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Classification of medical images of Alzheimer's disease using deep learning techniques

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Abstract

Medical images are used in clinical diagnosis, physician treatment, training, and research, among other things. Alzheimer's disease is the most prevalent type of dementia, which is caused by a build-up of protein in and around nerve cells and results in a continuous decline in memory. It usually begins in middle or late age. Alzheimer's disease (AD) is initially diagnosed as mild cognitive impairment (MCI), moderate cognitive impairment (MCI), It is required for effective therapies since some MCI patients change to AD and others remain stable MCI-nc, not all MCI patients convert to AD. Deep learning system (CNN) was used to classify images of MCI subjects as being developing Alzheimer's disease (MCI-c) or being stable (MCI-nc). Because MCI is regarded an intrusive window to stop the harmful evolution of the disease and implement preventative measures as much as possible before permanent brain damage occurs, this type is considered one of the most essential forms of classification. The method of pre-processing images of MCI patients to improve the accuracy and speed of detection of Alzheimer's disease (AD), because it is crucial to initiate effective treatment in order to slow or prevent the disease progression and thus patients can maintain their independence for a lengthy span of time. that the researcher touched on Preparation and initialization of the CNN deep learning algorithm, and the model achieved an accuracy of 96.67%, to classification MCI-c in 6 month vs MCI-c 12 month vs MCI-c 18 month vs MCI-c non time vs MCI-nc

Keywords

Medical Data, CNN, Deep Learning, MCI, MCI-C, AD

1. Introduction

Alzheimer's disease (AD) is the most common type of dementia, accounting for 60-80 percent of all cases. It typically starts in middle or late life, and it may begin with protein deposition in and around neurons, leading to a slow decline in memory (associated with synaptic dysfunction, brain shrinkage, and cell death). The brain grows the first changes before cognitive decline occurs. Some vital indications may become abnormal during this early stage. According to studies, brain changes related with Alzheimer's disease may begin at least 20 years before symptoms appear. Alzheimer's disease patients in stage I show moderate cognitive impairment (MCI). Mild cognitive impairment (MCI) is a type of memory loss that occurs between the onset of normal aging and the onset of Alzheimer's disease. Around 20 to 50 percent of people over 65 have moderate cognitive impairment, with 30 to 40% getting Alzheimer's disease within five years. Even though it takes an average of 18 months, the time it takes to transfer varies from 6 to 36 months. MCI patients have either been diagnosed with Alzheimer's disease (MCI-C) or are in a stable state (MCI-NC). This indicates if the patient got Alzheimer's disease (AD) within the previous 18 months [1]. MCI is frequently regarded as a precursor to Alzheimer's disease. As according previous research, the pathological time axis of Alzheimer's disease (AD) can start years or decades before clinical diagnosis. It begins with no symptoms and progresses to the level of MCI. As a result, early detection, prevention, tracking, and prognosis of Alzheimer's disease (AD) are crucial. It could help prevent Alzheimer's disease (AD) or slow the progression of neurodegeneration [2].

2. related works

In 2019, Yechong Huan and colleagues proposed the use of the Deep Learning algorithm, a therapeutic neural network (CNN), to integrate all multimedia information embedded in both T1-MRI and FDG-PET images of the HSN region. This method differs from traditional machine learning algorithms, and does not require hand-extracted features, instead using CNN networks to process 3D images to learn the advantages of a diagnosis or diagnosis of Alzheimer's disease. Pre-processing of data through zxtools, then training the compiler using T1-MR and FDG-PET images associated with ADNI data sets, including 731 unknown knowledge persons (CN) and 647 persons with Alzheimer's disease) Twice (MCI-nc) and 326 people with mild progressive cognitive impairment (MCI-c) were converted to higher accuracy of 90.10% for CN versus AD, 87.46% for CN versus c MCI and 76.90%

In 2019, Silv Basaia and colleagues built and validated a deep learning algorithm predicting individual diagnosis of Alzheimer's disease (AD) and moderate cognitive weakness to become AD (c-MCI) based on a structural MRI scan. Trophic neural networks (CNNs) have been applied to weighted T1 3D images of ADNI and subjects assigned to our institute (407 health control elements) [HC], 418 AD, 280c-MCI, 533s-MCI, 533s-MCI The performance of CNN in distinguishing between AD, c-MCI and s-MCI was tested. Data pre-processing was done on SPM12. High levels of accuracy were achieved in all classifications, with the highest rates achieved in AD versus HC classification tests using each group. CNNs identified c-MCI from s-MCI patients with an accuracy of up to 75% and no difference between ADNI and ADNI images. CNN networks provide a powerful tool for automatic individual diagnosis of the patient along the connected AD chain. This method performed well without any previous feature engineering and regardless of the variety of imaging protocols and scanners, indicating that it could be exploited by untrained operators and potentially generalizable to the patient's invisible data. CNN networks may quickly adopt structural magnetic resonance imaging into routine practice to help assess and manage patients. [4]

In 2018, Weiming Lin and his colleagues designed a deep learning approach based on trophic neural networks (CNN), to accurately predict the conversion of MCI to AD using MRI data. Second, local spots, grouped into 2.5 dimensions, are extracted from these images. Count that, corrections from AD and standard control elements (NC) are used to train CNN to identify deep learning features of MCI subjects. Next, structural brain image features are extracted using FreeSurfer to assist CNN. Finally, both types of features are fed into an auto-extreme classification to predict the transformation of AD. The proposed approach to standardized magnetic resonance imaging datasets has been validated from the ADNI project, achieving up to 79.9% accuracy and 86.1% area under the Future Operating Feature Curve in one-time collision checks. Compared to the latest methods, the proposed method surpasses others with higher accuracy and AUC, while maintaining a good balance between sensitivity and privacy. The results show significant potential for the proposed CNN-based approach to predicting the conversion of MCI to AD using MRI data only. Age correction and assisted structural brain image features can enhance the prediction performance of CNN [5].

In 2019, Rachna Jain and colleagues used a learning-based PFSECTL mathematical model where the CNN structure is used, with VGG-16 trained in the ImageNet data set being used as an advantage extract for the classification task. For preprocessor use, experiments were conducted on data collected from the ADNI database. The accuracy of the three-way classification using the method described is 95.73% for the validation group [6].

In 2020, Manu Raju and colleagues proposed a multi-category classification of AD, moderate cognitive impairment (MCI), and normal control subjects (NC) using a 3D teleological neural network with a Vector Machine support synthesizer. A CT study was conducted on the structural magnetic resonance imaging (MRI) data of 465 persons, including 132 patients with AD, 181 MCI and 152 NC. The highly complex spatial destroy patterns of the brain associated with Alzheimer's disease and MCI are extracted from magnetic resonance imaging images using sequential layers of the 3D tropic neural network. The frenzied retail and additional extraction of handmade features are eliminated. The full picture is taken into account for the processing (FreeSurfer), thus integrating each region into the brain for classification. The features extracted are fed using four consecutive layers of 3DCNN in the Super Vector Machine. The proposed method achieved 97.77% accuracy superior to the latest technology, and this algorithm is a promising indicator for the diagnosis of Alzheimer's disease.

3. Methodology

The study of neural nets and associated learning algorithm with much more than a hidden layer is known as deep learning (also known as deep formal education, hierarchy learning, or deep machine learning). It is a sub - set field of machine learning for learning representations. Study a lot of representation levels that match to various levels of abstraction. A hierarchy of ideas be built from levels. In a simple case, there are two groups of neurons, one of which accepts an input signal and the other of it emits signal. Whenever the input layer obtains an input, it transforms it as well and passes it to the next layer . Many deep learning architectures, including such deep learning models, deep convolution networks, deep belief networks, and recurrent neural networks, were used in areas like machine vision, speech processing, natural language processing, voice search, and bioinformatics but since they have been shown to provide outstanding results in a variety of tasks. [8].

3.1 CNN Building Components

In this part, images are entered directly into the neural network bypass algorithm (CNN) and this thing has helped to get good results, but if the image is not good, the change may lose algorithm recognition and learning. Split images by chapters, and each chapter contains images of them. Images are saved for each chapter, in aggregate, and each group has a difference in the number of images why an equal number of images were provided to the aggregates. Multi-layered CNNs have been considered to recognize directly the visible patterns from the pixel units of the image identified in terms of force to distortion. Layers are [8]

3.1.1 Convolution Layer

The parameters of this layer are determined by map sizes, core sizes and number of maps, each layer with M maps of equal size (M, M, C) representing (channels, width, height). Each map in the layer has also been connected to all maps in the layer. Neurons associated with a particular map share their weight values, but have different input fields. The main feature of the circumference process was weight sharing: The kernel was shared across all positions of the image[9].

3.1.2 Padding Layer

In general, using small grains, for some twists, may result in the loss of some pixel units, yet this may lead to the application of different later wrap layers. A key solution to this problem is to add more pixel units from stuffing around the input image boundary, thereby increasing the effective size of the images [9]

3.1.3 Max-Pooling

Compared to layer convolution, the assembly operator includes a fixed-form window that slips over all input areas on its step, estimating one output for each site that has been passed through the fixed-form window (often referred to as assembly window). However, unlike calculating the correlation with respect to the nucleus and the input into the lattice layer, the assembly layer does not include any filter parameters. However, aggregation factors have been considered inevitable, and are generally calculated either as the average maximum value of elements in the assembly window, and have been referred to as the average maximum assembly or assembly [9].

3.1.4 Dropout regularization

The phrase "dropout" relates to the procedure of randomly losing neurons (either concealed and apparent) in a neural network. To essentially address the issue of neural network overexploitation. The product of a given percentage of the neurons in a hidden layer is determined by seepage in the neural network, which is symbolized by the leak rate of 0, and the withdrawal ratio is only the possibility that such a neuron in a particular layer is deleted. If it's set to 1 for a hidden layer, then all neurons in that layer will exit at 0. The neurons that have been destroyed are not involved in the steps for anterior passage or reverse propagation. [6]

3.1.5 Fully Connection

The output markers for the assembly layer or final twist layer were generally maps, such as being converted into a D-1 matrix of numbers (or vector), as well as being connected to at least one fully connected layer, also referred to as dense layers, where each input was connected to each output through learnable weight. Once the features were extracted through the bypass layers and downwards samples were created through the assembly layers, they were assigned across a subset of layers that were fully connected to the final network output, including the probability of each category in the classification task. Furthermore, the final fully connected layer includes a similar amount of output contract to the number of categories [9].

3.1.6 non-linear layers

The activation function is the main part of the algorithm in order to find the best solution and is suitable for me to complete the series of equations. There are different types of activation functions and for each particular type of work. In this work, a different kind of activation function was used. Each one gave a certain result, the best activation function being (SOFTMAX and RELU) [9]

3.2 data set

Data used from the ADNI initiative was launched in 2003 as a public-private partnership, led by lead researcher Michael W. Weiner, MD. The primary objective of ADNI was to test whether sequential magnetic resonance imaging (MRI) could be combined with positron tomography (PET) and other biological markers and clinical and neuropsychiatric evaluation to measure the development of light cognitive vulnerability (MCI). (http://adni.loni.usc.edu/) Represents the location of the database.

After allowing access to data, brain visualization data for MCI patients were obtained for the database from (ADNI1/ADNI 2/ADNI GO) for magnetic imaging (MRI). MRI images were within the MP-RAGE protocol within a NIFTI file where data are kept within a unified format. 3D MRI images have been used to extract as many features as possible, and MRI is within a magnetic field (1.5 T1) Three-sliced Weight (sagittal, axial and coronal). MRI images have been divided into a group of categories, MCI-c who will convert to AD in 6 months and who will convert to AD in 12 months, Those who will convert to AD in 18 months, those who will convert to AD but have no time to convert, One MCI-nc category is the one who did not convert to stable AD with each category on (100).

3.2.1 Data preprocessing

Pre-processing is an important first step. The goal of pre-processing is to improve the quality of the image so that we can better analyze it through pre-processing of the image. We can suppress unwanted distortions. The pre-treatment here are the steps to remove the skull to extract the brain, remove the noise and improve the images of the three strips. The three strips were initially isolated from each other after the process had been completed. The treatment of the arrow slide is integrated:

- The initial step that was taken in the pretreatment is to improve the contrast of the magnetic resonance images (MRI), the mathematical model (percentage linear contrast stretch) was adopted, it was considered as the best contrast model, and then steps were applied Morphology Gray Scale) , which uses the closing process. Erosion is used to remove the dark details in the image, keeping the bright parts relatively unaffected. Erosion is then used to remove the pixels on the boundaries of the MRI of the brain. It is also used to eliminate non-brain areas such as the meninges and the skull. This was done by convolution of the structural element over the region of interest. Corrosion reduces the bright areas and enlarges the dark areas. The important step of masking to extract the brain is to increase and to define the areas of interest, i.e. the object, the object is separated from the black background by using the ots'u threshing algorithm, which separates the object from the background, then finds the largest area using the connecting component label method , by which each object is named, and then each area is counted for the three areas, The largest number of the three regions is the brain, i.e. choosing the largest region will be the mask and neglecting the rest of the regions, the morphological closure process is again applied, but on the mask that was designed to remove the holes in the designed mask and to remove Small dark spots and ligation of small bright cracks. Dilation morphology is applied to the mask that was designed after the closure process, as the dilation process reduces the dark areas and expands the bright areas. This is done by the structural element, where each pixel of the designed mask is wrapped and stretched. Thus, the process of making the mask, which is done by extracting the brain from the skull and other non-cerebral parts, has been completed, and then the content of the brain images is recalled by cannulation, and thus the process of stripping the skull of the sagittal slice was completed.

- The initial step that was taken in the pretreatment is to improve the contrast of the magnetic resonance images (MRI) of the axial and clinical two slices by adopting the mathematical model (percentage linear contrast stretch). The image of the clinical and axial brain was converted to Binary after that. Applying the connecting component label to the two slides in order to determine the part of the brain to be extracted from the other unwanted parts, and the connecting component label gives a color to each specific part.

In order to distinguish the part of the brain to be extracted clearly visually and to distinguish the area of interest (object) from the background, the ots'u threshing algorithm is applied, after the object of interest has been distinguished. On the background, the largest area is calculated and the rest of the areas are neglected, after the largest area that represents the mask has been determined, a closing process is performed to fill the existing holes, remove dark spots and connect the cracks in the area of interest, Dilation morphology will be performed on the mask that reduces the dark areas and expands the light areas. This is done through the structural element, where the process of wrapping each pixel of the mask that was designed, the stretching process, takes place.

Thus, the process of making the mask, which is done by extracting the brain from the skull and other non-cerebral parts, has been completed for both the axial and the axial slices.

- After extracting the images, the brain images are optimized by applying the CLAHE algorithm the CLAHE method is very useful where the brightness requirements are high and thus makes the hidden features of the image more visible It is used to reorganize the estimate of contrast or brightness of the image Provides CLAHE More detail compared to standard histogram equalization as CLAHE effectively improves image contrast.
- Noise Removing The methods of noise removal that the researcher touched on lie by using three types of filters, where the noise causes the classification problem to become more difficult. Noise removal is a very important stage as the data is improved after implementation that we can see more clearly:

❖ Mean Filter : Here the filter calculates the mean of the damaged image in a predefined area. Then the central pixel density value is replaced by that middle value. The arithmetic mean filter is a simple spatial filter, it's sliding window filters that replace the center value in the window[10]

❖ Median Filter : The median filter is used to reduce the amount of intensity contrast between one pixel and another pixel. In this filter, the pixel value is replaced by the median value. Then the median is calculated by first sorting all the pixel values in ascending order and then replacing the computed pixel with the middle pixel value[10]

❖ Gaussian Filter: The Gaussian filter is called a Gaussian Blur. The Gaussian filter is based on the Gaussian equation, and it can be used to create a kernel. The kernel is a (small) array which is a complex array used in various image filtering techniques for embossing, smoothing, sharpening, blurring, etc. Gaussian Blur can be applied for smoothing or filtering operations[11]

- Sharping (High Pass Filter): After completing the removal of noise from the brain image, the important and last step was taken to prepare the image for the model, which is the use of the High pass filter on the images from which filters were applied to remove noise. The application of sharpening the image is referred to as a method, enhances the edges and fine details of the image.

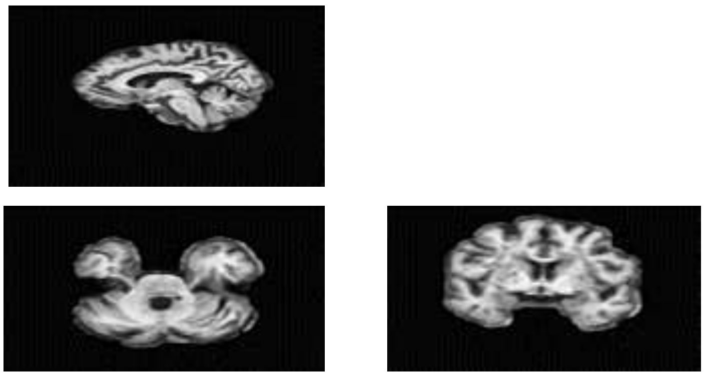
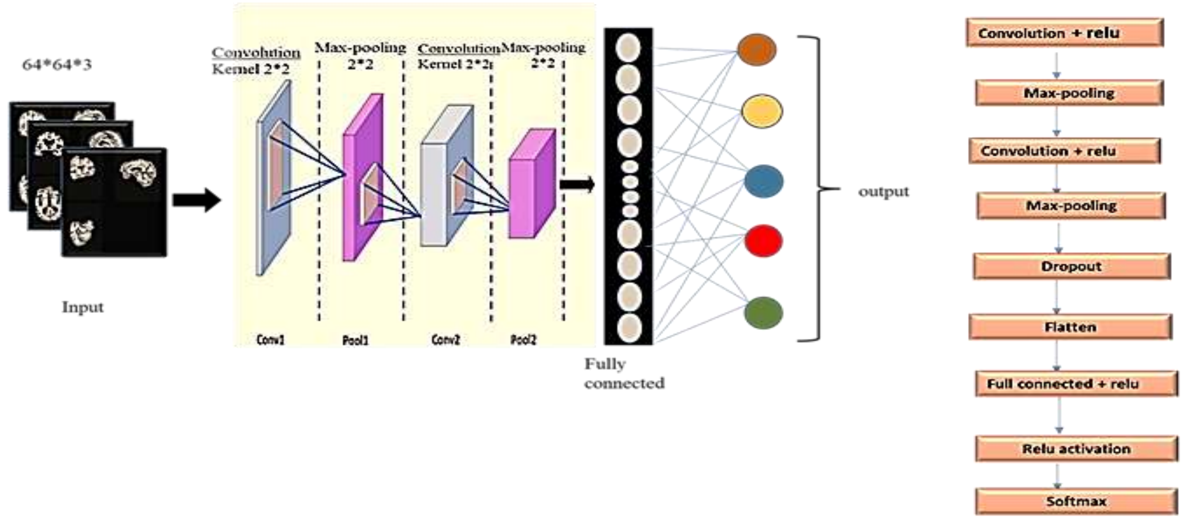


Figure 1. Represents the extraction of the brain from the skull for each of the three slices (sagittal, axial, coronal) for each separately and according to the method of treatment for each slice

3.2 Classification with CNN

After completing the pre-treatment steps for each of the three slices, the three slices were re-merged again to be one slice of the three types (sagittal, axial and coronal). Then the normalization of the image pixel values was performed. It represents the important steps taken by the researcher to prepare and configure the model by dividing the data into (75%) Training and (25%) Testing, which is considered the important initial step in the network. Convolutional neural, hidden layers include layers that perform convolution operations. This typically includes a layer that bitmaps a convolution kernel with the input layer matrix. Convolutional Layers In a CNN the input inserted is a CNN (64×64×3), After passing through a kernel-like convolutional layer (2×2), the image becomes an abstraction of a feature map, also called an activation map. The convolutional layers wrap the input and pass its result to the next layer. Stride on how to customize the depth columns around width and height. If step 1, we move the filters one pixel at a time. Its activation function is usually ReLU, convolutional layers followed by aggregation layers Convolutional networks may include aggregation layers along with traditional convolutional layers. Pooling layers reduce data dimensionality by merging the output of groups of neurons in one layer into one neuron in the next layer. Local pooling combines small pools, and they use a size of 2 x 2. Global pooling works on all neurons in the feature map Max pooling uses the maximum value of each local neuron in the feature map. Fully Connected Layer After several convolutional layers and extreme aggregation, the final classification is done across fully connected layers. Neurons in a fully connected layer have connections to all the activations in the previous layer fully connected layers connect every neuron in one layer to every neuron in another layer. The flat matrix passes through a fully connected layer. To classify images Softmax classifiers give probabilities for each class label. To avoid overfitting Dropout (0.25,0.5) was used to drop hidden nodes, Optimizers(Adam) used to increase power and efficiency model, Batch size that was used (32).



4. Experimental results

The classification model is built using Keras, a high-level neural network API, written in Python. The results reached by the researcher as a result of the initialization and preparation of the deep learning CNN model, which is represented by the accuracy of classification. Accuracy is a measure that describes in general how the model performs in all categories. Useful when all categories are of equal importance. It is calculated as the ratio of the number of correct predictions to the total number of predictions

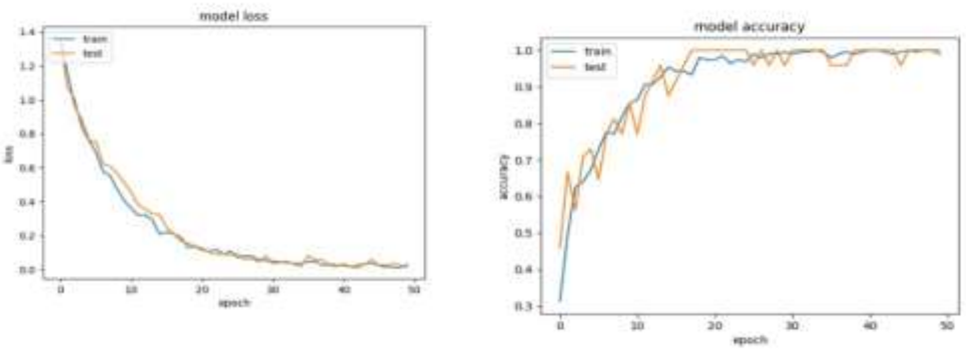


Figure 3. Represents the accuracy results achieved by the model from MCI-c VS MCI-nc with loss function index

5. conclusion

Using 3D-MRI images of MCI patients to predict conversion of MCI patients to AD is very important to take preventive measures and treatment as soon as possible before turning to neurodegeneration. The initial start of the pre-processing represented by Contrast Enhancement and then moving to the next stage of the pre-processing. The pre-treatment represented by discharging the skull Extracting the brain from the skull using Morphology gray level method to make a mask using the brain extraction method was considered an efficient method for extracting the brain from large number of images MCI patients. Using the CLAHE algorithm for medical images, the brain, which is one of the complex parts of the body, after the brain was extracted from the skull, to improve the images and clarify the details of the image. Noise removal using filters for this type of medical image (mean, median, Gaussain) in order to remove the most common noises. Integrating the three slides, brain images extracted from the skull into one slice, preparing and preparing the 2D-CNN deep learning algorithm model for three-dimensional MRI images, which is appropriate for this type of medical image, which produced an efficient model in Category. Three degrees of epoch were applied and the epoch=50 achieved the appropriate accuracy of 96.67%.

Reference

[1] M. A. Ebrahimighahnavieh, S. Luo, and R. Chiong, "Deep learning to detect Alzheimer's disease from neuroimaging: A systematic literature review," *Computer methods and programs in biomedicine,* vol. 187, p. 105242, 2020.

[2] Y. Zhang, S. Liu, and X. Yu, "Longitudinal structural MRI analysis and classification in Alzheimer's disease and mild cognitive impairment," in *International Journal of Imaging Systems and Technology* vol. 30, ed, 2020, pp. 421-433.

[3] Y. Huang, J. Xu, Y. Zhou, T. Tong, X. Zhuang, and A. s. D. N. Initiative, "Diagnosis of Alzheimer’s disease via multi-modality 3D convolutional neural network," *Frontiers in Neuroscience,* vol. 13, p. 509, 2019.

[4] S. Basaia, F. Agosta, L. Wagner, E. Canu, G. Magnani, R. Santangelo, M. Filippi, and A. s. D. N. Initiative, "Automated classification of Alzheimer's disease and mild cognitive impairment using a single MRI and deep neural networks," *NeuroImage: Clinical,* vol. 21, p. 101645, 2019.

[5] W. Lin, T. Tong, Q. Gao, D. Guo, X. Du, Y. Yang, G. Guo, M. Xiao, M. Du, and X. Qu, "Convolutional neural networks-based MRI image analysis for the Alzheimer’s disease prediction from mild cognitive impairment," *Frontiers in Neuroscience,* vol. 12, p. 777, 2018.

[6] R. Jain, N. Jain, A. Aggarwal, and D. J. Hemanth, "Convolutional neural network based Alzheimer’s disease classification from magnetic resonance brain images," *Cognitive Systems Research,* vol. 57, pp. 147-159, 2019.

[7] M. Raju, V. P. Gopi, V. Anitha, and K. A. Wahid, "Multi-class diagnosis of Alzheimer’s disease using cascaded three dimensional-convolutional neural network," *Physical and Engineering Sciences in Medicine,* vol. 43, pp. 1219-1228, 2020.

[8] P. Ongsulee, "Artificial intelligence, machine learning and deep learning," in *2017 15th International Conference on ICT and Knowledge Engineering (ICT&KE)*, 2017, pp. 1-6.

[9] D. Sarvamangala and R. V. Kulkarni, "Convolutional neural networks in medical image understanding: a survey," *Evolutionary intelligence,* pp. 1-22, 2021.

[10] F. Mohd Padzil, "Linear and nonlinear filter for image processing using MATLAB's image processing toolbox," Murdoch University, 2016.

[11] B. Desai, U. Kushwaha, S. Jha, and M. S. C. S. s. NMIMS, "Image filtering-Techniques Algorithms and Applications," *Applied GIS,* vol. 7, p. 101, 2020.