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A fuzzy integral method based on the ensemble of neural networks to analyze fMRI data for cognitive state classification across multiple subjects

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The huge number of voxels in fMRI over time poses a major challenge to for effective analysis. Fast, accurate, and reliable classifiers are required for estimating the decoding accuracy of brain activities. Although machine-learning classifiers seem promising, individual classifiers have their own limitations. To address this limitation, the present paper proposes a method based on the ensemble of neural networks to analyze fMRI data for cognitive state classification for application across multiple subjects. Similarly, the fuzzy integral (FI) approach has been employed as an efficient tool for combining different classifiers. The FI approach led to

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the development of a classifiers ensemble technique that performs better than any of the single classifier by reducing the misclassification, the bias, and the variance. The proposed method successfully classified the different cognitive states for multiple subjects with high accuracy of classification. Comparison of the performance improvement, while applying ensemble neural networks method, vs. that of the individual neural network strongly points toward the usefulness of the proposed method.

Keywords: FMRI; artificial neural network; fuzzy integral; classifier ensemble; machine learning; cognitive states.

1. Introduction

The key challenge in cognitive neuroscience is to effectively map the mental state of a subject onto the neural activity patterns. Functional magnetic resonance imaging (fMRI) brain–computer interface is a powerful tool for cognitive neuroscience research, which measures neural activation via the blood oxygen level-dependent (BOLD) signals and provides quantitative data to infer such neural signals or brain patterns (Poldrack, 2008; Haxby *et al.*, 2001). To accurately assess the neural activation, machine-learning classifiers were employed to decipher brain patterns and the state-of-the-art ensemble technique was used for a more accurate classification (Kuncheva & Rodŕiguez, 2010; Zanzotto & Croce, 2010; Naselaris *et al.*, 2011).

The ensemble techniques have recently garnered much interest in computational neuroscience owing to their unique advantages in dealing with complex data structure (Helmy *et al.*, 2012). Ensemble techniques have thus been proposed as the tools for improving classification performance. These techniques combine the outputs of the different member classifiers, each developed in a different context, for an entirely different representation trained to do the same task/problem. The combination of the multiple classifiers run in parallel, which is one of the popular fields in pattern recognition. The integration of multiple classifiers increases the overall predictive accuracy in comparison with any single classifier (Wanas & Kamel, 2001; Granitto *et al.*, 2005) through a suitable combiner. The use of different combination approaches leads to different ensemble techniques. Most common ensemble techniques are bagging, boosting, and stacking (Islam *et al.*, 2008). The ensemble constructions that independently and sequentially train individual artificial neural networks (ANNs) using various training sets are the methods of bagging and boosting functioning.

The fusion of ANNs, fuzzy systems, and evolutionary computing techniques is useful to offset the demerits of any of the individual technique by the merits of the other. Regarding the ensemble, varieties of classifier combination schemes have been proposed, wherein the most often schemes are selected by majority vote, average vote, weighted average, Dempster Shafer theory (Wanas & Kamel, 2001), Bayes and probabilistic schemes (Tenenbaum *et al.*, 2006), and fuzzy integrals (FIs) (Cho, 2002).

Although the ensemble of neural networks method based on FI approach have shown promising results while classifying fMRI patterns for a single subject

(Parida *et al.*, 2014), in this paper we extended this method to multiple subjects to further refine the performance and usefulness of the technique.

2. Machine-Learning Techniques

The state-of-the-art machine-learning techniques are popularly used by neuroscientists for a variety of fMRI data analyses (Parida & Dehuri, 2013). Most of the machine-learning algorithms possess several parameters that affect the algorithm's behavior and performance. There are, however, potential benefits to having several parameters that generally indicates that an algorithm has greater flexibility. In this paper, we have described the proposed machine-learning technique and its application to approximate classification.

2.1. *Multi-layer perceptron artificial neural network*

A multilayer perceptron (MLP) ANN is a machine-learning implementation that depends on a set of real-valued parameters (weight of the ANN), which has been applied to solve a broad range of problems (see Fig. 1). Here, we describe the MLP-based classification that is essential for explaining its application to fMRI (do Espí rito Santo *et al.*, 2007; Kozyrev, 2012).

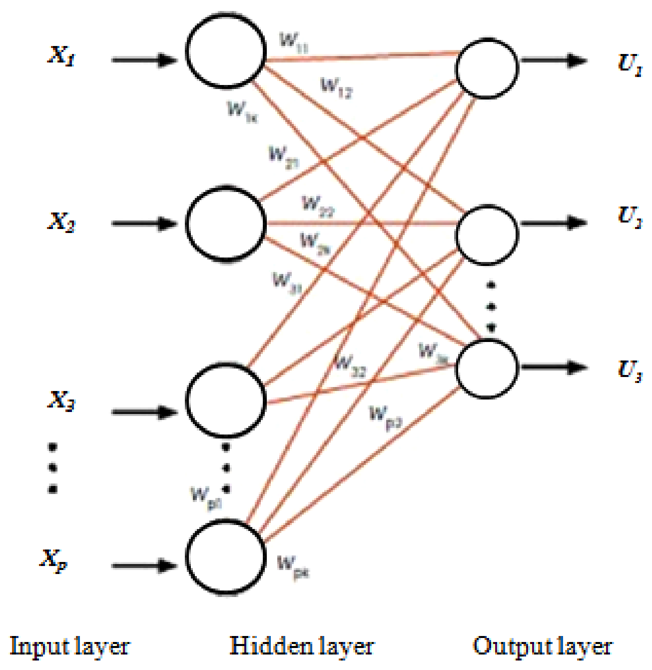


Fig. 1. A set of synaptic weights for connections: a signal at the input synapse j connected to the neuron k is multiplied by the weight synapse; input signals weighted by the correspondingly synaptic weights are summed with other input signals in a linear combination fashion, an activation function that limits the amplitude of the output signals. The activation function (.) defines the output neurons in terms of the active signal level in its input and provides a nonlinear characteristic to the MLP.

2.2. *Classifier ensemble method*

The ensemble is a machine-learning paradigm, where multiple learners are trained to solve the same problem. The ensemble is generally much stronger than any of the individual classifiers, which makes it more useful. Thus, combining the predictions of an ensemble of more than one classifiers generates more accurate and more efficient prediction than any of the individual classifiers (c.f., Parida *et al.*, 2015; Zhang & Yang, 2008). In this context, uncorrelated errors of the individual classifiers can be eliminated by averaging (Granitto *et al.*, 2005). Generally, the steps for the ensemble involve training multiple individual classifiers and then combining their individual predictions. An ensemble of classifiers is a set of classifiers whose individual decisions are combined by some method (typically by weighted or unweighted voting) to classify new samples (Dietterich, 2000). There are several factors that differentiate among the various ensemble methods that include inter-classifier relationship, combining method, diversity generator, and ensemble size. The performance of an ensemble depends greatly on the accuracy and diversity among base learners in the ensemble (Chekina *et al.*, 2012). The goal therefore is to create an accurate ensemble by using component learners that are relatively accurate, but highly diverse.

ANNs provide a methodology for solving several types of nonlinear problems that are otherwise difficult to solve with traditional techniques (Maqsood *et al.*, 2004). ANN ensemble is an output of separately trained ANNs to form unified predictions. The performance of the entire ensemble is mostly superior when compared with the performance of any of its individual ANNs. The ensemble design must focus on the method of training the ANNs such that it encourages the diversity of behaviors and the mechanism to decide the final output based on the individual output (Pardoe *et al.*, 2005). A variety of ways to construct the ANN ensemble are based on the diversified ANNs by using different training sets, architectures, and learning methods (Akhand & Murase, 2001). The diversity can be induced in several different ways such as architectures, input variables, and training algorithms (Figueiras-Vidal & Rokach, 2012).

2.3. *The fuzzy integral*

Several complex problems are transformed or broken down into simpler problems using fuzzy logic that uses approximate reasoning. Fuzzy logic has the potential to process incomplete date and provide approximate solutions. The FI is one of the most popular approaches in combining classifiers, which can produce better performance with subjectively assigned importance of an individual ANN (Cho, 2002). FI has been applied to classifier combination and has been used in several contexts to provide good results (Kuncheva & Rodríguez, 2010; Grabisch, 2000).

In this paper, we consider the problem of combining classifiers, where Z represents a set of classifiers, A is the object under consideration for classification, and $h_k(z_i)$ is the partial evaluation of the object A for class w_k. For each classifierz_i, the degree of importance, g^i, reflects how good is z_i in the classification of class w_k must be given.

These densities can be induced from a training dataset (Al-Ani & Deriche, 2002). For a given finite set of elements Z, let the fuzzy measure be defined as the set function that satisfies the following conditions (Al-Ani & Deriche, 2002):

(1) $g(\emptyset) = 0, g(Z) = 1$,
(2) $g(A) \leq g(B)$ *if* $A \subset B$
(3) *if* $\{A_i\}_{i=1}^{\infty}$ is an increasing sequence of measurable sets, then $\lim_{i\to\infty} g(A_i) = g(\lim_{i\to\infty} A_i)$,
(4) $g(A \cup B) = g(A) + g(B) + \lambda_g(A)g(B)$

for all $A, B \subset Z$ and $A \cap B = \emptyset$, and, for some, $\lambda > -1$.

Note λ is given by solving: $\lambda + 1 = \Pi_{i=1}^{n}(1 + \lambda_g^i)$, where, $\lambda \in (-1, \infty)$, and $\lambda \neq 0$. It can be calculated by solving an $(n-1)$ degree polynomial and finding the unique root < -1.

3. Method

The overall framework of the method proposed is depicted in Fig. 2.

Let $\{D_1 \ldots, D_L\}$ be the set of the L classifiers. The output of the ith classifier is represented as (Kuncheva *et al.*, 2001), $D_i(x) = [d_{i,1}(x), \ldots, d_{i,c}(x)]^T$, where, $d_{i,j}(x)$ denotes the degree of "support" given by classifier D_i to the hypothesis that x comes from class j. The $\hat{D}$ is the fused output of the L classifiers as $\hat{D} = F(D_1(x), \ldots, D_L(x))$, where F is called the aggregation rule. The classifier outputs are arranged in a decision profile (DP) matrix, as shown in Fig. 3.

These types of combiners that use the DP matrix in a class-by-class manner are called class-conscious combiners. Some of the class-conscious operators are average, minimum, maximum, product, and FI (Kuncheva *et al.*, 2001; Ghosh *et al.*, 2010).

We followed the procedure described by Kuncheva *et al.* (2001) to calculate the degree of support. For an input x, calculate c vectors of length L where, each vector corresponds to a class and contains L values of a fuzzy measure. The ith column of the DP (with L values of support for class i) is sorted and fused with the fuzzy measure to obtain $\mu_{\hat{D}}^{k}(x)$ for that class. The technique of fuzzy integration is to identify the maximal grade of agreement between the objective evidence (provided by the sorted classifier outputs for class i) and the expectation (the L fuzzy measure values).

4. Data Acquisition

The experiment was conducted on the platform of 32 bit, Intel 2.70 GHz processor, 4.00 GB RAM, running under Windows 7 operating system. The programs for the experiment were coded using MATLAB software. The fMRI dataset was collected from the Carnegie Mellon University public StarPlus fMRI data repository (Just & Mitchell, 2001). The dataset contained data on six subjects (04847, 04799, 05710, 04820, 05675, and 05680). The experiment consisted of a sequence of trials. For some

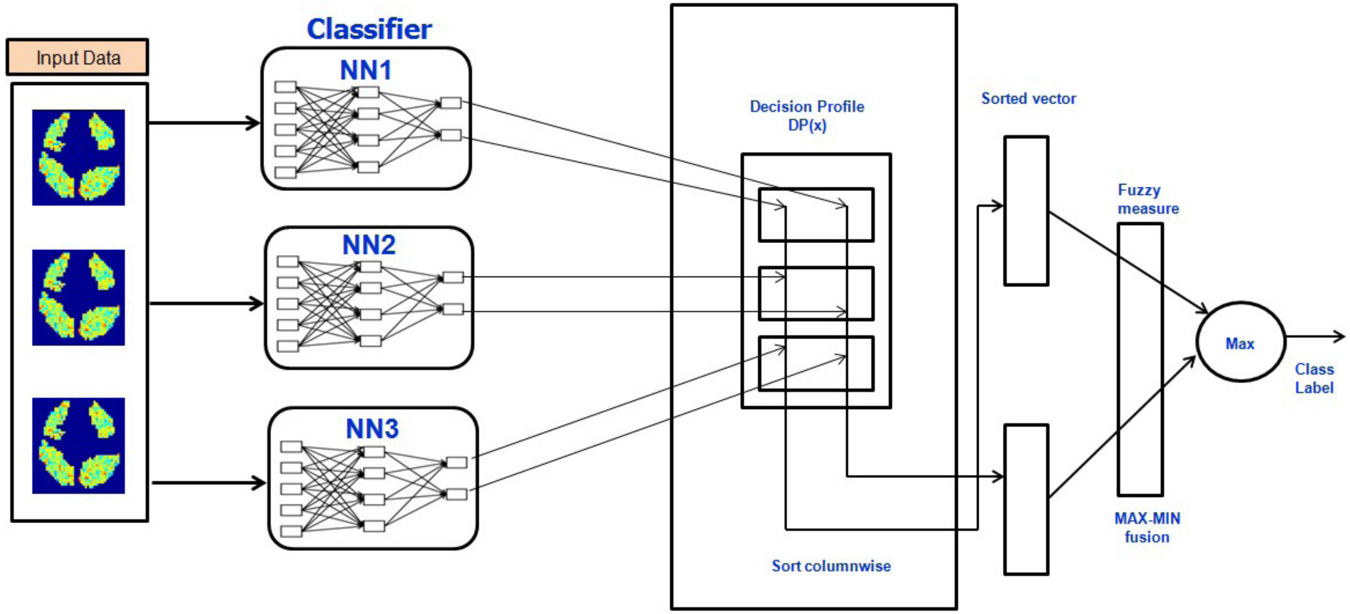


Fig. 2. A framework illustrating an overall process of our proposed method. The processed fMRI data is passed on to the ANNs. A FI is used to combine the outputs of the neural classifiers in an ensemble. The individual ANN is then trained and tested using the input fMRI data and finally combined using the FI to measure the ensemble performance.

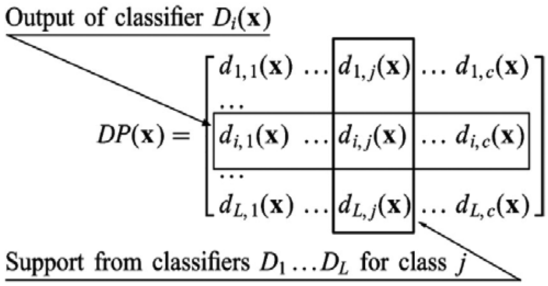


Fig. 3. The classifier outputs can be organized in a DP as the matrix, wherein the row represents the output of classifiers and the column represents the support from classifiers. The shown DP matrix defined for L classifiers and C classes, where $d_{i,j}(x)$ represents degree of "support" given by classifier D_i to the hypothesis that x comes from class j.

of these intervals, the subject simply rested or gazed at a fixation point on the screen. In other trials, the subject was shown a picture and a sentence and instructed to press a button to indicate whether the sentence correctly described the picture, as shown in Fig. 4.

The images were collected every 500 ms. Only a fraction of the brain of each subject was imaged. The data were marked up with 25–30 anatomically defined regions (called the "Regions of Interest" (ROIs)). There were 54 trials, totaling 2800 snapshots. The data were stored in a cell array, with one cell per trial in the experiment. Each element in the cell array was an array of observed fMRI activations, and each array contained a number of voxels (features) per snapshot. The sample of voxel activity over a specific time period is shown in Fig. 5.

During the initial population generation, we ignored the rest condition. The dataset represented as a pattern and feature matrix of size 2196 and 4698 i.e., $X = (.)_{2196X4698}$ for subject 1, where X is denoted as a dataset for each subject. The dataset for subject 2, subject 3, subject 4, subject 5, and subject 6 are based on the number of pattern and features as shown in the Table 1.

We segregated the training from the test sample in a 80:20 ratio. The initial dataset X for each subject contains data of all the 25 ROIs termed 'CALC',

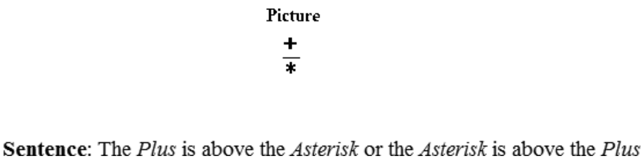
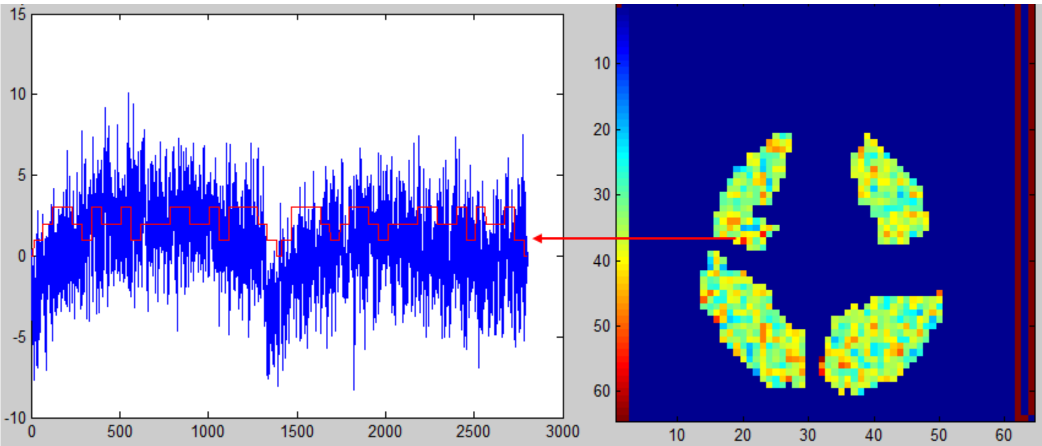


Fig. 4. The geometric arrangement of the two symbols + and *. In the first half of the trials, the picture was presented first and then the sentence. In the remaining trials, the sentence was presented first and then the picture. The first stimulus (sentence or picture) was presented at the beginning of the trial (image = 1). After 4 s (image = 9), the stimulus was removed and replaced by a blank screen. After 4 s (image = 17), the second stimulus was presented. This remained on the screen for 4 s or until the subject pressed the mouse button, whichever occurred first. A rest period of 15 s (30 images) was added after the second stimulus was removed from the screen. Thus, each trial lasted for a total of approximately 27 s (approximately 54 images).



(a) (b)

Fig. 5. (Color online) The voxel activity in a particular course of time. The image (a) shows the time series data of a single voxel (arrow marked). The X-axis shows the time, and Y-axis shows the activation. The histogram (marked red) indicates the signal intensity. The image (b) shows the 2D slice image for a particular trial (trial = 4) and the scale interval [1, 64] (default MATLAB color map) is shown on the X and Y axes.

Table 1. Number of voxels (features) for each subject.

Subject	Nos. of Pattern	Nos. of Voxels (Features)
Subject 1 (04847)	2196	4698
Subject 2 (04799)	2196	4949
Subject 3 (05710)	2196	4634
Subject 4 (04820)	2196	5015
Subject 5 (05675)	2196	5135
Subject 6 (05680)	2196	5062

'LDLPFC', 'LFEF', 'LIFG', 'LIPL', 'LIPS', 'LIT', 'LOPER', 'LPPREC', 'LSGA', 'LSPL', 'LT', 'LTRIA', 'RDLPFC', 'RFEF', 'RIPL', 'RIPS', 'RIT', 'ROPER', 'RPPREC', 'RSGA', 'RSPL', 'RT', 'RTRIA', and 'SMA'.

For MLP, we used the Matlab 'nntraintool' to train the ANN. To evaluate the performance of the proposed network scheme, we implemented three different ANNs, each of which is a two-layered ANN with different number of input neurons. The training parameters with the results of the 3 ANNs are shown in Figs. 6–8.

The performance evaluation of the ensemble method was obtained by implementing three two-layered ANNs (NN1, NN2, and NN3). Each of the three ANNs was trained with 80% of the training data and tested with the 20% of the test data. The classification accuracy for the individual ANN and the ensemble result with a different set of ANNs are shown in Table 2 and in Fig. 9. The classification accuracy for the individual ANNs (NN1, NN2, and NN3) vs. the FI for each of the six subjects

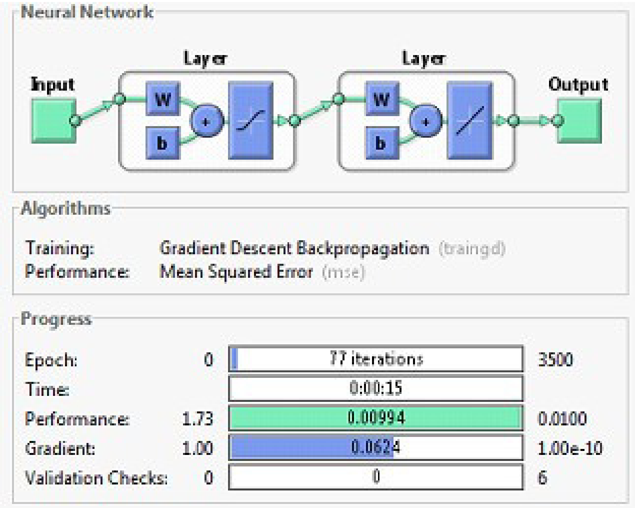


Fig. 6. A snapshot from the 'nntraintool' of the MATLAB tool during NN1; the first layer has 20 'tansig' neurons, the second layer has one 'purelin' neuron, the learning rate is 0.05, the momentum constant is 0.7, and the maximum number of epochs is 3500.

are shown in Table 2. The performance comparison graphs (classification accuracy) of individual ANNs (NN1, NN2, and NN3) with the FI ensemble for each of the six subjects are illustrated in Fig. 9. From the comparison graph, it is found that the FI ensemble performance is better than the individual ANNs.

To obtain the maximum accuracy for a given number of ANNs, the experiment was performed for all the six subjects with an NN set, as shown in Table 3. The FI ensemble results in terms of classification accuracy for the range of ANNs (NN3,

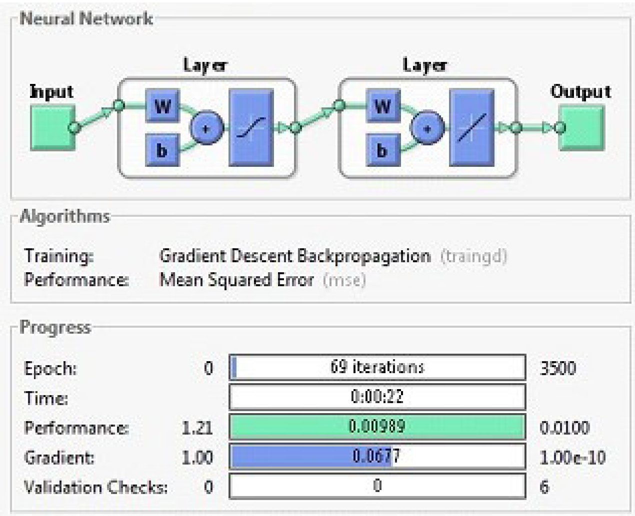


Fig. 7. A snapshot from the 'nntraintool' of the MATLAB tool during NN2 training. For NN2, the first layer has 25 'tansig' neurons, the second layer has one 'purelin' neuron, the learning rate is 0.05, the momentum constant is 0.7, and the maximum number of epochs is 3500.

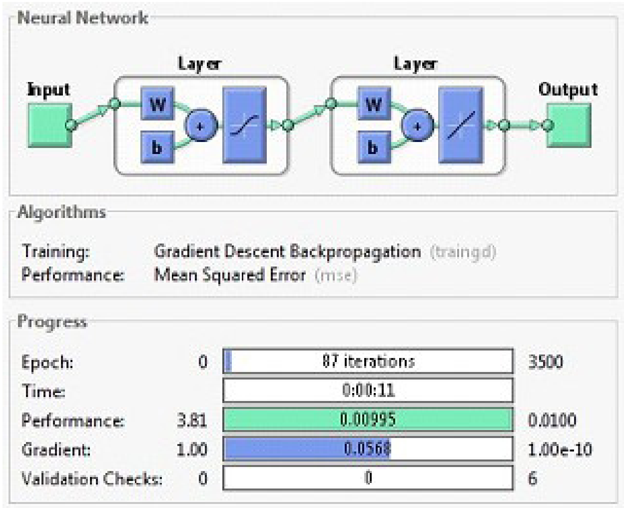


Fig. 8. A snapshot from the 'nntraintool' of the MATLAB tool during NN3 training. For NN3, the first layer has 30 'tansig' neurons, the second layer has one 'purelin' neuron, the learning rate is 0.05, the momentum constant is 0.7, and the maximum number of epochs is 3500.

Table 2. Accuracy (Independent vs. Ensemble).

Subject	Individual Neural Network Accuracy			FI Accuracy (%)
	NN1	NN2	NN3	
Subject 1 (04847)	93.2	89.46	86.65	93.67
Subject 2 (04799)	94.44	93.23	93.23	96.13
Subject 3 (05710)	85.9	80.83	82.15	90.52
Subject 4 (04820)	91.33	90.63	90.39	92.97
Subject 5 (05675)	91.66	89.63	91.44	96.62
Subject 6 (05680)	88.62	92.41	90.81	94.31

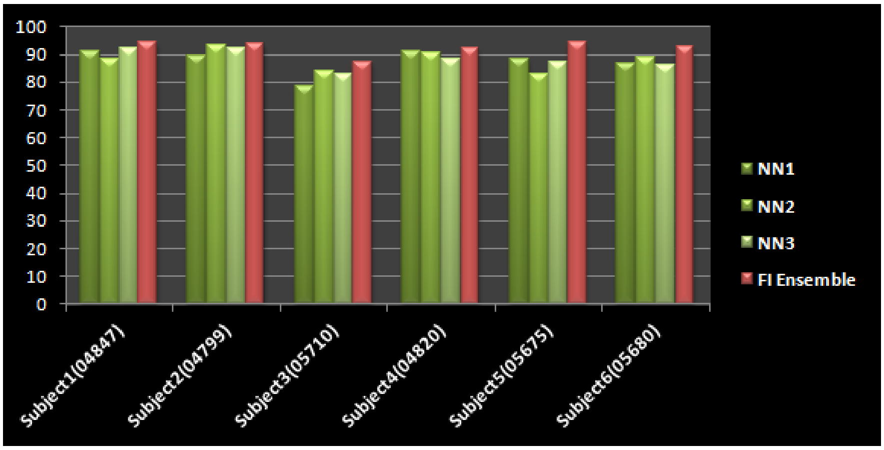


Fig. 9. The NN3 Performance Comparison Graph. For each subject, the bar represents the individual NN and the ensemble accuracy. It is clearly evident that the ensemble accuracy is more than the individual NN accuracy.

Table 3. Ensemble accuracy.

	Numbers of Ensemble							
Subjects	NN3	NN5	NN7	NN9	NN11	NN13	NN15	NN17
Subject 1 (04847)	93.67	97.57	97.65	97.34	98.18	95.75	97.43	97.07
Subject 2 (04799)	96.13	98.14	97.53	99.23	98.78	98.55	99.24	98.38
Subject 3 (05710)	90.52	94.29	96.02	95.86	96.75	96.89	96.99	97.82
Subject 4 (04820)	92.97	97.12	96.70	96.29	98.28	98.14	98.12	98.22
Subject 5 (05675)	96.62	98.10	93.08	96.34	98.18	98.60	96.40	98.08
Subject 6 (05680)	94.31	97.37	95.09	97.68	97.16	97.56	99.22	98.41

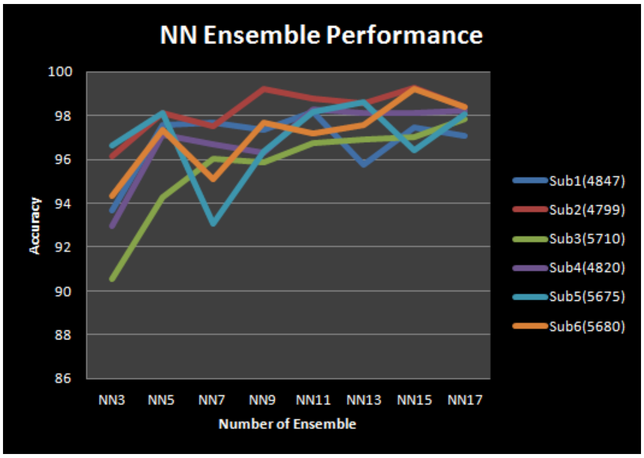


Fig. 10. The NN Ensemble Performance Graph for multiple subjects. The graph shows different ensemble accuracy ranging from NN3 to NN17 for each subject.

NN5, NN7, NN9, NN11, NN13, NN15, and NN17) for each of the six subjects are shown in Table 3. It is observed that the classification accuracy improves up to a specific number of ensembles and beyond which there is no improvement.

The performance graph for the ANN ensemble is shown in Fig. 10. The numbers of ensembles (NN3–NN17) vs. the classification accuracy for each of the six subjects are depicted in the performance graph.

5. Discussion

The confusion matrix and performance value of the proposed method (FI) are listed in Tables 4 and 5. The element of ith row and jth column denotes the classification accuracy belonging to class i are assigned to class j after the classification. The class 'Picture' denotes pictures before sentences, and the class 'Sentence' denotes sentence before picture.

The preceding discussion highlights the potential benefits of the proposed ANN ensemble based on FI for classifying the cognitive states. We had shown that the

Table 4. Confusion Matrix (FI).

Subject		Predicted: Picture	Predicted: Sentence
Subject 1 (04847)	Picture	229 (TP)	6 (FP)
	Sentence	21 (FN)	171 (TN)
Subject 2 (04799)	Picture	199 (TP)	1 (FP)
	Sentence	15 (FN)	199 (TN)
Subject 3 (05710)	Picture	190 (TP)	1 (FP)
	Sentence	15 (FN)	199 (TN)
Subject 4 (04820)	Picture	229 (TP)	6 (FP)
	Sentence	24 (FN)	168 (TN)
Subject 5 (05675)	Picture	201 (TP)	8 (FP)
	Sentence	7 (FN)	228 (TN)
Subject 6 (05680)	Picture	340 (TP)	27 (FP)
	Sentence	12 (FN)	307 (TN)

Table 5. Performance value (FI).

Subject	Sensitivity (%)	Specificity (%)	Accuracy (%)
Subject 1 (04847)	57.25	96.61	93.67
Subject 2 (04799)	50	99.5	96.13
Subject 3 (05710)	46.22	88.04	90.52
Subject 4 (04820)	57.68	96.55	92.97
Subject 5 (05675)	46.85	96.61	96.62
Subject 6 (05680)	52.55	91.91	94.31

performance of the ensemble method was reliable (c.f., Table 2) supporting the efficiency of the ensemble technique as compared with the individual classifiers. We analyzed a range of ANNs vs. the classification accuracy (c.f., Fig. 10). In particular, the trend clearly illustrates that increasing the ANN may not improve the classification accuracy beyond a threshold. Hence, identifying an optimal number of ANNs for an ensemble can be considered as an optimization problem. In view of this, the impact of the number of ANNs in an ensemble vs. classification accuracy can be a further extension of this work. Moreover, combining different types of machine-learning classifiers in an ensemble for cognitive state classification through the fMRI data improves classification if the component classifiers perform better than chance.

The method we proposed can be further extended to different types of cognitive states. In conclusion, the ensemble approach combines the strength of each classifier to improve the performance as compared to single classifier. The classification tools have several important strengths that can advance neuroscience research. Nonetheless, ensemble learning also pose certain challenges that must be acknowledged to fully harness their potential as the best possible classifier.

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