Hybrid Deep Learning Approach for Classifying Alzheimer Disease Based on Multimodal Data

Arifa Shikalgar and Shefali Sonavane

Abstract Alzheimer's disease (AD) is a category of dementia that is difficult to identify under clinical supervision. Currently, there is no remedy for AD, but its initial indication is essential for effective treatment. AD causes memory, thinking, and hence behavior problems. AD symptoms usually develop gradually and become worse from time to time, which can interfere with daily activities. Traditional machine learning algorithms do AD classification usually based on only single input that is the brain's magnetic resonance imaging (MRI) inspection. The proposed hybrid deep neural network classifies according to multimodal data in the form of MRI images and EEG signals. The hybrid method is to model the behavior of the time-watch and use the model to select the most interesting features from multimodal data. The key objective of this method is to enhance learning procedure in which the weight factor of DNN is incorporated with CNN for dealing with multimodal heterogeneous information. This paper describes the study related to how the hybrid classifier's accuracy depends on (the number of features). As the number of features increase, the classification error decreases resulting in improving the accuracy of the classifier. Furthermore, other more traditional methods based on correlation measures and mutual information are also compared with the proposed approach. Experimental results show that the proposed approach categorization accuracy is better than other classification methods.

Keywords Alzheimer's disease (AD) · Deep neural network (DNN) · Multimodal data

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1 Introduction

Dementia syndrome is a brain disorder that causes people to have problems with various activities like remembering events, progressive memory loss, orientation, language understanding, and judgment. Alzheimer's disease (AD) is a very real case of dementedness that affects 65-year-old people and increases with their age. While estimating the scanned-based manual guidance and visual readings, the initial detection for AD is still a challenge. To diagnose AD various machine learning methods and computer aided diagnostic (CAD) systems have been proposed [1]. However, there work on only biomedical image data like MRI (magnetic resonance imaging) and PET (positron emission tomography). Biomedical data assumes in various structures, for example, image, signal and video concerning the highlights of data [2].

A machine learning approach works in four phases as data organization, learning, modeling, and estimation. All machine learning mechanisms required domain experts for transforming raw data into suitable internal representation [3]. In machine learning field, a lot of learning algorithms invented in terms of classification and clustering. Initially, such machine learning algorithms were used to work on a standalone machine [4]. But the need for faster computing and reliability gave birth to distributed computing and frameworks [5]. These frameworks deal with greater volumes of information effectively and in a variety of data dimensions. Deep learning is a mathematical model and type of the machine learning method in which the representations are learned from raw data. The deep and conventional networks (ANN) differ in terms of hidden layers, connections, and ability to learn appropriate observations from the input [6].

Mostly classifier's accuracy depends on what is the input's dimensions. Dimensions are the number of features. The commonly employed data-driven models predict one-dimensional patterns. There are lots of studies which focuses on dimension reduction. Most of them have concentrated on homogeneous data and proven to be expensive for large-scale input data [7].

From clinical datasets most of data are high dimensional and multimodal in nature, like Alzheimer's disease neuroimaging initiative (ADNI) databank and genome data. In such data, the amount of features are usually bigger than the amount of samples available. But the old methods of machine learning are based on a single-modal input samples. They can work only on single dimension data and predict discrete output in classification and regression. Entire data of single pattern has given at a time to machine learning algorithm. Current machine learning algorithm works on only single or bimodal data. Hence, there is need for machine algorithm which can work on such biomedical multimodal high dimensional data.

This study focuses on comparing various deep learning techniques for handling multimodal data. Two forms of data inputs are used for experimentation. One form of input data is MRI image and the other is EEG signal.

2 Literature Survey

For early Alzheimer's diagnose Agarwal et al. [8] uses visual image parity. This improves the performance of the users' feedback for the purpose of classification. Wu et al. (2016) evaluated a nonstop gesturer perception by hypothesizing a deep powerful neural network on multimodal data which is fused with various parameters, for example, image, RGB-D(depth data), and its fundamental qualities [9]. The required data is separated from the data by utilizing deep neural networks [10]. The model fuses different component learning methods, for example, deep conviction and 3D convolution neural networks for multimodal input data for preparing basic highlights and RGB-D data. Kan et al. (2016) as curtained the advancement of a multitier discriminate investigation process for object recognition from multiple views [11]. He formulated a generalized Rayleigh quotient leading to a systematic solution and obtained better results during heterogeneous face recognition.

Yu et al. (2016) exploited both chromatic features and click features in DML. He proposed a Deep-MDML strategy in cooperating a basic structural ranking model [12]. Also, ideal weights concerning various modalities appointed by Qi et al. (2016) to embrace a novel MDML approach with gradient advancement [13]. Varol et al. (2017) introduced heterogeneity through discriminative analysis (HYDRA) to distinct two groups by developing a nonlinear classification margin [14]. The nonlinear classification boundary was built using multiple linear hyperplanes. The performance of the method was evaluated to structural imaging and genetic. This revealed the subtypes that were consistent with the existing neurodegeneration and function of SNPs. Chen et al. proposed a hyperspectral data classification method by using extracted deep features [15]. The AE extracted features are used for classification purpose. It is found that deep-learning-based classification of hyperspectral facts increases the accuracy of SVM and logistic regression. Also in terms of accuracy it performs best than PCA, KPCA, etc. This research also suggests that higher classification can be achieved with deeper features. Training time consumed is high, but it is more faster than the other methods such as SVM or KN [15]. Further, the deep learning method is compared with the prediction techniques and existing feature extraction methods. The results suggested that deep learning methods improve the analytical performance.

3 Research Methodology

In the exploration, the different multimodality concepts are utilized for data analytics. For experimentation, dataset is considered as magnetic reverberation imaging (MRI) images which are taken from ADNI (Alzheimer's Disease Neuroimaging Initiative) and electroencephalography (EEG) flag. Two types of data undergo with pre-handling stage in which the MRI image gets preprocessed by using median filter and EEG by applying Gaussian filter. This Gaussian filter is preferred for EEG signal because of the nearness of Gaussian disorder in EEG signals. The pre-handled data experiences through component extraction with the guide of gray level co-event matrix (GLCM) method. Following to include extraction, the grouping happens in which ANN, CNN, and DNN strategies are tested to structure different types of contributions to a solitary arrangement.

Further, to achieve upgraded yields, coordinated model of arrangement procedures, for example, CNN and DNN is created. The propelled model of coordinated grouping is inferred by utilizing relapse examination. Fine-tuning and improvement approach influences the progressed incorporated model to beat than the individual order approach. In this stage, the parameters, for example, the time required for preparing data, data size, handling result, accuracy, precision, recall, exactness arrangement, dimensionality reduction ratio, and execution with switch entropy is then dissected. Figure 1 demonstrates the block diagram of the proposed hybrid approach.

3.1 Data Acquisition and Preprocessing Phase

The neuroimaging data used in this study is acquired from the database of the ADNI [https://adni.loni.ucla.edu]. The datasets include MRI images in axial plane with 256×256 plane resolution. EEG of AD patient's dataset is referred from R. Polikar Rowan University (Fig. 2).

A median filtering is a nonlinear process which is used in minimizing the impulsive noise. This method is used to preserve the edges of an image. The window slides along the image and intensity value becomes the output intensity of the pixel which is being processed. When the EEG signal is transmitted, white Gaussian noise may occur. Hence, Gaussian filtering is used to describe a probability distribution for the noise. The Gaussian filtering distribution in 1D is given as

$$G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{z^2}{2\sigma^2}} \tag{1}$$

In which, σ represents the standard deviation of the distribution.

3.2 Feature Extraction

Gray level co-occurrence matrix is used to extract the texture properties of an image. The image properties such as regularity, coarseness, and smoothness are evaluated by the texture descriptors. The relative positions of the pixels of an image are to be considered in the GLCM technique. Specifically, a co-occurrence matrix can be

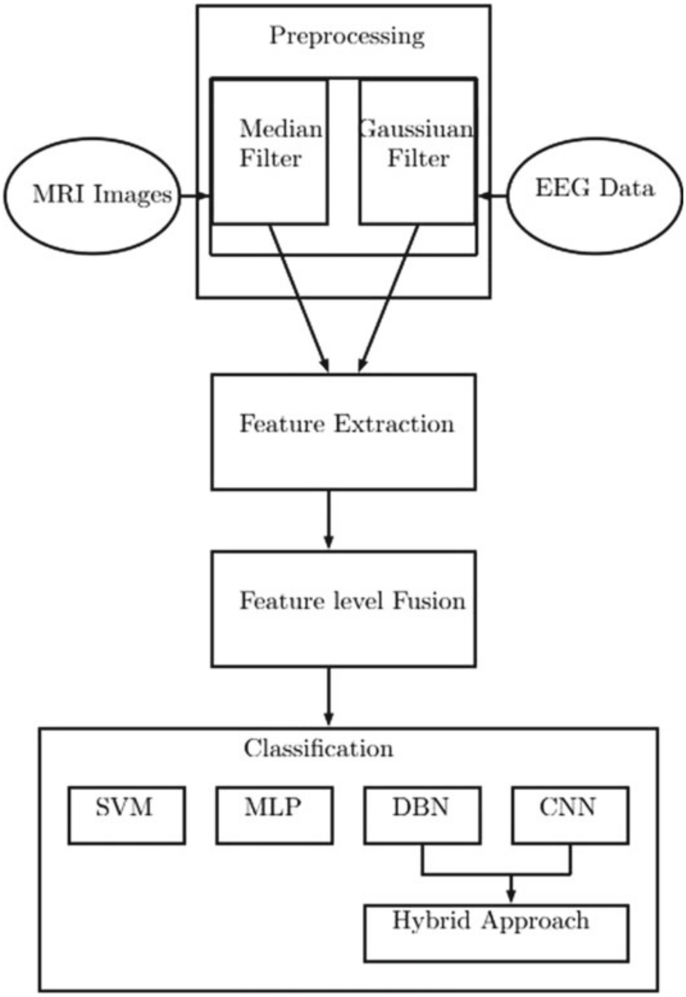

Fig. 1 Proposed hybrid method

evaluated from an original image by a specific relative position and a certain gray level. The gray level co-occurrence matrix can be given by as

$$g(i,j) = \sum_{x=1}^{m} \sum_{y=1}^{n} \begin{Bmatrix} 1 \ \mathit{if} \ \mathrm{f(x,y) = i \, and \, f(x + \Delta x, y + \Delta y) = j} \\ 0 \qquad \qquad \mathit{otherwise} \end{Bmatrix} \tag{2}$$

$$p(i,j) = g(i,j) / \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} g(i,j) \tag{3}$$

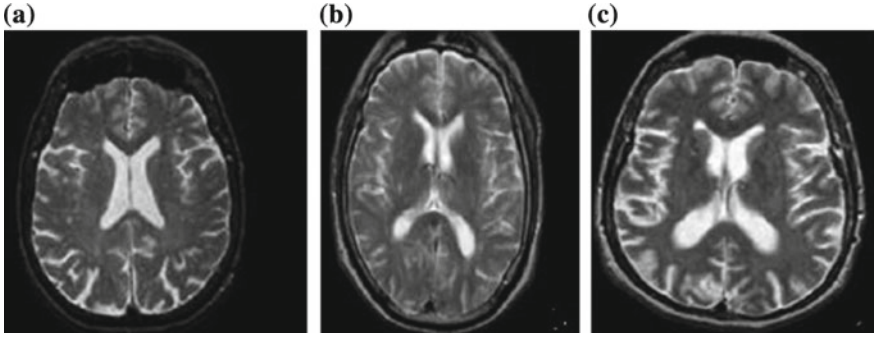

Fig. 2 **a** Normal brain MRI images; **b** Alzheimer's disease; **c** Alzheimer's Disease + visual agnosia

where, g(i, j) is the element of gray level co-occurrence matrix, f is the original image, Q is the specific relative position, L is the certain gray level (x, y), and (x + Δx, y + Δy) the location of reference pixel along with its neighbor.

3.3 Classification Using Hybrid Deep Learning Approach

In this experimentation to overcome the confinements of multilayer perceptron (MLP), convolutional neural network (CNN), and deep belief networks (DBN) such as stuck in local minima, variation in weight factors in each iteration, tedious training process due to contrastive divergence, and Gibbs sampling, respectively. The hybrid deep learning approach is incorporated for handling multimodal data. In this model of CNN and DBN that is deep convolutional neural network (HDCNN) utilizes the weight factor offering to the two convolutional layers. One of the yield mixes of the coordinated model is given in Fig. 3.

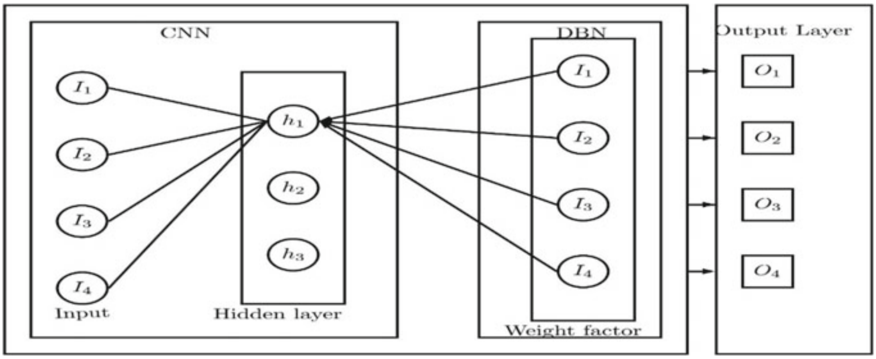

Fig. 3 Hybrid model

The model is fed with feature maps extracted by DBN and its weight factors are shared to CNN.

3.4 Mathematical Model of Hybrid CNN-DNN

$$\text{Let Input,}\ \ i_p = \{i_{p1}, i_{p2}, i_{p3}, \ldots, i_{px}\} \tag{4}$$

$$\text{Hidden layer} = \{h_1, h_2, \ldots., h_x\} \tag{5}$$

Weight can be calculated as

$$Weight = \sum_{i=0}^{n} (x_i y_i h_i) \otimes (x_{i+1} y_{i+1} h_{i+1}) \tag{6}$$

DNN weights are shared with CNN for each input with each layer and can be written as

$$\begin{aligned} Weight = \sum_{i=0}^{n} & (x_1 y_1 h_1)_{CNN} * (x_1 y_1 h_1)_{DNN} + (x_2 y_2 h_1)_{CNN} \\ & * (x_2 y_2 h_1)_{DNN} + \cdots + (x_n y_n h_n)_{CNN} * (x_2 y_2 h_n)_{DNN.} \end{aligned} \tag{7}$$

$$O_p = \{h_1(O_p) * i_p\} \tag{8}$$

$$\begin{aligned} Output = \sum_{i=0}^{n} & (x_1 y_1 h_1)_{CNN} + (x_1 y_1 h_1)_{DNN} * w_1 + (x_2 y_2 h_1)_{CNN} \\ & + (x_2 y_2 h_1)_{DNN} * w_2 + \cdots + (x_n y_n h_n)_{CNN} + (x_2 y_2 h_n)_{DNN} * w_n \end{aligned} \tag{9}$$

3.5 Experimental Results

In this section, the performance of hybrid deep learning classifier is evaluated and compared with various other techniques like SVM, MLP, CNN, and DBN. The experiments are carried out on the MATLABR2017a platform. The classification is done in four types based on condition like Alzheimer's disease, minor Alzheimer's disease, Huntington's disease, and normal. For doing so, the following performance evaluation metric parameters are used: true positive (α_p), true negative (α_n), false positive (βp), and false negative (β_N).

1. **The Sensitivity (SEN)**: Sensitivity (SEN) is a test which defines probability of disease in the patient. It is known as (Recall) or true positive rate.

$$\mathrm{SEN} = \alpha_p / \left(\alpha_p + F_N\right)$$

2. **The Specificity (SPE)**:

$$\mathrm{SPE} = \alpha_n / (\alpha_n + \beta p)$$

3. **The Accuracy (ACC)**:

$$\mathrm{ACC} = \left(\alpha_n + \alpha_p\right) / \left(\alpha_p + \alpha_n + \beta p + \beta_N\right)$$

4. **The Matthews correlation coefficient (MCC)**: MCC is a measure that balances prediction sensitivity and specificity. Accurate descriptions for accuracy can be calculated with help of mathematics correlation coefficient (MCC) [1] (Table 1 and Fig. 4).

$$MCC = \left\{(\alpha_p * \alpha_n) - (\beta p * \beta N)\right\} / \sqrt{\left\{\left(\alpha_p + \beta p\right) * \left(\alpha_p + \beta_N\right) * (\alpha_n + \beta p) * (\alpha_n + \beta_N)\right\}}$$

Table 1 Performance metrics in percentage of different algorithms on Alzheimer dataset with MR and EEG data

Methods	Accuracy	Sensitivity	Specificity	MCC
SVM	50.45	58.36	87.2	76.8
MLP	53.79	52.14	82.66	81.2
CNN	84.6	84.11	86.98	86.88
DBN	84.5	82.86	83.75	82.05
Hybrid	92.5	90.89	90.67	93.5

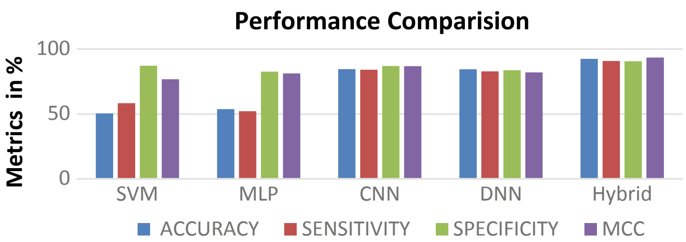

Fig. 4 Performance comparison of hybrid algorithm

4 Conclusion

In this paper, to identify multiclass dementia Alzheimer's disease, a simple and robust classification hybrid deep learning approach is proposed. This approach handles multimodal data (MRI scans and EEG). The execution of a coordinated approach is enhanced on the grounds that the model is fed with feature maps extracted by DBN and its weight factors are imparted to CNN. The features hence derived are utilized for the purpose of training a hybrid approach in order to classify into four classes like Alzheimer's, mild Alzheimer's, Huntington's disease, and normal. Also, the experimental result exhibit that the suggested method offers improved classification accuracy compared to traditional methods like SVM, CNN, and DNN. In the perspective of this work, it is planned to custom optimization techniques for reducing the time and to overcome the overfitting problem.

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