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Predicting Alzheimer's Disease using Grey Wolf Intelligent Algorithm

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Abstract

The neurodegenerative dementia which mainly affects people who are older than 65 years is mostly caused by untreated Alzheimer's Disease (AD). The irreversible brain disturbance tardily breaks down the memory and thinking abilities and finally collapses the capability to achieve easy actions. The early diagnosis of AD slows its advance and reduces its symptoms. In this paper, an intelligent computer system which predicts AD with high accuracy was built to read images of various MRIs of the brain and then a series of sequential processes are performed as the preprocessing of the image. After that, s histogram of oriented gradients (HOG) algorithm is used to extract important features. Grey Wolf Optimizer (GWO) is then used to classify brain images into Mild cognitive impairment MCI or Cognitive Normal CN.

1 Introduction

Alois Alzheimer discovered AD in 1907 but it was not considered as a major disease until the 1970s. AD is a slowly progressive brain disease which is characterized by a decline in memory which eventually leads to confusion in reasoning, planning, language, and perception [1] [2]. In 2019, more than

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5.8 million people worldwide of different ages were suffering from AD. Researchers predict that more than 14 million persons will have AD in 2050 the majority of whom will be older than 65. Women are more likely to be infected with AD than men [3].

In the U.S., AD is considered to be the sixth main cause for death, and for the ages 65 and above it is the fifth main cause for death [4]. There are multiple risk factors that are believed to promote the increase in AD especially age, heredities, smoking, drinking, cholesterol drop, hypertension, head injury, and depression to name a few [5] [6]. Early diagnosis slows the disease progression and consequently reduces health care [7] [8]. The diagnosis can be done by MRI using magnetic fields and radio waves to produce 3D brain images [9] [10]. Generally, there are several stages in AD. Compared to the Normal control group (NC), AD is in a patient with brain degenerative disease, MCI is a precursor to AD [7] [11]. An AD study shows that every year 10-30% of patients diagnosed with MCI have been converted to AD; the conversion rate for normal elderly is 1-2% [12]. Nerve cells and tissues of the brain die off because of AD, thereby decreasing the overtime size of the brain changing it rapidly and affecting most of its functions [13].

This research aims to build an intelligent computer system for AD classifications into MCI or CN. The system was implemented in stages and image processing and artificial intelligence were used to reach accuracy in diagnosis.

2 Literature Review

Several methods have been proposed in recent years to predict and diagnose AD. Many studies were conducted on this topic and the most important findings of the previous researchers in their studies were: Anusha and Siva [14] designed an intelligent system to detect and predict AD using the K-NN algorithm. They predict the scarcity in memory that occurs in the influenced brain. They tried to classify the brain image by extracting the features of the brain image and used the k-means algorithm to identify the region of interest. Debesh and Jin [15] suggested DTCWT to extract features from the image by using PCA; afterwards, the feature vectors are passed to FNN to differentiate AD and HC from the MRI images. Heba and El-Dahshan [16] proposed another method for feature extraction using DWT and reducing feature vectors by PCA and then applying the LDA classifier. Geetha and Pugazhenthi [17] used the brain MRI to detect AD by applying the FNN method for classification. In addition, they applied ACO to remove the noise from MRI images before using DWT for feature extraction.

3 Histogram of oriented gradient (HOG)

HOG suggested by Triggs and Dalal is a traits descriptor applied in computer vision and image processing for the purpose of object detection [18] [21]. HOG uses a local intensity gradient or a distribution in the edge direction to describe the appearance and shape of an object. HOG features can effectively solve the classification and identification problems [20]. HOGs calculation is done by finding the horizontal and vertical gradients in the image which are usually found by convolution in the image using a separate derivative mask from one point for both the horizontal and vertical directions as shown below:

$$[-1 \quad 0 \quad 1] \text{ and } \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$$

At each pixel the value of the gradient can be evaluated according to the equation:

$$G = \sqrt{g_y^2 + g_x^2} \tag{3.1}$$

Also, the angle of the gradient can be calculated for each pixel by the equation:

$$\theta = arctan(g_y/g_x), \tag{3.2}$$

where g_y is the result of convolution in the vertical direction and g_x is the result of convolution in the horizontal direction [18].

4 Grey Wolf Optimization (GWO)

GWO is a new meta-heuristic algorithm inspired by nature. It was proposed by Mirjalili et al. in 2014 and has been widely used in science and industry. The hierarchy social behavior of grey wolf in hunting is simulated in this algorithm [22]. The grey wolf is one of the predators that forms the top of the food chain [22].

The individuals in the grey wolf society are classified into four levels: the most suitable solution is labeled as α, the second and third best are labeled β and δ. All other solutions are (w) and follow the other three types [23].

We simulate the process of surrounding a prey by calculating a distance vector and use it to update the wolf's position. Hunting is usually guided by alpha and occasionally press beta and delta. Eliminating uncertainty is based on mathematical modeling, assuming that the best three solutions have better knowledge regarding optimality, all other solutions are based on α, β, and δ [24]. The mathematical representation process includes the stages of the grey wolf algorithm [25]:

- Searching for prey (exploration stage): The search process begins with the creation of a random community of grey wolves in the algorithm. The search was done by relying on the locations of α, β and δ wolves as they spaced from each other to search for prey. Then they meet to attack the prey.

- Surrounding prey: For the purpose of mathematical representation of the encirclement process, the following equations are used:

$$\overrightarrow{D} = \left|\overrightarrow{C}.\overrightarrow{X_p}(t) - \overrightarrow{X}(t)\right| \tag{4.3}$$

$$\overrightarrow{X}(t+1) = \overrightarrow{X_p}(t) - \overrightarrow{A}, \overrightarrow{D} \tag{4.4}$$

where $\overrightarrow{D}$ is the distance between prey and wolf, $\overrightarrow{A}$ and $\overrightarrow{C}$ are the vector coefficient, $\overrightarrow{X_p}(t)$ is vector prey location, and $\overrightarrow{X}(t)$ is a vector grey wolf location in the current cycle. Vectors $\overrightarrow{A}$ and $\overrightarrow{C}$ are calculated with the following equations:

$$\overrightarrow{A} = 2.\overrightarrow{a}.\overrightarrow{r1} - \overrightarrow{a} \tag{4.5}$$

$$\overrightarrow{C} = 2.\overrightarrow{r2} \tag{4.6}$$

where $\overrightarrow{a}$ decreases linearly from 2 to 0 during the cycle
and $\overrightarrow{r1}$, $\overrightarrow{r2}$ are random vectors ranging from 0 to 1.

- The hunt: It is assumed that the α, β and δ wolves have the best knowledge of the potential location of prey so the locations of these wolves are the best solution and the rest of the wolves are forced to update their location according to the location of the best wolf as in the following equation:

$$\overrightarrow{X}(t+1) = [(\overrightarrow{X1} + \overrightarrow{X2} + \overrightarrow{X3})/3], \tag{4.7}$$

where $\overrightarrow{X1}$, $\overrightarrow{X2}$ and $\overrightarrow{X3}$, can be calculated by:

$$\begin{cases} \overrightarrow{X1} = \overrightarrow{X_\alpha}(t) - \overrightarrow{A1}.\overrightarrow{D_\alpha} \\ \overrightarrow{X2} = \overrightarrow{X_\beta}(t) - \overrightarrow{A2}.\overrightarrow{D_\beta} \\ \overrightarrow{X3} = \overrightarrow{X_\delta}(t) - \overrightarrow{A3}.\overrightarrow{D_\delta} \end{cases} . \tag{4.8}$$

Here $\overrightarrow{D_\alpha}$,$\overrightarrow{D_\beta}$ and $\overrightarrow{D_\delta}$ can be generated as:

$$\begin{cases} \overrightarrow{D_\alpha} = \overrightarrow{C1}.\overrightarrow{X_\alpha} - \overrightarrow{X} \\ \overrightarrow{D_\alpha} = \overrightarrow{C2}.\overrightarrow{X_\beta} - \overrightarrow{X} \\ \overrightarrow{D_\alpha} = \overrightarrow{C3}.\overrightarrow{X_\delta} - \overrightarrow{X} \end{cases} . \tag{4.9}$$

- Attack of prey (exploitation): Grey wolves end hunting by attacking prey. When they stop moving, the mathematical representation of the process of prey is reduced by decreasing the value of $\overrightarrow{a}$ as in the following equation [26]:

$$\overrightarrow{a} = 2 - cycle * (2/MCN) \tag{4.10}$$

Cycle: Refers to the current iteration.
MCN: Indicates the total number of iteration.

5 The Proposed Algorithm

In this research, the MRI images were obtained from the ADNI data set which consists of records of 260 subjects within the age of 50-70 years. Here we have involved 182 image samples to train the model on MCI and CN and, on the other side, 78 image samples for testing.

5.1 Preprocessing Stage

The preprocessing is represented by the following steps:

Step 1: All images are placed in a single large three-dimensional matrix. After that, the images are converted to black and white to reduce the number of colors and distinguish the brain color from the background color. Then the vertical and horizontal scans are applied to crop origin objects from the images as in Figure 1.

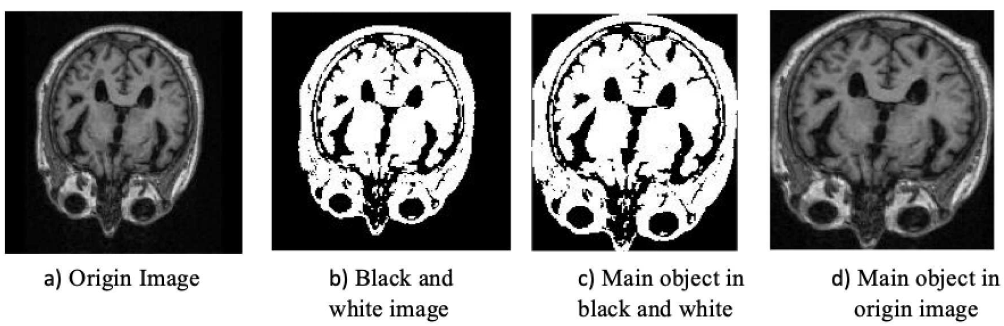

Figure 1: Preprocessing steps for origin images

Step 2: In this step, the color image segmentation is performed using $k-$means Clustering. This process includes converting RGB color space to Lab color space and classifying the color in Lab color space. As the image has three colors, three types of images are created as shown in Figure 2. Then one type of them is identified.

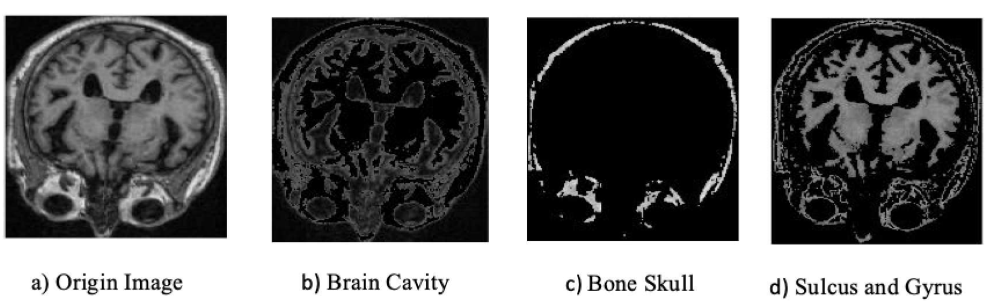

Figure 2: MRI images types for brain

Step 3: Convert RGB images to Gray images and resize it to be 10241024.
Step 4: Low pass and high pass decomposition filters are generated for the Haar wavelet. The Haar wavelet transform is applied to evaluate images well and professionally at different resolutions. It is applied to acquire the approximation coefficients and detail coefficients at several levels.
Step 5: The HOG algorithm is then applied to extract the feature vectors.
Step 6: The grey wolf algorithm is applied for image classification into MCI or CN.

5.2 Results and Discussion

In our work, the algorithm was applied to the training and testing of the system to detect and classify the images. Three types of MRI images are employed, namely Brain Cavity, Bone Skull, Sulcus, and Gyrus. One type of these images was used at each execution to display and compute the feature vector of the image. After that, the image was passed to GWO for classification into MCI or CN. The accuracy is computed using the following equation:

$$Accuracy = [\frac{\text{Number of Correctly Classified Images}}{\text{Total Number of Testing Images}}]x100 \qquad (5.11)$$

The results show that when the selected image size was 1024, HOG-cell size 32 and HOG-block size 2 according to Brain Cavity, the best accuracy (96.2%) was achieved, as shown in Table 1.

Table 1 shows that the best accuracy obtained has the value 96.2% depending on the choice of the Brain Cavity image type. Therefore, this type of image can be used to distinguish between the affected brain and the healthy brain. This supports the fact that most people with AD suffer from expansion of internal Brain Cavity.

6 Conclusion

The proposed system finds the discriminant patterns that an expert clinician may detect in similar images by mixing HOG with GWO. You can classify possible MCI and CN patients with an accuracy of 96.2%. It would be interesting to see how the results differ by using other MRI image types and the different sizes of MRI images. There are also some other possible extensions

Table 1: Description of each network models.

Exp. Exp. No.	**HOG-Cell Size**	**HOG-block size**	**Initial Popu. of wolf**	**Max no. of Iteration**	**Seg. Level**	**Accu-racy %**
1	8	2	30	300	*Brain Cavity*	91
2	8	2	30	300	*Bone Skull*	92.3
3	8	2	30	300	*Sulcus &Gyrus*	94.9
4	16	2	30	300	*Brain Cavity*	93.6
5	16	2	30	300	*Bone Skull*	88.5
6	16	2	30	300	*Sulcus &Gyrus*	94.9
7	32	2	30	300	*Brain Cavity*	96.2
8	32	2	30	300	*Bone Skull*	93.6
9	32	2	30	300	*Sulcus &Gyrus*	94.9

such as Hog-cell size, Hog-block size, and increasing the number of the iteration involved in computational tasks for the final prediction step. In future studies, other features and machine learning can be used to improve the accuracy of the classification. Moreover, the same system can be extended to be applied to lung diseases, different types of cancer recognition, etc.

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