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Analysis of the Hippocampal Region in an MRI for Alzheimer's Disease Using Machine Learning

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Abstract—

Alzheimer's disease is the most common type of Dementia in those aged 65 and over; it is a degenerative neurological disease with no cure. The prodromal stage of Alzheimer's disease should be aggressively sought out because of the significant reduction in brain damage that may result from an early diagnosis. In this research, we describe a method that uses Machine Learning to analyze MRIs for Alzheimer's disease. The distinct phases of Alzheimer's disease are identified by first extracting texture and shape information from hippocampal MRI scans, and then using a Neural Network as a Multi-Class Classifier. The proposed approach is now being implemented, and it is expected that its accuracy will increase in comparison to the current state of affairs.

I. INTRODUCTION

Dementia is more common in those aged 65 and over, with Alzheimer's disease (AD) being the most common cause. It's a neurodegenerative disease for which there is currently no treatment. Brain damage that progresses in a regular way as the disease worsens. It may take as long as a decade for memory and other cognitive impairments brought on by brain injury to become noticeable. Plaques and Tangles are important features of Alzheimer's disease.

The hippocampus is the first brain region to sustain injury, and for good reason: it plays a pivotal role in learning and memory and works as a relay between the brain and the rest of the body. Alzheimer's sufferers have an aberrant atrophy of their hippocampus at a rate of 2.2% to 5.9% every year. Hippocampal atrophy results mostly from cell loss and network disruption. The inability of neurons to communicate with one another via the breakdown of synapses. As a result, severe phases are marked by a breakdown in brain connection and difficulty in forming and consolidating recent memories. Alzheimer's disease may be classified as mild, moderate, or severe, depending on the patient's condition. Individual differences in Alzheimer's disease progression mean that no two people will have the same experience with the illness. Patients with Alzheimer's disease in the early stages of the disease often continue to live independently. However, the person may still feel as if they are having memory lapses, such as forgetting the meaning of everyday words or where they put everyday objects. The Alzheimer's disease intermediate stage often takes the longest. Destroying brain cells at this point may hinder one's capacity to communicate and do everyday tasks. Many others around you have probably recognized the signs by now. By this point, the patient's disease has deprived them of their ability to engage in meaningful dialogue, much alone take control of their own bodies. Patients with advanced dementia need progressively high levels of support with even the simplest of activities. Unfortunately, only a tiny percentage of people with AD get their condition detected early, before it has progressed too far. Monitoring brain changes and identifying Alzheimer's disease in its early, curable stages may be possible using neuroimaging methods including positron emission tomography (PET), single-photon emission computed tomography (SPECT), and magnetic resonance imaging (MRI). Mini-Mental State Examination (MMSE)

and Clinical Dementia Rating are two examples of non-automated diagnostic tools now in use with cognitive impairment evaluation.

II. RELATED WORK

Hybrid Forward Sequential Selection (HFS) is a feature-selection based approach developed by Yang Han and Xing-Ming Zhao [6] for the diagnosis of Alzheimer's disease. Disease. This approach suggests combining the filter and wrapper strategies to better discover significant features in MRI data from the Alzheimer's disease Neuroimaging Initiative (ADNI) database. The attributes were ranked, and the first k were selected for this technique. We employed a Support Vector Machine (SVM) as the underlying classifier. In terms of computational cost, diagnostic accuracy, and overall performance, the authors claim their method excels above that of competitors. In [8], Devi Rwanda and Alhadi Bustamam propose an ALBP method. The ALBP method was introduced as a strategy for extracting features in both 2D and 3D. Principal component analysis (PCA) and factor analysis were employed for feature selection to limit down the massive quantity of features provided by ALBP. The Support Vector Machine was used for this multiclass classification job. The authors state that their new method is more efficient and accurate than the previous Local Binary Pattern (LBP) method. The average accuracy was one hundred percent when using data from the complete brain and the hippocampus together. An average accuracy of 96.28% is claimed for multiclass categorization of whole-brain pictures using the uniform rotation invariant ALBP sign magnitude. Due to the enormous dimensionality and high processing needs of feature extraction from large MRI datasets of the brain, using parallel computing may improve the extracted feature vector.
S.Saraswathi et al. [9] proposed a method for diagnosing Alzheimer's disease that makes use of a trisect of machine learning algorithms. The Genetic Algorithm (GA) is often used when deciding which qualities to emphasize. Vowel-based morphometry is the technique we use to extract these features. Classification is handled by an Extreme Learning Machine (ELM), and then the results are fine-tuned using the Advanced Particle Swarm Optimization (PSO) technique. An average training accuracy of 94.57% and an accuracy in testing of 87.23% have been attributed to the GA-ELMPSO classifier.
Using mathematical and visual processing approaches, Riel Mahmud and Bashed Grimier [14] developed an automated way to diagnosing Alzheimer's disease. A multi-class neural network was used to categorize the dimensions produced from Principal Component Analysis, which reduced the high dimensional vector space to 150 dimensions. The classifier was trained and evaluated using the OASIS database. The authors claim that their methodology achieves an accuracy of around 90%. M.Evanchalin Sweaty and G.Wiselin Jiji[15] proposed using Particle Swarm Optimization (PSO) in conjunction with a Decision Tree Classifier to diagnose Alzheimer's.

Images created by the proposed approach are normalized and noise is reduced using a Markov random filter. Features are extracted from the normalized images using Moments and Principal Component Analysis. While a Decision Tree Classifier is used to classify data, Particle Swarm Optimization is utilized to minimize the number of extracted features. The authors claim that their proposed method yields an accuracy of 92.07% on SPECT images and 86.71% on PET images for similar work.

Devi Sardinia and Animate M. Ramamurthy [10] proposed a computer-assisted strategy for texture analysis based on a feature selection approach using 3D MR images. By combining the feature selection (using Kernel PCA) and feature extraction (using magnitude from three orthogonal planes and Complete Local Binary Pattern of Sign) methods, we have developed a unique approach to characterizing 3D objects. The classification work is performed by a Support Vector Machine. The authors claim that their methodology reliably differentiates between Alzheimer's disease and healthy brain tissue. It is also claimed that the proposed method can identify Alzheimer's disease and moderate cognitive impairment with an accuracy of 84%.

To estimate the chance of early detection of Alzheimer's disease using image processing on MRI images, Chetan Patil et al. [12] proposed an approach. Applications of image processing techniques such as k-means clustering, wavelet transform, watershed algorithm, and an original algorithm devised by the authors were shown using the open-source Opens and Qt platforms. T1-weighted MRI image processing was proposed as a means of detecting

Hippocampal atrophy. Using a border detection technique, the ROI was recovered, and then the picture was segmented using k-means clustering. The size of both the brain and the hippocampus grow. The scientists state that Alzheimer's patients have a larger gap between grey and white matter and a lower total brain volume. They believe that their research might have applications in both the medical and technical fields. In the context of Alzheimer's illness, Mayan Agawam and Jived Mustafa [11] introduced Viewfinder Medicine (vim), an example of content-based image retrieval. Evidence linking medical diagnoses to health problems. For both discovering similar scans and classifying them, the vim makes use of textual information and low-level properties. In order to determine the efficacy of the method, it was applied to T1-weighted contrast enhanced MP-RAGE MR images in a series of tests. The classification module of the system was tested experimentally to measure its efficiency and the accuracy of its classifications. Using a cross-validation method with 10 repetitions, we calculated the classifier's accuracy. Different combinations of DCT, DWT, LBP, and others were tried to discover which produced the best reliable classifications.

We explore how to classify these models in relation to the fusion model. The authors of the research claim that compared to DCT and DWT, LPB provides superior results. In addition, they note that excluding out skull data enhances classification accuracy, and that the fusion model can achieve an accuracy of up to 86.7%.

III. PROPOSED APPROACH

Stage one of the suggested strategy involves... A group of labeled MRI images are preprocessed for region-of-interest (ROI) extraction and segmentation during the training phase. The Here is a quick rundown of the training phase:

a) Take the MRI images that have already been processed and pull out properties like texture, shape, and area.

b) Use these features to train an ANN classifier

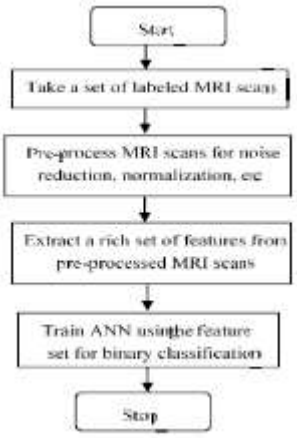
As a result of the training process, a classifier is produced that can make accurate predictions about the label assigned to a given MRI scan by using just that scan's attributes. Measures such as accuracy, sensitivity, and specificity may be used to assess the trained classifier's efficacy.

Classification: The key points of this stage are as follows:

a) Utilize a patient's MRI as the input.

To b) Prepare the MRI scans for analysis.

The third step is to "extract the necessary features" from the MRI image of the patient. In step d), we put the learned classifier to use by trying to guess the diagnosis from the MRI image. The result of this step is a categorization label that indicates the subject's most likely AD stage.



Training Phase

Phase of Classification of the Proposed Method

Dataset, A.

The Open Access Series of Imaging Studies (OASIS) is a project with the goal of making MRI data sets of the brain publicly accessible to the scientific community, and this article takes a look at one of their MRI-based datasets. In this case, MR pictures that have been processed are the data. The ages and sexes of patients, as well as their levels of education and income, as well as their scores on the Mini-Mental State Examination (MMSE), are also included in the data sets.

Calculating Return on Investment (B)

The hippocampus is among the first brain areas to be impacted by Alzheimer's disease. For this reason, the proposed study would extract the hippocampus area as the Region of Interest from the MRI scan in order to identify Alzheimer's disease. The region of interest (ROI) will be extracted using a correlation approach based on masking. By applying a mask containing previously extracted ROIs to the subject picture and then computing the greatest correlation value, we may isolate the hippocampus area of the subject image to use as the ROI.

C. Feature Extraction: The Hippocampus will have its Texture, Shape, and Area characteristics extracted so that AD may be identified. The texture features will be retrieved using the Gray Level Co-occurrence Matrix and the shape and area features will be extracted using the seven moment invariants. The variables of the dataset that are accessible via extraction will also be used, including age, gender, education, socioeconomic status, and Mini-Mental Examination Score. The feature vector will be created using the retrieved features.

To extract the second order statistical texture information, one may utilize the Gray Level Co-occurrence Matrix (GLCM). It's a matrix with as many rows and columns as there are shades of grey in the original picture. Image GLCM computation Using a vector of motion d(r,), where r is the radius and is the orientation. As applying a high displacement value to a small texture would produce a GLCM that does not capture precise textural information, the

optimal values for the radius are 1 and 2, with the range running from 1 to 10. Each pixel is surrounded by seven others, giving us eight possible values for (0 degrees, 45 degrees, 90 degrees, 135 degrees, 180 degrees, 225 degrees, 270 degrees, and 315 degrees). However, if you set = 0 degrees, you'll get the same co-occurring pairings as if you set = 180 degrees. This idea also works at angles of 45°, 90°, and 135°. This means that you have four options when deciding on the value of.
In this work, we use GLCM to extract six critical texture properties, including:

I. Entropy: It measures the complexity in the image.

$$Entropy = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} -P_{ij} * \log P_{ij}$$

II. Energy: It is a measure of global uniformity in the image.

$$Energy = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} P_{ij}^2$$

III. Local Homogeneity: It is a measure of local uniformity in the image.

$$Local\ Homogeneity = \frac{\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} P_{ij}}{1+(i-j)^2}$$

IV. Contrast: It measures intensity variation between a pixel and its neighborhood.

$$Contrast = \sum_{i,j=0}^{N_g-1} P_{ij}(i-j)^2$$

V. Correlation: It is a measure of linear dependency between gray levels.

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right]$$

In 1962, Hub presented the concept of moment invariants for the first time. Six orthogonal absolute invariants and a tilt there was a derivation of an orthogonal invariant from algebraic invariants. All four of these dimensions (placement, size, orientation, and parallel projection) had no effect on the generated invariants. Using these invariants, one may determine a set of attributes of an area that can be utilized for both class and shape identification.

The Crucial Points Are:

$$\mu_{p,q} = \sum_{x,y} (x-x_c)^p (y-y_c)^q$$

Central moments can be standardized to make them scale independent,

$$\eta_{p,q} = \frac{\mu_{p,q}}{\mu_{0,0}^{\gamma}}$$

Where,

$$\gamma = \frac{p+q+2}{2}$$

Hub proposed seven moments that is true regardless of translation, rotation, or scale.

$$\phi_1 = \mu_{2,0} + \mu_{0,2}$$

$$\phi_2 = (\mu_{2,0} - \mu_{0,2})^2 + 4\mu_{1,1}^2$$

$$\phi_3 = (\mu_{3,0} - 3\mu_{1,2})^2 + (\mu_{3,0} - 3\mu_{1,1})^2$$

$$\phi_4 = (\mu_{3,0} + \mu_{1,2})^2 + (\mu_{0,3} + \mu_{2,1})^2$$

$$\phi_5 = (\mu_{3,0} - \mu_{1,2})(\mu_{3,0} + \mu_{1,2})\left[(\mu_{3,0} + \mu_{1,2})^2 - 3(\mu\_2,1 + \mu\_0,3)^2\right] + (3\mu_{2,1} - \mu_{0,3})(\mu_{2,1} + \mu_{0,3})\left[3(\mu_{3,0} + \mu_{1,2})^2 - (\mu_{2,1} + \mu_{0,3})^2\right]$$

$$\phi_6 = (\mu_{2,0} - \mu_{0,2})\left[(\mu_{3,0} + \mu_{1,2})^2 - (\mu_{2,1} + \mu_{0,3})^2\right] + 4\mu_{1,1}(\mu)(\mu_{2,1} + \mu_{0,3})$$

$$\phi_7 = (3\mu_{2,1} - \mu_{0,3})(\mu_{3,0} + \mu_{1,2})\left[(\mu_{3,0} + \mu_{1,2})^2 - 3(\mu_{2,1} + \mu_{0,3})^2\right] - (\mu_{3,0} - \mu_{1,2})(\mu_{2,1} + \mu_{0,3})\left[3(\mu_{3,0} + \mu_{1,2})^2 - (\mu_{2,1} + \mu_{0,3})^2\right]$$

A feature vector is created by summing all the retrieved features. The MRI feature vectors serve as the training set. There are 18 features in each feature vector. The following table provides a quick overview of how many features fall under each heading.

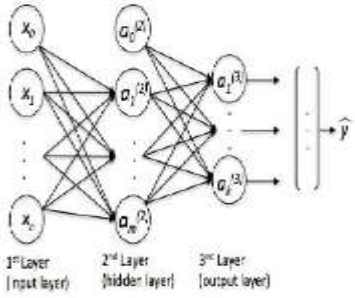
Summary of the feature vector

GLCM	Moments	MRI	Total
		Dataset	
06	07	05	18

D. Artificial Neural Network: Multi-class classification is utilized to divide AD into its several phases. For those unfamiliar, an A.N.N. often used for the aim. When training an ANN to distinguish between n distinct classes, the network will include an output layer with n neurons, where each neuron will represent a different class. Since feature vectors in the proposed work are also 18 neurons in length, the number of neurons in the ANN's input layer is also 18. Subjects are categorized as normal, mild, moderate or severe based on the output of the four neurons in the output layer. There is also thought given to a hidden layer, the size of whose neuronal population is a function of those of the input and output layers.

$$n = (input\_neurons + output\_neurons)/2$$

The architecture of the neural network is shown in Figure 2.



See also: Figure 1: The exposed components of ANN architecture
For this purpose, we will use the Error back propagation (EBP) training method to educate the neural network on 100 reference MR images. Algorithm. The network will be ready for AD categorization after training is complete. In our scenario, we anticipate a CDR of 0 in the absence of AD, CDR 0.5 in the presence of mild AD, CDR 1 in the presence of moderate AD, and CDR 2 in the presence of severe AD.
There are two computational passes, a forward pass and a backward pass, in Error Back-Propagation training. Initially, each weight is set to a very low random value. On the input layer's nodes, the input vector is used in the forward pass. Each layer's output vector serves as input for the subsequent layer. Forward pass utilizes a static weighted network. The network's ultimate response may be thought of as the output of the output layer. Forward pass errors are computed using this output and the labeled training set. During the forward pass, this mistake is sent down to the input layer from the output layer. The network weights are adjusted during this pass to make the subsequent forward pass more accurate. Iterating this method reduces the error until it is no longer significant.
By the time the procedure finishes, the network's weights will have been trained using the input features. Figure 3 depicts the algorithm's execution flow. The EBP algorithm concludes the training step of the proposed method.

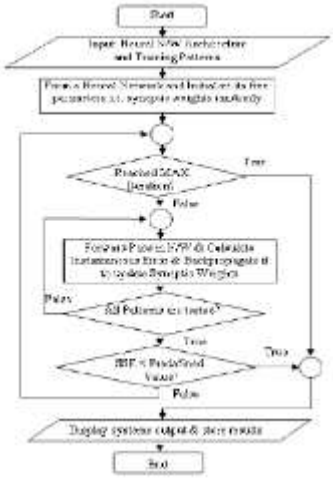


Figure 3: The EBP Algorithm in Flowchart Form
The end result of the training process is a trained network with fine-tuned weights.
During the sorting process:
This procedure consists of the stages listed below.
The first step is to prepare the MRI image for region-of-interest (ROI) extraction.
Determine the hippocampus's extent, shape, and texture (ROI). Third, use the ANN's learned classification capability by feeding it the feature vector.

IV. CONCLUSION

This research introduces an ANN-based method for identifying Alzheimer's disease in MRI scans. By combining GLCM with Moment Invariants, the suggested method since the hippocampus region is the first to deteriorate in AD, it is important to extract characteristics from MRI scans of that area. This method, which is now being put into practice, is predicted to diagnose AD earlier than traditional methods.

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