



Horned Lizard Optimization-Driven CA-InceptionResNet Framework for Enhanced Dementia Diagnosis

Killamsetti vijeta¹, S. Sangeetha², V. Kavitha³, S. Kanimozhi⁴,
S. Dhanalakshmi⁵ and M. J. D. Ebinezer⁶

ABSTRACT

Dementia is a progressive neurological disorder affecting millions worldwide. It places a tremendous burden on global healthcare systems and research. Early detection and accurate diagnosis are essential for effective disease management. The purpose of this paper is to present an integrated framework using Deep Learning (DL) to help improve dementia diagnosis. The framework uses an Adaptive Difference of Gaussian (ADoG) filter to sharpen important edges on neuroimaging scans while reducing background noise, producing sharper (more focused) data in neuroimaging scans that contain significant amounts of data. To segment brain tissue into anatomical regions affected by neurodegenerative disorders using the Hybrid Agglomerative Clustering Refinement (HACR) technique. The segmented anatomical regions are analyzed using a polar-coordinate-based Gray-Level Co-Occurrence Matrix (GLCM) to extract rotation-invariant texture features, ensuring robust and orientation-independent characterization of tissue patterns. For a classification stage, proposed framework utilizes a Channel-Attention Inception-ResNet (CA-InceptionResNet) model. By integrating feature extraction strength of InceptionResNet architecture with channel-attention mechanism, proposed model effectively captures discriminative features and improves classification of dementia sublevels. For classifier performance optimization, the Horned Lizard Optimization (HLO) algorithm is employed to optimize the model's hyperparameters. The proposed model is implemented in Python and achieved an accuracy of 98.98%, precision of 99.12%, recall of 98.96%, F-score of 99.04% and specificity of 99.58%, demonstrating its effectiveness in accurate and reliable classification.

Article information:

Keywords: Dementia, Difference of Gaussian Filter, Hybrid Agglomerative Clustering Refinement, Gray level co-occurrence matrix, InceptionResNet, Horned Lizard Optimization

Article history:

Received: December 22, 2025

Revised: April 22, 2026

Accepted: June 19, 2026

Published: August 22, 2026

(Online)

DOI: 10.37936/ecti-cit.2026204.265393

1. INTRODUCTION

Dementia is a neurodegenerative disease that progressively causes cognitive function and memory to deteriorate and leads to Howan alterations in behavior. Older people often develop dementia, which leads

to a diminished ability to perform everyday tasks. Patient experiences progressive cognitive deterioration alongside poor reasoning abilities and problems with communication throughout the disease progression [1,2]. Disease progression causes brain atrophy, resulting in a substantial reduction in gray matter

¹The author is with the Department of Computer Science and Engineering (IoT, Cyber Security including Blockchain Technology), Dayananda Sagar College of Engineering, Bengaluru, India, Email: vijetha258@gmail.com

²The author is with the Department of Information Technology, Vel Tech Multi Tech Dr.Rangarajan Dr.Sakunthala Engineering College, Avadi, Chennai, Tamil Nadu, India, Email: sangeetha@veltechmultitech.org

³The author is with the Department of Electronics and Communication Engineering, Anna University Regional Campus Madurai, Tamil Nadu, India, Email: mail2kavieceian@gmail.com

⁴The author is with the Department of Computer Science and Engineering, Arunai Engineering College Tiruvannamalai, Tamil Nadu, India, Email: kanimozhi274@gmail.com

⁵The author is with the Department of Electronics and Communication Engineering, Bannari Amman Institute of Technology, Sathyamangalam, Erode - 638401, Tamil Nadu, India, Email: dhanalakshmi@bitsathy.ac.in

⁶The author is with the Department of Computer Science and Engineering, Koneru Lakshmaiah Education and Foundation, Vaddeswaram, Guntur (Dist), AP-522302, India, Email: ebinezer.mjd@gmail.com

¹Corresponding author: vijetha258@gmail.com

volume and damage to neural network connections. Dementia causes problems beyond cognitive decline because it affects both people who have the disease and their family members [3]. The psychological distress which patients experience leads them to experience mood swings while developing depression and becoming more dependent on their caregivers. Families who need long-term care arrangements experience both economic and emotional burdens from the disease's prolonged nature [4]. The progressive destruction of neurons causes patients to experience difficulties with speech, problem-solving and motor function. The healthcare delivery system faces severe strain because of rising case numbers and the need to develop new methods for early detection and treatment. Health disorder creates major societal challenges, which make it essential to develop effective diagnostic approaches along with personalized therapy and proper support networks [5].

The collected neuroimages often include noise, non-uniform illumination, and variations; thus preprocessing is essential to ensure that the medical images are optimized for subsequent analysis and enhancement procedures. The preprocessing approaches correct image artifacts, improve image quality, and reduce image representation complexity. Histogram Equalization (HE) enhances image contrast and improves the visibility of structures by redistributing pixel intensities to produce a more uniform histogram. Yet, HE treats all regions equally, which is not efficient for images with varying illumination [6]. A Gaussian filter is a non-uniform low pass filter that possesses a Gaussian function as its impulse response, minimizing distortion across both low and high frequency components. However, it is susceptible to salt and pepper noise and requires a longer computational processing time [7]. Median filtering, a non-linear technique, is commonly employed to eliminate salt-and-pepper noise by ranking the intensity values of neighboring pixels and selecting the median as the output. Many users have difficulty separating fine details from the noise of an image using the method described above and, therefore, lose important information regarding that particular image [8]. The adaptive spatial AdoG-based preprocessing filter addresses some of these limitations by enabling adaptive adjustment of both filtering and contrast sensitivity, resulting in effective noise suppression while preserving the critical structure of the image.

After enhancement, segments created from the filtered images allow for accurate detection of anomalies in the brain. Edge-based segmentation identifies and connects edge segments generated by variations in image characteristics such as gray levels and colors. In most cases, the resulting segmented edges correspond to object boundaries. The effectiveness of edge-based segmentation techniques is influenced by the presence of noise and weak edges [9]. Otsu's

method is one of the most widely applied thresholding techniques for image segmentation because it determines the threshold value that maximizes the between-class variance of the object and background classes. The optimal threshold is obtained iteratively by maximizing the variance between two or more until best class separation is achieved. Still, it struggles with images of complex intensity distributions [10]. Region-based segmentation methods rely on the principle of homogeneity, whereby pixels with similar characteristics are grouped to form a homogeneous regions. However, these methods may result in under segmentation or over segmentation of image regions [11]. To address these limitations, the HACR segmentation approach merges similar clusters while preserving boundary integrity.

Furthermore, combining segmentation with four component region reference labels facilitates the extraction of highly discriminative features through localized feature extraction techniques. SIFT descriptor provides local image feature encoding as a 128-dimensional vector that is created by getting all of the gradient magnitudes and orientation of the interest region, then dividing them into a 4×4 spatial grid and 8 bins of orientations, and using a Gaussian window to weight the gradients of the pixels away from the center to emphasize them. However, the performance of these methods are influence by variations in image intensity and contrast levels, making the results sensitive to image quality [12].

Local Binary Pattern (LBP) is an illumination-invariant texture descriptor that characterizes each pixel by comparing its intensity with those of its neighboring pixels. Binary values of 1 or 0 are assigned based on whether the neighboring pixels are brighter or darker than the center pixel, enabling robust texture representation under varying lighting conditions. These pixel-to-pixel comparisons are then compiled into a histogram of pixel values for the region being analyzed, which then represents the texture features of that region. The problem with using LBP for texture analysis is that the comparisons only incorporate small-radius neighborhoods, thereby limiting LBP's ability to capture broader-scale texture patterns or structures [13]. By combining the polar GLCM method with local GLCM statistics calculated on a pixel-by-pixel basis, we can improve the extraction of features from MRI neuroimaging data because the polar GLCM calculates spatial relationships between pixel intensity values (from the left, right, above and below the center pixel) like LBP and provides second order statistical texture analysis such as contrast, correlation, energy and homogeneity. This allows for greater discrimination of structural changes that have occurred to the brain when scanning for dementia using neuroimaging.

Numerous classification algorithms has been reported in the literature for the diagnosis and clas-

Table 1: Review of DL Approaches.

Ref.	DL based Classification Model	Application	Operations	Limitations
[16]	Deep Reinforcement Learning (DRL)–based Neural Network	Early diagnosis and stage-wise classification of dementia using MRI data from the OASIS database	• The model integrates reinforcement learning with deep neural networks to handle class imbalance. • It generates high-resolution dementia probability maps across four stages, improving trial accuracy (6%), precision (9%), recall (13%), and F-score (9–10%).	Despite improved metrics, the system remains sensitive to dataset imbalance and requires extensive computational resources for training.
[17]	CNN architectures	Automated diagnosis and stage-wise classification of AD	• Model employs transfer learning-based convolutional neural networks (DenseNet 169 and ResNet 50) trained on MRI datasets • DenseNet 169 achieved superior training/testing accuracy (0.977/0.8382) compared to ResNet 50 (0.8870/0.8192).	Although DenseNet 169 offers higher accuracy and training stability, it demands greater memory usage.
[18]	Transfer Learning CNN Models have	Multi-class classification of vascular dementia using resting-state fMRI scans	• It applies CNN architectures with transfer learning and activation functions (ReLU, Leaky ReLU) to counter vanishing gradient issues. • DenseNet 121 achieved the highest classification accuracy (84.67%) through balanced data.	It exhibits lower prediction stability and higher model complexity
[19]	Parallel Recurrent Convolutional Neural Network (PRCNN)	Dementia recognition using standalone speech features (MFCC, GTCC, formants, fundamental frequency, log energy) from the Pitt corpus	• The model extracts 62 speech features per frame and employs PRCNN for classification. • The model achieved 85.0% accuracy and 85.1% precision, highlighting effectiveness of DL techniques for dementia detection.	DL performance (85%) is slightly lower and requires larger datasets for stability.
[20]	CNN with Transfer Learning	Automated identification and stage-wise classification of dementia (Non Demented, Very Mild, Mild, Moderate) using MRI brain images	• The model employs a pretrained CNN fine-tuned for dementia classification. • It learns hierarchical features from MRI scans and achieves 84.12% accuracy.	Moderate accuracy (84.12%) indicates room for improvement with larger, more diverse datasets.

sification of various clinical types of dementia. SVM (Support Vector Machines) has been studied for a couple of years for dementia diagnosis and provides high classification accuracy with the ability to model complex datasets. It operates by creating a hyper-plane decision boundary that can either be linear or non-linear in shape, based on how the data is structured. However, there are times when SVM may not generalize well across all populations [14]. Classification of features into malignant or benign from MRI neuroimaging also be performed using a Back Propagation Neural Network (BPNN). However, these approaches are limited by factors such as training times, susceptibility to local optima, and limited interpretability. These factors impact the accuracy and reliability of diagnostic outcomes [15].

Dementia classification model performance is improved by using optimization algorithms to enhance

network parameters and improve diagnostic accuracy. Particle swarm optimization (PSO) is a metaheuristic algorithm inspired by the group behavioural patterns of birds searching for food. It is characterized by fast convergence, minimal parameter requirements and easy for use in finding optimal solutions. A lack of performance in high-dimensional datasets is a common limitation when using of PSO, as it often converges prematurely and becomes trapped in local optima. Ant Colony Optimization (ACO) is a metaheuristic algorithm based on behavioral patterns of ants when foraging for food. ACO utilizes artificial agents to traverse a graphical search space and leave pheromones behind for future travelers following the same path [21]. The implementation of the ACO algorithm shows significant promise in enhancing the performance of classification model's for dementia detection tasks. However, it often suffers from early

convergence, which limits its effectiveness. Model interpretability is constrained by both the structural complexity of the algorithm and the characteristics of the tested dataset. Performance is further limited when faced with highly imbalanced test datasets or restricted feature diversity.

1.1 Related Works

In recent years, researchers have developed a wide range of ML and DL algorithms for the diagnosis of dementia and its subtypes, primarily utilizing brain imaging data. **Charlotte James *et al.* (2021) [22]** have presented an Extreme Gradient Boosting (XGB)-based ML approach for predicting dementia progression, demonstrating its potential in handling complex clinical datasets with improved predictive accuracy. XGB adds regularization to avoid overfitting and is useful in dealing with unbalanced clinical data due to its fast learning ability and strong generalizability. XGB still overfits when dealing with small or imbalanced datasets. **Subrato Bharati *et al.* (2022) [23]** introduced a Random Forest (RF) based ML approach for dementia classification. Nevertheless, the interpretability of the model remains limited due to its ensemble nature and its performance tends to degrade when confronted with highly imbalanced datasets or insufficient feature diversity. **Suriya Murugan *et al.* (2021) [24]** implemented a DL solution that utilizes a Convolutional Neural Network (CNN) to facilitate the early detection of dementia. CNNs are trained using individual photographs with no accommodation for the temporal progression of disease. However, CNNs process images independently and lack mechanisms to capture temporal progression of disease, which is crucial in dementia diagnosis. **Fatma M. Talaat *et al.* (2024) [25]** have developed an approach for diagnosing dementia called Grey Wolf Optimization (GWO). GWO has been widely applied to solving complex optimization problems due to its balance between exploration and exploitation. It consists of initializing feature sets, forming grouping models, evaluating Fitness, and using wolf-inspired heuristics to solve problems. Although GWO is computationally efficient, it can be expensive for real-time use or in resource-limited environments. **Govada Anuradha *et al.* (2024) [26]** have proposed using a Decision Tree (DT) based on Genetic Algorithm (GA) for detecting dementia. DTs are highly sensitive to hyperparameter settings, which directly influence both the structure of the tree and the accuracy of its prediction.

1.2 Problem Statement

In the midst of highly published literature that underlines the importance of brain imaging for the staging of dementia and for aiding in clinical decisions, appropriate and early diagnosis of the disease

remains a daunting challenge. Conventional clinical workflows for dementia diagnosis are primarily on MRI scanning, symptomatic assessment, and the subjective knowledge of clinicians. Such dependence injects heterogeneity and doubt, frequently making the diagnostic process more challenging and even causing delays in timely interventions. The fundamental research issue explored in this research is the challenge of accurately detecting dementia with existing clinical and imaging devices. Diagnosis tends to rely on physician's interpretation, leading to variable results and greater potential for patient harm. To overcome these limitations, a robust DL-based diagnostic system is proposed, designed to enhance accuracy and reliability in dementia detection.

The contributions of the proposed dementia diagnosis classification model are listed below:

- The quality and accuracy of input neuroimaging data are enhanced by the integration of spatial ADOG, which improves the visibility of neuroanatomical boundaries and reduces noise.
- The anatomically important areas are clustered, and neurodegenerative regions are localized through HACR, achieving advanced tissue segmentation essential for staging dementia.
- The textural features from segmented brain structures are extracted by the polar GLCM, allowing robust characterization of structural patterns irrespective of orientation or scale.
- Salient features are accurately selected by combining multi-scale spatial feature learning with channel attention mechanisms, providing high-accuracy dementia stage classification.
- The efficiency of the proposed DL is enhanced through bio-inspired HLO mechanisms, which tunes hyperparameters to achieve faster convergence and higher diagnostic accuracy across evaluation measures.

2. PROPOSED SYSTEM DESCRIPTION

The proposed framework for enhanced dementia diagnosis integrates advanced classification techniques with an optimization model, as illustrated in figure.1. Neuroimages are provided as input, enabling high-accuracy classification of dementia stages.

The attained neuroimages comprise of noise artifacts and impurities, which hinder diagnostic quality and reduce the reliability of subsequent analysis. The spatially ADOG filter is applied to enhance edge features while suppressing background noises, thereby improving the visibility of structural abnormalities associated with neurodegeneration. The refined images are segmented using the HACR approach, which groups pixels of similar intensities into coherent clusters, essential for isolating relevant brain regions. The segmented regions are transformed into polar space by polar-coordinate GLCM, extracting textu-

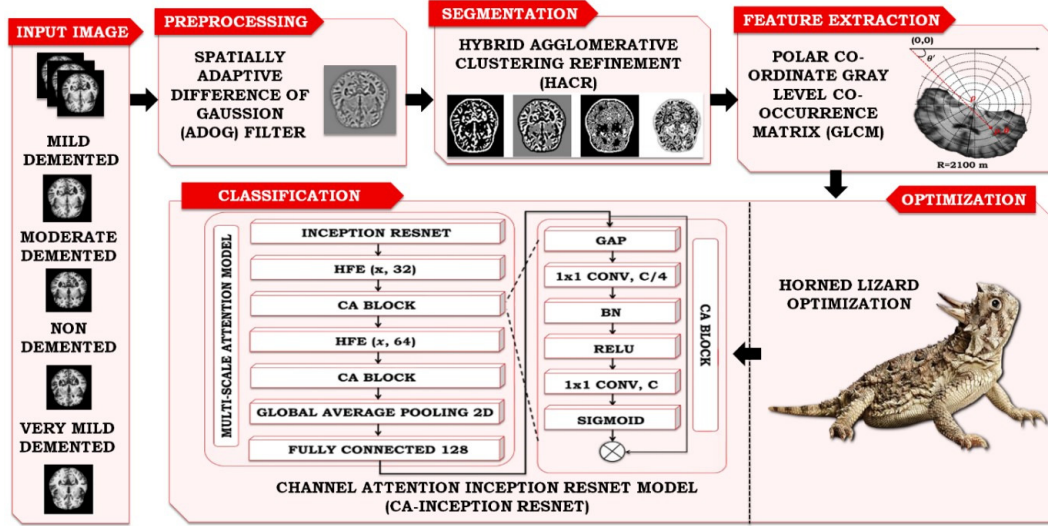


Fig.1: Proposed dementia diagnosing framework.

ral features that remain consistent throughout rotations and translations. The extracted features are fed into the classification block, which utilizes CA-InceptionResNet architecture. The InceptionResNet backbone combines inception modules capable of capturing multi-scale spatial features with residual connections that facilitate gradient flow and prevent vanishing gradients in deep network. The channel attention module calculates attention weights for every feature channel by aggregating global context through average and max pooling operations. These weights are subsequently utilized to recalibrate the feature maps, enabling the network to focus on diagnostically informative patterns such as cortical thinning, white matter lesions, and hippocampal atrophy. The classification accuracy is further improved by optimizing the hyperparameters of the CA-InceptionResNet model with the HLO algorithm. This dynamic search method allows the HLO to effectively search the hyperparameter space and converge the best configurations that achieve maximum diagnostic performance.

3. PROPOSED SYSTEM MODELLING

3.1 Adaptive Difference of Gaussian filter

he proposed method reduces visual interpretability of background regions that do not add relevant information while increasing the visual interpretability of structural edges, especially along the anatomical contours. For the adaptive Difference of Gaussian (DoG) processing step in the proposed procedure, two standard deviations denoted by σ_1 and σ_2 are computed for each row of the input image. The value σ_1 is computed from a small local window, whereas σ_2 is computed from a larger window that includes multiple rows centered on the current row.

When σ_1 is less than σ_2 , the DoG filter is applied to that row; otherwise, the row is left unchanged.

This is effective because each row corresponds to the reflections that reach the eye from each object in the scene at different time intervals (due to sound waves taking longer to reach the ear). Thus, this row-wise method allows DoG filter to be designed to target reflections at different time intervals. ADOG output, obtained by subtracting the original image X with dimensions of $M \times N$. ADOG process outlined in Table 2.

Table 2: Adaptive Difference of Gaussians.

```

FOR  $m = 3 : M - 2$ 
  (i)  $\sigma_1 = STD2\{X(m-2:m+2,:)\}$ 
  (ii)  $\sigma_2 = STD2\{X(m-1:m+1,:)\}$ 
  (iii) IF  $\sigma_1 < \sigma_2$ 
     $H = \psi(\sigma_1, \sigma_2; K)$ 
     $G = X(m,:) * H$ 
     $Y(m,:) = G(K/2 + 1, K/2 + 1 : K/2 + N)$ 
  ELSE
     $Y(m,:) = X(m,:)$ 
  ENDIF
ENDFOR

```

In this context, STD2 refers to the standard deviation of a two-dimensional sub-image, and notation $(m-2 : m+2, :)$ indicates a block of rows from $(m-2)$ to $(m+2)$. It creates a $K \times K$ matrix based on the difference between two 2-dimensional Gaussian functions with 0 mean and standard deviations of σ_1 and σ_2 .

$$\psi(\sigma_1, \sigma_2; K) = \frac{1}{2\pi} \left[\frac{1}{\sigma_1} \exp\left(-\frac{t_1^2 + t_2^2}{2\sigma_1^2}\right) - \frac{1}{\sigma_2} \exp\left(-\frac{t_1^2 + t_2^2}{2\sigma_2^2}\right) \right] \quad (1)$$

A 2D convolution operation occurs with the condition of $(\sigma_1 < \sigma_2)$, providing the Laplacian filter's approximate function. To preserve important anatomical boundaries while removing non-informative regions, ADOG filter suppresses cases where $(\sigma_1 > \sigma_2)$

and retains image information at $m = 50$. However, at $m = 110$ ($\sigma_1 < \sigma_1$), the DoG will be applied to reduce noise from the background. The output from ADOG enhances diagnostic quality by eliminating redundant structures and highlighting the critical structural features of brain tissue.

After enhancement, the next step is accurate tissue segmentation using the HACR method, which groups pixels of similar intensities to ensure that brain regions associated with neurodegenerative changes are precisely isolated.

To quantitatively assess enhancement performance, an energy-based metric is computed across image columns using:

$$M(n) = \sum_{m=1}^M X^2(m, n), \quad n = 1 \dots N \quad (2)$$

The spatial intensity distribution, where Higher Energy (H.E.) This metric represents values that correspond to more prominently visible features, thereby quantifying the strength of diagnostically relevant patterns. After critical structural details have been enhanced using the spatially adaptive DoG filter, the next step is tissue segmentation. This is accomplished through the HACR method, which accurately isolates brain regions associated with Neurodegenerative change.

3.2 Hybrid Agglomerative Clustering Refinement

HACR method creates accurate final segmentation results of affected regions in scans of the affected individuals' brains. HACR method comprises the strengths of agglomerative clustering and adaptive refinement strategies, creating a robust framework for accurate tissue segmentation. In standard agglomerative clustering, each superpixel is considered its own cluster. Subsequently, clusters are iteratively merged based on a similarity metric, typically intensity similarity or spatial proximity. Gaussian Blur is employed within HACR framework, where the degree of blur is controlled by predetermined standard deviations. This adds aspect of spatially adaptive, improving the clarity of neuroanatomical boundaries while reducing irrelevant background noises.

Gaussian Blurring whereby each standard deviation of Gaussian kernels varies based on local structural characteristics. The dynamic adjustment of blurring techniques allows for more aggressive smoothing within homogeneous or noisy regions while retaining fine structures within high-contrast areas. HACR process is mathematically defined as having two stages:

Agglomerative Clustering Stage

The image is represented by a set of superpixels $X = \{x_1, x_2, \dots, x_n\}$, where each $x_i \in R^d$ encodes intensity and spatial location.

Initialization:

Each superpixel $(, x - i.)$ is assigned to its own cluster,

$$C_i = \{x_i\} \quad (3)$$

Iteration:

At each step, merge the pair of clusters (C_i, C_j) that minimizes the distance function:

$$D(C_i, C_j) = \|\mu C_i - \mu C_j\| \quad (4)$$

Where, μC_i and μC_j denote the mean feature vectors of clusters C_i and C_j , respectively.

Hybrid Refinement Stage

After achieving the clustering threshold, the refining function R is applied to the clusters, using their predominant characteristics to improve segmentation accuracy. Hence, the refined cluster is expressed as follows:

$$C_{refined} = R(C, F, P) \quad (5)$$

Here, C denotes existing cluster set, F represents extracted features set, P corresponds to previous knowledge.

Following the successful segmentation of brain tissues using HACR analysis, extraction of textural characteristics from the regions assists in establishing a definitive diagnosis. To accomplish rotation-invariant analysis of tissue patterns, the polar GLCM is applied, yielding a GLCM reference plane based on polar co-ordinates.

3.3 Polar Co-ordinate Gray-Level Co-Occurrence Matrix

Traditional GLCMs produce appropriate texture data extraction within the Cartesian co-ordinate system, but GLCM not produce appropriate information for the analysis of textural characteristics of polar co-ordinate information that require rotation-invariant texture analysis as the anatomical structures being analyzed have differing orientations in neuroimaging from one image scan to another. Thus, polar coordinate GLCM model is introduced to resolve this issue and expand field of conventional GLCM regarding polar domains and thereby enhance clinical viability through improving convergence and robustness of clinical texture analysis.

Using a joint cost function, iteration k generates a covariance value (Z_k) for the co-occurrence matrix, based on covariance and directional parameter values. Rule for determining covariance is provided.

$$Z_{k+1} = \sup \left\{ \frac{1}{Z} \mid Z_k = \min_{Z,k} P_Z^k(r, \theta; \rho, \varphi) \right\}, \quad 0 \leq r \leq r_h, \theta_s \leq \theta \leq \theta_e, 0 \quad (6)$$

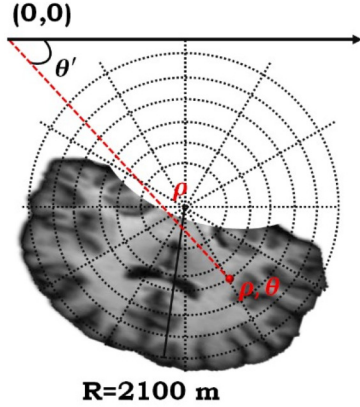


Fig.2: Polar co-ordinate system.

At iteration k , the optimal matrix value is defined by Z_k . The GLCM process is applied at the polar coordinate pair (r, θ) and respective offsets (ρ, φ) to $P_Z^k(r, \theta; \rho, \varphi)$.

The supremum identifies the optimal solution from all iterations. The amplitude threshold is defined as r_h . Angular domain is defined by s (the angle's lower bound) and e (the angle's upper bound). The global polar coordinate pair (r, θ) provides a reference location for a pixel on the polar-transformed image, whereas the relative polar coordinate pair (ρ, φ) is defined with relative to this reference.

The gray-level range at any (r, θ) is $(0 \text{ to } N - 1)$, forming an $N \times N$ square matrix for the complete GLCM at that pixel location. Unlike traditional Cartesian GLCM, which evaluates pixel relationships in fixed directions, the polar GLCM calculates co-occurrence probabilities based on angular and radial offsets. For a given position (r, θ) , the matrix element is computed by counting pixel pairs that satisfy the relative offset condition.

$$P(r, \theta; \rho, \varphi) = \frac{\text{card} \left(\begin{array}{l} ((i, j) | f(i, j) = m - 1) \\ f(i + \rho \cos \varphi, j + \rho \sin \varphi = n - 1), \\ (i, j) \in \mathcal{P}, (i + \rho \cos \varphi, j + \rho \sin \varphi) \in \mathcal{P} \end{array} \right)}{\mathcal{Q}(\rho, \varphi)} \quad (7)$$

Here, $\text{card}(\cdot)$ denotes cardinality function (the number of valid pixel pairs), while $\mathcal{Q}(\rho, \varphi)$ represents normalization factor that ensures ensuring statistical consistency.

The weighted co-occurrence matrix is then defined as:

$$\mathcal{Q}(\rho, \varphi) = \text{card} \{ (i, j) | (i, j) \in \mathcal{P}, (i + \rho \cos \varphi, j + \rho \sin \varphi) \in \mathcal{P} \} \quad (8)$$

Where $\bar{\omega}(r, \theta)$ is a spatial weighting function given by:

$$\bar{\omega}(r, \theta) = 1 + \exp(-d[(r, \theta) | (r_0, \theta_0)]) \quad (9)$$

Here, $d[(r, \theta) | (r_0, \theta_0)]$ measures the distance between the current co-ordinate and a reference orientation point. To determine the optimal texture direction, the matrix is integrated over the angular domain:

$$Z'(\varphi) = \int Z(\rho, \varphi) d\varphi \quad (10)$$

In discrete form, this becomes:

$$Z'(\varphi) = \sum_{\rho=1}^R \sum_{r=1}^N \sum_{\theta=1}^N \bar{\omega}(r, \theta) \times P(r, \theta; \rho, \varphi) \quad (11)$$

The best orientation φ_{min} is identified by minimizing the integrated texture function:

$$\varphi_{min} = \arg \left(\min_{\varphi} Z'(\varphi) \right) \quad (12)$$

This formulation enables the polar coordinate-GLCM to adaptively capture rotation-invariant texture features, which are critical for accurately identifying neuroanatomical changes in dementia diagnosis. As a result, the emphasis shifts to precisely categorizing these features in order to differentiate between healthy brain regions and those affected by neurodegeneration. This is accomplished by introducing a CA-InceptionResNet model as the fundamental classification framework.

3.4 CA-InceptionResNet architecture with Horned Lizard Optimization (HLO)

In the CA-InceptionResNet architecture, Figure.3 residual connections are a key component in reducing the vanishing gradient problem that is typically found in deep networks. The residual connections are integrated nicely into every Inception module to create composite Inception-ResNet blocks. The feature representation is improved in every block by combining multi-scale convolutional branch outputs with the original input through a skip connection.

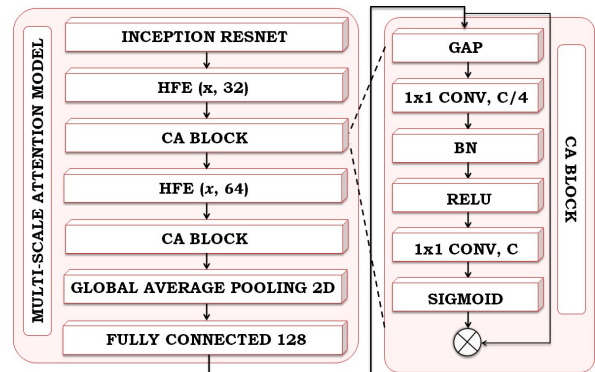


Fig.3: CA-Inception ResNet block.

If X represents input to an Inception-ResNet block, the output is written as,

$$F_{\text{Inception-ResNet}}(X) = F(X, \{W_i\}) + X, \quad (13)$$

where $F(X, \{W_i\})$ is the operation carried out by the parallel convolutional filters, and (W_i) are the corresponding learnable parameters. The skip connection allows continuous gradient flow through the network to ensure stable and efficient training. By stacking several Inception-ResNet blocks, the design builds a deep hierarchical model that can extract progressively abstract features. This type of design benefits particularly well in medical imaging tasks, as capturing slight structural differences is important for accurate diagnosis. By combining residual learning with inception modules, classification accuracy is significantly increased while maintaining computational efficiency.

Channel Attention Module (CAM) enhances the model's ability to identify diagnostically significant areas in brain images. This capability is essential in diagnostic imaging, particularly when distinguishing between subtle features that are often very small. Taking an input feature map $X \in \mathbb{R}^{H \times W \times C}$, where H , W , and C represent spatial dimensions and number of channels, CA module follows a three-step operation, ensuring both accuracy and interpretability in feature refinement. First, spatial information is reduced by determining a channel-wise descriptor through Global Average Pooling (GAP). For every channel c , the descriptor z_c is determined as:

$$z_c = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W X(i, j, c) \quad (14)$$

This process maps the feature map X into a dense vector $z \in \mathbb{R}^c$, summarizing the global spatial information. To capture inter-channel dependencies in an efficient way, a 1D convolution is then applied to z , allowing the mechanism to learn cross-channel interactions without paying a heavy computational price.

$$s = \sigma(W_{1D} * z) \quad (15)$$

Here, (W_{1D}) are the learnable weights of the 1D convolutional layer, $(*)$ is the convolution operation, and (σ) is the sigmoid function to normalize the output $s \in \mathbb{R}^c$. These attention weights indicate the relative importance of each channel.

The original feature map X is recalibrated by applying the attention weights to every corresponding channel to obtain the refined feature map $\hat{X}$

$$\hat{X}(i, j, c) = s_c \cdot X(i, j, c) \quad (16)$$

Channel-wise multiplication amplifies the presence of useful features and reduces the effect of less useful features, hence enhancing model's capacity to highlight important patterns in an image.

The working process of the CA mechanism is described in Table 3, which summarizes its simple yet efficient architecture:

Table 3: Channel Attention Mechanism.

- 1: Input: Feature map $X \in \mathbb{R}^{H \times W \times c}$,
- 2: Channel Descriptor Generation: Calculate $z \in \mathbb{R}^c$ by taking spatial dimensions' average:

$$z_c = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W X(i, j, c)$$
- 3: Cross-Channel Interaction Modeling: Use 1D convolution with kernel size k , then sigmoid activation to get attention weights $s \in \mathbb{R}^c$:

$$s = \sigma(W_{1D} * z)$$
- 4: Feature Recalibration: Scale each channel of the input feature map by its corresponding attention weight:

$$\hat{X}(i, j, c) = s_c \cdot X(i, j, c)$$
- 5: Output: Calibrated feature map $\hat{X}$, highlighting informative channels.

By applying both fully connected layers and 1D convolution, the CA mechanism achieves computational efficiency while effectively modeling channel-wise dependencies. The reduced architecture imposes minimal overhead and thus is exceptionally well-suited for deep learning in medical imaging. The recalibration process ensures that the network remains focussed on diagnostically important features, thereby maximizing classification accuracy without compromising performance. As shown in Table 4, with a learning rate of 0.00015, batch size of 35, 10 epochs, the Adam optimizer and a dropout rate of 0.23, the proposed configuration improves classification accuracy while reducing overfitting.

Table 4: Training Hyperparameters.

Hyperparameter	Optimized Value
Learning Rate	0.00015
Batch Size	35
Epochs	10
Optimizer	Adam
Dropout Rate	0.23

The horned lizard optimization algorithm improves the efficiency of the Channel-Attentive InceptionResNet classifier by adaptively tuning its architectural weights and hyperparameters using biologically rooted defense techniques. HLOA borrows from the survival mechanisms of the horned lizard crypsis, thermoregulatory modulation of skin, blood-squirting, and evasive movement to convert them into mathematically regulated search operators that strike a balance between exploration and exploitation in solution space.

Crypsis-tuned feature selection

The crypsis-motivated process from horned lizard camouflage is theoretically formulated to inform

adaptive feature selection and spatial attention. Crypsis is the ability of an organism to blend visually with its surroundings by aping ambient properties like color, texture, and translucency thus making itself less detectable to predators or prey.

To simulate this biologically adaptive characteristic, HLO takes advantage of the principles of color science, namely the CIE-defined $L*a*b$ and $L*C*h$ color spaces. These models measure color perception relative to standardized light emission in the visible spectrum (400–700 nm), facilitating accurate chromatic modeling.

$$a^* = \begin{array}{l} +a, \text{ indicates Red} \\ -a \text{ indicates Green} \end{array} \quad (17)$$

$$b^* = \begin{array}{l} +b, \text{ indicates Yellow} \\ -b \text{ indicates Blue} \end{array} \quad (18)$$

In the $L*a*b$ space, $L*$ is used to encode brightness, with $a*$ and $b*$ representing chromaticity along red–green and yellow–blue axes, respectively.

In $L*C*h$ space, $L*$ is lightness, $C*$ describes chroma (color saturation), and $h*$ determines the hue angle, which ranges from 0° to 360° around a circular color wheel from red via yellow, green, blue, and return to red.

By converting Cartesian chromatic co-ordinates to polar co-ordinates, HLO automatically adjusts search agent locations to mimic environmental blending.

$$c^* = \sqrt{a^{*2} + b^{*2}} \quad (19)$$

$$h = \arctan\left(\frac{b^*}{a^*}\right) \quad (20)$$

The values c^* and h stand for chroma (or saturation) and hue, respectively. The value of the hue h is an angular value measured in degrees between 0° and 360° and specifies the position of the color in the circular hue space. In order to convert polar co-ordinates into Cartesian, the following inverse relations are employed:

$$a^* = c^* \cos(h) \quad (21)$$

$$b^* = c^* \sin(h) \quad (22)$$

Given two different color vectors in form of ordered pairs (a_p^*, b_q^*) and (a_r^*, b_s^*) where $p \neq q \neq r \neq s$, new combined color variations named as $colorVar_1$ and $colorVar_2$, are created by performing the following arithmetic computations:

$$colorVar_1 = b_q^* - a_q^* - a_r^* + b_s^* \quad (23)$$

$$colorVar_1 = b_q^* - a_q^* + a_r^* - b_s^* \quad (24)$$

These color combinations are encapsulated in the equation provided below.

$$colorVar = b_q^* - a_q^* \pm [a_r^* - b_s^*] \quad (25)$$

Equation (25) is rewritten in polar form to represent chromatic variation by using hue angles and chroma values. This gives rise to the following representation:

$$colorVar = c_1 \sin(h_p) - c_1 \cos(h_q) \pm [c_2 - \sin(h_r) - c_2 \cos(h_s)] \quad (26)$$

The equation (27) is the inverse polar form of color variation

$$colorVar = c_1 \sin(h_p) - \cos(h_q) \pm [c_2 - \sin(h_r) - \cos(h_s)] \quad (27)$$

Here, h_p, h_q, h_r, h_s represent different hue angles ($h_p \neq h_q \neq h_r \neq h_s$), while $(c_1 \neq c_2)$ denotes chroma values chosen from the normalized color palette. These parameters guarantee direction diversity and intensity modulation in search dynamics. To reduce computation, the chroma terms are factorized:

$$\vec{x}_i(t+1) = \vec{x}_{best}(t) + \left(\partial - \frac{\partial \cdot t}{Max_{iter}} \right) \left[c_1 \left(\sin(\vec{x}_{r_1}(t)) - \cos(\vec{x}_{r_2}(t)) \right) - (-1)^\sigma c_2 \left(\cos(\vec{x}_{r_3}(t)) - \cos(\vec{x}_{r_4}(t)) \right) \right] \quad (28)$$

At iteration $t+1$, the position of the i^{th} search agent's $(x_i^{(t+1)})$ is updated relative to the best agent at iteration t , $\vec{x}_{best}(t)$. Randomly chosen agents $(t, \vec{x}_{r_1}, \vec{x}_{r_2}, \vec{x}_{r_3}, \vec{x}_{r_4})$ are selected such that $r_1 \neq r_2 \neq r_3 \neq r_4$. The maximum number of iterations is denoted as Max_{iter} , while c_1 and c_2 are chroma values taken from normalised palette.

Thermoregulatory Skin Modulation

Horned lizards have a biologically mediated capacity to change the pigmentation of their skin in relation to the ambient temperature, lightening their skin to reflect solar radiation or darkening their skin to increase heat absorption. This thermoregulatory adaptation is controlled by the same physical laws that control light energy, with light skin reducing thermal gain and dark skin increasing it. Within the HLO framework, this adaptive process is modeled mathematically in order to direct search agent updates. Two separate strategies are utilized: one mimicking skin lightening and one modeling skin darkening. They are defined as follows:

Lightening Strategy:

$$\begin{aligned}\vec{x}_{worst}(t) = & \vec{x}_{best}(t) + \frac{1}{2}Light_1 \sin(\vec{x}_{r_1}(t) - \vec{x}_{r_2}(t)) - \\ & (-1)^\sigma \frac{1}{2}Light_2 \sin(\vec{x}_{r_3}(t) - \vec{x}_{r_4}(t))\end{aligned}\quad (29)$$

Darkening Strategy:

$$\begin{aligned}\vec{x}_{worst}(t) = & \vec{x}_{best}(t) + \frac{1}{2}Dark_1 \sin(\vec{x}_{r_1}(t) - \vec{x}_{r_2}(t)) - \\ & (-1)^\sigma \frac{1}{2}Dark_2 \sin(\vec{x}_{r_3}(t) - \vec{x}_{r_4}(t))\end{aligned}\quad (30)$$

Where, $\vec{x}_{best}(t)$ and $\vec{x}_{worst}(t)$ are best- and worst-performing agents at iteration (t) , $\vec{x}_{r_1}, \vec{x}_{r_2}, \vec{x}_{r_3}, \vec{x}_{r_4}$ are randomly chosen agents, with $r_1 \neq r_2 \neq r_3 \neq r_4$, σ is a binary switch controlled by Algorithm 1, $Light_1$ and $Light_2$ are sampled from the normalized interval $[0, 0.4046661]$, describing reflective tones, $Dark_1$ and $Dark_2$ are sampled from $[0.5440510, 1]$, describing absorptive tones. This strategy replaces the performing agent with the lowest performance with a new agent that approximates the horned lizard's temperature-induced pigmentation change. In this way, HLO adaptively balances exploration and exploitation, improving the CA-InceptionResNet's capacity to converge on optimal feature representations under diverse data conditions.

Projectile-Based Blood-Squirting Mechanism

One of the horned lizard's most unique defense mechanisms is forcibly expelling a stream of blood from its eyes to discourage predators. This violent strategy is replicated in HLOA as a projectile motion, preserving both the direction dynamics and acceleration profile of the stream of blood. The simulation is broken down into two orthogonal components: horizontal (X-axis) and vertical (Y-axis), to deduce the motion equations.

Horizontal Component: Uniform Linear Motion

Horizontally, the blood stream travels along a constant velocity path. The displacement as a function of time (t) is represented by:

$$\vec{v} = \vec{v}_0 + \int_0^t \vec{g} dt = \vec{v}_0 + \vec{g}t \quad (31)$$

Vertical Component: Uniformly Accelerated Motion

Vertically, the motion is subject to gravitational acceleration, so the path is parabolic. Displacement is given by:

$$\vec{r} = \vec{r}_0 + \int_0^t (\vec{v}_0 + \vec{g}t) dt = \vec{r}_0 + \vec{v}_0 t + \frac{1}{2} \vec{g} t^2 \quad (32)$$

$$\vec{r}_0 = \vec{0} \quad (33)$$

The entire motion is represented through vector equations for position and velocity:

$$\vec{v}_0 = v_0 \cos(\alpha) \vec{j} + \left((v_0 \sin(\alpha) t) - \frac{1}{2} g t^2 \right) \vec{k} \quad (34)$$

$$\vec{v} = \vec{r}' = v_0 \cos(\alpha) \vec{j} + \left((v_0 \sin(\alpha) t) - \frac{1}{2} g t^2 \right) \vec{k} \quad (35)$$

The final trajectory equation is therefore represented as,

$$\begin{aligned}\vec{x}_i(t+1) = & \left[v_0 \cos \left(\alpha \frac{t}{Max_{iter}} \right) + \varepsilon \right] \vec{x}_{best}(t) + \\ & \left[v_0 \sin \left(\alpha - \frac{\alpha t}{Max_{iter}} \right) - g + \varepsilon \right] \vec{x}_i(t)\end{aligned}\quad (36)$$

Rapid Evasion through Local-Global Movement

Horned lizard employs rapid, erratic movement when trying to escape predators, modeled mathematically through a hybrid local/global search process. The proposed methodology incorporates an update function that combines a random walk around the current position with a directional preference toward the best-established region, thereby enhancing convergence and solution stability. The combined methodologies improve exploratory search processes and allow for more efficient discovery of solutions to avoid local minima.

$$\vec{x}_i(t+1) = \vec{x}_{best}(t) + walk \left(\frac{1}{2} - \varepsilon \right) \vec{x}_i(t) \quad (37)$$

Where $\vec{x}_i(t+1)$ is the new position of the i^{th} search agent, $\vec{x}_{best}(t)$ is the currently best-performing agent at iteration (t) , $walk$ is a random scalar sampled uniformly in $[-1, 1]$, $\left(\frac{1}{2} - \varepsilon \right) \vec{x}_i(t)$ introduces localised perturbation, and a Cauchy-distributed random variable (mean = 0, scale = 1) modulates the step size. This definition allows agents to execute evasive maneuvers while preserving convergence pressure towards promising areas of the search space.

Adaptive Skin Coloration through α -MSH Rate

Horned lizards have thermoregulatory skin coloration mediated by α -melanophore stimulating hormone (α -MSH), permitting them to adjust solar heat absorption. This biological phenomenon is generalized to the optimization framework as a fitness-dependent adaptation rate, controlling selective agent replacement.

$$melanphore(i) = \frac{Fitness_{max} - Fitness(i)}{Fitness_{max} - Fitness_{min}} \quad (38)$$

Where $Fitness(i)$ is the fitness of the i^{th} agent, $Fitness_{max}$ and $Fitness_{min}$ are the worst and best fitness values in generation (t) and $melanphore(i)$ is the normalized adaptation rate

Agents with low α -MSH rates (i.e., $melanphore(i) < 0.3$) are replaced using a recombination strategy based on differential evolution:

$$\vec{x}_i(t) = \vec{x}_{best}(t) + \frac{1}{2} [\vec{x}_{r_1}(t) - (-1)^\sigma \vec{x}_{r_2}(t)] \quad (39)$$

Here, $\vec{x}_{r_1}(t), \vec{x}_{r_2}(t)$ represent randomly chosen agents with indices r_1 and r_2 . This update encourages diversity and introduces exploratory behavior into stagnation areas..

Table 5: Hornerd Lizard Optimization.

Parameter	Value
Population Size	20
Maximum Iterations	40
Exploration Factor	0.7
Exploitation Factor	0.3
Random Perturbation	[0, 1] uniform
Step Size	0.05

The control parameters utilized in HLOA for adaptive tuning of the Channel-Attentive InceptionResNet classifier are summarized in Table.5. While the exploration and exploitation factors regulate the balance of global and local search, the algorithm's population size and iteration count determine the search depth and convergence stability. A step size of 0.05 ensures smooth convergence toward ideal hyperparameter values, whereas random perturbation within a uniform [0, 1] range introduces stochastic diversity. When combined, these parameters improve training stability and avoid early convergence during optimization.

As shown in Figure 4, the proposed HLO algorithm further boosts performance by adaptively tuning model parameters through biologically inspired search strategies. This ensures robust and efficient learning for nuanced diagnostic tasks.

4. RESULT AND DISCUSSION

This section presents a detailed description of the proposed approach, with the aid of descriptive text as well as visual images. The primary outcomes are presented through graphical results plotted in the form of Python-generated plots that provide easy insight into the functioning of the system. Furthermore, comparative analyses are conducted across multiple datasets

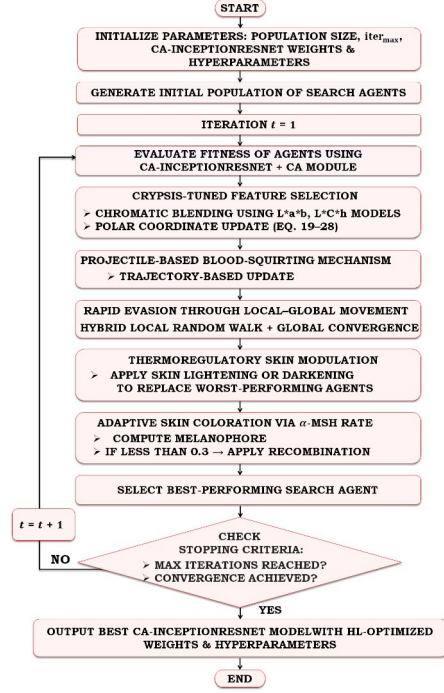


Fig.4: Flowchart of HLO-based CA-InceptionResNet.

using classifier systems demonstrate enhanced efficiency compared to existing methods that rely on state-of-the-art algorithms.

Experimental Setup:

Proposed model is created using an Intel Core i7 CPU with 16 GB of RAM and 512 GB of Solid-State Drive (SSD) storage. The model's software configuration runs on the Windows 10 operating system with Python 3.10 as primary programming language. The model is built, trained, and displayed using Jupyter Notebook. Therefore, Jupyter Notebook provided an interactive coding platform for executing code, monitoring results, and displaying graphics.

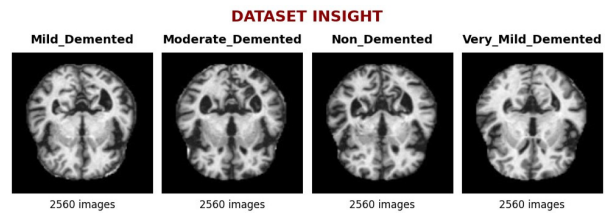


Fig.5: Dataset insight.

Figure 5 presents representative input samples from which to classify an individual as having dementia. Dataset1, used in this model, is the Alzheimer's Disease Multi-class Dataset which contains approximately [10, 240]. This dataset provides axial brain (MRI) scans categorized into 4 diagnostic classes: non-demented, very mild demented, mild demented and moderate demented. Each classification contains 2, 560 images. The dataset distribution is therefore,

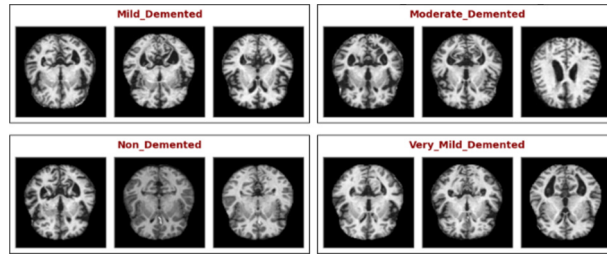


Fig.6: Input image a) Mild Dementia b) Moderate Dementia c) Non-Dementia d) Very – Mild Dementia.

balanced across all classes, allowing for efficient training and validation of the model developed from the provided data.

As shown in Figure 6, brain scans are categorized according to dementia severity, allowing for visualization of subtle anatomical differences in individuals' brains becoming worse based on increasing levels of cognitive decline/severity. Differences in image contrast facilitate more precise extraction of ROI, extraction based on varying levels of cognitive decline and disease severity. It provides reliability and robustness of the filter when comparing against respective noise levels.

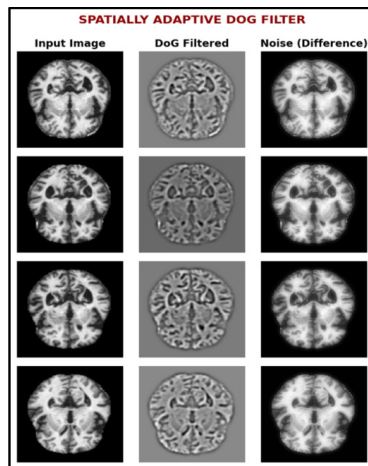


Fig.7: Spatially Adaptive DOG Filter Images.

Figure 7 represents the application of the spatially adaptive difference of Gaussian filter to brain scan images. There are three columns in each of the four types: input image is the original MRI scan, or baseline anatomical structure. The filtered output from applying the adaptive DoG filter, which sharpens fine structural detail but eliminates background noise. The residual image emphasising filtered noise, created by subtracting output of the DoG filter from the original scan. This residual highlights the filter's capacity to preserve and enhance fine anatomical and textural details such as cortical thinning and hippocampal shrinkage that are essential for distinguishing between dementia stages.

Figure 8 demonstrates the use of the HACR method to divide dementia-impacted brain areas. It

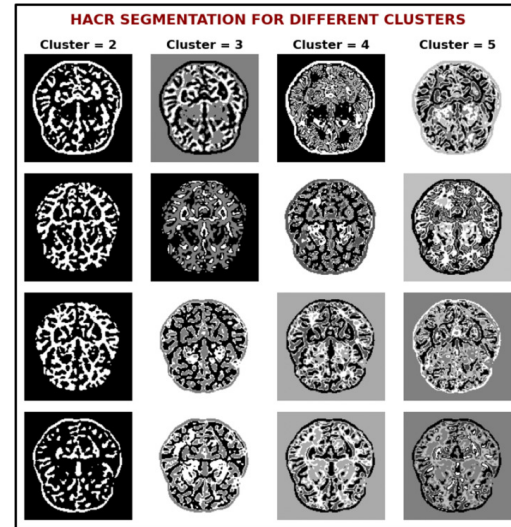


Fig.8: Dementia region segmented using HACR.

is divided into four columns, each of which corresponds to a unique level of clustering: Cluster = 2, Cluster = 3, Cluster = 4, and Cluster = 5. Each column contains segmented MRI scans that differ in the level of detail, with anatomical regions of the brain identified at varying cluster levels. The more clusters, the more detailed the segmentation, and thus structures and their borders become increasingly specified. Progressive segmentation illustrates HACR's ability to provide a balanced representation of structural readability along with computational optimality. Therefore, ability to establish structural readability while providing computational optimality makes HACR an essential component of medical imaging & diagnosis.

Table 6. illustrates the extracted GLCM features derived in polar co-ordinates from MRI brain images. The four digital images contain four different images of a subject at four different angular degrees (0° , 45° , 90° , and 135°) taken at various stages of their development. Contrast provides insight into the degree of local variance in brightness; higher values indicate greater observable structural variance. Dissimilarity measures how different nearby pixel pairs are from each another. This metric helps identify unwanted textures or external factors, that interfere with diagnostic accuracy. Homogeneity represents uniformity;

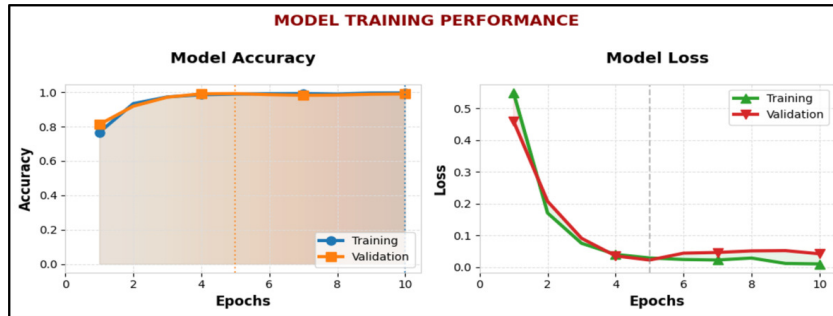
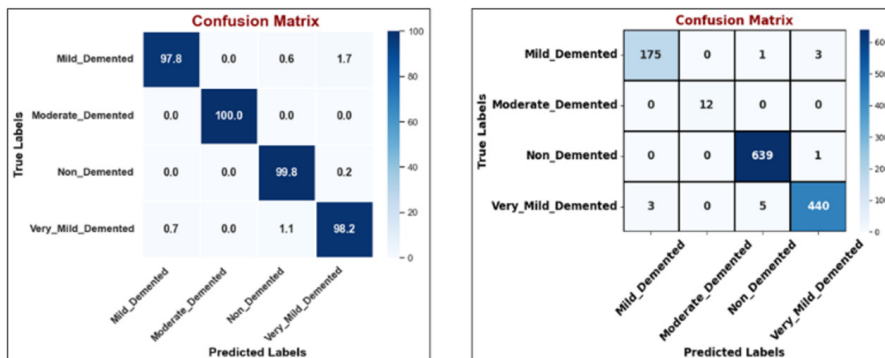
Table 6: Gray-Level Co-occurrence Matrix in Polar Co-ordinates.

	Image	Contrast	Dissimilarity	Homogeneity	Energy	Correlation
1	Angle 0°	1.2331	0.4898	0.8294	0.5881	0.5563
	Angle 45°	1.4032	0.5768	0.7942	0.5661	0.4972
	Angle 90°	1.1437	0.4595	0.8387	0.5925	0.5885
	Angle 135°	1.4445	0.5828	0.7948	0.5667	0.4824
2	Angle 0°	0.9188	0.4038	0.8496	0.4998	0.7077
	Angle 45°	1.0689	0.4869	0.8147	0.4799	0.6604
	Angle 90°	0.8484	0.3773	0.8585	0.5053	0.7301
	Angle 135°	1.0259	0.4680	0.8218	0.4833	0.6741
3	Angle 0°	0.6871	0.3655	0.8494	0.5325	0.5990
	Angle 45°	0.9393	0.4829	0.8042	0.5081	0.4555
	Angle 90°	0.7172	0.3775	0.8452	0.5311	0.5815
	Angle 135°	0.9399	0.4816	0.8050	0.5085	0.4551
4	Angle 0°	0.6029	0.3349	0.8594	0.5712	0.6272
	Angle 45°	0.8669	0.4597	0.8109	0.5426	0.4678
	Angle 90°	0.6228	0.3408	0.8578	0.5710	0.6149
	Angle 135°	0.8273	0.4397	0.8189	0.5474	0.4920

greater values indicate smoother areas. Energy measures textural uniformity and repetition; greater energy signifies more regular textures. Correlation measures linear dependency among pixel pairs, suitable for identifying directional texture directions.

Figure 9 presents two major performance measures accuracy and loss plotted over 10 training epochs for the proposed model. Model accuracy graph displays training accuracy and validation accuracy increasing steadily with epochs. As early as the 10th epoch, training accuracy is close to 1.0, while validation ac-

curacy is at around 0.9, showing excellent generalization and successful learning. The smooth rising trend with little divergence between the two lines testifies to a well-regularized model with minimal overfitting. The model's loss graph demonstrates a steady decrease in both training loss and validation loss over-time, proving stable convergence and effective optimization. Both loss have a monotonically decreasing trend, meeting close to 0.1 in the last epoch. The simultaneous decrease of both loss indicates steady optimization and strong convergence. It affirms that

**Fig.9:** Model Training performance graph.**Fig.10:** Confusion Matrix.

the proposed CA-InceptionResNet with HLO model achieves high accuracy at low error rates and proves robust stability and reliability throughout training.

Figure 10 displays two confusion matrices: one showing percentage accuracy and the other presenting raw predictions counts for the model classifying four dementia stages. For instance, the Moderate Demented category is predicted with 100% accuracy, the Non-Demented category achieves 99.8% accuracy. There are also high correct prediction rates of 97.8% and 98.2% for mild demented and very mild demented, respectively. Misclassifications are minimal and primarily localised between the Mild and Very Mild Demented categories, reflecting the clinical challenge of distinguishing between close related stages. These matrices emphasize the proposed CA-InceptionResNet with HLO model's high classification accuracy, assessing diagnostic reliability and leading to future model sensitivity and specificity enhancements.

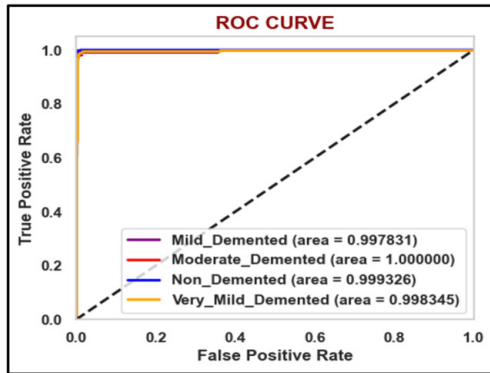


Fig.11: ROC Curve.

Figure 11 displays the Receiver Operating Characteristic (ROC) curves of a multi-class classification model differentiating between four stages of dementia. Each curve indicates True Positive Rate (Sensitivity) against the False Positive Rate as a measure of the model's discriminatory power to differentiate each class from the rest at different decision thresholds. The proposed model demonstrates enhanced discriminative performance, achieving near-perfect classifications across dementia phases: Moderate Demented (AUC = 1.000000, ideal classification), Non-Demented (AUC = 0.999326), very mild demented (AUC = 0.998345), Mild Demented (AUC

= 0.997831), reflecting enhanced discriminative performance, the proposed model's ability to differentiate even minute differences in dementia phases.

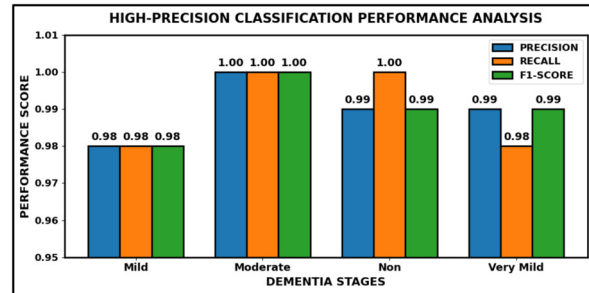


Fig.12: Class-Wise model performance metrics.

Figure 12 visualizes the class-wise performance metrics for dementia classification. The moderate Demented Class achieves ideal precision, recall, and F1-score metrics of 1.00, reflecting ideal identification of this category. Mild demented scores 0.98 for all performance metrics, indicating robust and well-balanced performance in both identifying and accurately predicting this phase. Non-demented class has 0.99, indicating high consistency and few false positives or false negatives. Very Mild demented precision is marginally higher (0.99) than Recall and F1-Score (0.98), indicating model's class-wise accuracy, especially in its capacity to differentiate between subtle phases such as Very Mild and Mild Dementia, and validates it for real-world diagnostic implementation.

The benchmarking outcomes of different DL architectures that were trained and assessed using the Alzheimer's Disease Multi-class Dataset are presented in table.7. In comparison to traditional CNN, VGG19, DenseNet121, and InceptionV3 architectures, the proposed Channel-Attentive InceptionResNet classifier optimized using HLOA demonstrated superior generalization and diagnostic reliability, achieving the highest accuracy (98.98%), precision (99.12%), Recall (98.96%), F1-score (99.04%), specificity (99.60%), sensitivity (98.96%) and cohen's Kappa (98.32%), thus improving overall stability among all evaluated models.

Table 7: Comparative Performance of DL Models on AD Multi-class Dataset.

Model	Accuracy	Precision (Macro)	Recall (Macro)	F1-Score (Macro)	Specificity	Sensitivity	Balanced Accuracy	Cohen's Kappa
CNN	0.9623	0.9635	0.9618	0.9626	0.9730	0.9618	0.9618	0.9455
VGG19	0.9756	0.9768	0.9745	0.9756	0.9858	0.9745	0.9745	0.9608
DenseNet121	0.9782	0.9790	0.9775	0.9782	0.9885	0.9775	0.9775	0.9652
InceptionV3	0.9821	0.9830	0.9812	0.9821	0.9915	0.9812	0.9812	0.9718
Proposed Model	0.9898	0.9912	0.9896	0.9904	0.9960	0.9896	0.9896	0.9832

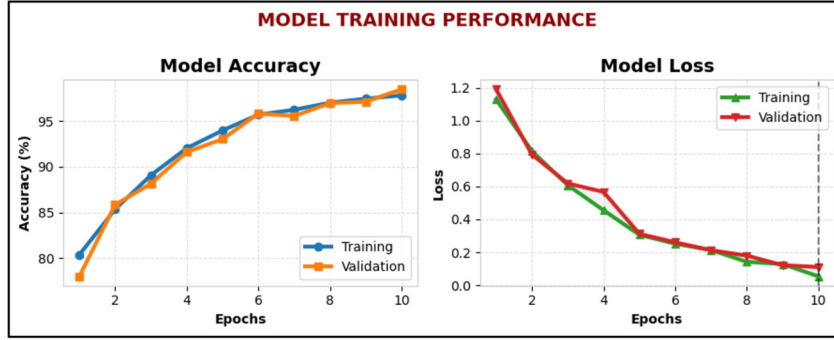


Fig.13: Model Training Performance.

Dataset 2:

The second dataset is the OASIS MRI dataset. The model is developed and evaluated using the OASIS MRI dataset. Based on Alzheimer's progression, it comprises approximately 80,000 brain MRI images. A total of 461 patient MRI scans were uploaded to a GitHub repository to ensure accessibility after pre-processing. The original.img and.hdr files were converted to the NIFTI (.nii) format using FSL software, enabling standardized handling and compatibility with neuroimaging tools. A balanced dataset is created for training using 2D slices along the z-axis (100–160 out of 256 per scan). Metadata and Clinical Dementia Rating (CDR) values to indicate illness phases are used for classification. For effective processing, the.nii files were subsequently converted into the.jpg format, yielding a 1.3GB dataset appropriate for DL-based dementia detection.

The training behavior of the proposed dementia classification model is illustrated in Figure 13. Over

the course of ten epochs, model accuracy plot demonstrates a consistent increase in both training and validation accuracy, going from roughly 80% to above 95%, signifying efficient learning and little overfitting. Stable convergence and effective optimization with the chosen hyperparameters are confirmed by the model's loss plot, which shows a steady decrease in training and validation loss from 1.2 to less than 0.2, demonstrating reliable learning dynamics.

Trained model's diagnostic evaluation is displayed in Figure 14. For all four dementia classes, such as non-demented (0.9932), very mild demented (0.9921), mild demented (0.9911), and moderate demented (0.9952), the ROC curve shows high Area-Under-Curve (AUC) values, indicating excellent discrimination capabilities. Strong classification accuracy is further confirmed by the confusion matrix, which shows few misclassifications and the majority of samples accurately recognized in their respective categories.

The evaluation results of several DL architectures trained on the OASIS MRI dataset are illustrated in

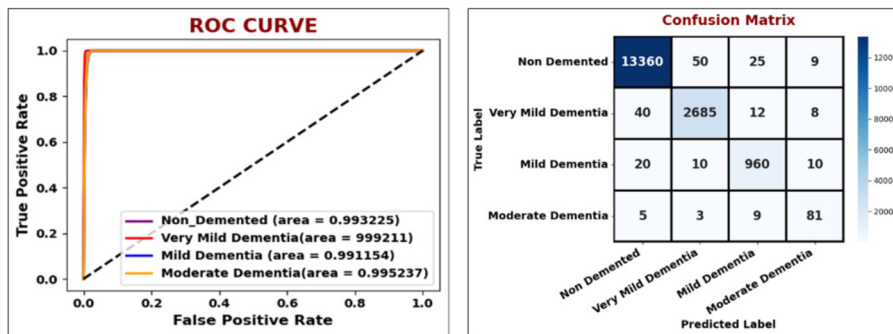


Fig.14: ROC Curve and Confusion Matrix.

Table 8: Comparative Performance of DL Models on AD Multi-class Dataset.

Model	Accuracy	Precision (Macro)	Recall (Macro)	F1-Score (Macro)	Specificity	Sensitivity	Balanced Accuracy	Cohen's Kappa
CNN	0.9562	0.9365	0.9218	0.9291	0.9782	0.9218	0.9500	0.901
VGG19	0.9711	0.9522	0.9435	0.9478	0.9856	0.9435	0.9645	0.929
DenseNet121	0.9824	0.9688	0.9597	0.9642	0.9921	0.9597	0.9759	0.954
InceptionV3	0.9845	0.9715	0.9628	0.9671	0.9934	0.9628	0.9781	0.958
Proposed Model	0.9901	0.9792	0.9656	0.9723	0.9967	0.9656	0.9812	0.971

Table 8. Proposed Channel-Attentive InceptionResNet model optimized with horned lizard optimization achieved 99.01% accuracy, 97.92% precision, 96.56% recall, 97.23% F1-score, 99.67% specificity, 96.56% sensitivity, 98.12% balanced accuracy, and a Cohen's Kappa of 0.971. When compared to CNN (95.62% accuracy), VGG19 (97.11% accuracy), DenseNet121 (98.24% accuracy), and InceptionV3 (98.45% accuracy), the proposed method demonstrates superior diagnostic robustness and dependability, underscoring its efficacy in early Alzheimer's detection.

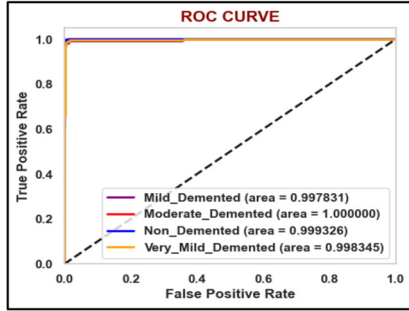


Fig.15: Comparison of accuracy.

Figure 15 shows the classification accuracy of different existing models with the proposed CA-InceptionResNet framework for diagnosing dementia. The models being compared are Parallel Recurrent Convolutional Neural Network (PRCNN) [27] with 85%, Random Forest (RF) [28] with 88.36%, XGBoost (XGB) [29] with 92%, Support Vector Machine (SVM) [30] with 93.50%, DEMentia NETwork [25] with 95.23% and the proposed CA-InceptionResNet exhibits a maximum accuracy of 98.98%. This performance gain results from the synergy between CA-InceptionResNet architecture, which excels at identifying intricate anatomical and textural features of dementia, and the HLO approach, which optimizes the model for classification tasks.

Table 9: Comparative Analysis of Performance Metrics.

Classifiers	Precision (%)	Recall (%)	F-Score (%)
RF [28]	66.01%	57.06%	61.21%
PRCNN [27]	85.9%	87.2%	86.6%
SVM [30]	80.0%	95.6%	81.9%
Proposed	99.12%	98.96%	99.04%

Table 9 illustrates the relative performance measures including precision, recall, and f-score, providing a holistic assessment of dementia classification models. Of the classifiers listed, the developed HLO-based CA-InceptionResNet model exhibits outstanding diagnostic performance, with 99.12% precision, 98.96% recall, and an F-score of 99.04%. Conventional approaches such as RF [28] exhibit poor performance, with a precision of 66.01% and recall of

57.06%, indicating high rates of misclassifications. Moderate performances are seen with deep learning algorithms like PRCNN [27] and SVM [30], with PRCNN demonstrating good precision and recall of 86% and SVM having high recall of 95.6% but less precise prediction (80%), where the model tends to over-predict positive cases.

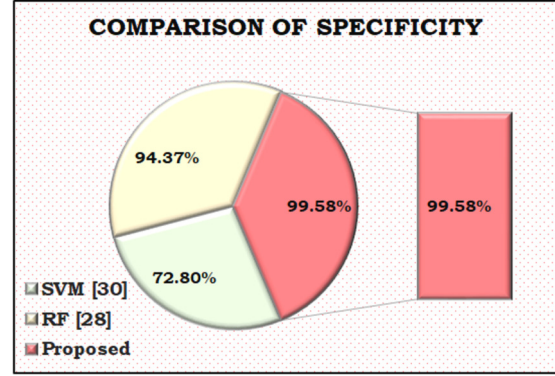


Fig.16: Comparison of specificity.

Figure 16 reveals the comparative analysis of the relative specificity attained by each model for dementia stage classification. The proposed approach achieves a leading specificity of 99.58% outperforming SVM [30] 94.37% and RF [28] 72.80%. This highlights the system's superior discriminative power in avoiding false positives during dementia diagnosis.

5. CONCLUSION

The proposed deep learning-based hybrid CA-Inception ResNet model, optimized using the horned lizard optimization algorithm and integrated with advanced techniques, significantly enhances dementia diagnostic precision. The spatially adaptive DoG filter improves image visibility in axial MRI scans, while anatomical features are accurately segmented using the HACR approach. Moreover, by employing texture analysis using polar coordinate GLCM, the extracted features become richer in their representation. The polar co-ordinate GLCM captures spatial patterns in a rotationally invariant manner, enabling improved detection and classification of dementia stages. Channel Attention InceptionResNet model classifies dementia stages effectively by utilizing both spatial attention mechanisms and deep hierarchical features that allow the model to locate areas of clinical significance within the brain and minute neuroanatomical differences across MRI scans in an axial orientation. Based on the performance metrics 98.98% accuracy, 99.12% precision, 98.96% recall, 99.04% F-score, and 99.58% specificity, model demonstrates excellent reliability in identifying subtle neuroanatomical changes across different dementia stages. Future research could explore ways of implementing this framework on longitudinal data sets, fusing multiple types of data and integrating it into

actual clinical practice to promote more thorough and proactive management of neurodegenerative diseases.

AUTHOR CONTRIBUTIONS

Conceptualization, Killamsetti Vijeta. and S. Sangeetha.; methodology, Killamsetti Vijeta.; validation, Killamsetti Vijeta, S. Sangeetha. V. Kavitha, Kanimozhi S, S. Dhanalakshmi and Dhanalakshmi.; data curation, Killamsetti Vijeta.; writing—original draft preparation, Killamsetti Vijeta.; writing—review and editing, S. Sangeetha. V. Kavitha, Kanimozhi S, and S. Dhanalakshmi.; supervision, Killamsetti Vijeta.; All authors have read and agreed to the published version of the manuscript.

References

- [1] U. Anwar, T. Arslan, A. Hussain, T. C. Russ and P. Lomax, "Design and Evaluation of Wearable Multimodal RF Sensing System for Vascular Dementia Detection," in *IEEE Transactions on Biomedical Circuits and Systems*, vol. 17, no. 5, pp. 928-940, Oct. 2023.
- [2] K. Aishwaryameenakshi, S. H. Banu, A. K. Priya, and S. Chitrakala, "Image Indexing using Edgel Index for Sketch-based Image Search and Retrieval," *International Journal of Wisdom Based Computing*, vol. 1, no. 3, pp. 134-138, 2011.
- [3] V. Jain, O. Nankar, D. J. Jerrish, S. Gite, S. Patil and K. Kotecha, "A Novel AI-Based System for Detection and Severity Prediction of Dementia Using MRI," in *IEEE Access*, vol. 9, pp. 154324-154346, 2021.
- [4] M. M. Hussain, D. Weslin, S. Kumari, S. Umamaheswari, and K. Kamalakannan, "Enhancing Parkinson's disease identification using ensemble classifier and data augmentation techniques in machine learning," *Clinical eHealth*, vol. 6, pp. 150-158, 2023.
- [5] J. Wei, B. Jiao, H. Lin, X. Tian, L. Shen, and J. Liu, "Multi-Scale Adaptive Graph Learning Based on Multi-Wave EEG Data for Dementia Diagnosis," *Big Data Mining and Analytics*, vol. 8, no. 5, pp. 1023-1043, 2025.
- [6] S. Hong, J. H. Park, W. Cho, H. Choe, and J. H. Cheon, "Secure tumor classification by shallow neural network using homomorphic encryption," *BMC Genomics*, vol. 23, no. 1, p. 284, 2022.
- [7] T. G. Devi, N. Patil, S. Rai, and C. S. Philipose, "Gaussian blurring technique for detecting and classifying acute lymphoblastic leukemia cancer cells from microscopic biopsy images," *Life*, vol. 13, no. 2, p. 348, 2023.
- [8] M. S. Priyadharsini and J. G. R. Sathiaselan, "The new robust adaptive median filter for denoising cancer images using image processing techniques," *Indian Journal of Science and Technology*, vol. 16, no. 35, pp. 2813-2821, 2023.
- [9] O. Ali, H. Ali, S. A. A. Shah and A. Shahzad, "Implementation of a Modified U-Net for Medical Image Segmentation on Edge Devices," in *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 69, no. 11, pp. 4593-4597, Nov. 2022.
- [10] Y. Du, H. Yuan, K. Jia, and F. Li, "Research on threshold segmentation method of two-dimensional Otsu image based on improved sparrow search algorithm," in *IEEE Access*, vol. 11, pp. 70459-70469, 2023.
- [11] I. Hussain and J. Muhammad, "Efficient convex region-based segmentation for noising and inhomogeneous patterns," *Inverse Problems and Imaging*, vol. 17, no. 3, pp. 708-725, 2023.
- [12] S. M. Jihad, A. Aalsaud, F. H. Almukhtar, S. Kareem, and R. Z. Yousif, "Investigating feature extraction by SIFT methods for prostate cancer early detection," *Egyptian Informatics Journal*, vol. 29, p. 100607, 2025.
- [13] M. Gül, "A novel local binary patterns-based approach and proposed CNN model to diagnose breast cancer by analyzing histopathology images," in *IEEE Access*, vol. 13, pp. 165688-165703, 2025.
- [14] A. Sharma, S. Kaur, N. Memon, A. J. Fathima, S. Ray, and M. W. Bhatt, "Alzheimer's patients detection using support vector machine (SVM) with quantitative analysis," *Neuroscience Informatics*, vol. 1, no. 3, p. 100012, 2021.
- [15] S. J. Ben, M. Dörner, M. P. Günther, R. von Känel, and S. Euler, "Proof of concept: Predicting distress in cancer patients using back propagation neural network (BPNN)," *Heliyon*, vol. 9, no. 8, p. e18648, 2023.
- [16] A. Hashmi and O. Barukab, "Dementia classification using deep reinforcement learning for early diagnosis," *Applied Sciences*, vol. 13, no. 3, p. 1464, 2023.
- [17] W. Al Shehri, "Alzheimer's disease diagnosis and classification using deep learning techniques," *PeerJ Computer Science*, vol. 8, p. e1177, 2022.
- [18] H. Tufail, A. Ahad, M. H. Naqvi, R. Maqsood, and I. M. Pires, "Classification of vascular dementia on magnetic resonance imaging using deep learning architectures," *Intelligent Systems with Applications*, vol. 22, p. 200388, 2024.
- [19] M. R. Kumar, S. Vekkot, S. Lalitha, D. Gupta, V. J. Govindraj, K. Shaikat, Y. A. Alotaibi, and M. Zakariah, "Dementia detection from speech using machine learning and deep learning architectures," *Sensors*, vol. 22, no. 23, p. 9311, 2022.
- [20] A. Marab and A. Bhadrashetty, "A novel approach using deep convolutional neural networks for automated dementia detection and classification," *Edraak*, vol. 2023, pp. 16-20, 2023.

- [21] A. A. Soladoye, N. Aderinto, B. A. Omodunbi, A. O. Esan, I. A. Adeyanju, and D. B. Olawade, "Applications of artificial intelligence in dementia diagnosis and management: A systematic review," *Current Research in Translational Medicine*, vol. 72, no. 4, p. 103460, 2024.
- [22] C. James, J. M. Ranson, R. Everson, and D. J. Llewellyn, "Performance of machine learning algorithms for predicting progression to dementia in memory clinic patients," *JAMA Network Open*, vol. 4, no. 12, p. e2136553, 2021.
- [23] S. Bharati, P. Podder, D. N. H. Thanh, and V. S. Prasath, "Dementia classification using MR imaging and clinical data with voting based machine learning models," *Multimedia Tools and Applications*, vol. 81, no. 18, pp. 25971–25992, 2022.
- [24] S. Murugan, C. Venkatesan, M. G. Sumithra, X. Z. Gao, B. Elakkiya, M. Akila, and S. Manoharan, "DEMNET: A deep learning model for early diagnosis of Alzheimer diseases and dementia from MR images," in *IEEE Access*, vol. 9, pp. 90319–90329, 2021.
- [25] F. M. Talaat and M. R. Ibraheem, "Dementia diagnosis in young adults: A machine learning and optimization approach," *Neural Computing and Applications*, vol. 36, no. 34, pp. 21451–21464, 2024.
- [26] G. Anuradha, H. Davu, and M. Karri, "Genetic algorithm-based decision tree optimization for detection of dementia through MRI analysis," *Informatyka, Automatyka, Pomiar w Gospodarce i Ochronie Środowiska*, vol. 14, no. 1, pp. 83–89, 2024.
- [27] H. Wang, L. Sheng, S. Xu, Y. Jin, X. Jin, S. Qiao, Q. Chen, W. Xing, Z. Zhao, J. Yan, and G. Mao, "Develop a diagnostic tool for dementia using machine learning and non-imaging features," *Frontiers in Aging Neuroscience*, vol. 14, p. 945274, 2022.
- [28] E. Cho, S. Kim, S. J. Heo, J. Shin, S. Hwang, E. Kwon, S. Lee, S. Kim, and B. Kang, "Machine learning-based predictive models for the occurrence of behavioral and psychological symptoms of dementia: Model development and validation," *Scientific Reports*, vol. 13, no. 1, p. 8073, 2023.



Killamsetti Vijeta completed M.Tech (Master of Technology) in Computer Science Engineering with specialization of Artificial Intelligence at Medicaps University - Indore. I have pursued B.Tech (Bachelor of Technology) in Electrical and Electronics Engineering at Aditya Institute of Technology and Management -Tekkali, Srikakulam, under JNTU Hyderabad. I have more than thirteen years of full-time teaching experience after my post-graduation degree. I have published five

research papers in International Journals indexed in Scopus. I have published papers at various National and International Conferences. My main interests are Artificial Intelligence, Data Science, Machine learning and its applications in Electric Vehicles. <https://orcid.org/0000-0002-7925-5596>



S. Sangeetha is an Assistant Professor in the Department of Information Technology at Vel Tech Multi Tech Dr. Rangarajan Dr. Sakunthala Engineering College, Avadi. She is committed to excellence in engineering education and is dedicated to fostering technical knowledge, critical thinking, and innovation among students. She obtained master's degree in communication software and networks in Nanyang Technological University, Singapore (2012) and UG B.Tech (IT) in Adhiparasakthi Engineering College in 2006. Her Research interest in deep learning, machine learning, Artificial Intelligence. As a faculty member, Ms. Sangeetha strives to create an interactive learning environment that bridges theoretical concepts with real-world applications. She remains committed to lifelong learning, professional development, and contributing to the growth of the academic community. <https://orcid.org/0009-0003-4235-9118>



V. Kavitha is pursuing a full-time Ph.D from IIIT, Trichy. I have pursued an M.E (Master of Engineering) in VLSI DESIGN at the College of Engineering, Guindy, under Anna University, Chennai. I have pursued B.E (Bachelor of Engineering) in Electronics and Communication Engineering at Hindusthan College of Engineering and Technology, under Anna University. I have more than five years of full-time teaching experience after my post-graduation degree and three years of industry (software) experience after graduation. I have published five research papers in International Journals indexed in SCI and Scopus. I have published papers at various National and International Conferences. My main interests are Digital and Analog VLSI, Signal Processing, and Wireless Communication. <https://orcid.org/0009-0009-4970-3333>



S. Kanimozhi received her Bachelor's degree in Electronics and Communication Engineering in 2013 from Anna University and obtained her Masters of Engineering M.E in Anna University, Coimbatore Campus and pursuing her Doctor of Philosophy in Machine Learning in Dr. MGR Educational and Research Institute, Chennai. She is a member of IEEE and National society of Professional Engineers. She is a full time

Assistant Professor in Arunai Engineering college, An Autonomous Institute, Tiruvannamalai. Her research interests includes Energy Conversion systems, AI and Machine Learning.



S. Dhanalakshmi is an Assistant Professor (Level III) in the Electronics and Communication Engineering Department at Bannari Amman Institute of Technology, Sathyamangalam, Erode. She obtained her undergraduate degree in Electronics and Communication Engineering from P.G.P College of Engineering and Technology, Namakkal, and her M.E. degree in Applied Electronics from K.S.R College of Technology, Tiruchengode, Namakkal. Currently, she is pursuing her Ph.D. from Anna University. With 19 years of teaching experience, her research interests include Low Power VLSI, Image Processing, and Signal Processing. She is a life member of ISTE and has published papers at both national and international levels. <https://orcid.org/0009-0004-2291-7431>



M. J. D. Ebinezer is an Assistant Professor at K L Deemed to be University, Vaddeswaram, with over 10 years of experience in academia and software development. His research focuses on Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Explainable AI (XAI), Internet of Things (IoT), Cybersecurity, Medical Image Analysis, Healthcare Analytics, and Smart Systems. He has published 11 research papers, including 4 SCI-indexed publications, with 2 papers in Q1 journals and several articles in reputed Scopus-indexed journals. His work emphasizes developing intelligent, data-driven solutions for real-world challenges in healthcare, agriculture, cybersecurity, environmental monitoring, and smart energy systems. His current research interests include fraud detection using deep learning, explainable artificial intelligence, predictive analytics, synthetic data generation, medical image processing, IoMT (Internet of Medical Things), reinforcement learning, and secure AI-enabled systems. He actively collaborates on interdisciplinary research and is committed to advancing innovative AI methodologies that improve decision-making, enhance security, and support sustainable technological development. His contributions have been published in leading journals such as Scientific Reports (Nature Portfolio), Computers Security (Elsevier), Applied Sciences (MDPI), and other internationally recognized journals, reflecting his dedication to high-impact research and academic excellence. <https://orcid.org/0009-0005-1147-2040>