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Quality Analysis of Various Deep Learning Neural Network Classifiers for Alzheimer's Disease Detection

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Abstract: Over the past decade, deep learning has become a powerful machine learning algorithm in the classification of clinical data for human conditions such as Alzheimer's disease which can extract low-to-high-level features. Classification of clinical data for Alzheimer's disease has always been challenging as there is no clinical test for Alzheimer's disease. Doctors diagnose it by conducting assessments of patient's cognitive decline. But its particularly difficult for them to identify Mild Cognitive Impairment (MCI) at an early stage when symptoms are less obvious. Also, it is difficult to predict whether MCI patients will develop Alzheimer's disease or not. The accurate diagnosis of Alzheimer's disease in the early stage is important in order to take preventive measures and to reduce the progression and severity before irreversible brain damages occur. This study gives the performance of different classifiers on deep learning neural network for Alzheimer's disease detection.

Key words: Alzheimer's disease, machine learning, artificial intelligence, computer aided diagnosis, artificial neural network, feature extraction

INTRODUCTION

Alzheimer's disease is a progressive and irreversible neurological brain disorder. It is a disease that slowly destroys brain cells and thereby resulting in memory losses and ultimately loss of the ability to carry out even the simplest tasks. The cognitive decline caused by this syndrome ultimately leads to dementia (Pan *et al*., 2015). It is the most common form of dementia in adults aged 65 and older. The worldwide prevalence of AD was reported 26.6 million in 2006 and is expected to rise to over 100 million by 2050 (Nie *et al*., 2015; Yang *et al*., 2015). The disease begins with mild deterioration and gets progressively worse. Detecting Alzheimer's disease by psychologists requires very careful medical assessments and physical and neurobiological exams.

Deep learning is a machine learning technique that allows computer programs to learn when exposed to new data without being programmed (Jin *et al*., 2014). Researchers have integrated deep learning methods with special techniques that measure the various brain parameters to detect early forms of dementia such as Mild Cognitive Impairment (MCI) (Alzheimer's Association, 2014; Duchesne *et al*., 2009). The automated deep machine learning program is trained to recognize patterns to distinguish among patients with varying levels of cognitive impairment and predict the various stages of Alzheimer's disease (Swarnalatha and Prasad, 2009). The system was able to distinguish effectively among participants with Alzheimer's disease (Stonnington *et al*., 2010). Recently, the researchers are able to successfully predict the Alzheimer's disease progression in patients with a high degree of accuracy using various classifiers in machine learning techniques. Figure 1 shows the difference in the conventional learning algorithms and

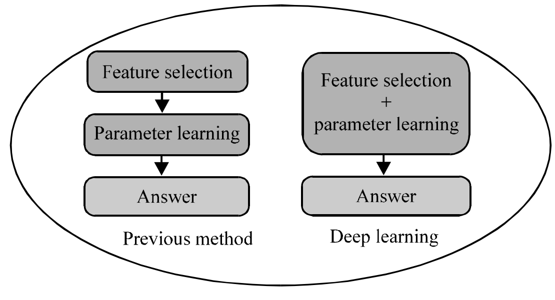

Fig. 1: Difference in the conventional learning algorithms and deep neural network algorithms

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deep neural network algorithms. Machine learning techniques other than deep learning uses various algorithms to parse data, learn from it and make a prediction out of the input data given. So, in order to accomplish a particular task, the system is "trained" using algorithms which provides the ability to learn and perform the task (Zhou *et al*., 2011). Deep learning is a subset of machine learning algorithms which uses cascade chains of different processing units for feature extraction and transformation. Each of the successive layers utilizes the output from the previous layer as inputs (Kumar, 2013). The algorithms used may be supervised for pattern analysis applications and unsupervised for applications includes classifications.

MATERIALS AND METHODS

Various methods of diagnosis of Alzheimer's disease using deep learning

Neural network: In Alzheimer disease, death of brain cells occurs which results in memory loss. Early diagnosis of AD is important for the control of the disease and for preventing the loss of ability to carry out even the simplest tasks. Deep learning is a powerful machine learning algorithm in classification that extracts low-high-level features from MRI images (Yuan *et al*., 2012). The recent deep learning neural network models used for the detection of Alzheimer's disease are as follows.

Voxel based method using classifier ensembles: Armananzas *et al*. (2017) proposed a voxel-based diagnosis of Alzheimer's disease using classifier ensembles. The images were first pre-processed using the statistical parametric mapping toolbox to output individual maps of statistically activated voxels. A fast filter was applied afterwards to select voxels commonly activated across demented and nondemented groups. Four feature ranking selection techniques were embedded into a wrapper scheme using an inner-outer loop for the selection of relevant voxels. The classification accuracy of the proposed method is 97.14%.

Discriminative sparse learning method with relational regularization: Lei *et al*. (2017) proposed a novel discriminative sparse learning method with relational regularization to jointly predict the clinical score and classify AD disease stages using multimodal features. A discriminative learning technique is applied to expand the class specific difference and include geometric information for effective feature selection. The classification accuracy of the proposed method is 94.68%.

Grading biomarker using sparse representation techniques: Tong *et al*. (2017) proposed A novel grading biomarker for the prediction of conversion from mild cognitive impairment to Alzheimer's disease. Using the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, the proposed global grading biomarker achieved an area under the receiver operating characteristic curve (AUC) in the range of 79-81% for the prediction of MCI-AD conversion within three years in tenfold cross validations. The classification AUC further increases to 84-92% when age and cognitive measures are combined with the proposed grading biomarker.

SVM and wavelet transform: Thakare and Pawar (2016) developed Alzheimer disease detection AI system. In this research using wavelet transform four features are extracted and classification is done by support vector machine. It gives an accuracy of 94%.

Shape-constrained regression-forest algorithm and SVM: Zhang *et al*. (2016) proposed a landmark-based feature extraction method based on based on a shape-constrained regression-forest algorithm. The AD classification accuracy is 83.7%.

Multimodal stacked deep polynomial networks: Shi *et al*. (2017a, b) proposed a multimodal neuroimaging feature learning with multimodal stacked deep polynomial networks for diagnosis of Alzheimer's disease. This method provides an accuracy of 97%.

Relationship induced multi-template learning: Liu *et al*. (2016) introduced a relationship induced multi-template learning for diagnosis of Alzheimer's disease and mild cognitive impairment. The classification accuracy is found to be 93.06%.

Voxel-stand-D GM and SVM: Cuingnet *et al*. (2011) proposed an automatic classification of patients with Alzheimer's disease from structural MRI. This method uses voxel-stand-D GM along with SVM classifier. This method gives an accuracy of 88.58%.

ROI GM and SVM: Zhang *et al*. (2011) proposed a multimodal classification of Alzheimer's disease and mild cognitive impairment using ROI GM and SVM classifier. Experimental results provides an accuracy of 86.20%.

ROI-wise cortical thickness measurements and Linear Discriminant Analysis (LDA): Eskildsen *et al*. (2013) introduced a method for prediction of Alzheimer's disease with mild cognitive impairment from the ADNI cohort using patterns of cortical thinning. The classification technique used for this method in linear discriminant analysis. Accuracy rate is found to be 84.50%.

Voxel-wise GM and LDS: Moradi *et al.* (2015) proposed a machine learning framework for early MRI-based Alzheimer's conversion prediction based on Voxel-wise GM and LDS. Experimental results provide an accuracy of 83%.

Cortical thickness and PCA-LDA: Cho *et al.* (2012) proposed an individual subject classification for Alzheimer's disease based on incremental learning using a spatial frequency representation of cortical thickness data. The classification technique used is PCA-LDA which gives an accuracy rate of 82%.

Voxel-wise GM and RVR: Gaser *et al.* (2013) proposed a method for early detection of Alzheimer's disease using Voxel-wise GM and Relevant Vector Regression (RVR) classifier. The accuracy rate is found to be 84.6%.

Tensor-base morphometry and linear regression: Koikkalainen *et al.* (2011) introduced a multi-template tensor-based morphometry for early diagnosis and analysis of Alzheimer's disease. The accuracy rate of this method is 86%.

Multi method analysis using four MR features and LDA: Wolz *et al.* (2011) put forward a multi-method analysis of MRI images using four MR features in early diagnostics of Alzheimer's disease. The classification method used is LDA and it gives an accuracy rate of 89%.

Data-driven ROI GM and SVM: Min *et al.* (2014) proposed a multi-atlas based representations for Alzheimer's disease diagnosis using data-driven ROI GM and SVM classifier. This method provides an accuracy rate of 91%.

Data-driven ROI GM and SVM ensemble: Liu *et al.* (2015c) introduced a view-centralized multi-atlas classification for Alzheimer's disease diagnosis using data-driven ROI GM and SVM ensemble as classifier. The experimental results provides an accuracy rate is 92.51%.

Predictive Markers and SVM: Hinrichs *et al.* (2011) proposed predictive markers for AD in a multi-modality framework which uses SVM classifiers. The accuracy rate is 87.6%.

Ensemble random forests: Gray *et al.* (2013) proposed Random forest-based similarity measures for multi-modal classification of Alzheimer's disease. The accuracy rate determined from experimental results is 89%.

Multimodal DBM and SVM: Suk *et al.* (2014) proposed a Hierarchical feature representation and multimodal fusion with deep learning for AD/MCI diagnosis. The accuracy rate is 95.35%.

MKL: Zhang *et al.* (2011) introduced a multimodal classification method for the detection of Alzheimer's disease and mild cognitive impairment using MKL deep learning technology. The accuracy rate is found to be 93.20%.

SAE: Liu *et al.* (2015a, b) put forward a multi-modal neuroimaging feature learning for multiclass diagnosis of Alzheimer's disease using Stacked Auto Encoders (SAE). The accuracy rate obtained is 91.40%.

SDSAE: Shi *et al.* (2017) proposed a nonlinear feature transformation and deep fusion for Alzheimer's disease staging analysis using SDSAE. The accuracy rate is 91.95%.

NGF: Tong *et al.* (2017) proposed a multi-modal classification of Alzheimer's disease using Non-linear Graph Fusion (NGF). The accuracy rate obtained is 91.80%.

Dropout-DL: Li *et al.* (2015a) developed a robust deep model for improved classification of AD/MCI patients using Dropout-DL. The accuracy rate is 91.40% (Fig. 2).

Different recent deep learning techniques used for the automatic diagnosis of Alzheimer's disease is shown in (Table 1).

Table 1: Algorithm comparisons-recent deep learning techniques used for the automatic diagnosis of Alzheimer's disease

Machine learning techniques	Researchers	Accuracy (%)
Statistical parametric mapping, Stochastic searches	Armananzas *et al.* (2017)	97.14
SVM, SVC	Lei *et al.* (2017)	94.68
Sparse representation techniques	Tong *et al.* (2017)	92.00
DWT,SVM	Thakare and Pawar (2016)	94.00
Non-linear registration, shape-constrained regression-forest algorithm, SVM	Zhang *et al.* (2016)	83.70
Multi-modal stacked deep polynomial	Shi *et al.* (2017a)	97.00

Table 1: Continue

Machine learning techniques	Researchers	Accuracy (%)
Relationship induced multi-template learning	Liu *et al.* (2016)	93.06
Voxel-stand-D GM,SVM	Cuingnet *et al.* (2011)	88.58
ROI GM,SVM	Zhang *et al.* (2011)	86.20
ROI-wise cortical thickness, LDA	Eskildsen *et al.* (2013)	84.50
Voxel-wise GM,LDS	Moradi *et al.* (2015)	83.00
Cortical thickness, PCA-LDA	Cho *et al.* (2012)	82.00
Voxel-wise GM, RVR	Gaser *et al.* (2013)	84.60
Tensor-base morphometry, linear regression	Koikkalainen *et al.* (2011)	86.00
Four MR features, LDA	Wolz *et al.* (2011)	89.00
Data-driven ROI GM, SVM	Min *et al.* (2014)	91.00
Data-driven ROI GM, SVM ensemble	Liu *et al.* (2015b)	92.51
Predictive Markers, SVM	Hinrichs *et al.* (2011)	87.60
Ensemble Random forests	Gray *et al.* (2013)	89.00
Multimodal DBM, SVM	Suk *et al.* (2014)	95.35
MKL	Zhang *et al.* (2011)	93.20
SAE	Liu *et al.* (2015c)	91.40
SDSAE	Shi *et al.* (2017b)	91.95
NGF	Tong *et al.* (2017)	91.80
Dropout-DL	Li *et al.* (2015)	91.40

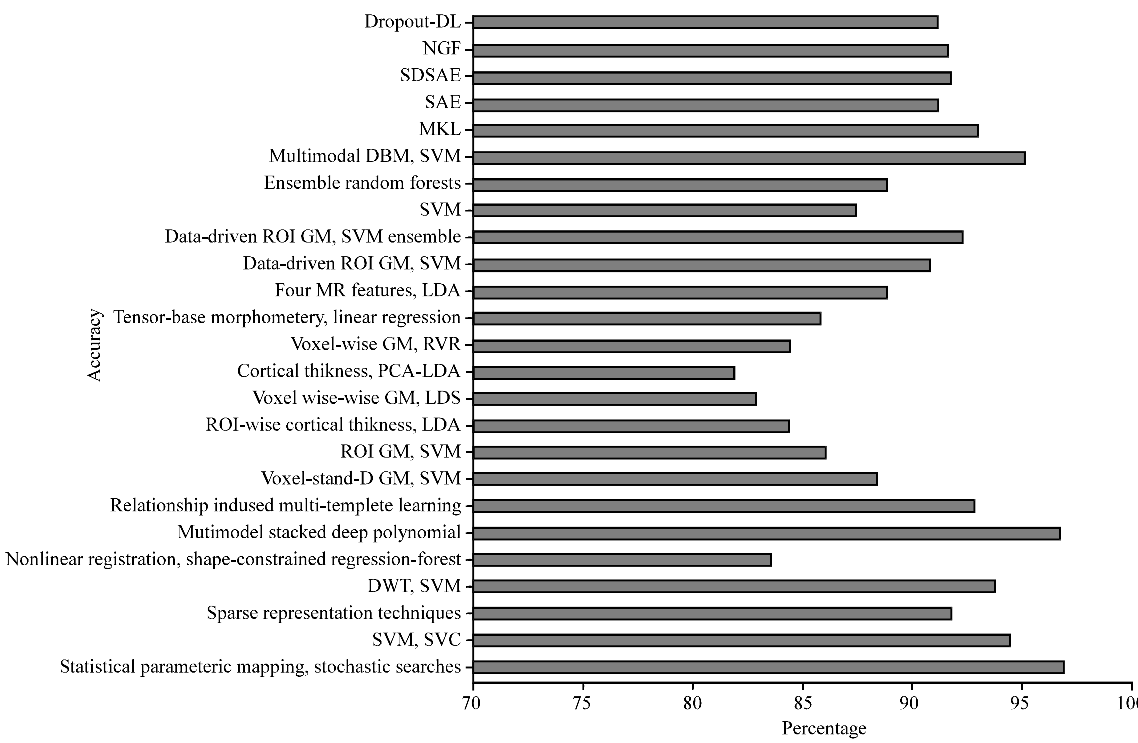

Fig. 2: Represents the plot of accuracy of different deep learning neural networks; accuracy values of different methods

RESULTS AND DISCUSSION

For diagnosis of Alzheimer's disease, several deep machine learning algorithms perform very well. From the study, it is observed that voxel based method using classifier ensembles and statistical parametric mapping for stochastic searches offers highest accuracy rate of 97.14% for Alzheimer's disease diagnosis. The AD classification performance using nonlinear registration of shape-constrained regression-forest algorithm and SVM is approximately 50 times faster than region-based and voxel-based methods. Hence, it can be utilized for large-scale subject indexing or retrieval. The numerical accuracy results support the use of deep machine learning approaches as an important tool to be included in the diagnoses of AD (Martinez-Martin and Avila, 2010; Albu and Stanciu, 2015). In addition to these quantitative approaches, several other types of clinical data are being collected by transnational efforts which aim to develop early Alzheimer diagnosis tools (Risacher and Saykin, 2013). In the long run, all clinical information should be dynamically integrated at the point of care using advanced machine learning approaches.

CONCLUSION

This study provides the comparative analysis of different deep machine learning algorithms for diagnosis of Alzheimer's disease. It brings attention towards the ability of deep machine learning algorithms that are capable for the analysis of diseases and decision-making process accordingly (Liu *et al*., 2015a, b). Many algorithms have shown excellent results because they identify the attributes accurately. From the study, it is observed that voxel based method using classifier ensembles using statistical parametric mapping and stochastic searches offers highest accuracy rate 97.14% for Alzheimer's disease diagnosis. From analysis, it is clear that almost all recent algorithms provide an enhanced accuracy on the decision making process in Alzheimer's disease detection.

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