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Detection of Alzheimer's Disease and Dementia States Based on Deep Learning from MRI Images: A Comprehensive Review

Emre Altinkaya[1], Kemal Polat[2,*], Burhan Barakli[3]

[1] Ph.D. Student at School of Natural Sciences, Department of Electrical and Electronics Engineering, Sakarya University, Sakarya, Turkey, Email: mr.altinkaya@gmail.com
[2] Department of Electrical and Electronics Engineering, Faculty of Engineering, Bolu Abant Izzet Baysal University, 14280, Bolu, Turkey, Email: kpolat@ibu.edu.tr
[3] Department of Electrical and Electronics Engineering, Sakarya University, Sakarya, Turkey, Email: barakli@sakarya.edu.tr
*Corresponding Author: Prof. Kemal Polat, Email: kpolat@ibu.edu.tr

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Abstract

Many studies have been conducted to examine abnormal conditions in brain structures and to detect Alzheimer's and Dementia states using features derived from medical images. From these data, it is very important to detect the diagnosis of Alzheimer's and Dementia disease early and to provide appropriate treatment to the patients. Quality magnetic resonance (MR) images are requested to make this diagnosis. But while producing a quality image, it also brings less spatial coverage and longer scanning and identification time. In this context, biomedical image processing has undergone a serious expansion and has become an interdisciplinary research field that includes many fields. Computer Aided systems have become an important part in the diagnosis process. With the development of computer aided systems, producing quality information for the diagnosis of disease in image processing applications has caused various problems. Such difficulties are tried to be overcome with artificial intelligence technology and super-resolution (SR), which has gained great importance in image processing lately. Using the super resolution methodology, a high resolution image is obtained from the low resolution image. Thus, the image processing timing is shortened and an image with desired features can be obtained. This shortens the irritating and long-lasting MR imaging process. In addition, it provides convenience for the diagnosis of the disease with the improvements it provides on MR images. Recovering the image is an important step in this process. The quality of the reconstructed image depends on the restoration methods. The functionality of artificial intelligence technology in image processing and biomedical fields is increasing day by day. The deep learning method is preferred in techniques aimed at obtaining a reconstructed quality image. At the same time, various artificial intelligence methods are widely used for classifying and detecting the data obtained. One of the most common of these is neural network (NN) methods.. Deep learning, a special method of neural networks, is widely used in classification methods due to its superior structural properties. When studies are examined, it is seen that DL methods are widely used. The success of the proposed methods is increasing day by day.

Keywords

Alzheimer's disease; Dementia disease; super-resolution; Deep learning

1. Introduction

Computer-aided detection systems (CADS) are tools for detecting abnormal conditions in medical imaging processes and increasing diagnostic accuracy using advanced image processing and pattern recognition techniques.

Due to the prevalence of Alzheimer's and dementia disease, many studies have been carried out on the automatic detection of these diseases with computer-aided systems in recent years. Biomedical imaging has been developed for the purpose of patient care as well as for the study of biological structure and function, and to address some disorders. In this context, it can help diagnose Alzheimer's and Dementia diseases in the early stages, which can lead to more effective treatments. Advances in magnetic resonance imaging (MRI), a technique of digital radiography, serve this purpose.

1.1. Magnetic Resonance Imaging (MRI)

Magnetic resonance imaging (MRI) is a medical imaging technique that uses synchronously with computer-assisted systems to produce images of various regions of the body. It is often used for disease detection and diagnosis. It is based on a technology that takes advantage of the movement change in the axis of the protons in the water that make up living tissues.

An MRI scanner contains two powerful circular magnets. The human body is largely made up of water molecules consisting of hydrogen and oxygen atoms. At the center of each atom are protons that act as a magnet and are sensitive to the magnetic field. These protons are stimulated by the application of radiofrequency current on the patient. This application spins the various protons of the body. When the radiofrequency field is closed, the signal detected by the receiver part of the MRI scanner is exposed. Signals are processed using biomedical imaging methods and an MR image is created.

The patient should remain still for a long time during the imaging process, so as not to blur the MR image. This brings some problems with it. In order to obtain the image quickly, the intravenous method is used on the patient before MRI or during the procedure. This process improves image quality and acquisition speed. However, recently, various biomedical imaging methods have been used to increase the speed and quality of image acquisition. The scheme of the operation of the computer-aided system is shown in figure 1.

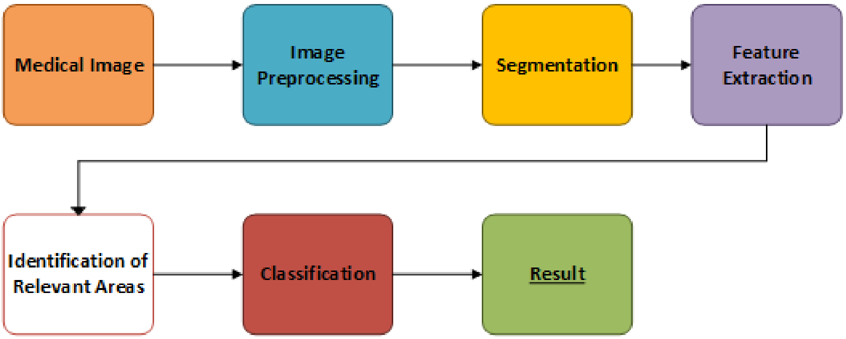

Figure 1. Functioning scheme of computer aided system

1.2. MRI Applications

MRI scan helps to provide a precise diagnosis in many cases and positively affects treatment. In addition, MRI is frequently used in the follow-up of healed diseases. The main usage areas are listed below.

- **Cardiovascular:** Magnetic resonance imaging (MRI) is preferred in cardiovascular imaging due to its high efficiency for blood circulation and cardiac motion analysis [10].
- **Musculoskeletal:** MRI has experienced great advances in image contrast. This feature is used for disease detection and diagnosis. It provides evaluation of tissue structures and bone marrow deformations in bones. It provides visualization of structures around the bone marrow, such as adipose tissue. Also provides visualization of muscle diseases [11].
- **Liver and gastrointestinal:** Liver and gastrointestinal tumors are independent tumors that spread in the region where they are located. Cancer cells can spread out of the tissue in which they are located, or directly to other areas by blood-lymph vessels. With MRI, it is possible to detect these cancerous areas in the gastrointestinal region and liver [12].
- **Angiography:** Magnetic resonance angiography (MRA) is used effectively in the diagnosis of vascular-related diseases in the brain. The vascular network is desired to be examined in three dimensions in the brain. In this case, due to the excess data in the three-dimensional MR image, the scanning time will be longer [13].
- **Neuroimaging:** MRI is preferred for the diagnosis of many diseases as it

provides visualization of brain anatomy containing brainstem and cerebellum. It allows diagnosis of many neurological diseases, especially Alzheimer's disease and dementia. Therefore, MRI is frequently preferred for Neuroimaging.

1.3. Recent Studies

Alzheimer's disease is a neurological disorder. As time progresses, these disorders increase their effects and cause a loss of memory and thinking skills. As these disorders progress, the patient's cognitive loss increases and leads to dementia. [14]. In research and results, progressive brain disorder is the most common cause of dementia in older people [20]. AD destroys nerve cells and causes tissue loss in the relevant region. Thus, it significantly reduces the volume of the disease-related region in the brain over time [9]. This decrease in volume disrupts the functions that will take place in that region or completely eliminates its effect. Besides Alzheimer's psychological activities, it also significantly affects people's daily routine. It is estimated that the number of people affected by the disease will double in the coming years, and one in 85 people is expected to have AD [15]. Morbidity represents the frequency of a disease or the amount of the disease, if any, and the symptoms caused by the disease [20]. Figure 2 also shows the morbidity rate of the most common neuro-psychiatric and neurological diseases.

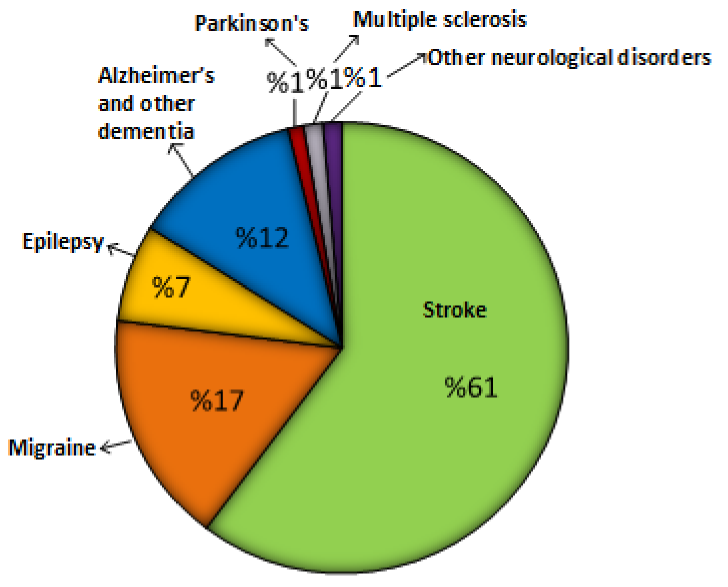

Figure 2. Morbidity rate of Neuro-psychiatric and Neurological Diseases [64]

In many studies in the literature, imaging biomarkers of Alzheimer's and dementia diseases have been identified using the magnetic resonance imaging (MRI) method.

In current studies, computer-aided detection systems continue to be developed for Alzheimer's and dementia disease detection using brain MR images.

2. Models

In recent years, Deep Learning (DL) techniques based on Artificial Neural Network (ANN) have been successfully applied for diagnosis and detection of diseases. The basic operation in the networks established in these techniques is designed by inspiring the work of the human brain. Nonlinear operations are applied using many signals entering the system and output signals are created. These techniques reflect representative learning. Because these models do not use an explicit method when extracting features from the data. The feature extraction process is performed by using hidden data layers from the data [20]. For the feature extraction process in deep learning models, it is not necessary to extract features separately as in the machine learning technique [20]. In previous studies, techniques such as support vector machine, k-tools and neural network were used in the diagnosis of neurological diseases [16]. In addition, the techniques used in the diagnosis of some disorders that cause disease in humans have been inspired by nature and have provided important achievements [17, 18]. Early diagnosis in Alzheimer's disease (AD) is very important in preventing the progression of the disease and ensuring its treatment. For AD detection, features extracted from brain MR images are classified [19]. Features should accurately represent AD-related regions of structures such as ventricular size, hippocampus shape, cortical thickness, and brain volume [19]. The MRI neuroimaging tool has been explored to develop such a system [21, 22]. Features derived from existing MRI images are divided into three groups: Alzheimer's disease, mild cognitive impairment (MCI), normal control (NC) group and classification is established [23, 24, 25, 26]. This article examines the deep learning methods used to diagnose Alzheimer's and dementia based on MRI scans. Deep Neural Network (DNN) [28, 34-42], Deep Belief Networks (DBNs) [20, 43, 44], Restricted Boltzmann Machines (RBMs) [20], Deep Auto-encoder (DA) [32, 45-48], Recurrent Neural Network (RNN) [49], Deep Boltzmann Machine (DBM) [50], and Convolutional neural networks (CNN) [33, 51-61] are important and widely preferred deep learning models. As a result of the research, it has been seen that the methods are also applied in different diseases.

In this section, 4 different models emerging within the scope of deep learning are examined. Deep Neural Network (DNN), Convolutional Neural Networks (CNN), Deep Automatic Encoder (DA), Deep Boltzmann Machine (DBM) models are described below.

2.1. Model-1: Deep Neural Networks (DNN)

Deep Neural Network (DNN) has a structure consisting of input layer, output layer and hidden layers [27]. Deep learning allows to learn the representations of the data obtained thanks to the numerous calculation layers in its structure [28]. DNN uses the feed forward feature of the neural network for data detection [20]. In the method, feature extraction and clustering are carried out with an unsupervised approach. In the field of biomedical imaging, DNN is mostly used for classification and reducing the symptoms of the related disease. Figure 3 shows the architecture of the DNN learning process.

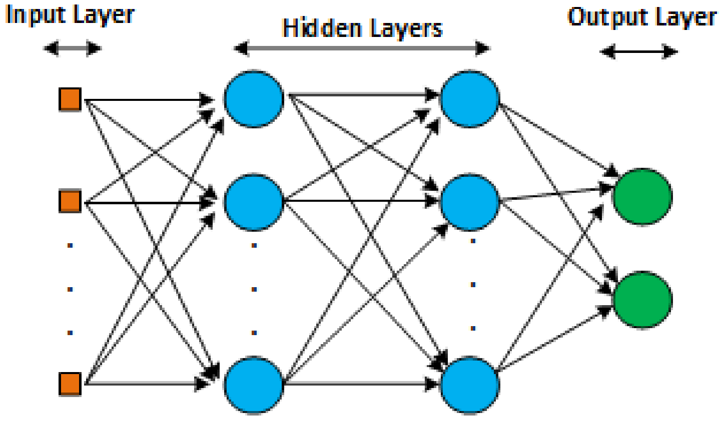

Figure 3. Architecture of DNN

2.2. Model-2: Convolutional Neural Networks (CNN)

CNN is one of the most widely used deep learning techniques. CNN is a model in which the image information is taken from the input in the method, transferred to the output in one direction and obtained the output according to the desired classification. CNN consists of input, output and multiple hidden layers [20]. CNN topology uses relationships between data to reduce the number of parameters required in education. At the same time, thanks to these relationships, forward feeding improves [14]. An exemplary model is shown in Figure 4. This proposed model is called 3D adaptable CNN. While the lower layers of a 3D-CNN developed for a specific purpose separate and detect the general properties, the upper layers make it easier to classify the problem by using these properties [29].

2.3. Model-3: Deep Automatic Encoder (DA)

Features extracted using data-based learning in artificial intelligence architecture can often be more accurate. However, Deep Auto Encoder (DA) has the same number of input and output nodes and is trained to rebuild the input vector instead of assigning a class tag [30]. For this reason, Deep Auto Encoder (DA) is a type of neural network performed unsupervised. The Deep Autoencoder model consists of three layers: input (encoder), output (decoder) with the same number of nodes as input, and hidden (code). The number of hidden layer nodes is less than the same number of input and output node layers. Encoder layers encode the input data (MRI). With this coding process, the size of the input is reduced. In the next process, this data is presented to the decoder by the hidden layer. In the last step, the decoder layers return the input data to their original form [20]. The architecture of DA is shown in Figure 5 [31]. The feature extraction method in the DA model is not linear [32]. Therefore, it does not need to classify the data used in education.

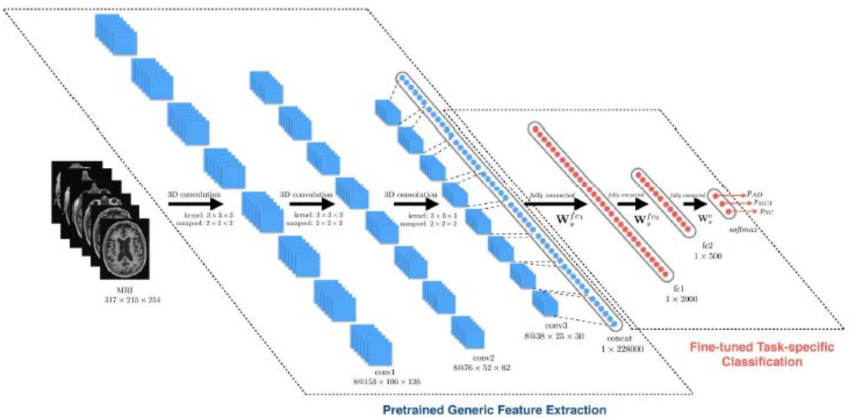

Figure 4. Proposed CNN structure [19]

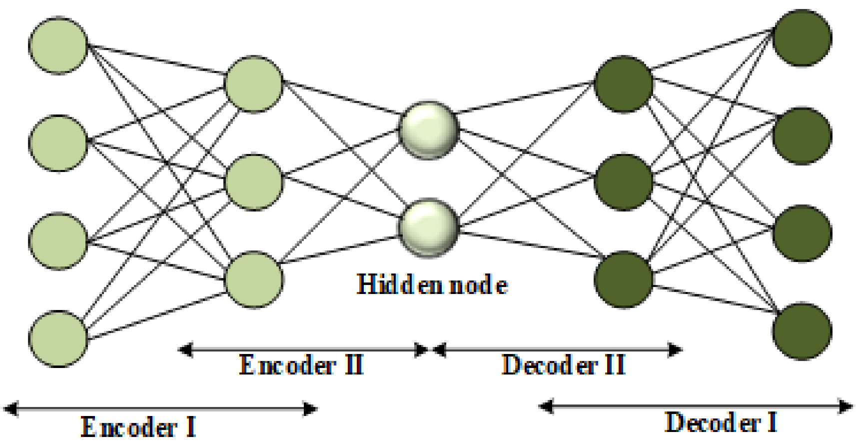

Figure 5. Architecture of DA

2.4. Model-4: Deep Boltzmann Machine (DBM)

The Deep Boltzmann Machine (DBM) is an unsupervised model, such as DNN, that does not have a complete relationship between its layers. This model contains a large number of hidden unit nodes. The Deep Boltzmann machine (DBM) is formed by the combination of the Restricted Boltzmann Machines (RBMs). Multiple RBM structures are combined into consecutive structures to establish DBM structures [20]. There is no interlayer link in RDBMs. Existing connections are only available between adjacent layer units.The same applies to DBM as its structure has RBM structure properties. The DBM method can be routed for complex and ambiguous inputs and provides robust output data. The structure of DBM is shown in Figure 6.

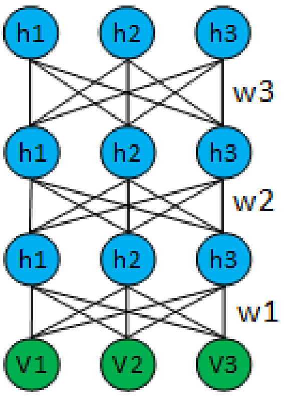

Figure 6. Architecture of DBM

3. Results and Comparisons

In all models examined, the data are from ALzheimer's Disease Neuroimaging Initiative (ADNI) [33]. Results and comparisons were made in this dataset. In the table, the accuracy rate of the disease diagnosis, instances and modality are given for the four models examined. Accuracy values are represented in percentage (%).

Table 1. Accuracy Diagnostic Studies of Models Examined on AD.

	Model			
	DNN[35]	CNN[52]	DA[45]	DBM[50]
Accuracy	99.2	99.9	91.95	95.35
Instances	1409	302	338	
Modality	MRI	MRI and Functional MRI	MRI	PET and MRI

When the accuracy rates in the table are examined, different effects of deep learning methods are observed. The imaging technique used and the number of samples used by the models may be different. The differences between the sample numbers affect the accuracy rates.

In this study examines four deep learning models for Alzheimer's and Dementia disease. In the literature review, it is observed that these four models are widely used for the diagnosis of other neurological disorders. The ratio of the studies carried out using these four DL techniques between 2010-2019 in Google Scholar is shown in Figure 7.

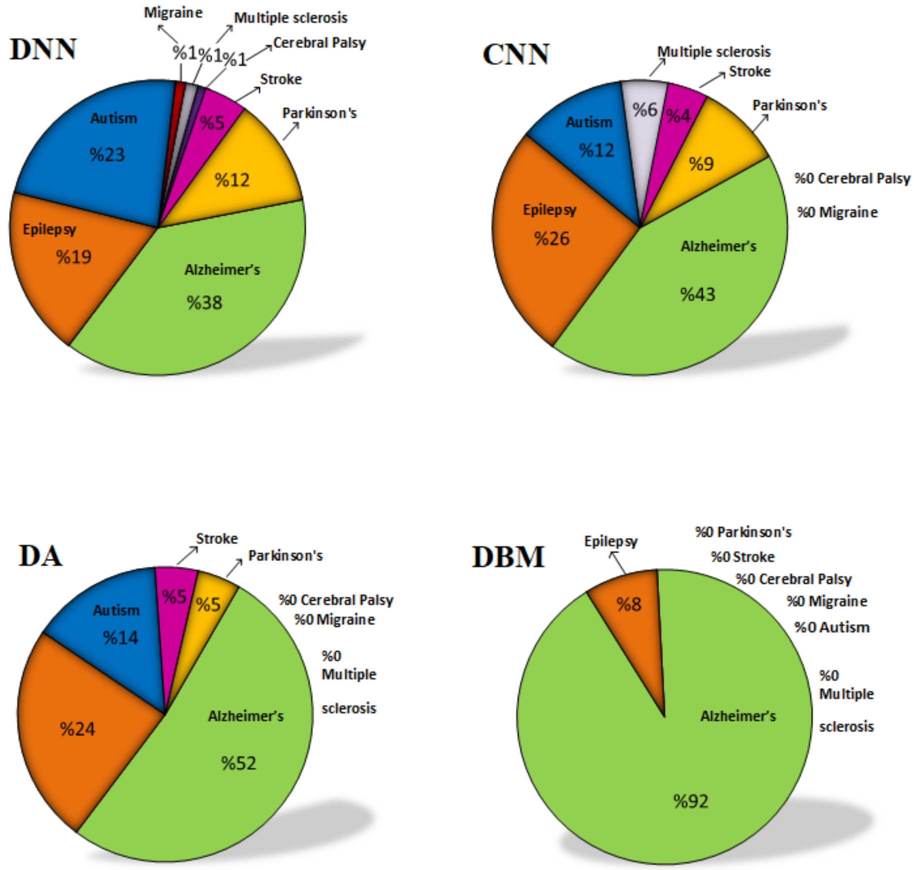

Figure 7. The ratio of the articles on other diseases in the Google Scholar database (2010-2019) of the four Deep Learning techniques examined in our study [20].

4. Conclusion

Neurological disorders negatively affect human life and even threaten human life in the future. In recent years, with the development of computer-aided systems, DL techniques have also been improved and have been widely preferred in establishing neurological diagnoses. The data used in the diagnosis of the disease are the MR image data that are consumed in large quantities in storage environments that are significantly higher. The processing and training of this large volume of data is one of the challenges that can be encountered in techniques.

In this study, a compilation of DL methods used for the diagnosis of Alzheimer's and Dementia diseases commonly seen from Neurological and Neuropsychiatric Disorders is presented. It has been observed that MRI image data are used effectively in the diagnosis of Alzheimer's and Dementia diseases. Four deep learning techniques commonly used for the detection of these diseases are briefly described. The high accuracy rates of these DL methods applied to MRI images in disease diagnosis are remarkable. In addition, the usage rates of these four techniques for other major Neurological and Neuropsychiatric Disorders have been found. This study did not aim to compare methods with each other. Undoubtedly, biomedical imaging and deep learning techniques are improving day by day and new methods will continue to be discovered.

Conflicts of Interest

There is no conflict of interest.

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