



Deep Learning Framework of Convolutional Neural Network (CNN) and Attention CNN for Early Diagnosis of Alzheimer's Disease

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Abstract

One of the biggest killers in the industrialized world is Alzheimer's disease (AD). Although computer-aided techniques have shown promising outcomes in laboratory experiments, they have yet to be used in a clinical setting. Recently, deep neural networks have gained traction, particularly for image processing tasks. There has been a dramatic increase in the number of publications written on the topic of identifying AD using deep learning since 2017. It has been observed that deep networks are more efficient than standard machine learning methods for detecting AD. It remains difficult to identify AD because distinguishing between comparable brain signals during categorization needs an extremely discriminative depiction of features. This paper proposed a deep neural network method for prediction the AD. Low-level computer vision has been a hotspot for research into deep convolutional neural networks (CNNs). Studies often focus on enhancing performance through the use of very deep CNNs. Yet, as one goes deeper, the effect of the shallow layers on the deeper ones gradually diminishes. Prompted by reality. This paper compared with the CNN and attention CNN models. The proposed model applied in the AD dataset which contains 5121 images for the train set. The results showed the attention CNN model is better than the CNN model in accuracy, precision, recall, loss, and AUC.

Keywords: Deep Learning; Convolutional Neural Network (CNN); Attention CNN; Alzheimer's disease; Neural Network; Accuracy; Precision; Recall; Loss.

1. Introduction

Alzheimer's disease (AD) is a degenerative neurological illness that erodes cognitive abilities over time, making it hard to carry out even the most basic tasks like eating or dressing. It will ultimately prove deadly. It is thought that between 60 and 80 percent of the instances of dementia are attributable to AD. It often begins in middle age or old age, and its progression to memory loss (connected with a synaptic malfunction, brain atrophy, and cell loss) is thought to be triggered by protein buildup close to neurons[1]–[4].

Some indicators may become aberrant before cognitive decline even occurs when the brain undergoes its first alterations. According to studies, AD-related brain alterations may begin two decades before problems show[5]–[7].

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Mild cognitive impairment (MCI) is the diagnostic label given to individuals in the early stages of Alzheimer's disease, while not all people with MCI go on to acquire the more severe form of the disease. Mild cognitive impairment (MCI) occurs when a person's cognitive abilities have changed somewhat from normal yet they are still functional enough to go out of their daily lives without assistance[8]–[10].

About 15% to 20% of those aged 65 and above have MCI, and 30% to 40% of those with MCI progress to AD during the same time frame. Time to convert might be anything from 6 months to 36 months, with the average being about 18 months. Following 18 months of observation, individuals with MCI are classified as having converted to AD (MCIC) or not converting (MCINC). Other forms of MCI, like early/late MCI, are seldom discussed in research[11]–[13].

The existence of AD-related genes in a person's genome and a personal or family history of the disease are the two most important risk factors. A thorough clinical evaluation and in-depth interview with the individual in question and their family are required for the identification of AD. However, an autopsy is the only way to get a 'ground truth' assessment of AD, and this is not useful in clinical practice. Individuals having an established diagnosis of AD at autopsy are used[14]–[16].

In recent years, techniques for deep learning have surpassed other approaches to overcoming these limitations as a result of their superior modelling capabilities. To restore the distorted picture, denoising (DnCNN) was initially devised, which used residual learning (RL) and batch normalization (BN). Deep CNNs with such adaptable component designs are thus widely used in image tasks. Multi-denoising problems, including those involving Gaussian noise, JPEG compression, and low-resolution pictures, are all within the scope of the suggested DnCNN framework[17], [18].

The problem with DN, nevertheless, is that their performance might degrade as their depth increases. To address this issue, researchers used recurrent and skip link processes in CNNs for picture restoration. In restoring images, for instance, a DRRN used both global and local RL approaches to improve the trained model's representational power. The blurring efficiency of a deeply recursive (DRCN) was enhanced in a similar fashion by fusing information from all of the network's layers into a single, final layer using an RL approach. Widening the framework helps mine extra data for use in picture demising. The education in restoring images may be sped up significantly by merging the previous and CNN[19], [20].

2. Alzheimer's Dementia

Memory and other cognitive tests, as well as assessments of functional abilities and changes in behavior, are used by clinicians in making a diagnosis of Alzheimer's dementia. A battery of diagnostic procedures is also carried out to rule out further potential sources of dysfunction [1, 3].

There are a number of diagnostic approaches available for Alzheimer's disease. Alzheimer's disease is often identified during a medical checkup. Your symptoms and indicators will be assessed by a battery of diagnostic procedures. In order to get insight into symptoms and behaviour, they may consult with loved ones.

Alzheimer's disease is the most frequent kind of dementia, thus a proper diagnosis is crucial. Obtaining a proper diagnosis is crucial to receiving the necessary care, therapy, family education, and future planning [2,3].

- The first Alzheimer's dementia symptoms include:
- Disabilities in recalling recent or past events
- Trouble focusing, making plans, or addressing problems
- Difficulty doing routine home or office duties like writing or using dining utensils
- Disorientation about time or place
- having trouble processing spatial information, which may lead to problems like poor depth perception when driving or constant misplacing of belongings.
- Issues communicating due to a lack of language or difficulty finding the right words to use
- Absence from scheduled activities (at work or elsewhere)

- Depression and other changes in behavior and personality are examples of shifts in mood.
- Dementia caused by Alzheimer's disease may have far-reaching consequences.
- It's crucial to acquire a correct diagnosis as soon as possible when the first indications of Alzheimer's dementia arise.

3. Convolutional Neural Network (CNN) and Attention CNN

In this section, we introduced the CNN and attention CNN model.

Convolutional Neural Network (CNN) For picture categorization and object recognition, CV, and image analysis is now extensively employed in practically all fields. Convolutional neural networks (CNNs) are a popular form of deep neural network utilized for identifying variations among sets of visually similar pictures that may be distinguished by a human specialist. A CNN may consist of a variety of layers, including convolutional, activation, pooling, fully connected, and the last classification layer[21], [22].

The filter, which acts as an attribute detector, is convolved with the input picture using the operator known as convolution. The output of a convolutional layer is fed into a layer that applies a non-linear activation method. This layer is called an activation plane. Activation mechanisms like the Sigmoid, tanh, Rectify Linear Unit, Leaky Relu, etc. are often employed to determine if or not a cell will be triggered. The primary purpose of layer pooling is to assist reduce overfitting by regulating variables by decreasing the input's size and breadth. CNN uses a variety of pooling methods, including Max pooling, Mean pooling, and others. A neural network's dropout layer aids in regularisation by turning off both its hidden and its exposed units. The output of the convolutional and pooling layers is flattened to go into the fully linked layer at the very end of the system. Figure 1 shows the design of CNN model[23], [24].

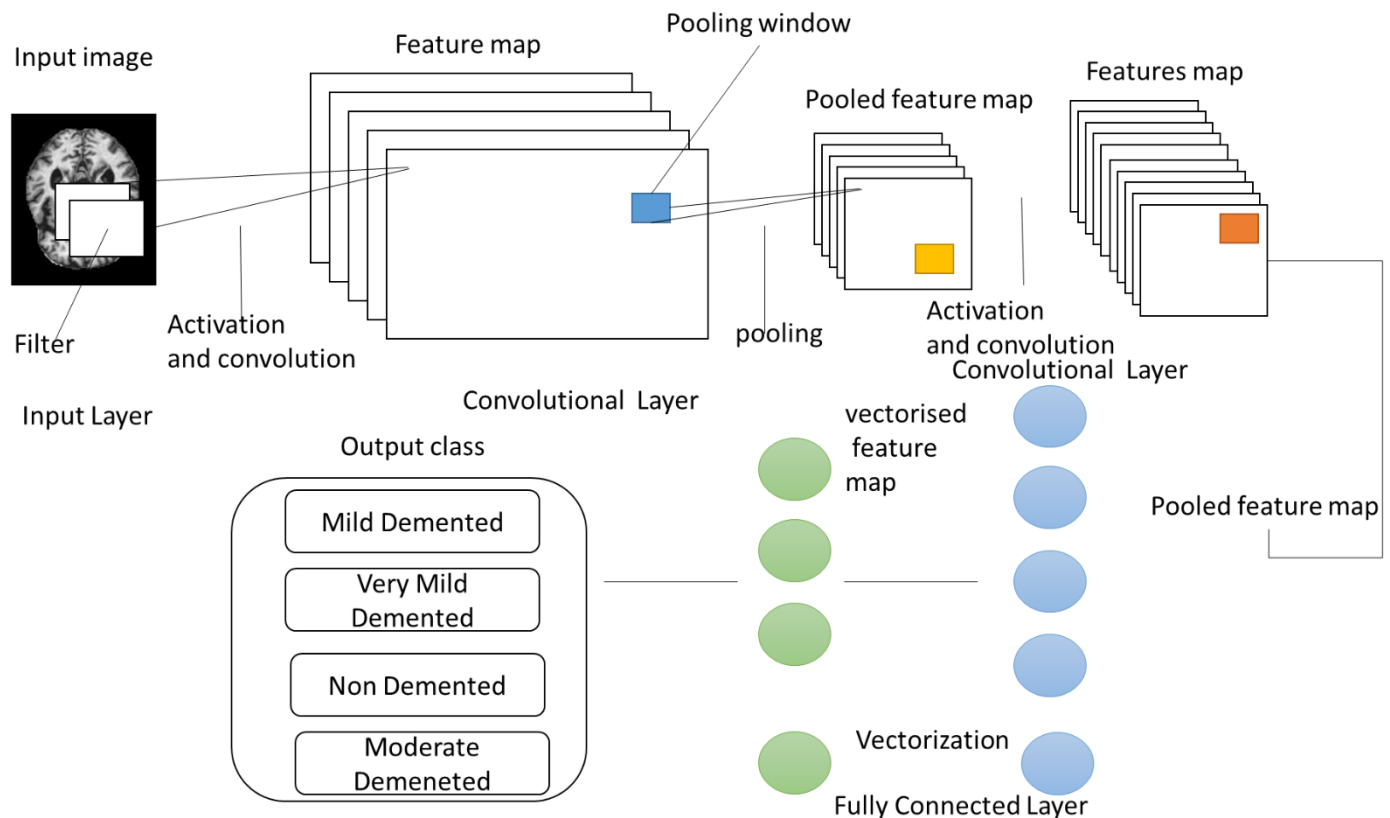


Figure 1: The design of CNN model.

Attention Block (AB) CNN

Knowing that the characteristics of video and picture apps might be readily hidden by a complicated backdrop can make training more challenging. In this work, we use an AB to direct the CNN during elimination model instruction. For uncertain blurry pictures, such as blind eliminating and actual noisy pictures, the AB employs the present phase to direct the preceding step to acquire the noise characteristics. The 1-layer AB consists of a single convolution and has an identical dimension, where is the amount of layers in the provided distorted picture[25], [26]. In order to execute the attention procedure, the AB takes use of the next two processes. To begin, the characteristics collected are condensed into a vector using a convolution of size $2h \times 1 \times 1 \times h$ in the seventeenth level to serve as weights for altering the prior phase, which may further enhance the eliminating performance. The result of the sixteenth layer is then multiplied by the weights we've gathered in order to pull out more pronounced noise characteristics. Figure 2 shows the attention block of CNN[27], [28]. The method of implementation may be recast in the form of subsequent formulations.

$$P_t = h(P) \quad ()$$

$$I = P_t \times P \quad ()$$

Where P refers to the output of the convolution.

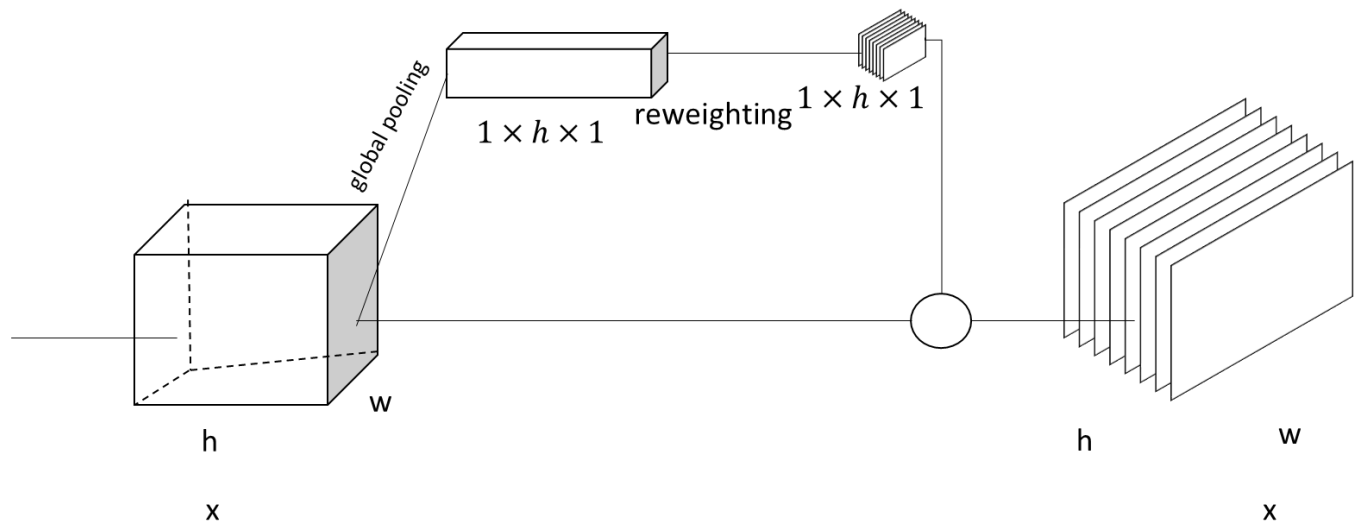


Figure 2: The structure of attention block

4. Results

This section introduced the applied of proposed method in the Alzheimer dataset (AZD). We collected this dataset from Kaggle. This dataset contains train and test folder; each folder has four classes. The number of images in the train folder are 5121. Figure 3 shows the number of images per class. The first class named non demented has the largest number of images flowed by very mild demented class, then mild demented, and finally the fewest number of images in moderated demented class. Figure 4 shows the four images in each class.

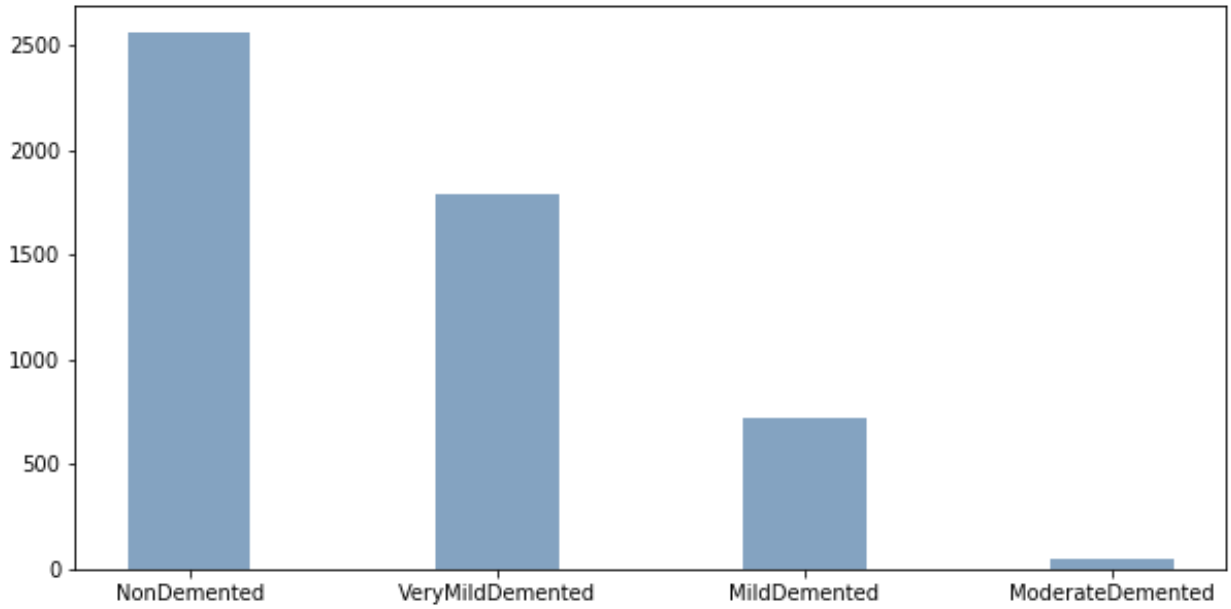


Figure 3: The number of images per class.

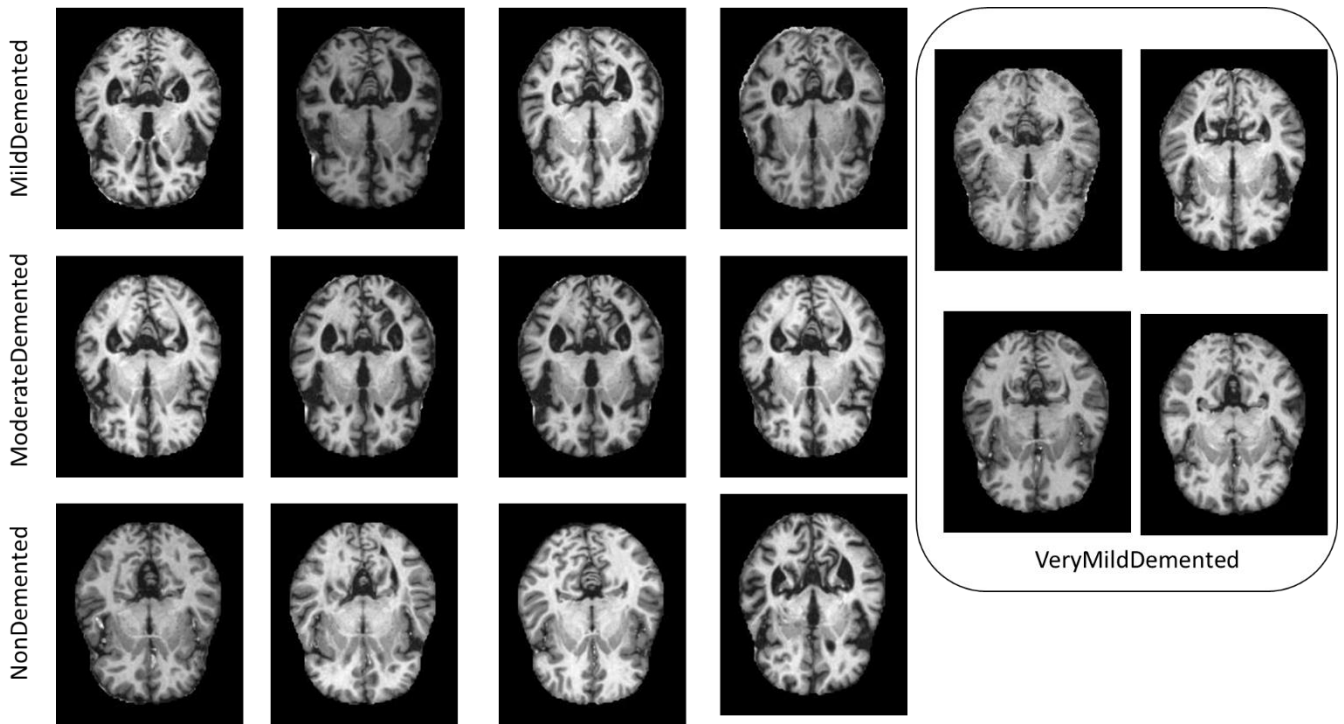


Figure 4: The 16 images from 4 classes

We applied the CNN model and attention CNN model into the AZD dataset. The flowchart of the proposed model is shown in Figure 6. The comparison between two model is shown in Figure 7. From Figure 7 the attention CNN is better than CNN.

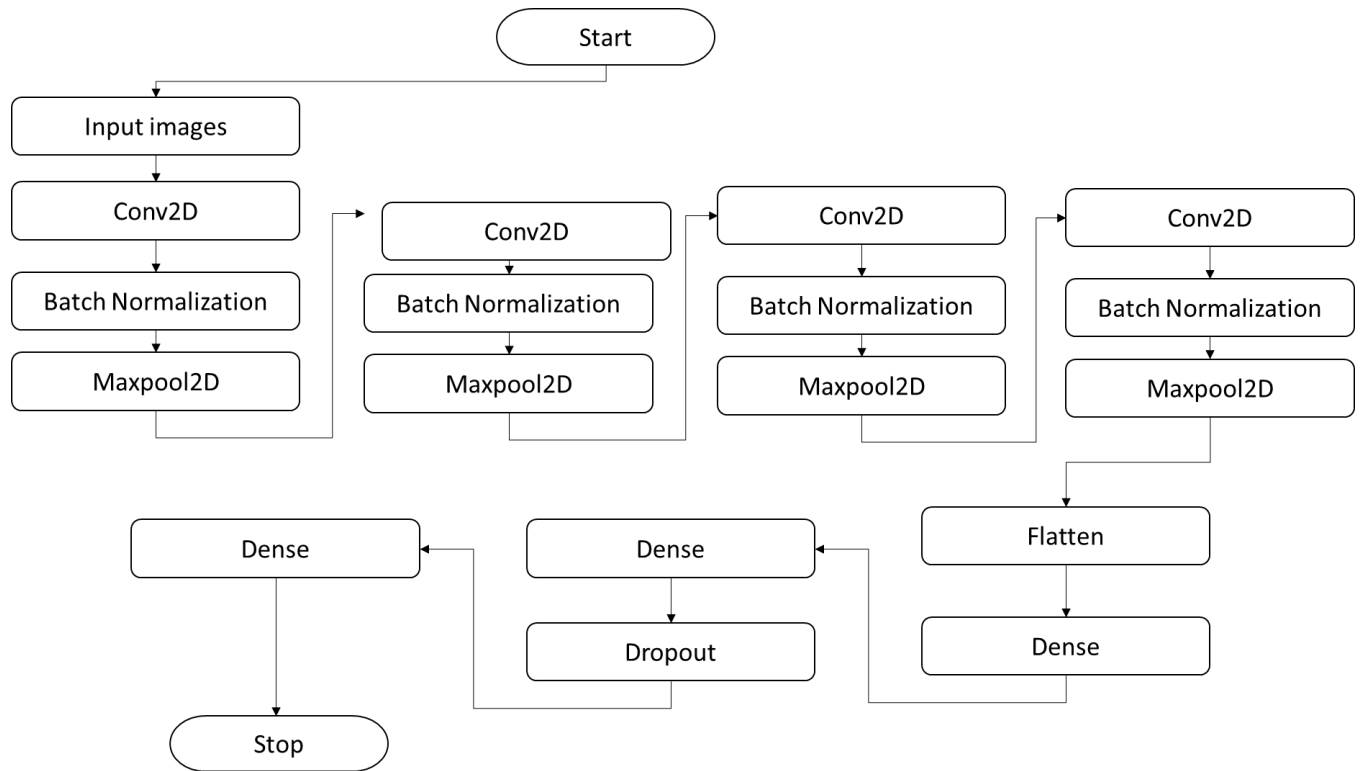


Figure 6: The flowchart of the proposed model.

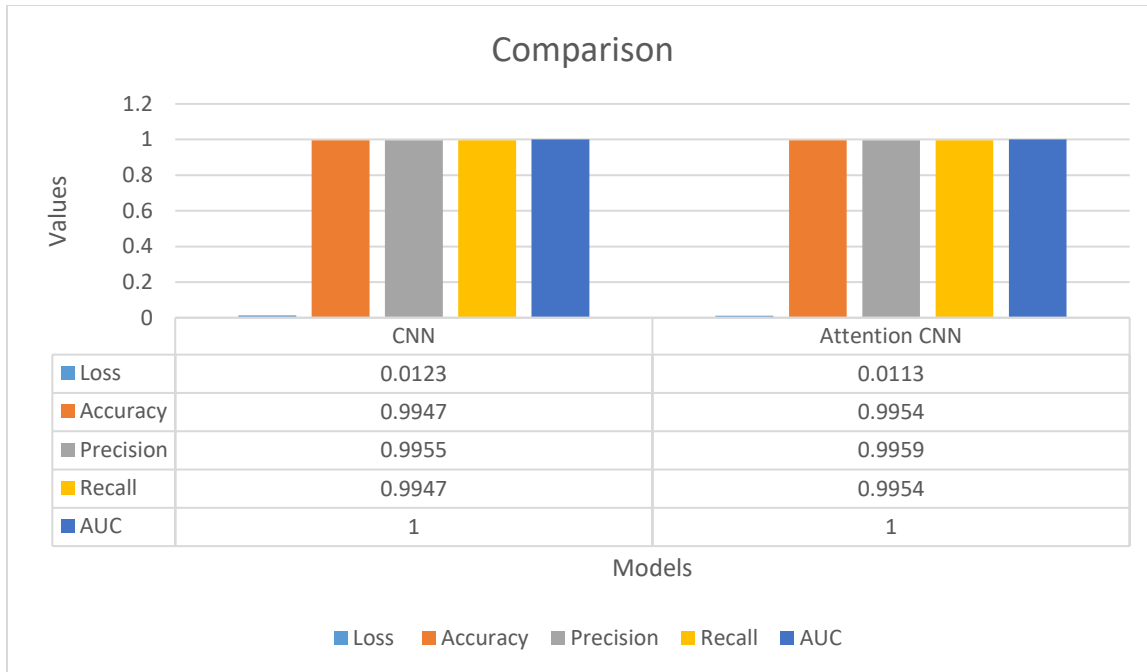


Figure 7: Comparison between evaluation matrices between CNN and attention CNN.

Figure 8 shows the difference between loss and validation loss, and Figure 9 shows the difference between accuracy and validation accuracy.

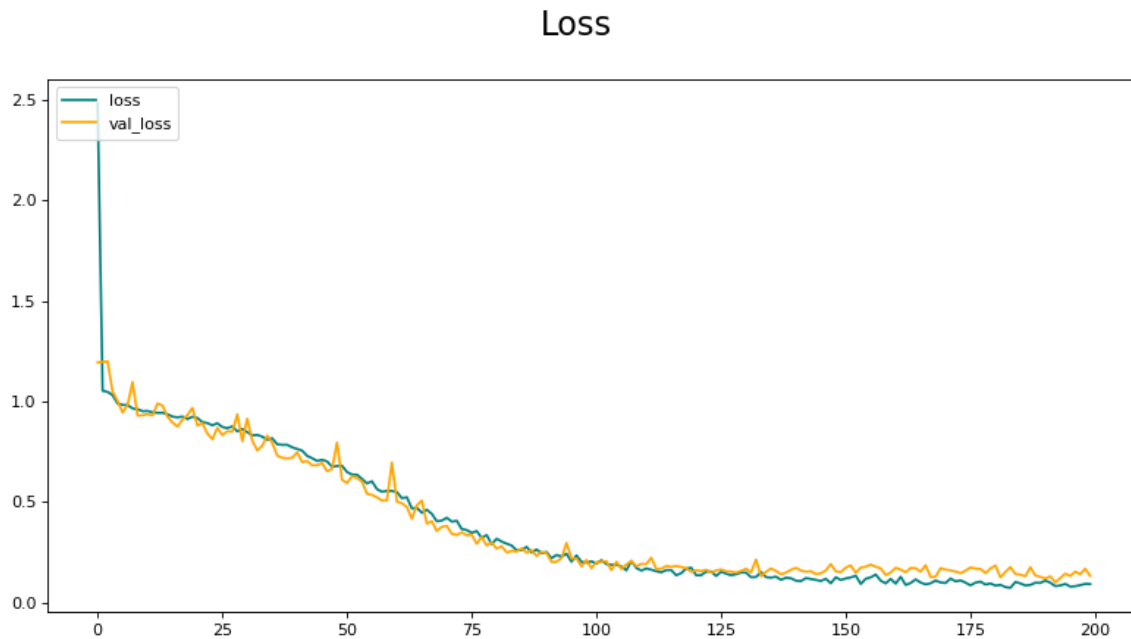


Figure 8: Difference between loss and validation loss

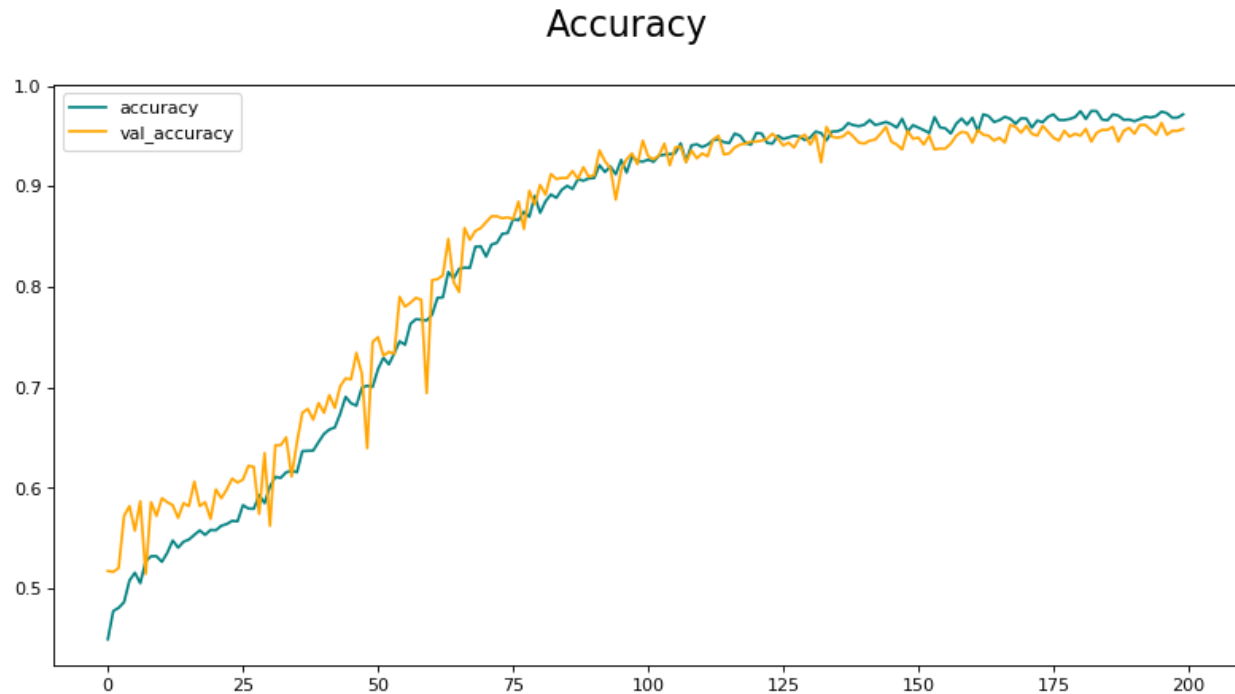


Figure 9: Difference between accuracy and validation accuracy.

5. Conclusion

In affluent nations, AD ranks high among the primary causes of mortality. The employment of computer-based methods in conjunction with medical specialists has much to suggest in identifying AD since this is a difficult job in clinics. Deep learning has received a lot of focus lately for this purpose. Herein, we detail how deep learning has contributed to the evolution of the identification of AD tools. In the first part of this study, we introduced Alzheimer's disease (AD) and its manifestations. This paper introduced the comparison between CNN and attention CNN models. These models are applied in the AD dataset which contains four targets class. The results showed the attention CNN model is better than the CNN model. This paper used performance matrices to show the robust of the model like accuracy, precision, recall, loss, and AUC. The accuracy of the attention CNN model reached to the 99.5%.

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