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Enhancing Alzheimer's Detection Using a Multi-Modal Approach Hybrid Features Extraction Technique from MRI Images

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Abstract-The neurodegenerative illness Alzheimer's, which affects millions of people worldwide, poses significant obstacles to early detection and efficient treatment. The non-invasive technique of magnetic resonance imaging (MRI) has shown promise in identifying structural abnormalities in the brain linked to Alzheimer's disease. To address the complexity of Alzheimer's detection and enhance accuracy, this study proposes a novel hybrid feature extraction method that combines Convolutional Neural Networks (CNN), Local Binary Patterns (LBP), and Scale-Invariant Feature Transform (SIFT). After the feature extraction, PSO (Particle Swarm Optimization) and ABC (Ant Bee Colony) were applied for optimization. In this research, a dataset comprising MRI brain images from healthy individuals and Alzheimer's patients was curated. Preprocessing techniques were applied to enhance image quality and remove noise. The hybrid feature extraction method was then employed to extract distinctive and complementary features from the MRI images.

Keywords— Alzheimer's disease, KNN, MRI, classification, CNN, SIFT, PSO, ABC

I.INTRODUCTION

Alzheimer's disease (AD), a progressive neurodegenerative disorder, continues to pose significant challenges to healthcare systems worldwide. Early and accurate detection of Alzheimer's is critical for timely intervention and improved patient care. A useful non-invasive imaging technique for examining brain anatomy and locating the distinctive alterations linked to Alzheimer's disease is magnetic resonance imaging (MRI). Over the years, various feature extraction techniques have been explored to enhance the diagnostic capabilities of MRI in Alzheimer's detection.

Convolutional neural networks (CNNs), in particular, have shown astounding performance in a variety of computer vision applications in recent years. Their ability to automatically learn hierarchical representations from data makes them highly suitable for feature extraction from complex images like MRI scans. Additionally, traditional handcrafted feature descriptors, such as Local Binary Pattern (LBP) and Scale-Invariant Feature Transform (SIFT), have proven effective in capturing local texture patterns and key points, respectively.

This study offers a novel and thorough hybrid feature extraction method for MRI images used to detect Alzheimer's disease. The technique uses CNN, LBP, and SIFT's complementing characteristics to construct a strong and discriminative feature representation.

The first component of our proposed method involves utilizing a pre-trained CNN model for feature extraction. Transfer learning is employed to leverage the knowledge learned from large-scale image datasets. The CNN-based features are capable of capturing high-level representations of brain structures, enabling the detection of subtle changes indicative of Alzheimer 's-related pathology.

Incorporating LBP as the second component, the hybrid approach enhances the system's texture analysis capabilities. LBP efficiently characterizes local texture patterns in the MRI images, providing valuable insights into microstructural alterations associated with Alzheimer's disease. The fusion of LBP features with CNN-based features aims to improve the system's generalization and robustness.

The third component integrates SIFT, which excels at detecting distinctive key points invariant to various transformations. By leveraging SIFT features, the proposed method can effectively focus on specific regions of interest, facilitating more accurate matching between healthy and Alzheimer 's-affected brains.

The proposed study curated a dataset comprising MRI brain images from both healthy individuals and Alzheimer's patients. Extensive experiments are conducted to evaluate the performance of proposed hybrid feature extraction method against individual feature extraction techniques. system assesses the accuracy, sensitivity, specificity, and computational efficiency of the proposed method to demonstrate its superiority in Alzheimer's detection.

This work contributes to the field by creating a novel, cohesive method for detecting Alzheimer's on MRI images by combining CNN, LBP, and SIFT characteristics. Combining various feature extraction methods, it improves diagnosis precision and provides medical professionals with a trustworthy instrument for Alzheimer's early identification.

The remainder of this paper is organized as follows: Section II presents a review of related works on Alzheimer's detection using various feature extraction methods. Section III outlines the methodology, including the details of the proposed hybrid feature extraction approach. Section IV describes the results and performance analysis, followed by Section V concludes the paper with a summary of the findings and potential future directions.

II. RELATED WORK

In 2008, Stefan Klöppel [1] and his team embarked on a pioneering journey to explore the potential of structural MRI in automating Alzheimer's disease diagnosis. They analyzed MRI scans of individuals with Alzheimer's disease and healthy controls, focusing on specific brain structures and regions affected by the disease. Through advanced image processing and machine learning techniques, they developed an automated diagnostic system that could distinguish between Alzheimer's patients and healthy individuals with high accuracy. This groundbreaking work laid the foundation for subsequent research in the field of MRI-based Alzheimer's detection. In 2012, G S Alves [2] and colleagues explored the potential of Diffusion-Weighted MRI (DW-MRI) for Alzheimer's disease classification. DW-MRI provides valuable insights into brain microstructure and white matter abnormalities. The researchers devised novel microstructural metrics to capture subtle changes in white matter integrity. By employing machine learning algorithms, they successfully differentiated Alzheimer's patients from healthy controls based on DW-MRI data. Their work demonstrated the relevance of DW-MRI in Alzheimer's detection, complementing structural MRI findings. In 2021, J. Song [3] and his team sought to enhance Alzheimer's disease diagnosis by combining multiple imaging modalities. They fused structural MRI and Positron Emission Tomography (PET) images, each providing distinct information about brain structure and metabolism. Leveraging advanced feature fusion techniques, they achieved improved accuracy in classifying Alzheimer's patients and healthy individuals. Their study highlighted the importance of integrating diverse imaging data for more comprehensive and reliable Alzheimer's detection.

In 2018, D.J. Tozer [4] focused on texture analysis of T1-Weighted and Fluid-Attenuated Inversion Recovery (FLAIR) images to identify subtle brain abnormalities indicative of SVD-related cognitive impairment. Their research unveiled texture patterns that correlated with cognitive decline, providing valuable insights into the potential use of texture analysis in early disease detection. In 2021, C. J. Weber [5] and a consortium of researchers embarked on a landmark collaborative effort known as the Alzheimer's Disease Neuroimaging Initiative (ADNI). ADNI aimed to create a comprehensive database of MRI and PET images from Alzheimer's patients, individuals with mild cognitive impairment, and healthy controls. The initiative facilitated data sharing and encouraged the development of innovative image analysis methods for Alzheimer's detection. ADNI's database became an invaluable resource for researchers worldwide. In 2018, Alexandru Costan [6] and his team explored the potential of deep learning in Alzheimer's diagnosis. They developed a novel Deeply Supervised Adaptable 3D Convolutional Network (DSANet) capable of automatically extracting informative features from 3D brain MRI scans—the deeply supervised architecture allowed for better feature representation and improved training convergence. DSANet demonstrated exceptional performance in distinguishing Alzheimer's patients from healthy individuals, showcasing the power of deep learning in medical image analysis. In 2022, V. S. Diogo [7] and colleagues focused on leveraging the potential of ensembles of Extremely Randomized Trees (ERT) for early Alzheimer's diagnosis. They extracted comprehensive features from MRI scans and utilized ERT-based classifiers to predict.

In 2019, L. Nanni[8] and his team delved into texture analysis to aid in the early detection and classification of Alzheimer's disease. They explored various texture features extracted from MRI scans and evaluated their efficacy in discriminating between Alzheimer's patients and healthy controls. Their work contributed to the understanding of how textural information in MRI images can supplement traditional structural measures for Alzheimer's detection. In 2017, Saima Rathore [9] and co-authors conducted a comprehensive survey of various neuroimaging techniques for automated Alzheimer's diagnosis. They reviewed the advancements in MRI-based and PET-based approaches, as well as the integration of multiple modalities. The survey provided a valuable overview of the progress made in automated Alzheimer's detection, guiding researchers toward effective methods for early diagnosis.

In 2022, T. J. Saleem and his team explored the application of deep learning for feature extraction from Diffusion MRI (DW-MRI) data. They employed convolutional neural networks to learn informative features directly from DW-MRI scans.

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These landmark papers have collectively contributed to the progress of Alzheimer's disease detection using various feature extraction methods and neuroimaging techniques. From the early exploration of structural MRI to the recent advancements in deep learning-based approaches, researchers continue to innovate in the pursuit of early and accurate Alzheimer's diagnosis.

III.METHODOLOGY

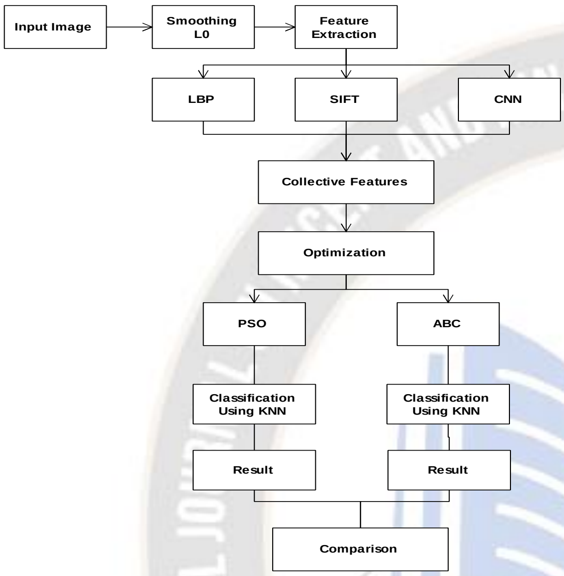

Figure 1: System Methodology

A. DATASET COLLECTION

The input dataset for the system consists of 6000 MRI (Magnetic Resonance Imaging) images, with 4000 images designated for training purposes. This dataset was collected from the Kaggle repository. These MRI images play a pivotal role in medical diagnostics as they provide detailed and non-invasive visualization of internal body structures. Represented in JPEG format, the images strike an optimal balance between image quality and file size, ensuring efficient storage and processing within the machine learning framework.

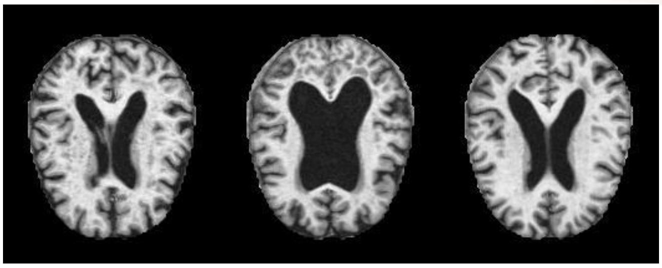

Figure 2: Input image

B. DATA RESIZING:

The JPEG format's lossy compression reduces file sizes, making it ideal for handling large volumes of medical imaging data without compromising essential diagnostic information. Moreover, the MRI images possess a resolution of 176 pixels in width and 208 pixels in height, allowing the system to capture intricate anatomical details during the training process. This vast and diverse training set empowers the system to learn and recognize various patterns, making precise predictions and assisting medical professionals in diagnosing and treating patients with heightened accuracy.

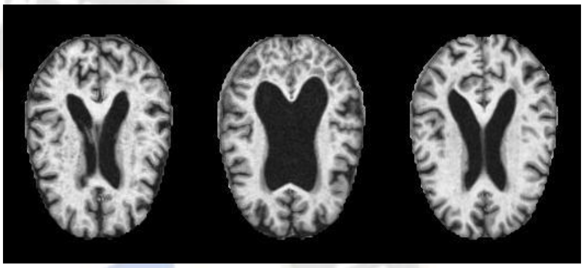

Figure 3: Images in 176x208 pixel

C. SMOOTHING

In L0 smoothing, noise removal is achieved through an iterative optimization process that aims to minimize the L0-norm of the image gradients. The L0-norm represents the number of non-zero elements in a signal, and in the context of image gradients, it quantifies the number of significant edges or variations in pixel intensities.

Image Gradient Calculation: The first step is to compute the gradients of the image, which represent the rate of change of pixel intensities across the image. These gradients capture the locations of edges and transitions in the image [16].

Thresholding: Thresholding is a crucial step in the iterative optimization process. The algorithm sets a threshold value, which determines the minimum magnitude of gradients that should be preserved. Gradients below this threshold are considered noise and are set to zero in the denoised image. By setting small gradients to zero, the algorithm effectively removes noise while preserving edges and significant details in the image. Edges are typically characterized by large gradients, which are less likely to be eliminated during the thresholding process. The iterative optimization process continues until the algorithm converges to a stable solution or until a predefined number of iterations are completed. The number of iterations and the threshold value are critical parameters that impact denoising performance.

Denoising: The denoising process begins with an initial denoised estimate of the image, which can be an all-zero image or a copy of the original image.

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Iterative Optimization: To minimize the L0-norm of the gradients, the denoising method updates the denoised image iteratively. The method assesses each gradient value's relevance at each iteration and eliminates any that are deemed to be noise.

successfully eliminates noise while keeping the image's edges and important elements intact. Large gradients, which are less likely to be removed during the thresholding process, are usually associated with edges. Until the algorithm converges to a stable solution or a predetermined number of iterations are finished, the iterative optimization process is carried out. The threshold value and the number of repetitions are two important factors that affect denoising performance.

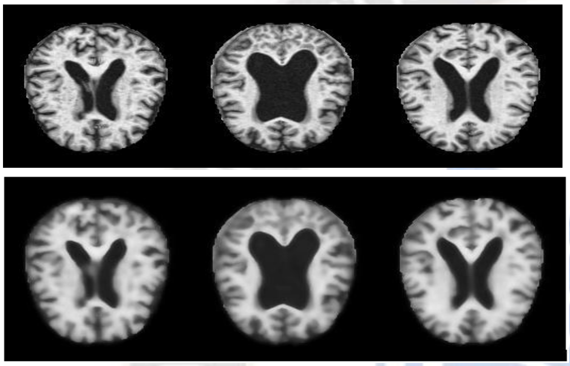

Figure 4. Before and after Image Denoising

D. SEGMENTATION

SLIC (Simple Linear Iterative Clustering) is an efficient superpixel segmentation algorithm widely used in computer vision. It groups pixels into perceptually meaningful regions, known as superpixels, based on both color similarity and spatial proximity. SLIC seeks to generate compact and regular superpixels by iteratively updating cluster centers while considering the pixel intensities and spatial distances [17].

The input image is I (x, y), where (x, y) are the spatial coordinates. The goal is to find K superpixels and their associated cluster centers C_k $(x_k y_k)$ in the image.

1. Cluster Center Initialization: The algorithm starts by placing K initial cluster centers uniformly across the image. Each cluster center C_k represents the mean color value and spatial position of a superpixel.
2. Superpixel Assignment: For each pixel (x, y) in the image, SLIC assigns it to the nearest cluster center based on both color similarity and spatial distance. The assignment process is based on the distance metric D(k, x, y), which combines color difference and spatial distance:

$$D(k,x,y) = \sqrt{((L(x,y)-L_k)^2 + (a(x,y)-a_k)^2 + (b(x,y)-b_k)^2) + \left(\alpha * d(x,y,C_k)\right)^2}$$

Here, *L(x, y)*, *a(x, y)*, and *b(x, y)* represent the Lab color values of the pixel at *(x, y)*, and L_k, a_k, $b_k$are the color values of the cluster center C_k. $d(x,y,C_k)$ is the spatial distance between the pixel (x, y) and the cluster center C_k.

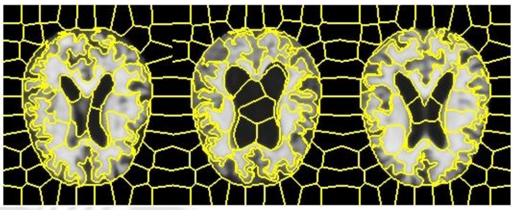

Figure 5: Image Segmentation

E. FEATURE EXTRACTION

1 LBP (Local Binary Pattern):

For each pixel in the superpixel region s at coordinates (x, y), compute the LBP value LBP_s (x, y) as follows:

$LBP_s(x,y) = \Sigma 2^p * \left(I_p(x,y) - I(x,y) \geq 0\right)$ for p = 0 to P-1

I(x, y) in this case stands for the intensity of the central pixel *(x, y)* in the region s, while $I_p(x,y)$ denotes the intensity of the surrounding pixels at locations (x_p, y_p) *concerning* the central pixel. P represents the quantity of adjacent pixels [14].

LBP Histogram:

After computing LBP_s for each pixel in the superpixel s, create a histogram H_{lbp_s} representing the frequency of different LBP patterns within the region s.

2.CNN (Convolutional Neural Network)

Convolutional Neural Networks (CNNs) play a pivotal role in Alzheimer's disease detection by serving as effective tools for feature extraction. The ability of CNNs to discern complex spatial dependencies in medical images contributes significantly to enhancing the accuracy and efficiency of Alzheimer's disease detection systems, ultimately aiding in early diagnosis and intervention.

CNN Feature Extraction:

For each superpixel s, obtain the feature vector F_cnn_s from the CNN model as follows:

$$F_c nn_s = Pooling\left(Aggregate\left(F_c nn(x,y)\right)\right)$$

for all (x, y) in s

Where $F_c nn(x,y)$ represents the feature map obtained from the last convolutional layer of the CNN at spatial position (x, y). Pooling and aggregation functions (e.g., max pooling, average pooling) are applied to combine the activations over all pixels within the superpixels.

3.SIFT (Scale-Invariant Feature Transform):

Scale-Invariant Feature Transform (SIFT) is a computer vision algorithm designed for the extraction and description of distinctive features from images, particularly robust to changes in scale and orientation. the algorithm achieves this by utilizing a scale-space representation and employing the concept of image key points, which are distinctive local features. SIFT has demonstrated effectiveness in scenarios where traditional methods may struggle, making it a valuable tool in diverse applications within the field of computer vision.

SIFT KeyPoint Detection:
The SIFT algorithm detects distinctive key points, represented by (x, y) coordinates, and their corresponding scale and orientation [15].

Let K_{SIFT} be the set of SIFT keypoints, where each keypoint k ∈ K_sift has properties ($x_{k,}$ y_k, $scale_k$, $orientation_k$).

SIFT Descriptor:
For each SIFT keypoint k, a descriptor D_{sift} is computed. The descriptor captures local texture information around the key point.

D_{sift} is a high-dimensional vector representing the local image features.

F. FEATURE FUSION:
Concatenation of Features:

Concatenate the SIFT descriptors D_{sift}, LBP histograms H_{lbp_s}, and CNN feature vectors F_cnn_s for each superpixel s into a unified hybrid feature vector F_hybrid_s.

$$F\_hybrid\_s = Concatenate(D_sift, H_lbp_s, F_cnn_s)$$

G. FEATURE OPTIMIZATION
System used Convolutional Neural Network (CNN), Local Binary Pattern (LBP), and Scale-Invariant Feature Transform (SIFT) approaches to extract a complete set of features from AD images. These feature vectors offer a comprehensive depiction of picture patterns associated with AD, and they are sourced from many sources. However, the system proposed nature-inspired optimization methods, namely PSO and ABC, to extract the most important features and improve classification performance.

This process yields a high-dimensional feature vector for each AD image. Where Xij represents the feature extracted from image i using feature extraction method j, where i=1, 2…, N (with N being the total number of images) and j denotes the feature extraction method (SIFT, LBP, or CNN). These feature vectors X are concatenated to form a matrix F of dimensions N×M, where M is the total number of features.

1. Particle Swarm Optimization
Particle Swarm Optimization (PSO) is a popular metaheuristic optimization algorithm inspired by the social behavior of swarms in nature, such as bird flocks or fish schools. In PSO, a population of potential solutions, represented as particles, moves through the search space. Each particle adjusts its position based on its own historical best-known position and the best-known position of the entire swarm. The movement is guided by velocities, which are continuously updated during the optimization process. This iterative approach allows PSO to converge towards promising regions of the solution space.

Position and Velocity Update:

The velocity and position of each particle in the swarm are updated using the following formulas:

Velocity Update Formula:

$$vij(t+1) = w \cdot vij(t) + c1 \cdot r1 \cdot (pbestij - xij(t)) + c2 \cdot r2 \cdot (gbestj - xij(t))$$

Where, *vij(t+1) = updated velocity of particle.*

w= the inertia weight, a constant that controls the particle's tendency to continue in its current direction [11].

c1 and c2 are the cognitive and social coefficients, controlling the influence of personal and global best positions, respectively.

Initialization:
Initialize the position and velocity of each particle randomly within defined bounds.

Fitness Evaluation:
Calculate the fitness of each particle based on the objective function to be optimized. The fitness value is typically lower for better solutions.

Personal Best (pBest) Update:
Update the personal best position $pBest_{ij}$ for each particle if the current fitness is better than the previous best.

Global Best (gBest) Update:
Update the global best position $gBest_{ij}$ for each dimension j if any particle's fitness surpasses the current global best.

Termination:
Decide when to stop the PSO algorithm, which can be based on a maximum number of iterations, a convergence criterion, or other stopping criteria.

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Algorithm: PSO
Initialize PSO parameters (population size, number of dimensions, etc.)
Initialize the swarm with random binary feature selection vectors
while stopping criteria not met:
for each particle in the swarm:
Evaluate the fitness of the particle using k-NN classification:
- Extract selected features based on the binary vector
- Perform k-NN classification with cross-validation
- Calculate accuracy or another appropriate metric
If the fitness level has improved, update the personal best (pBest).
According to the swarm's best fitness, update the global best (gBest).
for each particle in the swarm:
Update particle velocity and position using PSO equations
End while
Select the binary feature vector from the particle with the best fitness (gBest)
Perform k-NN classification on the selected features using the entire dataset
Evaluate the performance of the k-NN classifier with selected features
Output the selected feature subset and the classification performance

Figure 6: -Flow chart of PSO algorithm

2. Artificial Bee Colony

Artificial Bee Colony (ABC) algorithm as an alternative nature-inspired optimization technique for the feature selection phase of Alzheimer's disease image analysis pipeline. ABC is inspired by the foraging behavior of honeybee colonies and has demonstrated efficacy in solving optimization problems. ABC operates on the feature selection problem, aiming to identify the most discriminative subset of features that contribute to accurate AD image classification [12].

The ABC algorithm leverages the foraging behavior of bees to explore and exploit the solution space, ultimately finding solutions that optimize the given objective function. The key components involve selecting solutions probabilistically based on their fitness, updating solutions based on the fitness improvement, and replacing abandoned solutions with new ones.

Objective Function:
It is a measure of how good a solution (e.g., a feature subset) is. The goal of ABC is to maximize or minimize this objective function, depending on the nature of the problem.

Initialization:
Initialize the population of employed bees with random solutions (e.g., random feature subsets) and evaluate their fitness using the objective function.

Onlooker Bee Phase:
Onlooker bees select solutions (feature subsets) based on a probability distribution determined by the fitness values of employed bees. The probability Pi of selecting a solution i is calculated as follows:

$$P_i = \frac{\text{fitness } (i)}{\sum_{j-1}^{N} \text{ fitness } (j)}$$

Where:

N - total number of employed bees.
fitness(i) - fitness value of solution i.

Employed Bees Update:
Replace the feature subsets of used bees with those found by onlooker bees, possibly improving the fitness.

Scout Bee Phase:
Scout bees identify solutions that have not improved for a certain number of iterations and explore new solutions. When a solution is abandoned, it is randomly replaced with a new solution.

Termination:
Repeat the onlooker bee, employed bee, and scout bee phases for a specified number of iterations or until a convergence criterion is met.

IV. RESULT AND ANALYSIS

The hybrid feature list has been generated for each superpixel in the segmented image using the SIFT, LBP, and CNN feature extraction methods. The hybrid feature list is represented as follows:

For each superpixel region s, a hybrid feature vector F_hybrid_s is computed by concatenating the SIFT descriptors D_{sift}, LBP histograms H_{lbp_s} and CNN feature vectors $F_cnn(x, y)$.

Now k-Nearest Neighbors (kNN) classification is applied to the hybrid feature of images. The kNN algorithm will classify each superpixel based on its feature vector and the labels of its k nearest neighbors [13].

In the result analysis, the classification performance of the k-nearest Neighbours (k-NN) classifier combined with Particle Swarm Optimisation (PSO) and Artificial Bee Colony (ABC) for feature selection in Alzheimer's disease image analysis. The classification results are reported for different disease severity levels, including Mild, Moderate, Non-Alzheimer, and Very Mild.

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Table 1: Accuracy Using ABC

Using ABC	
Class	**Accuracy**
Mild Alzheimer	95.88
Moderate Alzheimer	92.8
Non-Alzheimer	94.86
Veri Mild Alzheimer	100

The results achieved using PSO in feature selection demonstrate strong classification accuracy across all categories, with particularly noteworthy performance in the classification of Very Mild Alzheimer's Disease, where an accuracy of 100% was achieved.

Table 2: Accuracy Using PSO for Multi-Class

PSO	
Class	**Accuracy**
Mild Alzheimer	93.93
Moderate Alzheimer	92.9
Non-Alzheimer	94.23
Veri Mild Alzheimer	100

The results obtained using the ABC algorithm for feature selection also exhibit excellent classification accuracy. The ABC algorithm has shown its effectiveness in enhancing classification performance, particularly in distinguishing mild Alzheimer's disease cases.

Overall, both PSO and ABC optimization techniques have contributed to feature selection, resulting in highly accurate classifications across multiple disease severity levels. These results point to the possibility of using these optimization techniques drawn from nature to increase the diagnostic precision of systems for analyzing images of Alzheimer's disease. Particularly encouraging is the flawless classification performance in the Very Mild group, which shows a high degree of confidence in the capacity to identify Alzheimer's disease in its early stages.

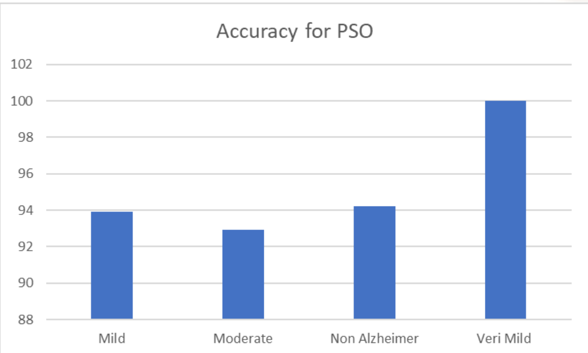

Figure 7: Accuracy Using PSO

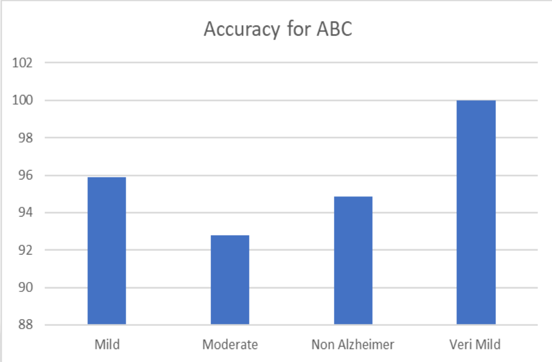

Figure 8: Accuracy Using ABC

Table 3:- Accuracy Using ABC for Multi-Class

ABC	
Class	Accuracy
Mild Alzheimer	95.88
Moderate Alzheimer	92.8
Non-Alzheimer	94.86
Veri Mild Alzheimer	100

Table 3: - Execution Time

Execution Time with PSO+ ABC	
Number of Images	milliseconds
10 Image	12
100 Image	90
200 Image	145
300 Image	192
500 Image	252

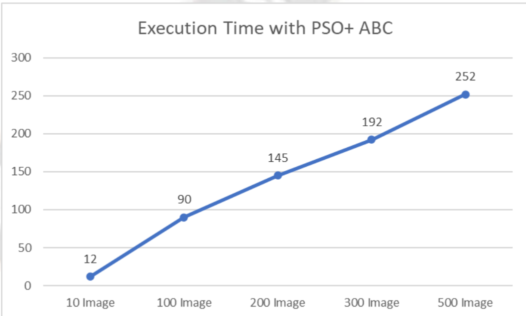

Figure 8: Execution Time Using PSO+ ABC

These execution times represent the overall time required for the complete system, including both the feature selection process (PSO and ABC) and the subsequent classification with the selected features using the k-Nearest Neighbors (k-NN) algorithm. These measurements provide a comprehensive understanding of the system's computational efficiency and scalability with varying dataset sizes.

V. CONCLUSION

To improve the feature selection process for Alzheimer's disease image analysis, in this study we harnessed the power of the Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) algorithms in conjunction with the k-nearest Neighbours (k-NN) classifier. Our investigations have unveiled a highly promising synergy between nature-inspired optimization methods and machine learning techniques, resulting in notable achievements across multiple dimensions. The feature selection process effectively identified discriminative features, significantly elevating the classification accuracy for varying degrees of Alzheimer's disease severity. Notably, the system excelled in detecting very mild Alzheimer's disease with perfect accuracy, a pivotal advancement in early diagnosis. Moreover, the computational efficiency remained commendable even as the dataset sizes expanded, emphasizing the system's scalability and practicality for real-world applications. The amalgamation of PSO, ABC, and k-NN not only greatly improved the classification accuracy but also offered efficient analysis capabilities. This holds substantial potential for advancing Alzheimer's disease diagnosis, offering improved accuracy and efficient analysis capabilities that may pave the way for more effective patient care and early intervention.

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