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Research Article

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Alzheimer's Disease Classification via Convolutional Neural Networks

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Abstract

Dementia most frequently results from Alzheimer's disease (AD). The disease steadily worsens, starting with modest memory loss and perhaps progressing to speech loss and loss of sensation of one's surroundings. Genetic, environmental, and behavioral factors are probably important factors, as well as age-related changes in the brain. When the disease is still in its early stages, a correct diagnosis of AD is crucial for patient treatment because it allows patients to begin preventative measures before irreversible brain damage happens. Most machine detection approaches are limited by congenital findings, despite the fact that computers have been used to diagnose AD in several recent studies.

Keywords

Dementia, Alzheimer's disease, Deep learning, Nanomedicines, Challenges, Clinical development

Introduction

The brain is the most crucial organ in the human body. Because most cognitive changes are persistent in extreme cases [1], it is imperative to treat brain disorders. Impairment of memory and cognitive function is referred to as dementia [2]. AD was the most prevalent contributing factor of dementia. At first, humans in their late-60s or older are often affected by AD [3]. AD is thought to affect around 5.5 million population. AD manifestation comprises memory casualty, linguistic problems, and behavioral abnormalities. Non-memory symptoms include difficulties discovering words, vision impairments, poor judgment, and reduced reasoning. The biological indicators are blood, cerebrospinal fluid, and brain imaging. Minimal AD, intermediate AD, and extreme AD are the three basic forms used to describe this illness.

Early-onset AD has a hereditary member [4], but late-onset this disease was caused by a complex series of changes in the brain. The build-up of protein Tau Tangle and amyloid plaques throughout the brain causes cells to halt their function, and when that happens, the link with the other cell is severed and the neuron dies. The injury will initially impact the hippocampus, the area of the brain responsible for publicizing remembrances. Deliberately, it disseminates to further parts of the body, as well as the brain affected through this toxin began to shrink, and by the last stage, the entire brain size had shrunk dramatically.

The intersection of Convolutional Neural Networks (CNNs) and nanotechnology offers a groundbreaking approach to the classification of AD. Nanotechnology, with its ability to manipulate matter at the nanoscale, provides a unique avenue for precise and targeted detection of biomarkers associated with AD. Nanosized sensors, engineered to interact with specific molecular entities implicated in the disease, are strategically deployed within the neural environment. As for the usage of nanotechnology in AD, it seems to be more prevalent in treatment rather than diagnosis or classification.

In image processing, magnetic resonance imaging (MRI) scans [5] can be used to measure the chance of early AD detection [4]. Numerous images processing techniques, including intensity modulation, K-means clustering, and the region expanding method for isolating white and grey material, are employed in MRI. The assessment of neural activity may be carried out using the same methodology. The axial plane (top view), coronal plane (back side), and sagittal plane of brain MRI scans are used for statistical and therapeutic literature appraisal utilizing MATLAB software (top view). The extraction of its focus region out of a visual using image processing and analysis algorithms is known as image enhancement. Image segmentation techniques encompass region expansion, watershed, thresholding, divide and merge, and the K-means clustering strategy [6]. Multimodal framework is also used to detect dementia [7]. Defects including porosity and absence of fusion, incomplete penetration, and wormhole are found when radiographic [8] weld photos are segmented using the segmentation techniques described. Using this method, faulty areas are identified. They are therefore frequently used in the processing of industrial radiography, human computer interaction, recognition of optical characters and diagnostic imaging [9].

Once the process has started, all points with marginally different intensities move towards their respective centroids. On an MRI when all the groups have been finished, the tumour is clearly visible. AD is identified and diagnosed using the double-cubic interpolation method. Within brain MRI, dead and healthy tissue are distinguished by pixel intensity. The disorder does not necessarily result in a change in the form of the brain. There is a natural process that causes the brain to shift shape. As a result, it could be difficult to tell through image processing whether a disease has changed the structure of a brain. To identify the origins of distortion, a mathematical model might be developed. For reasons unrelated to methodology, the elasticity of the brain is cited as the explanation for the distortion. This will enable us to detect the pathologically induced assortment of different of the brain. According to illnesses like AD, schizophrenia, normal pressure hydrocephalus, and healthy volunteers, this method is used to categorize individuals.

Experimentation

Proposed model

This process flow includes locating the brain parts connected with brain atrophy and hippocampus by using different types of CNN. In the domain of profound understanding, CNN, figure 1, is mostly deployed in the field of image recognition. CNN employs an extremely unique technique known as Convolution. The mathematical definition of convolution is applying a mathematical operation on two functions resulting in a 3rd function that shows what factors can affect a function's structure, modified by the other function [10].

CNN are built using a variety of communications network layers. The summation of inputs and outcomes is calculated

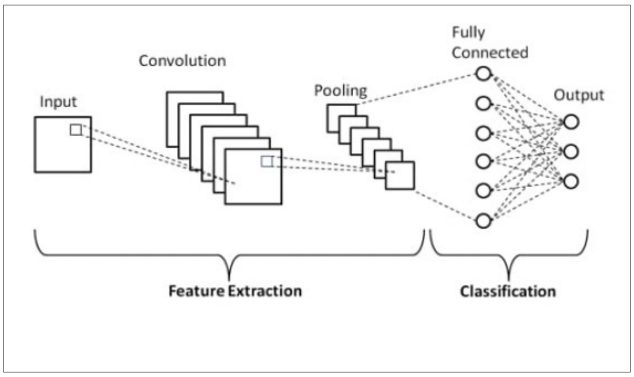

Figure 1: CNN architecture.

using artificial neurons, which produce an activation level consequently. Those seem to be comparable towards the neural stem cells used by the neural network to transmit diverse sensory control signal as well as other activities. When an input picture is fed into a CNN, each inner layer generates a unique set of activation maps. Activation maps draw attention to the important parts of the input image.

Every CNN neuron receives data in the form of a pixel patch, merges the values (colored) even by amount of its own parameters, combined altogether, then receives input via relevant learning algorithm. The very first stratum of a CNN often distinguishes several features of the input picture, including certain edges which run longitudinally, radially, and diagonally. The second level uses the result of the first layer as an input and examines more intricate components from the pixel intensity, as with border and edges combinations. Each CNN neuron's characteristics depend on how important it is. Artificial neurons in a CNN can identify a wide range of sensory properties and criteria if fed with pixel values.

The proposed system uses CNN to predict AD. So, in order to find out the best algorithm we have used Vgg16, Alexnet, Mobilenet and Resnet algorithms. That helps us to use the best accurate model. The CNN known as Vgg-16 has 16 layers in total. More trained models and improved accuracy are both aided by it. Five deep networks and three fully linked levels help compensate the CNN known as Alexnet. It facilitates model training more quickly. Resnet is a neural network having 50 layers. It can be used to train large number of layers with limiting the error percentage.

The past few years, researchers have also explored how nanomaterials might be used in precision medicine. As the only available treatment for AD cannot cross the blood brain barrier, it is limited to relieving symptoms. The numerous advantages of nanotechnology-based therapy suggest that this limitation may eventually be overcome. The Food and Drug Administration has approved a wide range of nanocarriers for drug delivery to treat various disorders. Nanocarriers are used to treat various neurological disorders, including AD and brain cancer.

Experimental procedure

Data collection

The data used contains 6400 MRI images of different classes. There are four different classes in the dataset. They range from being non-demented to very mildly, mildly, and moderately demented. These images are passed to the model for further process.

Pre-processing

Data pre-processing leads us to better classification performance. It is also used to speed up the training. To make the database larger and enable effective model training, we have additionally applied picture augmentation techniques.

Training dataset

The training data contains the large dataset of images with their corresponding class or output. It helps us to train the model. We have used 4098 images for training dataset.

Testing dataset

Testing dataset contains a small set of images. It is the response of our model to find the resultant classes for these images. We have used 1279 images for testing dataset.

Deep learning models

The CNN algorithms like Alexnet, Vgg 16, Mobilenet and Resnet are used to develop a predictive model. The best model is chosen based upon the values of accuracy and precision.

Results and Discussion

Table 1 displays the results of comparison of the different CNN models. Resnet has the highest accuracy among all the algorithms. The comparison of accuracy, precision, and F1_Score among all the algorithms were shown in figure 2, figure 3, and figure 4, respectively.

Conclusion

This paper clarifies every issue caused by AD for people worldwide. In this study, we analysed the ability of neuroimaging to identify AD. It develops the model using the white and grey matter in the brain MRI picture. The resultant data will be classified as non-demented, very slightly demented, mildly demented, or moderately demented in any of the categories. Different algorithms and architectures can be explored to increase the accuracy and efficiency of the model. We can also analyse the effect of different parameters on the results.

Table 1: Accuracies of all the algorithms.

Model	Accuracy	Precision	F1_Score
VGG16	53.91%	54%	43%
Alex net	50.47%	33%	33.86%
Mobile net	69.14%	53.45%	38.22%
Resnet	77.52%	58.13%	44.24%

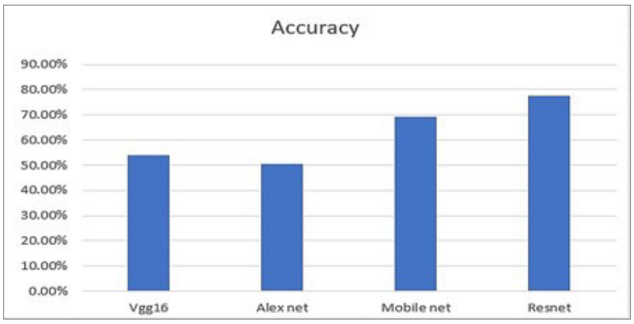

Figure 2: Comparison of accuracies among all the algorithms.

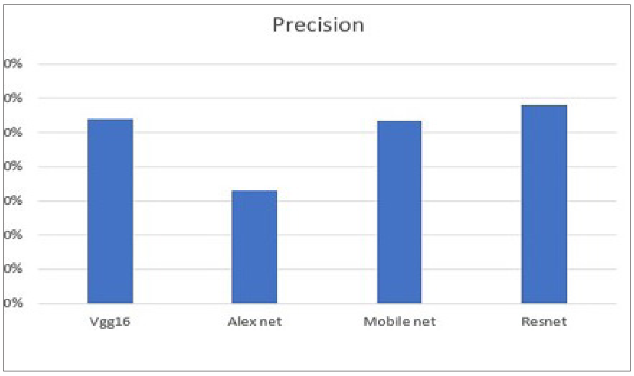

Figure 3: Comparison of precision for all the algorithms.

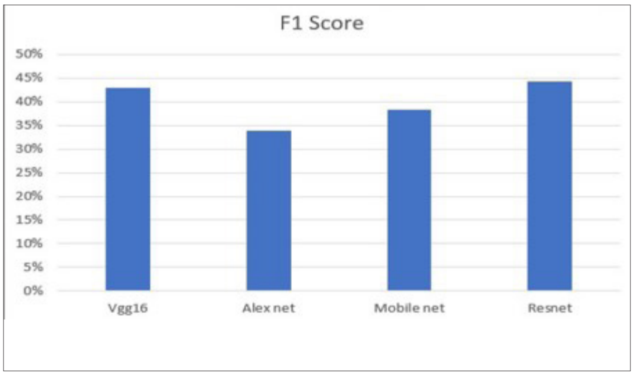

Figure 4: Comparison of F1_Scores for all the algorithms.

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None.

Conflict of Interest

None.

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