

# cAlzheimer's Disease Classification using Leung-Malik Filtered Bank Features and Weak Classifier

Shaik Basheera, M Satya Sai Ram



**ABSTRACT** We propose a frame work to classify Brain MRI images in to Alzheimer's Disease (AD), Cognitive Normal (CN) and Mild Cognitive impairments (MCI). We use 114No's of T2 weighted MRI Volumes. We extracted relative texture features from Leung-Malik Filter bank,  $k$  means is used to generate Bag of Dictionary (BoD) from LM Filtered images. We performed binary classification and Multi class Classification using different Classifiers, Adaboost Classifier gives better performance both in binary and multi class classifications in comparison with other classifiers. Performance of proposed system is enhanced than compared to the existing techniques. It has Sensitivity for AD-CN 89.8, AD-MCI 78.82, AD-CN-MCI 77.77, Specificity for AD-CN 79.22, AD-MCI 80.00, AD-CN-MCI 58.88, and positive prediction value for AD-CN 79.48, AD-MCI 83.75, AD-CN-MCI 68.47 and Accuracy AD-CN 84.24, AD-MCI 79.33, AD-CN-MCI 72.88.

**Keywords:** Machine Learning, Image segmentation, Feature Extraction, Support vector machines, Gaussian NB, Decision Trees, AdaBoost

## I. INTRODUCTION

As per the latest health survey, Alzheimer's is the 6th leading cause of death in United States. AD is the most predominant age related dementia. Memory loss is the first symptom related to AD, it effect a person's day to day activities. Due to AD, brain structure get change as hippocampus get shrinks, ventricular get enlarge and cause more CSF, reduce white matter and increase gray matter. This is due to the person's family history and presence of Apo lipoprotein e4 gene. AD is irreversible progressive disease where the brain cells are gradually destroyed and loss connection of the neuron cells. Diagnose the AD is the most crucial task.

AD is diagnosed by patient medical history, neurological examination, physical examination, examine the persons memory and thinking using a innovatory questionnaire specially designed by the doctors also use dementia rating and Mini mental state examination (MMSE). First Clinical criteria is developed by National Institute of Aging Alzheimer's Association for diagnose AD. Along with the above clinical techniques different Imaging techniques are used to diagnose the Alzheimer's disease stage.

In recent day's neurological imaging techniques such as Magnetic resonance imaging (MRI), Positron emission tomography (PET) is used to analyze and evaluate different neurological disorders. By using imaging techniques radiologist diagnose the disease. As the AD progress it leads to shrink in brain volume and decline hippocampus size, texture of the brain MRI play major role to identify the stage of disease. Computer aided diagnose (CAD) techniques are used in diagnose AD.

From past decade Machine learning is used in CAD to diagnose AD. CAD provide assessable measurements. Software modalities are used to give assistance to the radiologist to diagnose the disease. In this paper we use T2 weighted MRI images to perform classification of AD stages as AD, Mild Cognitive impairment's, and Cognitive Normal (CN). [1] Regional based biological change in different regions of functionally connected anatomical regions may differ the AD, MCI, and CN. [2] An automatic algorithm Hippocampal volume Integrity is developed to estimate the hippocampal volume to differentiate AD, MIC and CN. [3] Change in White matter is estimated to analyse the effected area of brain due to Alzheimer's.[4] Multiple morphological features are merged and perform the classification using Random forest with 2000 trees. [5]Multiple image visual features are merged from multiple kernels and perform the classification. [9][10] Gray level Co-occurrence features of voxel neurological analysis is used to classify AD and CN. [11]Gabor filters textures are used to extract texture data of AD and CN images. [6] Brain topological organization captured by a novel brain model using multiplex graph network to summarize NC, AD and MCI. [12] Regional volume of hippocampus, ventricles, and gray matter of brain subcortical regions are used to analyze the neuroimaging data such as AD, MCI and CN. [7] Region of interest is an automatic method to detect AD and progression of MCI to AD. [13] Uses deep learning approach with Multi phase features with soft max as classifier they take MMSE and Multi-mode Neuroimaging data as features.

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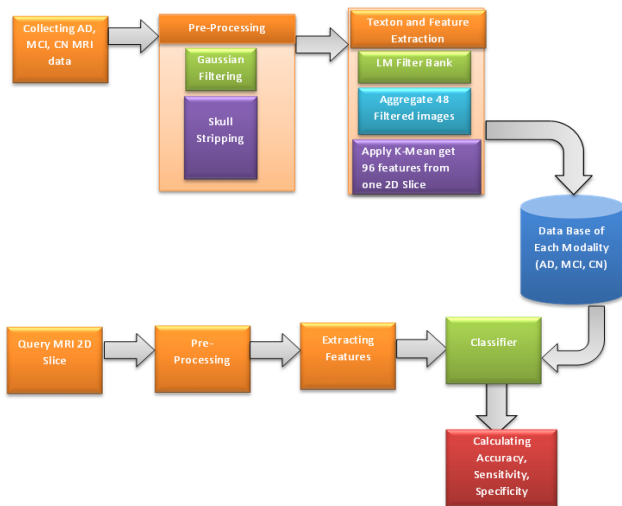


Fig.1. Overall Block Diagram of Proposed System

II. MATERIALS AND METHODOLOGY

The proposed system is divided into two steps as train the classifier and test the classifier. The functional block diagram is shown in Fig.1. Before train the images are pre-processed, Texton features are extracted from the image to perform the image recognition.

III. DATA COLLECTION AND PRE PROCESSING

A. Data Collection

Most of the AD research, the inventers are using the online data base. Our proposed system required T2 MRI image data set collected from Alzheimer's disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu)[16]. The primary goal of ADNI is to combine PET, MRI to measure the progression of MCI to AD. It is launched in 2003 under public and private partnership, directed by principle investigator W. Michel Weiner. For our work we collected 70 MRI Volumes from AD, as listed in Table 1

Table 1: MRI images Collected and Demographic representation

Date Source	Research Group	Sex	Age (Years)	Number of MRI Volumes	Image Slices	Imaging Protocol
ADNI	AD	F	58-90	32No's	284No's	Axial, 2D,
		M	55-92	38No's		1.5Tesla Field Strength
	CN	F	71-96	10No's	300	
		M	70-95	10No's	No's	
	MCI	F	61-96	12 No's	300	
		M	61-90	12 No's	No's	

\*\*ADNI: (alzheimer 's Disease Neuroimaging Initiative)

B. Pre-processing

We collected T2 MRI Volumes from publically available ADNI online respiratory. T2 weighted MRI is preprocessed by collecting Slices from MRI images, these MRI Voxels are filtered using 5x5 median filter and skull stripped[14] the resultant skull stripped image is shown in Fig. 2.



Fig. 2. Skull Stripped Image (a) Original Filtered image (b) Skulls Stripped Image

C. Feature Extraction

Textures of an image are extracted using Different Filter banks and the advantage of using filter bank is exploited. [8] Leung-Malik Filter bank (LM Filter bank) of 48 filters that address texture classification, applied on pre-processed image.

D. LM Filter Bank

Texture of an image is having spot, Line, Edge and Bar type descriptors in different orientations, scales. Edge and Bar type descriptors are collected using 1<sup>st</sup> and 2<sup>nd</sup> derivative of Gaussian filters in 6 orientations with 3 scales as  $\{\sqrt{2}, 2, \sqrt[3]{2}\}$  total 36 filters, 4 rotation in variant Gaussian low pass filters, 8 Laplacian of Gaussian Filters total 48 Filters are used to analyse the texture of image, 48 filters are shown in Fig. 3.

Edge, Bar descriptors are generated by convolve the image with 1<sup>st</sup> and 2<sup>nd</sup> derivative functions of Gaussian with  $\theta$  as orientation in 6 direction,  $\sigma$  as scaling factor given as equation (2),(3),(4),and (5).

$$h(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

$$h'_{\theta x}(x, y) = -h(x, y, \sigma) \frac{(x)}{\sigma^2} \tag{2}$$

$$h'_{\theta y}(x, y) = -h(x, y, \sigma) \frac{(y)}{\sigma^2} \tag{3}$$

$$h''_{\theta x}(x, y) = -h(x, y, \sigma) \frac{x-\sigma^2}{\sigma^4} \tag{4}$$

$$h''_{\theta y}(x, y) = -h(x, y, \sigma) \frac{y-\sigma^2}{\sigma^4} \tag{5}$$

Laplacian of Gaussian (LoG) filter is applied to find the rapid changes in the image as edges, as derivative filters are sensitive to noise so before apply the Laplacian to an image it is first processed by Gaussian filter and then edges are detected with  $\sigma = \{\sqrt{2}, 2, \sqrt[3]{2}, 4\}$ ,  $3\sigma = \{3\sqrt{2}, 6, 3\sqrt[3]{2}, 12\}$ , total 8 Laplacian filters are considered LoG filter with scaling is given as equation (6).

$$h(x, y, \sigma) = -\frac{1}{\pi\sigma^4} \left[ 1 - \frac{x^2+y^2}{2\sigma^2} \right] e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{6}$$

Four Gaussian Filters are applied to the image with  $\sigma_x, \sigma_y$  given as  $\sigma_x = \{\sqrt{2}, 2, \sqrt[3]{2}, 4\}, \sigma_y = \{3\sqrt{2}, 6, 3\sqrt[3]{2}, 12\}$ ,

$$h(x, y, \sigma_x, \sigma_y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\left(\frac{x^2}{2\sigma_x^2} + \frac{y^2}{2\sigma_y^2}\right)} \quad (7)$$

Filtered image  $g(x, y)$  is generated as

$$g(x, y) = (f \otimes h)(x, y) = \int_{-\infty}^{\infty} f(\tau)h(t - \tau)d\tau \quad (8)$$

**E. Aggregate filtered images**

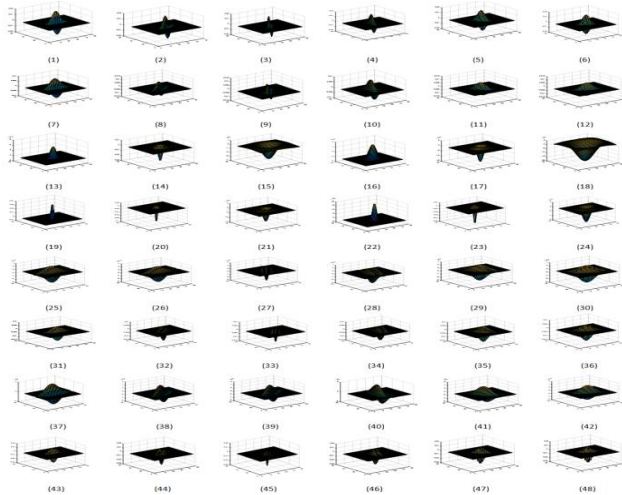
Filtered images  $g(x, y)$  are aggregated to reduce the size of the data and memory required, increase accuracy in feature collection and speed in classification. We select every 4<sup>th</sup> pixel from the filtered image and collected Maximum intensity to make the aggregated image.

$$N = \text{size}(g(x, y)) \quad (9)$$

$$n = \text{factor of aggregation}$$

$$j(x, y) = g(x, y) \forall x, y: \xi \times n, \text{ where } \xi = 0, 1, 2 \quad (10)$$

$$i(x, y) = \max(j(x, y)) \quad (11)$$



**Fig.3. LM Filters for extracting Spot, Line, Edge, Bar**  
Texture features, 1-18 are 1st derivative Gaussian Filters with  $\{\sqrt{2}, 2, \sqrt[3]{2}\}$  as scaling, 19-36 show 2nd derivative Gaussian Filter with  $\{\sqrt{2}, 2, \sqrt[3]{2}\}$  as scaling. 37-40 shows rotation invariant Gaussian function, 40-48 shows Laplacian of Gaussian Filters with, 3  $\sigma$  as scaling factors.

**F. K-Means**

It is an unsupervised machine learning algorithm generates clusters without inferences form the data set as label [15].

Initial clusters are selected at randomly as

$$\mathcal{C} = \{c_1, c_2: \in \mathcal{R}\}$$

$$\mathcal{G}^{(x)} = \text{argmin} \|i^{(x)} - c_{(x)}\|^2 \quad (12)$$

$$C(y) = \frac{\sum_{i=1}^m 1\{\mathcal{G}^{(x)}=y\}i^{(x)}}{\sum_{i=1}^m 1\{\mathcal{G}^{(x)}=y\}} \quad (13)$$

We use to generate 2 clusters, their cluster centers are used as features, Euclidean distance, and mean of the set is used to find the centroids with number of iterations. Form a single sliced 2D image 96 features are extracted and form as a data base for AD, MCI, and CN.

**G. Classifier**

Binary and Multi Class Classification of Alzheimer’s was performed. SVM, Regression model, Gaussian NB, Decision Tree, and Adaboost. These classifiers are trained to perform Binary Classification as AD-MCI, MCI-NC, and AD-NC. Along with them Multi class classification also carried as AD-MCI-NC using SVM, Regression Model, Gaussian NB, Decision Tree and Adaboost.

• **Adaboost Classifier:**

It is a combination of weak classifiers and form as strong classifier, it use stump with one node and two leaves, as Stump is a weak classifier. Adaboost make them as strong classifier where one stump depend on the another stump it means error carried by on stump carried further.

N: total number of Samples of dataset  $\{x_1, x_2, x_3, x_4, \dots \dots \dots x_N\}$

All the N samples are having equal weight  $\alpha_i = 1/N$

Calculate the Gini coefficient as  $Gini = 1 - \sum_{i=1}^N (P_i)^2$  where  $P_i$  is the probability of every sample and it provide the binary splitting if Gini coefficient is near to 0 then it provides good splitting among the entire stumps low Gini coefficient stump is chosen. Calculate the total error that a stump is providing at the end of the classification using

$$S_i = \frac{1}{2} \log \left( \frac{1 - \text{total error}}{\text{total error}} \right).$$

Based on the gini coefficient it emphasis the need for next stump to correctly classify it by increasing weight of the sample that perform incorrec classification and decrease the weight of the remaining samples.

To update the incorrecly sample weight as  $\alpha_j = \alpha_i \times e^{S_i}$

Now decrease the sample weights of remaining samples  $\alpha_j = \alpha_i \times e^{-S_i}$

Normalize the new sample weights  $\alpha_n = \frac{\alpha_j}{\sum_{j=1}^N \alpha_j}$

We continue to pick random numbers and add samples to the new collections until the new collection of sample is same as the size of the original dataset. And perform the same operation of updating the sample weight.

Final mode prediction by using strong classifier as  $H(x) = \text{sign}\{\sum_{t=1}^N \alpha_j h_t(x): t = 1, 2, 3 \dots M, x = 1, 2, 3 \dots N\}$

• **Training with ensemble Adaboost classifier:**

We use ensemble classifier using multiclass boosting algorithm

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- Step-1:**  $\{x_1, x_2, x_3, x_4, \dots \dots \dots x_N\}$  are  $N$  samples,  $y = \{y_1, y_2, y_3, y_4 \dots \dots \dots y_N\}$  are the labels,  $y_i \in \{0, 1, 2\}$ , Label 0  $\rightarrow$  NC, Label 1  $\rightarrow$  AD, Label 2  $\rightarrow$  MCI
  - Step-2:** Initialize the weight of each sample as there are N samples are equally initialized as  $\alpha_i = 1/N$
  - Step-3:** M: Total Number of iterations
  - Step-4:** Calculate Gini Coefficient stumps; select a weak classifier with smallest Gini coefficient classifier.
  - Step-5:** Update the sample weights  $\alpha_j = \alpha_i \times e^{-S_i}$ ,  $S_i = \{-ve, +ve\}$ , +ve to decrease the weights  $\alpha_j$ , -ve to increase the weights  $\alpha_j$
  - Step-6:** Normalize the weights  $\alpha_n = \frac{\alpha_j}{\sum_{j=1}^N \alpha_j}$
  - Step-7:** Get Final Strong Classifier.
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**IV. RESULT AND DISCUSSION**



# Alzheimer's Disease Classification using Leung-Malik Filtered Bank Features and Weak Classifier

We use T-2 weighted standard data base of AD, MCI, CN MRI images from The Alzheimer's Disease Neuroimaging Initiative (ADNI). Collected MRI volumes are axial, 2D, 1.5Tesla Field Strength; volumetric slices are collected from MRI images using ITK-snap with automatic contrast adjustment of 256x256 sizes. These images are preprocessed by skull stripping and removing unwanted information from the slices and noise is removed from the slices using Gaussian filter.

We use 200 patients' data that include 70 AD, 20 CN, and 24 MIC, from publicly available repository. These images are used as input to extract features. Preprocessed images are passed through the 48 filters of LM filter bank. Filtered images are aggregated and calculating 2 cluster centers using K-means as features of each image. 48x2 Features are extracted from each image and formed as data base in .csv format. Performance of the method is measured by using Sensitivity (SE), specificity (SP), Precision or Positive prediction value (PV) and Accuracy (AC).

## A. Experiment setup:

To perform the experiment we use the data set and split the data in to 75% as trained and 25% of data to perform testing with 10 as random seed and performed 10 fold cross validation. Table 2 show the resultant for each model of Decision tree, Gaussian NB, SVM with rbf as kernel, and Ada Boost (AB).

Table 2: Performance of Different Models on Different Classes

Model	Model Parameters	Class	Sensitivity	Specificity	Positive prediction value	Accuracy
Decision Tree	Depth=100	AD (vs) CN	82.6	76.6	76	79.45
Gaussian NB	--					
NB			47.82	64.93	55	56.84
SVM	C=1		71.01	56.75	56.3	62.32
AdaBoost	Iteration =100, learning rate=1, SAMM E.R algorithm					
Decision Tree	Depth=100	AD (vs) MIC	89.85	79.22	79.48	84.24
Gaussian NB	--					
NB			67.81	66.66	73.75	67.33
SVM	C=1		59.45	52.63	55	56
AdaBoost	Iteration =100, learning rate=1, SAMM E.R algorithm		60.27	53.24	55	56.66
Decision Tree	Depth=100	AD (vs) MIC (vs) CN	78.82	80	83.75	79.33
Gaussian NB	--					
NB			53.94	35.22	44.56	51.58
			46.15	46.26	32.6	42.08

SVM	C=1	44.82	44	14.13	36.19
AdaBoost	Iteration =100, learning rate=1, SAMM E.R algorithm	77.77	58.88	68.47	72.88

On comparing four models Adaboost model having good Accuracy, Sensitivity, Specificity and Positive prediction Value followed by decision tree. Gaussian NB is far less than the accuracy achieved by Adaboost while comparing AD vs CN, AD vs MCI. Dramatically SVM produce low performance metrics at AD vs MCI vs CN as shown in Fig 4.

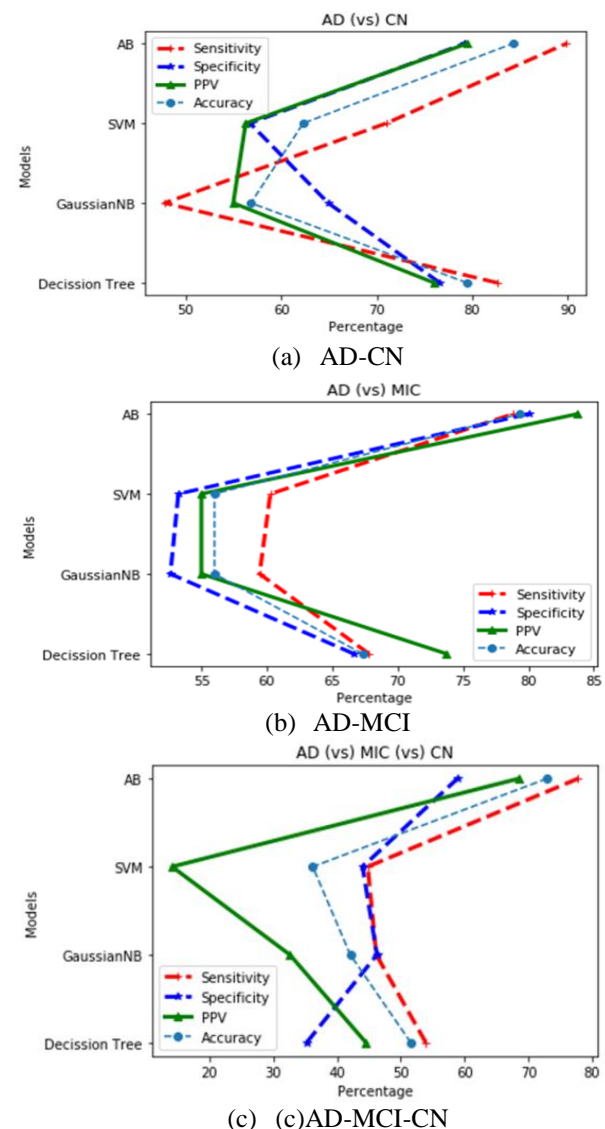


Fig 4: Performance analysis of Different Machine learning Models

Proposed approach gives better results than compare with existing techniques, whereas existing techniques are concentrated on Binary classification only whereas proposed system work on Binary and Multi Class Classification and give recognizable results as shown in Table 3.

**B. Discussion:**

Binary Classification of the Alzheimer’s as CN (vs) AD, AD (vs) MCI gives significant results whereas Multi Class Classification is still a challenging task. Where the features

of Images are calculated from 48 LM Filtered images and Multi class classification gives better results.

Table 3: Performance Comparison of Proposed Frame work with Different other techniques

Approach	Modalities	Classifier	SE (%)	SP (%)	PV (%)	AC (%)
Diana L. Giraldo et al.[1]	66 CN, 50 MCI, 20 AD, T1 MRI images	SVM	80.0	95%	NA	NA
Ardekani BA et al. [2]	164 Patients	RF	86	78.2	NA	82.3
Maggipinto T et al. [3]	40 HC, 40 MCI and 39 AD, T1, T2, MRI	RF	NA	NA	NA	HC/MCI=60 HC/AD=75
Dimitriadis SI et al.[4]	60 HC, 60 MCI, 60 cMCI and 60 CE, T1, PD MRI	RF	61.9	60.5	60.2	61.9
Yasmeen Farouk et al [6]	275 T1 MRI images	SVM	92.59	81.42	NA	83.27
Prabhakar T [7]	135 NC, 100 AD images	KNN	72.09	75.72	NA	74.73
Xinyang Feng [9]	189 AD, 389 MCI and 224 CN, T1 MRI	RF	NA	NA	NA	AD-CN=MCI=57.1 AD vs CN =84.2 MCI vs CN= 72.0
Seong-Jin Son [10]	CN 35, MCI 40, AD 30	RF	NA	NA	NA	53.33
Lui et al[11]	NA	CNN+ Soft max	NA	NA	NA	53.8
Proposed	CN-70, AD-70, MCI 60 MRI Volumes, 900 Images	AD-CN AD-MCI AC-MCI-CN	89.85 78.82 77.77	79.22 80.00 58.88	79.48 83.75 68.47	84.24 79.33 72.88

**V. CONCLUSION**

In this work we proposed a Machine learning frame work that collect the features from LM filtered Structural MRI images of AD, MCI and CN. It concluded that Ada Boost classifier with LM features gives 1% improvement in Accuracy in comparison with SVM Classifier with GLCM. While comparing with remaining techniques it gives better results. As the accuracy of the system get improved then the system will be more reliable. The work is extended by including clinical data with the image features that are extracted to improve robust ness in the system performance

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