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A Deep Convolutional Neural Network based Computer Aided Diagnosis System for the Prediction of Alzheimer's Disease in MRI Images

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- A CAD system is proposed to detect and classify Alzheimer Disease on MRI real image
- Uses MRI differentiation method to differentiate the tumor from the non-tumor cells
- Image preprocessing is performed using 2D-ABF and AHA algorithms
- Image segmentation is done to retrieve ROI using MEM algorithm
- Features are retrieved using GLCM and DCNN is to classify normal and abnormal image

ABSTRACT

In the recent past, biomedical domain has become popular due to digital image processing of accurate and efficient diagnosis of clinical patients using Computer-Aided Diagnosis (CAD). Appropriate and punctual disease identification and treatment arrangement directs to enhance superiority of life and improved life hope in Alzheimer Disease (AD) patients. The cutting-edge approaches that believe multimodal analysis have been shown to be efficient and accurate are improved compared with manual analysis. Many tools have been introduced for detection of Alzheimer but still it is a financially high costly diagnosis system gives detection of disease with low accuracy and efficient due to performance of Magnetic Resonance Imaging (MRI) scanning devices. A novel methodology is proposed in this research as CAD process using various algorithms for predicting AD. The MRI images from scanning device are a highly noisy image due to thermal activities of hardware involved in scanning device. The image restoration technique is applied using 2D Adaptive Bilateral Filter (2D-ABF) algorithm. The quality of image in terms of brightness and contrast are improved using image enhancement techniques based on Adaptive Histogram Adjustment (AHA) algorithm. The Region of Interest of Alzheimer disease is segmented using Adaptive Mean Shift Modified Expectation Maximization (AMS-MEM) algorithm. The various features are calculated using second order 2-Dimensional Gray Level Co-Occurrence Matrix (2D-GLCM). Based on selection of features, the Deep Learning (DL) approach is used to classify the disease images and its stages. The Deep Convolutional Neural Network (DCNN) is the classification technique implemented to classify disease for proper diagnostic decision making. The experimental results prove that the proposed methodology provides better accuracy and efficiency than existing system.

Keywords: CAD, MRI, 2D-ABF, AHA, GLCM, ML, DL

1. INTRODUCTION

Computer Aided Diagnosis (CAD) is an attractive subject of studies into Alzheimer's disease (AD). A fairly broad training database is used to base several implementations. Limited hospitals, however, are typically unable to obtain enough materials for rigorous identification training. Although the exchange of information in scientific research is growing, it is unclear if a system based on one database is very well adapted for other resources. Compared to a system based on the initial limited dataset, the accuracy improved by around 20 per cent. The results showed that the proposed solution is an innovative and efficient method of CAD in clinics only with limited data set for learning. Continuous work is under way to accurately diagnose AD focused on conventional deep learning methods, and its related strategies have become a common alternative for AD diagnostics [1]. However, it is time-consuming and difficult to gather evidence from various modalities, and certain modalities may have side effects on radioactivity. The object of our research is systemic Magnetic Resonance Imaging (sMRI). Their aims are as follows: 1) to improve the degree of precision equivalent to the cutting-edge approaches; 2) to address the question of overcoming and; 3) to examine established brain indications that have perceptible AD diagnostic functionality. The specificity of an AD assessment relies largely upon the disease biological markers.

During the early stages of AD, hippo-campal shrinkage is specified which has an established association with memory loss [2]. A very common and successful method for diagnosing AD is systemic MRI analysis. The effectiveness of software-aided models of diagnostic using brain MRI image largely depends on factors such as steps: 1) nonlinear identification through content of image, 2) clustering of tissues in brain. For addressing constraint a method is proposed for removal of landmark dependent features that does not involve nonlinear identification and clustering of tissues. An innovative neighborhood filter that retains edge is suggested for image filtering. The filter's key objective is a hybrid de-noising feature in order to compensate quality of image although attempting to retain edge of the image [3].

The proposed method uses image boundaries to filter the region in an edge-conserving way. Response of a variable, in a pixel region, in filtering, relies on the region between the object and the sensor. In addition, the measurement edge between it and the pixel does not lead to the calculation of the gray point image average decreases vibration which has other damaging consequences content blurring. During noise level low, the impact of content in image loss may be higher than the impact of noise cancellation and grouping of the initial image yields better results than grouping the normal image [4]. Computer representations findings demonstrate that the approach overcomes the drawbacks of modern approaches based on calculations of the vector image efficiency. It is also narrative basic and fast to deploy [5].

The paradigm of MRI is an effective approach for brain analysis. While collection, MRI brain images could be integrated through interference that decreases image quality with limits the diagnostic efficiency and accuracy. Eliminating noise of clinical images is an essential activity in per-processing and various approaches occur to remove noise in clinical images. Various de-noising methods such as non-local measures, important element investigation, bilateral and temporally high adaptive non-local means (TANLM) filter is analyzed in this work to remove noise in MR. A structural association histogram is a grayscale-based study of the pixel brightness distribution degree by creating histogram correlation which could be increased effective contrast improvement in different artifacts. Approach achieves important effects during pre-processing of contrast improvement and encourages corresponding CAD procedures, thus reducing the time for detection and increasing accuracy. Popular approaches for improving contrast images include histogram equalization (HE) and selective eclipse of the adaptive histogram (CLAHE). HE builds up the image pixel elements values histogram in image depends to the initial exported MRI brain image shows every pixel element functions in the image. It also adjusts the initial pixel quantities to increase the contrast between the images [6].

The dynamic model focuses on individual artifacts to reflect the pixel similarity functions for optimization and governs the intensity of each single entity in an evolutionary way [7].Thus, implementing the segmentation of medical data remains a constant difficult task that has attracted a few researchers' attention in the last year. MRI differentiation is implemented to region of interest. The concept is to treat this issue as a classification task in which the goal is to differentiate among normal and abnormal elements on MRI image based on several characteristics, including levels of intensity and shape. More specifically, suggest using Support Vector Machine (SVM) and are within common and well-motivated classification techniques [8].The deep neural network is an evolving method of deep learning, which has verified its suitability for different image classification. Particularly, the CNN controls different picture recognition tasks for better performances. Clinical image databases, though, are challenging to obtain as they need a great deal of technical experience to mark. The research explores how the CNN related algorithm can be extended to a chest X-ray dataset to identify pneumonia.

These are kernel support vector machine classification with local free spinning and direction characteristics, transferring learning from ground up on two CNN models: probabilistic neural Group i.e., VGG16 and Inception V3, and module network training. Information raise is a form of pre-processing data and is applicable to all three processes. Results from the experiments indicate that information increase is usually an efficient way to boost efficiency for all three algorithms. Transfer learning is also a more efficient form of identification on a restricted database when opposed to a help support vector with stable, isolated basic characteristics and capsule network based fast and Rotating Binary (RB). Retraining of particular applications on a current goal set of data is vital for achieving efficiency in transfer learning. And, the second important factor is an appropriate difficulty of the system which fits the set of data measure [9].Statistical method of several neurological diseases varies depending on the computerized and precise differentiation and structural categorization. Because of their self-learning functionality over vast quantities of set of data, the DL based recognition and segmentation system have obtained research interest nowadays. Convolutional neural network (CNN) needs to take preprocessed feature maps in the Curvelet framework to categorize the set of data for the MRI brain image. Curvelets have improved feature vector and due to its multi-directional functionality, the extracted features are much more accurate than conventional wavelet transformation. Next, the methods of differentiation to research anatomical structures and location of brain tumors are dealt with and finally the CNN quality is mentioned. The function extraction in the Curvelet domain and CNN offer an improvement in precision compared with the wavelet transformation and identification utilizing conventional classification techniques such as SVM and Probabilistic Neural Network (PNN) [10]. In this research paper, section 2 consists of related works of various researchers and motivation behind this work is given. The proposed system is elaborated in section 3 and then experimental results are shown in section 4. Finally, section 5concludes the entire research with future work.

2. RELATED WORKS

Krystyna Malik, et. al [11] has proposed the filter design was a refinement of bilateral de-noising methodology that obtains relation resemblance color pixels elements and temporal range of pixel elements. Rather than direct measurement of the dissimilarity factor, therefore, the cost of a link is measured across a digital route that connects the fundamental pixel of the processing window and its surroundings. As in the traditional bilateral filter, the filter performance was measured like weighted standard of the pixels that have local relationship through de-noising window and weights vectors are components of the marginal contact element. The most commonly used filtering models are focused on the Vector Median Filter (VMF) method, whose performance is determined using the vector organizing principle for a collection of pixels from the processing window. Sorting the accumulated ranges from a specified pixel to all other pixels through the filtering window determines the sorting of the vectors.

Jun Wang, et. al [12] has discussed various component-based transforms for momentum and magnetic data sets that can be used to illustrate related functionality. Nearly all of them, though, face the uncertainty issue in differential estimation. Hence, noise removal is sometimes implemented before implementing component-based transforms to increase the accuracy of the results. V. Anoop1, et. al [13] has proposed the impulse noise and Rician noise using Bilateral Filter (BF) the clinical MR images are eliminated. Improved grasshopper simulation methodology (EGOA) is used to refine the BF variables. The occurred impulse and Rician noises are used to mimic the clinical MR images (with varying differences). In checking regions of window height, space and strength scope, the EGOA is added to the noisy image in order to get the filter specifications efficiently. For optimization, the PSNR is used as the health benefit.

After maximum certainty of variables, it is analyzed the proposed effects of the methodology with other MR images. The findings of the suggested de-noising approach are compared with other previously used BFs, genetic algorithm (GA), generalized search algorithm (GSA) utilizing consistency parameters such as Signal-to-Noise Ratio (SNR), the image quality measuring metric is structural similarity index metric (SSIM), error parameter is mean squared error (MSE) and Peak Signal to Noise Ratio (PSNR) to explain choice value of image quality measuring parameters.

The surroundings weighted average of the pixel is used to remove the pixel. For this equation, the weights can be obtained by the physical and magnitude range of a pixel from its region. In a pixel neighborhood the spectral range is defined with the parameters of the field (spatial) filter while the weights of the filter set (intensity) are proportional to the isotopic range of the pixel. Rinkal Patel et. al [14] has designed the AD neuro-imaging research was the most popular technique, where different brain regions/voxels are studied independently. Such methods are successful in other situations. However, they did not shed light on the interaction of the inner brain region correlated with brain activity or fascinating illness. Human brain is, in essence, anatomically a rather complicated organ and the functional connections among its regions are much more so. Consequently, comprehension of this interdependence or connectivity between brain regions is required. The deep learning methodology named "Sparse Inverse Covariance Analysis" for learning functionality in the brain field, with limited computing expense and densely the correct degree. Within Gaussian hypothesis, any dimension of the vector of reverse covariance expresses conditional dependency between the pair of variables in the constituent, provided all parameters. Through implementing sparsely restriction, excessive/noisy structural constraints are abolished through placing the component factor at zero, participating in the factor pairs becoming conditionally autonomous [22], [23].

All radioactive MRI and FDG-PET may be used to support doctors in the diagnostic process, i.e. assessing the brain regions and classifying the disease as Normal Controls (NC's), MCI (Mild Cognitive Impairment), AD or any other Alzheimer struggling. Diagram representation of image data is a moment operation and often vulnerable to mistake. The visual assessment has been suggested with mathematical methods in location (or in comparison to).Mostafa Amin-Naji, et. al [15] has proposed the Deep learning (DL) approaches currently have been used in the detection and diagnosis of radiography and have greatly enhanced method efficiency. Since Alzheimer's disease (AD) is among the most financially costly disorders, several scholars have focused on developing a high precision software system for the diagnosis of AD and Normal Control (NC) instances. A modern computational approach focused on deep learning is used for diagnosing Alzheimer's disease. Here between DL networks, the Siamese Convolution Neural Network (SCNN) is introduced with triple ResNet-34 divisions to differentiate through the Structural MRI among the AD and the NC. A SCNN comprises rather than two CNN groups which are mostly similar to each other. The division contains convolution sequence, ReLU, accumulating, and totally linked surfaces. These dual-branches of CNNs are concurrently training on multiple image objects and are generating segments of the same direction function. The similitude of input objects is obtained by measuring the resemblance and range of the variables of the source function.

The negative image is likewise the randomly chosen item from the same anchor image mark. It has been common to assess Alzheimer's disease (AD) from moderate cognitive disorder (MCI) and executive norm (CN). Recent neuro-imaging developments in acceptance of machine-learning technologies are particularly useful for pattern analysis in radiography to assist the doctor in early detection of AD. Early pathological brain atrophy and stable brain atrophy are found to be similar. In our endeavor, suggested a model that can more reliably distinguish mild cognitive impairment (MCI) to improve early detection of AD. MRI's are initially split into slides to conduct the clustering of T2 weighted MRI images. Through skull stripped software, the non-brain substances are separated from the frames. Increases in brain shape and appearance are used to distinguish stable and deformed, and improved Independent Component Analysis (ICA) is used to classify brain imaging into WM, GM, and Cerebrospinal Fluid (CSF). Atrophy of the brain tissue is required for the identification of stage AD. AD is a chronic condition, improvements in the brain function perception of GM, structure and thickness of the WM, as well as blood vessel extension. Define the AD in our task, based on GM degeneration. GM includes nerve cell bodies or glial cells, and semi-neuron neurons. GM undergoes production and development during infancy and adolescence; it is used to bring sugar to the brain; perception, voice, and cognitive function improve in this impact. In our research concentrated primarily on the gray matter, in order to identify the AD. It is included CNN as a discriminator from the past few years that is used in various computer perception strategies. The definition of a combination model is implemented in our suggested Hybrid Improved ICA and it is defined in groups which are mutually dependent.

Utilizing Markov Random Field (MRF) Cognitive information is applied to Gaussian Mixture Model (GMM) in the updated GMM method and takes into consideration temporal concentration. In Expectation Maximization (EM), Predicted phase is determined using mean log probability and deviation is measured using updated K-mean and endogenous factor is measured using Gibbs volume. The above listed variables are used to conduct clustering of the Brain MRI slides as input variables to HEICA. Shanthi K J,, et. al [16] has proposed the quality of brain MRI clustering relies on the precision with which the brain structures are separated from the MR images. While the skull removed image would only have significance in the cerebral regions. Skull grinding may be extended with effectiveness to both convective and axial images. The standard distressed image of the skull has three sections of White Matter (WM), Gray Matter (GM) and Cerebrospinal fluid (CSF) substances. The skull stripped image histogram reveals no clear peaks and troughs referring to certain groups. WM pixels are lighter in T1 weighted images, CSF pixels are darkest, and GM pixels are aligned on a contrast higher side. In the proposed work, weighted vector image data T1 structures are used as the test images. The initial peak is equivalent to white matter, the second peak corresponds to GM and the final peak related to CSF.R. Thillaikkarasi., et.al [17]has investigated brain tumor may be produced by an unpredictable rise in irregular cells in brain tissue and has two forms in cancers: one is harmless and the other is malignant. The benign brain tumor may not influence the adjacent usual and stable tissue however the malignant tumor that influence the adjacent brain tissues, which may contribute to person's death. Early diagnosis of brain tumor could be important to ensure patient life.

A deep learning - based algorithm (kernel-based CNN) with M-SVM is introduced for automated and effective segmentation of the tumor. This proposed research involves many measures that include preprocessing, processing of features image identification and brain tumor segmentation. G. K. Reynolds et. al [18] has proposed diffusion MRI (dMRI) modern indications for disease diagnosis not possible using normal anatomical MRI. Here, a novel approach is implemented for designing the signal directly to derive features for classification of Alzheimer's disease (AD) patients against Healthy Control System (HCS).

Jun Zhang et. al [19] has proposed structural magnetic resonance imaging (MRI) effective method for Alzheimer's disease (AD) detection. Using these temporal and statistical characteristics, a dynamic support vector machine (SVM) is eventually introduced to separate AD objects or Moderate Cognitive Disability (MCD) samples from Healthy Controls (HCs).Ramy A. Zeineldin et. al [20] has developed

DeepSeg, as a structure for modular decoupling. It consists of two main parts linked, centered on a connection of encoding and decoding. The encoder component is a Deep Neural Network (DNN) which is accountable for processing of spatial information. The subsequent semantic graph is placed into the portion of the decoder to get the chart of likelihood of maximum resolution. Various CNN models such as residual neural network (ResNet), deep convolutional network (DenseNet), and NASNet were used based on modified U-Net design. Owing to their malignant existence and accelerated development, Gliomas are the most frequent and violent form of brain tumors. Differentiating cancer cell boundaries from healthy cells continues to be a difficult challenge in medical diagnosis. Fluid-attenuated Inversion Recovery (FLAIR) MRI method could provide tumor diffusion details for the doctor. Runhong Zhang et. al [21] has adopted NGI-ADP surface design for limit equilibrium research, on the basis of which the impacts of soft clay anisotropy on the deformation of the diaphragm wall in approaches to the study is analyzed. It studied quantitatively more than one thousand cases of finite elements, accompanied by substantial numerical simulations.

2.1 Motivation

The AD is a medical illness which produces loss of memory and cognitive impairment by the killing of brain cells. A degenerative form of Alzheimer, the condition begins slightly, and is slowly becoming worse. Brain image processing is a significant field of scientific study, findings for the diagnosis of brain disorders. Small brain function and blood pressure are the primary triggers for Alzheimer's diseases. In specific the procedure of clustering is used for the medical images. Hippocampus is an essential part of the brain. Human typical activity is based on the Hippocampus features. It takes several hours for a doctor to physically section the Hippocampus. In this research, a improve method is used to separate the hippocampus region, based on the watershed segmentation methodology. Using two methods, the brain images were translated to binary form. The first solution is principles of block say, mask and marking and the second method is concept of top hat, mask and marking. But some portion of the image is found to contain holes that disrupt the segmentation phase. The image hole filling strategies are applied to solve this issue, and relevant components are grouped into linked modules. The type study of the function of the hippocampus may aid in the analysis of Alzheimer's disease (AD).

2.2 Existing Methodology and its Disadvantages

The existing method is to continuously separate regular tissues and irregular tissues through images of the MRI tumors. Such MR brain images are observed to be distorted with Strength in objects of homogeneity that induce excessive variance in strength and noise that impair the output of brain image processing. Due of this type of substances one form of normal tissue in MRI is wrong classified as another standard tissue which contributes to diagnostic error. The approach involves of preprocessing using 2D wrapping-based Curvelet transformation for eliminating noise with adjusted contextual fuzzy C means procedure implies taking into consideration the spatial details and fragments of natural structures as the surrounding pixels are strongly associated and often spontaneously construct up the original participation matrix. The cancer cells are often segmented by method. The conventional method is not capable of finding Alzheimer disease.

3. MATERIAL AND METHODS

The proposed system is made up of four steps, which include pre-processing, segmentation of region of interest, extraction of features and classification of disease. The training MRI Brain image is given as input to the network during the training period and is exposed to all of the above mentioned steps. A classification model is chosen, and the extracted features are used along with the class labels to train a classifier. Now the algorithm turns into a classification algorithm. A test brain MRI image is information into the structure during the testing stage, and the image moves through all of the above steps mentioned. The qualified classifier now recognizes the characteristics of the test object and can add a class mark to the test object as whether 'affected disease' or 'unaffected disease' using the information it has previously acquired during the training process. The research introduces a modern predictive approach for segmenting the entire brain into image sequence using magnetic resonance (MR) and measuring its density to diagnose disease. The relevant MRI brain images have been collected from the website of the Alzheimer's Neuro-imaging Initiative (ADNI). In participants entire MRI brain T1-weighted MRI was considered at 1.5 T level as given in the specification. The proposed automated clustering approach is considered on the image numerical anatomy and our proposed methodology is named as "head prototype" to restrict the MRI brain pixel range.

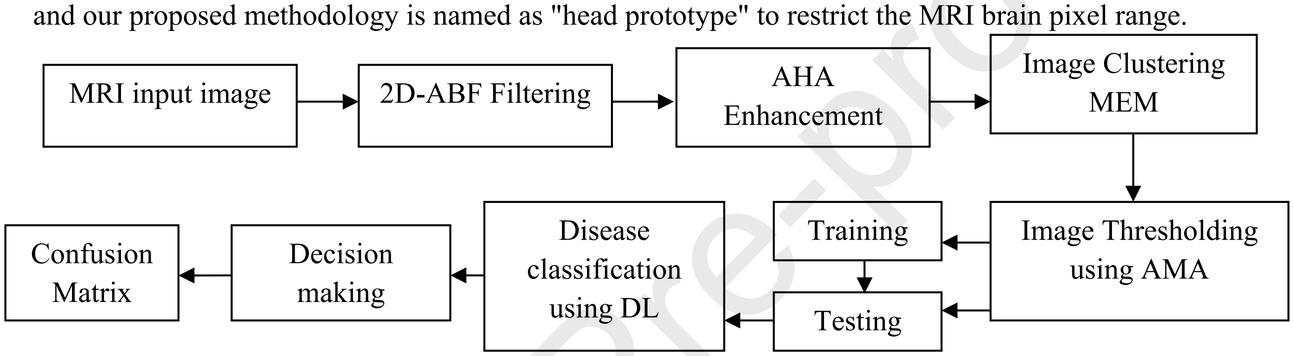
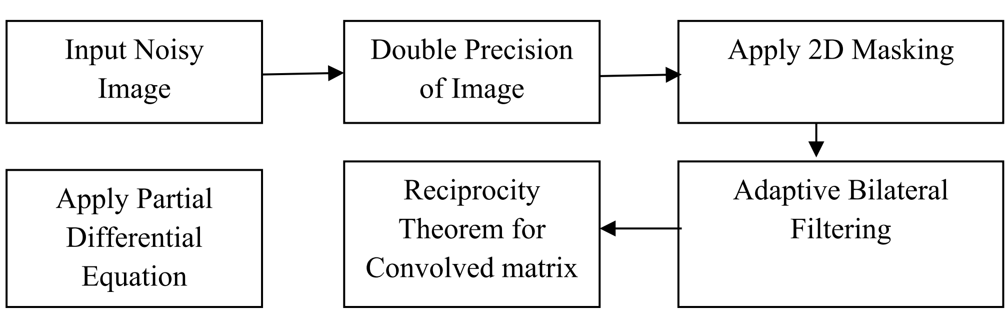


Figure 1: Architecture diagram for proposed methodology

3.1 MRI brain image Pre-processing

Figure 1 shows overall architecture of proposed methodology. The MRI image preprocessing technique is fulfilled with two techniques called image restoration and image enhancement. The image restoration of image is completed using 2D Adaptive Bilateral Filter (2D-ABF) algorithm. The 2D-ABF is used to eliminate unwanted noises like speckle noise, binary noise and random noise.

The 2D ABF is used to filter noises without degradation of original information content in MRI image. The image quality enhancement technique can be proposed using 2D Adaptive Histogram Adjustment (2D AHA) algorithm. The 2D AHA is used to enhance visual contrast and brightness for enhancing image consistency. The gray image is the useful format for MRI brain image segmentation. If it chooses MRI color image, it has to be converted from color image to gray image. The MEM algorithm will cluster abnormal pixels on gray images.



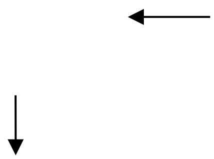


Figure 2: Block diagram of 2D-ABF

3.2 Image Restoration using 2D Adaptive Bilateral Filter (2D-ABF)

The figure 2 shows the proposed block diagram of image filtering using 2D-ABF. De-noising has often been a research priority and yet there is still scope for progress, particularly when it comes to image de-noising. When high frequency distortion is to be extracted from the distorted image, the basic temporal filtering of a distorted image can be effective. The biggest problem connected with this is the complexity of the calculation involved in making the convolution. The wavelength-based de-noising approaches use low-pass filtering to remove most high-frequency elements in attempt to de-noise the signal, as the noise is scattered over all wavelengths. It is generally not successful though, because it disrupts both noise and other elevated-frequency image characteristics, leading in an excessively smooth denoted image. The goal of image de-noising is to eliminate the noise whilst preserving as much clarity as possible of the essential image features such as boundaries. In the existence of exponential noise, vector filters, which comprise of transforming the image with a steady vector to produce a linear mixture of neighborhood values, is commonly used for noise reduction.

It can therefore create a blurry and smooth image with inadequate approximation of features and insufficient noise suppression. Gaussian-based filters are especially important as their forms are easily defined and both the forward and reverse Fourier transformations of a Gaussian function are true Gaussian structures. Alternatively, because the frequency domain filter becomes smaller, the temporal domain filter would be broader and would modulate the low frequencies leading in improved smoothing / blurring. Such Gaussian filters are traditional linear filters which were commonly used to de-noise images. The suggested image de-noising system utilizes the 2D Adaptive Bilateral Filter. A disparity between the initial image and its de-noised version indicates the algorithm's erased noise, which is considered process noise. The vibration of the system will sound like a stimulus in theory. Although even good quality images have some noise, it makes sense to test some de-noise approach in this manner, without the conventional trick of "using noise and then deleting it". Precisely, it is known by

$$MN = A - IF \qquad (1)$$

where, A is the initial (not inherently noisy) image, and IF is the de-noising driver output for an input image A. Applying the bilateral filter to the noisy image combines the distortion together with the image information while maintaining the borders / sharp borders very well given the normal distortion variance is less than the opposite edges. His process interference in Gaussian filter is negligible in harmonic sections of the image and very high close borders or texture, where the Laplacian cannot be low. Consequently, in flat regions of the image the Gaussian convolution is ideal but the borders and shadow are distorted. To obtain what the bilateral filter takes out of the distorted image, the system noise concept is redefined as the gap between the distorted image and its opposed value. So, Eq. (1) is expressed as

$$MN = I - IF \qquad (2)$$

where, $I = A + Z$ is A distorted image acquired by destroying the initial image A by a white Gaussian distortion Z and IF is a Bilateral filter source for an input image I. As all noise and image information have been extracted by the bilateral filter by combining the pixels, the process noise should comprise of distortion and image information together with certain borders. The distortion of the system due to Gaussian filtering would have better borders relative to that of bilateral filtering because the borders are maintained by filtering spectrum (πr). The process noise MN is a mixture of image information D and a white Gaussian distortion N.

$$MN = D + N \qquad (3)$$

Now the challenge is to approximate the information image D, which has just the actual image attributes and edges/sharp borders that Bilateral filter eliminates, as reliably as necessary according to certain parameters and is merged with the Bilateral filtered image IF to get a stronger de-noise image with info. In class Wavelet, Eq. (3) can be replicated as

$$Y = W + Nw \qquad (4)$$

Where Y is a distorted wavelet coefficient (method noise), W is the real wavelet coefficient (detailed image) and Nw is Gaussian distortion free.

The noisy images $I \in R^{M \times N}$ were first filtered using 2D-ABF. In this filtering technique, the image $I(m,n)$ is convolved using function $u(m,n)$ using the following equation

$$u(m,n) = \iint_{\Omega} I(\xi,\eta) g(m-\xi, n-\eta) d\xi d\eta \qquad (1)$$

In our work, we have employed ABF function family. It is defined as follows

$$g_{\lambda,\theta,\phi}(m,n) = e^{-((m'^2+\gamma^2 n'^2)/2\sigma^2)} \cos(2\Pi \frac{m'}{\lambda} + \phi) \qquad (2)$$

Here, $m' = m\cos\theta + n\sin\theta, n' = -m\sin\theta + n\cos\theta$, $\sigma = 0.56\lambda$ and $\gamma = 0.5$ .Here, σ represents the scaling factor and θ represents the orientations of the filter functions. Thus, filtered images $I^F \in R^{M \times N}$ were obtained by convolving input images with the function defined in Equation (2).

3.3 Image Enhancement using 2D Adaptive Histogram Adjustment (2D-AHA)

Figure 3 shows block diagram of 2D- Adaptive Histogram Adjustment. 2D Adaptive Histogram Adjustment (2D-AHA) is a machine-based type of image analysis used to boost or increase image intensity. AHA is ideally used for natural and therapeutic images. In this approach, it is done independently on sub-images, rather than implementing map or conversion to the entire image. AHA implements a method to correctly run the sub-image and merge it. Image quality improvement technique introduced in image histogram adjustment methodology to boost the over-amplification of noise issue occurring. This is distinct from normal histogram correction since it operates on specific segment of the MRI image quality being improved by multiple histograms all relative with a single region of the image then utilizing to reallocate image quality metrics like brightness or contrast calculation. AHA rather than normal histogram equalization increases the contrast of an image in which it provides rather clarity but also appears to intensity the distortion.

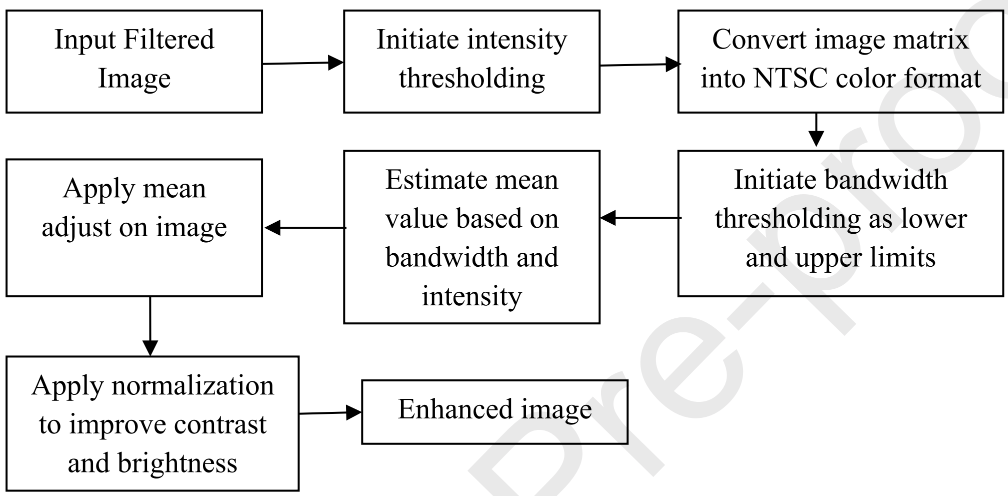


Figure 3: Block diagram of 2D-AHA

3.4 Proposed System

Step 1. Input (MRI image) is interpreted or perused.

Step 2. Change the MRI image into MRI at Gray point.

Step 3. To maximize the image quality, add or conduct the Histogram Equalization technique to the reference image.

Step 4. Take the improved-image histogram.

Step 5. Consider or execute the Local Equalization Histogram (LHE). Apply method for improving image contrast on the input image (MRI image).

Step 6. Step 4 has to be repeated.

Step 7. Enable or execute Adaptive Histogram (AHA) Adjustment. Apply method for improving viewpoint intensity on the reference image (MRI viewpoint).

Step 8. Do again step 4.

Step 9. To improve image quality, apply or execute the quality dependent adaptive histogram equalization technique on the input image.

Step 10. Repeat step 4

Pseudo code

Start
Read MRI image
Apply Filtering with 2D- ABF
Apply Enhancement using AHA
Clustering for pixels
Segment region of interest
Estimate features
DL classification
END

3.5 Alzheimer segmentation using Modified Expectation Maximization (MEM)

Firstly, the principle of Expectation-Maximization is used to approximate the MRI information spread. Category number is determined by the Bayesian Criteria of information. The Highest Probability is used to group the pixels in images into the closest section. The consistency of the approach introduced is separate of the original calculation and can be used in unsupervised clustering of the data. The Gaussian Mixture Attributes of the MRI was initialized using the K-means method. Expectation maximization method is implemented, and the Bayesian criterion is used to calculate the mixed model type numbers. This approach sets the calculation of parameters and the collection of templates in one step and that is a clustering that is completely unsupervised. Gaussian Mixture system is briefly implemented in the second section, and approach is suggested based on the methodology 'Expected Total Bayesian Information Criterion.' A full system of clustering shall be provided in the third section. The fourth element is the analysis, actual MRIs are used in the clustering process and the findings indicate utility of the procedure in this research. The K-means algorithm performed initial clustering. The phase in measurement may be described as:

Step 1. Start Select the original segmentation centers by the number of groups k.

Step 2. Categorized the pixel details are given into the category whose middle has the least pixel size.

Step 3. Start. Calculate the mean of the pixel values inside the class after a classification process.

Step 4. Unless the terms with the clusters have the same meaning, the present designation is the product of clustering of the K-means.

Step 5. Edit the meaning of the clusters by means of the current level, and perform step 2.

Modified Expectation Maximization algorithm relies heavily on activation of clustering of pixels in various regions in image based on gradient. Using the calculation of Peak Probability to determine the final choice is a standard method, but it introduces heavy workload to the calculation. In this research, the mixture specifications are initialized using average K process. The explanation for utilizing Gaussian mixture is the complexity of calculating class level. Too many approaches presume that the amount is explicitly identified, that is, the amount of the type of images is decided by clustering. Clearly it is a process which is regulated or semi-supervised. A selection criterion for the model Bayesian Information Criteria (BIC) is used in this work to solve this issue. Clustering Methodology comprises of two steps: class approximation is the first step. The 'Expected Limit with Bayesian Criterion' approach is applied to approximate the numbers of the mixing variables and Gaussian elements. The second stage is sorting by pixels. According to the Maximum Likelihood rule per pixel is categorized towards a certain class.

Expectation step:

The probability that a pixel at $I^E(u,v)$ belongs to a particular Gaussian G_i with mean μ_i and standard deviation σ_i is given by

$$P_{uv}^i = \frac{\exp\left(-\frac{(I^E(u,v)-\mu_i)^2}{2\sigma_i^2}\right)}{\sum_{j=1}^{V}\exp\left(-\frac{(I^E(u,v)-\mu_j)^2}{2\sigma_j^2}\right)} \tag{6}$$

Maximization step:

In this step, the values of mean μ_i and standard deviation σ_i of the Gaussian G_i are estimated again using

$$\mu_i = \frac{1}{Z}\sum_{u,v} P_{uv}^i I^E(u,v) \tag{7}$$

$$\sigma_i = \sqrt{\frac{\sum_{u,v} P_{uv}^i (I^E(u,v)-\mu_i)^2}{Z}} \tag{8}$$

The above two expectation and maximization steps are iterated until convergence state is achieved. The quality of clustering result obtained mainly depends on the initial values of the EM algorithm. In a conventional EM algorithm, these initial values are obtained using k-means algorithm. To further improve the accuracy and reliability of clustering result, in this work, we propose novel Enhanced Expectation Maximization algorithm. In this algorithm, instead of using k-means, the initial values are computed using Fuzzy C Means Clustering [36]. That is, the initial values are computed using

$$J = \sum_{i=0}^{255} \sum_{q=1}^{C} f_{iq} d(i, \theta_q) \quad (9)$$

where f_{iq} refers to the fuzzy membership between pixel x_i and histogram of cluster with center θ_q and $d(i, \theta_q)$ refers to the distance between pixel x_i and histogram of cluster with center θ_q. The output of clustering step is represented as $I^C \in R^{U \times V}$.

3.6 Threshold using Adaptive Mean Shift (AMS)

Threshold methodology plays an important role in segmenting images and identifying trends. It's a method of splitting an image into various regions. The most stepped-forward method is to select appropriate some gray scale value as thresholds and categorize the image into more than one area. Two major classes are categorized into automated threshold techniques: global and local. A constant pixel values for the whole image is used in global approaches, while thresholds shift dynamically in local techniques. Though both of these strategies refine a criteria feature based on knowledge derived either from the development of histograms or from spatial distribution. One of the well-known and generally recognized adaptive threshold techniques, AMS threshold process, is focused on differentiate analysis to determine the highest class separable and is used to do histogram-based image threshold efficiently. AMS threshold ensures effective clustering by taking into consideration all pixels with a category value. Within the standard Fuzzy C Means the output threshold is contingent on the input threshold that has been randomly set, thus a suitable initial threshold is found within order to solve the complexities. The variable chosen for Fuzziness is the gray color values. Abnormal pixels separation is determined by conducting the threshold algorithm Fuzzy c means preceded by the hardening system. Fuzzy threshold is an enhancement for edge detection of the fuzzy clustering by including only the relevant features as a function. For fuzzy c-means which reduce objective functions.

Input:

Clustered image $I^C \in R^{U \times V}$.

Output:

Segmented image $I^S \in R^{U \times V}$.

Steps:

1. Divide the entire image $I^C \in R^{U \times V}$ into non-overlapping blocks of size $n \times n$.
2. Compute the histogram of each block B_i.
3. Identify the highest two peaks P_1 and P_2 in the histogram of each block.
4. The threshold T_i for block B_i is computed as

$$T_i = \frac{P_1 + P_2}{2}$$

5. Segment the pixels $I_i^C(u, v)$ in block B_i using

$$I_i^S(u,v) = \begin{cases} 1\,; I_i^C(u,v) \geq T_i \\ 0\,; I_i^C(u,v) < T_i \end{cases}$$

3.7 Feature Extraction using 2D-GLCM

At this process, the feature report based on a biased image is quickly classified as normal and abnormal for extraction of features. Feature extraction is a method to depict the raw image to a segment that requires removal from the MRI image by classifying the characteristics. Feature extraction shows a reduction in the amount of data required to reliably defining broad database the characteristics used as inputs to identify and are positioned in the class described. The objective of extraction of the feature is to decrease the actual information by evaluating the beneficial property, or qualities that differentiate between one sample is placed and the other. Taking into account numerical feature vectors are valuable for indexing and detection of similar images. The texture function offers details on the characteristics of image strength at the diffusion stage such as homogeneity, softness, angularity, and contrasting. Statistical texture features consisting of mean, kurtosis, variance, image energy, standard deviation, skewness, entropy, and smoothness are computed based on the likelihood and allocation of the pixel level intensity.

Analysis of textures effectively distinguishes natural from irregular materials for human sensory perception from deep learning. It also creates differentiation among regular and malignant tissues, which might not be noticeable to human eyes. It improves precision by selecting effective early diagnostic comparative characteristics. During the initial step, data from the histogram of pixel intensity was obtained from the first-order statistical textural information associated and grey - level frequencies were evaluated at arbitrary image locations. It does not find association among pixels, or co-occurrences. In the next step, the textural evaluation-features of the second order were obtained based on the likelihood of pixel values at arbitrary ranges and over whole image configurations. Since, consistency of a classification method is dependent primarily on the correct selection of the function, a sufficient range of attributes needs to be defined. A feature matrix 2D-GLCM is applied in this classification procedure that is a mathematical approach that allows use of the pixel temporal association. By applying the GLCM, it is figure out which attributes are to be created depending on the cluster of a pixel. The research is done by guiding the distribution of 2D-GLCM features in such a way and suggested a series of statistics that are invariant to rotation. The scalar invariant attributes of rotation may be derived from vectors of co-occurrence by taking the average and distribution of each form of function over the four shapes that are used. Another type of definition of the texture is the gray-level variation data, which is directly linked to 2D-GLCM. A matrix of co-occurrence, also called a distribution of co-occurrence, is specified over an image to be the spectrum of co-occurring elements at a defined offset. It describes the structural association of distance and angle over an image sub-region of similar scale. The 2D-GLCM is formed from an image on a gray level. The 2D-GLCM is measured how much a gray-level pixel value appears horizontally, vertically, or diagonally to neighboring pixels with the value. The 2D-GLCM matrix could be a known statistical procedure for obtaining texture details from images in the second order. One of the most common and successful types of characteristics in texture evaluation is the 2D-GLCM vector. 2D-GLCM is the vector of all quantities for all gray level couples for a region identified by a user set frame. For this process, rather than the original gray-level pixel quantities, attributes are determined based on the absolute discrepancies between couples of gray-lines or mean 2D-GLCM lines. This feature makes the figures a little more reliable for differences of lighting than in the GLCM situation. The vector of the frequency of the gray level co-extracts from the above images.

For this research classification may be identified as the recognition function within which a collection of category the image belongs, either regular or impaired by Alzheimer disease. The recognition decision-making functions can be effectively achieved by utilizing Deep Learning (DL).

It is computed as

$$G(m,n)=\frac{\#\{[(m_1,n_1),(m_2,n_2)]\in S \mid f(m_1,n_1)=g_1 \,\&\, f(m_2,n_2)=g_2\}}{\# S} \tag{10}$$

Using this technique several statistical features like contrast, energy, homogeneity, correlation was extracted.

Angular second moment:

Angular second moment represents the uniformity of the distribution of the image. It is computed using the following formula

$$A_{sm}=\sum_{m}^{M}\sum_{n}^{N}G(m,n)^2 \tag{11}$$

Correlation:

Correlation value indicates the similarity of the texture of the image in the two perpendicular directions namely, the horizontal and the vertical directions. It is computed using

$$C_{or}=\frac{\sum_{m}^{M}\sum_{n}^{N}(m-\overline{x})(n-\overline{y})G(m,n)}{\sigma_x\sigma_y} \tag{12}$$

Contrast:

Contrast value indicates the variation of depth and smooth regions of the image and is computed as

$$C_{on}=\sum_{m}^{M}\sum_{n}^{N}(m-n)^2 G(m,n) \tag{13}$$

Entropy:

Entropy is the measure of information content and is computed using

$$E_{nt}=-\sum_{m}^{M}\sum_{n}^{N}G(m,n)I_g G(m,n) \tag{14}$$

3.8 Alzheimer disease classification Deep Learning (DL)

The DCNN is derived from CNN technique. DCNN is nothing but the multiple stacked CNN model. The multiple stacks of layers will provide better recognition efficiency. Alzheimer's disease is divided into with

2 types: benign and malignant. For these cases, effective and accurate disease diagnosis and care plan contributes to better quality of life and a longer life expectancy. Using DNN is one of the most functional and effective approaches [20]. A DCNN was used to diagnose a disorder through images from body MRI images. The suggested methodology is used by CNN to classify and characterize the disorder from brain scans. The key distinction among the neural network's major channels with the conventional neural network is that they are able to retrieve the attribute from each image dynamically and globally. These types of networks take the form of neurons that can be learnt with weights and biases. For recovery functionality the deep learning algorithm is used. The used algorithm was the clustering algorithm implemented to the data set, and the images are then implemented to the DCNN. Results indicated that the approach proposed was successful [21]. The objective of obtaining the property before implementing to the DCNN is to evaluate fatty masses as disorder in some images, or the disorder is mistakenly regarded as fat in some images and should have expanded medication errors. Extracting the parameter first and then adding the DCNN results in better network performance and enhanced precision. Deep learning is one of the most current practical ways of learning machines [22]. To put it another way, learning is called architecture deep-seated. In fact, those implementations are the same old nerve systems that have become DNN. Such networks are data based and function creation is performed automatically and does not mess with it, so that's just what makes such networks reliable so outstanding efficiency in various fields. This is in essence a deep learning of a series of nerve related strategies that learns features dynamically from our own input results. The CNN is a specific kind of DNN whose framework is motivated by the perception cortex of cat genetics. The CNN consists of many levels and has a hierarchical framework [23]. Input layer, output layer, convolution layers, pooling layers, standardization layers and Totally Connected layers are all used in CNN. CNN is distinctive in terms of the amount of layers used, the scale, amount of images and the form of kernel function used. The parameters are selected in the CNNs, centered experimental results and experimentally on trial and error [24]. In other terms, each CNN consists of many layers in which the key layers are the Convolutional layer and the Sub-sampling layer added in the following points:

1) Convolution layer: Standard parameters have defined values such as metrics are essentially the same as other sections of the image. It implies that learned characteristics from one segment of the image will be added to other parts as well, and identical characteristics are included in all sections of the image. After the system of the application, the Convolutional layer functions are used to classify images [25].

2) Sub-sampling layer: This layer functions are conducted to decrease the complexity of the image input. It obtains a position matrix from the layer at the end of the DCNN. The process of aggregation or Sub-Sampling is known as the mean pooling or peak pooling [26].

In a few instances, certain regions of fat in the images are incorrectly identified as sickness, or the physician does not recognize the disease; the most precise diagnosis relies solely on the abilities of the physician. For this paper the DCNN was used by brain scans to diagnose illness [27]. Extra margins of the images taken from the imaging centers are included. Both margins have been clipped to keep the images from producing noise. Some of the key factors for utilizing and integrating the extracting features strategy with the DCNN are to recover the object extraction of the images to improve the network's reliability. In order to enhance network accuracy, a new strategy which is a mixture of cluster analysis for decomposition of feature and DCNN is presented in this research, as per the results of the DCNN on the initial images [28].

In DCNN, we have used transfer learning strategy that is used for training on issues similar to the same issue that may be resolved. Multiple stacks of layers through the training model can be used in a training model on the classification [29].

The images were originally added to the CNN without any form of extraction of features. The DCNN architect was used to recognize and categorize images consisting of 5 Convolutionary layers and 3 layers of sub-sampling layers, standardization layers, standardization layers, Fully Connected layers, and ultimately classification layers [30]. The layers are fully connected, with 4096 neurons. In this layer, it has two classes: patient with brain disease, and regular patient. The DCNN used appears in figure 4.

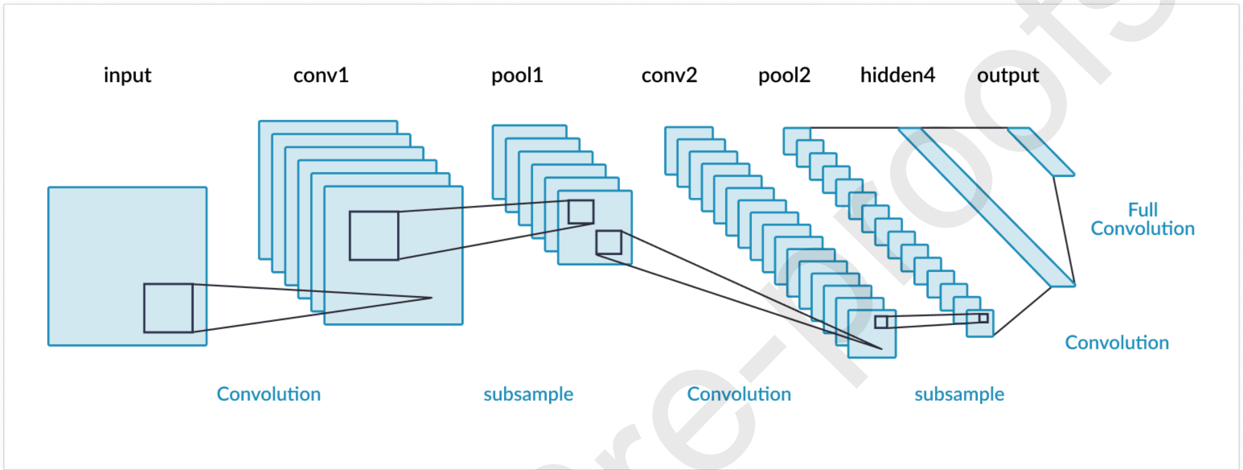


Figure 4: Architecture of DCNN

Figure 4 shows architecture diagram of DCNN. In this research DCNN architecture is implemented to classify Alzheimer disease. Experimental findings reveal that our innovative DCNN design produces optimal efficiency and beats most of the cutting-edge systems performance. The result clearly shows the successful effectiveness and benefits of the proposed two-stage transfer learning strategy, as well as the possibilities of learning knowledge from MRI data.

4. RESULTS AND DISCUSSION

This segment describes the real MRI image using proposed methodology experimental results are discussed. The experiments are done based on different standard of gray-scale MRI images with different size. The MRI images are corrupted by salt and pepper noise, speckle noise and random noise produced by MRI scanning devices as shown in figure 5 (a). The de-noising process is done based on these three noise aspects. The 2D Adaptive Bilateral Filter (2D ABF) is applied to noise corrupted image in order to remove all noises without degradation of original content of image as shown in figure 5 (b). To authorize the suggested methodology, their presentation are evaluated in terms of visual quality, PSNR and MSE are computed and tabulated using proposed algorithm called 2D ABF.

In the figure 5 (a) MRI brain input image is shown for processing further to segment ROI. The 2D ABF filter is applied to eliminate noises such as Gaussian noise, binary noise and random noise are eliminated as shown in figure 5 (b). The filter image is further processed to improve quality of image using AMA algorithm. The contrast and brightness is improved using AMA algorithm as shown in figure 5 (c).

The PSNR and MSE are calculated for existing preprocessing techniques and proposed preprocessing technique. The values are tabulated in Table 1.

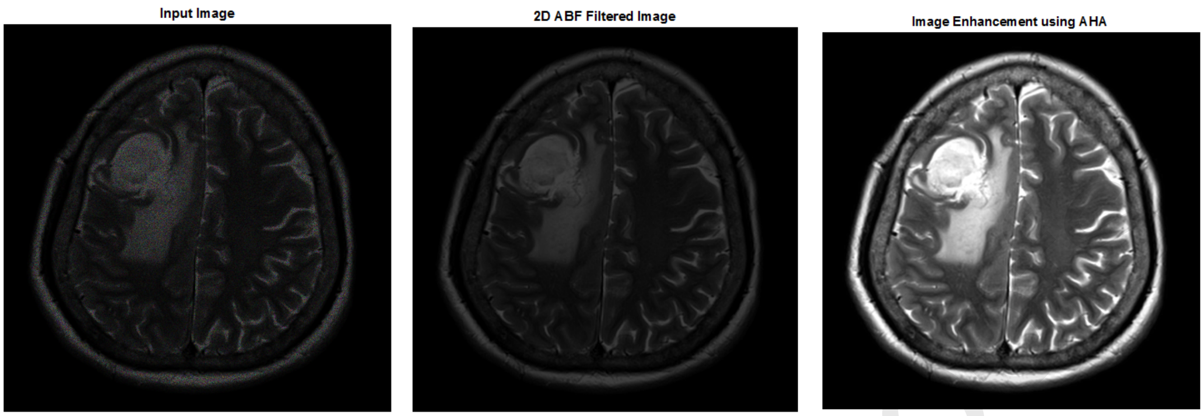


Figure 5: (a) Input MRI image, (b) 2D ABF Filtered Image, (c) Image Enhancement using AHA

The figure 5 (c) shows enhancement image using Adaptive Histogram Adjustment (AHA) by improvement of contrast and brightness. The quality of image is improved using AHA algorithm.

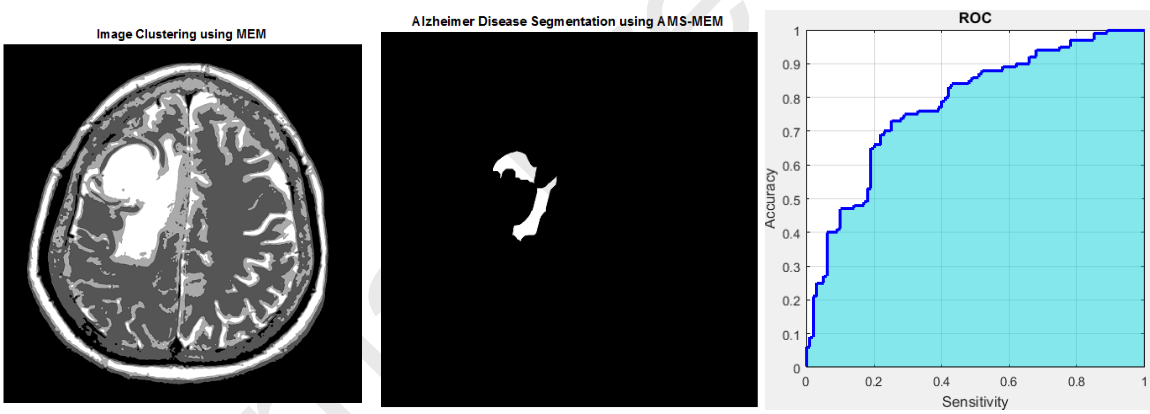


Figure 6: (a) Image Clustering using AMS MEM algorithm, (b) Alzheimer disease segmentation using AMS MEM algorithm, (c) ROC Curve

Figure 6 (a) shows clustered image using AMS-MEM algorithm. The different intensity pixels are grouped using AMS-MEM algorithm. The Bayesian Threshold technique is applied to AMS-MEM algorithm in order to segment Alzheimer disease as displayed in figure 6 (b). The figure 6 (c) shows ROC curve of DCNN classifier. The 6 (c) shows Area Under Curve (AUC) value is 98 %.

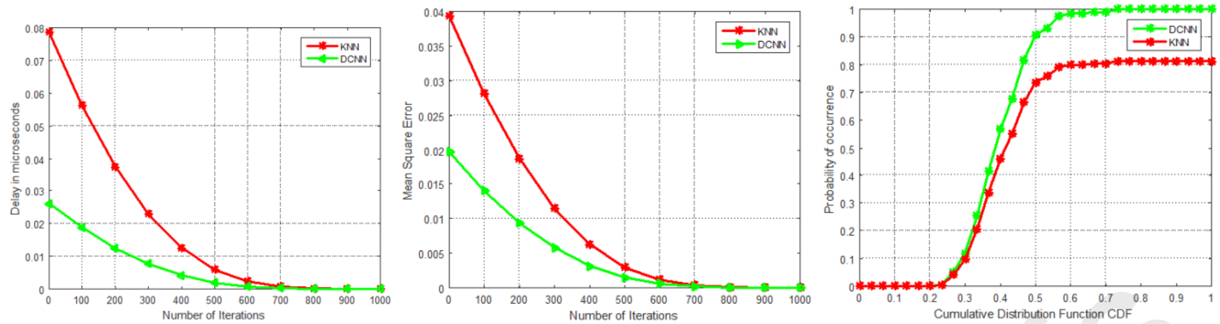


Figure 7: (a) Delay minimization of DCNN, (b) MSE of KNN and DCNN, (c) Probability of Occurrence

Figure 7 (a) displays delay (Latency) estimation for KNN and DCNN classifier approaches. The DCNN classification delay is considerably decreased thus compared to KNN. Figure 7 (b) shows Mean Square Error (MSE) estimation for KNN and DCNN. The MSE of DCNN is lesser than KNN. Probability of occurrence is represented for KNN and DCNN classifier in figure 5 (c). The table 1 shows the numerical values comparison between existing filters and proposed 2D ABF. The table 2 shows various features estimated using GLCM algorithm. AD disease image and normal image are compared and listed in the table 2.

Table 1 Image Quality Measurement

S. No	Algorithm	PSNR	MSE
1	2D Median Filter	32.9383	2.8383
2	2D Bilateral Filter	38.3989	1.3989
3	2D Adaptive Bilateral Filter	47.3989	0.0938

Table 2 GLCM Feature extraction

S. No	GLCM Features	Alzheimer Disease (AD) Image	Normal Image
1	Entropy	0.4544	1
2	Auto correlation	0.8333	1
3	Contrast	3.8498	9.9309
4	Cross Correlation	1	0
5	Cluster Prominence	5.9383	9.0393
6	Cluster shade	5.0909	9.6353
7	Energy	2.9389	8.3988
8	Homogeneity	1.9389	9.3987
9	Dissimilarity	9.3876	0.9387
10	Energy	1.9333	9.3987
11	Maximum Probability	0	1

Table 1 shows image quality measurements using PSNR and MSE for various filters such as 2D Median Filter, 2D Bilateral Filter and 2D Adaptive Bilateral Filter. Compare to all three images, 2D ABF performance is better than all other filters. The AHA is applied to improve image quality. The proper preprocessing method is used to segment the ROI. The Table 2 shows various GLCM features are calculated for classification using DCNN. The table 3 shows precision and recall computation using True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values.

Table 3 Precision and Recall

Testing formula	Description	CM
1. Precision (P)	Classifier correctness.	P = TP / (TP+ FP)
2. Accuracy (A)	Prediction algorithm accuracy.	A=(TP+TN) / N Where N- Total No. of samples

The confusion matrix is given below which forecast experimental results on a deep learning classification problem. The amount of right and incorrect forecasts are estimated with calculation ranges and given by every class. Table 4 shows the confusion matrix values of TP, TN, FP and FN.

Table 4 Confusion Matrix

	Class 1 Prediction	**Class 2 Prediction**
Class 1 Actual	TP	FN
Class 2 Actual	FP	TN

	Class 1 Prediction	**Class 2 Prediction**
Class 1 Actual	50	10
Class 2 Actual	5	100

Table 5. Performance evaluation using Jaccard Coefficient

Images	**Coefficient of Jaccard**		
	Fuzzy C Means (FCM) clustering	Fast Fuzzy C Means Clustering	Proposed MEM Clustering
1	0.3336	0.5783	0.9389

2	0.4837	0.5837	0.9382
3	0.4193	0.6938	0.8397
4	0.4684	0.6376	0.8376

Table 5 shows the performance evaluation using Dice Coefficient. From Table 5, the average value of Dice Coefficient for FCM clustering was 0. 4837. Similarly, the average value of Dice Coefficient for Fast FCM Clustering was 0. 6938. But the proposed MEM Clustering achieved a maximum Dice Coefficient of 0.9389. Thus, our proposed framework achieves best performance in terms of Dice Coefficient.

Table 6 Precision and Accuracy

Using table 6, precision and accuracy are estimated and tabulated as given below. In the table 5, the proposed classification is compared with K-nearest neighbor (KNN) algorithm. The KNN is the kind of supervised Machine Learning (ML) method that can be applied for both classification and regressive prediction issues.

Classification	Algorithms	Precision in %	Accuracy in %
ANN	KNN	82	84
DL	DCNN	97	96

The experimental results are given on different types of images such as normal and abnormal with various noise levels. The 2D Adaptive Bilateral Filter is used for de-noising and adaptive mean adjustment (AMA) is applied for image enhancement. The PSNR is calculated by applying the formula is,

$$PeakSignaltonoiseRatio = 10 * \log_{10}\left(\frac{255^2}{mse}\right) \text{ in dB}$$

Where, the MSE is estimated by using the below formula is,

$$mse = \frac{1}{IxJ}\sum_{i=1}^{I}\sum_{j=1}^{J}[x(i,j) - \hat{x}(i,j)]^2 \quad (15)$$

Pseudo code for ANN-KNN

The proposed DCNN classification technique is compared with ANN-KNN classification technique. ANN-KNN diverge the difference between a selection of new data and all learning data sets, and the minimum distance is found as better neighbor. The k value is calculated objectively, using Sorting error for the Learning sample. The ANN-KNN is one of the important classification techniques to given better accuracy and efficiency.

1. Initialize the training data and testing data

```
2. Select the range of K value
3. For every position in testing data:
      - Estimate the Euclidean distance to each training data position
      - accumulate the Euclidean distances in a record and arrange it
      - decide the initial k position
      - allocate a class to the testing position using the significance of classes available in the selected positions
4. End
```

Pseudo code for DCNN

```
for classification patterns
% Feed Forward computation
for each neurons (nn)
for each weights vector of the neuron (nx)
Estimate net using Sigmoid function
end;
Estimate deep convolution
Estimate neuron output;
Estimate neuron slope;
end;
for all outputs (no)
estimate error;
Deep convolution computation
initial delta as slope;
for all neurons preliminaryas of output neurons (nn)
for the weights connected to other neurons (ny)
multiply delta through weights
sum the backpropagated delta at proper nodes
end;
multiply delta by slope (for hidden neurons);
end;
end;
end;
```

Overall accuracy:

Overall accuracy indicates the overall classification performance of the classifier.

$$Overall\, accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{21}$$

where TP refers to true positives, TN refers to true negatives, FP refers to false positives and FN refers to false negatives.

Recall:

The recall ratio of number of positive cases is correctly classified to the total number of positive cases.

$$Recall = \frac{TP}{TP + FN} \tag{22}$$

Precision:

The precision is the ratio of number of positive cases that are correctly classified to the total number of cases classified as positive.

$$Precision = \frac{TP}{TP + FP} \tag{23}$$

Specificity:

The specificity is the ratio of number of negative cases that are correctly classified to the total number of negative cases.

$$Specificity = \frac{TN}{TN + FP} \tag{24}$$

F-score:

The F-score is computes as

$$F - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{25}$$

The classification is also performed using traditional machine learning algorithms like KNN and DCNN for comparison. Table 6 shows the results obtained in terms of overall accuracy. From Table 5, we see that Logistic Regression algorithm produces the best results compared to all other traditional classification algorithms.

5. CONCLUSION

The Computer Aided Diagnosis (CAD) system is proposed using various algorithms to detect and classify Alzheimer disease on MRI real images. The Alzheimer disease a most threatening image and tool for testing of disease is very costly. The automatic segmentation and classification of Alzheimer disease (AD) in MRI brain images is implemented. The proper preprocessing is applied on the tool using 2D Adaptive Bilateral Filter (2D ABF) and Adaptive Histogram Adjustment (AHA). The segmentation ROI is done using Modified Expectation Maximization (MEM). The various image features are retrieved using GLCM and the DCNN classification technique is used to classify normal and abnormal image. The accuracy of classification is more than 98% using Deep Convolutional Neural Network.

FUTURE WORK

In future, CAD system may be applied for cancer cells identification by proper segmentation of Gray Matter (GM), White Matter (WM) and CSF. The adaptive clustering technique can be applied to segment disease region without pixels error. The DCNN can be applied to distinguish regular and anomalous MRI brain images.

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Cover Letter

Dr V Sathiyamoorthi

[04.06.2020]

Dear Editor

I/We wish to submit an original research article entitled "**A Deep Convolutional Neural Network (DCNN) based Computer Aided Diagnosis (CAD) System for the Prediction of Alzheimer's Disease in MRI Brain Images**" for consideration by **Measurement**. I/We confirm that this work is original and has not been published elsewhere, nor is it currently under consideration for publication elsewhere.

We have no conflicts of interest to disclose.

Please address all correspondence concerning this manuscript to me at sathyait2003@gmail.com

Thank you for your consideration of this manuscript.

Sincerely,

Dr V Sathiyamoorthi

CREDIT AUTHOR STATEMENT

Sathiyamoorthi V: Conceptualization, Methodology, Software, Visualization,
Sathiyamoorthi V and **Ilavarasi A K**: Data curation, Writing- Original draft preparation.

Sathiyamoorthi V and **Murugeswari K:** Formal Analysis, Investigation.

Sathiyamoorthi V and **Syed Thouheed Ahmed***:* Supervision.

Sathiyamoorthi V and **Aruna Devi B:** Validation.

Sathiyamoorthi V and **Murali K:** Reviewing and Editing

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: