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# Alzheimer's Disease Classification by Extracting Salient Brain Patterns

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***Abstract*— Neurodegenerative diseases are the progressive loss of structure or function of neurons in the nerve system, including death of neurons. Many neurodegenerative diseases are in modern society; Alzheimer's disease, Parkinson's disease etc. Neuroimaging is the process of producing images of the structure or function of the brain; it is used for the diagnosis of neurodegenerative diseases. The radiologist can't diagnosis neurodegenerative diseases by direct analysis because it is difficult to quantify systematic differences in the brain image. The proposed method presents a new fully automatic two- phase visual saliency model. In which the magnetic resonance images are processed and find out the neurodegenerative diseases based on the discriminative brain patterns. This method based upon bottom-up and top-down approaches. In bottom-up approach, information comes from a multiscale analysis of different image features. And the top-down approach includes learning and fusion. These learning processes are described using support vector machine (SVM) and neural networks (NN). And the classification accuracy, sensitivity, and specificity of SVM are greater than NN.**

***Keywords*— *Alzheimer's disease (AD), Magnetic resonance imaging (MRI), Support vector machines (SVMs), Neural networks (NNs).***

## I. INTRODUCTION

The term neurodegeneration is a combination of two words neuro and degeneration – "neuro" referring to nerve cells and "degeneration" referring to progressive loss or damage. Then "neurodegeneration" is the loss of nerve structure or function. Neurodegenerative diseases caused by the progressive loss of structure or function of neurons in the nerve system. Alzheimer's disease, Parkinson's disease etc are different type of neurodegenerative diseases. These neurodegenerative diseases occur as a result of degenerative processes of neurons. These diseases are incurable, resulting in progressive degeneration and/or death of neuron cells. Alzheimer's disease is a complex illness affects the brain tissue, by progressive and degenerative loss in the structure or function of neurons. The radiologist can't detect neurodegenerative diseases by direct analysis because it is difficult to find out the systematic differences in the brain image. By analyzing structural brain MR images and its main aim is to find anatomical changes. It difficult to find out the anatomical changes associated with Alzheimer's disease.

Neuroimaging includes the use of different techniques to either directly or indirectly image the structure or function of the nervous system. It is a valuable tool for the diagnosis of neurodegenerative diseases. Alzheimer's disease is a neurological disorder in which the death of brain cells causes memory loss. In worldwide, nearly 44 million people suffering by Alzheimer's or a related dementia, in which only 1-in-4 people with Alzheimer's disease have been diagnosed. No single, simple test exists to diagnose Alzheimer's disease. The proposed method is based on a two-phase visual saliency, it find the salient region in the brain MR images and detect Alzheimer's disease. In which analysis the magnetic resonance images and find out the neurodegenerative diseases based on the discriminative brain patterns.

## II. RELATED WORK

Benoit Magnin, Lilia Mesrob, and Serge Kinkingnehun proposed support vector machine-based classification of Alzheimer's disease from whole-brain anatomical MRI [2], in 2009. In which show and assess a computerized technique based on support vector machine (SVM) for classification of whole-brain imaging (MRI) to patients with Alzheimer's disease (AD) and elderly control subjects (CS). From the MRI of brain image, find region of interest and extract gray matter from each region of interest. Then classification is done based on these extracted features. These feature parameters that showed a discriminating power between patients with AD and healthy CS, and used these feature parameters to make a classifier that can diagnosis whether a single subject belongs to the CS or the AD group. And this classification done by support vector machine (SVM), in which involves a nonlinear mapping from the input parameter to the feature space. The nonlinear mapping of SVM was performed using a radial basis function.

M. Garca-Sebastian, A. Savio, M. Grana, and J. Villanua proposed a method for alzheimer's disease detection use of morphometry based features [3] in 2009. Voxel-based morphometry (VBM) features are extracted in the feature extraction processes for the detection of Alzheimer's disease on brain MR Imaging. Voxel-based morphometry detect clusters of voxel locations it is used to select voxel intensity values upon that the classification features were computed. It has explored the use of the data from the MRI volumes and the GM segmentation volumes. In this method, use the support vector machine (SVM) algorithm to perform classification as Alzheimer's disease and control subjects.

P. Padilla, J.M. Gorriz, J. Ramırez, R. Chaves, F. Segovia, I. Alvarez, D. Salas-Gonzalez, M. Lopez and C.G. Puntonet proposed Alzheimer's disease detection in functional images using 2D Gabor wavelet analysis [4] in 2010. In this method a Gabor wavelet (GW) based analysis of brain images by integrating the 2D GW representation of the images for classification applied to diagnosis of Alzheimer's disease. In which compute GW feature from the input image, for that take brain image of one patient and then slice the image into N images. Then apply GW for each slice of image. Then get a set of GWs, for different scales and orientations. From that extracting the most relevant features, using PCA technique. The resulting reduced feature vector obtained from the different GW-based images is finally taken for classification. The classification is achieved through SVMs.

Margarida Silveira, Jorge Marques proposed Boosting algorithm for Alzheimer's Disease Diagnosis [5] in 2010. This method use of PET images from ADNI database for the diagnosis of AD. It is a boosting classification method, initially generates simple classifiers then combines these simple classifiers. In which at each round of learning the performance of the weak classifier is boosted by a re-weighting. Evaluates the performance of the classifier, with the lowest error is chosen. After each round, the weights are updated to minimize the error. The weights are subsequently normalized. The final strong classifier is a weighted combination of the weak classifiers followed by a thresholding operation. In this technique is based on a mixture of simple classifiers, which performs feature selection concurrently with the segmentation. The boosting classifier adopted to select a small number of voxels from the whole volume and it provides a robust classification.

Sandhya Joshi, Deepa Shenoy, Vibhudendra simha G G., L M Patnaik proposed classification of alzheimer's disease (AD) and parkinson's disease (PD) by using machine learning and neural network methods [6] in 2010. It is a new model for the classification of AD and PD by considering the most influencing risk factors. In this method begins with the collection of patients records with AD, PD and normal. Then preprocessing of data set it converting the data in to numeric values. The main task is the selection of most influencing risk factors for both AD and PD. Attribute evaluation scheme with ranker search method used to select of most influencing risk factors. For the given data set the five different methods for attribute selection; chi squared attribute evaluation, gain ratio attribute evaluation, info gain attribute evaluation, similarly one r attribute evaluation, symmetrical uncertain attribute evaluation. Finally classification by using neural networks and machine learning methods. It shows that some specific genetic factors, age, diabetes, and smoking were the strongest risk factors for Alzheimer's disease. Similarly, for the classification of Parkinson's disease, the risk factors such as genes, stroke, diabetes and age were the vital factors.

Dong Hye Ye, Kilian M. Pohl and Christos Davatzikos proposed an image-based classification method for Alzheimer's disease detection [7], in 2011. In this method features are extracted from the MR image after dimensionality reduction using nonlinear manifold learning techniques. In the feature extraction, use the RAVENS maps for characterizing the image feature. The brain image is segmented based on its tissues as, gray matter, white matter and cerebrospinal fluid, then individual image the template to be registered. This creates the RAVENS map by registering the each structural MRI scan using HAMMER algorithm. To reduce the noise, the RAVENS maps are smoothed by using Gaussian kernel. The high dimensionality of the image information is reduced using nonlinear manifold learning techniques. And the dimensionality of RAVENS maps is relatively high; and it reduced by using ISOMAP algorithm. Based on the extracted features classification is done using semi-supervised classifier.

P. Padilla, M. Lopez, J. Gorriz, J. Ramirez, D. Salas-Gonzalez, and I. Alvarez proposed NMF-SVM based technique for computed aided diagnosis of the Alzheimer's disease [8] in 2012. The proposed technique is based on the combination of nonnegative matrix factorization (NMF) method for feature selection, reduction and SVM for classification. The initial features are selected based on discrimination capability. The features are selected by using Fisher Discriminant Ratio (FDR). The selection of voxels based on the FDR threshold value. It selects lower number of variables in each observation. Nonnegative matrix factorization (NMF) method for locating parts-based linear representations of nonnegative data, it is useful decomposition tool for multivariate data. Applying the Fisher discriminant ratio (FDR) and nonnegative matrix factorization (NMF) methods for feature selection and extraction of the most relevant features. The resulting NMF-transformed sets of data, which contain a reduced number of features. And then these features are used for classification with SVM. The results of the proposed NMF-SVM method have high classification accuracy with high sensitivity and specificity values.

M. Liu, D. Zhang, P. Yap, and D. Shen proposed a hierarchical ensemble of multi-level classification algorithm for diagnosis of Alzheimer's disease [9], in 2012. The proposed classification framework, T1-weighted MRI brain images are used for demonstrating its classification performance. Preprocessing of the images was performed before using them for classification; skull-stripped and cerebellum-removed from all T1-weighted MRI. Then, each brain image is segmented into three brain tissues: gray matter, white matter and cerebrospinal fluid. And all these brain tissues are spatially normalized onto a standard space by a mass-preserving deformable registration algorithm. The spatially normalized gray matter volumes, i.e., gray matter densities, are used as the imaging features. And learning process done by using supervised learning. Based on these extracted features low-level and high-level classifiers are generated. Combine all these high-level classifiers and make final decision. The proposed hierarchical ensemble classification algorithm, which consists of four main steps: patch extraction, construction of low-level classifiers, high-level classifications and final ensemble. Ensemble of the M high-level classifiers is performed by weighted voting to make the final decision.

Luis Javier Herrera, Ignacio Rojas, H. Pomares, A. Guillen, O. Valenzuela, O. Banos proposed a method, classification of MRI image for Alzheimer's disease detection [10], in 2013. In this method uses large database of MR images, more than one thousand patient records. The main steps are feature extraction, feature selection and classification. This methodology includes wavelet feature extraction, dimensionality reduction using principle component analysis, feature selection by normalized mutual information feature selection and Support Vector Machines for classification. In the feature extraction process, the DWT is applied to each dimension separately, and decomposing an image into four sub-bands which are low-low, low-high, high-high and high-low. And wavelet coefficients represent the features of the image. Dimensionality reduction is a complex problem and the objectives of dimensionality reduction are decrease the model complexity and increase the performance. It offers two main alternatives: feature reduction and feature selection. Normalized mutual information feature selection (NMIFS) algorithm is a powerful technique derived from the minimum Redundancy Maximum Relevance which has shown to present good results in selecting the most relevant features. It is based in the Mutual Information measure taken from the Information Theory. Support Vector Machines (SMV) is used as classification technique. SVMs are originally formulated for binary classification. And multi-classification performed by combination of different binary classifiers.

Pedro M. Morgado, Margarida Silveira and Jorge S. Marques proposed local binary patterns to 3D for the diagnosis of alzheimer's disease [11], in 2013. In this method, explore the discriminative power of the Local Binary Patterns (LBPs) texture descriptor to detect AD and MCI from 3D brain images. For this purpose, propose a novel extension of LBPs to full 3D data. A novel approach to full three-dimensional, using uniform and rotation invariant LBPs.

In the feature selection process only the most discriminate features were retained, by using a ranking selection procedure. It is based on the Pearson Correlation Coefficient between each feature and class label i.e., by selecting only the features with highest correlation with the class. Based on these extracted features, classification is done by using SVM algorithm. SVM is one of the most popular discriminative models for classification. It has good generalization ability and produces good results even in the presence of small training sets. The linear kernel was used in this classification.

## III. METHOD

The proposed method is based on a two-phase visual saliency model that achieve correct classification of brain MR images as AD or normal by combines bottom-up and top-down approaches. In bottom-up approach information comes from a multiscale analysis of different image features. Then saliency map is generated for each extracted features. In the top-down approach includes learning and fusion. These learning processes are described using support vector machine and neural networks. In SVM, generalized multiple kernel learning (GMKL) used for learning different combinations of kernels. And neural network it have mainly three phases; training, testing, and classification. Then it will find out the Alzheimer's disease (AD) using discriminative anatomic patterns. The proposed method described within the figure1 and the Algorithm 1.

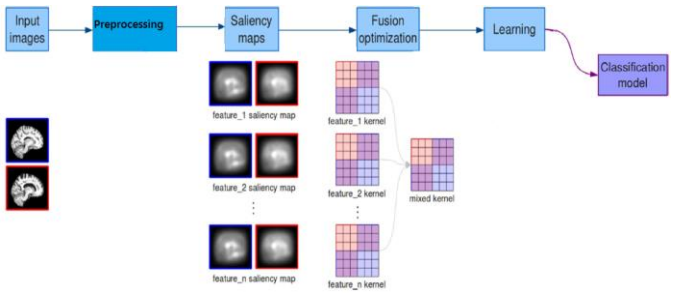



Fig 1: Proposed frame work

Algorithm 1: Saliency –based pattern Extraction

Input: N structural brain volumes
Output: Classification of neurodegenerative diseases
Step 1: Calculation of saliency map
Step 2: Bottom-up saliency fusion
Step 3: Top-down learning

### A. *Preprocessing*

Before processing all the captured data needs to be organized in a particular format or pattern, these process of organizing data is known as preprocessing. The main aim of preprocessing is an improvement of the image data that suppresses unwanted distortions or enhances image features important for further processing. Mainly three processes in the preprocessing step of brain MR images. First process is removing skull from the input images; remove all unwanted parts from the brain image. In the second process noise reduction; noise is any degradation in an image signal caused by external disturbance. This noise can be reduced by using Wiener filter. In the last process, contrasts enhancements in which adjust image intensity values and enhance the image.

### B. *Calculation of Saliency Maps*

The search of particular patterns among the anatomical areas in structural brain MR images, these images is considered as a fully connected graph. In which each node represents particular anatomical region and each edge represents similarity or dissimilarity measure between regions. If an image is partitioned in different scale then each parts of the image is considered as a fully-connected graph, then measure similarity or dissimilarity between the regions. And Markov chains used to model saliency and attentional fixations in the images. Based on the similarity or dissimilarity measure of the regions, detect the salient region of the brain image. Salient region of the image is the

most discriminative part of the image. The graph-based visual saliency (GBVS) approach, measure dissimilarities between feature pixels by closeness measure in the graph connections. Then it detects most discriminative pixels in the image, i.e., salient pixels. By analysis the magnetic resonance images and find out the discriminative brain patterns.

Saliency map of brain MR images is calculated by extracting set of features from given image x, $\{T^{\phi}(x)\}_{\phi}$, where $\phi \in \Phi$ denotes a particular combination of scale and visual feature. Commonly used features include; intensity, orientation, and edge information. Intensity information of the image is the individual gray value of each voxel; orientation information is calculated using a bank of Gabor filters with four different orientations ( 0 , 45 , 90 , 135 ) ; and finally, edge information is extracted by applying a Sobel operator. These features are extracted from the brain image and saliency map is generated. And the haralick texture features are also used for image classification it includes 13 features they are; normalization, energy, correlation, sum of variances, inverse difference moment, entropy, information measures of correlation, sum average, sum entropy, sum variance, difference variance, contrast, and difference entropy values of the image. Take the MR brain data into these three different scales (1/4, 1/8, 1/16) for each feature. It performs dimensionality reduction, an important factor for proper classification. These features aim to approximate the sparsity of the Human Visual System; by showing that sparse coding of images produces Gabor-like oriented filters that resemble the receptive fields of simple cells in the visual cortex. And considered that the relevance of visual information is proportional to its coherence through different scales. The feature maps are also calculated at three different scales by sub-sampling the original image volume. It will generate set of saliency maps based on each features and scales.

The structural brain MR images are considered as a fully connected graph. Features maps are generated by extracting features at different scale; per-slice-fully-connected graph $G^{\phi}_{A}$ is associated to each feature map $T^{\phi}(x)$. The graph vertices denoted to the image pixels and the edges denoted the regional dissimilarity between nodes. As, the edge weight between graph nodes $g^{A}_{i,j}$ and $g^{A}_{p,q}$ is calculated using Eq.1

$$w\left(g^{A}_{i,j}, g^{A}_{p,q}\right) = d\left(g^{A}_{i,j}, g^{A}_{p,q}\right).F(i-p, j-q) \quad (1)$$

Where $d\left(g^{A}_{i,j}, g^{A}_{p,q}\right)$ calculates the dissimilarity and $F(i-p, j-q)$ calculates the closeness between nodes. Dissimilarity is calculated using Eq. 2

$$d\left(g^{A}_{i,j}, g^{A}_{p,q}\right) = \left| log \frac{T^{\Phi}(v)_{i,j}}{T^{\Phi}(v)_{p,q}} \right| \quad (2)$$

Where calculating dissimilarity the logarithmic metric guarantees that larger feature dissimilarities pop out easily, in which find out the salient features of the image. And, the closeness is measured using Eq.3

$$F(a,b) = \exp\left(-\frac{a^2+b^2}{2\sigma^2}\right) \quad (3)$$

Where σ is a free parameter of the GBVS algorithm. This means that feature dissimilarity information of the input image is modulated by the spatial distance between nodes, and regional dissimilarity information at the graph edges.

After dissimilarity and closeness measure from the feature map of the input image, the activation map $A^{\phi}$ is generated. The activation map that point out connected regions of high dissimilarity value, are estimated by constructing a Markov Chain on each $G^{\phi}_{A}$. And then estimating its equilibrium distribution as the principal eigenvector of the stochastic matrix, using the Power Iteration Method. Once activation maps are generated, then normalize the activation map to guarantee that these maps concentrate the saliency only. The same Markovian approach is applied to each activation map $A^{\phi}$, using a new graph $G^{\phi}_{N}$ with image pixels as vertices, but edges now storing information about regional activation calulated using Eq.4

$$w_N\left(g^{N}_{i,j}, g^{N}_{p,q}\right) = A^{\Phi}(p,q).F(i-p, j-q) \quad (4)$$

So the equilibrium distribution of a new Markov chain on each $G^{\phi}_{N}$ highlights pixels with high activation or saliency. Finally, the feature saliency map $S^{\phi}(x)$ for the whole volume x is constructed. The saliency map calculation process is described in Algorithm 2.

Algorithm 2: Calculation of saliency map

Input: N structural brain volumes
Output: N set of saliency maps
Step 1: Multi-scale decomposition of image volume
Step 2: Feature extraction per each scale
Step 3: Construction of fully-connected graph, using dissimilarity and closeness measure
Step 4: Construction of Markov chain upon graph
Step 5: Calculation of equilibrium distribution of the Markov chain
Step 6: Normalize the map

*C .Bottom-Up Saliency Fusion*

In the previous section calculation of saliency map provides a set of saliency maps for given volume x,$\{S^{\phi}(x)\}_{\phi}$, with different scales and different features. Where each saliency map calculated by the combination of different scale and features. Each saliency map is calculated by using a function $S^{\phi}: I \rightarrow [0,1]^{m \times n \times l}$, where $\phi \in \Phi$ represents a particular combination of scale and visual feature, and I represents the volume representation space which is usually $\{0,.....,255\}^{m \times n \times l}$, with (m,n,l) the volume size.

Then fuse set of saliency maps with different scales and different visual features. In this fuse all saliency maps and produce final saliency map with most salient features.

There are different methods to fuse information from set of saliency maps. A common fusion method is used, that to weight the maps and then sum them up to calculate an overall saliency map using Eq.5

$$S^*(x) = \sum_{\sigma,\phi} w_{\sigma,\phi} S_\sigma^\phi(x) \quad (5)$$

The proposed fusion strategy that takes all the information from the different saliency maps and only fuse them. Based on this information decisions are made. The saliency maps are used as input to a discriminant function and that detect probable AD cases. Where $\Psi:[0,1]^{m\times n} \rightarrow F$ is a mapping function that maps each saliency map $S^\phi(x)$ to a new feature space F. And it indicates the relative importance of each saliency map $S^\phi(x)$ based on the discriminant features. This provides the advantage as improving the flexibility of the model. An important parameter of the model is the function $\Psi$ which maps a saliency map to a new feature space. Then it provide the transformation from complex nonlinear patterns to linear, and it is potentially high-dimensional in new feature space. This is a strategy used in kernel methods, kernel tricks. Where the mapping function implicitly induced by a kernel function. A kernel is a function associated with mapping of saliency map. Kernel matrix is generated for each saliency map. These kernel functions measure the similarity and generate final saliency map. In the proposed model, the input space is the saliency maps, and kernel function measures the similarity between saliency maps. This step described as detailed in Algorithm 3.

Algorithm 3: Bottom-up saliency fusion

Input: N set of saliency map
Output: S feature scale kernel matrices
Step 1: For each combination of feature and scale normalize all saliency map
Step 2: Calculate kernel function, i.e. measure similarity among pair of volumes.

The mapping function that used as the histogram intersection kernel defined in Eq.6. The histogram intersection kernel that normalizes the all input saliency maps and it produce final saliency map.

$$k_{hi}(s_p, s_q) = \sum_i \sum_j \sum_k \min(s_p(i,j,k), s_q(i,j,k)) \quad (6)$$

### C. Top-Down Learning

Classification is the most frequently encountered decision making tasks of human activity. Many decision-making tasks are the one instance of classification problem or can be easily formulated into a classification problem, e.g., prediction and diagnosis tasks, forecasting tasks, and pattern recognition. In this proposed method classification problem is diagnosis of Alzheimer's disease. Here classification done using support vector machine (SVM) and neural networks.

In the top-down model, the most discriminative image features in the different saliency maps used for classification. It uses domain knowledge codified as a set of labelled training volumes, to find optimal values that maximize the discriminative ability of the model.

$$min_{w,\tau}\, C \sum_{i=1}^{N} \max(0, 1 - y_i gw, \tau(x_i)) + \|W\|_2^2 + \|\Gamma\|_2^2 \quad (7)$$

Where $x_i$ represents a training volume, yi $\epsilon\{-1,1\}$ represents the corresponding label, N is the number of training samples, and C controls the regularization. The first term is a loss function that penalizes the wrong classification of training samples, the second and the third terms are regularizes the classification.

The regularization is used to finding a max-margin classifier as done for support vector classification, and the regularization is aims to find the sparsest set of feature weights.

The proposed model saliency map fusion is done by, fuses the information from the different saliency maps by combining the respective kernels instead of directly adding the saliency map. This means that the optimization problem is a multiple kernel learning (MKL) problem, where a good discriminant hyperplane determined for classification. Several MKL formulations have been proposed, here describes a generalized multiple kernel learning (GMKL), used for learning different combinations of kernels. Learning of the classification model using SVM is presented in Algorithm 4. In this classification step it also check the haralick features of the brain image.

Algorithm 4: Top-down learning using SVM

Input: S feature scale kernel matrices, N class labels
Output: Trained classification model
Step 1: Solve Min-max-margin-discrimination optimization problem
Step 2: Generate optimal kernel using linear combination of the feature scale kernels
Step 3: Obtain the single optimal kernel

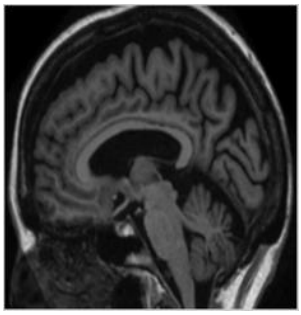
The second method for classification by using neural networks. In neural networks, classification processes have mainly three phases training, testing, and classification. Create an initial neural network, by set the input patterns and target output. Then train the neural network using training parameters. Then testing done using testing data and classify the testing data into normal or AD. The learning process using neural networks is described in Algorithm 5.

Algorithm 5: Top-down learning using NN

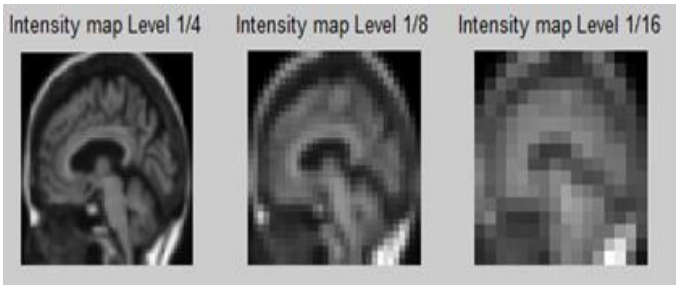
Input: S feature scale kernel matrices, N class labels
Output: Trained classification model
Step 1: Create an initial neural network and set the input patterns and target.
Step 2: Train the neural network using training input values.
Step 3: Then testing done using testing data.
Step 4: Classify the testing data into normal or AD.

## IV. EXPERIMETAL RESULTS

In this method detect Alzheimer's disease (AD), by extracting salient brain patterns from the brain image. Saliency map is generated from the input image, after feature extraction. Intensity, orientation, edge information are used for saliency map generation, it is shown in figure 2 . And haralick features are used for classification. A set of saliency maps are generated at different features and scales. Fuse all these saliency maps, and then obtain a final saliency map. The final saliency map that contain most discriminant features it is used for learning. The learning phase use two methods SVM and neural network, then classification is done and result is obtained as AD or normal.



(a)

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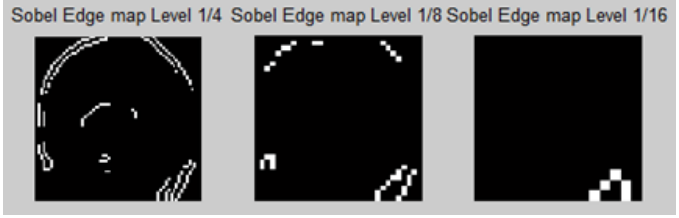


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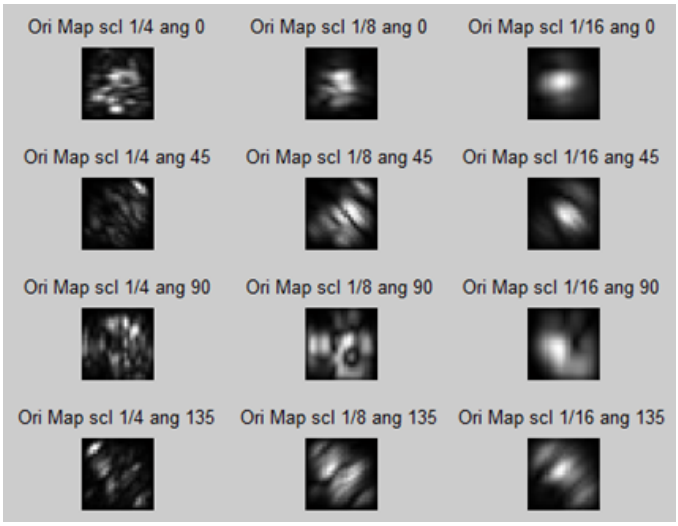


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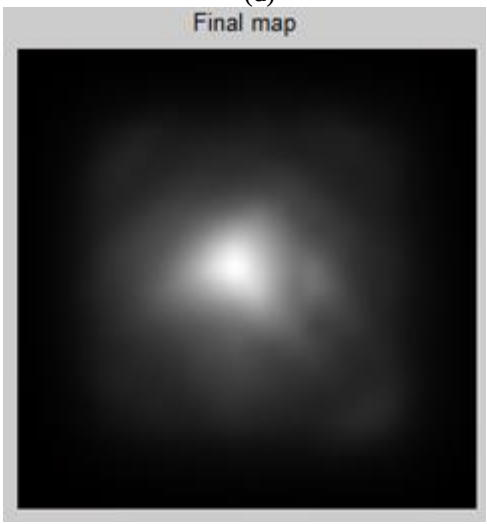


(e)

Fig 2: (a) Input Image, (b) Intensity map, (c) Edge map, (d) Orientation map, (e) Final map

### A. *Performance Analysis*

The OASIS (Open Access Series of Imaging Studies) data set is used to evaluate the performance of the proposed method. In this datasets contain brain MR image from normal subjects and Alzheimer's disease patients. Each subject has been previously analyzed with Clinical Dementia Rating (CDR), and diagnosed as normal controls (NC) or with probable Alzheimer's disease (AD) using the scores obtained in the CDR tests.

In this OASIS data set is dividing into two groups, training group and testing group. In this classification system uses 166 MR images are used for training, in which contain 83 normal control and 83 patients suffering Alzheimer's disease. And in testing uses 76 MR images, in which contain 38 normal control and 38 patients suffering Alzheimer's disease.

The classification performance of the proposed method was evaluated using the following metrics,

Accuracy (Acc) = ( TP + TN ) / ( TP + TN + FP + FN ) (8)
Sensitivity (Sens) = TP / ( TP + FN ) (9)
Specificity (Spec) = TN / ( FP + TN ) (10)
Error rate = 100 – Acc (11)

Where TP stands for true positives (AD individuals correctly classified), TN for true negatives (NC individuals correctly classified), FP for false positives (NC individuals misclassified), and FN for false negatives (AD individuals misclassified).

Then analysis the performance of SVM and NN based on accuracy, sensitivity, specificity, and error rate values. The table 1 shows accuracy, specificity, sensitivity and error rate values of SVM and NN. The performance analysis of SVM and neural networks are graphically represented in figure 3.

TABLE 1: Performance analysis of SVM and NN

| Measures | SVM | NN |
|---|---|---|
| Accuracy | 84.21 | 65.78 |
| Sensitivity | 76.31 | 60.52 |
| Specificity | 92.10 | 71.05 |
| Error rate | 15.78 | 34.21 |

In table 1 shows the performance analysis of SVM and NN, in which measure accuracy, sensitivity, specificity and error rate values. The classification accuracy of SVM is 84.21%. The sensitivity of SVM is 76.31 %, specificity of SVM is 92.10 %, and error rate of SVM is 15.78 %. The classification accuracy of NN is 65.78%. The sensitivity of NN is 60.52 %, specificity of NN is 71.05 %, and error rate of NN is 34.21 %.

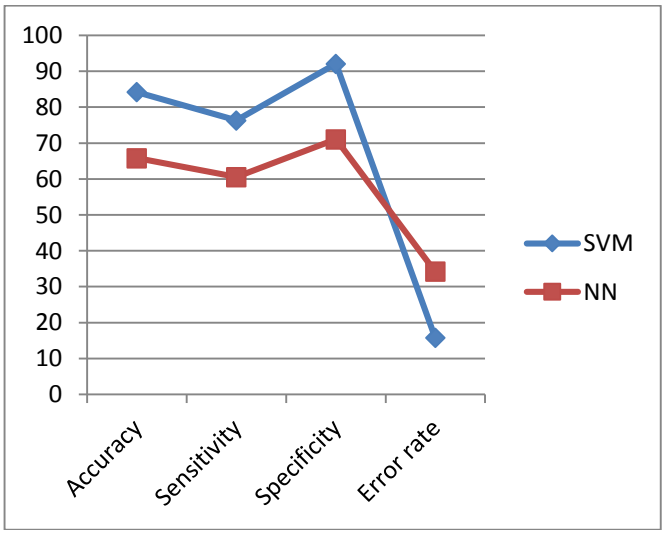


Fig 3: Performance Analysis

In this analysis shows that SVM have high performance than neural networks. The SVM have high accuracy, sensitivity, and specificity value, and low error rate value.

In this method extract salient features of the brain image. The salient region of the image is the most discriminative part of the image. Based on the extracted salient features are used for classification of brain images.

## V. CONCLUSION

The proposed method presents a new fully automatic two-phase visual saliency model for diagnosis of Alzheimer's disease. In which analysis and process the magnetic resonance images and find out the Alzheimer's diseases based on the discriminative brain patterns. This method based upon bottom-up and top-down approaches. In bottom-up approach information comes from a multiscale analysis of different image features. Then saliency map is generated for each extracted features. And the top-down approach includes learning and fusion. These classification of MR images by using support vector machine and neural networks, and diagnose Alzheimer's disease based on salient features of brain image. In this method SVM have high performance than NN. In which SVM have accuracy 84.2%, specificity 92.1%, sensitivity 76.31%, and it also low error rate 15.78 %.

## VI. FUTURE WORK

Image classification is an important part of the remote sensing, image analysis and pattern recognition. The satellite images are classified easily using the proposed method. The proposed model is based on two phase visual saliency model that combine bottom-up and top down approaches. In which extract salient patterns from the satellite image and generate saliency map. Then classify the satellite image effectively based on the extracted discriminant patterns.

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