Classification Techniques to Enhance the Performance in Diagnosis of Alzheimer's Disease

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Abstract

A novel method is proposed for the Alzheimer's Disease (AD) conversion. Various relevant parameters are analyzed based on the feature selection, age factor, accurate prediction and the amount of training data. In accordance with the analysis of the above parameters, method. The proposed ADNI dataset achieves an area in global grading. The classification improves when age and cognitive methods are combined with proposed grading. Finally, the architectures classifying Pap Smear Images into broader classes that will define the exact precancerous stages could be developed for better clarity in medical diagnosis. The K-SVM classifier gives better accuracy of 96% than the other existing classifiers when compared to other models.

Keywords: *Alzheimer's disease, Classification*

1. Introduction

Recent years, health problems associated to aging population are facing most critical issues. However, elderly persons are becoming at high risk of those issues. In worldwide, forty million above people alive with dementia, randomly and moreover this prediction is to increase in double by 2050 [1]. ALZHEIMER’s disease (AD) which is a kind of brain disease for elderly people who have symptoms consist of difficulties with thinking, memory loss, problem-solving, and completely affect the quality of patient’s daily life. Early diagnosis is mandatory for accurate treatment and significant reduction. There are no medications available for the AD but for reducing a few symptoms like cognitive issues and memory loss with some drugs. However, the early detection of Alzheimer’s disease is demanding task. It will provide solutions by continuous clinical examinations.

For the past several decades, various imaging modalities such as Positron Emission Tomography (PET), Diffusion Tensor Imaging (DTI), Single Photon Emission Computed Tomography (SPECT), Structural Magnetic Resonance Imaging (MRI), and also Diffusion Tensor Imaging (DTI) have been developed for the diagnosis of AD. The prediction of AD is possible with the help of Magnetic Resonance Imaging (MRI) [4] which is used most extensively when compared to other methodologies for monitoring brain activity and detection of brain disease. Patient who has affected by AD will get abnormal structures include widen ventricle, cortical atrophy and etc., in the brain. Those structural changes have been easily captured by the MRI. Several investigations have been conducted for the amygdale, hippocampus and entorihinal to AD pathology.

Several studies have been carried out for Computer-Aided Diagnosis (CAD) systems through machine learning concepts to predict AD from MRI modality scans. Though, many problems are there for several applications and development of CAD as well. Data set is the significant thing in the AD diagnosis research. Some prestigious institutions and associations have their own data sets. They planned to share their data to the AD research diagnosis, such as the Alzheimer's disease Neuroimaging Initiative (ADNI) [4]. Automatic AD Diagnosis: (CAD tool types) Statistical Parametric Mapping (SPM) is a tool which is used for neuroscience which compares multiple images. Regions of Interest (ROIs) is also an important analysis for automatic AD detection in brain functions such as hippocampus, entorhinal cortex, or neocortex. ROI is classified as based on the number of ROI as follows. 1. Single ROI methods and 2. Multiple ROIs methods. In order to obtain hippocampus, Chupin et al. [13] proposed a method with segmentation which compares the volumes of hippocampal to automatically among AD, HC and MCI subjects.

The important features of hippocampus visual and volume of Cerebro Spinal Fluid (CSF) Alzheimer's disease diagnosis by Ahmed et al., Magnin et al. have proposed 90 ROIs to differentiate among AD and HC subjects for representing entire brain features through general template. Moreover, 83 ROIs are used to represent the features of whole brain in [8]. Multiple ROIs methods are used for most of the techniques, since brain structural abnormal ailments like AD may not take place using single ROI. Moreover, disease level induced in the brain not only because of structural changes, but also the relationship between the ROIs. Consequently, the connection changes are more proficient to distinguish among AD, MCI and HC.

2. Literature Review

Brain analysis have been carried out in [5] for Automatic AD diagnosis by the following methods: 1. Deformation-Based Morphometry (DBM) 2. Voxel-Based Morphometry (VBM) (TBM) and 3. Tensor-Based Morphometry.

DBM method is suitable for identifying the different shapes of individual brain structures. For measuring the differences between brain structures TBM is opted. Comparison of brain images based on voxel basis occurred in VBM. In order to diagnose AD in mild cognitive impairment, [6] has developed a DBM multivariate method. Hua et al. [7] introduced TBM method for exemplifying brain images in diseases like AD and MCI. Nowadays, research based on brain morphometric analysis focuses on single template as the standard space for comparing different brains. Multi template method attains minimum registration error when compared to the Single template based methods.

Inherent Structure Based Multi-View Learning (ISML) classification method [2] aimed at Alzheimer's disease which includes multi-view feature extraction through template selection and feature extraction along with feature selection-sub-class clustering to exclude the redundancy features, and SVM-based Classification. Feature selection can be done with the following models: 1. Wrapper to 2. Filter to attain maximum relevance. and 3. Embedded preferred for improving performance when compared to filter and wrapper models. In order to select features for the Alzheimer's diseases two filter and one wrapper models preferred in [5]. Many researches have been carried out for the feature selection models like Sparse Multi-Task Learning and Sparse Multi-Task Learning with Subspace Regularization.

This proposed design was erudite the dataset by means of the classifiers such as Linear and BRF kernel support Vector Machine (SVM), Linear Discriminant Analysis (LDA) and K-Nearest Neighbors (KNN) [10-13]. Comparison of classifiers based on accuracy also carried out in this paper. The generation of multiple ROIs [8] to disclose the differences of anatomical structures against the other diseases of various patients. This method focused on whole brain hierarchical network (WBHN) in which the whole brain of each subject is subdivided with reference to Automated Anatomical Labeling (AAL) as 90, 54, 14 and 1 parts. Link between each pair of parts is calculated using Pearsons correlation coefficient. The classification algorithm used in this method is multiple kernel boosting (MKBoost) to improve the accuracy. A method [9] explained about modified subspace alignment along with small sample datasets for enhancing the accuracy. Cloud computing for wearable devices are discussed in [5].

3. Deep learning for Alzheimer's disease

Deep Learning is a new technique that recently has been experiencing an explosive growth as computers have gotten faster. More and more fields of research incorporate Deep Learning in their solutions and the set of problems solvable with Deep Learning has only recently started to be explored. Thus, aside from trying to create a finished product in the form of a diagnostic tool, the project is meant as a learning process to prepare us for working with Deep Learning in the future and to investigate how the process of solving this task would progress and what pitfalls one might encounter along the way.

A neural network is a structure which takes in data points and performs some non-linear transformation as to produce an output. A Deep Neural Network (DNN) is composed of several hidden layers, the more layers the deeper the network. There are many different types of layers which differ in the transformations they exert on the data.

Due to compression of images, ROIs extraction provides huge information loss. Researchers investigate tissue density measurement methods include cerebrospinal fluid, white matter and grey matter for feature acquisition. Though, brain image volumes have a large amount of voxels, while considering the minimum samples. Therefore, the over-fitting problem can arise. The aim of our project is to work on the above limitations and improve the performance and accuracy of Pap smear screening exploiting the powers of deep learning.

Conventional machine learning techniques depend on manual feature extraction, which based on time taken, proficient knowledge and repetitive efforts. In order to address this issues, convolutional neural networks (CNNs) are used for extensive solution. In image classification one type of layer that has proven to be very efficient is called a Convolutional layer.

Networks made up of several convolutional layers are referred to as a Convolutional Neural Network or in short CNN. However, those researches were incapable for a deep 3D-CNN framework, like VGG, ever since this is more complex to attain a large number of data. Therefore, 3D-CNN models are chosen. Genctav proposed an unsupervised approach to partition Pap smear cells from datasets of Herlev and Hacettepe Pap smear. This approach can also deal with images comprises a single cell along with overlapping cells. The two stage segmentation is proposed where first stage undertakes multi-scale hierarchical segmentation method to make segments the cell image into parts depending on circularity and homogeneity.

The morphological operation along with automatic thresholding algorithm splits the cell parts. Second phase uses a binary classifier to differentiate these regions into nucleus and cytoplasm. They used five various types of classifiers to analyse the performance. These classifiers are [3]: Decision tree classifier, Bayesian classifier, Support Vector Machine and combination of above three classifiers using product and sum of individual posterior probabilities.

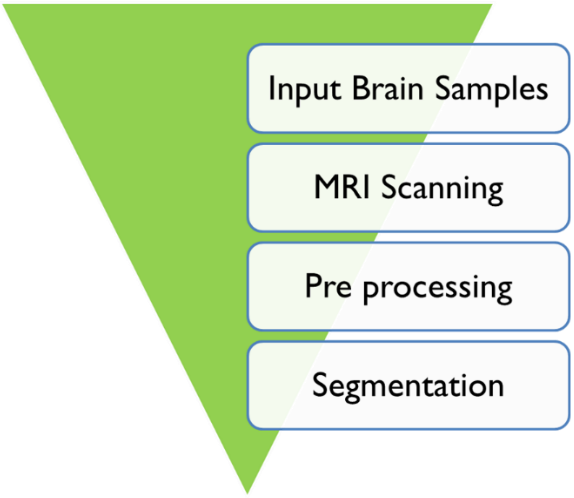

Figure. 1 Processing

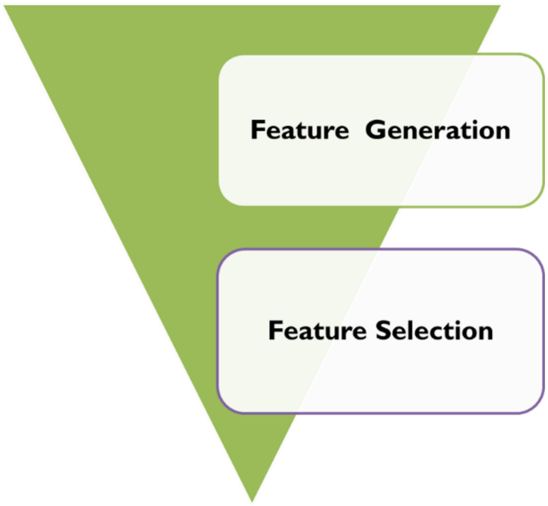

Figure. 2 Feature Generation and Selection

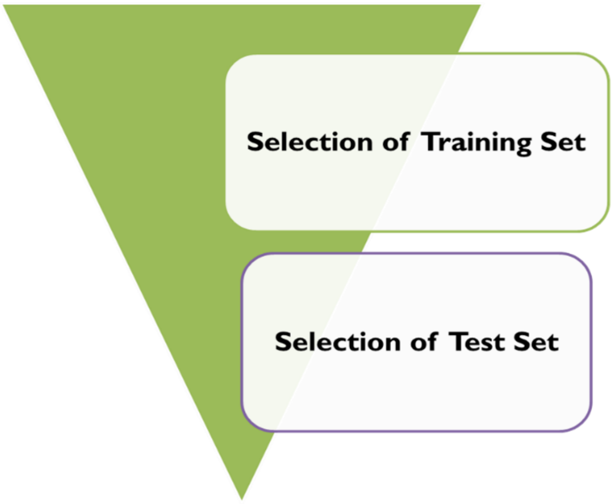

Figure. 3 Segregation of training set and test set

4. Proposed Method

For the feature extraction the following steps to be considered.

a) Background elimination / Binarization: Capture the image changes using thresholding. Thresholding signals "1" where the other pixels belong to "0".

b) Noise Reduction: A filter is used the binary image to eradicate black pixels on background. The black pixels will be higher white pixels, the selected pixels are black.

c) Width Normalization: Brain Image dimensions hold differences. Hence, image measurement is altered to a default value and height will variation on height-to-width ratio.

d) Thinning: It eliminates the unused regions in the image and compression. This technique required to apply by appropriate care, hence it brings sudden alterations to input image.

4.1. Image Segmentation

- A process of segregating a digital image into several sections
- Image segmentation is used to find substances and margins in images.
- Additional accurately, image segmentation is the procedure of assigning a label to every pixel in an image

4.2 Feature Generation

- In order to produce feature comparison dimensions.
- The issue of image verification is extremely complex process.
- So produced one feature in order to improve the precision of output.

Eccentricity is called as the essential part in a thing.

Skewness is a quantity of symmetry, or more exactly, the lack of symmetry.

Kurtosis is a measure of the data compressed, comparative to a usual distribution.

Classification is the method of individual each cell and distributing to that precise size.

4.3 Feature Selection

- Numerous dynamic features of digital images

Segregation of Training and Testing Data

For example, 3 normal brain images/day on a 90 days duration, 6 disguised images/day on a 90 days duration were collected.

5. Results and Discussions

The simulation results in terms of performance for SVM, ANN and KNN are obtained. K-kNN method is less in its performance in terms of accuracy value 93 %. The K-SVM classifier gives better accuracy of 96% than the other existing classifiers. After supervised training and testing, K- SVM was found to have the best accuracy and system performance among the four, for classification algorithms. Performance Comparisons based on Accuracy, SEN., and SPE is stated in Table. 4.

Table. 1 Performance of SVM

S.No	Epochs	Training	Testing
1.	0	0.00	0.50
2.	20	0.40	0.60
3.	40	0.50	0.70
4.	60	0.60	0.75
5.	80	0.65	0.80
6.	100	0.70	0.88
7.	120	0.78	0.90
8.	140	0.85	0.92
9.	160	0.88	0.94
10.	180	0.93	0.96

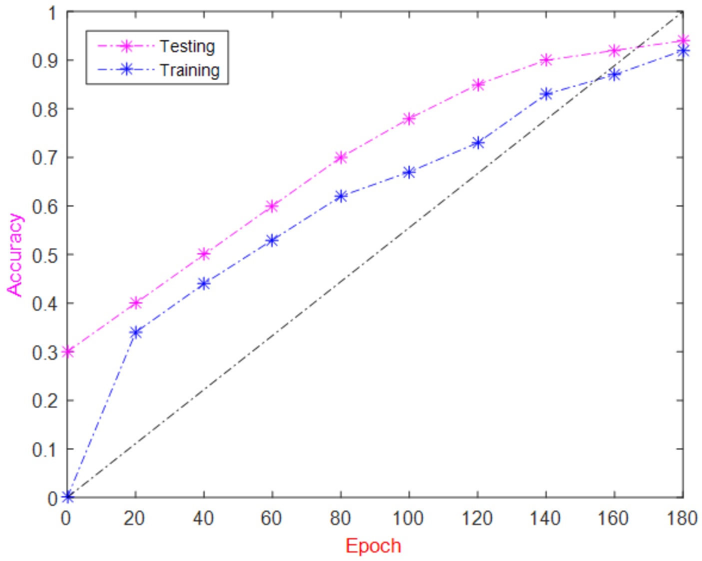

Figure. 4. Performance of SVM in Testing and Training

Table. 2 KNN Performance

S.No	Epochs	Training	Testing
1.	0	0.00	0.00
2.	20	0.30	0.42
3.	40	0.38	0.47
4.	60	0.43	0.55
5.	80	0.54	0.61
6.	100	0.67	0.68
7.	120	0.71	0.75
8.	140	0.83	0.84
9.	160	0.87	0.89
10.	180	0.91	0.93

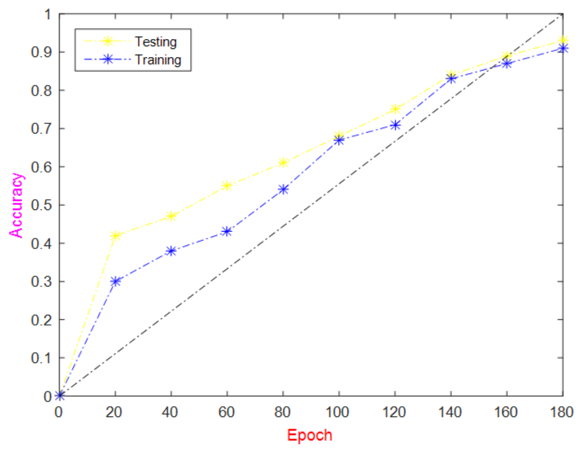

Figure. 5. Performance of KNN in Testing and Training

Table. 3 ANNs Performance

S.No	Epochs	Training	Testing
1.	0	0.00	0.00
2.	20	0.15	0.18
3.	40	0.25	0.29
4.	60	0.37	0.39
5.	80	0.48	0.49
6.	100	0.53	0.54
7.	120	0.56	0.57
8.	140	0.60	0.61
9.	160	0.62	0.63
10.	180	0.64	0.66

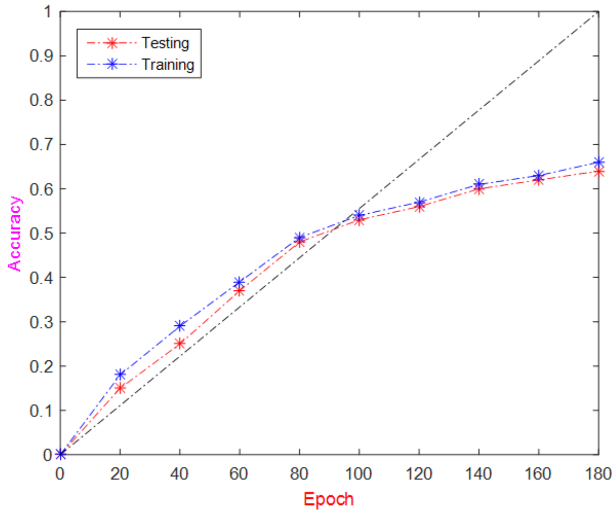

Figure. 6. Performance of ANN in Testing and Training

Table. 4 Performance Comparisons based on Accuracy, SEN., and SPE

S.No	Type	Feature-type	Classifier-method	AC Vs.NC			PMCI vs SMCI		
				Accuracy (%)	SEN (%)	SPE (%)	Accuracy (%)	SEN (%)	SPE (%)
1.	Morphometry [6]	TBM	Linear regression	86. 00	81. 00	91. 00	72. 10	77. 00	71. 00
2.	Multi-method analysis [7]	TBM	Linear discriminant analysis	87. 00	84. 00	90. 00	64. 00	65. 00	62. 00
3.	Multi-atlas based [8]	Data-Driven ROI GM	SVM	91. 64	88. 56	93. 85	72. 41	72. 12	72. 58
4.	Maximum-margin based [9]	Data-Driven ROI GM	SVM	90. 69	87. 56	93. 01	73. 69	76. 44	70. 76
5.	Proposed method	Data-Driven	SVM	**92. 62**	**92. 98**	**88. 35**	**78. 81**	**85. 54**	**76. 09**

6. Conclusion

Despite good accuracy in the classification for the dataset of Herlev, this method misclassifies a few images. Classification accuracy desires to be investigated further broadly in the forthcoming analysis. Subsequently, a screening system is predictable to avoid misclassifying the abnormal cells. Real-time process is complex hence more analysis are required for the results of this work to practice. Finally, CNN architectures classifying Pap Smear Images into broader classes that will define the exact precancerous stages could be developed for better clarity in medical diagnosis. Not only Alzheimer’s diseases screening, deep learning might also provide a new dimension in Automation assisted medical diagnosis of various diseases. An ideal screening system should perfectly classify the cells and the future work is dedicated to improving and achieving a near to ideal screening system. Also, the current experiment was conducted on various images with separate cells.

References

11.1. Journal Article

[1] *M. Prince, E. Albanese, and M. Guerchet, "World Alzheimer Report 2014,"(2014)*

[2] *Liu, Mingxia, Daoqiang Zhang, Ehsan Adeli-Mosabbeb, and Dinggang Shen. "Inherent Structure Based Multi-view Learning with Multitemplate Feature Representation for Alzheimer's Disease Diagnosis", IEEE Transactions on Biomedical Engineering, (2015).*

[3] *Jin Liu, Min Li, Wei Lan, Fang-Xiang Wu, Yi Pan, and Jianxin Wang, "Classification of Alzheimer's Disease Using Whole Brain Hierarchical Network", IEEE/ACM Transactions on Computational Biology and Bioinformatics, (2015), vol. 14, No. 8.*

[4] *Wei Li., Yifei Zhao, Xi Chen, Yang Xiao, Yuanyuan Qin, "Detecting Alzheimer's Disease on Small Dataset: A Knowledge Transfer Perspective", IEEE Journal of Biomedical and Health Informatics.*

[5] *N. Subbulakshmi, R Manimegalai, R.Chandru, "Cloud Computing for Wearable Electronic Devices", International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249 – 8958, Volume-8, Issue-3S, (2019)*

11.2. Conference Proceedings

[1] *Bharti Sharma, Kamaljeet Kaur Mangat. "An improved nucleus segmentation for cervical cell images using FCM clustering and BPNN", 2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI), (2016)*

[2] *"Medical Image Computing and Computer-Assisted Intervention – MICCAI 2009", Springer Science and Business Media LLC (2009)*

[3] *Mingxia Liu, Daoqiang Zhang, Ehsan Adeli-Mosabbeb, and Dinggang Shen, "Inherent Structure Based Multi-view Learning with Multi-template Feature Representation for Alzheimer's Disease Diagnosis, IEEE Transactions on Biomedical Engineering.*

[4] *S. J. Teipel, C. Born, M. Ewers, A. L. Bokde, M. F. Reiser, H.-J. Möller, and H. Hampel, "Multivariate deformation-based analysis of brain atrophy to predict Alzheimer's disease in mild cognitive impairment," Neuro Image, (2007), vol. 38, pp. 13-24.*

[5] *X. Hua, D. P. Hibar, C. R. Ching, C. P. Boyle, P. Rajagopalan, B. A. Gutman, A. D. Leow, A. W. Toga, C. R. Jack Jr, D. Harvey, M. W. Weiner, and P. M. Thompson, "Unbiased tensor-based morphometry: Improved robustness and sample size estimates for Alzheimer's disease clinical trials," NeuroImage, (2013), vol. 66, pp. 648-661.*

[6] *J. Koikkalainen, J. Lötjönen, L. Thurfjell, D. Rueckert, G. Waldemar, and H. Soininen, "Multi-template tensor-based morphometry: Application to analysis of Alzheimer's disease," NeuroImage, (2011), vol. 56, pp. 1134-1144, 2011.*

[7] *R. Wolz, V. Julkunen, J. Koikkalainen, E. Niskanen, D. P. Zhang, D. Rueckert, H. Soininen, J. Lötjönen, and A. s. D. N. Initiative, "Multi-method analysis of MRI images in early diagnostics of Alzheimer's disease," PloS one, (2011), vol. 6, p. e25446.*

[8] *R. Min, G. Wu, J. Cheng, Q. Wang, and D. Shen, "Multi-atlas based representations for Alzheimer's disease diagnosis," Hum Brain Mapp, (2014), vol. 35, pp. 5052-5070.*

[9] *R. Min, G. Wu, and D. Shen, "Maximum-margin based representation learning from multiple atlases for Alzheimer's disease classication," presented at the Medical Image Computing and Computer-Assisted Intervention, Boston, USA, (2014)*