Performance Analysis of SVM Classification Model for Diagnosis of Alzheimer's Disease

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ABSTRACT
Alzheimer's disease (AD) is a type of Dementia which affects the brain and causes memory loss. It disrupts a person's ability to function independently. In this paper we have considered some measures such as Age, MMSE scores, whole brain volume and endocrinal volume. In our work, we have proposed a classification model using SVM model and anlaysed the performance of SVM model for different kernel methods. Moreover a five fold cross validation approach is used to improve the performance oof the model. The results shows that linear and polynomial kernel methods give a classification accuracy of 73.2% and AUC of 0.7.

Keywords
Alzheimer's Disease (AD), MiniMental State Examination (MMSE), Dementia, Support Vector Machine(SVM)

1. INTRODUCTION
ALZHEIMER's disease (AD) is a neurodegenerative disorder characterized by progressive impairment of memory and other cognitive functions, associated with behavioral disturbances, and progressively leads to total dependency [1]. Identifying the neuroanatomical basis of cognitive impairment in AD is an important research topic because it can help us understand brain structural changes related to cognitive impairment and potentially predict the progression of AD [2-5].

The most common initial symptom is worsening of memory. Memory gets worse over time. The challenge in in AD is early diagnosis of the disease. Early diagnosis will slow and stop the disease.

Studies of structural magnetic resonance imaging (MRI) have shown that the brain undergoes profound age-related neuroanatomic changes during the normal phase of growth and aging. Such MRI studies showed that the amount of global gray matter was decreasing linearly with age, but the regional gray matter had heterogeneous effects on age. The amount of gray matter in the frontal and parietal lobes and some regions of the temporal lobe decreased significantly with age, while some subcortical areas, such as the caudate and the hippocampus, displayed nonlinear trends. More

Specifically, several structural MRI studies found that the brain displayed age-related network-level changes[1]. The default mode network (DMN), for example, exhibited substantial differences in the volumes of gray matter among healthy young, middle aged and older subjects [10]. Throughout recent years, several researchers have been carried out on an early prediction of Alzheimer's disease from MRI images.

2. RELATED WORK
In [7] Zing Wan and Zhilin Zang combine a novel method for grading medial temporal lobe structures with robust cortical thickness measurements to predict AD among subjects with mild cognitive impairment (MCI) from a single T1-weighted MRI scan. A sparse multivariate regression model is used for this task and proposed an empirical sparse Bayesian learning algorithm. Different from existing sparse algorithms, the proposed algorithm models the response as a nonlinear function of the predictors by extending the predictor matrix with block structures.

In [8] Cyrus Raji, James Becker, Owen Thomas Carmichael has done a study on the relation between Age, Brain Structure and Alzheimer's disease. The study showed that the analysis using the entire sample of 202 subjects accurately represents the effects of age on brain structure. Brain atrophy with aging was observed in supratentorial and infratentorial areas. Age and Alzheimer disease exert independent gray matter atrophy patterns, but these effects overlapped substantially in the hippocampus and entorhinal cortex.

IPanagiotaPapapostolou, F Goutsaridou,MArvaniti [9] has done the study on total Brain Volume Correlation to Cognitive Function and Education in Patients with Alzheimer Disease. Volumetric study of the total brain volume by calculating separately grey matter, white matter and CSF was done.

Classification of the patients are made and made the correlation between those with six or fewer years of education and those with twelve or more years of study. Correlating the whole brain volume measurements of patients with Alzheimer disease and the same MMSE but different levels of education showed that there is no significant difference between the total brain volume of the two groups of study.

In[10] Personalized relevance parameterization methods (PReP-AD) based on artificial intelligence computation techniques are introduced to investigate the impact of gene expressions on Alzheimer's disease (AD) progression. PReP-AD methods make use of the expressions of the genes that affect AD-related protein biomarkers, mini mental state examination (MMSE) scores and hippocampal volume measurements. An average error rate of 4.8% with PReP-AD-MMSE over a 72-month period and 1.63% with PReP-AD-HVL over 12 months is observed. Results indicate that artificial intelligence based computation methods can be utilized to build decision support tools for AD progression.

Viraj Adduru, Stefi Baum, Maria Helguera, RaminZand[11] used CT images to detect brain atrophy in Alzheimer's Disease. In this work an automated head CT segmentation method (CTseg) to estimate total brain volume and total

intracranial volume is carried out. When CTseg was applied to a cross-sectional Alzheimer disease dataset (58 with Alzheimer disease patients and 58 matched controls), CTseg detected a loss in percentage total brain volume (as a percentage of total intracranial volume) with age (P , .001) as well as a group difference between patients with Alzheimer disease and controls (P, .01).

In[14] Amira Ben Rabeh, BenzartiFaouzi, Hamid Amiri used support vector Machine to detect the early diagnosis of Alzheimer's disease. The work yielded an accuracy of 90.66%. In this work the authors has done diagnosis using hippocampus,corpus callosum and the cortex section of the brain.

Ramesh Kumar Lama,1,2 Jeonghwan Gwak,1,3 Jeong-Seon Park,4 and Sang-Woong Lee [16] has compared AD diagnosis approaches using structural magnetic resonance (sMR) images to discriminate AD, mild cognitive impairment (MCI), and healthy control (HC) subjects using a support vector machine (SVM), an import vector machine (IVM), and a regularized extreme learning machine (RELM). . The results showed that multiclass classification assisted by RELM is effective compared to the other considered representative classifies.

3. DATA SET DESCRIPTION

The dataset used is longitudinal MRI dataset from Oasis which is also available in Kaggle. It has details of 374 patient details which includes 190 demented records, 37 converted and 146 non-demented records. The dataset includes 160 records of male patients and 213 records of female patients. The dataset also includes records of patients of age 60 to 89 and all having educational qualification varying from 6 years to 23 years. The other data which is taken are normalised whole brain volume, endocrinal brain volume and Atlas scaling factor, MMSE (Mini-Mental State Examination, Clinical Dementia rating .The number of times visit made is also considered. All the records considered here are right-handed.

4. PROPOSED WORK

In the proposed work, SVM algorithm is used to create a classification model. The dataset is first analysed to findout the features that contribute for the diagnosis of the disease.

The selected features are then given as input to the SVM algorithm to build a classification model.

The parameters gamma and C are fine tuned so that the model does not overfit the given dataset.

The performance of SVM classification model for different kernel methods are analysed and a five fold cross validation is done to improve the classification accuracy of the model.

Results are tabulated and performance graph shown in the following sections of this paper.

4.1 Support Vector Machines

Support Vector Machine is a supervised and linear machine learning algorithm used for classification. SVM generates a line that can linearly separate two classes which is determined by margin and support vectors. It has been used in the neuroimaging field and considered as one of the most popular machine learning tools in the neuroscience domain in the last decade. It is a supervised classification algorithm and finds the optimal hyperplane that separates both classes with maximum margin from support vectors during the training phase.

For the testing of new data points, the classifier's decision is based on the estimated hyperplane. For the linearly separable patterns, linear SVM is used.

However, linear SVM cannot guarantee better performance in complex cases with non separable patterns. In such scenario, linear SVM is extended using kernel trick. The input patterns are mapped into a higher dimensional space using linear and nonlinear functions known as kernels. Linear and nonlinear radial basis function (RBF) kernels are widely used SVM kernels.

a)Kernel Methods in SVM

Linear Kernel

It is used when data is linearly separable.

Polynomial kernel

It represents the similarity of vectors in training set of data in a feature space over polynomials of the original variables used in kernel.

The equation is

$$K(x, y) = \tanh(\gamma . x^T y + r)^d , \gamma > 0$$

Gaussian radial basis function (RBF)

Adds radial basis method to improve the transformation.

The equation is

$$k(x_i , x_j) = \exp(-\gamma || xi - xj ||^2)$$

Sigmoid kernel

This kernel function is equivalent to a two-layer, perceptron model of neural network, which is used as activation function for artificial neurons..

Equation is

$$k(x,y) = \tanh(\alpha\, x^T\, y + c)$$

b) Tuning Parameters C and gamma

Tuning the parameters for SVM improves the performance of the model

The parameter C controls the trade off between smooth decision boundary and classifying training points correctly. Larger value of C leads to more intricate decision curve trying to fit in all the points . In this work, various values of C parameter has been tried to avoid overfitting.

The parameter gamma defines the influence of single training example. If the value of gamma is high, then the decision boundary is going to be dependent upon the points which are very close to the line and ignores the point which are far away from the decision boundary which results in a wiggly curve. If the gamma value is low, the far away points get considerable weight and we get a more linear curve.

5. RESULTS

Table1: Performance Analysis of SVM Kernel Methods

Kernel	C	Gamma	Accuracy before cross validation	recall	AuC	5-foldCV
rbf	10	0.001	0.658	0.764	0.668	0.5446
linear	10	0.001	0.763	0.705	0.757	0.732
poly	10	Deg=3	0.763	0.705	0.757	0.732
sigmoid	10	0.001	0.44736	1.0	0.5	0.5446

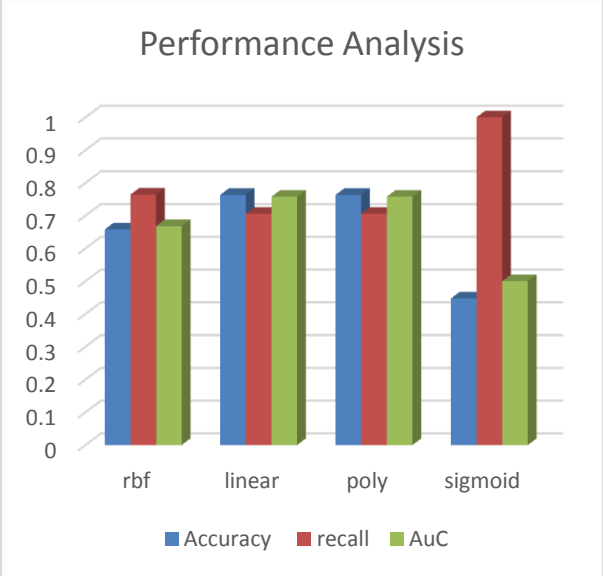

Figure1: Accuracy, Recall and AUC for different SVM kernel

From the results, it is shown that linear and polynomial kernel has given an accuracy of 76.32% before cross validation and with an AUC of 0.7. An AUC >0.5 leads to a good classifier.

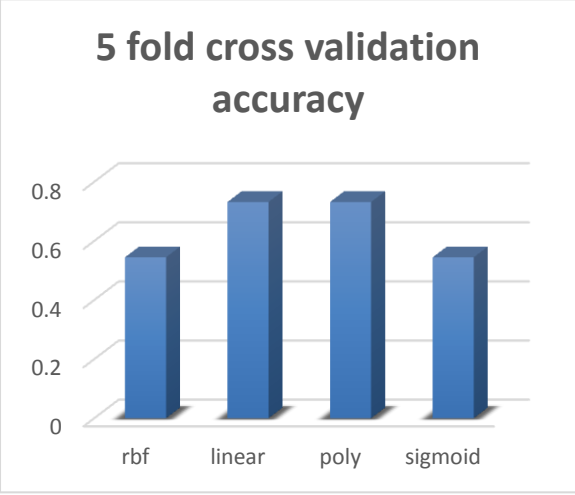

Figure2: Accuracy for different SVM kernel

The 5 fold cross validation results shows an accuracy of 73.20% for both linear and polynomial kernel methods.

6. CONCLUSION

In this paper we have analysed the performance of different kernel methods of SVM by tuning the parameters of gamma and C. We have also applied five fold cross validation technique to improve the performance of the model. In the future work, we propose an ensemble method for classification which will improve the classification accuracy.

7. REFERENCES

[1] G. McKhann et al., "Clinical diagnosis of Alzheimer's disease: Report of the NINCDS-ADRDA work group under the auspices of Department of Health and Human Services task force on Alzheimer's disease,"

[2] Neurology, vol. 34, no. 7, pp. 939–939, 1984.humanbrainsNeuroimage. (2001) 14:21–36. 10.1006/nimg.2001.0786

[3] Valizadeh S, Hänggi J, Mérillat S, Jäncke L. Age prediction on the basis of brain anatomical measures. Hum Brain Mapp. (2017) 38:997–1008. 10.1002/hbm.23434

[4] Fjell AM, Westlye LT, Amlien I, Espeseth T, Reinvang I, Raz N, et al. . High consistency of regional cortical thinning in aging across multiplesamples. CerebCortex. (2009) 19:2001–12. 10.1093/cercor/bhn232

[5] Lin L, Jin C, Fu Z, Zhang B, Bin G, Wu S. Predicting healthy older adult's brain age based on structural connectivity networks using artificial neural networks. Comput Methods ProgramsBiomed. (2016) 125:8–17. 10.1016/j.cmpb.2015.11.012

[6] Nagesh Adluru, Cole H. Korponay, Derek L. Norton, Robin I. Goldman & Richard J. Davidson (2020): BrainAGE and regional volumetric analysis of a Buddhist monk: a longitudinal MRI case study, Neurocase

[7] Jing Wan, Zhilin Zhang, Bhaskar D. Ra ,Shiaofen Fang, Jingwen Yan, Andrew J. Saykin, Li She ,"Identifying the Neuroanatomical Basis of Cognitive Impairment in Alzheimer's Disease by Correlation and Nonlinearity-Aware Sparse Bayesian Learning", IEEE Transactions On Medical Imaging, Vol. 33, No. 7, July 2014

[8] Cyrus Raji, James Becker,Owen Thomas Carmichael,"Age, Alzheimers Disease and Brain Structure", Article in Neurology · October 2009, DOI: 10.1212/WNL.0b013e3181c3f293,Source: PubMed

[9] Panagiota Papapostolou, F Goutsaridou, M Arvaniti," Is Total Brain Volume Correlated to Cognitive Function and Education in Patients with Alzheimer Disease?" Volume: 21 issue: 4, page(s): 500-504 DOI: 10.1177/197140090802100405

[10] Aydin Saribudak, Adarsha A Subick, Na Hyun Kim, Joshua A Rutta, M UmitUyar, "Gene Expressions, Hippocampal Volume Loss, and MMSE Scores in Computation of Progression and Pharmacologic Therapy Effects for Alzheimer's Disease" IEEE/ACM Trans Comput Biol Bioinformdoi: 10.1109/TCBB.2018.2870363. Epub 2018 Sep 14.

[11] VirajAdduru, Stefi Baum, Maria Helguera, RaminZand ," A Method to Estimate Brain Volume from Head CT Images and Application to Detect Brain Atrophy in Alzheimer Disease", American Journal of Neuroradiology · January 2020, DOI: 10.3174/ajnr.A6402

[12] C. Plant et al., "Automated detection of brain atrophy atterns based on MRI for the prediction of Alzheimer's disease," Neuroimage, vol. 50, no. 1, pp. 162–174, 2010.

[13] M. Radanovic et al., "White matter abnormalities associated with Alzheimer's disease and mild cognitive impairment: A critical review of MRI studies," Expert Rev. Neurotherapeut., vol. 13, no. 5, pp. 483–493, 2013.

[14] A. Chincarini et al., "Alzheimers disease markers from structural MRI and FDG-PET brain images," Eur. Phys. J. Plus, vol. 127, no. 11, pp.1–16, 2012.

[15] Amira Ben Rabeh, BenzartiFaouzi, Hamid Amiri"Diagnosis of Alzheimer Diseases in Early Step Using SVM (Support Vector Machine)" 13th International Conference on Computer Graphics, Imaging and Visualization (CGiV), DOI 10.1109/CGiV.2016.76.

[16] Ramesh Kumar Lama,1,2 Jeonghwan Gwak,1,3 Jeong-Seon Park,4 and Sang-WoongLee ," Diagnosis of Alzheimer's Disease Based on Structural MRI Images Using a Regularized Extreme Learning Machine and PCA Features" Hindawi Journal of Healthcare Engineering Volume 2017, Article ID 5485080, 11 pages https://doi.org/10.1155/2017/5485080.