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Machine Learning Approach for Identifying Dementia from MRI Images

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***Abstract*—**This research paper presents a framework for classifying Magnetic Resonance Imaging (MRI) images for Dementia. Dementia, an age-related cognitive decline is indicated by degeneration of cortical and sub-cortical structures. Characterizing morphological changes helps understand disease development and contributes to early prediction and prevention of the disease. Modelling, that captures the brain's structural variability and which is valid in disease classification and interpretation is very challenging. Features are extracted using Gabor filter with 0, 30, 60, 90 orientations and Gray Level Co-occurrence Matrix (GLCM). It is proposed to normalize and fuse the features. Independent Component Analysis (ICA) selects features. Support Vector Machine (SVM) classifier with different kernels is evaluated, for efficiency to classify dementia. This study evaluates the presented framework using MRI images from OASIS dataset for identifying dementia. Results showed that the proposed feature fusion classifier achieves higher classification accuracy.

***Keywords*—**Magnetic resonance imaging, dementia, Gabor filter, gray level co-occurrence matrix, support vector machine.

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I. Introduction

MRI, an imaging technique, evolved as a clinical modality over 30 years [1], [2]. Medical imaging techniques/ analysis tools enable doctors and radiologists to reach a specific diagnosis. Medical image analysis and processing has significance in medicine especially in non-invasive treatment and clinical study. Medical image processing is an important tool to identify and diagnose various disorders. Imaging helps doctors visualize and analyze the image to understand abnormalities in internal structures. Medical images data use imaging techniques like Computed Tomography (CT), MRI and mammogram indicating the presence or absence of lesions with patient history [3], [4]. MRI is a scanning device using magnetic fields and computers to capture brain images on film. It does not use x-rays and provides pictures from various planes permitting doctors to see a tumor's three-dimensional image. MRI detects signals from normal and abnormal tissue and ensures clear tumor images [5]. It is a widely used method of high quality medical imaging, especially in brain imaging where soft tissue contrast and non-invasiveness are advantages.

MRI examined by radiologists is based on visual interpretation of films to identify abnormal tissue. Brain images are selected for image reference for this research as brain injuries affect large areas of the organ. The brain controls and coordinates movement, behavior, and homeostatic body functions like heartbeat, blood pressure, fluid balance, and body temperature. Brain functions are responsible for cognition, memory, emotion, motor learning and other learning [6]. Brain MRI data classifications as normal and abnormal is important to prune normal patient and consider only those with the possibility of having abnormalities/tumor [7]. Fewer Radiologists' and large volume of MRI to be analyzed, make readings labor intensive and costly. This needs an automated system to analyze and classify all medical images. Results of human analysis concerning false negative cases must be very low when dealing with human life. Double medical imaging readings lead to better tumor detection.

Classification is assigning a physical object or incident to predefined categories. Medical image databases for image classification or teaching has various modality images, taken under differing conditions with variable accuracy of annotation. This is true for various on-line resource images, including those accessing journals on-line content. Approaches mixing visual and textual techniques for classification have promise in medical image classification. Fig. 1 is an overview of steps in medical image processing [8]. Preprocessing helps remove noise from the images, global and local features are extracted from which a subset of features are selected which is then classified.

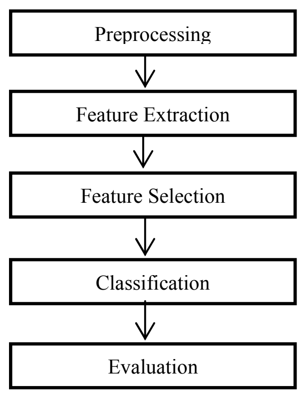

Fig. 1 Overview of the steps involved in medical image processing

Texture classification is assigning an unknown sample image to one of known texture classes set. Texture classification is main domain in texture analysis and important in many computer image analysis applications for image classification/segmentation based on local spatial variations of intensity or color. Successful classification/segmentation

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needs efficient image texture [9] description.

Classification in data mining technique is used to predict group membership for data instances. Data mining is the use of data analysis tools to locate relationships in large data sets. Data mining is not managing data but data analysis/prediction. A classification technique processes various data than regression and is increasingly popular. Neural Networks (NN) are classification tools. Research in neural classification proved that NN is an alternative to varied classification methods. The advantage of NNs resides in the following theoretical aspects. First, NNs are data driven self-adaptive methods in which they can adjust themselves to the data, without any explicit specification of functional or distributional form with the underlying model. Second, NNs are universal functional approximations which can approximate any function with arbitrary accuracy. Since any classification procedure finds a functional relationship between the group memberships with the attributes of the object, accurate identification of this underlying function is very important. Third, NNs are nonlinear models, which make them flexible in modeling complex real world applications. Finally, they are able to estimate the posterior probabilities, which provide the basis in establishing the classification rules and performing statistical analysis [10]. NNs have been successfully applied to a wide variety of real world classification such as speech recognition, fault detection, medical diagnosis etc.

Dementia is an age-related neurodegenerative disorder whose exact cause is still unknown. Alzheimer's disease, a general form of dementia, is seen by loss of neurons and synapses in cerebral cortex and certain subcortical regions. Though most dementia patients are old, not all old people suffer from dementia meaning that dementia is not part of normal ageing. Dementia can happen to any person, but is common after 65 years. Persons in their 40s and 50s of both sexes can have dementia, but it is more common in men [11].

Dementia is of many types and each has its causes. Some common dementia types are: Alzheimer's disease, Lewy Body Dementia (LBD) and Fronto Temporal Dementia (FTD). Alzheimer's disease is a common cause for dementia. It accounts for 50% to 70% of all dementia cases. It is a progressive, degenerative illness attacking the brain causing shrinkage and disappearance of brain cells. Then, abnormal material builds up as "tangles" in brain cells center and as "plaques" outside brain cells. These interrupt messages in the brain destroying connections between brain cells. Sooner or later, brain cells die and information is unable to be recalled or taken in. As Alzheimer's disease affects brain's neurons, certain functions are affected. Memory of recent events is affected at the start, but long-term memory is affected as the disease progresses [12].

LBD is due to degeneration and death of brain nerve cells and it accounts for 10% to 15% of dementia cases. The name is from the occurrence of abnormal spherical structures, named Lewy bodies that develop inside nerve cells. It is thought these lead to brain cells death. People suffering from LBD hallucinate visually, experience stiffness or shakiness with their condition fluctuating rapidly, often from day to day or hour to hour.

FTD occurs when there is degeneration in the brain's one or both frontal or temporal lobes. FTD is a common subtype accounting for 10% of all dementia cases. It is mainly a behavior disorder. People suffering from FTD are disinhibited or apathetic [13].

The proposed framework uses MRI images from OASIS to identify dementia. Features extraction is through Gabor filter with 0, 30, 60, 90 orientations and GLCM. Features are normalized and fused. ICA is used for feature selection. SVM classifier with various kernels is investigated. Comparison is with Gabor only, GLCM, and proposed fused features. 280 normal MRI image and 140 images with dementia are used and classification accuracy determined.

The rest of the study is as follows: Section II gives literature survey, Section III methodology, Section IV results and discussion, and Section V conclusion.

II. Literature Survey

ICA-based feature extraction and automatic classification of AD-related MRI data was proposed by [14]. It is a new method based on ICA, an increasingly important biomedical signal processing technique enabling separation of blindly observed signals to original independent signals to identify potential AD neuroimaging biomarker(s). Experiments on MRI data from Open Access Series of Imaging Studies revealed that ICA-based method discerned AD and MCI cases from age matched controls.

Investigation of MRI-based cortical surface structure complexity by sample entropy in dementia, for the first time to use SampEn to evaluate cortical surface structure complexity in early stage dementia compared to healthy controls was proposed by [15]. Results reveal an overall larger SampEn in the demented group compared to a non-demented group ($p < 0.05$) indicating a structural irregularity increase of cortical surface in dementia.

A new method of MRI images classification for Alzheimer's disease detection was proposed by [16] presenting Alzheimer's disease classification from MR images medical support. A large database of more than 1000 patients was used. Two problems were tackled in this work; the first where a classification method classified MR images as normal or with Alzheimer's disease and a second to identify and classify between normal subjects, MCI patients, and AD patients.

Advanced systems in medical decision-making by using intelligent computing were suggested by [17]. Application of a new methodology for MR images classification was proposed using a large database. It had two objectives, the first where a classification method classified MR images as normal or with Alzheimer's disease and a second with the ambitious goal of identifying and classifying between normal subjects, MCI patients and AD patients.

Diagnosis of Alzheimer's disease based on Voxel-Based Morphometric (VBM) and SVM was proposed by [18]. It is proposed that VBM and SVM be combined and introduced to diagnose AD for clinical applications. First, with VBM, 20

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features were got from accurate structure imaging of possible AD and controls, and then PCA was used for feature dimensionality reduction to improve efficiency. Results were slightly better under PCA with fewer features. It was proved that combining VBM with SVM could be an automatic tool for early AD diagnosis.

Reference [19] proposed a MRI-based classification framework based on shape and volume features to distinguish AD's patients from those normal. 3-D volumetric features along with 2-D shape features were first extracted from MRI data. Then, PCA decreased feature space dimensions. Lastly, a SVM classifier was trained for AD classification, the Classification accuracy improved from 64% by using 3-D volumetric features and 72% by using 2-D shape features, to 84% by using both features with the proposed framework.

Feature ranking based nested SVM ensemble for medical image classification was suggested by [20] which presented a method to classify structural brain MRI. An ensemble of linear SVMs was used to classify a subject as either work patient or normal control. Image voxels were ranked based on voxel wise t-statistics between voxel intensity values and class labels. Then voxel subsets were chosen based on rank value using a forward feature selection scheme. Finally, an SVM classifier trained on every of image voxels subset. A test subject's class label was calculated combining individual SVM classifiers decisions using a voting mechanism.

Automatic computer aided analysis tool using component-based SVM was proposed by [21], with the approach being based first on an automatic feature selection and secondly combining component-based SVM classification and a pasting vote's technique of SVM classifier ensembles.

Automated Alzheimer's disease diagnosis with degenerate SVM-Based focus on automated diagnosis of AD was proposed by [22] based on researches on neuropathology; it adopted cortex regions thickness from the MRI to characterize AD pathology. 3D reconstruction technique extracted feature vectors from structured MRI data.

Multiclass classification of Alzheimer's disease's initial stages using structural MRI phase images was proposed by [23]. This was a new method based on progressive two class p TCDC-PSVM classifier to differentiate between elderly AD patients, MCI and NC. Structural phase images were formed to extract features using ICA which was subsequently used to classify. Results showed the approach's efficacy and the advantages linked with using structural MRI phase images in discriminating AD's early categories.

Joint independent component analysis (jICA) of brain perfusion and structural MRI in dementia was presented by [24]. The authors tested benefits of joint analysis of multimodality MRI data using jICA and compared to unimodality analyses. They specifically designed a jICA to decompose multimodality MRI data joint distributions across image voxels and subjects to independent components that explain joint variations between image modalities across subjects. They applied jICA to MRI data from 12 patients identified with behavioral variant FTD (bvFTD), a dementia type and 12 healthy elderly individuals. Findings demonstrated jICA's power to evaluate multimodality brain imaging data.

Alzheimer's disease recognition by a self-adaptive resource allocation network classifier was proposed by [25] which was a new approach using VBM detected features with a SRAN classifier for AD detection from MRI scans. For feature reduction, PCA was performed on morphometric features from VBM analysis and reduced features were inputs for SRAN classifier. It indicated that the new PCA-SRAN classifier's approach performs accurate AD classification using reduced morphometric features.

III. Methodology

MRI images collected from OASIS identify dementia in this work. Features extraction is by using Gabor filter with 0, 30, 60, 90 orientations and GLCM. Features are normalized and fused. ICA is used for feature selection. SVM classifier with various kernels is also investigated. Comparison is with Gabor only, GLCM and proposed fused features. 280 normal MRI image and 140 images with dementia are used and classification accuracy determined.

A. OASIS Data Set

OASIS data set has a collection of 416 subjects covering adult life aged 18 to 96 including individuals with early-stage AD [6]. Ninety eight right-handed women (65-96 years) were selected from OASIS database. It ruled out a set of 200 subjects with incomplete demographic, clinical or derived anatomic volumes information. For this study, the images of 49 subjects normal subjects and 49 diagnosed with very mild to mild AD is used. Table I reveals a summary of subject demographics and dementia status.

TABLE I
Experimental Results

	Very mild to mild AD	Normal
No. of subject	49	49
Age	78.08 (66-96)	77.77 (65-94)
Education	2.63 (1-5)	2.87 (1-5)
Socioeconomic status	2.94 (1-5)	2.88 (1-5)
CDR (0.5/1.2)	31/17/1	0
MMSE	24 (15-30)	28.96 (26-30)

B. OASIS Imaging Protocol

The OASIS database was built following a strict imaging protocol, to avoid imaging protocol variations which posed big image normalization problems. Multiple high-resolution structural T1-weighted Magnetization-Prepared Rapid Gradient Echo (MP-RAGE) images were acquired in a single imaging session [26].

C. Gabor Filters

A one-dimensional Gabor filter is defined as multiplication of a cosine/sine (even/odd) wave with Gaussian windows as,

$$g_e(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{x^2}{2\sigma^2}} Cos(2\pi w_o x) \quad (1)$$

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$$g_o\left(x\right)=\frac{1}{\sqrt{2\pi\sigma}}e^{\frac{x^2}{2\sigma^2}}Sin(2\pi w_o x) \tag{2}$$

where w_o defines centre frequency (frequency where filter yields greatest response) and σ spread of Gaussian window [27].

Gabor filter is got by modulating a sinusoid with a Gaussian. For one dimensional (1D) signals, a 1D sinusoid is modulated with Gaussian. This filter responds to some frequency, but only in the signal's localized part. Let g(x, y, θ, φ) be function defining a Gabor filter cantered at origin with θ as spatial frequency and φ as orientation. Gabor filter is defined as

$$g\left(x,y,\theta,\phi\right)=\exp(-\frac{x^2+y^2}{\sigma^2})\exp(2\pi\theta i\left(x\cos\phi+y\sin\phi\right))) \tag{3}$$

It was shown that σ, standard deviation of Gaussian kernel depends on spatial frequency measured, i.e. θ.

D. Grey-Level Co-Occurrence Matrix

In a statistical texture analysis, texture features are computed on statistical distribution of pixel intensity at a position relative to others in a pixel representing image matrix. Depending on the pixels or dots in a combination, there is first-order statistics, second-order statistics or higher-order statistics [28].

GLCM based feature extraction is second-order statistics that analyses image as texture. GLCM (also called grey tone spatial dependency matrix) is a frequencies tabulation of how often a combination of pixel brightness values occurs in an image. Fig. 2 represents formation of GLCM of grey-level (4 levels) image at distance d = 1 and direction of 0°.

0	0	1	1	1
0	0	1	1	1
0	2	2	2	2
2	2	3	3	3
2	2	3	3	3

(a)

	0	1	2	3
0	2	2	1	0
1	0	4	0	0
2	0	0	5	2
3	0	0	0	4

(b)

Fig. 2 (a) Image with 4 grey level (b) GLCM for distance 1 and direction 0°

In addition to horizontal direction (0º), GLCM can be formed for direction of 45º, 90º and 135º as seen in Fig. 3. From centre to pixel 1 representing direction = 0° with distance d = 1, to pixel 2 direction = 45° with distance d = 1, to pixel 3 direction = 90° with distance d = 1, and to pixel 4 direction = 135° with distance d = 1.

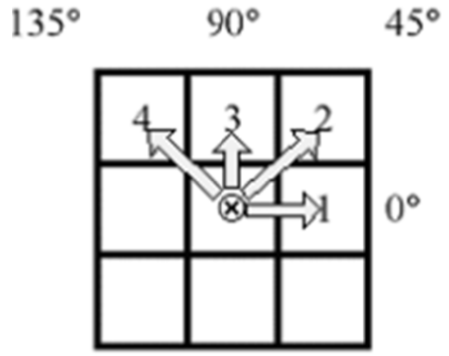

Fig. 3 Direction of GLCM generation

E. ICA

ICA is an unsupervised high order statistics based learning method. ICA is separation of independent sources from observed linear mixtures. The ICA system model is given as

$$X \ = AS \tag{4}$$

where A denotes mixing matrix, S denotes source matrix with statistically independent source vectors in rows and X denotes data matrix. In ICA method, only information which is there are observations, and neither mixing matrix nor sources distribution is known. Assuming that sources are statistically independent and non-Gaussian (one of them may have Gaussian distribution), the un-mixing matrix W is located by maximizing some independence measure. A separation matrix, W, is estimated, which, under ideal conditions, is inverse of mixing matrix A [29].

$$Y = WX\ and\ W = A^{-1}\ and\ Y^{-S} \tag{5}$$

F. SVM

SVM is a linear machine that constructs a hyper plane as decision surface [30]. SVM provides good generalization performance for pattern classification. SVM algorithm's principle is based on inner-product kernel between "support vector" x_i and vector x from input vector.

SVM uses mapping to larger space to compute cross products with variables in original space making computational load easier. In larger space, cross products are defined using a kernel function *K(x,y)* which is chosen to suit the problem domain. Cross products with a space vector, if constant define hyper planes [31]. Vectors defining hyper planes are chosen to be linear combinations with parameters αi of feature vectors occurring in the data base. Once a hyper plane is chosen, points x in feature plane is defined by:

$$\alpha i K(xi,x) = constant\ i \tag{6}$$

If *K(x,y)* becomes small when y grows further from x, degree of closeness is given by the sum measures of closeness of test point x to corresponding data base point x_i. This study uses Radial Basis Function (RBF) kernel.

$$RBF = Exp\ (-\gamma\, |\, xi - xj\, |\, 2) \tag{7}$$

The above method can measure closeness of each test point to data points from data sets to be discriminated. As points set mapped are quite convoluted, complex discrimination occurs between sets far from convex in original space.

SVM performed well as a learning algorithm in the past and perform well on various classification tasks. Also, SVMs allow rapid classification from trained models and can handle very high-dimensional input vectors.

Error function used in this implementation is given by (8)

$$\tfrac{1}{2} w^T w + C \sum_{i-1}^{N} \xi_i + C \sum_{i-1}^{N} \xi^{\bullet} i \tag{8}$$

This can be minimized to

$$w^T \phi(x_i) + b - y_i \le \varepsilon + \xi_i^{\bullet} \tag{9}$$

$$y_i - w^T \phi\,(x_i) - b_i \le \varepsilon + \xi_i \tag{10}$$

$$\xi_i, \xi_i^{\bullet} \ge 0, i = 1, ..., N \tag{11}$$

where C is capacity constant, w vector of coefficients, b a constant and ξ_i parameters to handle non separable data (inputs). Index i labels N training cases.

G. Radial Basis Function (RBF) Classifier

A RBF network is an NN that uses a radial basis function as its activation function. This classifier is different from other NNs by possessing distinctive features such as more compact topology and faster learning speed [32]. The RBF classifier basically consists of three different layers: the input layer, one hidden layer and one output layer [33]. In this network, the determination of number of neurons in the hidden layer is very important. This is because it affects the network complexity and the generalizing capability of the network. If there are an insufficient number of neurons present in the hidden layer then the RBF network cannot learn the data adequately. Poor generalization will occur if there is more number of neurons. Training procedure of RBF networks includes an optimization of spread parameters of each neuron. The weights are selected between the hidden layer and output layer appropriately. The bias value added with each output is determined in the RBF network training [34].

Flowchart of the proposed methodology is shown in Fig. 4.

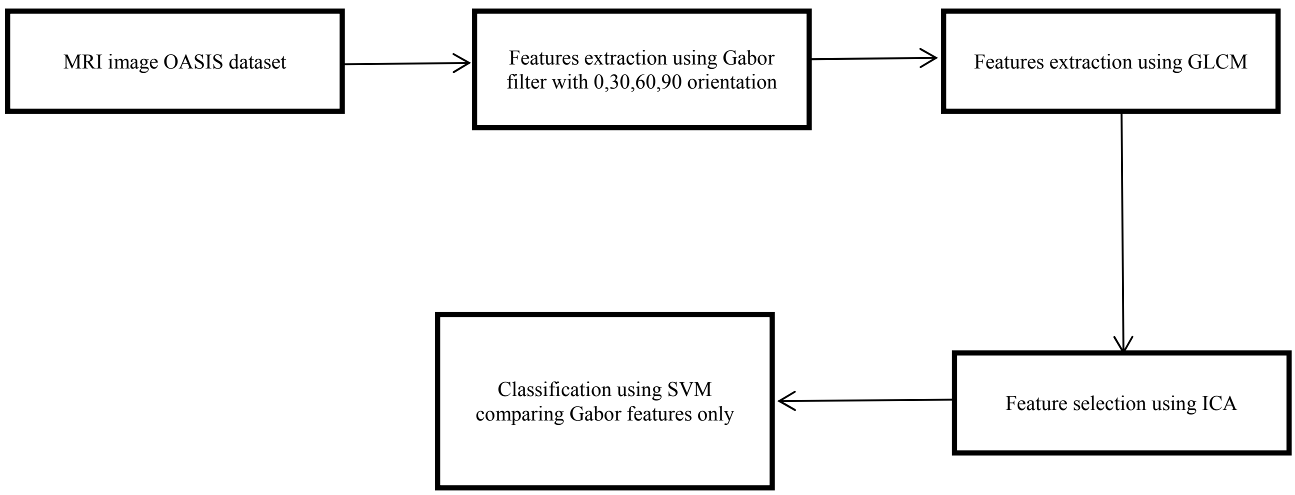

Fig. 4 Flowchart of the proposed method

IV. Experimental Results

In this work, MRI images collected from OASIS are used to identify dementia. Features are extracted using Gabor filter with 0, 30, 60, 90 orientations and GLCM. Features are normalized and fused. ICA is used for feature selection. SVM classifier with various kernels is investigated. Comparison is done with Gabor only, GLCM and proposed fused features. 280 normal MRI image and 140 images with dementia are used. The results obtained are shown in Figs. 5-8.

From Fig. 5, it is seen that the proposed feature fusion with RBF classifier has the highest classification accuracy of 90.24% when compared to all other methods. It is better by 2.71% than Gabor features with RBF classifier and better by 5.78% than GLCM features with RBF classifier.

From Fig. 6, it is seen that the proposed feature fusion with RBF classifier has higher average precision of 0.9065 compared to all the other methods. It is better by 1.43% than Gabor features with RBF classifier and better by 5.27% than GLCM features with RBF classifier.

From Fig. 7, it is seen that the proposed feature fusion with RBF classifier has higher average recall of 0.8714 compared to all other methods. The recall is better by 4.72% than Gabor features with RBF classifier and better by 8.34% than GLCM features with RBF classifier.

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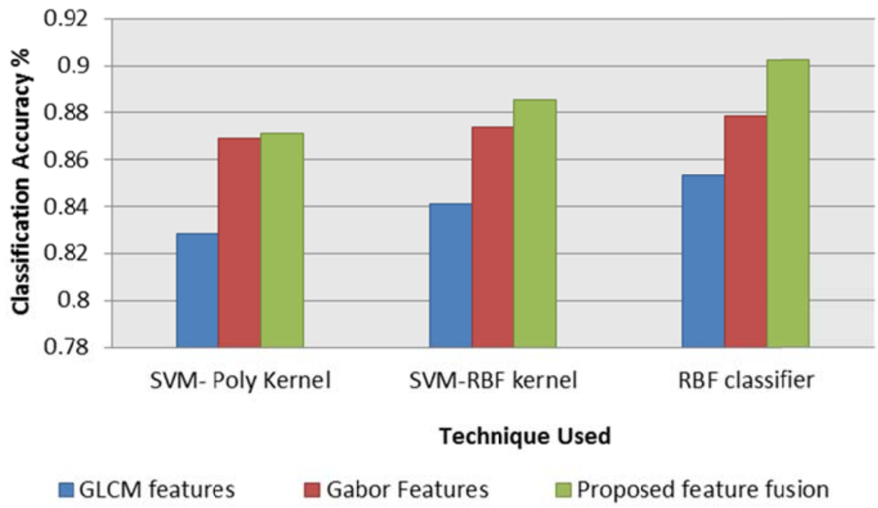

Fig. 5 Classification Accuracy

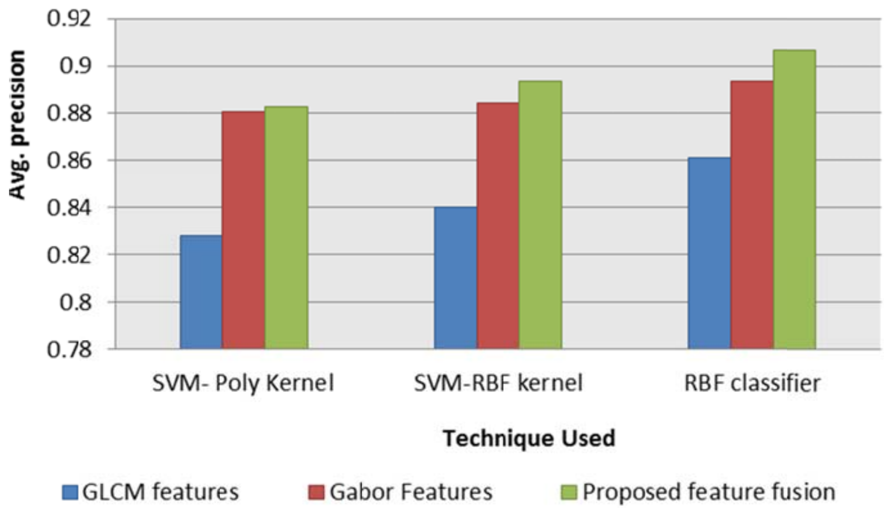

Fig. 6 Precision

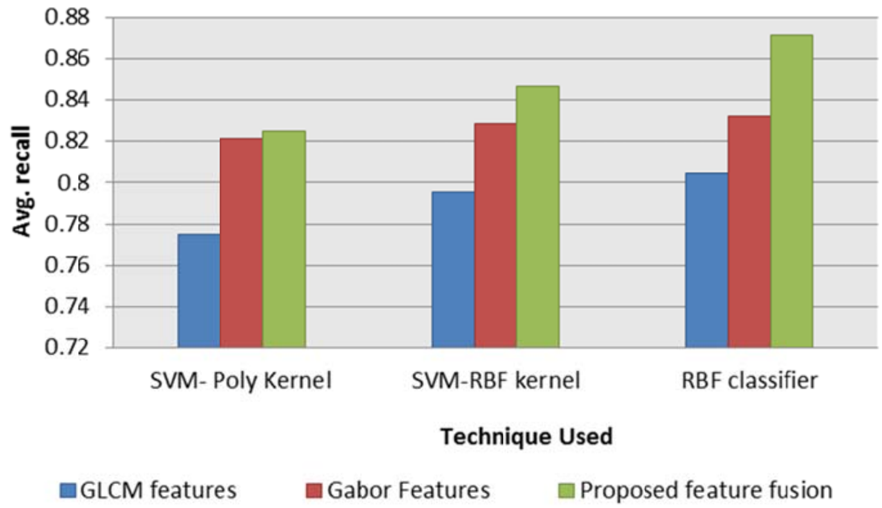

Fig. 7 Recall

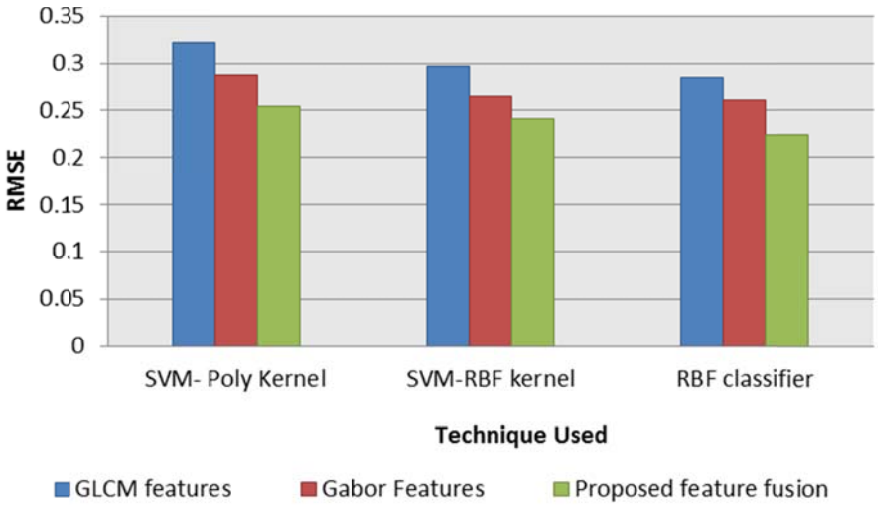

Fig. 8 RMSE

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From Fig. 8, it is seen that the proposed feature fusion with RBF classifier has lower RMSE of 0.2246 compared to all other methods. It is less by 13.98% than Gabor features with RBF classifier and less by 21.03% than GLCM features with RBF classifier.

It is inferred from the experimental results that the RBF classifier achieves better performance when compared to SVM polykernel and RBF kernel. The proposed feature fusion significantly improves the efficiency of the classifier.

V. Conclusion

Brain image analyses relied on univariate voxel-wise analyses like Voxel-Based Morphometry (VBM) for structural MRI. Recently, there is interest in SVM methods to overcome univariate analyses limits. Some studies involved neuropsychological measures for dementia diagnosis and progression from MCI to AD. This study evaluated MRI images from OASIS to identify dementia. Feature extraction is by using Gabor filter with 0, 30, 60, 90 orientations and GLCM. Features are normalized and fused. ICA is used for feature selection. SVM classifier with various kernels and RBF classifier is investigated. The effect of features on classifier is evaluated using Gabor only, GLCM and the proposed fused features. 280 normal MRI image and 140 images with dementia are used and results showed that the proposed feature fusion classifier achieves higher classification accuracy of 0.9024%, higher Average Precision of 0.9065%, higher Average recall of 0.8714% and lower RMSE of 0.2246% compared to GLCM features and Gabor features.

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