convolutional Neural Networks, convolutional layers are used as an essential part. It consists of a CNN convolutional layer, pooling, and fully connected layers. The visual sequentially passes through these layers and begins to enter the deep learning model. The purpose of CNNs is the same as neural networks. However, with the various transformations of the inputs, representations of a more abstract level are obtained [7].

In the convolution layer, a filter smaller than the size of the image travels through the entire image. This filter is used to scan for specific features in the image. The filter should be self-updatable. These values are taught the values in CNN algorithms. Thus better-detecting features in the image [8]. CNN has standard steps. Convolution is the first step. In this step, the features in the image are found, and the filter is applied to the entire image. The convolution operation is done with a kernel filter. Convolution means the replacement of one shape by another. A feature map is created when the filter kernel has hovered over the entire input—the filter values that change the feature map and how many steps this filter operation takes. For example, images are matrices of pixels. The feature map is found after the kernel filter captures parts of the image and multiplies and sums each value with its corresponding value [9]. The mathematical expression of the convolution operation is expressed as f*g. (f) can be thought of as a filter, (g) as a whole image. When the filter has hovered, a third function called (h) is created, expressing the amount of overlap [10]. Officially, it is defined as:

$$h(t) = (f*g)(t) \int_{-\infty}^{\infty} f(T)\, g(t - T)\, dT \qquad (1)$$

Each convolution layer has an activation. Finally, an operation is applied that transforms the data into a nonlinear data tensor.

2.4. Max Pooling

Many activation processes, such as smoothed linear units (ReLu), are used in deep learning. The most popular is the activation method called ReLu [11]. The next step is the Max Pooling method. Max Pooling is the most popular among pooling operations. The task of the Max Pooling layer is the sampling method applied to reduce the number of parameters. In this way, overfitting is prevented, and unnecessary features captured are discarded. A kernel filter is also used on the image, as in the convolutional layer. Retrieves the most significant value in the area covered by the filter. Thus, we have important values. Let us explain this process through an example. First, let's create a [2, 2] size filter and then apply this filter to the (4x4) picture below. The filter you see below takes the highest number of layers of the image, allowing the neural network to use smaller outputs to make the right decision [12]. The max pooling process is shown below in Figure 2.

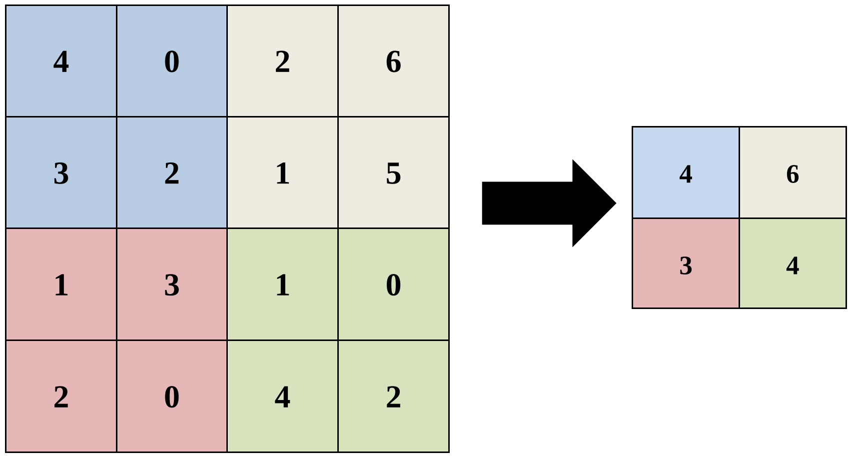

Figure 2. Max Pooling operation

```
Model: "cnn_model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 176, 176, 16)      448

 conv2d_1 (Conv2D)           (None, 176, 176, 16)      2320

 max_pooling2d (MaxPooling2D  (None, 88, 88, 16)       0
 )

 sequential (Sequential)     (None, 44, 44, 32)        14016

 sequential_1 (Sequential)   (None, 22, 22, 64)        55680

 sequential_2 (Sequential)   (None, 11, 11, 128)       221952

 dropout (Dropout)           (None, 11, 11, 128)       0

 sequential_3 (Sequential)   (None, 5, 5, 256)         886272

 dropout_1 (Dropout)         (None, 5, 5, 256)         0

 flatten (Flatten)           (None, 6400)              0

 sequential_4 (Sequential)   (None, 512)               3279360

 sequential_5 (Sequential)   (None, 128)               66176

 sequential_6 (Sequential)   (None, 64)                8512

 dense_3 (Dense)             (None, 4)                 260

=================================================================
Total params: 4,534,996
Trainable params: 4,532,628
Non-trainable params: 2,368
_________________________________________________________________
```

2.5. Flattening

The task of this layer is to make multiple feature maps obtained by the pooling operation one-dimensional, multi-line. In the pooling process, the maximum values of the data were obtained. Unnecessary data was discarded. These features are listed below the other as input data in this layer. (Fig.3)

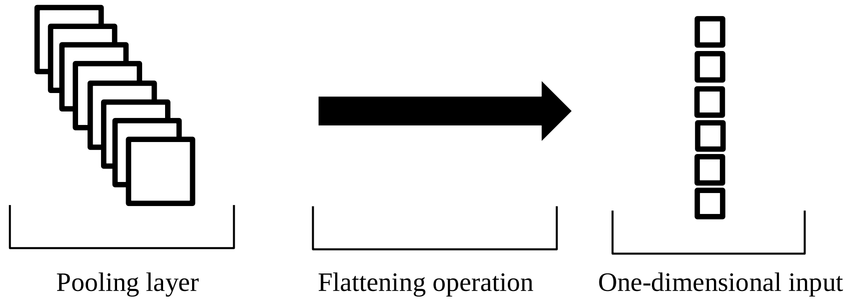

Figure 3. Flattening operation

2.6. Batch Layers

The batch layer provides speed-up training. It is necessary to normalize the data before it enters the network. It makes the mean of the inputs 0 and the standard deviation 1. The resulting data is rescaled [13]. After adding the batch layer, problems such as stuttering during the training of the system are solved.

2.7. Dropout Layer

The dropout layer is known as damping. The number of neurons is reduced at a specified rate. Thus, the performance of the model increases. Overfitting is blocked. This process only happens during training (Fig. 4) [14].

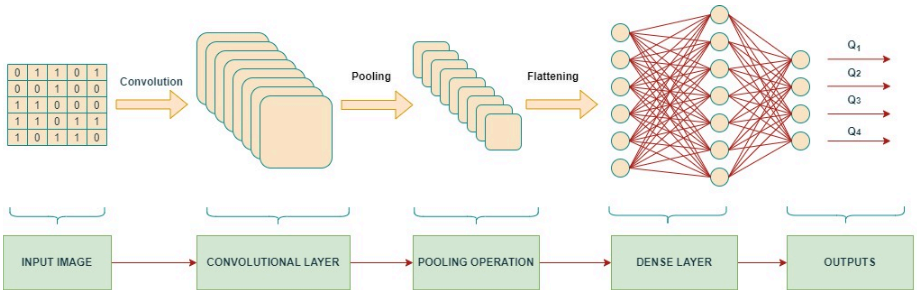

Figure 4. Flowchart of applying dropout layer to dense layer

3. Results

This section explains how the experiment is done and which hardware and software tools are used. The experiment was conducted using Python software and a JupyterLab environment. Tensorflow [15], seaborn [16], numpy [17], pandas [18], matplotlib [19], keras [20], image PIL [21], SMOTE [22], scikit learn [23] libraries for Python software used. An accuracy rate of %96.35 was achieved in the experiment. The ratio is shown in the picture given below in Figure 5.

```
60/60 [==============================] - 12s 199ms/step - loss: 0.1582 - acc: 0.9635 - auc: 0.9922 - f1_score: 0.9639
Testing Accuracy: 96.35%
```

Figure 5. Testing accuracy

The model was evaluated according to the accuracy of the classification of the disease, its cross-categoric entropy, and MRI images. The following chart shows the accuracy rate according to the train and validation dataset.

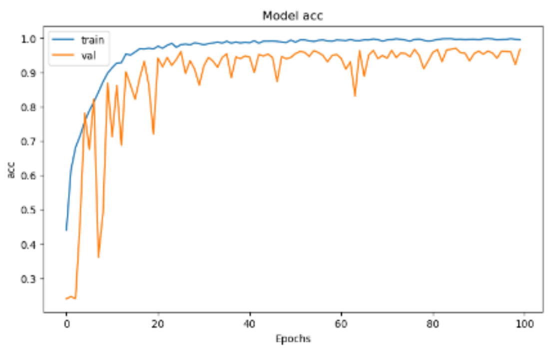

Figure 6. Model accuracy

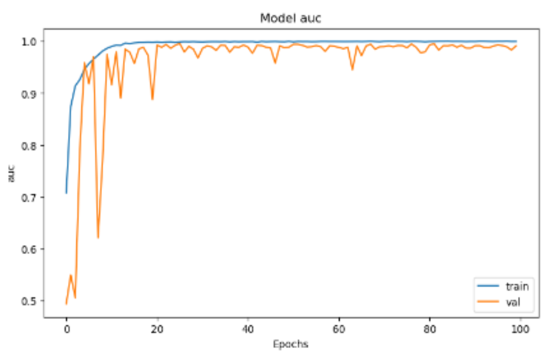

Figure 7. Model auc

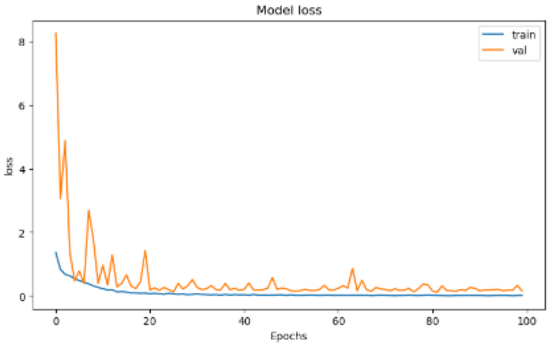

Figure 8. Model loss

The results obtained in the above graphics are recpectively, (Fig. 6) The accuracy of model, (Fig. 7) model auc curve, and (Fig. 8) model loss is shown.

Recall, precision, specificity, and accuracy criteria are used to measure classification performance [24]. Precision is essential here. The reason is that we want to be sure of the prediction [25].

$$Precision = \frac{\text{True Positive}}{\text{True Positive+False Positive}} \quad (2)$$

The Recall value indicates the success rate of predictions of positive values.

$$Recall = \frac{\text{True Positive}}{\text{True Positive+False Negative}} \quad (3)$$

F1Score is the harmonic average of recall and precision. For F1Score to be strong, it must have values close to 1[26, 27].

$$f_1Score = 2 * \frac{\text{Precision}*\text{Recall}}{Precision+Recall} \quad (4)$$

Accuracy is the ratio of correct guesses to overall forecast.

$$Accuracy = \frac{\text{True Positive+True Negative}}{\text{All predictions}} \quad (5)$$

The picture below shows the f1score, recall, precision, accuracy and support values of Alzheimer's disease from 4 different classes. Table 1 shows the precision, recall, f1-score, accuracy and support values of Alzheimer's disease.

Table 1. The obtained precision, recall, f1-score, accuracy and support values of Alzheimer's disease with the proposed model

AD classification	Precision	Recall	F1-Score	Support
Nondemented	0.99	0.98	0.98	474
Very mild demented	1.00	1.00	1.00	473
Mild demented	0.93	0.95	0.94	507
Moderate demented	0.94	0.93	0.93	466
Micro average	0.96	0.96	0.96	1920
Macro average	0.96	0.96	0.96	1920
Weighted average	0.96	0.96	0.96	1920
Samples average	0.96	0.96	0.96	1920

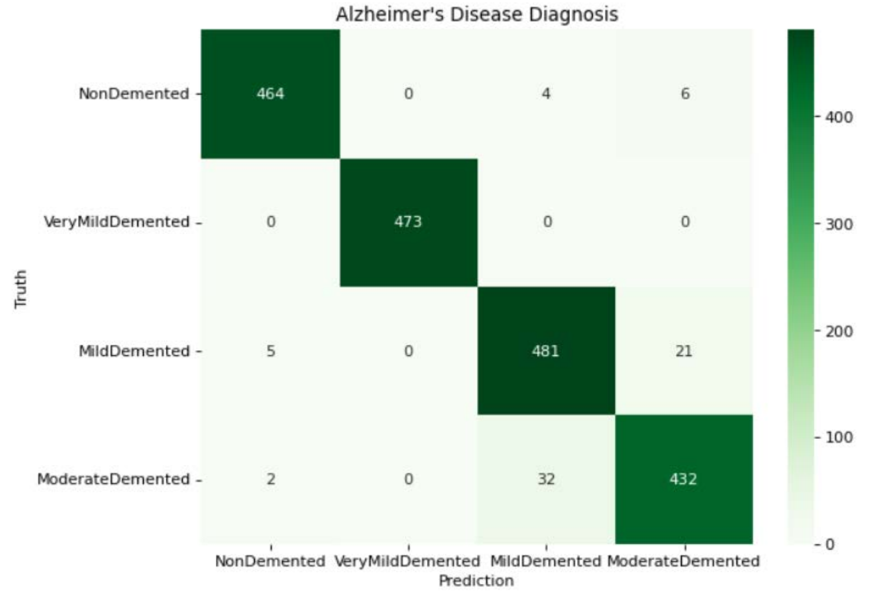

Figure 9. Confusion matrix

In the table above, (see Fig.9) confusion matrix data is presented with the help of the Softmax classifier. Classification performance results are shown in the table. The classification of healthy individuals and individuals with Alzheimer's disease was made using MRI images together with the model created with deep neural networks. According to these data, the classification success achieved is 96.35%. Considering the accuracy of the model, the CNN model plays an important reole in the diagnosis of Alzheimer's disease.

4. Discussions

In the table 2 shows the success of the proposed model and other studies. In our study, four stages of the disease were tried to be classified. In literature studies, Alzhemier's disease is divided into two stages. In the study conducted by Yildirim M., et al. [31] 2020. Alzheimer's disease was divied into four classes and 90% success was achieved. With the proposed model success has been improved. It has been achieved 96.35%.

Table 2. Proposed model and other studies

Authors	Year of Publish	Methods	Accuracy
Lee et al.,[28]	2019	Deep CNN	75.0%
Goo et al.,[29]	2017	CNN	87.62%
Ortiz et. al.,[30]	2017	Deep CNN	90%
Yildirim et al.,[31]	2020	CNN	90%
Proposed Model	**2023**	**3D CNN**	**96.35%**

5. Conclusion and future directions

We used sequential architecture in this application. We created the model with the datasets we got from the website Kaggle. There are 4 different classes available. The sequential model yielded improved results. The results of LeakyReLu in the activation process increased the model's performance. The architecture is complex, though sequential. Convolution processes take a long time. It has been observed that the model's performance will decrease when the data is scarce, and the data is increased. In the future, models can be improved by using more data types or adding CT and MRI images. The proposed model has achieved a success of 96.35% in performance.

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