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Alzheimer's disease Classification from Brain MRI based on transfer learning from CNN

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***Abstract*— Various Convolutional Neural Network (CNN) architecture has been proposed for image classification and Object recognition. For the image based classification, it is a complex task for CNN to deal with hundreds of MRI Image slices, each of almost identical nature in a single patient. So, classifying a number of patients as an AD, MCI or NC based on 3D MRI becomes vague technique using 2D CNN architecture. Hence, to address this issue, we have simplified the idea of classifying patients on basis of 3D MRI but acknowledging the 2D features generated from the CNN framework. We present our idea regarding how to obtain 2D features from MRI and transform it to be applicable to classify using machine learning algorithm. Our experiment shows the result of classifying 3 class subjects patients. We employed scratched trained CNN or pretrained Alexnet CNN as generic feature extractor of 2D image which dimensions were reduced using PCA+TSNE, and finally classifying using simple Machine learning algorithm like KNN, Navies Bayes Classifier. Although the result is not so impressive but it definitely shows that this can be better than scratch trained CNN softmax classification based on probability score. The generated feature can be well manipulated and refined for better accuracy, sensitivity, and specificity.**

***Keywords*—CNN, MRI, generic feature, PCA, TSNE, Classifier**

I. Introduction

With the breakthrough of various imaging techniques like MRI (Magnetic Imaging Resonance), PET (Positron-emission tomography), Computed Tomography (CT) scan in medical examination, there have been lots of efforts to process, simulate and interpret the result for the purpose of Computer Aided Diagnosis (CAD) that will be of vital importance for medical professionals. Similarly, various research using MRI as the main biomarker has been carried out by several researchers to efficiently develop Computer Aided Diagnosis (CAD) system for Alzheimer's diseases diagnosis and detection.

Y. Zhang et al.[1] proposed method of classification of Alzheimer's disease (AD), Mild Cognitive Impairment (MCI) and Normal Control (NC) using Singular Value Decomposition (SVD) algorithm for brain segments feature extraction and used Principal Component Analysis (PCA) for feature reduction. They finally used 22 representing features to be classified by Kernel SVM-Decision Tree. Chaplet et al.[2] proposed a two-dimensional Discrete Wavelet Transform (2D-DWT) with Daubechies wavelet decomposition to obtain the approximation coefficient as well as utilized a self-organization map and Support Vector Machine (SVM). Slantlet transform was used by Maitra et al. [3], which is an improvised version of DWT that they used for intelligent MRI classification system. El-Dahshan et al. [4] extracted all the coefficients using the multi-resolution decomposition of a DWT so that the features were reduced in smaller dimension using PCA. Zhang et al. [5] achieved 100% success rate by using a feed-forward back propagation neural network and Scaled Chaotic Artificial Bee Colony (SCABC) to classify normal and abnormal MRI images.

II. Background

Convolutional Neural Network (CNN) was successfully employed in the larger database with a minimum error rate in 2012 by A. Krizhevsky et al. [6] in ImageNet Database for classification of 1000 image types (class). Later various variants and advancement of CNN were proposed by the different researcher for Object recognition and Image classification like Resnet [7], GoogLenet [8], and R-CNN [9] etc. Regarding CNN implication in the medical field, using MRI, X-ray imaging was successfully tested as well. Nima Tajbaksh et al. [10] tested CNN in Medical Images for poly detection and Pulmonary embolism detection, where they highlighted pretrained or fined tuned CNN performed well as scratch trained CNN and suggested layer-wise tuning for practical performance. Similarly, Hoo-Chang Shin et al. [11] tested CNN architecture for Lymph-Node detection and Interstitial Lung disease Classification, where they also tested pretrained CNN network (Alexnet, GoogLeNet and CifarNet [12]) and also used transfer learning technique from this CNN.

A. CNN and transfer learning

Convolutional Neural Network designed for Object detection finds its use in Image classification, Segmentation, Pattern recognition etc. It has been developing as an important tool for machine vision and AI, due to its autonomous working nature.

Transfer Learning in CNN can be done in mainly two ways, either the weights of all CNN structure gets cascaded to another CNN layer with classification Layer output or simply using "off-the-shelf CNN features" [13] where CNN acts as a generic feature extractor to be evaluated further. We will present a comparative analysis of this both idea and later simplify the operational process and makes the CAD system more flexible.

B. Methods and Methodology

We have utilized Alzheimer's disease Neuroimaging Initiative (ADNI) database (http://www.loni.ucla.edu/ADNI) for our experiment. The ADNI was launched in 2003 by the

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National Institute on Aging (NIA), the National Institute of Biomedical Imaging and Bioengineering (NIBIB), the Food and Drug Administration (FDA). The training and testing sets were adapted from Rémi Cuingnet et al. [14]. The total number of subjects includes 81 NC, 69 AD and 38 MCI for training and 81 NC, 68 AD and 37 MCI for testing.

Here, we have used the generated off-the-shelf features from a raw MRI file to get features of each slice in a single box. The generated CNN features are of dimension 609×512 (230- Axial slice, 230- coronal slice and 149 sagittal slices, some of the non-informative slices have been excluded) for a single patient. 609 represents the number of total slices and 512 represent the number of activated features for each image output from 'FCL_7' layer of CNN. Then, PCA+ TSNE is applied on features for dimension reduction, as this becomes highly complex for classification. The reduced dimension now becomes 609×3 =1827 (after flattened, of which 230×3 is an axial feature, 230×3 is a coronal feature and 149×3 is sagittal features) for single patients, so now it's our choice to use either all features or partial features.

If full features are applied T1×1827 features are employed for training and T2×1827 features are applied for testing classifier models, where T1 represents the number of Training set patients and T2 represents the number of the testing set patient. Later, performance parameters are analyzed from the classifier model, by applying feature selection process to identify the best number of features, and hence we finalize the classification process. Regarding classifier, we have selected two classifiers of different working principle to compare the results, i) Navies Bayes Classifier- which works on the class wise conditional probability of each predictor/features and ii) KNN is a simple machine learning technique which calculates the distance (e.g. Euclidean, Mahalanobis, cosine etc.) of single point with its k- neighbor and gives the class scores with majority voting.

The proposed method has been shown in Fig. 1, along with the dimension size of the feature vector that goes down the process. One of the important questions during MRI processing is, how many slices and what orientation slices to be taken for processing? We have tried to solve this problem to some extent using our proposed method.

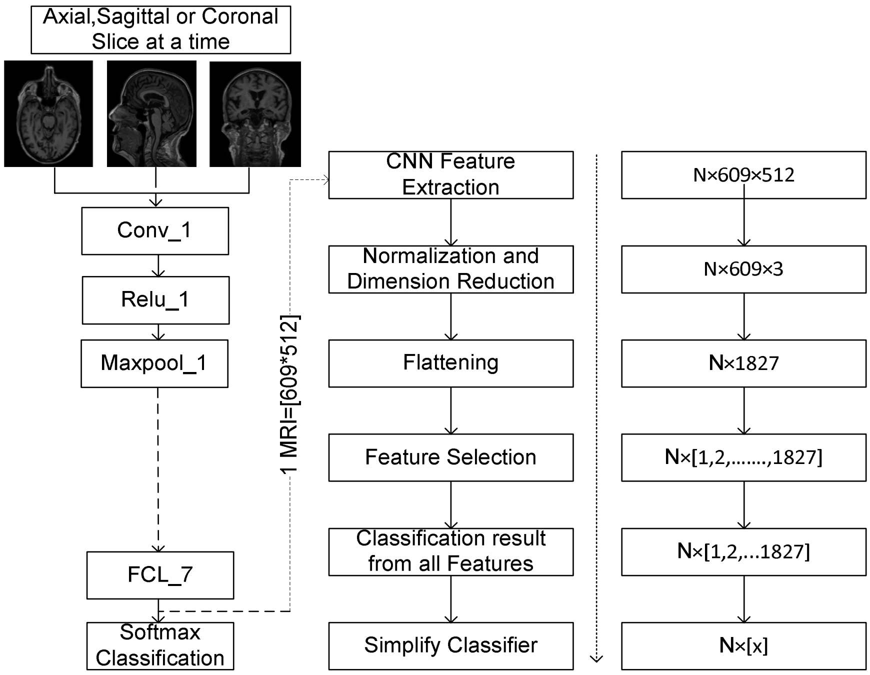

Fig. 1: Proposed method along with dimension on the side, 'N' represents the total number of the subject under study, 'x' denotes the number of features used to build classifier model for training and testing

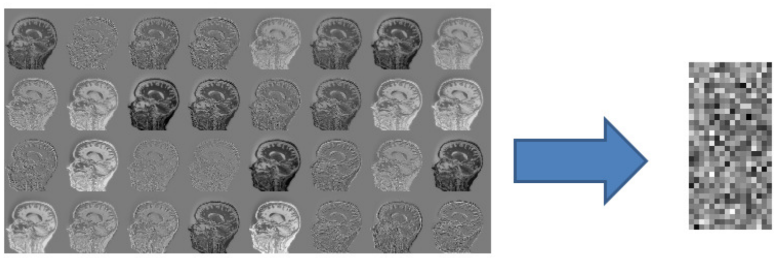

Fig. 2: Feature transformation from 1st convolution (176×220) to last FCL_7 (512) layer in single MRI image (axial slice).

TABLE I. ACCURACY TABLE FOR 3 CLASS CLASSIFICATION OF AD-MCI-NC, X=DENOTES THE NUMBER OF FEATURES USED TO BUILD CLASSIFIER MODEL FOR TRAINING AND TESTING, *LARGE SIZE ARRAY.

Method	Random Accuracy: Scratch trained CNN	Optimal Accuracy: Trained CNN+FR+FS+NB Classifier	Optimal Accuracy Trained CNN+FR+FS+KNN Classifier	Optimal Accuracy: Alexnet CNN+FR+FS+NB	Optimal Accuracy from Alexnet CNN+FR+FS+KNN
Axial features	41.62	42.47(x=671)	43.55(x=4)	41.94(x=9)	44.09(x=52)
Sagittal features	43.4	42.31(x=1)	45.16(x=104)	46.24(x=3)	43.01(x=2)
Coronal features	39.83	40.32(x=2)	42.47(x=3)	41.94 (x=203)	40.30(x=7)
All features (trained CNN)	NA*	38.17(x=3)	44.09(x=17)	41.94(x=3)	45.70(x=882)

TABLE II. ACCURACY BAR CHART CALCULATED SEPARATELY FOR SCRATCH TRAINED CNN FEATURES AND ALEXNET CNN FEATURES, USING ALL FEATURES (AXIAL, SAGITTAL AND CORONAL FEATURES)

	AD-MCI-NC	AD-MCI	AD-NC
All features (trained CNN)	38.17(x=3), 44.09(x=17)	54.36(x=3), 53.69(x=27)	57.14(x=1), 64.76(x=36)
All features (Alexnet CNN)	41.94(x=3),45.70(x=882)	51.86(x=1),60.40(x=863)	67.62(x=2), 67.62(x=301)

The features are automatically investigated from low-level features like edge, blob, line etc. to high-level features like color, shape, detail etc. in a hierarchical manner by each layer. The activation layer like ReLu helps to make those features more clear and computable. Hence, we can easily get the feature extracted for each MRI image from the trained model.

III. RESULT AND OBSERVATION

The result of the experiment has been tabulated in Table I and Table II. Table I shows the result of 3 class classification compared with scratch trained CNN with the proposed idea and Table II presents comparative accuracy with trained CNN with pretrained Alexnet Model including 3 class and 2 class classification result.

CONCLUSION

Hence we experiment our idea of transfer learning from CNN to other classifiers, with sequential steps followed. We are able to conclude followings:

- Transferring learned parameters/features from trained CNN can be distinguishing characteristics for training the classifier.
- CNN features trained classifier gives better performance than CNN networks itself if the feature transformation, selection, and classification are done wisely.
- Performance can even be improved if CNN architecture can be well modified, fine-tuned and also if the classifier is optimized well.

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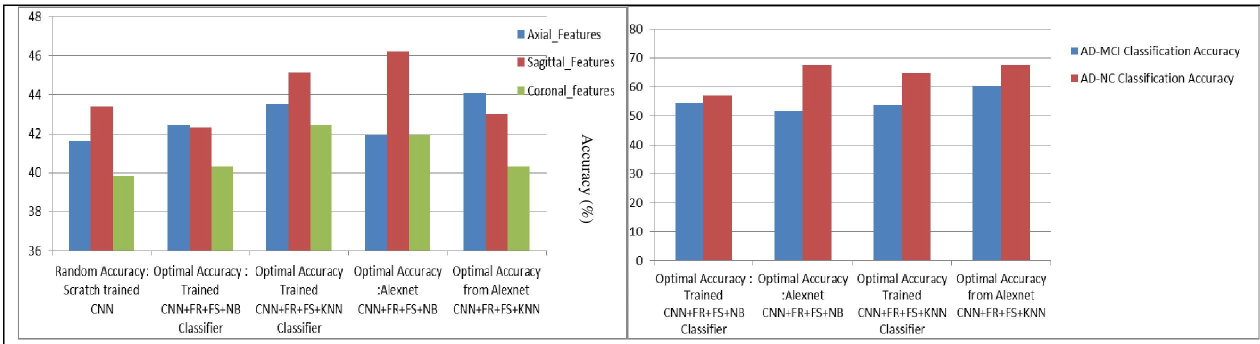

Fig. 3: Accuracy bar chart calculated separately for axial, sagittal and coronal features using the method mentioned below the graph. FR- feature reduction (PCA+TSNE), FS-(Feature Selection, ReliefF), KNN (k-Nearest Neighbor), NB (Navies Bayes classifier) vs. Binary class classification accuracy for 'x' number of features indicated in Table II

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