Tensor Based Multi-linear Feature Selection Models to Predict Alzheimer Disease

Sai Sindhuri Nasina[1], Prof. A. Rama Mohan Reddy[2]

[1]Research Scholar, Computer Science and Engineering, Sri Venkateswara University College of Engineering, Tirupati.
[2]Professor,Computer Science and Engineering, S V University College of Engineering, Tirupati, India.

ABSTRACT

Alzheimer's disease is one of the progressing diseases that affect the brain cells cruelly. It triggers nerve cell death and brain tissue loss. It also starts slowly and worsens overtime. The signs of Alzheimer's disease depend on the severity of the condition from person to person. It displays behavioral effects such as poor speech, lack of memory, longer time to complete daily tasks and change of mood and behavior. It cannot be fixed if the condition worsens over time. This means that at the earliest point it should be detected and the patient should be cared with a normal life alone. Deep learning algorithms have wonderful success in detecting complex patterns in vast quantities of high-dimensional medical imaging knowledge over traditional machine learning algorithms. Therefore, a great deal of attention was paid lately to applying profound learning to medical diagnosis. The goal of this investigation is to identify the various phases of Alzheimer's disease from the Magnetic Resonance Imaging (MRI) images by using the Multi-Linear Singular Value Decomposition (MLSVD) and the tensors inspired Multi-Linear Principal Component Analysis (MLPCA) models. An ADNI dataset is experimented and the findings demonstrate that excellent precision has been obtained by the proposed models.

KEYWORDS

Alzheimer's disease, Machine Learning, Disease Prediction, MRI.

INTRODUCTION

In elderly adults, Alzheimer's disease is a condition which is more rapidly progressing, normally slowly beginning and affecting the brains and causing brain cells to die. People with Alzheimer's disease are increasingly losing their thought and ignoring their everyday routines. Often you can't do your daily job and take longer to remember your close family names too. The phases of Alzheimer's disease are cognitive normal (CN), mild cognitive dysfunction (MCI) and dementia (AD). Early Mild Cognitive Disability (EMCI) and Late Mild Cognitive Impairment (LMCI) are respectively called MCI's early and later stages. The MCI is a form of memory loss that occurs previous to AD or other dementia. If the individual always forgets his daily activities, it could mean that the person is influenced by MCI. MCI is likely to affect about 10 to 20 percent of people over 65. As indicated by the National Institute of Aging, about 10 people believed to have MCI amnesia continue the progression of Alzheimer's over a period of seven years. AD will better be handled with daily practice, dietary consumption, and time for family and friends. The prevalent dementia is AD, which causes difficulties in thought, memory and behaviour. Someone with advanced AD may be unable to live alone and may be nervous, unsure and unable to keep in touch with those in society. The risk of the patient surviving from severe AD is lower and therefore must be expected and handled early.

A variety of prediction models have been developed for the diagnosis of Alzheimer disease from MRI pictures using machine learning algorithms in the literature. By extracting the most important high-level features from MRI images, the author of the [1] ranking of various phases of Alzheimer's disease with Support Vector Machine (SVM). Yet function extraction is a challenging process in any machine learning algorithm. The SVM algorithm is dynamic, time-consuming, computationally powerful, and for processing and extracting the image attributes. Authors in [2-4] used the combination of algorithms for prediction of k-means, Random Forest and Area growth. The MRI image cluster was based on the k-means algorithm. The white and gray material was extracted with the Growing algorithm area from the clustered images. The features derived were used to characterize the disease with and sans neuro-anatomical restrictions by the Random Forest algorithm. The author has suggested an algorithm of profound learning using an AD-detected auto-encoder and a softmax output layer to restrict the learning algorithm. The AD and MCI phases of the illness were observed in this proposed method. In [6], the author analyzed the efficiency, by drawing most suitable 3D MRI images for Alzheimer's disease prediction, of the five evolutionary optimizing algorithms, including Particle Swar Optimization, Pattern Search, Bat Algorithm, Simulated Annealing, Genetic

Algorithms. These algorithms were used to achieve near-optimal solutions to large-scale problem optimisation. In [7-17], multiple algorithms of Machine learning were employed for classifying Alzheimer's disease through MRI images in the brain. A basic convolutions neural network pattern with fewer samples in [18-25] and the model is used to rate Alzheimer's disease. In [26], the authors retrieved Fuzzy Medical Picture (FMIR) in order to forecast cancer by integrating Vecto Quantization with fluorescent signatures and fuzzy s-trees.

The results, such as modeling error, a medium square error, and a percentage comparatively error in modeling, are evaluated in [27-28] on a sparsely based basis. Robot teleoperation is a good way to reach dangerous telepresence places. In [29], the authors provided a way to manage immense delays during the teleoperation of a remote operating robot in real time. The proper operation of the machine-learning algorithms requires the domain specialist to derive high-level functions by reducing the data complexities and making derived functions more available to the algorithms of learning. Highly important features affect the efficiency of the diagnostic method in conventional machine learning algorithms. However, it is very difficult to pick the most fitting features from extremely complex data and it takes time to build machine learning algorithms. But, with the domain knowledge not applicable to the complexities of the data, deep learning algorithms automatically choose better functions. This feature allowed us to use profound learning from MRI images to diagnose Alzheimer's disease. The authors have used the FMRIB Software Library (FSL, FMRIB) image processing method for the preprocessing of structural MRI images and deep neural networks for classification in [30-31]. During the preparatory phase various operations were conducted by means of brain removal tool (BET) and FMRIB's Automatic Segmentation Tool(FAST) in the preprocessing phasing stage, such as scalping, brain tissue separation and bias correction.

TENSOR BASED FEATURE SELECTION

Tensors play a major role in the process of image patterns by considering the concept of approximations by varying orders of polynomials. Tensor defines a natural decomposition of homogeneous patterns that leads the connection between the multivariate polynomials and symmetric tensors. Tensors can be written in different forms, for instance multidimensional arrays. Thus tensors are multi-linear objects that express the coefficients of linear combinations in some specific order.

One of the inductive learning concepts is feature selection. The selection of a subset of features from the given list of features is in different ways: 1) by considering an evaluation measure, the subset of features with specified size 2) the smaller size subset features satisfies with certain restriction on the chosen measure and 3) the set with best features among its size and the value of its measure. The main intention of this leaner is to improve the inductive learning process in terms of speed, capacity and representation of the feature patterns. In the concept of image analysis, feature extraction and selection is one key concept for the selection of best features in order to analyze and represent the patterns through the concept of Tensor objects. Numerous traditional approaches exists for the extraction of features in the process of image patterns such as Principal Component Analysis (PCA), Sparse PCA, Kernel PCA and its variants, Singular value decomposition (SVD), Sparse SVD, Kernel SVD and its variants, Discriminant Analysis, matrix factorization techniques, Optimization Techniques like Genetic Algorithm, Ant Colony Optimization (ACO),.. etc. Among these approaches, in the analysis of Tensor features for the classification and recognition, the author has chosen Tensor based Matrix factorization techniques for the extraction and selection of features.

The fundamental concept of Machine Learning is feature selection that identifies most salient features from image patterns, so that the Machine Learning algorithms focuses for the analysis of patterns in view of classification and recognition of the patterns. Feature selection removes the irrelevant features and reduces the dimensionality, increases accuracy and improves the comprehensive results. Author proposes an intuitive approach for feature selection using Tensor based Feature Selection (TFS) for the analysis features through tensor objects using matrix factorization techniques such as Multi-linear Singular Value Decomposition (MLSVD), Nonnegative Matrix Factorization (NMF), Nonnegative Tucker Factorization (NTF), Multi-linear Principal Component Analysis (MPCA) and Principal Tensor Analysis (PTA).

In the field of Computational streams, scalars and vectors hardly exhaust the class of quantities. There is some sort of quantities with more complex structure than scalars and vectors, of an order 2 or higher often called ***Tensors***, whose specifications are more than the concept of magnitude and direction. In the field of Image Processing, the patterns of images can be represented as an order of 2 or higher for the process of segmentation, dimensionality reduction and analysis of image patterns in terms of classification, recognition and matching. In this aspect, traditional approaches can be fitted due to consideration of higher order features from the image patterns. Thus, in order to process such patterns tensor based computational strategies to be considered for image pre-processing, segmentation, classification and analysis and also image matching methods. In this article, tensor based feature extraction and selection methods to be considered for the extraction of best features from the image datasets and then analyze such patterns through supervised learning methods such as nearest neighborhood and SVM classifiers.

The main objective of this article is to develop a tensor based feature selection and classification model to detect the progression of LMCI (i.e., last stage of Alzhemer disease).

RELATED WORK

Huang et coll. developed a random forest architecture focused on nonlinear managed sparse regression to assess a variety of clinical demographic diabetes [14] in order to acknowledge various patient AD groups. In order to determine the causal effects of uncommon non-coding variants for AD, Liu et al. provided a multi-sized simulation model of variants to function to network models[28]. Previtali et al. suggested a new brain RMI scan purpose extraction procedure for patients with AD[41]. The new classification problems algorithm for the CA belonging to T1's weighted T1 texture extraction technique[49] has been implemented by Vaithinathan et al. A alternate axis-based algorithm called the least square projective twin support vector clustering for identification of AD from MRI data has been studied by Richhariya et al. [42]. For AD recognition, Wang et al. demonstrated a spatially sparse feature-based learning technology with union-of-sub-pace representation for MRI data[53].

Some researchers have also investigated AD using multi-model data. Li et al. suggested the use of neuroimaging data sets as a multi-modal supervision system of separating dictionary learning based on a weighted combination for AD diagnostics[21]. To leverage the complementary knowledge among different modal data of AD[48], Tong et al. suggested a non-linear graph-fusion multi-modality classification model. In order to diagnose AD in multimodal medical imaging, Zhangetal et al. proposed a deep learning model using various convolutional neural networks[60]. Hao et al. have researched a new approach for choosing multi-modal neuroimaging functions, consistent metric limitations for the AD diagnosis classifications, which benefit from random forest strategies and multi-kernel vector support machines[11].

Deep learning technologies will embed feature education in the building phase of the model, minimize inadequacy from the features built artificially and also lead to AD prediction[6]. Zhang et al. suggested a new approach for profound learning based on a complicated network, drawing on the ResNeXt, Adam algorithms and benefiting from the technology of community convolution[62]. By using a variety of 3D convolutionary nerve systems and the long-term memory network for AD, Li et al. have provided a 4D deep learning architecture. Other AD-related causes have also recently been discussed. In order for physicians to be helpful when formulating diagnosis, Fiscon et al. proposed an approach of classification through supervised learning from the EEG biomedical signals of AD[8]. Zhang et al. have suggested a newnucation and genetic data to establish a new multi-view learning paradigm for AD detection[59]. For the auxiliary diagnosis and treatment of patients with AD, the relationship of the AD to the cerebral vasculature was reviewed [19,25]. In the early diagnosis and updated on the progress of major clinical trials [21], Pais et al. addressed new concepts and difficulties in the early diagnosis of AD. Li et al. studied a multivariable time series classification model through an AD estimation neuronal attention-based, profound learning approach that is useful to patients in the early detection of possible risk of AD[20]. Alberdi et al. performed a study on early AD auxiliary recognition multimodality signals[1]. Zhang et al. introduced a new paradigm called sparse sparse representation of the force and resemblance group which is used to recognize moderate cognitive disability participants and stable controls (i.e., one early stage prior to confirmed DA)[63]. In order to calculate the spatial gradients to assess early stage AD [40], Pan et al. modified the histogram of directed gradient descriptores. On the basis of the above, many conventional machine learning and deep learning approaches were introduced with single-mode ultrasound, text information and multi-modality medical data for AD classification and prediction. Simultaneously, early-diagnosis methods for AD have steadily been attracted and the seriousness of the AD condition has also been studied. Learning from different backgrounds for AD is, however, a minority. In this article, MRI data from MRI data was built from the original MRI data in experiments, and a new clustering approach developed that is consistent over many views. In the next part, we will clarify the methodology for the multi-stage prediction of our proposed CMC model in AD..

PROPOSED TECHNIQUE

Tensor based Feature Selection methods (TFS):

From the observation of traditional feature extraction/selection method SVD decomposition X=UVW, the data(columns) of U are the eigen vectors of the matrix XX^t, whereas the data(rows) of W are the eigen vectors of the matrix X^tX. Eigen vectors are orthogonal and therefore $U^tU=I$ and $WW^t=I$. by applying the dimensionality reduction, the approximation $X = UnVnWn$ is minimizing the matrix representation error $\in= \left\|X - \hat{X}\right\|^2 = trace\left\{\left(X - \hat{X}\right)\left\langle X - \hat{X}\right\rangle^t\right\}$. Genelized version of SVD modifies the orthogonal constraints such that $U^tC_uU=I$ and $WCwW^t=I$, where C_u and C_w are the two constraints matrices. By performing the reduction process, the approximation is the one minimizing $\left\{\in= trace\{Cu\left(X - \hat{X}\right)Cw\left\langle X - \hat{X}\right\rangle^t\right\}$.

Thus, Generalized SVD is a very versatile tool by the consideration of constrain matrices that can be particularized to correspondence analysis. For the analysis of categorical variables (a generalized version of factor analysis), C_u is the relative frequency of the rows of the data matrix, X , and C_u is the relative frequencies of its rows, as in the discriminant analysis and canonical correlation analysis - is a procedure for analyzing two groups of continuous variables and performing simultaneously two dimensionality reductions so that the two new sets of features have maximum cross correlation.

a) Multi-Linear Singular Value Decomposition (MLSVD):

Multi-Linear Singular Value Decomposition (MLSVD)[3] is one of the tensor based decomposition method for generalization of pair-wise symmetric tensors through symmetric eigenvalue decomposition strategy. The concept of MLSVD is an appropriate generalization of the link the row (column) vectors and the right (left) singular values of the matrix. A simple representation of MLSVD is depicted as in figure 4.2. Let T be the tensor of size $I_1 X\ I_2 X\ I_3\ .....X\ I_N$ as a multi-linear tensor matrix product of core tensor S with size $R_1 X\ R_2 X R_3 ......\ X R_N$, $U^{(n)}$factors of N, size $I_n X R_n$

$$T \approx S._1^1U._2^2U._3^3U.\dots._N^NU.$$

Where $._n$is a tensor matrix product of mode n.

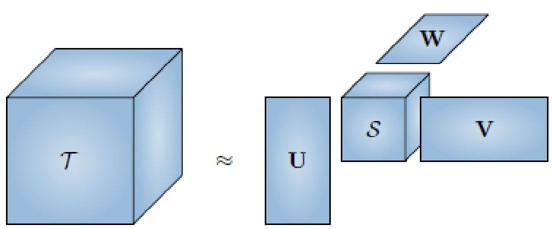

Figure 1. Multi-Linear Singular Value Decomposition

One of the fruitful developments of linear algebra in image processing is the prime concept of SVD representations for the analysis of Image patterns in terms of features. Mulit-Linear SVD[3] is one of the concept of SVD with generalization of Tucker decomposition method (Tensor decomposition). The MLSVD is a basis of an approximate generalization of the relation between two vectors column/row and left/right singular vectors of the matrices. In the concept of tensors, the matrix representations of the tensor is in the form of column/row vectors are stacked one after other i.e. matrix unfoldings.

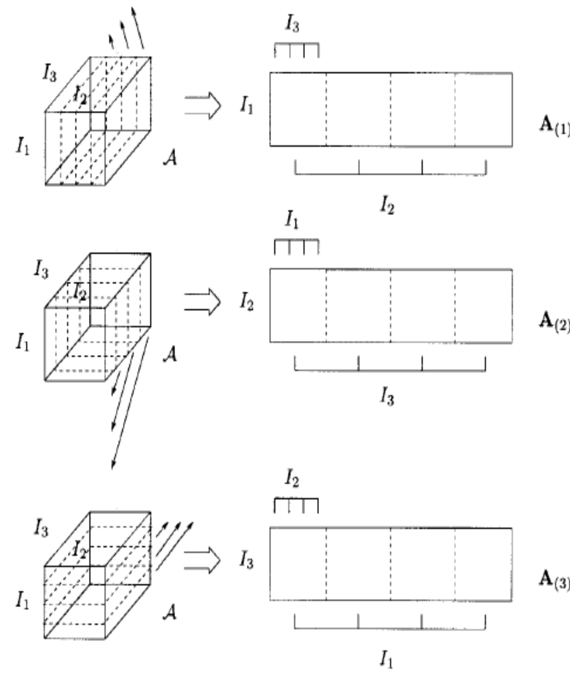

FIG. 1. *Unfolding of the $(I_1 \times I_2 \times I_3)$-tensor $\mathcal{A}$ to the $(I_1 \times I_2 I_3)$-matrix $\mathbf{A}_{(1)}$, the $(I_2 \times I_3 I_1)$-natrix $\mathbf{A}_{(2)}$ and the $(I_3 \times I_1 I_2)$-matrix $\mathbf{A}_{(3)}$ $(I_1 = I_2 = I_3 = 4)$.*

b) Mulit-Linear Principal Component Analysis (MLPCA)

Haiping Lu et al, proposed Multi-Linear PCA[4] is one of the important PCA algorithm with Tensor based feature extraction methods to extract the features in the form tensor objects from the image patterns. It's a new way of dimensionality reduction and feature extraction method in which performing the tensor modes that allows to capture the projected tensors from the original tensor patterns to determine the low dimensionality. In the analysis of MLPCA, the projection refers to multi linear projections that transforms into independent subspace projections and then obtained eigenvectors with comprised patterns directly for later usage. Such eigenvectors can be considered as subspace tensor features often called tensor objects for better analysis with classification and prediction approaches. The detailed procedure for MLPCA is discussed in [4]

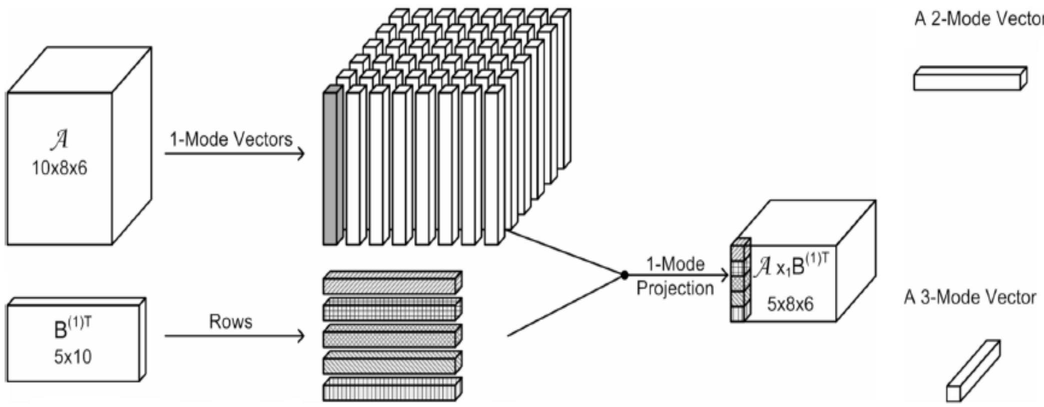

Figure 2. Detailed presentation of multi-linear projection using MLPCA

PREDICTION RESULTS

This experiment obtains data sets from the ADNI database, which is freely accessible. The archive includes information on various brain views, such as axial vision, coronal vision and sagittal view. Physicians use these images to verify if patients are normally or afflicted by some condition and use them to schedule care so the images demonstrate the severity of the disorder.

The proposed classification model uses 1000 brain samples, including 250 CN images, 250 EMCI images, 250 LMCI images and 250 AD images. These pictures are used in the preparation of both DCNN and VCNN models to classify various AD levels. As samples, images from T1 w MRI input are used. The comprehensive level of participants for individual classifications is described in Table I. 70% of the pictures are taken for preparation and 30% of the pictures are taken for researchAs the sampled range of medical data is normally minimal, the attribute information in such restricted samples must be thoroughly learned. Therefore the processes of multiview data building are conducted in the initial brain MRI datasets, to further discover secret knowledge and to gain adequate information from the data samples. This section initially introduces the comprehensive method of creating multi-visual data sets using MLPCA, MLSVD, and Gabor filter techniques. The PCA and the normalized processing system was used to prepare all the multi-view datasets to achieve an abundance of features.

As MLPCA is a feature descriptor with scale invariance and lighting invariance that can guarantee MRI content details effectively[24]. Extraction feature: MLPCA The MLPCA extraction approach is then chosen to obtain local characteristics for the initial datasets. For one sample of aXI MRI i.e, the image was extracted using MLPCA. Figure 3 shows View 1 (a). In addition, for a SAG MRI study the picture has been analyzed with MLPCA. Figure 3 shows View 2 (b). Fig's intuitive analysis. 3 shows MLPCA matching between different MRI images offers the information that different artifacts have repeatedly extracted MLSVD features. MLSVD is also a nonlinear scale detection feature. MLSVD is a feature point detection technology. This nonlinear space shows that the degree of data loss at the edge of the image is minimal, so that the image specifics are preserved greatly [2]. The MLSVD is also used to retrieve original data attributes. The MLSVD extracted images are shown in Figure 4 for a sample of AXI and SAG data views. An insightful Fig evaluate. 4 displays the AXI MRI chart on the left and the MLSVD technology on the right side on the SAG MRI map. Also in the image, the positions of the main points catch the specifics of the brain MRI. Extracting features from the Gabor filter In addition to this, Gabor Filter is a Fourier Window transform that can remove associated features in various sizes and directions in the frequency domain and is useful for extracting biological images from texture characteristics. We follow six scale Gabor filters [7, 9, 11, 13, 15, 17] to extract spatial local frequency features of the original two views in the four directions of the [0 morning, 45 pound, 90 pound and 135 pounds] data sets to further gain further perspectives and collect more powerful information from MRI images. The map of these six scale and four directions of the Gabor filters is shown in the diagram. 5. A comparative Fig review. Five shows that when the scale is set to 15, Gabor filters function superior. We use Gabor's 15 and four directions one-scale filters [0 kilometer, 45 kilometer, 90 kilometer, 135 kilometer] to generate 8 texture views. And in the figure are shown the samples of images filtered from the original Gabor filter brain AXI MRI data-sets. 6. An insightful Fig evaluate. 6 demonstrates Gabor filtered brain MRI results on one scale, 15 and 4 directions from [0 pour, 45, 90 pour, 135 pour]. The SAG MRI results seen are very similar to the figure in the filtered brain. 6, but here's not introduced. Preprocessing of multi-view datasets The initial two views are extended separately to 12 views for each dataset, based on the above experiments. In addition, every MRI features 1024 pixels. For each view in the ADNI2 database, there are therefore 1.118 objects, 1024 characteristics and 6 topics. Furthermore, ADNI3 database provides the 752 objects, 1024 features and 6 subjects for any view. In view of the vast quantities and operational reliability of data it is appropriate to pick and process valuable information on 1024 features. Practically, we use the PCA approach to minimize image data dimensions while retaining the bulk of data set improvements [46]. Every view in ADNI2 and every view in ADNI3 database has 800 characteristics chosen by the PCA system and 500 features are eventually normalized

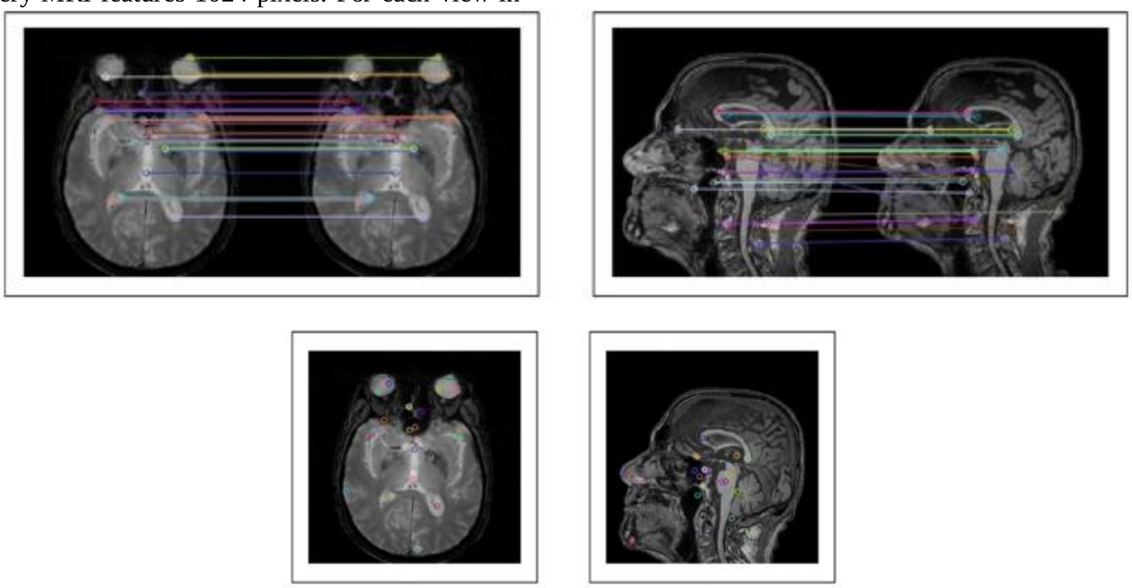

Fig3. Tensor based Feature mapping using MLPCCA and MLSVD

CONCLUSION

In MLSVD and MLPCA models, the proposed method has successfully categorized the AD and its level. These models are trained and tested with a sagittal view of 1000 MRI images. In both versions, more than 90% of the precision is reached. MLSVD produces higher precision among these two versions. With the right choice of the number of layers, the number of filters, filter height, padding layers, dropout layers etc. a more realistic model can be constructed by keeping the model's size at a minimum. Through applying further samples from various data sets, the MLPCA model can be further enhanced. The key focus of this research was the sagital view of the MRI images weighed by T1. As a further development, we will also consider other viewpoints, including coronal and axial views. Precision, reaction time and failure can be further enhanced by using other profound learning algorithms.

REFERENCES

[1] M.Tanveer, B.Richhariya, R.U.Khan, A.H.Rashid, P.Khanna, M.Prasad et al., “Machine learning techniques for the diagnosis of Alzheimer’s disease: A review,” ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), vol.16,no.1S, pp.1-35, 2020, doi:10.1145/3344998.

[2] C.K.Fisher, A.M.Smith, J.R.Walsh,“Machine learning for comprehensive forecasting of Alzheimer’s disease progression,” Science Reports 9, vol.13622, 2019, doi:10.1038/s41598-019-49656- 2.

[3] J. De Velasco Oriol, E. E. Vallejo, K. Estrada, G. Taméz Peña and ADNI, “Benchmarking machine learning models for late-onset alzheimer’s disease prediction from genomic

data," BMC Bioinformatics 20, vol.709, 2019, doi:10.1186/s12859-019-3158-x.

a.L. R. Trambaiolli, A. C. Lorena, F. J. Fraga, , P. A. M. Kanda, R. Anghinah & R. Nitrini, "Improving alzheimer's disease diagnosis with machine learning techniques," Clinical EEG and Neuroscience, vol.42, no.3, pp.160–165, 2011, doi:10.1177/155005941104200304.

[4] S. Basaia, F. Agosta, L. Wagner, E. Canu, G. Magnani, R. Santangelo et al., and Alzheimer's Disease Neuroimaging Initiative, "Automated classification of Alzheimer's disease and mild cognitive impairment using a single MRI and deep neural networks," NeuroImage: Clinical Journal,vol.21,no.1, pp.1-8, 2019, doi:10.1016/j.nicl.2018.101645.

[5] O. Geman, H. Costin, "Automatic assessing of tremor severity using nonlinear dynamics, artificial neural networks and neuro-fuzzy classifier," Advances in Electrical and Computer Engineering, vol.14, no.1, pp.133-138, 2014, doi:10.4316/AECE.2014.01020. [20] Y. LeCun, Y. Bengio, G. Hinton "Deep learning," Nature, vol.521, no.1, pp.436–444,2015, doi:10.1038/nature14539.

[6] A. Krizhevsky, I. Sutskever, G. E. Hinton, "Imagenet classification with deep convolutional neural networks," Communication of the ACM, vol.60, no.6, pp.84-90,2017, doi:10.1145/3065386.

[7] N. Sharma, V. Jain & A. Mishra, "An analysis of convolutional neural networks for image classification," Procedia Computer Science,vol.132, pp.377-384, 2018, doi:10.1016/j.procs.2018.05.198.

[8] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, H. Adeli, D. P. Subha "Automated EEG-based screening of depression using deep convolutional neural network," Computer Methods and Programs in Biomedicine, vol.161, pp.103–113, 2018, doi:10.1016/j.cmpb.2018.04.012.

[9] S. E. Spasov, L. Passamonti, A. Duggento, P. Lio, N. Toschi , "A multi-modal convolutional neural network framework for the prediction of Alzheimer's disease," Conf Proc IEEE Eng Med Biol Soc. 2018, pp.1271-1274, 2018, doi:10.1109/EMBC.2018.8512468. [

[10] A. Payan, G. Montana, "Predicting Alzheimer's disease: A neuroimaging study with 3D convolutional neural networks," arXiv, February 10, 2015, arXiv:1502.02506.

[11] J. Nowaková, M. Prílepok & V. Snášel, "Medical image retrieval using vector quantization and fuzzy S-tree," Journal of Medical Systems, vol. 41, no. 18, pp. 1-16, 2017, doi:10.1007/s10916-016- 0659-2

[12] A. Alberdi, A. Aztiria, A. Basarab, On the early diagnosis of Alzheimer's disease from multimodal signals: a survey, Artif. Intell. Med. 71 (2016) 1–29.

[13] P.F. Alcantarilla, A. Bartoli, A.J. Davison, KAZE features, in: Proceedings of the European Conference on Computer Vision, 2012, pp. 214–227.

[14] S. Arora, R. Ge, R. Kannan, A. Moitra, Computing a nonnegative matrix factorization-provably, in: Proceedings of the Annual ACM Symposium on Theory of Computing, 2012, pp. 145–162.

[15] R. Brookmeyer, E. Johnson, K. Ziegler-Graham, H.M. Arrighi, Forecasting the global burden of Alzheimer's disease, Alzheimer's Dementia 3 (3) (2007) 186–191. [5] X. Cai, F. Nie, H. Huang, Multi-view K-means clustering on big data, in: Proceedings of the International Joint Conference on Artificial Intelligence, 2013, pp. 2598–2604.

[16] B. Richhariya, M. Tanveer, Least squares projection twin support vector clustering (LSPTSVC), Inf. Sci. 533 (2020) 1–23.

[17] A. Salah, M. Ailem, M. Nadif, A way to boost semi-NMF for document clustering, in: Proceedings of the ACM Conference on Information and Knowledge Management, 2017, pp. 2275–2278.

[18] D. Steinley, K-means clustering: a half-century synthesis, Br. J. Math. Stat. Psychol. 59 (1) (2006) 1–34.

[19] R.H. Swerdlow, Pathogenesis of Alzheimer's disease, Clin. Interv. Aging 2 (3) (2007) 347.

[20] A. Tharwat, Principal component analysis: an overview, Pattern Recognit. 3 (3) (2016) 197–240.

[21] L. Tong, W.K. Wong, C. Kwong, Differential evolution-based optimal Gabor filter model for fabric inspection, Neurocomputing 173 (2016) 1386–1401.

[22] T. Tong, K. Gray, Q. Gao, L. Chen, D. Rueckert, et al., Multi-modal classification of Alzheimer's disease using nonlinear graph fusion, Pattern Recognit. 63 (2017) 171–181.

[23] K. Vaithinathan, L. Parthiban, et al., A novel texture extraction technique with T1 weighted MRI for the classification of Alzheimer's disease, J. Neurosci. Methods 318 (2019) 84–99.

[24] S.A. Vavasis, On the complexity of nonnegative matrix factorization, SIAM J. Optim. 20 (2009) 1364–1377.

[25] H. Wang, Y. Yang, T. Li, Multi-view clustering via concept factorization with local manifold regularization, in: 2016 IEEE 16th International Conference on Data Mining (ICDM), IEEE, 2016, pp. 1245–1250.

[26] H. Wang, Y. Yang, B. Liu, GMC: graph-based multi-view clustering, IEEE Trans. Knowl. Data Eng. 32 (6) (2019) 1116–1129.

[27] L. Wang, Y. Liu, X. Zeng, H. Cheng, Z. Wang, Q. Wang, Region-of-interest based sparse feature learning method for Alzheimer's disease identification, Comput. Methods Prog. Biomed. 187 (2020) 105290.

[28] M.W. Weiner, D.P. Veitch, P.S. Aisen, L.A. Beckett, N.J. Cairns, R.C. Green, D. Harvey, C.R. Jack Jr, W. Jagust, J.C. Morris, et al., Recent publications from the Alzheimer's disease neuroimaging initiative: reviewing progress toward improved AD clinical trials, Alzheimer's Dementia 13 (4) (2017) e1–e85

[29] J. Wen, Z. Zhang, Z. Zhang, L. Fei, M. Wang, Generalized incomplete multiview clustering with flexible locality structure diffusion, IEEE Trans. Cybern. (2020).

[30] R. Xia, Y. Pan, L. Du, J. Yin, Robust multi-view spectral clustering via low-rank and sparse decomposition, in: Proceedings of the AAAI Conference on Artificial Intelligence, 2014, pp. 2149–2155.

[31] T. Xia, D. Tao, T. Mei, Y. Zhang, Multiview spectral embedding, IEEE Trans. Syst. Man. Cybern. Part B (Cybernetics) 40 (6) (2010) 1438–1446.

[32] Y. Yang, H. Wang, Multi-view clustering: a survey, Big Data Min. Anal. 1 (2) (2018) 83–107.

[33] C. Zhang, E. Adeli, T. Zhou, X. Chen, D. Shen, Multi-layer multi-view classification for Alzheimer's disease diagnosis, in: Proceedings of of the AAAI Conference on Artificial Intelligence, 2018, pp. 4406–4413.

[34] F. Zhang, Z. Li, B. Zhang, H. Du, B. Wang, X. Zhang, Multi-modal deep learning model for auxiliary diagnosis of Alzheimer's disease, Neurocomputing 361 (2019) 185–195.

[35] H. Zhang, X. Huo, X. Guo, X. Su, X. Quan, C. Jin, A disease-related gene mining method based on weakly supervised learning model, BMC Bioinform. 20 (16) (2019) 1–11