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Convolutional Neural Networks for 3d Brain MRI Classification

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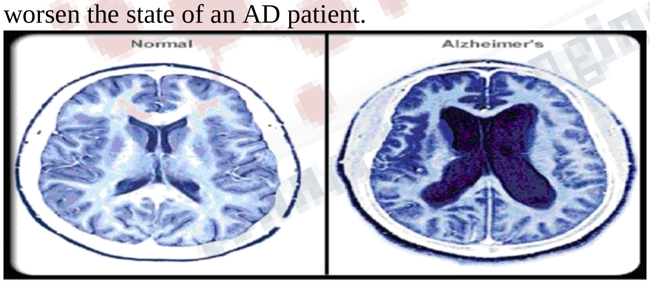
Abstract: In the recent years there have been a number of studies that applied deep learn-ing algorithms to neuroimaging data. Pipelines used in those studies mostly require multiple processing steps for feature extraction, although modern ad-vancements in deep learning for image classi cation can provide a powerful framework for automatic feature generation and more straightforward analy-sis. In this report, we show how similar performance can be achieved skipping these feature extraction steps with the 3D convolutional neural network archi-tectures. An accuracy of 84% has been achieved with a precision of 95%. The performance of the proposed approach outperforms various statistical machine learning based approaches such as SVM, Random Forest, Ada Boost etc.

I. INTRODUCTION

There are many structural and functional changes that take place in the brain due to Alzheimer's disease. The formation of tangles and plaques result in the shrinking of the brain due to which it loses functional capabilities as the neurons die. Computer aided image analyses make use of these changes and help detect the disease at an early stage. The prominent structural changes include atrophies in the hippocampal and temporal parietal regions. The best brain image acquisition required for this study is obtained by Magnetic Resonance Imaging because of high contrast, speci city, sensitivity and clarity it provides. MRI is also a safe method as it does not use X-rays or any foreign substance in the process which can otherwise, worsen the state of an AD patient.



II. METHODOLOGY

2.1Data

The dataset consists of MR images of the brains of patients of the age group 18-96 years. The images are T1 weighted and include both classes of data-people with AD and Cognitive Normal (CN) people i.e. people without the disease or any kind of dementia. Crucial data regarding the subjects apart from the age, sex and handedness have

also been provided along with the dataset for reference, like the Total Intra-cranial volume (TIV), the Clinical Dementia Ratio (CDR) and nWBV. CDR ratings vary from 0 to 2 with 0 being for non-demented, 0.5-very mild dementia, 1-mild dementia and 2-moderate dementia. The dataset mainly had Nifti les which include both hdr and img les. Each Nifti le in nii format gives a 3-Dimensional image showing all three views of the brain at di erent pixel positions (Axial, Coronal and Sagittal).

2.2 Convolutional Neural Networks

A Convolutional Neural Networks is a type of feed-forward arti cial neural net-work in which the connectivity pattern between its neurons is inspired by the organization of the animal visual cortex. In a CNN, convolution layers play the role of feature extractor. But they are not hand designed. Convolution lter kernel weights are decided on as part of the training process. A CNN architec-ture is formed by a stack of distinct layers that transform the input volume into an output volume. Various types of layers are as follows :

1. Convolution Layer: Consist of a set of learnable lters, each of which is convolved through the whole input image. We can control the size of output volume through 3 hyperparameters :

(a) Number of lters(D) : Number of lters in a CNN gives the depth of the volume.

(b) Filter Size(S) : It speci es the height and width of the lter which is to be convolved. It is same for all the lters.

(c) Zero-Padding(Z) : Sometimes input is padded with zeros on the bor-der of the input volume. This is done so that the size of output layers being formed do not keep on shrinking.

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2. Pooling Layer: The pooling/subsampling layer reduces the resolution of the features and makes the features robust against noise and distortion. There are 2 ways to do pooling: max pooling and average pooling.

3. ReLU Layer: This is a layer of neurons that applies non-saturating activation function f(x) = max(0; x) on the layer.

4. Fully Connected Layer: Neurons in a fully connected layer have full connections to all activations in the previous layer, as seen in regular Neural Networks.

2.3. Classi cation

The method involves classi cation of the available datasets into AD and Normal classes as its nal step. Since the number of classes required is two i.e. AD or Normal, we use binary classi cation for the purpose. The accuracy, sensitivity and speci city were calculated using the Confusion Matrix. A confusion matrix (Kohavi and Provost, 1998) contains information about actual and predicted classi cations done by a classi cation system. Performance of such systems is commonly evaluated using the data in the matrix. The following table shows the confusion matrix for a two class classi er.

III. RESULTS

The results of the binary classi cation task are shown in the Table below:

Approach/Metric	Accuracy	Precision	Recall	F1-Score
SVM+ANOVA	69.9%	79.0%	55.2%	64.8%
2D-CNN	78.9%	91.2%	75.4%	82.2%
3D-CNN	84.3%	94.2%	78.6%	85.2%

1. SVM+ANOVA: A univariate feature selection has been performed be-fore running a SVC (support vector classi er) to improve the classi ca-tion scores. SVM weights are very noisy, partly because heavy smoothing is detrimental for the prediction here. A standard analysis using mass-univariate GLM (here permuted to have exact correction for multiple com-parisons) gives a much clearer view of the important regions. Linear kernel is used for SVM. The value of k(features selcted by ANOVA) is choosen as 2000. The accuracy obtained is 69.9% with a F1-Score of 64.8%.

2. 3D-CNN: The architecture developed has 21 layers containing six blocks. There are 8 lters in the rst 2 blocks, followed by 16 in the next two. The

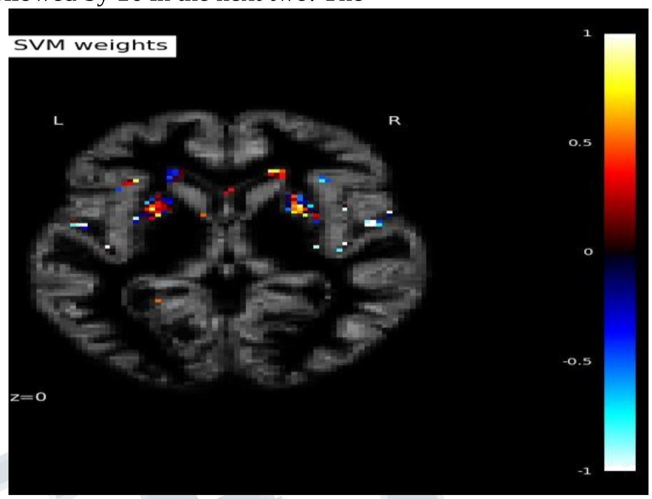

Figure 1: SVM Weights learned

output of the last block is sent to a pooling layer to further reduce it to 2 * 2 * 2 * 128, followed by a fully connected layer with 128 hidden units and an output for binary classi cation with softmax nonlinearity(Fig.2). A dropout, with p=0.7 and Batch Normalization is induced after fully-connected layer of 128 hidden units. The accuracy of the resulting model is 84.3% with an F1-Score of 85.2%.

3. 2D-CNN: To demonstrate the usefulness of 3-dimensional CNN, we also compare it with 2D-CNN. The architecture of the net is the same as that of 3D-CNN, except that now the strides and pooling is 3 3 instead of 3 3. The number of lters, neurons in FC layer, dropout value are kept the same as 3D-ConvNet. The accuracy of the resulting model is 78.9% with an F1-Score of 82.2%. It can be seen that the last approach outpeforms all other approaches in terms of accuracy, precision, recall, f1-score. The achieved f1-score of 85.2% is very high as compared to other approaches. A 2-fold, 5-fold and 10 {fold cross validation process is carried out. The samples are divided into 5 (or 2 or 10) sub-samples. One of the sub-samples is retained as the testing data and the remaining 4 (or 1 or 9) sub-samples are used as the training data. This is repeated for 5 (or 2 or 10) iterations, using one of the sub-samples as testing data each time. Average accuracy calculated was recorded as follows:

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Folds	Accuracy
2	87.9%
5	84.3%
1082.2%	

IV. CONCLUSION

We proposed deep 3D convolutional neural network architectures for a task of classi cation of brain MRI scans. We demonstrated performance of the 3D convolutional neural networks based on the OASIS dataset. We showed that applying the proposed models to MRI classi cation problem yields results com-parable to previously used approaches. The major advantages of our method are the ease of use and no need for handcrafted feature generation. In the future, we would like to predict other properties of patients from brain scans like Age, eTIV, MMSE, ASF, nWBV using deep learning techniques. We could make use of multi-task learning to predict these properties using a single uni ed model.

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