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ALZHEIMER'S DISEASE DETECTION AND CLASSIFICATION ON MRI IMAGES USING GREY WOLF OPTIMIZATION BASED ELEPHANT HERDING OPTIMIZATION (GWO-EHO)

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Abstract

Alzheimer's disease (AD) is a degenerative neurological disorder that causes brain deterioration. Alzheimer's disease can be effectively treated and the degradation of brain tissue can be halted with early detection. Memory loss is one of the symptoms of AD. Even though AD has no known cure and severely impairs the lives of those who suffer from it, early identification may be helpful in starting the appropriate course of treatment to stop further brain deterioration. The sources of the data are the ADNI datasets. The images are preprocessed in order to lower noise in the resulting dataset. During the pre-processing stage, a nonlocal means filter is used. The Histogram of Gradients (HOG) Model is used to extract the feature. Using magnetic resonance imaging (MRI) and a proposed deep learning model known as Grey Wolf Optimization based Elephant Herding Optimization (GWO-EHO) architecture, the work focuses on early AD detection. The four types of AD are normal controls, early mild cognitive impairment, and late mild cognitive impairment. Data from the AD neuroimaging study were used to assess this method's ability to identify the illness early. The proposed GWO-EHO approach has attained maximum precision, sensitivity, recall, and accuracy, according to the test findings.

Keywords: GWO-EHO Algorithm, HOG, Deep learning model, classification, MRI imaging, Alzheimer’s disease, Earlier detection, Nonlocal Means Filtering.

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1. Introduction

A significant global public health concern is Alzheimer's disease neurological condition. It has a significant effect on people and society as a whole and is typified by behavioral changes, memory loss, and cognitive decline. In order to execute prompt interventions and individualized treatment options and ultimately lessen the burden imposed by the disease, early and precise diagnosis is essential. EEG has emerged as a potential biomarker for AD categorization and is a useful tool for studying brain function [1]. The most recent study focused on using machine learning techniques for CAD of AD. Due mostly to the inherent limits of the chosen learning models, the majority of these studies have shown a performance bottleneck in the diagnosis [2]. EEG waves were used to calculate Multiscale Fuzzy Entropy (MFE), a preprocessing step. To find unique patterns, a k-means clustering algorithm was used [3]. Convolutional neural networks (CNN) learnt by transfer and MRI data are used in a novel method of diagnosing AD [4]. The optimum precision of 97.66% and 97.58%, respectively, was attained by the Adam and SGD impetus optimizers [5].

Contribution of this Work

The main stages of the recommended strategy are as follows; for further details, see:

1. The datasets from ADNI the sources of the information.
2. To improve the quality of the images, a Nonlocal Means Filtering is used during the pre-processing stage.
3. HOG with texture and statistical features are used for extraction of AD.
4. In classification, GWO-EHO in deep learning method is used.

The following is a description of the approach taken to create the paper: The introduction is shown in Section 1. Section 2 provides a summary of the relevant works. Section 4 presents the experiment's results, Section 3 explains the recommended method, and Section 5 offers a conclusion and recommendations for additional research.

2. Related Work

Mehmood et al. [6] have described to solve this issue by using tissue early stages of AD can be identified by layer-by-layer knowledge transfer. We employed the VGG group's structure for layer-wise learning by transfer using weights that had already been trained. According to the proposed paradigm, people are divided into four groups: LMCI, NC, AD, and EMCI.

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According to Arafa et al. [7], one of the many researchers' objectives is to accurately and successfully diagnose AD in order to slow or stop the disease's progression proposed by Qin et al. [8] for the secondary diagnosis of AD using 3D MR imaging. Deep learning-based MR image processing has drawn more and more attention, and its main component is the creation of an effective model for identifying and extracting the essential elements of the images. Deepa et al. [9] have described the categorization of AD, the AOA was used to recommend an improved VGG-16 architecture.

A mixed deep learning method for AD early detection is offered by Balaji and associates [10]. Marwa et al. have developed analytical pipelines using 2D T1-weighted MR brain images and shallow CNN architecture [11]. A modified 3D Efficient Net and the multiscale features of brain MRI data for AD classification have been discussed by Zheng et al. [12]. This upgraded version includes a 3D MBConv block with successive linkages.

Alp et al. [13] have proposed a CNN with BiL-STM and ViT with Bi-LSTM. Excellent precision, recall, F-score, and accuracy 99% are achieved in the diagnosis of AD using the suggested strategy. Proposed approach offers researchers a way to improve early clinical diagnosis and treatment.

3. Proposed System

The proposed GWO-EHO Deep Learning approach is shown in Figure 1. Image acquisition was the first stage, using the open-source MRI image ADNI dataset. The images are preprocessed to lower noise in the resulting dataset. A nonlocal means filter is employed in the pre-processing phase. The HOG Model is used to retrieve the feature. The work focuses on using MRI and a proposed deep learning model dubbed GWO-EHO to diagnose AD early. AD comes in four different forms: normal controls, late mild cognitive impairment, and early mild cognitive impairment [14].

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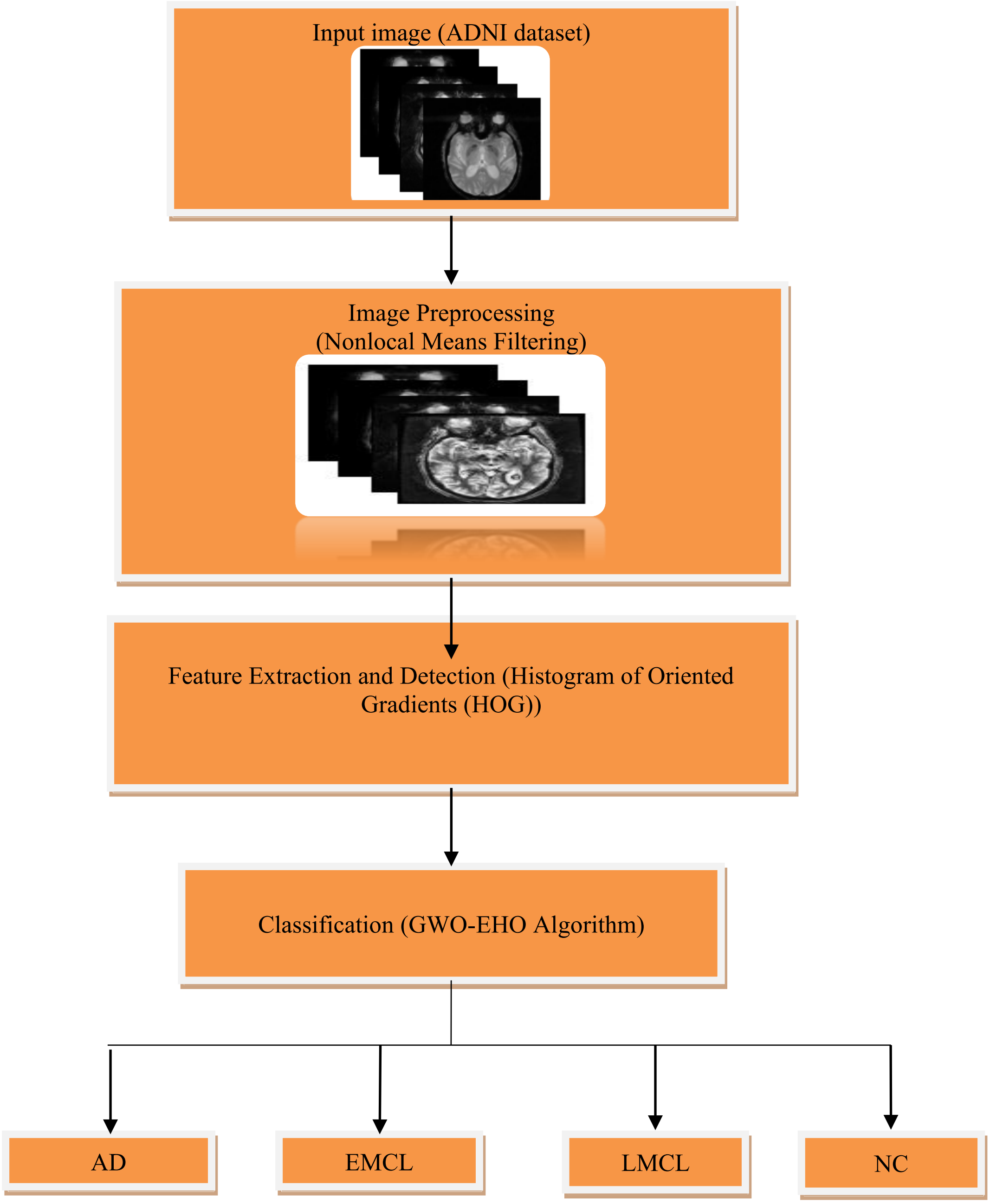

Figure 1: Diagram for the proposed GWO-EHO model for AD detection and Classification

3.1. Nonlocal Means Filtering

The nonlocal means filter's fundamental concept is that a given noise image $f : \Omega \subset R^2 \rightarrow R$ is filtered by,

$$u(x) = \int w_f(x, y) f(y)\, dy \qquad (1)$$

where, $w_f : \Omega \times \Omega \rightarrow R^+$ is a normalized weight function expressed as, and u: $\Omega \rightarrow$ R

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represents the denoised image.

$$w_f(x,y) = \frac{e^{-\frac{d_f^2(x,y)}{h^2}}}{\int e^{-\frac{d_f^2(x,y)}{h^2}}} \quad \text{for} \quad d_f^2(x,y) = \left\|f_x - f_y\right\|_{G_\sigma}^2 \qquad (2)$$

Where, the similarity between two patches of f centered in x and y is measured by the map $d_f(x,y)$.

3.2. Feature Extraction and Detection using HOG model

Greyscale image, the descriptor is used in MRI datasets without any color. The MRI features are generated by HOG, while the shape and appearance of the object are evaluated by LBP.

Each block builds the density of its intensity gradients during the HOG computation. The two 2-dimensional gradients, [1, 0, 1] and [1, 0, 1]^{m}, are calculated by filtering the image with the respective filters $\partial f(a,b))/\partial a \; and \; \partial f(a,b))/\partial b$

$$G_x = \partial f(a,b))/\partial a = \frac{f(a+1,b)-(a-1,b)}{(a+1)-(a-1)}$$

(3)

$$G_x = \partial f(a,b))/\partial b = \frac{f(a+1,b)-(a-1,b)}{(b+1)-(b-1)} \qquad (4)$$

The weighting, $\Delta f(a,b)$, and orientation, $(\theta f(a,b)$, for an image pixel can be calculated as

$$\Delta f(a,b) = \sqrt{(G_a^2 + G_b^2)} \qquad (5)$$

$$\theta(a,b) = tan^{-1}(\frac{G_a^2}{G_b^2}) \qquad (6)$$

The size of the vectorial sum of the 2-D (a and b) directional derivatives is the weighting, $\Delta f(a,b)$. The gradient vector's orientation, $\theta(a,b)$, is the angle it makes with the positive x-axis. The orientation is evenly distributed and lies either in the range [0,π] or [0, 2π]. Textures and deformable objects can be effectively described by using the HOG descriptor.

The HOG features are expressed as being obtained from each individual cell as f_{cell}, and the generated features are equal to the number of bins, with the features being represented in equation.

$$f_{cell} = \frac{\sum_{a,b\in(a,b)block} G(a,b)+\epsilon}{\sum_{a,b\in(a,b)} G(a,b)+\epsilon} \qquad (7)$$

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Where ∈ an irrational smaller quantity and each cell's normalized is block characteristics, derived from dimension vector d, are the same as the sum of all the block's cells and its oriented bins, which is the block's final descriptor.

3.3. GWO-EHO Algorithm for Classification

The hybrid GWO-EHO algorithm divides the wolf population into a predetermined number of clans based on elephant clan life. The top three best responses were kept for mathematical modeling in the current work, while additional agents were encouraged to shift their places in response. In this context, the following formulas are recommended:

$$\left|\overrightarrow{-X}\overrightarrow{X_\delta}\cdot\overrightarrow{C_3}\right| = \overrightarrow{D_\delta}, \left|\overrightarrow{-X}\overrightarrow{X_B}\cdot\overrightarrow{C_2}\right| = \overrightarrow{D_B}, \left|\overrightarrow{-X}\overrightarrow{X_\alpha}\cdot\overrightarrow{C_1}\right| = \overrightarrow{D_\alpha} \tag{8}$$

$$\overrightarrow{-A_3}\cdot\overrightarrow{D_\delta}\,\overrightarrow{X_\delta} = \overrightarrow{X_3}, \overrightarrow{-A_2}\cdot\overrightarrow{D_B}\,\overrightarrow{X_B} = \overrightarrow{X_2}, \overrightarrow{-A_1}\cdot\overrightarrow{D_\alpha}\,\overrightarrow{X_\alpha} = \overrightarrow{X_1} \tag{9}$$

$$\left(\vec{X}(t+1)\right) = \frac{\overrightarrow{X_1}+\overrightarrow{X_1}+\overrightarrow{X_1}}{3} \tag{10}$$

Where, since the ideal answer is believed to be α, the second and third-fittest alternatives are called β and δ, respectively.

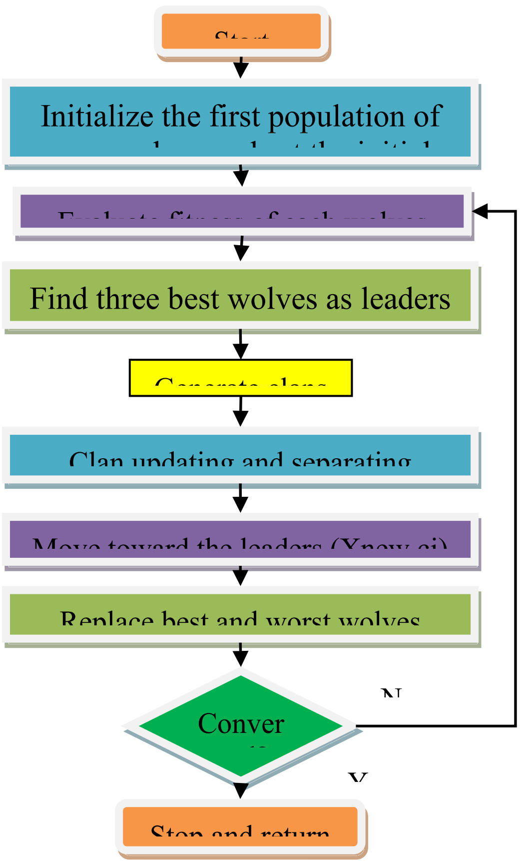

Figure 2: Flowchart for GWO-EHO algorithm

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$$X_{new,ci,j} = X_{ci,j} + \alpha \times (X_{best,ci} - X_{ci,j}) \times r \quad (11)$$

Where, Elephant J's current location in clan ci is $X_{new,ci,j}$, while its previous location is $X_{ci,j}$. The GWO-EHO algorithm flowchart is displayed in Figure 2. Algorithm 1 demonstrates the GWO-EHO model's pseudocode.

Algorithm 1: Pseudocode for GWO-EHO algorithm

Begin
Setting up
for ci=1 to the number of clans (for each clan within the wolf population)
    for each wolf in Clan Ci (j = 1 to nci)
        In compliance with GWO-EHO by Eqs, update xci,j and generate xnew,ci,j. (8), (9), and (10)
        If xci,j is equal to xbest,ci
          Using Equation (11), update xci,j and generate xnew,ci,j.
        end if
      end for j
    end for ci
End

3.4. Performance evaluation of classification results

Formulas for performance evaluation matrices are shown as,

$$\text{Accuracy} = \frac{\text{TP}}{\text{TP+TN+FP+FN}} \quad (12)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+TN}} \quad (13)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (14)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (15)$$

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4. Results and Discussions

The demographic information for 300 subjects is shown in Table 1 from the ADNI dataset. 300 people' demographic information from the ADNI dataset. 300 patients make up the dataset, which is separated into the four classifications AD, EMCI, LMCI, and NC. There are 80 patients in each class, producing a total of 24 pictures and 816 scans. 4968 photographs make up the AD class, 5513 images make up EMCI, 3357 images make up LMCI, and 6592 images make up NC.

Table 1.Information on the dataset's demographics

Parameter	AD	EMCI	LMCI	NC
Subject	350	298	157	752
Male/Female	1375/1106	2158/1386	1093/970	3423/4186
Mean (age)	76.51	77.81	75.30	76.58
Standard Deviation (age)	7.41	7.86	7.66	7.04

4.1. Input image

The ADNI dataset's data input images are shown in Figure 3. To improve both contrast and image quality, MRI images are passed into a preprocessing method.

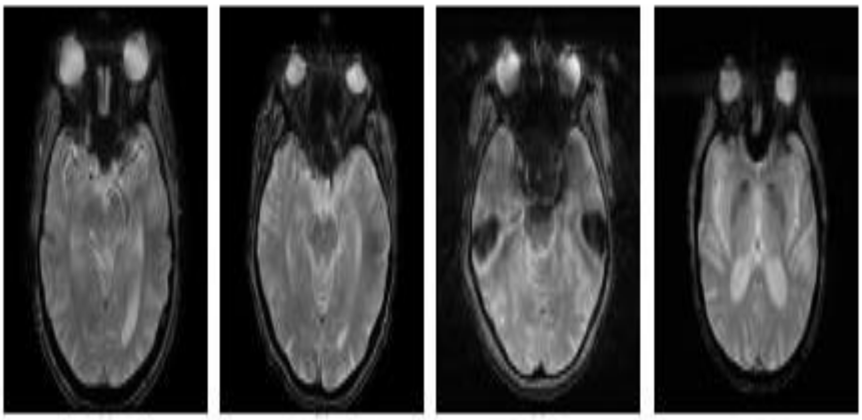

Figure 3: input image

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4.2. Image Preprocessing

The suggested approach preprocesses the brain MRI pictures in Figure 4 using a Nonlocal Means Filtering. As shown, the filter smoothes and sharpens the image's edges. Preprocessing techniques are used to improve the image's pixel quality. The Statistical Parametric Mapping (SPM) tool will first be used to pre-process the MRI [15].

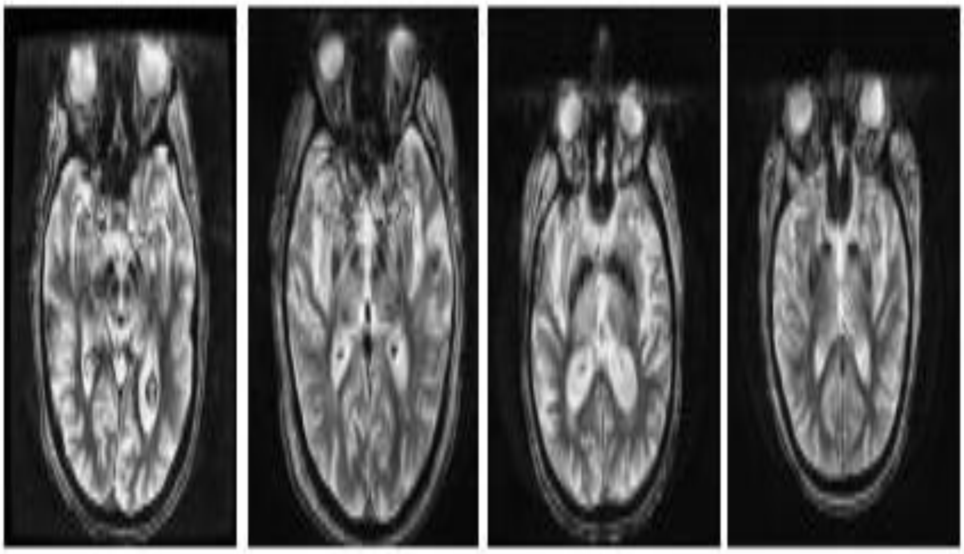

Figure 4. Preprocessed images by using Nonlocal Means Filtering

4.3. Feature Extraction and Detection

The extraction of images of brain image is shown in Figure 5. The outcomes were contrasted with ground truth labeling generated at the pixel level by neurologists.

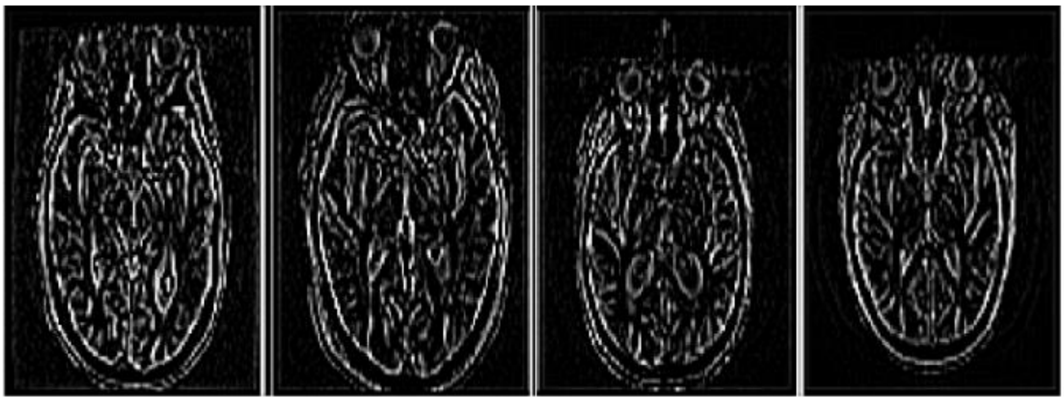

Figure 5. Feature Extraction using HOG

Figure 6 depicts the GWO-EHO deep learning architecture's confusion matrix for categorizing the phases of dementia in order to predict AD. The projected class and labelled classes from the four separate categories are plotted on the matrix of confusion. The

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confusion matrix shows how effective the model was on the training dataset.

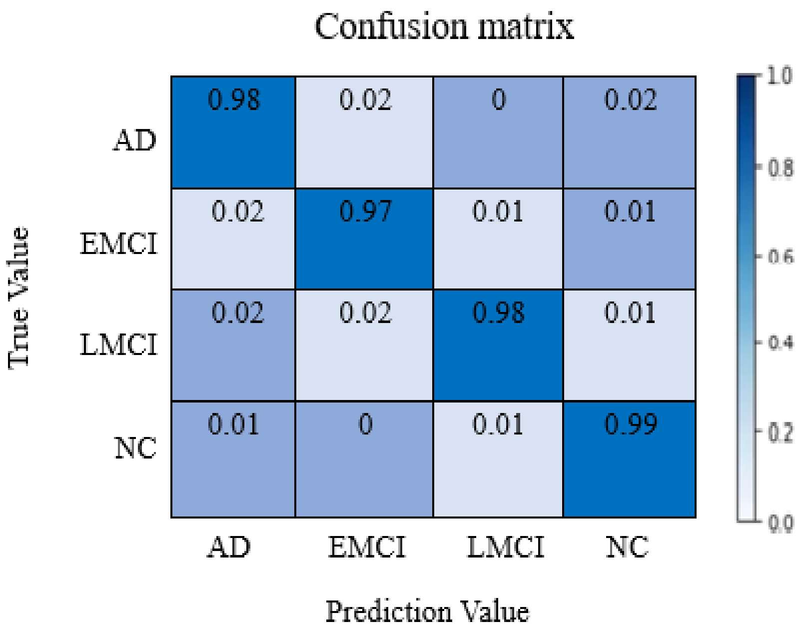

Figure 6. Confusion matrix of GWO-EHO deep learning model with four classes.

The ROC-AUC for the GWO-EHO deep learning model, with class AD, EMCI, LMCI, and NC, is depicted in Figure 7 in the appropriate order.

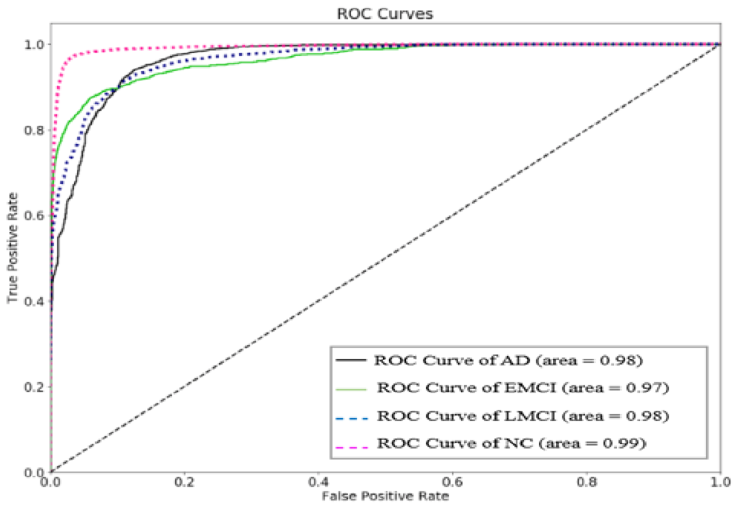

Figure 7. The ROC-AUC of the proposed GWO-EHO deep learning model

GWO-EHO Deep Learning Model Comparison Accuracy with Other Models When using binary and multi-class classification methods for medical images, the suggest the GWO-EHO

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deep learning approach. The accuracy metric will be used to compare these models' performance to other state-of-the-art algorithms, as indicated in Table 2.

Table 2: A comparison between the most sophisticated models and the GWO-EHO deep learning model

Approach	Type of classification	Accuracy
Graph convolutional neural networks [16]	Multi-classification (NC/EMCI/LMCI/AD)	89%
CNN [17]	Three class (EMCI/LMCI/NC)	95.73%
Finetuned VGG19 [18]	Multi-classification (NC/EMCI/LMCI/AD)	97%
GWO-EHO deep learning model (Proposed)	**Multi-classification (NC/EMCI/LMCI/AD)**	**99%**

5. Conclusion

The datasets from ADNI the sources of the information. Preprocessing is applied to the images in order to minimize noise in the generated dataset. During the pre-processing stage, a nonlocal means filter is used. The feature is retrieved using the HOG Model. The effort focuses on using MRI and a proposed deep learning model dubbed GWO-EHO to diagnose AD early. AD comes in four different forms: normal controls, late mild cognitive impairment, and early mild cognitive impairment. The proposed GWO-EHO model outperforms the other techniques by having a classification accuracy of 99%, according to experiments on a dataset. Future work aims to extend the proposed GWO-EHO model to larger multi-modal datasets and enhance clinical interpretability for real-world Alzheimer’s diagnosis.

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