Using Hybrid Neural Networks for Identifying the Brain Abnormalities from MRI Structural Images

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Abstract. In this study, we present the investigations being pursued in our research laboratory on magnetic resonance images (MRI) of various states of brain by extracting the most significant features, and to classify them into normal and abnormal brain images. We propose a novel method based on deep and extreme machine learning on wavelet transform to initially decompose the images, and then use various features selection and search algorithms to extract the most significant features of brain from the MRI images. By using a comparative study with different classifiers to detect the abnormality of brain images from publicly available neuro-imaging dataset, we found that a principled approach involving wavelet based feature extraction, followed by selection of most significant features using PCA technique, and the classification using deep and extreme machine learning based classifiers results in a significant improvement in accuracy and faster training and testing time as compared to previously reported studies.

Keywords: Deep Machine Learning, Extreme Machine Learning, MRI, PCA.

1 Introduction

Magnetic Resonance Images (MRI) is an advance technique used for medical imaging and clinical medicine and an effective tool to study the various states of human brain. MRI images provide the rich information of various states of brain which can be used to study, diagnose and carry out unparalleled clinical analysis of brain to find out if the brain is normal or abnormal. However, the data extracted from the images is very large and it is hard to make a conclusive diagnosis based on such raw data. In such cases, we need to use various image analysis tools to analyze the MRI images and to extract conclusive information to classify into normal or abnormalities of brain. The level of detail in MRI images is increasing rapidly with availability of 2-D and 3-D images of various organs inside the body.

Fully automatic normal and diseased human brain classification from magnetic resonance images (MRI) is of great importance for research and clinical studies. Recent work [2, 5] has shown that classification of human brain in magnetic resonance (MR) images is possible via machine learning and classification techniques such as artificial neural networks and support vector machine (SVM) [2], and

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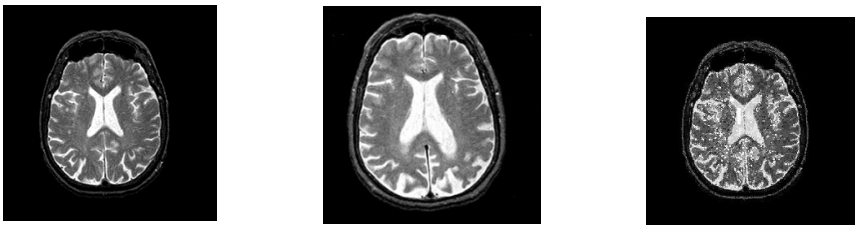
unsupervised techniques such as self-organization maps (SOM) [2] and fuzzy c-means combined with appropriate feature extraction techniques [5], [16], 17]. Other supervised classification techniques, such as k-nearest neighbors (k-NN), which group pixels based on their similarities in each feature image [1, 6, 7, 8] can be used to classify the normal/pathological T2-weighted MRI images. Inspired by new segmentation algorithms in computer vision and machine learning, we propose an efficient semi-automatic and deep learning algorithm for white matter (WM) lesion segmentation around Region of Interest (ROI) based on extreme and deep machine learning. Further, we compare this novel approach with some of the other supervised machine learning techniques reported previously.

2 Materials and Methods

2.1 Datasets

The input dataset consists of axial, T2-weighted, 256 X 256 pixel MR brain images (Fig. 1). These images were downloaded from the (Harvard Medical School website (http:// med.harvard.edu/AANLIB/) [9]. Only those sections of the brain in which lateral ventricles are clearly seen are considered in our study. The number of MR brain images in the input dataset is 60 of which 6 are of normal brain and 54 are of abnormal brain. The abnormal brain image set consists of images of brain affected by Alzheimer's and other diseases. The remarkable feature of a normal human brain is the symmetry that it exhibits in the axial and coronal images. Asymmetry in an axial MR brain image strongly indicates abnormality.



(a) (b) (c)

Fig. 1. (a) T2, weighted an axial MRI Brain Image; (b) T2, weighted an axial MR brain image as abnormal brain; (c) T2, weighted an axial MR brain image as normal brain after Wavelets Decomposition and denoising

A normal and an abnormal T2-weighted MRI brain image are shown in Fig. 1(a) and 1(b), respectively. Indeed, for multilayer learning models like deep and extreme machine learning algorithms needed big datasets for training, however due to lack of availability of proper datasets in MRI imaging, we used this dataset for examining the performance of proposed approaches for this paper, but acquiring other suitable datasets for future studies. At each decomposition level, the length of the decomposed signals is half the length of the signal in the previous stage. Hence the size of the approximation component obtained from the first level decomposition of an NXN

image is N/2 X N/2, second level is N/4 X N/4 and so on. As the level of decomposition is increased, compact but coarser approximation of the image is obtained. Thus, wavelets provide a simple hierarchical framework for interpreting the image information.

2.2 Deep Belief Nets

DBNs [10] are multilayer, stochastic generative models that are created by learning a stack of Restricted Boltzmann Machines (RBMs), each of which is trained by using the hidden activities of the previous RBM as its training data. Each time a new RBM is added to the stack, the new DBN has a better variation lower bound on the log probability of the data than the previous DBN, provided the new RBM is learned in the appropriate way [11].

A Restricted Boltzmann Machine (RBMs) is a complete bipartite undirected probabilistic graphical model. The nodes in the two partitions are referred as hidden and visible units. An RBM is defined as

$$p(v,h) = \frac{e^{-E(v,h)}}{\sum_u \sum_g e^{-E(u,g)}} \tag{1}$$

Where v ϵ V are the visible nodes and h ϵ H are the latent random variables. The energy function E (v,h,W) is described as

$$E = -\sum_{i=1}^{D} \sum_{j=1}^{K} v_i W_{ij} h_j \tag{2}$$

Where W ϵ R^{DXK} are the weights on the connections, and where we assume that the visible and hidden units both contain a node with value of 1 that acts to introduce bias. The conditional distribution for the binary visible and hidden units are defined as

$$p(v_i = 1/h, W) = \sigma(\sum_{j=1}^{K} W_{ij} h_j) \tag{3}$$

$$p(h_j = 1/v, W) = \sigma(\sum_{i=1}^{D} W_{ij} v_i) \tag{4}$$

Where σ is the sigmoid function. Using above equations, it easy to go back and forth between the layers of RBM. While training, it consists of some input to the RBM on the visible layer, and updating the weights and the biases such that p(v) is high. In generalized way, in as set of C training cases $\{v^c \text{ I } c \in \{1,\ldots,C\}\}$, the objective is to maximize the average log probability defined as

$$\sum_{c=1}^{C} \log p(v^c) = \sum_{c=1}^{C} \log \frac{\sum_g e^{-E(v^c,g)}}{\sum_u \sum_g e^{-E(u,g)}} \tag{5}$$

The whole training process involves updating the weights with several numbers of epochs and the data is split in 20 batches which we take it randomly and the weights are update at the end of every batch. We use the binary representation of hidden units activation pattern for classification and visualization. The autoencoder with N_h hidden nodes is trained and fine-tuned using back-propagation to minimize squared reconstruction error, with a term encouraging low average activation of the units.

2.3 Extreme Machine Learning

The Extreme Learning Machine [12, 13, 14] [15] [18] is a Single hidden Layer Feed forward Neural Network (SLFN) architecture. Unlike traditional approaches such as Back Propagation (BP) algorithms which may face difficulties in manual tuning control parameters and local minima, the results obtained after ELM computation are extremely fast, have good accuracy and has a solution of a system of linear equations. For a given network architecture, ELM does not have any control parameters like stopping criteria, learning rate, learning epochs etc., and thus, the implementation of this network is very simple. Given a series of training samples $(x_i, y_i)_{i=1, 2 \ldots N}$ and $\widehat{N}$ the number of hidden neurons where $x_i = (x_{i1},\ldots x_{in}) \epsilon R^n$ and $y_i = (y_{i1},\ldots y_{in}) \epsilon R^m$, the actual outputs of the single-hidden-layer feed forward neural network (SLFN) with activation function g(x) for these N training data is mathematically modeled as

$$\sum_{k=1}^{\widehat{N}} \beta_k g\big((w_k, x_i) + b_k\big) = 0_i \,, \forall = \mathrm{i} = 1, \ldots\ldots, N \tag{6}$$

Where $w_k = (w_{k1},\ldots..,w_{kn})$ is a weight vector connecting the k^{th} hidden neuron, $\beta_k = (\beta_{k1},\ldots\ldots \beta_{km})$ is the output weight vector connecting the k^{th} hidden node and output nodes. The weight vectors w_k are randomly chosen. The term (w_k, x_i) denotes the inner product of the vectors w_k and x_i and g is the activation function. The above N equations can be written as $H\beta = O$ and in practical applications $\widehat{N}$ is usually much less than the number N of training samples and $H\beta \neq Y$, where

$$H = \begin{bmatrix} g\big((w_1, x_1) + b_1\big) & \cdots & g\big((w_{\widehat{N}}, x_1) + b_{\widehat{N}}\big) \\ \vdots & \ddots & \vdots \\ g\big((w_1, x_{1N}) + b_1\big) & \cdots & g\big((w_{\widehat{N}}, x_N) + b_{\widehat{N}}\big) \end{bmatrix}_{NX\widehat{N}} \tag{7}$$

The matrix H is called the hidden layer output matrix. For fixed input weights $w_k = (w_{k1},\ldots..,w_{kn})$ and hidden layer biases b_k, we get the least-squares solution $\hat{\beta}$ of the linear system of equation $H\beta = Y$ with minimum norm of output weights β, which gives a good generalization performance. The resulting $\hat{\beta}$ is given by $\hat{\beta} = H + Y$where matrix H^+ is the Moore-Penrose generalized inverse of matrix H [14].

2.4 Trained Classifiers and Feature Selection Evaluators

In this study, apart from deep learning based on Restricted Boltzmann machines and extreme machine learning based on Single hidden Layer Feed forward Neural Network (SLFN) architecture as classifiers, several other classifiers are also examined in terms of accuracy and performance, including K-nearest neighbor, SVM , Naive Bayes, MultiboostAB, Rotation Forest, VFI, J48 and Random Forest.

To reduce the dimensionality of the large set of features of dataset, in our study, we propose the use of three optimal attribute selection algorithms: correlation based feature selection (CFS) method, which evaluates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them, secondly an approach based on wrappers which evaluates attribute sets by using a learning scheme. Also in this study, three search methods are also examined: the Best First, Greedy Stepwise and Scatter Search algorithms. These search algorithms are used with attribute selector's evaluators to process the greedy

forward, backward and evolutionary search among attributes of significant and diverse subsets. In total, these feature selection algorithms were tested to select nearly 10 optimal and significant features out of 1024 features. The whole proposed method is implemented using Weka 3.6 platform.

3 Experiments and Results

3.1 Level of Wavelet Decomposition

We obtained wavelet coefficients of 60 brain MR images, each of whose size is 256 X 256. Level-1 HAR wavelet decomposition of a brain MR image produces 16384 wavelet approximation coefficients; while level-2 and level-3 produce 4096 and 1024 coefficients, respectively. The preliminary experimental analysis of the wavelet coefficients through simulation in Matlab 7.10., we showed that level-2 features are the best suitable for different classifiers, whereas level-1 and level-3 features results in lower classification accuracy. We also use the DAUB-4 (Daubachies) as mother wavelets to get decomposition coefficients of MRI images at Level 2 for comparative evaluation of two wavelets decomposition methods in terms of classification accuracy.

3.2 Attribute Selection and Classification

The second step after Wavelet decomposition of MRI images is to select significant features among whole set of coefficients. Table 1 shows the accuracy of classification (percentage of correctly classified samples), True Positive Rate (TP), False Positive Rate (FP) and Average Accuracy (ACC) over all pair-wise combination with different feature evaluators and search algorithms with respect to multi-class classification.

Table 1 shows the performance of several learning classifiers, including K-nearest neighbor, SVM, Naive Bayes, MultiboostAB, Rotation Forest, VFI, J48 and Random Forest. Among the pair-wise classification, the lowest accuracy is observed for the classification VFI classifiers of 74.16% and the highest accuracy for the classification by Rotational forest of 97.06%. Moreover, the combination of CFS feature evaluator with the Best First search algorithm gives the highest classification accuracy compared to other feature evaluators and search algorithms. While Table 1 shows the performance of indivual classifiers, Table 2 compares the proposed method against a popular dimensionality reduction method, known as Principal Component Analysis (PCA). PCA applies an orthogonal linear transformation that transforms data to a new coordinate system of uncorrelated variables called principal components. We have applied PCA to reduce the number of attributes or feature to 18 attributes and plotted the ROC curves using several above mentioned learning classifiers in terms of True Positive and False Positive Rate, as seen in figure 2. As can be seen in figure 2, ROC curves for all the trained learning classifiers examined in this study, the curves lie above the diagonal line describing the better classification rather than any other random classifiers. The optimal points of various trained classifiers are indicated by bold solid points as False Positive rate (FP) and True Positive rate (TP). These optimal points in ROC curves show the maximum optimal value (FP, TP) of all trained classifiers.

Table 1. Various Classifiers comparision with respect Average Classification Accuracy(%) and other parameters

Classifiers	TP Rate	FP Rate	Precision	Recall	F-Measure	(ACC %)
KNN	0.935	0.917	0.826	0.853	0.839	91.04
SVM	0.912	0.912	0.831	0.912	0.87	91.17
Naive Bayes	0.868	0.916	0.828	0.868	0.847	86.76
MultiboostAB	0.91	0.91	0.829	0.91	0.868	91.04
Rotation Forest	0.971	0.285	0.971	0.971	0.968	97.06
VFI	0.742	0.049	0.93	0.742	0.796	74.16
J48	0.96	0.314	0.958	0.96	0.957	95.98
Random Forest	0.97	0.271	0.97	0.97	0.968	97.01

Table 2. Comparison using PCA and other feature attribute evaluators in terms of ACC (%)

Classifier	PCA (%)	CFS-Best First (%)	Wrapper-Best First (%)
KNN	91.38	91.04	89.32
SVM	96.24	91.17	90.65
Naive Bayes	85.63	86.76	85.44
MultiboostAB	94.52	91.04	89.39
Rotation Forest	97.06	97.06	93.78
VFI	77.12	74.16	72.22
J48	95.34	95.98	95.98
Random Forest	97.34	97.01	96.25

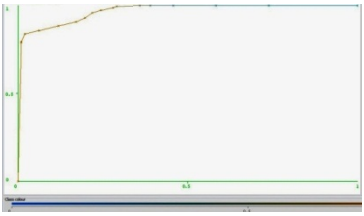


Fig. 2. Shows the ROC curve of the above mentioned trained classifiers

Table 3 describes the classification results using Extreme Machine Learning and Deep Machine Learning. In table 3, we compared the training time, testing time and classification error using extreme and deep machine Learning. As we can see in the table both learning algorithms are processed to many hidden layers and their evaluations is done in terms of various factors. As depicted in Table 3, it clearly shows that deep machine learning plays a major role in reducing the classification error. As Deep and extreme machine learning are designed to work on large datasets for it is difficult to compare the performance. However, they result in acceptable accuracy levels, and we are currently examining several other publicly available large MRI datasets for enhancing the performance of these two novel approaches (Deep learning and Extreme machine learning approaches).

Table 3. Classification results using Extreme Machine Learning and Deep Machine Learning

	Training Time(s)			Testing Time(s)			Classification Error		
Hidden Layers	**10**	**15**	**20**	**10**	**15**	**20**	**10**	**15**	**20**
Deep Learning	0.56	0.47	0.72	0.51	0.34	0.64	0.083	0.065	0.071
Extreme Learning	0.31	0.31	0.61	0.41	0.31	0.56	0.042	0.042	0.061

However, the deep learning networks do not need any particular feature reduction algorithms because of the inherent capability for feature reduction in terms of deep learning (learning through multiple layers). In case of extreme machine learning, the learning proceeds through random assignment of weights and hidden nodes (unlike gradient descendent based techniques). Due to this, there is a significant improvement in training and testing time as depicted in Table 3.

4 Conclusions

In this study, we have presented a principled approach for investigating brain abnormalities based on wavelet based feature extraction, PCA based feature selection and deep and extreme machine learning based classification comparative to various others classifiers. Experiments on a publicly available brain image dataset show that the proposed principled approach performs significantly better than other competing methods reported in the literature and in the experiments conducted in the study. The classification accuracy of more than 93% in case of deep machine learning and 94% in case of extreme machine learning demonstrates the utility of the proposed method. In this paper, we have applied this method only to axial T2-weighted images at a particular depth inside the brain. The same method can be employed for T1-weighted, proton density and other types of MR images. With the help of above approaches, one can develop software for a diagnostic system for the detection of brain disorders like Alzheimer's, Huntington's, Parkinson's diseases etc. Further, the proposed approach uses reduced data by incorporating feature selection algorithms in the processing loop and still provides an improved recognition and accuracy. The training and testing time for the whole study used by deep and extreme machine learning is much less as compared to SVM and other traditional classifiers reported in the literature. Further work will be pursued to classify different type of abnormalities, and to extract new features from the MRI brain images on various parameters as age, emotional states and their feedback.

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