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CONVOLUTIONAL NEURAL NETWORKS METHODOLOGIES FOR EFFICIENT ALZHEIMER'S DISEASE DIAGNOSIS: A SURVEY

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Abstract: - There are several diseases such as cancer, heart disease, skin lesions, brain damage, tumours etc that couldn't be identified at all. Alzheimer's disease is a one kind of degenerative disease that leads to degradation of memory and language. The symptoms in patients lead to shorten the survival of one up to 4 to 25 years. As the survival rate is very less in this disease this is taken as 6th place in death causing disease and has become a challenge to every health organization. Mild Cognitive Impairment-MCI lies on capturing the brain features and image data for diagnosis. The picking of Exact MCI is very tough from normal manager and AD and without experience it is impossible. In general the deep convolutional neural network is very useful in extracting resonance image. It is a step by step process in which is pre-processed in pipeline and each volume is re-sliced and given into deep CNN directly. This process undergoes final 4 stages and the process of CNN directly is ended. Then the researchers found that the neurological disease could also be found by MEG-magneto-encephalography signals. In order to increase the speed and efficiency Z-type CN structure is applied that also performs multi-model multi task learning for quick prediction. Then, several other Deep learning approach convolution neural network (CNN), which use neuro-imaging data without performing pre-processing for feature selection have yielded exact accuracy for AD and MCI prediction.

Keywords: - DCNN (Deep convolution neural network), MCI (Mild cognitive impairment), z-type structure, MEG (magneto-encephalography signals) and other techniques.

INTRODUCTION

Alzheimer's disease (AD) is represented by means of memory impairment, language dysfunction, and impairment of recognition and characterization the patients will not be in a stable state and becomes dependent [1]. The AD patients regularly face neuro-fibrillary tangles and inconvenience to themselves and to their surroundings [2]. Though there are treatments to trigger the symptoms but there is no cure for the disease. There are several clinical sources involved in diagnosis system of AD and many regression methods are used for identification of AD [3].

Recently, a set of researchers have started to adopt multimodal multitask data for Alzheimer's classification. The performance is far better when compared to the previously used methods related to one model data[4]. And obtained the improved performance compared with the methods based only on single-modal data [5]. However, to the best of our knowledge, the similar type of research in imaging-based regression such as detection of clinical scores in MM multi-model not calculated [6].

Here the aim is to overcome the limitation of nonlinear registration among subjects, and even brain tissue segmentation [7]. A landmark-related feature extraction method is followed which does not seeks nonlinear registration and tissue Segmentation format in it [8]. There are stages followed in this method:

[1] Training stage: In the training stage to derive Alzheimer's disease among health managements, set comparisons particularly on morphological features mainly performs brain set identification that contains set differences.
[2] Generally the middle region is chosen as the landmark for AD location differentiating the Health management.
[3] Testing stage: In the testing stage, by utilizing the learned AD landmarks, the significant landmarks are identified in a testing image. By using an effective technique related to a shape constrained regression algorithm.
[4] Related to the identified Alzheimer's disease landmarks, morphological features are separated in training a support vector machine (SVM) for predicting AD formation [9].

Gerardin et al. [10] separated hippocampus shape features related to a parametric origin description stating the structure by a parametric boundary.

Aguilar et al. [11] in specific enrolled a multivariate analysis model on various MRI measures. For instance, considering the volume of the boundary and the region thickness that permitted in training an AD classifier is defined. Formally the density or the volume measures is used for Alzheimer's disease diagnosis, but also cortical density [12] is constant than the other.

Specifically the cortical density is a far better measure because of the crypto architectural feature of the GM [13], [14]. Though, all those methods have been proven to be efficient in Alzheimer's disease classification [15]. The tissue and shape structure segmentation followers rely on nonlinear registration that is a very time-consuming process and even data loss may occur [16].

Altogether the manual measurements such as brain volume, cortical density, hippocampal volume, ventricular volume are not able to be captured when relating AD [17]. Several other technique focus on [18] automatic detection of anatomical variations among AD subjects and age-matched health management by means of using set comparisons [19].

Liu et al. used Sparse Auto-Encoders (SAE) and a Softmax Logistic Regressor-SLR as well as a zero-mask classification for data fusion to extract complementary information from multimodal neuro-imaging data was used [20].

Ngiam et al., described one of the modalities is randomly missed by shuffling the input values with 0 to converge various sets of image data for sparse auto-encoders. Also here, the deep learning technique has improvised accuracy for Alzheimer's disease or convolutional network classification by more than 90%. And recently again, Lu et al. used sparse auto-encoders for prior-training and DNN in the final stage that finalize an AD/CN classification efficiency and accuracy of 85% and an MCI prediction accuracy of with 83%.

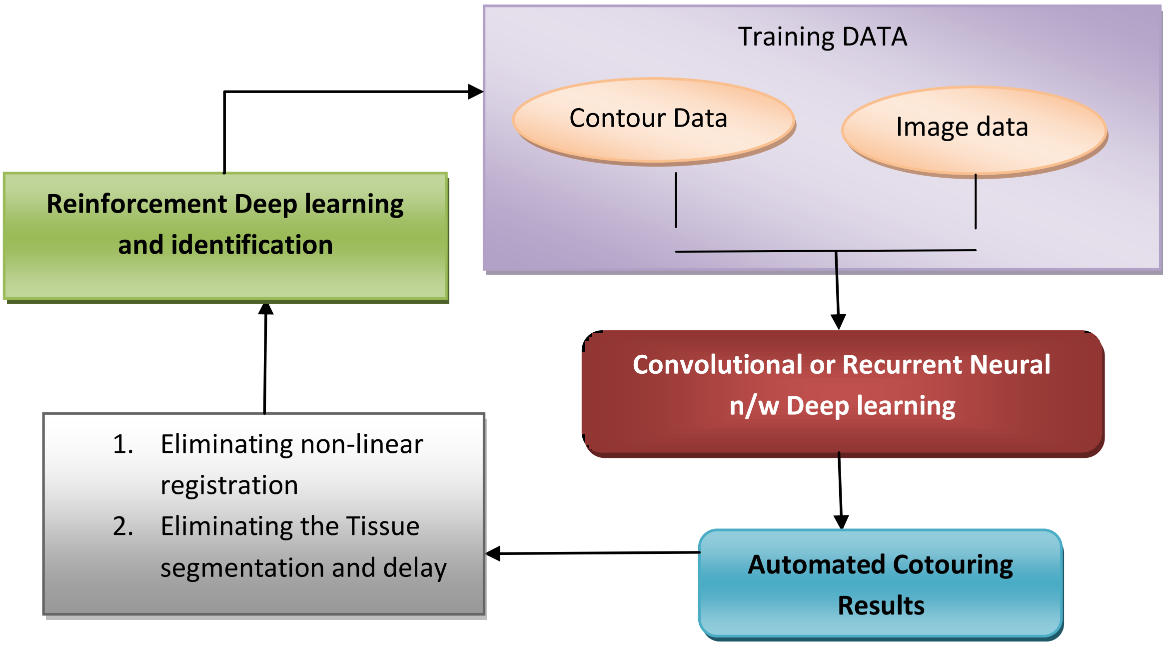


Fig 1. Deep Neural Network Learning

METHODOLOGY

1. AUTO-DETECTION OF ALZHEIMER'S DISEASE

Liu et al adapted a method a deep convolutional neural network is adapted to get the useful features of the magnetic resonance imaging-MRI where a strict pipeline is pre-defined [21]. The method involves percolating regions of interest in which each volume is re-sliced and taken directly to DCNN. As a final stage four levels of AD’s are defined the average accuracy is 95% for Neural computation (NC) vs LMCI, NC vs AD 97%, Late MCI (LMCI) & AD 97.5%, at last LMCI vs Early MCI (EMCI) are the four defined levels used and compared [22]. Here both the Late MCI and Early MCI are noted and maintained and compared with the AD value. NC the Neural computation is considered and the best results are taken for the AD diagnosis. Then the results shown in DCNN are high and best than other methods [23].

On the other hand Field Programmable Gate Array- FPGA implementation is done for convolutional neural networks with deep learning techniques. In process of increasing the efficiency and speed various depth algorithms are used. Z Convolutional Neural Network structure is established making easy for implementation with FPGA. Hereby, the need of harder multi-input and output application system the calculation speed is increased. A 3D Z-type CNN is implemented and circuit verification is done then and there by simulation [28,29].

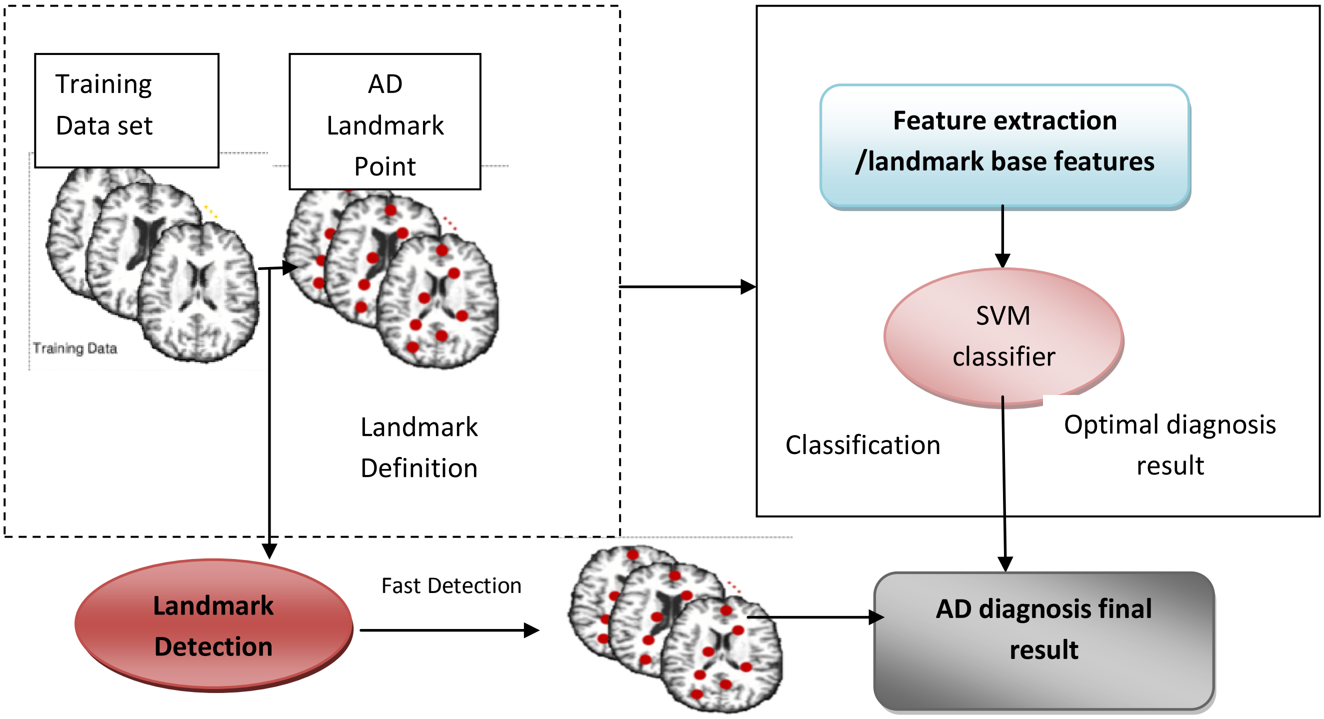


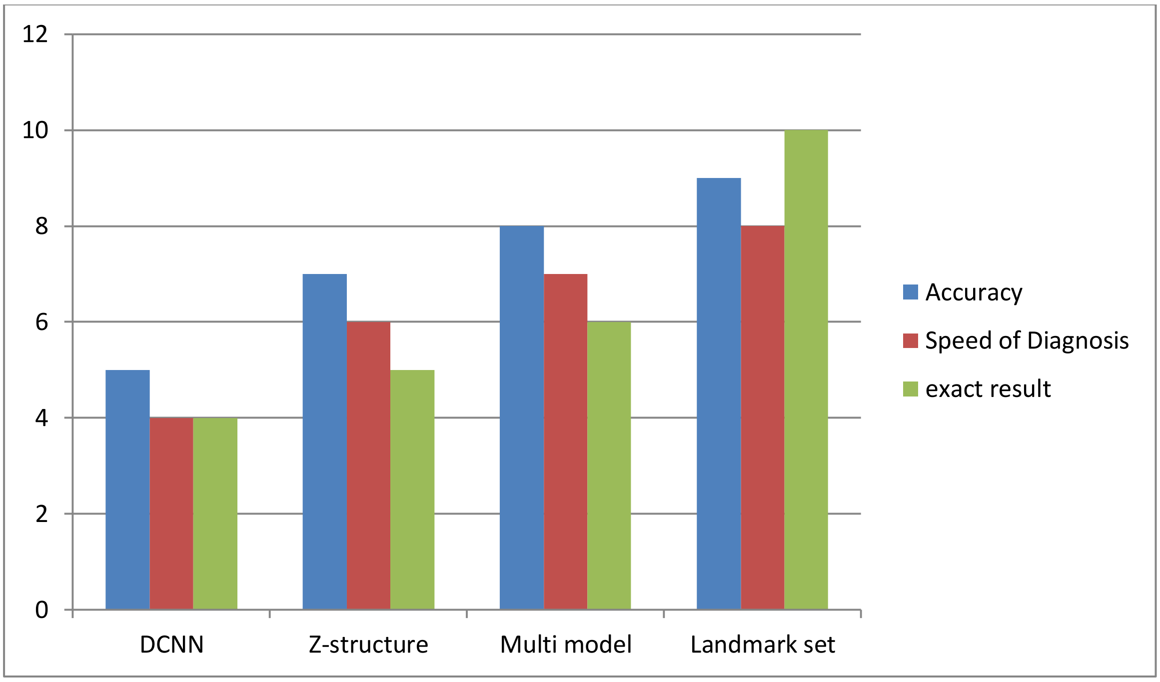
Fig 2. AD landmark detection with accurate diagnosis result of AD disease.

To achieve the diagnosis result a large group of landmarks are set in which the normal morphologies delivers a significant process among a set differences which are defined statistically [30].
This AD detection is a 3 step process the sequential steps are defined below [32]:

1) **Landmark Definition**: in this an idea of detecting landmarks within several millions of voxels in an image is defined [33].
2) **Detection.** Here in this detection phase the system searches for the location how could a landmark be identified efficiently in new testing image[34].
3) **AD classification and result:** At last the AD's are detected faster and the diagnosis result is delivered [35,36].

Here the nonlinear image registration in training level is included to locate the voxels among the training crowd [37]. In training region at first the brain regions are verified and predicted [39]. In common the middle part becomes the landmark that has capacity of differentiating the AD's from HC's [40]. In the testing level an automatic landmark identification is enabled whereas its not available in training set. And at last the accurate result is delivered [42].

RESULT COMPARISON



Algorithm Comparison

ALGORITHMS	ACCURACY	SPEED OF DIAGNOSIS	EXACT RESULT
DCNN	5	4	4
Z-Structure	7	6	5
Multi-Model	8	7	6
Landmark Set	9	8	10

CONCLUSION

In this survey several methodologies for efficient Alzheimer's disease diagnosis were discussed [44]. The main pre-defined models are Deep Convolutional neural network learning in which a deep learning process is handled and the AD values are noted and compared and the best result is produced. The main drawback of the defined method is non-linear registration and delay tissue segmentation must be eliminated [45]. To overcome this issue a speed process can be performed. In order to outsource a efficient result multi-model and Z-structure in FCA is used. Then to increase more efficiency and accuracy in AD diagnosis landmark region set is used. In which the process is classified as training set, definition of landmark, detection and classification / result. This method is far better when compared to the other technique. While using these methodologies an accurate and efficient AD diagnosis is obtained that pays way for many lives.

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