Alzheimer's Disease Image Diagnosis by Active Contour Segmentation &Bootstrap Bagging Learning Model

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ABSTRACT
AD is a neurodegenerative disease in which pathological changes occur decades before disease manifestation. The disease is characterized by the formation of senile plaques, NFTs and subsequent synaptic loss and neuro degeneration. Although AD affects a major part of the population worldwide, to date, there is no therapy to cure AD. Since disease-modifying therapies may be the most beneficial in early stages of the disease, it is important to diagnose AD as early as possible. This paper proposed a model of disease diagnosis and identify the class of input image into healthy, mild, severe. Input image was preprocessed in order to extract brain region by use of active contour method. Further image was break down into blocks and estimate the histogram features. Extracted features were used for the training of bootstrap bagging learning model. Experiment was done on real image dataset of Alzheimer's disease of all set of classes. Result shows that proposed Alzheimer's disease Class Prediction by BioGeographic Optimization & Bootstrap Model (ADCPBOBM) model has improved the work detection accuracy of correct.

Keywords: Digital Image processing, Image Segmentation, Brain tumor, Genetic Algorithm.

INTRODUCTION

Alzheimer's disease (AD) is a severe brain disorder that leads to dementia in the elderly. It results in cognitive decline, eventually making it difficult for individuals to perform everyday tasks [1]. This condition not only diminishes the quality of life for patients but also imposes significant stress on caregivers [2]. The production of amyloid peptides is associated with AD, and its symptoms typically start with mild memory loss before advancing to more severe brain dysfunctions [3]. Since there is no cure for AD, early detection at the prodromal stage, known as mild cognitive impairment (MCI), is crucial. Early MCI (EMCI) is an initial phase of cognitive decline that precedes MCI, and identifying EMCI early can help prevent its progression to AD.

The initial use of imaging techniques for AD diagnosis included computed tomography (CT) and MRI. Recently, neuroimaging techniques, especially Magnetic Resonance Imaging (MRI), have shown promise as biomarkers in the preclinical stages of AD. MRI uses magnetic fields and radio waves to create detailed two- or three-dimensional images of brain structures without the need for X-rays or radioactive tracers [4]. This technology has greatly aided in developing diagnostic models for AD, providing a non-invasive way to detect brain atrophy patterns associated with the disease. Modern imaging modalities focus on detecting either amyloid deposits or neurodegeneration [5].

Deep learning (DL) utilizing convolutional neural networks (CNNs) has gained recognition as a promising approach for aiding clinical decisions through the analysis of digital brain images in the context of Alzheimer's disease (AD). In numerous studies, three-dimensional (3D) brain MR images have been utilized as input data for DL algorithms focused on diagnosing AD. These 3D images offer comprehensive details about brain structures, which can significantly aid in the accurate detection of AD-related changes.

However, the application of 3D brain MRI in clinical practice faces several hurdles. One major issue is the longer acquisition time required for 3D MRI sequences compared to two-dimensional (2D) MRI sequences. This extended acquisition time leads to increased computational demands, higher storage requirements, and elevated costs, making 3D MRI less practical for widespread clinical use. To address these limitations, recent studies have proposed hybrid methods that integrate deep learning with heuristic or nature-inspired optimization techniques. These methods aim to enhance the classification of brain MRI images for AD diagnostics. For example, Pradhan et al. developed a hybrid approach combining the Salp Swarm Algorithm with an Extreme Learning Machine (ELM) to optimize the ELM model for MRI classification. This method harnesses the advantages of both the Swarm Algorithm and deep learning to

improve diagnostic accuracy. Similarly, researcher in [6], employed an Enhanced Squirrel Search Algorithm to select optimal weight parameters for a deep neural network (DNN) architecture, facilitating better classification of AD stages.
These hybrid techniques represent significant advancements in the field of AD diagnostics. By combining deep learning with advanced optimization methods, researchers are developing more efficient, accurate, and cost-effective tools [7]. These innovations not only improve diagnostic capabilities but also have the potential to enhance patient outcomes and alleviate the burden on healthcare systems [8]. The integration of these cutting-edge methods promises to revolutionize the early detection and classification of Alzheimer's disease, paving the way for more effective management and treatment strategies [9].

Problem
Medical image diagnosis has limitation of two class identification either healthy or infected. Further most of research work has low detection accuracy that may be due to poor pre-processing steps. Researcher need to train a model that takes less number of training features as well, hence compatible on any device.

Objective
In order to resolve above issue this paper has developed a model that improves pre-processing steps by removing noise. Further input image has background region that should be eliminate to improve learning of actual information. Image extracted feature will be optimize further for improving prediction class.
The paper is organized into several sections. The first section is the introduction, providing an overview of the topic. The second section delves into a review of various research efforts in the field of image classification for Alzheimer's disease (AD). The third section outlines the proposed method for identifying AD classes in detail. In the fourth section, the results of the proposed method are compared with those of other algorithms. The paper concludes with a summary of the findings and the effectiveness of the proposed model.

LITERATURE SURVEY

In their research, Young Kim et al. [10] developed a sophisticated model that employs MobileNetV3-Large as its core for optimized computation, integrating modifications inspired by the UNet architecture. To boost diagnostic performance, they incorporated an advanced attention mechanism. To further enhance the model's robustness against variations in image quality, they employed a novel training approach using input image masking and the random erasing data augmentation method.
G. P. Shukla et al. [11] presented innovative pre-processing techniques that significantly bolstered the classification accuracy of MRI images while simultaneously reducing the training time for various established learning algorithms. They utilized a dataset from the Alzheimer's Disease Neuro imaging Initiative (ADNI), transforming it from a 4D to a 2D format. Their pre-processing pipeline included selective clipping, grayscale conversion, and histogram equalization to refine the images. Post pre-processing, they introduced three advanced learning algorithms for AD classification: random forest, XGBoost, and convolutional neural networks (CNN), each contributing to improved diagnostic capabilities.
Balaji et al. [12] explored a Hybridised Deep Learning (DL) method for the early detection of Alzheimer's disease (AD). They utilized a combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models to train their system. Their research involved two datasets: one comprising 512 MRI images and another from Munich consisting of 112 images. To enhance the accuracy of their model, they employed Adam's optimization technique and adjusted the learning weights using their proposed methods.
Yan et al. [13] introduced a multi-scale feature fusion network specifically designed for disease classification, including Alzheimer's, using MRI data. Their approach integrated deep CNNs with other advanced deep learning techniques such as generative adversarial networks (GANs) and stacked deep polynomial networks, which have shown promise in diagnosing Alzheimer's disease.
Nawaz et al. [14] proposed and compared three distinct models to determine which yielded the highest accuracy. The first model involved preprocessing images, extracting handcrafted features, and then classifying them using support vector machines (SVM), k-nearest neighbors (KNN), and Random Forest classifiers. The second model trained a CNN deep learning model from scratch using the preprocessed dataset. The third model employed AlexNet to extract deep features, which were then used to identify the best classifier—SVM, KNN, or Random Forest. Upon comparison, the model based on deep features extracted by AlexNet, combined with the SVM classifier, achieved the highest accuracy.
In their study, Olle, D.G. et al. [15] investigated two different methods for diagnosing Alzheimer's disease using MRI. The first method involves noise reduction and correction of image distortions through a non-

linear filter with a 3x3 size. Following this, a k-means algorithm is applied to segment brain images into regions representing white and grey matter. A Convolutional Neural Network (CNN) is then trained to detect variations in these segmented regions and identify the presence of Alzheimer's disease.
The second method focuses on image feature reduction using Principal Component Analysis (PCA). This technique extracts three key features—white matter, grey matter, and cerebrospinal fluid—that are relevant for diagnosing Alzheimer's disease. A multilayer perceptron algorithm is then trained to classify Alzheimer's cases based on these extracted features.
Saleh, S. et al. [16] proposed an innovative ensemble voting classifier that integrates Convolutional Neural Networks (CNN) and K-Nearest Neighbors (KNN) to determine the presence of Parkinson's disease. Their approach involves separately predicting outcomes based on spiral and wave sketching. Unlike traditional CNNs, their proposed architecture provides greater flexibility for handling small or imbalanced datasets, thus reducing the risk of overfitting. Additionally, the system is designed to automate the feature extraction from images and perform the classification, making it a more efficient and adaptable tool for disease diagnosis.

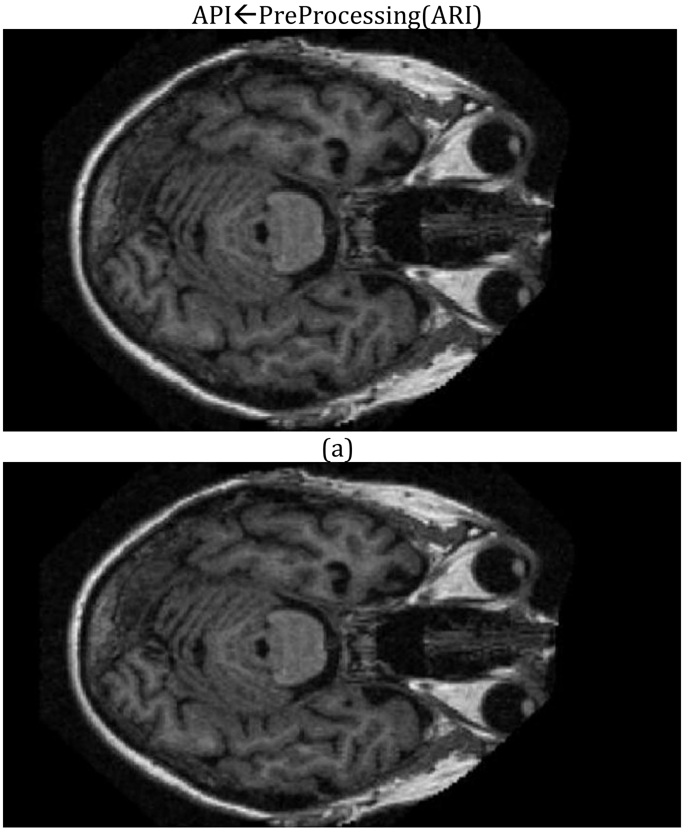
Proposed Model

Medical image of Alzheimer's diseasereports help medical officers to understand the severity of the disease. This section shows the steps of Alzheimer's disease (AD) diagnosis and identify the class of input image into healthy, mild, severe. Fig. 2 shows the block diagram of proposed Alzheimer's disease Class Prediction by Bio-Geographic Optimization & Bootstrap Model (ADCPBOBM). Each block of image was detailed in this section. Table 1 shows the notation used in the paper.

Visual Pre-Processing

In this stage, the raw input images are first resized into a uniform square matrix. The original dataset consists of images with varying dimensions, which can complicate the processing and analysis. By converting all images to a consistent square format, work ensure uniformity across the dataset. Following this, the images are transformed into grayscale, shown in fig. 1 (a) and (b). This step simplifies the data by reducing the complexity of color information, thereby decreasing the computational load on the model and streamlining the processing.

API $\leftarrow$ PreProcessing(ARI)



(a)

(b)

Fig 1. Input image (a) and pre-processed image (b).

Median Filter

The median filter operates by systematically processing each pixel in the image and replacing it with the median value of its neighboring pixels. This technique involves defining a "window," or a specific pattern of neighboring pixels, that moves across the image pixel by pixel. As the window slides over the entire image, it computes the median of the pixel values within the window for each position [17]. This approach effectively smooths the image by reducing noise and preserving edges, thereby enhancing the overall quality of the input data for subsequent analysis.

AFI←MedianFilter(API)----------------Eq. 1

The coefficients of the filter mask are assigned random values but with specific weighting rules For example consider a 3x3 mask applied to an image In this configuration the center pixel of the mask receives the highest weight making it the most influential in the filtering process [18]. The next highest weights are assigned to the four neighboring pixels that are directly adjacent to the center pixel situated to the north south east and west of it The lowest weights are given to the four diagonal pixels that surround the center pixel positioned at the corners of the mask shown in fig. 3. This weighted approach ensures that the central pixel and its immediate neighbors have a greater influence on the median calculation while the diagonal neighbors contribute less This selective weighting helps in achieving more accurate filtering results by emphasizing the central region of the image.

Table 1. Notation used in the proposed model explanation.

Notation	Meaning
ARI	Alzheimer Raw Image
API	Alzheimer Pre-processed Image
AFI	Alzheimer Filter Image
ASI	Alzheimer Segmented Image
CS	Contour smoothing
$E_{internal}$	Elastic Energy
$E_{external}$	Smooth Energy
E_{edge}	Edge Region
α, β, γ	Constants range in 0 to 1
n	Number of contour points
IB	Image Block Size
B	Bins
AHF	Alzheimer Histogram Feature
ADC	Alzheimer Desired Class
ADCDM	Alzheimer Disease Class Detection Model

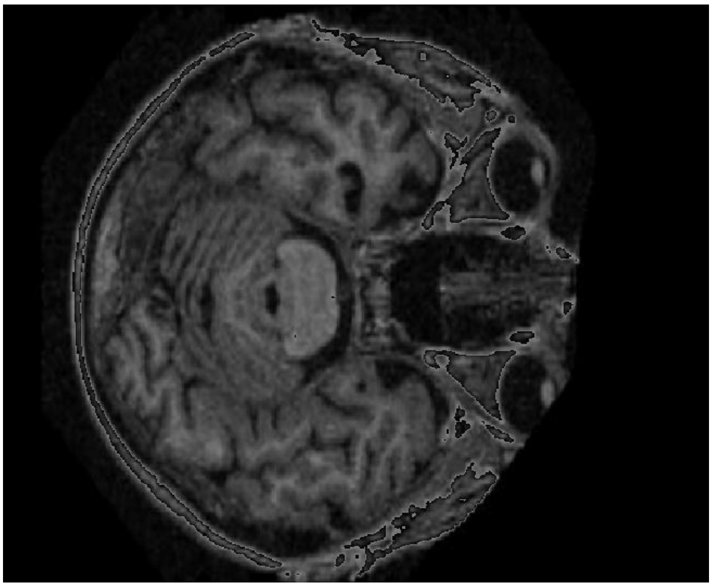


Fig 3. Image after median filter operation.

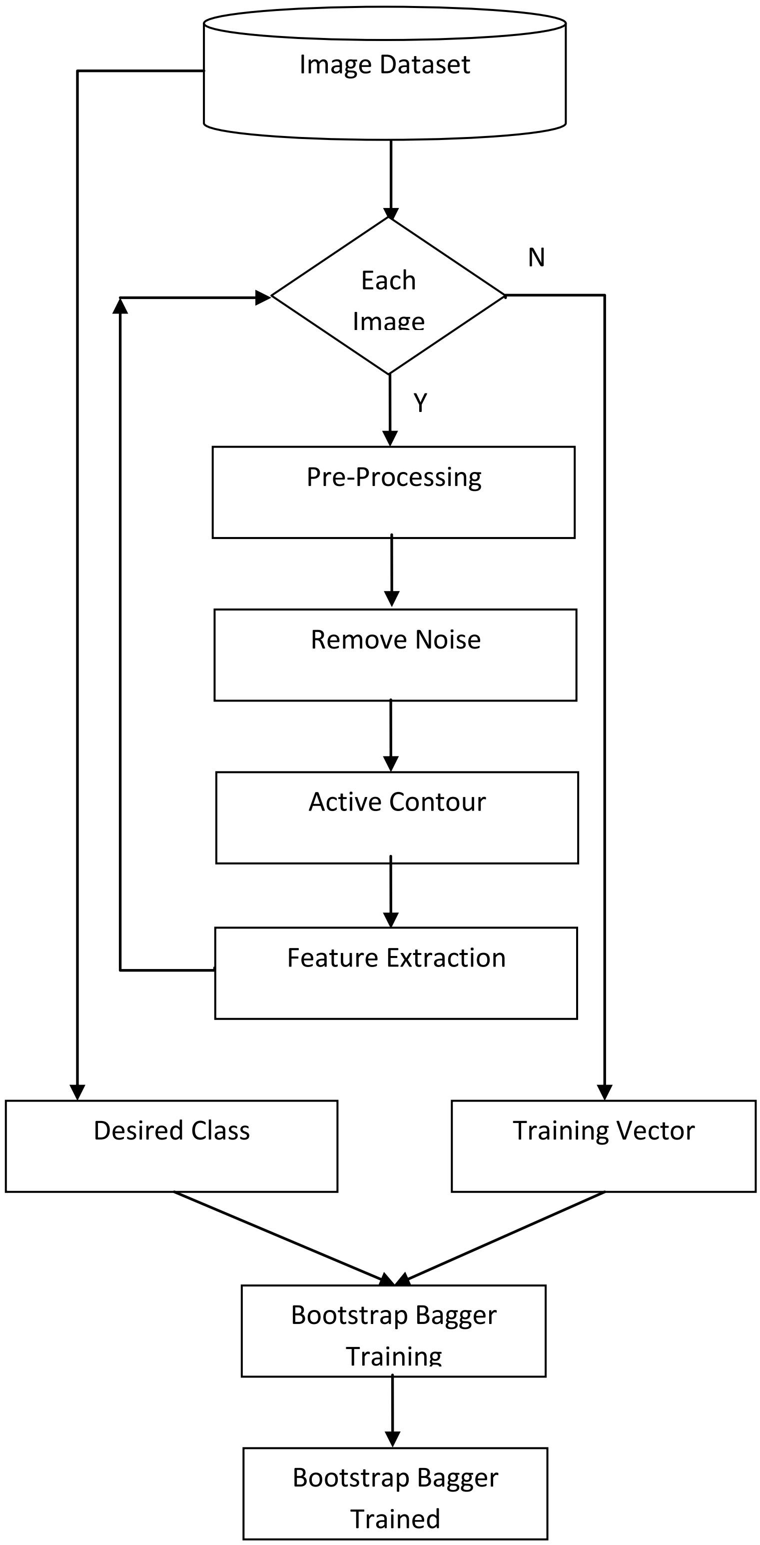


Fig 2. Proposed work block diagram.

Active contour segmentation

Active contour segmentation, also known as "snakes," is a sophisticated technique introduced by Osher and Sethian that has become a pivotal tool in various fields including image processing, fluid mechanics, pattern recognition, and computer vision [19]. This approach involves dynamically evolving a contour or curve to fit the features of an image by minimizing an associated energy function. The active contour method stands out for its ability to refine image segmentation with considerable accuracy. The core principle involves adjusting the contour to reduce the energy function, which is composed of two key components: internal and external forces. Internal forces help maintain the smoothness and continuity of the contour, penalizing deviations and ensuring the curve remains stable and well-defined. Conversely, external forces are derived from the image data and are designed to guide the contour towards significant features such as edges or boundaries. By balancing these internal and external forces, the active contour method effectively identifies and delineates important structures within the image, resulting in precise and meaningful segmentation.

Image Energy

E_{image} which includes information from the image itself, like gradients.

$E=\alpha\ E_{internal} + \beta\ E_{external} + \gamma E_{image}$----------------Eq. 2

$E_{internal} = \sum_{i=0}^{n}[(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2]$----------------Eq. 3

Internal energy is the elastic value of the points that need to be minimize.

$E_{external} = \sum_{i=0}^{n}[(x_{i+1} - 2x_i + x_{i-1})^2 + (y_{i+1} - 2y_i + y_{i-1})^2]$-Eq. 4

In above equation $E_{external}$ energy is the gradient or smoothness of the curve points that need to be minimize [20].

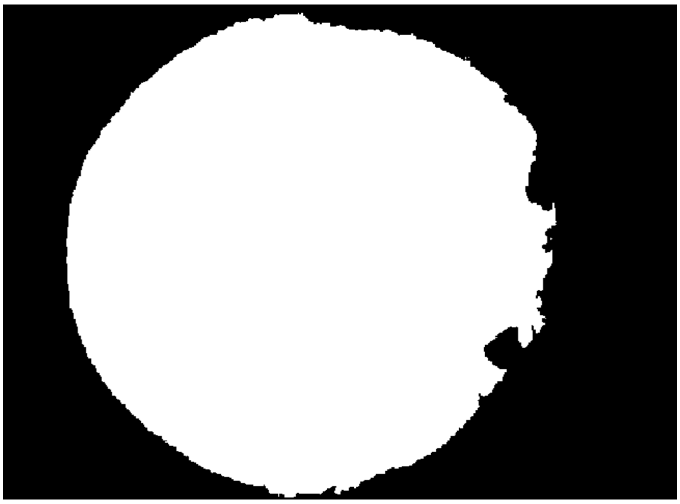


Fig 4. Active contour segmented region.

E_{image} is estimate by the edge points. Iteration ends when internal and external energy near to zero.
Once these contour were found in the image next is to update the different segment by finding the nearby distance from the segment region, shown in fig. 4. Here if distance is negative then value of the pixel or position of that pixel is consider as part of the segment. Here if distance is positive then value of the pixel or position of that pixel is consider as outside of the segment. Now next step is to update the segmented area by analyzing the nearby pixel values of the segment.

ASI←AFI having $(\alpha\ E_{internal} + \beta\ E_{external})$ equals to zero-Eq. 5

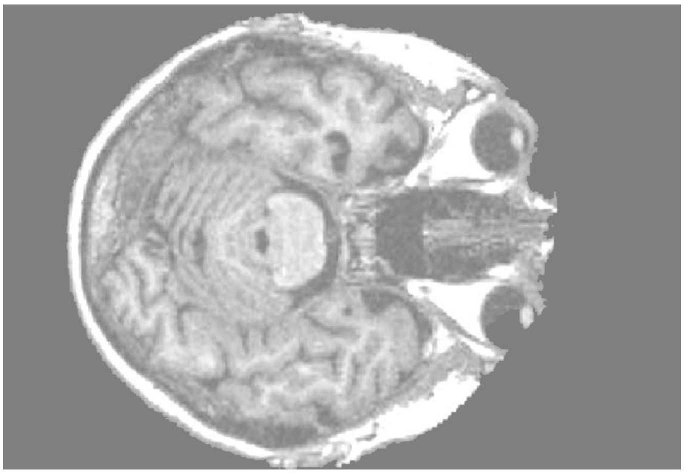


Fig 5. Brain region of input image for feature extraction.

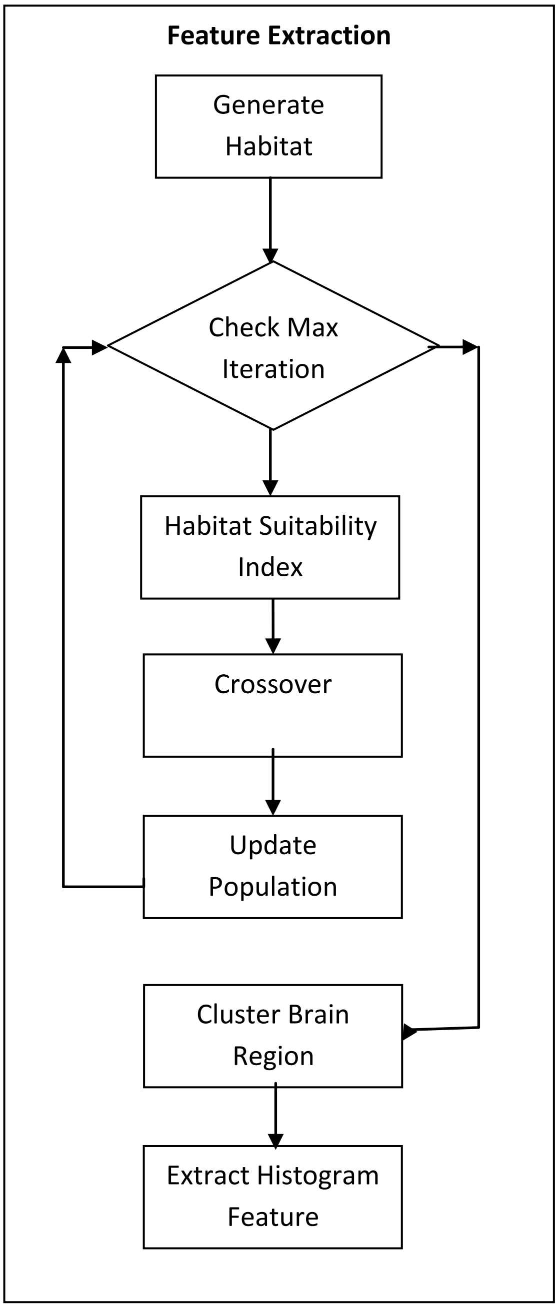


Fig 6. Block diagram of feature extraction.

Feature Extraction

The segmented brain regions of the image shown in fig. 5, were categorized into selected and unselected areas using a genetic algorithm. The blocks from the selected regions were then utilized for training the model. Bio-Geographic Algorithm was applied to identify similar regions [21]. As a result, the entire brain region was segmented into selected and non-selected areas based on these criteria.

Generate Habitats

In this step, a set of potential solutions, referred to as habitats, is generated by the algorithm. Each habitat represents a collection of possible cluster centers. Therefore, a habitat is defined as a combination H={U_1, U_s}, where the population consists of a total of h habitats. The function for generating this population in the algorithm is expressed by Equation 3:

H←HabitatAD(s, h)----------------Eq. 6

Habitat Suitability Index

(HSI) for a given habitat is determined based on distance metrics. It is calculated as the sum of the minimum distances between the representative pixels of the segments and the pixels being segmented in the image. This index reflects how well each habitat meets the suitability criteria based on these distances.

$F_h = \sum_{x=1}^{Column} \sum_{y=1}^{Row} Min(H_{h,s} - I(x,y))^s$ --------Eq. 7

$R = Rank(F_h, H)$----------------Eq. 8

$\lambda_R = (1 - \alpha_R)$----------------Eq. 9 Immigration

$\sigma_R = \frac{R}{h}$----------------Eq. 10 Emigration

Here, R denotes the rank of a habitat based on its Habitat Suitability Index (HSI) value, and h represents the total number of habitats.

Crossover

The crossover process, where pixels migrate from one habitat to another, relies on emigration dynamics. Conversely, the process of allowing new species to enter a habitat depends on immigration dynamics. Therefore, for effective crossover between habitats, both emigration and immigration values, denoted as λ and σ respectively, must be considered.

```
Loop x=1:h
    If Cross_Over_Limit >λR
        Loop y=1:h
            If Cross_Over_Limit >αR
                M←Rand()
                H[x, m]← H[y, m]
            EndIf
        EndLoop
    EndIf
EndLoop
```

In this context, Cross_Over_Limit is a random number ranging from 0 to 1, which determines the extent of the crossover operation [22]. The variables x and y represent the positions within the habitat, specifying the processes of immigration and emigration, respectively.

Stopping Iteration

After t iterations, the habitat with the highest fitness value is selected as the center of the resultant segment. This identifies the most likely regions within the brain image where relevant features are present.

Histogram Features

The selected regions of the image are divided into fixed blocks of size *b*×*b*. Each block is then processed to extract histogram features with 16 bins. This approach provides a diverse set of features from the same image, requiring less data for training the model on a specific disease class.

Bootstrap Bagging Model

This model uses histogram feature values extracted from image blocks and sequences of web page visits by a user within a fixed time frame. Bootstrap aggregation was employed to learn log patterns [15]. In this process, bagging is used to eliminate redundant features, while bootstrapping helps in generating new feature sets. Consequently, the input consists of a collection of histogram values. The BBM model then learns to predict the expected image class based on these inputs.

Proposed ADCPBOBM **Algorithm**

Input: ARI

Output: TMDM// Trained MDModel

1. API←PreProcessing(ARI)
2. AFI←MedianFilter(API)
3. ASI←Active_countour(AFI)
4. H←HabitatAD(s, h)
5. Loop 1:T
6. Loop 1:h
7. Loop 1:s
8. $F_h = \sum_{x=1}^{Column} \sum_{y=1}^{Row} Min(H_{h,s} - I(x,y))^s$
9. Endloop

10. Endloop
11. R = Rank(F_c, H)
12. $\alpha_R = \frac{R}{h}$
13. $\lambda_R = (1 - \alpha_R)$
14. H←CrossoverAD(H,α_R,λ_R)
15. EndLoop
16. R = Rank(F_c, H)
17. SI←Image_clustering(R, H)
18. MF←Histogram(SI)
19. TMDM←Train_Model(MF)

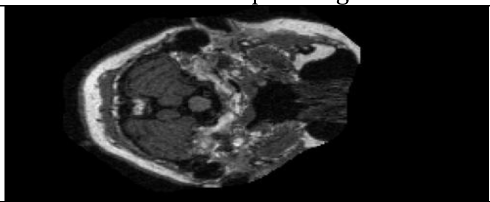
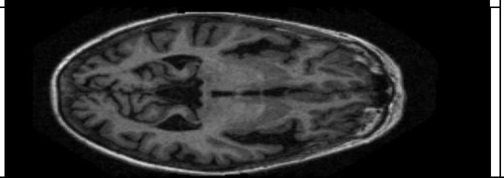
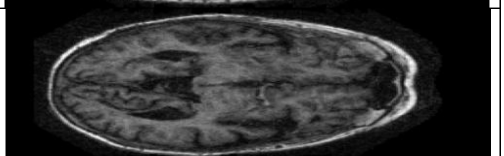
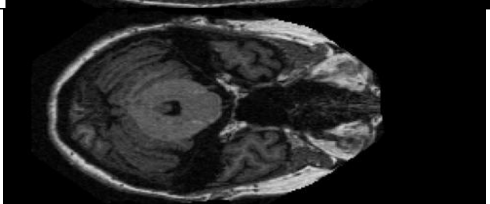
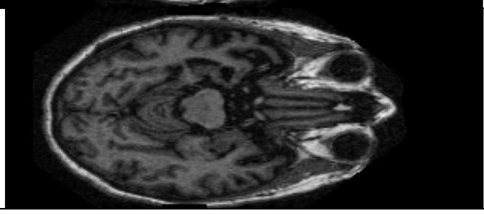
EXPERIMENT AND RESULTS

The experimental work for the proposed Alzheimer’s disease Class Prediction by BioGeographic Optimization & Bootstrap Model (ADCPBOBM)was conducted using MATLAB software on a machine with 4GB of RAM, a Windows operating system, and an Intel i3 processor. The results obtained were compared with those from the existing algorithm outlined in CNN-VGGNet [24].

Dataset

The OASIS MRI dataset, comprising 80,000 brain MRI images, is utilized in this study. The images are categorized into four classes corresponding to the stages of Alzheimer's progression. This dataset serves as a crucial resource for analyzing and detecting early indicators of Alzheimer's disease [25].

Table 2. Dataset sample images and classes.

<table>
<tr><th>Dataset Sample Images</th><th>Class</th></tr>
<tr><td></td><td rowspan="2">Very Mild
13725
Images</td></tr>
<tr><td></td></tr>
<tr><td></td><td rowspan="2">Mild
5002
Images</td></tr>
<tr><td></td></tr>
<tr><td></td><td rowspan="2">Moderate
488
Images</td></tr>
<tr><td></td></tr>
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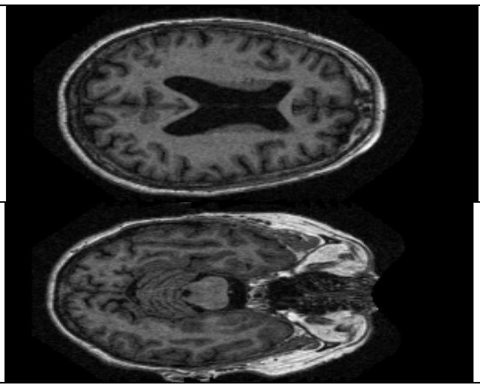	Non Demented 67222 Images

RESULTS

Table 3. Comparison of Precision values of AD class prediction models.

Image Sets	CNN-VGGNet	ADCPBOBM
60	0.6667	0.9787
100	0.9231	0.9524
200	0.7119	0.9522
300	0.7256	0.9626
400	0.6858	0.9529
500	0.6821	0.9554

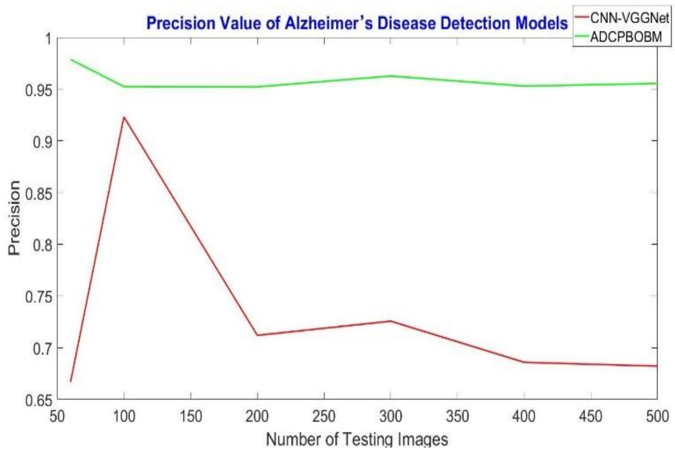

Fig 7. Precision value based comparison of Alzheimer's infected image classification models.

Table 4 shows that Alzheimer's disease class prediction precision values of the comparing models. It was found that ADCPBOBM has improved the precision value by 23.61% as compared to CNN-VGGNet model. Fig. 7 shows that Use of active contour for the image segmentation has increases the detection precision as background region was removed by the model.

Table 4. Comparison of Recall values of AD class prediction models.

Image Sets	CNN-VGGNet	ADCPBOBM
60	1	1
100	1	1
200	1	1
300	1	1
400	1	1
500	1	1

Recall value of healthy MRI image classification from the Alzheimer's infected class was shown in table 4. It was found that feature extraction by biogeographical optimization has increases the learning quality of the model. This paper has found that image brain region clustering has identify the infected part of the input image.

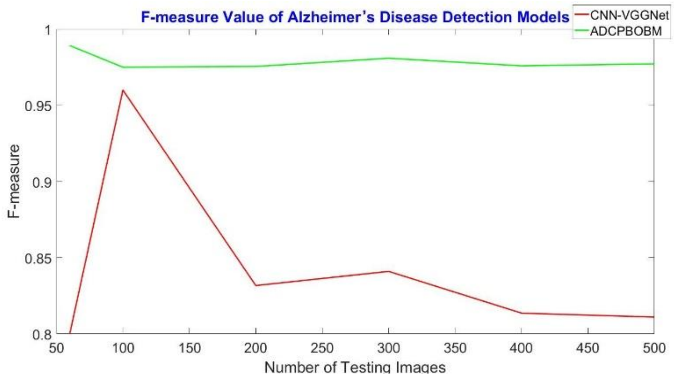

Fig 8. F-measure value based comparison of Alzheimer's infected image classification models.

Table 5. Comparison of F-measure values of AD class prediction models.

Image Sets	CNN-VGGNet	ADCPBOBM
60	0.8	0.9892
100	0.96	0.9756
200	0.8317	0.9755
300	0.841	0.9809
400	0.8136	0.9759
500	0.8110	0.9772

Table 5 shows that Alzheimer's disease class prediction f-measure values of the comparing models. It was found that ADCPBOBM has improved the precision value by 13.908% as compared to CNN-VGGNet model. Fig. 8 shows that use of active contour for the image segmentation has increases the detection f-measure as background region was removed by the model.

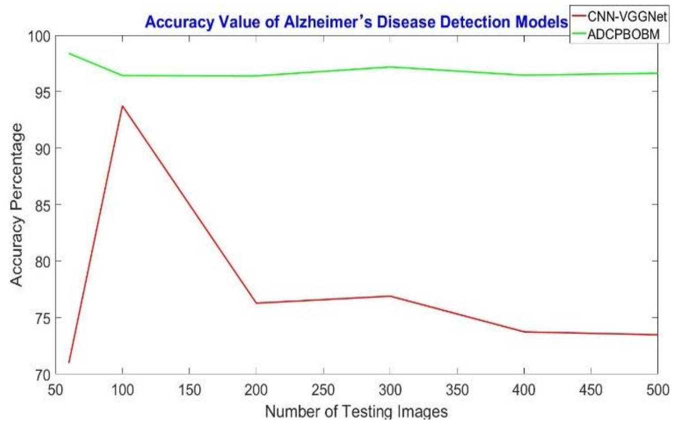

Fig 9. Accuracy value based comparison of Alzheimer's infected image classification models.

Table 6. Comparison of Accuracy values of AD class prediction models.

Image Sets	CNN-VGGNet	ADCPBOBM
60	70.97	98.39
100	93.75	96.43
200	76.28	96.4
300	76.9	97.19
400	73.74	96.46
500	73.48	96.64

Feature optimization by genetic algorithm has increases the learning and detection accuracy of model. It was found that use of ensemble model has improve the two class detection accuracy by 20.01%. Fig. 9 shows that background removal and selected region feature learning has increases the Alzheimer diseased detection accuracy.

Table 7. Comparison of accuracy values of very mild class Alzheimer's disease class prediction models.

Image Sets	CNN-VGGNet	ADCPBOBM
60	1	1
100	1	1
200	1	1
300	0.7439	1
400	0.7	1
500	0.6765	1

Table 8. Comparison of accuracy values of mild class Alzheimer's disease class prediction models.

Image Sets	CNN-VGGNet	ADCPBOBM
60	1	1
100	0.7037	1
200	1	1
300	1	1
400	0.9545	1
500	0.9632	1

Table 9. Comparison of accuracy values of moderate class Alzheimer's disease class prediction models.

Image Sets	CNN-VGGNet	ADCPBOBM
60	0.3125	0.9375
100	0.6988	0.8571
200	0.6296	0.8565
300	0.6988	0.8886
400	0.633	0.8578
500	0.6277	0.8668

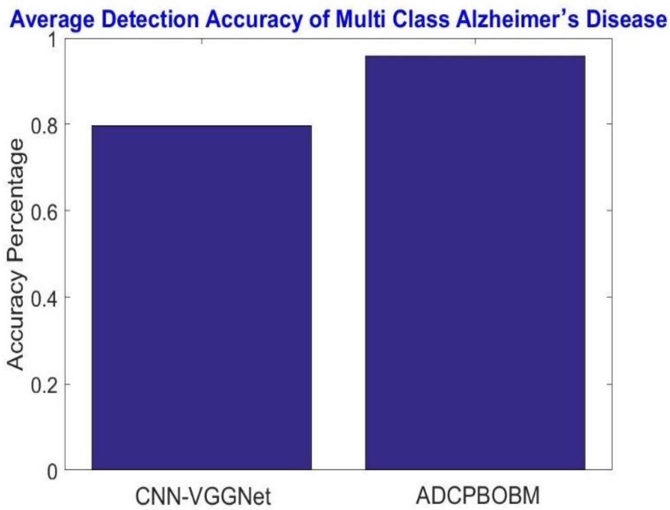

Fig 10. Average accuracy value based comparison of Alzheimer's infected multiclass image classification models.

Table 7, 8 and 9 shows the multiclass detection accuracy for very mild, mild, moderate class of Alzheimer. It was found that use of proposed model has increases the detection accuracy on all class. Fig. 10 shows that biogeographic optimization has increases the learning efficiency of the bootstrap ensemble model.

CONCLUSIONS

This work proposed a model that finds the Alzheimer disease from the input MRI image. Most of existing model finds the two class of disease, to resolve this issue proposed model classify images into multiclass of Alzheimer disease. Use of active contour model for the image brain region identification has increases the work learning accuracy. Feature optimization by the biogeographic optimization algorithm has increases the detection accuracy. Experiment was done real multiclass dataset and result shows that proposed model has increases the precision value by 23.61% as compared to comparing model. It was found that two class detection accuracy was improved by 20.01%, while multiclass prediction accuracy was improved by 16.23%. In future researchers can work to reduce the detection execution time.

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