JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

ALZHEIMER DETECTION

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Abstract : **—Alzheimer's disease is a neurological disorder in which the death of brain cells causes memory loss and cognitive decline. A neuro degenerative type of dementia, the disease starts mild and gets progressively worse. An important area under medical research is brain image analysis, results to detect brain diseases. The main causes for alzheimer's diseases is low brain activity and blood flow. In general segmentation technique is using for the medical images .one of the important component of the brain is hippocampus. The normal behavior of human beings is depends on the functionality of hippocampus. Manual segmentation by a specialist on the hippocampus takes many hours. In image processing there are various techniques available for segmentation process. In this paper we implement Deep learning algorithms. The brain hippocampus images converted into binary form using two approaches. The first approach is block mean, mask and labeling concepts and in the second approach top hat, mask and labeling concepts. We implement deep learning techniques to obtain better results in detection of the Alzheimer's . The shape analysis of hippocampus structure will result in classifying the alzheimer's disease.**

I. INTRODUCTION

Early detection of Alzheimer's Disease (AD) is essential for starting therapies as early as possible. For these diseases, in fact, there are no treatments that lead to healing, but there are therapies that are able to slow down disease effects, improving quality and life expectancy of patients. It is generally agreed that early signs of Alzheimer's disease produce alterations in handwriting. Alzheimer's disease (AD) is the most common form of dementia, and causes problems with memory, thinking and behavior. It is a degenerative brain disorder, characterized by progressive deterioration of nerve cells, eventually leading to cell death. Mild Cognitive Impairment (MCI) is a condition in which people show a slight, but noticeable and measurable decline in cognitive capabilities, beyond what is considered normal for their age. MCI is a transitional stage of dementia between NC and AD [1]. Older people with MCI may or may not progress to AD, though they have a higher risk of doing so. Accurate distinction of AD and MCI from normal control (NC) subjects is critical for early diagnosis and treatment of brain disorders. Traditional AD and MCI diagnosis methods are generally based on positron emission tomography (PET) and cerebrospinal fluid (CSF) [2]. In recent years, there has also been an increasing interest in noninvasive diagnosis methods based on electroencephalography (EEG) [3], structural magnetic resonance imaging (sMRI) [4], and functional magnetic resonance imaging (fMRI) .

II. LITERATURE SURVEY

2.1 Classification of Alzheimer's Disease, Mild Cognitive Impairment and Normal Control Subjects Using Resting- State fMRI Based Network Connectivity Analysis. (zhe wang 1 , yu zheng1 , david c. zhu 2 , andrea c. bozoki3 , and tongtong li) This paper proposes a reliable method for AD, MCI and NC subject classifification that is highly robust under size limited fMRI data samples, by exploiting brain network connectivity pattern analysis. To do it, first , we selected the right and left hippocampi regions and isthmus of the cingulate cortices (ICCs) as our ROI sub-network, and calculated the Pearson correlation coeffificients between all possible ROI pairs and used them to form a feature vector for each subject. Second, the vectors were projected into a one-dimensional axis using the proposed regularized LDA approach, where the differences between AD, MCI and NC subjects were maximized. Shrinkage based regularization procedures were taken to reduce the noise effect due to the limited sample size. Finally, a decision tree based multi-class AdaBoost , which is robust to noise effect, was applied to the projected onedimensional vectors to perform the classification. 2.2 Robust Hippocampus Localization From Structured Magnetic Resonance Imaging Using Similarity Metric Learning samsuddin ahmed 1 , (member, ieee), kun ho lee 2,3, and ho yub jung Our proposed pipeline demonstrated an error of 1.70 ± 0.50 mm for localizing the left hippocampus and an error of 1.66 ± 0.49 mm for localizing the right hippocampus in GARD dataset. The errors in ADNI dataset was 1.79 ± 0.83 and 1.55 ± 0.61 for localizing left hippocampus and right hippocampus, respectively. The results demonstrated a promising performance for anatomical landmark localization, specifically cerebral landmark localization in sMRI modality.

2.3 Hippocampal segmentation by Random Forest classification Creating a tool for reliable and accurate hippocampus segmentation is a crucial step for the quantitative analysis of brain images. It would allow the radiologist to assess easily the hippocampus and to make rapid diagnoses of neurodegenerative pathologies, like, for example, the Alzheimer's disease. With this aim, we proposed and developed an innovative approach based on a large number of discriminating features and their classification by means of a Random Forest classifier. 2.4 Diffusion Tensor Imaging retrieval for Alzheimer's disease diagnosis Olfa Ben Ahmed, Jenny Benois-Pineau, Michele Allard , Gwena elle Catheline and Chokri Ben Amar Proposed a classical CBVIR approach on the DTI MD maps to evaluate the performance of this scheme on the recent MRI modality. This scheme has not yet allowed us to compare our results with voxel- based approaches which use classification framework. Our work can be considered just as a first step for this or as a proof of concept of CBVIR for DTI modality. Despite the tests were conducted on a small (for cohort population reasons) test set, the results obtained are promising. Alone this modality shows rather high scores in a realistic situation of a small cohort. Furthermore, our approach, which do not require a precise segmentation of ROI, performs well not only on SMRI, what we showed in our previous work. 2.5 Generalized Deep Learning Model for Alzheimer's Detection Researchers of this paper ime This work creates a generalized deep learning model to classify Alzheimers on hippocampus images in three different deep learning architectures, namely ResNet50, GoogLeNet and ResNet-152. Unlike most of the previous works, here the training is done on four different datasets together and the testing is done on one. Even though the datasets show variability among themselves, for the five datasets tested and for three different architectures the model shows a comparable or better performance than a previous work 70% of the time.

III. 2.6 HUMAN ELECTROENCEPHALOGRAM DYNAMICS: APPLICATIONS TO DIAGNOSIS OF ALZHEIMERS DISEASE ZHENGHUI HU 1 AND PENGCHENG SHIIN CONCLUSION, PROPOSED BASED ON THE APPROXIMATE ENTROPY MEASURES, WE HAVE INVESTIGATED THE EEG COMPLEXITY AND REGULARITY FOR 20 HEALTHY SUBJECTS AND 14 AD PATIENTS, INCLUDING THE APEN ASYMPTOTIC NORMALITY IN REAL SYSTEM AND SUBSEQUENT STATISTICAL TESTING STRATEGIES. FROM OUR STUDY, WE OBSERVE THAT THE SIGNAL COMPLEXITY AND REGULARITY OF AD PATIENTS IS RATHER DIFFERENT (LOWER APEN VALUES AND STATISTICAL SIGNIFICANCE), ESPECIALLY FOR THE C3 AND O2 EEG RECORDING CHANNELS), FROM THAT OF HEALTHY SUBJECTS

IV. .EXISTING SYSTEM

In one study, bilateral and unilateral ground-glass opacity was detected in their patients. Among paediatric patients , consolidation and ground- glass opacities wereused respectively. This key characteristic may be useful in developing deep learning model to facilitate in screening of large volumes of radiograph images for Alzheimer's Dataset suspect cases. Deep learning has the potential to revolutionize the automation of chest radiography interpretation. More than 40,000 research articles have been published related to the use of deep learning in this topic including the establishment of referent data set , organ segmentation, artefact removal , multilabel classification , data augmentation , and grading of disease severity . The key component in deep learning research is the availability of training and testing data set, whether or not it is accessible to allow reproducibility and comparability of the research. One technique that is commonly used in Machine learning is transfer learning which enables adoption of previously trained models to be reused in a specific application . Machine Learning algorithms that has been developed but they have lower Accuracy, Machine learning algorithms worked well when the number of instances of one class are almost equal to the number of instances of other class. Class imbalance damage was caused during the classification result severely , data is over sampled using machine learning technique for instance, synthetic minority oversampling technique (SMOTE). The input data type was converted from numeric into nominal/numeric to nominal values so that the algorithms which uses said data type as input can be implemented. Attribute selection involves searching through all possible combinations of attributes in the data to find which subset of attributes works best for prediction and classification. It is helpful in the dimensionality reduction and omitting improper attributes. For classification tasks, it can lead to increased accuracy or to reduced computational costs. The third step is based on classification using AR mining with minimum support and minimum confidence. Classification is done using 10-fold cross validation that is, data is divided into 10 parts.

One part is used as test and remaining 9 are used as training data and Early Diagnosis of Alzheimer's Disease using The training set is used for classification in order to identify the specific parameters. The association rules results in unique associations among the attributes which are exploited in next step.

V. PROPOSED SYSTEM

Proposed System use different architectures of convolutional neural networks (CNNs) trained on DenseNet,Inception V3,Resnet,VGG16 and adapt them to behave as feature extractors for the Fundus images. Then, the CNNs are combined with consolidated machine learning method VGG Classifier. The results show that, for one of the datasets, the extractor-classifier pair with the best performance is the Densenet architect, which achieves an accuracy and an F1-score of 88.5%. For the other dataset, the best pair is DenseNet201 with MLP, achieving an accuracy and an F1- score of 85.6%. Thus, the proposed approach demonstrates efficiency in detecting Alzheimer disease in and from hippocampus images.

4.1 System Architecture

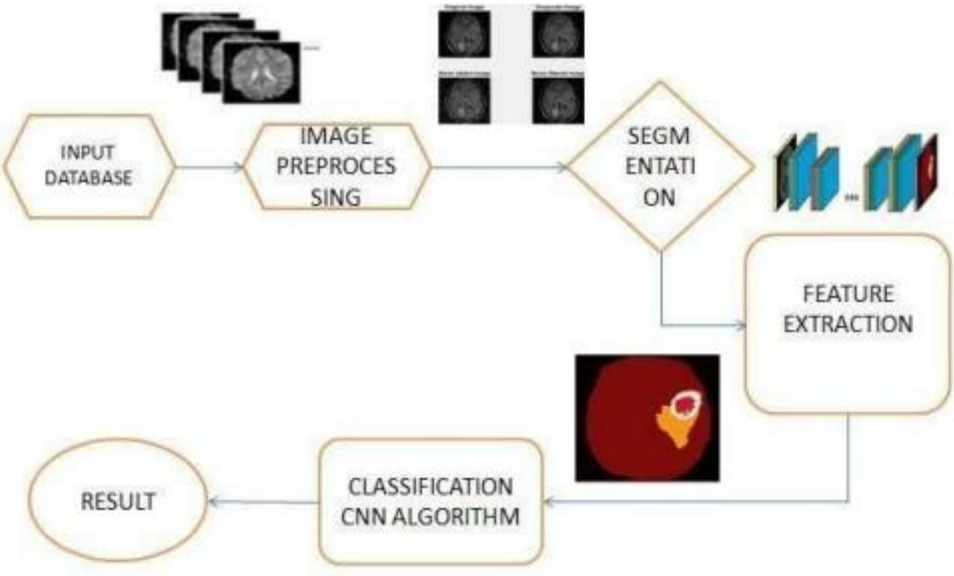

Fig 5.1 System Architecture

The dataset comes from the ‘‘International Competition on Alzheimier Disease Intelligent Recognition’’. The dataset is ‘‘real’’ patient data collected from different hospitals/medical centers. The training set is a structured ophthalmic database of 5000 patients with age photographs from left and right part of hippocampus images and doctors’ diagnostic keywords from doctors. The testing set is the color fundus photos of 500 patients, excluding age and gender. hippocampus images are captured by various cameras on the market, such as Canon, Zeiss and Kowa, thus resulting in various image resolutions. These data classify patient into eight labels, as shown in Fig.2 (a), including normal(N),Dataset consists of two files - Training and Testing both containing a total of around ~5000 images each segregated into the severity of Alzheimer's Classes: 1.MildDemented 2.VeryMildDemented 3.NonDemented 4.ModerateDemeneted

4.2 Algorithm Used- CNN

CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "full connectivity" of these networks make them prone to overfitting data. Typical ways of regularization, or preventing overfitting, include: penalizing parameters during training (such as weight decay) or trimming connectivity (skipped connections, dropout, etc.) CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble patterns of increasing complexity using smaller and simpler patterns embossed in their filters. Therefore, on a scale of connectivity and complexity, CNNs are on the lower extreme.

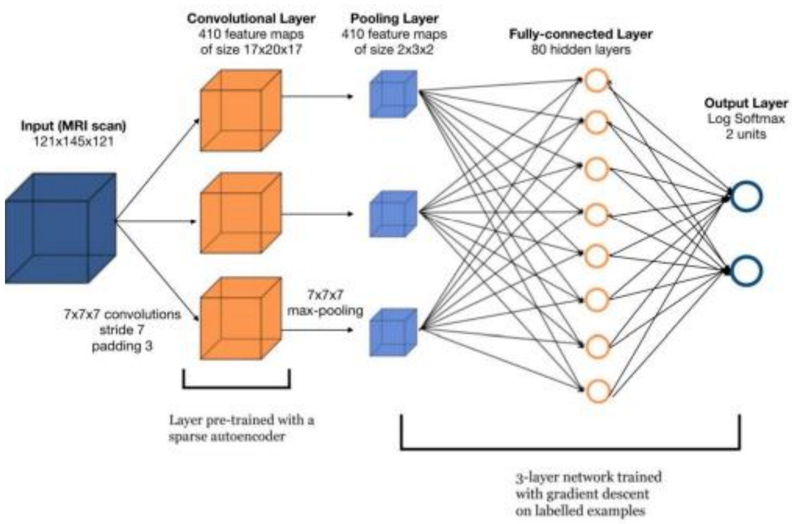

Fig 5.2.4 CNN

VI. Implementation

To do efficient training on our CNN model, a backpropagation algorithm is set to adjust the rate of learning and stop the model automatically once it reaches maximum accuracy. Since the learning rate is one of the hyperparameters that decides model accuracy and time to process the model. OASIS-3 dataset consisted of 2168 independent MRI scanners. Among the given images, 1,734 are used for training and 434 were used for validation purposes. Because of the large image dataset, 10- fold cross-validation has been used and we have used each fold 70% as training, 10% as validation, and 20% images are used testing. The distribution of the dataset is presented in Table 1. Table 1: Total image distribution. Total Images: 2168 Type Percentage Trained images 1517 (70%) Testing images 434 (20%) Validation images 217 (10%) The model-fitting has to be done on a sample of 100 epochs and to prevent model overfitting we stop the model early at the 80th iteration. The model took a run time of 138 min to process the trained images.

Table 1: Total image distribution.

Total Images: 2168	
Type	***Percentage***
Trained images	1517 (70%)
Testing images	434 (20%)
Validation images	217 (10%)

AUC and loss metrics after each iteration on both training and validation image data.

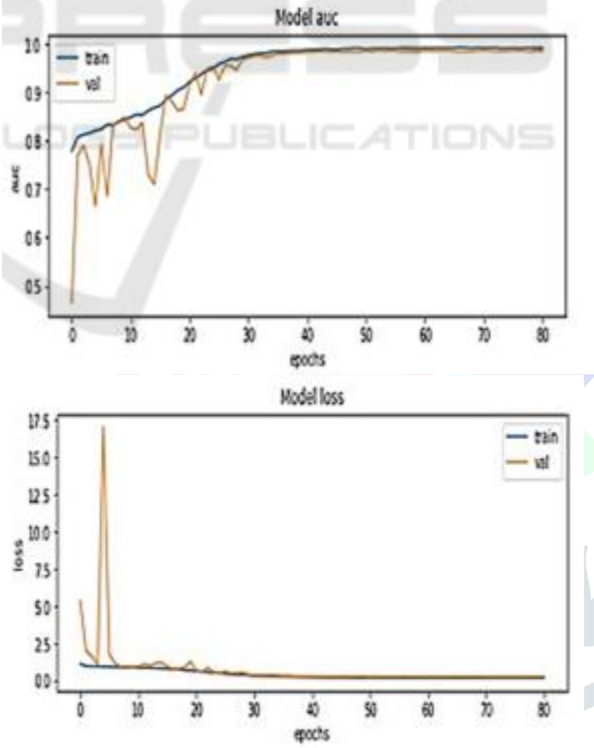

Figure 5: Model AUC and loss metric outcomes.

Though the model evaluation has been done on the validation dataset, we also perform the experiments on the testing dataset. The testing dataset model AUC curve outcome has presented in Figure 6 and the model achieved a ROC of 83.3% which is considered as an optimal classifier for AD image detection and this value is significantly higher than traditional ML approaches (Battineni, Chintalapudi, en Amenta 2019; A. Khan en Zubair 2020)

VII. Conclusion

In this work, we experimented with multiple Deep learning models in an attempt to classify the Alzheimer's affected patients using their MRI scans.In this several deep transfer learning model for detecting Eye Disorders automatically from images (Fundus Images) .The Model was trained using a pre-trained network,CNN ,RESNET, VGG-19 & Later, transfer learning is applied to the pre- trained network for faster and efficient training which improved the performance of the model. The system has demonstrated the novel application of image processing to derive a useful effective end product that can assist the doctors in their diagnosis. This Webapp tool can also serve as a teaching aid for the medical students to validate their understandings. The open source feature of the work encourages other engineers to build on this and create better technologies for medical science. The use of image processing for medicinal diagnosis and research is extensively growing and thus improving the lives of people. We believe that our work has contributed in this direction and hope that it will be helpful to both the technical and the medical community

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