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A voxel based morphometry approach for identifying Alzheimer from MRI images

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Abstract

A voxel based morphometry (VBM) which makes use of a structural brain magnetic resonance imaging (MRI) is now being employed widely for the purpose of assessing the various normal ageing of Alzheimer's diseases (AD). VBM of the MRI data will contain segmentation within the grey and white matter, the cerebrospinal fluid and its partitions along with that of their anatomical image and its standardization inside the analogous stereotactic region. It further includes the affine transformation with a non-linear warping of the smoothing as well as a statistical investigation. In case there is a cognitive failure that is related to age called Dementia that has been indicated with that of a degeneration of the cortical and the sub-cortical structures. The characterization of such types of morphological changes will help in the understanding of the development of these diseases and the modelling will tend to capture the structural variability of brain which is a valid classification for this disease and its interpretation is found to be quite challenging. Here such features have also been extracted by means of using a curvelet transform along with a principal component analysis (PCA) for this technique of reduction of dimensionality. The Bagging as well as the boosting classifiers have been duly evaluated for their efficiency in classifying dementia. The work will further evaluate the framework by using images from that of the Alzheimer's disease neuroimaging initiative (ADNI) for identifying dementia. Such results have shown that this classifier proposed has now achieved better accuracy.

Keywords Voxel based morphometry (VBM) · Magnetic resonance imaging (MRI) · Alzheimer's disease (AD) · Curvelet transform · Principal component analysis (PCA) · Bagging and boosting

1 Introduction

A magnetic resonance imaging (MRI) is that critical tool in the field of biomedical research and the clinical diagnosis. The scanners have also been estimated to be 20,000 approximately and their developing of such contrast agents used about one-third of about 50 million MRI examinations that have been performed every year and have contributed largely to this. There is a greater MRI quality that will considerably contribute to the decision making in various pulmonary diseases from that of lung cancer on malignant pleural mesothelioma, the pulmonary arterial hypertension, and the airway diseases, the acute pulmonary embolism and so on. The concepts for the MRI examinations of the whole body for that of screening and also for staging need a comprehensive chest work which have to be completed These MRI techniques will widen up in the cases of cardiovascular by means of the extension of the examination to that of the pulmonary circulation at other diseases that affect the heart vessels and in case of that of the lungs it will still remain a complex [1].

AD has become a type of pandemic all the world over more so in developing countries that affect people that are over 65 years. Right now there is no cure to this but a non-invasive detection of this at an earlier stage can enhance

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the life quality greatly for the patients as well as their families. It can also help the researchers in developing appropriate treatment. Further, a significant impact on the AD to the society this system will be for an automatic detection of AD which is greatly desirable. By means of using the data from MRI, in many approaches the AD is detected in the early stages.

Such concepts deal with the discriminative feature extraction and choice of several models of classification from computational intelligence and classification models [2].

The VBM, is that automated technique that has an unbiased assessment of the structure of the brain at the level of the voxel which does not need any prior assumptions that will concern the several structures for the assessment that is now a standard tool in examination of their morphological changes owing to the health ageing, the psychological disorders and the neurodegenerative diseases. Here the VBM has also been used in the comparing of the regional grey matter and its volume between the adult patients of hyper thyroid and matched healthy controls. This is found to be one of the first such works that is called the morphometric of the brain through VBM along with the diffeomorphic anatomic registration through this exponentiated lie algebra (DARTEL) approach [3]. This MRI is that type of imaging method employed in clinical diagnosis and biomedical research that can generate a greater contrast image of the human body part. The significant MRI benefits are its non-invasive nature and the wealthy information from soft tissue anatomy. Another precise MRI image investigation depends not just on their capability or the physicians however based on the techniques of automated feature extractions in the MRI images. The wavelet transform (WT) is recently used and will further provide good levels of localization in the spectral and the spatial domains. But these discrete wavelet transform (DWT) is completely variation in terms of translation which are found to be the coefficients of wavelet that behave in a very unpredictable manner [4].

In a real-world data, like that of speech signals, MRI scans and digital photographs, a high dimensionality has to be reduced. This is the transformation of a higher dimensional data. Ideally, the depiction will have to show a data size and the intrinsic data dimensionality. This intrinsic dimensionality will be the minimal number of parameters that are required for accounting for the observed properties of data. The reduction of dimensionality and the other properties that are undesired in the high-dimensional spaces. As a result of this, the reduction of dimensionality will facilitate the classification, the visualization and these higher dimensional data compression. The reduction of dimensionality was performed by using some linear techniques like classical scaling, factor analysis and PCA [5].

The classification of the MRI images in accordance to its anatomical field which is a necessary task in solving when being faced with an increasing quantity of such medical images. The MRI is that imaging technique which produces rich clinical diagnosis information as well as biomedical research. The MRI and its values are exaggerated by the accurate and automated classification along with daily clinical practice and automatic analysis of these medical images to determine the production of significant benefits that are based on the cost and time. There are several techniques that are reported in the classification of such tumors and in most situations the support vector machine (SVM) the neural network, the knowledge based techniques, the expectation maximization (EM) algorithms and the fuzzy C-means (FCM) clustering are used. This type of SVM is that machine learning system which has been developed by means of using statistical learning theories for classifying the data points into two. These SVM models are adapted widely for the classifying, the image and its recognition as well as bioinformatics [6].

Here in this work, a curvelet transform has been proposed along with PCA, bagging and some classifiers for the AD in an MRI. The rest of the investigation has been organized as below: in Sect. 2 the related work in literature have been discussed. Section 3 deals with methods used and Sect. 4 discusses the results of experiments. The conclusion is completed in Sect. 5.

2 Related works

Minhas et al. [7] made a presentation of a novel MRI-based method to predict Mild Cognitive Impairment (MCI)-to the AD conversion from that of 1–3 years prior to a clinical analysis. Using the ADNI data, an MRI biomarker will achieve a tenfold cross-validated area which is within a receiver operating characteristic curve (AUC) of about 0.7661 in the discriminating progressive MCI patients (pMCI) from the stable MCI patients (sMCI). An aggregate biomarker that is on the basis of MRI data with a baseline cognitive measurement and the age that is attained in a tenfold cross-validated AUC score of about 0.9020 in that of a discriminating pMCI from the sMCI. The consequences of this work showed that it had the potential of early diagnosis of AD and also played a significant part in the MRI mainly in MCI-to-AD conversion and its prediction and this is on the basis of test consequences that are cognitive that improved its accuracy. Khedher et al. [8] further presented another new CAD system that permits an early diagnosis of the AD using segmented images of the brain. This aims at discriminating between the MCI, the AD and the normal control of the elderly using various partial least squares (PLS) and the PCA. The feature extraction of the PLS and the linear SVM classifier are much more effective in extraction of discriminative information and relating to this a CAD system was developed that yielded a sensitivity that was maximum and also specificity and values of accuracy of about 85.11, 91.27 and 88.49%.

Kong et al. [9] presented another Infant–Toddler development training (ITDS), which was a method of robust brain MRI segmentation for the super voxel level segmentation. The ITDS also incorporated the discriminative learning concept by means of increasing the margins of various clusters using mutual information. When compared with some typical generative methods of clustering it can cope successfully with the tissue heterogeneity based on brain and also provides better results with a high level of confidence. At the same time the sound ITDS performance will be obtained efficiently in less than half minutes that is applied for clinical purposes. Villarini et al. [10] proposed a tool which can calculate, classify and also analyze the pancreatic volume and its curvature that follows a 3D reconstruction. The MRI uses pancreatic volume of 115 patients for a correlation between two of the variables. This is further incorporated into developing a medical image analysis and its software application in stratifying subjects and their therapies.

The MRI is one important diagnostic imaging technique to detect brain cancer early. The MRI brain image has a vital role to play for assisting the radiologists who have a tedious and time consuming process but the accuracy of this depends on the experiences. So, using computer aided systems are important and even though there are many such methods available MRI brain segmentation is a challenging issue owing to its complexity. Selvaraj et al. [11] proposed several methodologies of segmentation of brain images that that use automated algorithms that are also accurate and need very little interaction by users and the advantages are reviewed and discussed to produce results that are accurate. Prostate cancer is that cancer which is the second most reviewed one among med. The research based on computer aided systems have centered specifically on this cancer which is a young method and a dynamic field part that focuses this in the last ten years. The survey aims at providing a review that is comprehensive and state of the art. Lemaitre et al. [12] presented another comparison between the investigation and there was a debate on the probable avenues in upcoming research. Additionally, this work also presented another new online dataset that is available for research aiming at providing an evaluation framework that is common for the purpose of overcoming the present limitations.

Eldhashan et al. [13] further made a presentation of a technique of a hybrid intelligent machine for the computer aided detection system of the brain tumor using magnetic resonance images. This method has also been on the basis of the subsequent process of computation. A feedback which is of a much pulse-coupled neural network for the purpose of image segmentation, and these types of discrete wavelet transforms for extraction of features reduce wavelet coefficient dimensionality with a particular back propagation that is called a feed forward with a neural network for classifying them as normal and also abnormal. Such experiments had been carried out for about 101 images containing 14 and 87 normal and abnormal tumors from that of these real human brain MRI data. These types of classification accuracy on the training and the testing images were 99% being considerably better.

Zhu et al. [14] made a focus on the various joint regression as well as classification for the diagnosis of AD and also presented another feature selection technique by means of the embedding of relational information. This relational information have included three different relationships for the three types of similarity like their response variables, the samples and also the features. The using of a dimension-reduced data, the work will also train two models of support vector regression for prediction of the Alzheimer's disease and assessment scale (ADAS)-Cog with mini mental state examination (MMSE). Extensive experiments had been conducted and the experiments on the ADNI dataset for the purpose of validating these proposed methods and their effectiveness. The results have shown that this presented method had the efficacy of enhancing the prediction of such types of clinical scores and identification of disease status when compared to other methods. Owing to this type of hypo perfusion of the brain tissue that will precede a dementia and its atrophy where the detection can be advanced through the perfusion information. These facts are attained noninvasively using an arterial spin labeling (ASL), which is a comparatively novel MR method that quantifies cerebral blood flow (CBF). By using this type of an ASL and a structural MRI, Bron et al. [15] made an evaluation of the diagnostic classification in about 32 different prospective presenile early stage patients of dementia with 32 healthy controls. These patients were supposed of AD or of frontotemporal dementia had the voxel wise classification that had provided their controls with an AUC of 91%. Even though the CBF quantified with that of the ASL was a good marker of such dementia there was a similar accuracy as in the case of the GM in case of voxel based classifications that added value to the MRI not being important. Tzalavra et al. [16] made another investigation of multi-resolution schemes of wavelet for characterizing textures of breast tumors in the DCE-MRI. These texture features of each scheme were fed inside the classifiers. The results from the experiments showed high levels of accuracy in the classification of such breast tumor making use of the fast discrete curvelet transform (FDCT) along with linear discriminant analysis (LDA) that was used as a classifier. Hence, it may be terminated that curvelet may be the key to the detection of breast cancer. This mean as well as entropy of the sub-images for every one of the image schemes of decomposition have been fed as the input into various classifiers and the FDCT features that were nourished to that of a new LDA classifier gave a high performance of classification (93.18% accuracy).

3 Methodology

There are major improvements in the techniques of neuroimaging seen in the last few decades that include technical advances of acquisition of data and developing newer models. From among the neurodegenerative disorders the mainly common dementia cause is AD. In the modern techniques of MRI that are used for investigating the volume deficits in the regional volume debits with the structural brain abnormalities that are related with susceptibility in developing AD and also its progression. Here, the ADNI dataset has been used and a curvelet transform feature extraction method was used. The PCA for the reduction of dimensionality reduction with the bagging and boosting classifiers are used.

3.1 Alzheimer's disease neuroimaging initiative (ADNI) dataset

The data that had been used here has been obtained from a database of ADNI (http://adni.loni.usc.edu/). This ADNI had also been started in the year 2003 by the National Institute on Aging (NIA), and the National Institute of Biomedical Imaging and Bioengineering (NIBIB), with that of the Food and Drug Administration (FDA), along with some of the non-profit organizations and also some private pharmaceutical companies as a $60 million, in a 5-year public–private partnership. The main objective of this ADNI is to experiment if serial MRI, a positron emission tomography (PET), and certain type of different biological markers, along with some clinical and neuropsychological assessments that are merged for checking the progression of these mild cognitive impairment (MCI) and the early AD. Determination of the sensitive and specific markers in the early progression of AD was for the purpose of being able to assist the researchers/clinicians to grow particular novel treatments to bring down time and cost of the clinical experiments [17].

The main as well as the principal investigator has been Michael W. Weiner, MD, of the VA Medical Centre and University of California—San Francisco. The ADNI has been the consequence of a lot of efforts several co-investigators from among a broad academic institutions range along with some of the private corporations, with the subjects that continuously hired in over 50 sites in both the U.S. and Canada. The main objective of this ADNI has been the recruiting of more than 1500 adults falling between various the ages of 55 and 90. The duration of such follow up for each of these groups is duly being specified within protocols of the ADNI-1, the ADNI-2 and the ADNI-GO. The subjects that had been initially hired for the ADNI-1 and the ADNI-grand opportunities (GO) will now have the choice of being followed within the ADNI-2 [18].

For the purpose of getting modern information, go to www.adni-info.org. The data that has been now employed in this work has all the subjects where the baseline MRI data (the T1-weighted and the magnetization prepared rapid gradient echo (MP-RAGE) sequence at 1.5 T, characteristically $256 \times 256 \times 170$ voxels with that of the voxel size of approximately $1\ \text{mm} \times 1\ \text{mm} \times 1.2\ \text{mm}$), will in case of the least moderately confident diagnoses (which is the confidence N2), also the hippocampus volumes (the volumes of the left as well as the right hippocampi, that has been calculated by means of the Free Surfer Version 4.3), and also the test scores in some of the cognitive scales (the ADAS, that range 0–85; of the clinical dementia rating of 'sum of boxes' (CDR-SB), that have a range between 0 and 18; which is now a mini-mental state examination (MMSE), range of 0–30) [19].

For the purpose of diagnostic classification at its baseline, 825 subjects have been grouped as (1) the AD, within their diagnosis being the AD at baseline ($n = 200$); (2) the normal cognitive (NC), in case the diagnosis is normal at that of the baseline ($n = 231$); (3) the stable MCI (the sMCI), in case this diagnosis was the MCI at all of these accessible time points (between 0 and 96 months), but in case of 36 months (where $n = 100$); (4) this is a progressive MCI (the pMCI), in case the diagnosis had been the MCI at this baseline however conversion to that of the AD had been reported within about 1, 2 or 3 years, and also without any reversion to that of the MCI or the NC at any of the available follow-up which is (0–96 months) (where $n = 164$); (5) the unknown MCI (the uMCI), in case this diagnosis was at MCI at its baseline but all these subjects being missing a 36 month diagnosis at the time points (where $n = 100$). From the 164 pMCI subjects, about 68 different subjects had been converted to that of the AD inside its initial 12 months, and about 69 subjects that had been duly converted to that of the AD between 12 and 24 months and after one follow-up and the 27 residual subjects that had been converted to the AD among another follow-up of 24 and 36 months.

3.2 Feature extraction using curvelet transform

Fundamentally, these curvelet transforms will tend to be able to broaden their ridgelet transforms for that of a multiple scale analysis and also an image f (x, y), which is that continuous ridgelet from the coefficients that have now been expressed in the Eq. (1):

$$R_f(a,b,\theta) = \iint \psi_{a,b,\theta}(x,y) f(x,y)dxdy \tag{1}$$

In which, an indicates that scale parameter wherein a > 0, b ∈ R being the translation parameter with θ ∈ [0, 2π] as the parameter of orientation. The exact reconstruction has been completed and a ridgelet has been defined in Eq. (2) as: possible from all of these coefficients. A ridgelet may also be defined in Eq. (2) as

$$\psi_{a,b,\theta}(x,y) = a^{\frac{1}{2}}\psi\left(\frac{x\cos\theta + y\sin\theta - b}{a}\right) \tag{2}$$

In which θ denotes the orientation of a ridgelet that is a constant line of x cos θ + y sin θ = constant and the transverse to that of such ridges which are wavelets. These ridgelets are those basis elements in obtaining a high anisotropy that captures edge better over a conventional sinusoidal wavelet [20]. A curvelet transform that has been based on wrapping of these Fourier samples take a 2-D image as its input in a Cartesian array f [m, n] so that 0 ≤ m < M, 0 ≤ n < N and gets the curvelet coefficient that has been indexed by a scale j, with an orientation l along with two different parameters of such spatial location (k_1, k_2). Formation of these curvelet texture descriptors, needs statistical operations that are to be applied and these discrete coefficients of curvelets have been defined in Eq. (3):

$$C^D(j,\ l,\ k_1,\ k_2) = \sum_{0 \le m \le M} f[m,n]\phi^D_{j,l,k_1,k_2}[m,n] \tag{3}$$

In which, each $\phi^D_{j,l,k_1,k_2}[m,n]$ denote the digital curvelet waveforms implementing scaling law of effective parabolic on their sub-bands in this frequency. The curvelets will further now exhibit an oscillating behaviour edges. These wrapping based transforms are basically in case of a multiscale transform using the pyramid structure with several orientations on both the scales [21]. The product of this is the inverse fourier that has been transformed for the purpose of obtaining the curvelet coefficients. This process is now further described as the curvelet transform = the Inverse fast fourier transform (IFFT) [the fast fourier transform (the FFT) (curvelet) of this FFT (Image)] and the product of which from that of the multiplication will be the wedge.

3.3 Principal component analysis (PCA)

In case of the neuroimaging analysis, the reduction of dimensionality is a problem that is complex [22] having a twofold objective which are decreasing model complexity and increasing or maintaining performance. There are two alternatives that are offered reduction of feature and selection of feature. The work is efficient in methods of feature selectin in the PCA [23] that is used for reduction of dimensionality and as a result of this most of the information and their representative dimensions will be kept as the least important ones are removed. The PCA will generate some more new features to be presented as a linear combination of a given dataset that is present in the d-dimensional space for a k-dimensional subspace so that here k < d. A set of new k dimensions the principal components (PCs), and each of these PCs is directed towards the maximum variance which excludes the variance that is accounted for the preceding components and the first component subsequently covers the maximum of the variance and the one that follows covers the lesser value (4):

$$PC_i = a_1X_1 + a_2X_2 + \ldots + a_dX_d \tag{4}$$

In which PC_i is the ith PC, X_j denotes the original feature which is j, and a_j denotes a numerical coefficient for the X_j

3.4 Bagging classifier

The Bagging which is suggested by Breiman for reducing the error component that is done by the bootstrap sampling and is described below [24]:

$Input\ 1:\ Bagging\ A\lg orithm\ A$

$Input\ 2:\ Dataset\ D,\ item\ T$

$Output\ 1:\ \Pr ediction\ for\ a\ given\ test\ ins\tan ce\ x$

$1.\ For\ i = 1\ to\ T:\ Pick\ randomly\ class\ D\ (i)\ from\ D$

$2.\ Let\ M\ (i)\ become\ result\ of\ training\ A\ on\ D\ (i)$

$3.\ For\ i\ =\ 1\ to\ T:\ Chosen\ test\ class$

$2.\ Let\ C\ (i)\ =\ Output\ of\ M\ (i)\ on\ x$

$4.\ \mathrm{Re}turn\ class\ that\ appears\ most\ often\ among\ in\ C\ (1)...C(T)$

This has given error rate in a finite training dataset size and Breiman used the variability of the algorithm by reducing the term in this. For applying bagging, a neural network model was built but the initial conditions were leading to high variables in their predictions and these are considered to have low bias. The bagging makes use of D as its new training set D in which each size of n' = n, by sampling with some repetition of observation in D (1) and for a large n a set D (1) needs to have a fraction of (1-n/e) which is a unique example of D. The remaining that are duplicates the n models are suitable through the above n samples of bagging and are merged using an averaging of the output or its classification. This leads to an improvement in the unstable procedure which also includes the classification as well as the regression trees in linear regression [25]. Another interesting application in bagging has shown improvement in pre-image learning and can degrade mildly the stable methods and their performance.

Bagging technique permits the distribution of sampling of almost all types of classification by means of using methods of random sampling. The advantages of bagging is that it is straightforward in deriving the estimates of the errors and the complex estimates of the parameters. This is also an appropriate method to control and keep a check in the stability of these results.

3.5 Boosting classifier

This is an ensemble method generating strong classifiers combining weak classifiers and this is the one that has an accuracy that is a little more than 50%. Here the weak classifiers are the simple thresholds for each of the D features (dataset for dimensionality d) [26].

Most of these types of boosting algorithms function by means of a selection of some of the weak classifiers and then further combine them to form some strong classifiers by means of using some weighted summation wherein each classifier will have to be weighted based on the level of performance. All of these feature vectors are assigned originally using equal weightings. They are later re-weighted for every such iteration, and once another new weak classifier has been classified the examples keep decreasing. Some of these boosting algorithms also decrease their weightings for such types of misclassified examples to bring down outliers' influence.

There are several boosting algorithms that are available, where adaptive boosting (AdaBoost) is considered popular [27]. This AdaBoost algorithm is by assigning weightings to all of the N feature vectors, where $D_1(i) = {}^1/_N$. For each iteration $(j = 1, 2, \ldots, J)$, a weak classifier h_j results in a minimum classification error which is chosen from the set of classifiers H that are weak so that (5):

$$h_j = \arg\max_{h_j \in H} |0.5 - \in_j| \tag{5}$$

In which the error $\in_j$ will be the sum of weights of the wrongly classified examples. The chosen weak classifier h_j will be assigned a weight $\alpha_j = 1/2 \ln((1 - \in_j)/\in_j)$ based on its performance, and these weightings are later updated so that (6, 7):

$$D_{j+1}(i) = \frac{D_j(i) \exp(-\alpha_j t_i h_j(x_i))}{Z_j} \tag{6}$$

In which

$$Z_j = \sum_{i=1}^{N} D_j(i) \exp(-\alpha_j t_i h_j(x_i)) = \sqrt[2]{\in_j (1 - \in_j)} \tag{7}$$

The strong classifier is now constructed from that of the chosen weak classifiers as in (8):

$$y(x) = sign \sum_{j=1}^{J} \alpha_j h_j(x) \tag{8}$$

The actual difference that is between the bagging and the boosting is as below:

1. Every model has been built above the earlier ones for the cases of boosting but in case of bagging every model is individually built.
2. Boosting will bring down the variance and the bias of its base classifier but the bagging will bring down the variance alone.
3. During the noisy data, boosting performs better than that of bagging.

4 Results and discussion

Here, the PCA-bagging, the PCA-boosting the bagging and the boosting methods have been used. In Table 1 summary of results is shown. The number of images that are used: where 350 normal, 80 MCI, and 40 AD are used. The accuracy of classification, that is true predictive rate (being normal, MCI and lastly AD) and the true negative rate (which is normal, the MCI and the AD) as depicted in Figs. 1, 2 and 3.

From the Fig. 1, it can be examined that the PCA-boosting has higher classification accuracy by 5.09% for bagging, by 3.02% for boosting and by 1.24% for PCA-bagging.

From the Fig. 2, it can be observed that the PCA-boosting has higher average true positive rate by 5.16% for bagging, by 3.77% for boosting and by 2.09% for PCA-bagging.

From the Fig. 3, it can be observed that the PCA-boosting has higher average true negative rate by 3.03% for bagging, by 2.02% for boosting and by 0.64% for PCA-bagging.

Table 1 Summary of results

	Bagging	Boosting	PCA-bagging	PCA-boosting
Classification accuracy	0.8128	0.8298	0.8447	0.8553
True positive rate—normal	0.8771	0.8943	0.9057	0.9143
True positive rate—MCI	0.6375	0.675	0.725	0.7375
True positive rate—AD	0.6	0.575	0.55	0.575
True negative rate—normal	0.7813	0.7857	0.8081	0.8119
True negative rate—MCI	0.9194	0.9282	0.9339	0.9397
True negative rate—AD	0.904	0.9175	0.9259	0.9335

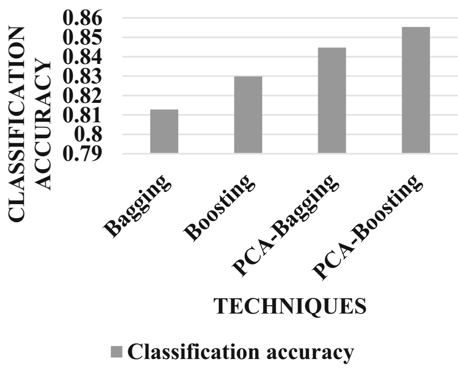

Fig. 1 Classification accuracy

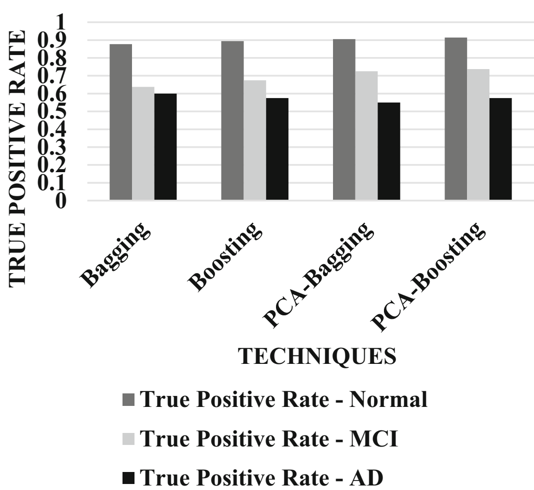

Fig. 2 True positive rate

5 Conclusion

This brain image analyses depends on univariate voxel-wise analyses like that of the VBM for aspects like structural MRI. The AD patients may tend to suffer from that of a lack of initiative, and the variations within their personality or their behaviour in day-to-day functions at work, or at home, or sometimes in care of themselves finally and eventually resulting in their death. Here, in this work the extraction of feature proposed making use of curvelet transform for reduction, the bagging as well as the boosting

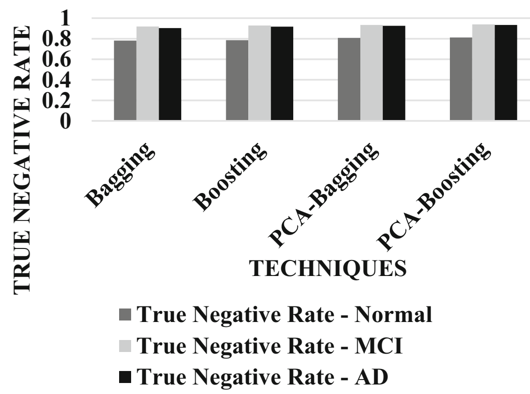

Fig. 3 True negative rate

of classifiers. Such curvelet transforms in case of the multi-scale directional transform which duly permits most of the optimal non adaptive sparse representation of these objects along with the edges. This curvelet transform will further be able to increase the interest among communities of the applied mathematics. The PCA is a technique of feature reduction that helps in converting a set of observations to that of a set of values of some uncorrelated variables that are called as PCs. The error of generalization will now converge to a limit as the actual number of the trees in this ensemble will tend to become large for bagging as well as boosting. This will depend completely on the individual trees strength and also the correlation between them. The actual improvement of bagging over that of the boosting goes up with the complexity of the task of classification. The results have shown that the higher classification accuracy that is PCA boosting based has a better accuracy of classification by about 5.09% for bagging, by about 3.02% for boosting and by about 1.24% for the PCA-bagging.

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