Dementia Detection and Classification from MRI Images Using Deep Neural Networks and Transfer Learning

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Abstract. In this paper, we present a new approach in the field of Deep Machine Learning, that comprises both DCNN (Deep Convolutional Neural Network) model and Transfer Learning model to detect and classify the dementia disease. This neurodegenerative disease which is described as a decline in memory, language, and other problems of cognitive skills to make daily activities, is identified in this study by using MRI (Magnetic Resonance Imaging) brain scans from OASIS dataset. These MRI brain scans are normalized before the image extraction with Bag of the features and the Learning classification methods into no-demented, very mild demented, and mild demented. Results showed that the DCNN model achieved significant accuracy for better Dementia diagnosis.

Keywords: Dementia · MRI · Bag of feature · K-means ·
Deep Machine Learning · DCNN · Transfer Learning

1 Introduction

Dementia disease is a neurological disorder that is characterized by a decline in memory, language, problem-solving and other cognitive skills. It involves a person's facility to perform everyday activities. The gradual loss and damage of the brain's nerve cells is considered as one of the major causes of Dementia [6]. It is responsible for more than 50% of dependency situations of the elderly people. In recent years, some studies of this disorder have estimated that by the year 2050, the number of 36 million new cases is expected to reach 100 trillion [1]. Neurological MRI is an imaging technique that provides doctors and radiologists with better tools to research a specific dementia diagnosis [6]. Therefore, it particularly helps doctors and specialists to make the best judgment about the reasons of symptoms based on the achieved tests. Classification methods in Data Mining and Machine Learning fields are used for early prediction and prevention of the disease. They are used to process large amounts of data compared to Regression method [3]. Recent research studies in neural classification have indicated

that neural networks are an alternative to traditional classification methods. In this work, we apply Deep Machine Learning techniques for dementia detection based on brain MRI dataset. Our goal is to provide a technique which aims to classify those MRI scans that display the most potential for the diagnosis of this neurodegenerative disease. The problem can be solved with minimal error rate by using the CNN that is a hybrid technique of Kernel convolutions and neural networks [16]. The rest of this paper structured as follows: First, in the Sect. 2, we present the OASIS dataset that contains both healthy and diseased brains. Second, Sect. 3 is about the related works of dementia detection and classification using Machine and Deep Learning algorithms. Third, Sect. 4 describes the methodology of this paper. Finally, Sect. 5, the results of Learning Classification models DCNN and Transfer Learning are presented.

2   MRI Data Collection

For our research work, we have utilized the MRI images from the open source, OASIS (Open Access Series of Imaging Studies) where the free project of this open source provides these MRI neuroimaging datasets of the brain. In particular, we have considered the cross-sectional MRI datasets (Oasis 1) for demented and non-demented subjects (Fig. 1). The subjects are right-handed and include both men and women, and the datasets includes young, middle aged and older adults. This set consists of a cross-sectional collection of about 416 subjects, who are aged between 18 to 96 years and in total of 436 imaging sessions [3, 4, 11].
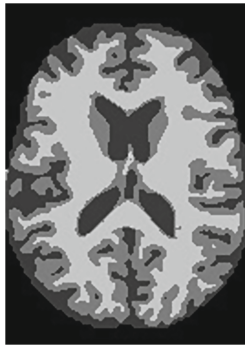

Fig. 1. Typical axial scan of a patient who does not have dementia from OASIS data collection.

In each case of those subjects, we can find the three or four individual T1-weighted MRI scans. Similarly, all right-handed obtained in single scan sessions are also included. 100 subjects have mild to moderate dementia and 198 subjects are all over the age of 60 as shown in Table 1. The existing data contain factors like CDR and MMSE, which are important in neurodegenerative diseases diagnosis such as Alzheimer's disease and Dementia.

MMSE is a mini mental state examination and CDR is clinical dementia rating which is an efficient scale to measure the severity of dementia.

CDR takes into consideration factors like impairments in memory orientation, judgement and problem solving.

Table 1. Type of OASIS dataset.

Dataset's name	Total of subjects aged 18 to 96	Subjects over the age of 60	Reliability dataset
OASIS 1	416 Subjects	100 Subjects, have been clinically diagnosed with very Mild to Moderate AD	20 Subjects as non-demented on subsequent visit within 90 days of their initial session

The dataset includes 218 no-demented subjects from the age group of 18 to 59 years and includes demented subjects from the age of 60 to 96 years with CDR scores shown in Table 2. Besides, it has 98 elderly subjects over the age of 60 with no-demented and CDR = 0. In our research study, we will use images within OASIS 1 dataset. In addition, we principally based our work on three cases of subjects; healthy with CDR = 0, Mild demented with CDR = 0.5 and Very Mild demented with CDR = 1, as found in Sect. 5 for results and discussion.

Table 2. Demographics of dementia status.

Age	Dataset's name			
	Number of subjects via age	Very mild dementia CDR = 0.5	Mild dementia CDR = 1	Moderate dementia CDR = 2
60–69	15	12	3	-
70–79	48	32	15	1
80–89	32	22	9	1
90–96	5	4	1	-

3   Related Works

In recent years, the existing approaches in health informatics and medical imaging using machine learning and Deep Learning have been subject to extensive research [4, 5, 13, 14]. Concerning neuroimaging studies, we have reviewed the literature from 2015 to late 2018, for machine and Deep Learning approaches for early dementia detection, and classification, using Brain MRI datasets such as OASIS dataset [2–4, 9, 10, 12, 13, 15–17].

Machine learning approach for identifying Dementia from MRI images, proposed by [3] presents a framework for classifying MRI images for dementia from OASIS dataset. Initially, they used the Gabor filters for extracted features with 0, 30, 60, 90

orientations and the GLCM (Gray Level Co-occurrence Matrix) to normalize and fuse the features. Then, they used ICA (Independent Component Analysis) for the features selection. Lastly, this study evaluated the dementia detection. Results showed that the proposed feature fusion classifier achieves higher classification accuracy.

Identifying Dementia in MRI scans using ANN (Artificial Neural Network) and KNN (K-Nearest Neighbor) is proposed by [10]. They used two models for dementia detection in MRI scans: (1) Artificial Neural Network (ANN) and (2) K-Nearest Neighbor (KNN). The first model is used in segmentation and the second model is used in the normalization of the images. Machine learning and artificial intelligence can generate adequate accuracy in the classification of demented and non-demented MRI scans. Based on the result, the KNN model has performed better than ANN model in all statistical measures of performance of binary classification models. The ANN implementation resulted in 69.81% accuracy and the KNN implementation resulted in 81.13% significant accuracy.

A brief review of automated identification of dementia using medical imaging: a survey from a pattern classification perspective, is provided by [17]. It is divided into two parts: feature extraction and classification. They reviewed in the first, the voxel-based, vertex-based, and ROI-based feature extraction methods and LDA-based, Bayesian, SVM-based, and in the second, ANN-based pattern classification methods used in various dementia identification algorithms in brain images of MCI patients. Furthermore, they compared the performance of some of those algorithms.

Review article presented by [16] using deep learning methods and applications to investigate the neuroimaging correlates of psychiatric and neurologic disease. They introduced the primary concepts of deep learning approach and reviewed the neuroimaging studies that have used this approach to classify brain-based disorders. The results of these studies indicate that Deep Learning could be a powerful tool in the current search.

A method to classify Dementia from MRI images with Feature extraction and classification using ANN, is proposed by [2]. Primarily, they used techniques of image processing for the statistical extraction features from MRI images of brain. Afterwards, they used discrete wavelet transform.

Deep machine learning application to the detection of preclinical neurodegenerative diseases of aging, presented by [15]. They explore an alternate model for artificial intelligence deployment. Correspondingly, they proposed that AI might provide highly accurate and reliable detection of preclinical disease states associated with neurodegenerative diseases of aging. In addition, they investigated an approach to developing AI platforms for individual monitoring and preclinical disease detection and examined its potential benefits. One of the major challenges facing clinical detection of preclinical phases of diseases such as dementia is the high degree of inter-individual variability in aging-related changes to cognitive function.

Machine learning of neuroimaging to diagnose cognitive impairment and dementia: a systematic review and comparative analysis is presented by [13]. They indicated that the development of more machine learning methods in neuroimaging requires the prediction of risks of dementia, which are not yet ready for routine use. They focused also on relevant outcomes to ensure that the resulting machine learning methods are robust and reliable before testing in clinical trials.

Detection of Alzheimer's disease from MRI using Convolutional Neural Network with Tensorflow is proposed by [4]. They have presented a new system with the latest dataset and the latest technology such as Tensorflow. They can scale a model to production instantly. Thus, they observed in testing part that the CNN has been successful and the problem is solved with minimal error rate. They propose to use the libraries (CUDA, CuDNN) for building and the use of GPU to achieve high performance with multiple cores/parallel computing to train models.

4   Methodology

In this project, our proposed methodology is a Deep Machine-Learning model as shown in Fig. 2. It includes the following steps: (1) Image pre-processing, (2) feature extraction, and (3) Learning classification model.
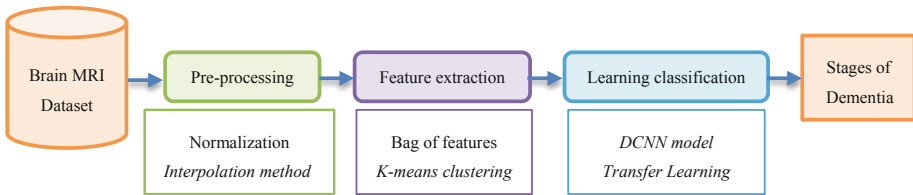
Fig. 2. Diagram of proposed methodology.

4.1   Image Pre-Processing

Image Pre-processing. The pre-processing is one of the major phases that needs to be considered in dementia detection using Brain MRI images from Oasis dataset. These images files contain raw information about each voxel. In fact, this type of image consists of a large number of features and a complexity in the classification model. Therefore, the images files cannot be directly used in detection and classification models. In our work, the pre-processing phase is based on normalization of the images before the extraction of the features for the deep machine-learning model.

Normalized Image Data. 23 layers from the top and 25 layers from the bottom of these images were loading by AlexNet, which is pre-trained for neural classification model. The size of the MRI images is reduced from 176 * 208 * 176 to 227 * 227 * 1 to facilitate our work. This process is repeated three times using the cubic interpolation method in order to reduce all images included in each folder of Brain MRI dataset.

4.2   Feature Extraction

From the above-mentioned Image Pre-processing, we mostly use Bag of features approach in Feature extraction phase. This phase is created and divided into three categories: one category for healthy patients who do not have dementia and two categories for patients who have dementia (mild and very mid demented). These

extracted categories that measured from normalized brain image, use a custom feature extraction function from 84 images and 192192 features. Thus, bag of features for the deep machine-learning model kept 80% of the strongest feature from each category.

K-means Clustering. That is a vector quantization method and probably the most common way of constructing the visual vocabulary. It aims to partition N descriptors into k clusters in which each descriptor belongs to the cluster with the nearest mean, serving as a prototype of the cluster [7]. In our work, K-means clustering method used to create a 500 words visual vocabulary where the number of the features 153753, 100% for the initialization clusters centers, and the number of clusters was 500. This clustering are completed 38% where 100 iterations converged in 38 iterations.

4.3   Learning Classification Models

DCNN Training Model. Deep Neural Network method is used for training. The CNN is one of the most popular algorithms for Deep Learning with regard to images processing of images [4]. DCNN model is particularly inspired by the computer vision to neural classification models. Like other neural networks, DCNN model is composed of input layers, output layers and other types of hidden layers in between. CNN model as shown in Fig. 3 is respectively used for classification. It often starts with two types of layers presented as follow as:

First, Convolutional layers which perform convolution operations with several filter maps of equal size. Second, *Sub-sampling layers* which reduce the sizes of proceeding layers by averaging pixels within a small neighbor. Accordingly, DCNN model is designed in feature detection phase with several layers performing one of three types of operations on the data: convolution, pooling, or rectified linear unit (ReLU). Each layer is connected to every other layer. These three operations are repeated over tens or hundreds of layers, with each layer learning to detect different features.
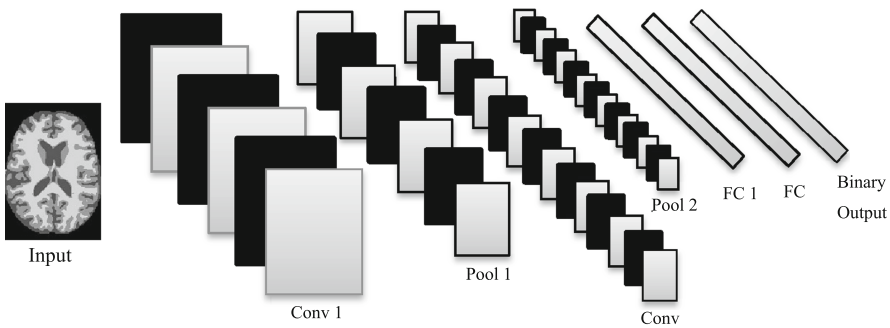

Fig. 3. Standard CNN model [4].

Convolution layers display the input images through a set of convolutional filters, each of which activates certain features from the images.

Additionally, *Pooling layers* simplify the output by performing nonlinear down sampling, and by reducing the number of parameters.

Rectified linear unit (ReLU) on the other hand allows for faster and more effective training by mapping negative values to zero and maintaining positive values. After the feature detection phase, the architecture of a CNN shifts to classification. The next-to-last layer is a fully connected layer (FC) that outputs a vector of K dimensions where K is the number of classes that the network will be able to predict. This vector contains the probabilities for each class of any image being subject to classification. The final layer of the CNN architecture uses a soft-max function to provide the classification output. However, with a small training dataset, this may result in the cost function that is being stuck in local minima, which may lead to overfitting/underfitting. A better alternative in such case is Transfer Learning, where pre-trained weights from the same architecture, but on a different larger dataset from the same/different domain is used to initialize the network layers. Only the last fully connected layer is pre-trained with the training data. This not only provides us with a robust set of pre-trained weights to work with, but also it gives us the opportunity to employ proven network architectures in our problem.

Transfer Learning for Testing Model. *VGG16* is a 16-layer network constructed by Oxfords Visual Geometry Group (VGG) [8]. It contributed in the ImageNet competition in ILSVRC-2014. One of the main reasons that VGG16 won the competition, is that it is one of the first architectures to discover network depth by pushing up to 16–19 layers and using very small (2 × 2) convolution filters.

5   Results and Discussion

In this paper, MRI images from the OASIS 1 dataset are being used for the detection of dementia and its classification into three stages; No-demented, very mild demented, and mild demented. Each class contains 14 subjects were used to train the DCNN training model. In addition, three classes are used for DCNN model such as for testing model where each class contains 14 subjects and it had different subjects than in the training model as shown in Table 3.

Table 3. OASIS 1 dataset for training and testing.

Dementia status	No dementia	Very mild dementia	Mild dementia
CDR	0	0.5	1
Number of subjects for training	14	14	14
Number of subjects for testing	14	14	14

The features extracted from the Brain MRI dataset for training and testing model are trained all through three stages; no demented, very mild demented, and mild demented as illustrated in Fig. 4 and displayed by MATLAB command.
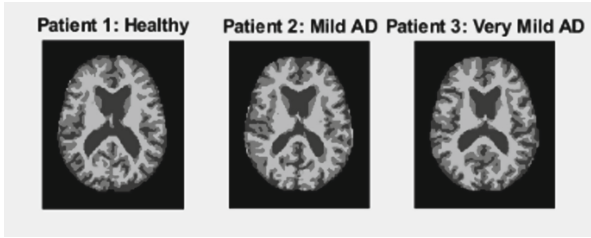
Fig. 4. The different stages of Dementia disease.

In our work, the performance of the Learning classification model is measured with reference to the accuracy as follows:

$$Accuracy = \frac{(T_p + T_n)}{(T_p + T_n + F_p + F_n)} \tag{2}$$

T_p: True positive,
T_n: True negative,
F_p: False positive,
F_n: False negative.

The dementia detection and classification approach from brain MRI images using DCNN model produced an important classification accuracy of 81.94% when the features are extracted. In opposition, the Transfer Learning model resulted an accuracy of 68.13%.

6   Conclusion and Future Works

Deep Machine Learning and computer vision domain can produce adequate accuracy in classification methods of no-demented, very mild demented and mild demented on the basis of brain MRI scans. From the above-mentioned results, we can see that the T-DCNN model has outperformed. Therefore, the level of diagnosis accuracy (>80%) for the dataset used is acceptable and produced by the DCNN model which has given maximum accuracy. In the future research work, we will use other neurodegenerative diseases such as dementia and we will use a large brain dataset is a wide range of subjects which could improve the accuracies of these Learning models by yielding better results.

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