Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume7-Issue1, January 2024
Paper: 70

A Survey on Image Processing Techniques Using Deep Learning for Neurological Disorder Diagnosis

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Abstract:

Deep getting to know has lately been used for the evaluation of neuroimages, such as structural magnetic resonance imaging (MRI), practical MRI, and positron emission tomography, and it has performed significant performance improvements over traditional system studying in computer-aided analysis of mind disorders. This paper opinions the programs of deep gaining knowledge of techniques for neuroimaging-based totally brain disorder analysis. We first offer a comprehensive review of deep getting to know techniques and famous network architectures by using introducing diverse sorts of deep neural networks and latest traits. We then review deep getting to know strategies for laptop-aided evaluation of four normal brain problems, which includes Alzheimer's disease, Parkinson's sickness, Autism spectrum sickness, and Schizophrenia, where the first two diseases are neurodegenerative issues and the last are neuro developmental and psychiatric problems, respectively. More importantly, we discuss the limitations of existing studies and present feasible future directions.

Keywords: Brain disorder, Convolutional neural networks, deep learning, Neuroimage

1. Introduction

We first offer a comprehensive review of deep getting to know techniques and famous network architectures by using introducing diverse sorts of deep neural networks and latest traits. We then review deep getting to know strategies for laptop-aided evaluation of four normal brain problems, which includes Alzheimer's disease, Parkinson's sickness, Autism spectrum sickness, and Schizophrenia, where the first two diseases are neurodegenerative issues and the last are neuro developmental and psychiatric problems, respectively. more importantly, we discuss the limitations of existing studies and present feasible future directions. Clinical imaging refers to several exceptional technologies which might be used to provide visual representations of the interior of the human frame which will aid the radiologists and clinicians to come across, diagnose, or deal with sicknesses early and more efficaciously. Over the last few many years, scientific imaging has quickly grow to be a dominant and powerful tool and represents numerous imaging modalities, which includes X-ray, mammography, ultrasound, computed tomography, magnetic resonance imaging (MRI), and positron emission tomography(pet) (Heidenreich et al., 2002).Each sort of those technologies gives diverse pieces of anatomical and purposeful records approximately the special body organs for analysis in addition to for studies. In clinical exercise, the element interpretation of scientific images desires to be achieved by way of human professionals, along with the radiologists and clinicians. but, for the substantial number of medical photos, the interpretations are time-ingesting and without problems encouraged by means of the biases and potential fatigue of human professionals. Therefore, from the early 1980s, docs and researchers have began to apply laptop-assisted prognosis (CAD) systems to interpret the clinical images and to improve their performance. clinical imaging refers to several exceptional technology which might be used to provide visual representations of the interior of the human frame which will aid the radiologists and clinicians to come across, diagnose, or deal with sicknesses early and more efficaciously (Brody, 2013).

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2. CONVOLUTIONAL NEURAL NETWORK

Many neurological diseases and delineating pathological regions have been analyzed, and the anatomical structure of the brain researched with the aid of magnetic resonance imaging (MRI). It is important to identify patients with Alzheimer's disease (AD) early so that preventative measures can be taken [2] . A detailed analysis of the tissue structures from segmented MRI leads to a more accurate classification of specific brain disorders. Several segmentation methods to diagnose AD have been proposed with varying complexity. Segmentation of the brain structure and classification of AD using deep learning approaches has gained attention as it can provide effective results over a large set of data. Hence, deep learning methods are now preferred over state-of-the-art machine learning methods. We aim to provide an outline of current deep learning-based segmentation approaches for the quantitative analysis of brain MRI for the diagnosis of AD. Here, we report how convolution neural network architectures are used to analyze the anatomical brain structure and diagnose AD, discuss how brain MRI segmentation improves AD classification, describe the state-of-the-art approaches, and summarize their results using publicly available datasets. Finally, we provide insight into current issues and discuss possible future research directions in building a computer-aided diagnostic system for AD. Accurate detection and classification of unhealthy tissue and its surrounding healthy structures are also important in the diagnosis of conditions such as AD. A large amount of data is required for more accurate diagnoses. However, it can be challenging for clinicians to analyze large and complex MRI datasets and to extract important information manually.

3. ANALYSIS OF BRAIN DISORDER WITH MEDICAL IMAGE

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The segmentation of GM, WM, and CSF from brain MRI is challenging due to their tissue intensities, non-uniformity (bias), noise artifacts, and partial volume effect. To overcome these difficulties, several deep learning techniques for brain MRI segmentation have been developed and will be reviewed. We also review various deep learning techniques for the early diagnosis of AD, which is a type of dementia that can cause thinking, memory, and behavioral issues. For the MRI classification of AD, significant patterns from raw data are considered, and these patterns are grouped into different categories based on their characteristics. Significant advances in imaging technology have led to the development of different applications of image segmentation and classification.

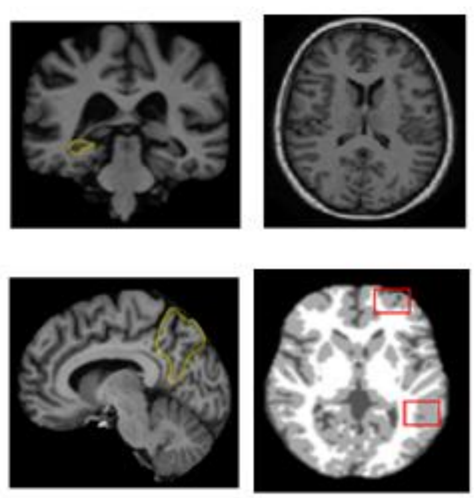

Fig: Brain MRI Segmentation patch regions for localization and bio-markers

Figure respreent the hippocampus (including its head, body, and tail) outlined on coronal MR images. These anatomical boundaries are used for volumetric measurements in the recuneus

and hippocampus.In summary, the main objectives of this review are to: Provide an overview of the current deep learning approaches for brain MRI segmentation and classification of AD. Identify the application challenges in the segmentation of brain structure MRI and classification of AD. Show that MRI segmentation of the brain structure can improve the accuracy of diagnosing AD.To more clearly capture how AD evolves, neuropsychological and anatomical Sensors 2020, 20, 3243 13 of 28 information from the patient needs to be examined at different transitional phases of the disease. From these aspects, the populations suffering from MCI have a high chance of converting disease status from MCI to AD.Here DP is the mask by the human evaluator and DQ is the mask generated by a segmented algorithm Using DP, DQ vaules the parameters such as Dice , Jaccard index, PPV (Postive predicted value) , True positive rate (TPR) , Lesion true postitive rate (LTPR) are estimated , average symmetric surface distance (ASSD). Some of the validation measures of brain segmentation metrics like True positive rate, Positive predictive rate PPV ,Negative predictive rate, Dice similarity coefficient, DSC TPR Volume difference rate, VDR Lesion-wise true positive rate, LTPR LTPR Lesion-wise positive predictive value, Specificity Accuracy ,Balanced Accuracy were obtained and analysed.

4. DEEP – LEARNING FOR NEURO-DISORDERS

Dataset such as MICCAI,NEOBRAIN, IBSR, OASIS ,BLSA, ADNI-1,ADNI-2 , Clinical data were used .However, it is noted that these results are not able to be accurately compared because these studies used different datasets and experimental conditions. Similarly strategies like patch-based, semantic wise with 2D & 3D were opted. Many challenges were faced in the pre-processing and initialization which affects the performance of the classification and deep methods involved . Mainly risky work due to the background noisy and low contrast .

Studying the Manifold Structure of Alzheimer's Disease: A Deep Learning Approach Using Convolutional Autoencoders. In this method they have attempted a new exploratory data analysis of AD based on deep convolutional autoencoders. We aim at finding links between cognitive symptoms and the underlying neurodegeneration process by fusing the information of neuropsychological test outcomes, diagnoses, and other clinical data with the imaging features extracted solely via a data-driven decomposition of MRI. Here MMSE and ADAS11 scores with manifold learning and data fusion implemented. With advancement in technology the even before dementia the degenerative disease can be predicted.

4.1 DEEP LEARNING FOR MCI, AD , PARKINSON, AUTISM,BRAIN TUMOUR

Auto encoders are interesting in the way in which they can model or train a numerous of dataset which has been already applied to the breast cancer detection and the brain disorders diagnosis. Convolutional Auto encoders use the convolutional neural networks which are efficient in the image processing fields.In this system they have utilized the 2-D CNN model to

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predict the Parkinson disease. When limited data was used then the drop- out method was assigned to reduce the over-fitting. For reducing cost they have extracted patches from MRI regions.The system used Support vector machine and Naïve Baies Classification method. Simulation results had shown better accuracy compared to other methods.Both the motor and non-motor features were used in the measurement. Cascading of the non-motor features has produced better results.Analysis showed that another disease similar to Parkinson ie PSP – Progressive supranuclear Palsy was found. PCA-Principal component analysis was used by the author and SVM for classification in order to achieve high levels of accuracy.

In case of structural images white matter and grey matter were extracted to estimate the classification accuracy.This research model used the PPMI dataset.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}}$$

Here sensitivity,specificity,accuracy were the parameters used to find the performance.
Where,

True positive (TP) = the number of cases correctly identified as patient

False positive (FP) = the number of cases incorrectly identified as patient

True negative (TN) = the number of cases correctly identified as healthy

False negative (FN) = the number of cases incorrectly identified as healthy

.

Table1: Overview of methods and dataset used in the Analysis of NeuroDisorder

Methods	Type of Dataset
SVM	MRI, SWI MRI
Naïve Bayes	MRI
Decision tree	MRI
ANN	TRODAT & SPECT imaging
GA-LM	MRI

The above mentioned methods listed in Table1 were analysed and the accuracy of 86 % to 96% achieved in the listed table. The system proposed the convoltutional neural network model which achived higher classification accuracy

In this model [4] they have depicted a computer aided diagnosis tool to evaluate the Parkinson disease severity and avoided the issue of over-fitting problem.The aged people are more prone to the neurological disorder due to stress as investigation shows. Hippocampus volume and few bio markers are used to predict the AD as per this model suggested. Here both convolution neural networks as well deep neural networks used in classifier for the hippocampus patches extracted. Accuracy of 94% achieved. Biomarkers and be helpful tool in diagnosis. They have suggested the Freesurfer software tool for computer aided diagnosis. Knowledge transfer plays priority role in deep learning techniques. ABOL BASHER, BYEONG C. KIM, KUN HO LEE proposed Discrete volume estimator DVE-CNN. Patch-wise volumetric features are used to train the DNN model. The average estimated probability of class is used to find the final prediction for any class. Region – based , patch wise , volumetric based features are used as the bio-markers . the main focus is in the hippocampus region with the GARD (Gwangju Alzheimer's and Related Dementia) dataset. LH-DNN and RH-DNN volumetric patch based feature extraction and 2 stage hough transform were employed .Loss and accuracy curves for all the cases were plotted and all folds average result with confusion matrix calculated. The author proposed the fusion of regression and classification which influence the coordinate of autoencoder diversified over the brain estimate. The system used normalize grey matter and white matter NORM images in ADNI dataset. Autoencoder architecture proposed with Z-layer features in classification and regression with ADNI dataset on Nvidia GTX 1080Ti GPU.To estimate correlation and regression performance Pearson's correlation coefficient PCC and determination coefficient R2 was used .Visualization of Area of influence which is much similar to PCA (Principal component analysis) was performed in the model.Regression result for different Z-layer and map plotted. Thus the deep convolutional auto encoder architecture with correlation and regression analysis paved way for more bio-markers to be effectively processed in the future. Lodewijk Brand, Kai Nichols, Hua Wang, Li Shen, and Heng Huang proposed joint multi-modal longitudinal classification and regression .With experiments in ADNI cohort to predict cognitive impairments of patients. The authors used the L_1 norm, L_2 norm, $L_{1,2}$ norm parameters because the joint classification and regression method outperformed the other methods.

5. CONCLUSION

The future method could be composed of image filtering, image enhancement, image clustering, image thresholding and image classification. It generates the requirement of software tool that can be developed to identify the specific condition of the brain MRI and enhance the diagnostic capabilities of the medical personnel. The radiologists can use these automated systems as an instrument for diagnosis, pre-surgical, and post-surgical procedures. The major motivation behind this survey is to develop an accurate multi-class brain MRI classifier, that is capable to diagnose the disease class in brain MRI. The proposed multi-class brain MRI classifier has a potential to classify various different brain diseases such as Alzheimer, Brain Tumor, AIDS dementia, cerebral calcinosis, glioma and metastasis. Solutions by formulating new insights and methodologies for optimization problems that take advantageof using deep learning approaches when dealing with big data problems. The traditional machine learning approaches show better performance with less input data.According to recent research, deep learning is promising for the analysis of brain MRI and can overcome the issues associated with the earlier state-of-the-art machine learning algorithms. Brain MRI analysis using computer-aided techniques has been

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challenging because of its complex structure, irregular appearance, imperfect image acquisition, non-standardized MR scales, imaging protocol variations, and presence of pathology. Hence, more generic methods using deep learning are preferable to manage these vulnerabilities.

Moreover, we discussed how brain structure segmentation improves the classification performance of AD. The segmentation for brain MRI helps to facilitate the interpretation and classification of AD. Brain MRI segmentation can be challenging work due to the images having a noisy background, partial volume, and low contrast. Furthermore, the automatic classification of AD is quite challenging due to the low contrast of the anatomical structure in MRI.

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