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Deep Learning with Feature Extraction for Alzhemier's Disease Classification by Using MRI Images

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ABSTRACT: Alzhemier's Disease (AD) is a chronic, progressive, and neurodegenerative brain disorder that damages the thinking skills, cognitive function. Conventional methods does not provide the accurate classification of AD. This research proposed the DenseNet 121 with Global Attention Module (GAM) for classifying the AD by using MRI images. The Non-Local Mean (NLM) filter is employ to pre-processing the MRI image to denoising and enhance the image quality. Then, the Adaptive Mean Thresholding (AMT) is provide for segmenting the relevant brain regions in image. The Grey Level Co-Occurrence Matrix approach (GLCM) offers to quantify textural information from the MRI images. The dataset named alzheimer's disease multiclass images dataset is used which is available in kaggle. Finally, Attention DenseNet121 is proposed that provides the high-precise classification of AD. Using Python software, the proposed Attention DenseNet121 achieved a higher uniform value of 99.58% across the accuracy, precision, recall and F1-Score which is highly efficient compared to the existing method.

Keywords: Alzhemier's Disease (AD), Magnetic Resonance Imaging (MRI) images, Attention DenseNet 121, Python, Non-Local Mean (NLM) filter.

1. Introduction

As the growing neurological condition, AD leads to loss in memory, changes in personality, and delusional ideas. These changes are often misidentified as normal aging or stress-based fatigue. In US, 5.1 million people are affected by the AD disease due to improper medical treatment [1]. The toxic clumps and pets in the brain, which damage the nerve cells. The early sign of AD is memorial issues such as trouble in word searching and the thought system, and damage the hippocampus [2]. Alzheimer's is a global crisis with new identification of new AD case in every 3 seconds, affecting 50 million people. Hence, it is crucial to early intervention and prediction at the correct time, the brain is not harm to the great extent [3].

Image pre-processing is the crucial step for the accurate classification of disease images. To enhance the accurate diagnosis in the medical field, denoising and image quality is important [4]. Adaptive filter is the prevalent image pre-processing technique, and it is used for noise elimination to enhance the damage image features by reducing the noise. However, adaptive filter techniques for image pre-processing include high computational complexity and cost [5]. At image filtration stage, the median filter is employed to denoise, and to detect the features. Although, the image filtering have blur the crucial information and it creates the unwanted artifacts [6]. The process of normalization is scaling the each pixel in the image from a specific range (0 to 255) to a value between 0 and 1. Nevertheless, the image normalization reduces the image clarity and erase the important information [7]. To overcome these limitations, this study proposes the NLM filter technique, it scan the entire image for similar patterns to remove noise and this technique remains edges and compact, never miss the important details, and make image clear, whereas conventional filter tend to make them blurry. To segment the relevant brain regions, the subsequent image segmentation process is necessary to segment the relevant brain areas accurately.

The image segmentation is the process of segments the images into non-overlapping groups. Otsu's technique is the important image segmentation based on the image thresholding and this method shows effective for only when the image histogram has bimodal distribution, this model underperforms in noisy image, low contrast, non-uniform image, especially when predicting small objects or when classes overlap significantly [8]. Watershed algorithm is a transformation which is applicable for grayscale image. By calculating the distance transform in which individual pixel indicates the distance to the neighbourhood background pixel, water algorithm isolates objects depends on these computed distance. Although, it is highly sensitive to noise and over-segmentation, often creating too many segments [9]. To maximize the sum of entropies for segmented regions, Kapur's method enhances multilevel thresholding to keep more information, applies the normalized grayscale histogram to compute probability distribution. Nevertheless, this method does not provide the higher accuracy in complex scenarios [10]. To fix these issues in medical imaging, this adaptive mean thresholding technique enable which segments brain tissue including GM, WM and CSF accurately even if the MRI scan have non-uniform intensity that may cause global thresholding to fail. To extract the particular image patterns and spatial relationship to detect the AD in MRI image, the feature extraction is needed.

By extracting the relevant patterns, it reduces computational complex and enhance the accurate classification of AD. Malu et al [11] proposes the Fractal Dimension (FD) and statistical feature extraction techniques for vertically symmetrical images and it is extract the structural boundary qualities. Nevertheless, FD calculation, particularly with techniques such as box counting, which is most sensitive to noise in the data. The LBP has inexpedience as a highly effective local feature descriptor, especially in the image recognition context. Nonetheless, the LBP missed the global texture information and highly sensitivity to noise in the data. The Boundary Intersection-Based Signature (BIBS) analyse shape boundaries to characterize complex geometrics, designed to focus the concave contours, identify multiple intersection points. Nonetheless, when transform the high dimensional data into a smaller, there is possible to losing the important information [13]. To addresses these limitation, this work proposes the GLCM based feature extraction which captures the statistical information regarding the spatial relationship and dependencies between pixel intensities which allows extract the high discriminative features that detect any changes in brain tissue. The precise AD classification is significant for enabling early, precise diagnosis which slows disease progression and enhance lifetime. The few techniques are reviewed in following section.

1.1 Related Works

Zhou et al (2023) [14] have developed the Graph Neural Network (GNN) models based polygenic risk analysis for forecasting the AD. Linear regression analysis utilized to investigate the relation between DL-based AD polygenic risk and AD endophenotypes. However, GNN model analyse genetic variants rather than considering epistatic interactions, fail to estimate individual's disease risk accurately.

Li et al (2023) [15] examine the Linear Regression (LR) and Gradient Boosted Tree (GBT) methods for AD prediction and Related Dementias (ADRD) using the real-world EHR. The GBT models trained with data-driven technique achieves the high AUC score for early prediction of ADRD and identify the clinical and socio-demographic factors. Nonetheless, this research does not address the advanced analytical methods required to handle the inherent challenges of real-world EHR data.

Zuo et al (2023) [16] have proposed Cross-model Transformer Generative Adversial Network (CT-GAN) for AD prediction to integrate the Functional Magnetic Resonance Imaging (fMRI) and Diffusion Tensor Imaging (DTI). The model operates as combined, end-to-end framework that extracts topological feature and creates the multimodal imaging data from the original imaging data. Although, the proposed method does not provide an evaluation and analysis of other neurodegenerative disease.

Gao et al (2023) [17] have developed the hybrid Shapley Additive explanation (SHAP) and eXtreme Gradient Boosting (XGBoost) techniques which leverages the combination of polygenic risk score and HER provides the strong framework for improving the early prediction of AD. By integrating the weighted XGBoost with SHAP based feature ranking to provide balance model training and transparent insights into predictive factors. Nevertheless, the proposed model have emergent behaviours, and feature importance does not completely reveal the complex biological pathways included.

Nandiraju et al (2022) [18] have proposed the Convolutional Neural Network (CNN) for early prediction of AD in healthcare. Instead of 2D kernels, this study utilize the 3D convolution kernels which capture the complex spatial relationships across multiple layers, enabling more comprehensive feature extraction from the volumetric data. Nonetheless, the proposed model lacks in clear interpretability for clinical decision-making.

Parameswari et al (2022) [19] have presented the thermal analysis for ad prediction by using Random Forest Classifier (RFC). To address classification tasks, this work implements the RFC, supervised learning method that enhance the predictive efficiency by integrating decision trees while automatically handling data gaps, outliers, and feature reduction. Nevertheless, this research focus only computer data to forecast early Alzheimer's disease, but it lacks to check physical signs like skin temperature.

Aqeel et al (2022) [20] have proposed the Long Short Term Memory (LSTM) for forecasting the biomarkers of AD patients. To forecast the long-term Alzheimer's progress, this study developed an LSTM-based architecture that uses baseline NM and MRI features vectors from patient to predict drastic changes in biomarkers at month intervals. However, this study uses the two-step AI process where errors might increase over time.

1.2 Research Gap

The major issue for using the ML model in medical research is the lack of model interpretability. Inspite of using the application of Explainable Artificial Intelligence (XAI) techniques including SHAP, Grad-CAM AI model often fail to show the complex biological pathways included in AD. The noisy and incomplete patient data poses a critical issue to training strong, high performance disease prediction models. While RL algorithm shown promise across different fields, and its direct application to AD diagnosis is limited.

1.3 Objectives

To overcome above limitations, this work proposes the following objectives which is given below;

- To preprocess MRI brain scan data by using NLM filter to enhance image quality.
- To segment the pertinent brain regions by using Adaptive mean Thresholding, segments the brain areas from the MRI image by adjusts threshold based on neighborhood intensity.
- To extract the specific image texture patterns from images by using GLCM to assist the model to make accurate classification of AD
- To implement an attention denseNet 121 architecture for experimental analysis and high accurate AD classification.

2. Proposed System

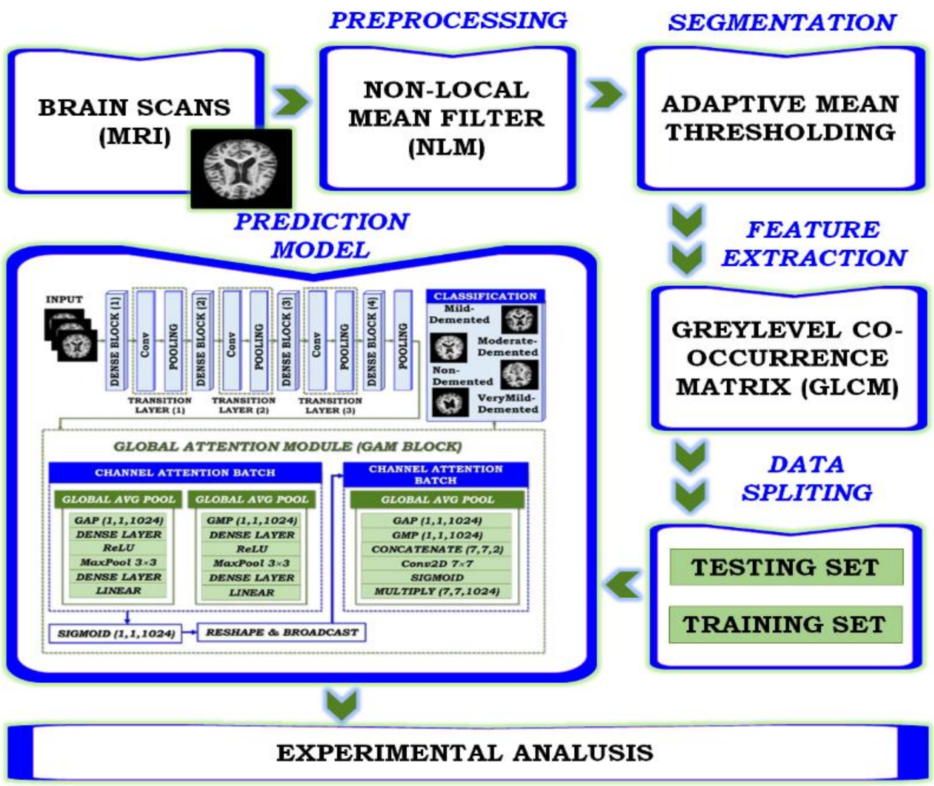

Figure 1: *Block diagram of proposed system*

Figure 1 illustrates the proposed model, automated system to analyse MRI brain scan for classifying the AD. The first stages is pre-processed the MRI brain scan data by using the NLM Filter for noise reduction and improve the image quality. Subsequently, adaptive mean thresholding is employed to segment and isolate relevant brain regions. The processed data is splitted into two sets: training and testing sets to prepare for model training. Furthermore, feature extraction is performed by using the GLCM technique to quantify textural information from the MRI images. The extracted features are serves as input to an Attention DenseNet 121 model to generate AD classification. In the final stage, this study analyze the performance of Attention Dense Net 121, using generated results to determine the accurate classification of AD.

3. Proposed System Modelling

3.1 Data Preprocessing by Non-Loal Mean Filter

NLM is a prevalent method for denoising and enhance the image quality in MRI images. It operates on the principle of image redundancy, handling patches with similar patterns as having identical pixel information. This method accepts structural redundancy, treats same image patches as having identical pixel intensity. NLM reduces image noise while preserving structural details by calculating the weighted average of pixel intensity depends on similarity between the reference patch and nearest patch.

For the MRI image measures the $N_x \times N_y \times N_z$ in the NLM filter which estimates the specific voxel intensity(x, y, z) and this estimated density is represented as $NLM\ (|i|(x, y, z))$ is computed as weighted average of intensities of all voxel presented in the input image $|i|$ which is defined as in eqn (1)

$$NLM\left(|i|(x,y,z)\right) = \sum_{l=0}^{N_a-1} \sum_{m=0}^{N_b-1} \sum_{n=0}^{N_c-1} w(x,y,z,l,m,n)|i|(l,m,n) \quad (1)$$

Here, $NLM\left(|i|(x,y,z)\right)$ represents as the denoised image intensity at the position (x, y), $|z|(l, m, n)$ denotes the original denoised image intensity at position (l, m, n) which provides the final denoised value, $w(x, y, z, l, m, n)$ is the weighted coefficient is mathematically computed as in eqn (2)

$$w(x,y,z,l,m,n) = \frac{1}{I(x,y,z)} e^{\frac{G_a \||i|(N_{x,y,z}) - |i|(N_{l,m,n})\|^2}{h^2}} \quad (2)$$

Where, h is the filtering degree. $N_{x,y,z}$ and $N_{l,m,n}$ indicates the blocks centered at voxel (x, y, z) and (l, m, n) with measuring blocks $n_a \times n_b \times n_c$, G_a is a Gaussian weighting function with zero deviation. $I(x, y, z)$ represent normalized constant is defined as in eqn (3)

$$I(x,y,z) = \sum_{l=0}^{N_a-1} \sum_{m=0}^{N_b-1} \sum_{n=0}^{N_c-1} e^{\frac{G_a |i|(N_{x,y,z}) - |i|(N_{l,m,n})^2}{h^2}} \quad (3)$$

The output of the NLM filter remove the noise from MRI images, which prevents the important key feature by using weighted average depends on patch similarity. But the pre-processed MRI image lacks continuous tone values, subsequent process is essential to detach the particular features from the MRI image to improve classification progression. Hence, Adaptive mean thresholding is required to segment and separate the relevant brain regions.

3.2 Adaptive Mean Thresholding

Furthermore, the pre-processed MRI images passed through the adaptive mean thresholding, which adjusts the threshold depends on the local pixel intensity of various regions. Effective thresholding assigns that foreground object have pixel intensity compared to background. This technique adjusts the threshold value T dynamically depend images progressively several different function characteristics. This technique uses spatially dependent threshold $(T(x, y))$ that has been refined for enhanced performance. The overview of the adaptive thresholding framework is given below:

- Applying the threshold T to converts the image to binary.
- Thin the threshold image
- Eliminate all intersection points from thinned image
- All pending endpoints are queued for analysis and will initiate the tracking process.
- Segment the region based on threshold T
- If the region has passed, T = T − 1, go to 5

The adaptive thresholding algorithm uses the NLM filter is applied for denoising and enhance the image quality while preventing structural integrity. The traditional local filter like symmetrical 2D Gaussian smoothing, median, the NLM algorithm influences the redundancy in image by calculating an average weight of pixels with similar neighbourhood patches through a broader search window. For adaptive thresholding, let $fs(n)$ indicates the sum of the s pixel value at point 'n'. $T(n)$ is a binary value, detecting pixel that are at least t percent darker than the moving average of the preceding s pixels. The mathematical expression is shown in eqn (4)

$$g(x,y) = \begin{cases} 1, & if P_n < \left(\frac{f_s(n)}{s}\right)\left(\frac{100-t}{100}\right) \\ 0, & otherwise \end{cases} \quad (4)$$

This technique is effectively segment and separates the relevant brains region from the MRI image. To analyse the image texture and spatial relation qualification, the Grey Level Co-Occurrence Matrix is required.

3.3 Grey Level Co-Occurance Matrix

After the segmentation, the GLCM proposed to evaluate MRI image texture through the spatial pixel relationships. The first order texture measurements employs statistical calculation depends on each pixel intensity, does not concern the spatial dependencies or relations between neighbouring pixels. Secondly, the inter-relationship of the initial pixel pairs is taken into the process. GLCM is mathematically expressed in eqn. (5)

$$GLCM_{\vec{r}}(x,y) = \left|I(a_x,b_y), I(a_x,b_y)\right|\vec{r} = \sqrt{(a_y-a_x)^2 + (b_y-b_x)^2}, \quad x,y \in N \quad (5)$$
$$where\ 0 \le I(a,b) \le 225$$

In this work, GCLM analysis is operated using 4 primary orientation angles such as 0, 45, 90 and 135 degree to capture the spatial relationships in multiple directions. Contrast measures the intensity variations between nearest pixel; it assumes as an indicator of how quickly pixel values change, with superior values indicating more defined textures which is computed in the eqn. (6)

$$Contrast = \sum_{n=1}^{L} n^2 \left\{\sum_{|i-j|=n} GLCM(x,y)\right\} \quad (6)$$

Correlation quantifies the linear relationship between nearest pixel intensity in the image. It is expressed in eqn. (7)

$$Correlation = \frac{\sum_{x=1}^{L}\sum_{y=1}^{L}(x-\mu_x')(y-\mu_y')(GLCM(x,y))}{\sqrt{\sigma_x^2\sigma_y^2}} \quad 7)$$

In GLCM analysis, energy is utilize to measure uniformity, highlighting the pixel intensity densely concentrate within the matrix. It is mathematically expressed in eqn. (8)

$$Energy = \sum_{x=1}^{L}\sum_{y=1}^{L}(GLCM(x,y)^2) \quad (8)$$

Homogeneity values are determined as the inverse of contrast values derived from eqn. (9)

$$Homogenity = \sum_{x=1}^{L}\sum_{y=1}^{L}\frac{GLCM(x,y)}{1+(x-y)^2} \quad (9)$$

GLCM technique is effectively extract the particular texture pattern from the MRI image. For enhance and accurate classification of AD, the Attention DenseNet 121 is required.

3.4 Attention Densenet 121

This study employs a Dense Convolutional Network (DenseNet) contains 121 layers to classify the Alzhemier disease. In a DenseNet architecture, layer are linked with dense block, which is that individual layer uses input from all last layers in order to generate the feature map that feed up into all following layers. Thus, the n^{th} layer get all previous feature maps $(x_0, x_1, \dots \dots \dots x_{n-1})$ as inputs. The mathematical expression is shown in below eqn. (10)

$$x_n = F_n([x_0, x_1, \dots \dots \dots x_{n-1}]) \quad (10)$$

Here, $[x_0, x_1, \dots \dots \dots x_{n-1}]$ indicates the concatenation of all preceding feature maps of n^{th} layer. x_n denotes output of the n^{th} layer. The n^{th} layer, represented byF_n, is a composition function of three successive operation involving ReLU activation function, batch normalization, and convolution. By leveraging feature reuse, DenseNet addresses gradient degradation which reduces the number of parameter count.

DenseNet-121 uses four dense blocks. These dense blocks are connected by transition layer that employs down sampling on the feature map to generate the 1x1 convolution and 2x2 average pooling layer. Dense blocks contains numerous convolutional layers that are linked in series and serve ad cross-layer connections between distant layers. DenseNet 121 employs ReLU layers to capture complex, enhance the non-linearity relationships within data. The mathematically representation of proposed ReLU activation is shown in eqn (11)

$$ReLU(x) = \max(0,x) \quad (11)$$

Global Attention Module (GAM) is integrated into the DenseNet121 to improve discrimination of predicting and classifying the AD. The module is composed of two primary sub-module, namely Channel Attention (CA) and Spatial Attention (SA).To adjust channel significant, CA module uses the integrated global average (GAP) and maximum pooling (GMP) to summarize spatial information, followed by applying the MLP and sigmoid activation. A channel attention map (M_c) applied to F', whereas, the SA module focus to capture the prevalent spatial features. It creates a spatial attention map (M_s), concentrating channel wise average and maximum projections, and followed by 7x7 convolution and sigmoid activation. This final map is applied to F' to produce the final attention enhanced output F'' is defined as in eqn (12) and (13)

$$F' = F \cdot M_c \tag{12}$$

$$F'' = F' \cdot M_s \tag{13}$$

The output comprises feature refined both channel and spatial module, improving the performance of DenseNet121 which focus the diagnostically relevant areas and textures for subsequent layers of the model for classification.

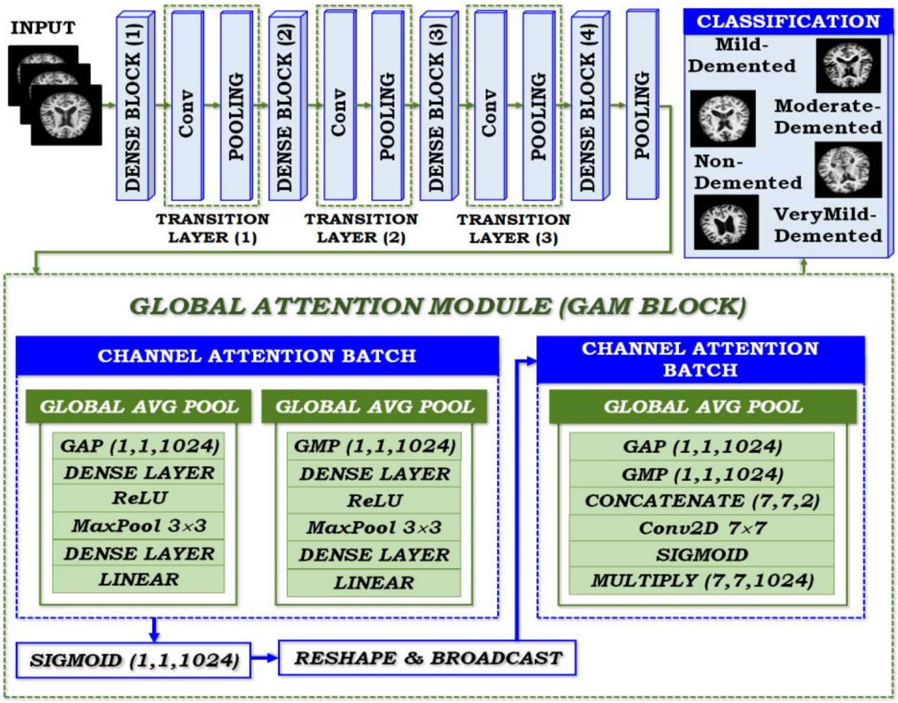

Figure 2: *Proposed model architecture*

Subsequently, feature extraction and improvement across the backbone of DenseNet121 and GAM, which results attention refined feature maps $F'' \in \mathbb{R}^{w\times h\times c}$ travelling through a classification layer to generate the final prediction for AD classification. This phase transforms high-dimensional, spatial feature maps into the smaller, class representative vector for final classification via softmax activation. GAP is the first phase in the classification layer, which minimizes the spatial dimension $h \times w$ of the feature map by calculating the individual channel. It is mathematically represented in (14)

$$i_c = \frac{1}{h\times w}\sum_{a=1}^{h}\sum_{b=1}^{w} F''(a,b,c), \quad \forall c \in \{1, \dots\dots, C\} \tag{14}$$

i_c indicates the pooled value for the channel c, the output is 1D feature vector . Therefore, the classification layer is compact, straightforward transformation procedure into class prediction of the high-dimensional attention aware features. The attention-based DenseNet features is highly precise the AD classification in very complicated MRI images.

4. Result and Discussion

This part describes the experimental outcome for Attention DenseNet 121 model for classifying the AD. The images used in this result section is taken from the AD multi class images dataset. The result is implemented by python software.

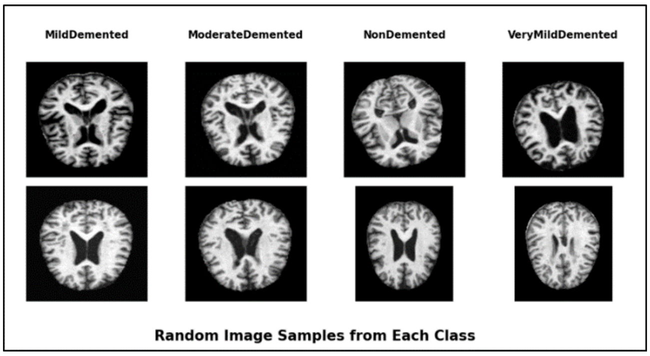

Figure 3: *Random Image Sample*

Figure 3 shows the random image sample of brain MRI scan which consists of 4 classes. The non-demented indicates no dementia. The very mild demented indicates the early sign of dementia, which means very mild symptoms. The mild demented denotes the clear sign of dementia, but still mild. moderated demented is moderate symptoms of severity of dementia. This images are randomly chosen from the dataset. This image illustrates the stages of AD progression.

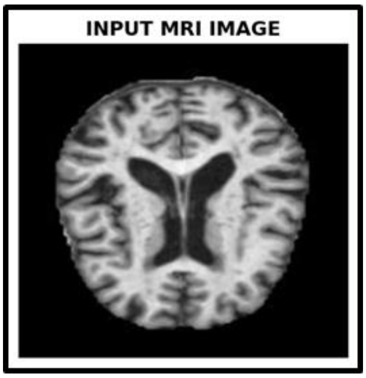

Figure 4: *Input image*

Figure 4 displays the input MRI scan image and this image is taken from the Alzheimer disease Multi class images dataset. The image is a sample from a dataset, often categorized into stages like non-demented or moderately demented. This MRI image used as input image for enhance the classification of AD diagnosis.

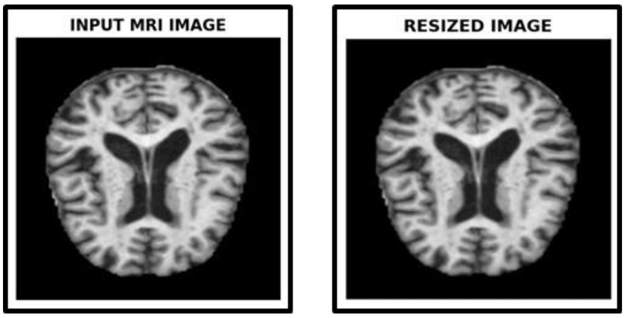

Figure 5: *Conversion of Input image to Resized image*

Figure 5 shows the conversion of an input MRI image into the resized image. The input image is transfer through the image resizing to normalize its dimensions to a fixed size. This conversion makes to enhance the AD classification.

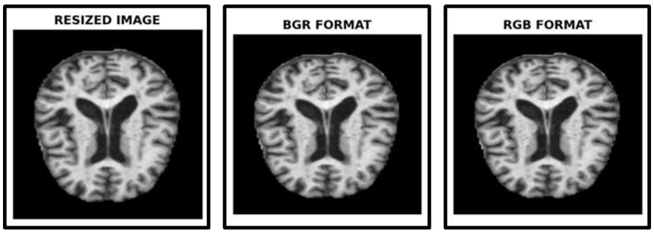

Figure 6: *MRI scan in Resized image, BGR format and RGB format*

Figure 6 demonstrates the various phases of processing the one MRI brain image. The conversion of resize image into the Blue Green Red (BGR) format and Red Green Blue (RGB) format.

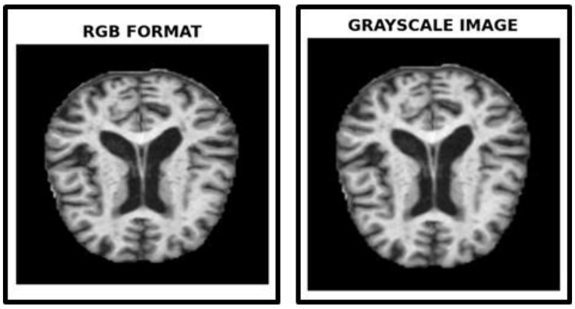

Figure 7: *Resized image to grayscale image*

The figure 7 conversion of resized brain image scan is processed into the grayscale image. By converting to grayscale image is transfer the color channel into one intensity channel which calculates the red, green, and blue values of individual pixel. This makes drastically decreases computational complex, enabling the Attention DenseNet 121 model to processing the crucial features effectively for AD classification.

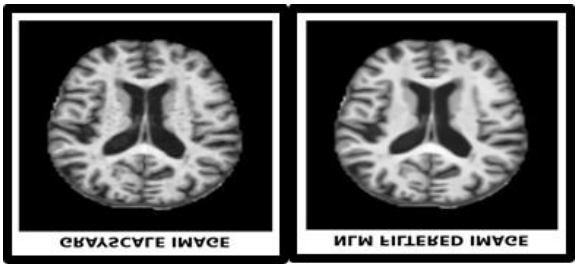

Figure 8: *Grayscale image to NLM filtered image*

This figure 8 illustrates the conversion of grayscale image and the NLM filtered image of the MRI brain scan. It improve the image quality and reduces the noise, while preserving the important edge information.

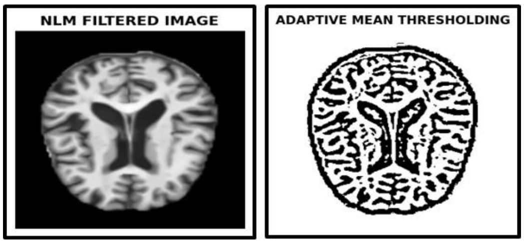

Figure 9: *NLM filtered image to Adaptive Mean Thresholding*

Figure 9 demonstrates the NLM filter reduces the noise in the MRI image while protecting the brain structure. Then, the Adaptive Mean Thresholding generates the binary image, which highlights the important feature of the MRI image. The improved is fed into the Attention DensNet 121 model, and the attention mechanism focus on complex disease areas for classifying the AD.

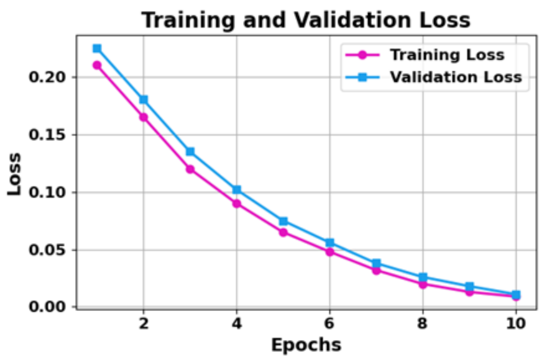

Figure 10: *Learning Curve Loss*

Figure 10 depicts the learning curve loss of the Attention DenseNet 121 method over 10 epochs. The both lossses decrease drastically, starts from the 0.20 and ends to 0.00, that indicates succeed model training and convergence with minimum overfitting.

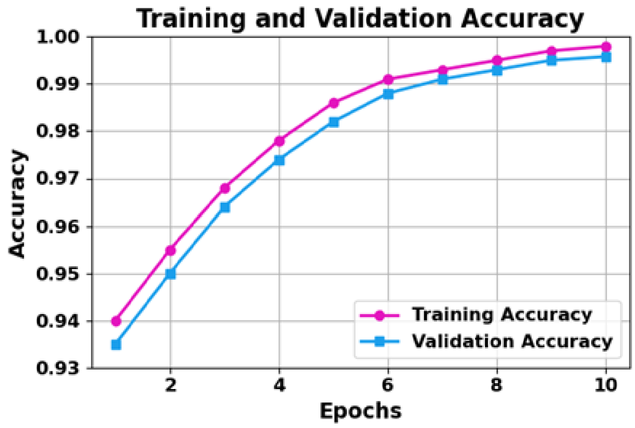

Figure 11: *Learning Curve Accuracy*

The learning curve accuracy of Attention DenseNet121 method for Alzheimer disease classification across ten epochs illustrates as figure 11. The Model Accuracy graph achieves increasing accuracy of 99.5 %, which the model achieves superior performance and minimal over fitting, and strong generalization for classification task.

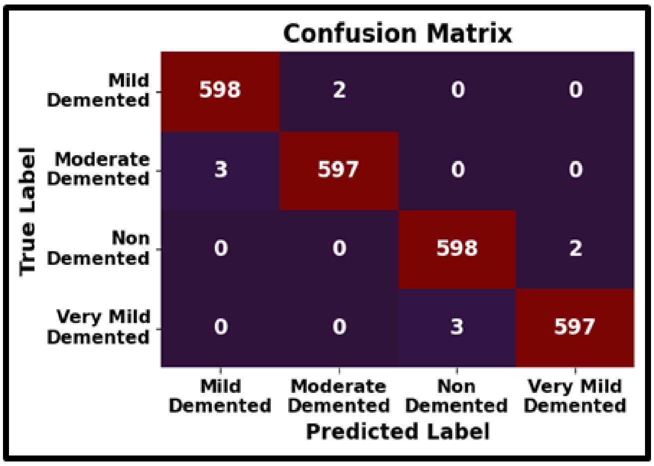

Figure 12: *Confusion Matrix*

Figure 12 shows the classification matrix comprises a true label and predicted label outcome is utilized to evaluate the Attention DenseNet 121 model performance of AD classification. The model shows that 598 mild demented cases, 597 moderate demented cases, 598 non demented cases and, 597 very mild demented cases have correctly identified. It provides the good diagonal values which represent superior accuracy and reduction of misclassification across all classes.

4.1 Performance Metrics

Table 1: *Evaluation metrics*

Metrics	Value
Accuracy	99.58 %
Precision	99.58 %
Recall	99.58 %
F1-Score	99.58 %
Specificity	99.58 %
Error Rate	0.42%
False Positive Rate	0.42%
False Negative Rate	0.42%
Balance accuracy	99.58 %
Matthews Correlation Co-efficient	0.99
Cohen's Kappa Score	0.99

Table 1 illustartes the inclusive evaluation of high classification model performance. The models performs with uniform 99.58% across accuracy, precision, recall, and F1-Score. A Matthews Correlation Coefficient and Kappa Score achieves 0.99, which shows the robust reliability and consistency.Overall, the Attention DenseNet121 achieves the 99.58% accuracy, and a minimal 0.42% error rate, the system have high predictive capacity and balance classification across all evaluation metrics.

4.2 Classification Report

Table 2: *Performance metrics for AD classification*

Class/ metrics	Precision	Recall	F1-Score	Support
Mild Demented	0.9950	0.9967	0.9958	600
Moderate Demented	0.9967	0.9950	0.9958	600
Non Demented	0.9950	0.9967	0.9958	600
Very Mild Demented	0.9967	0.9950	0.9958	600
Accuracy			0.9958	2400
Macro avg	0.9958	0.9958	0.9958	2400
Weighted Avg	0.9958	0.9958	0.9958	2400

Table 2 demonstrates the classification reports demonstrates the model achieves the 99.58% accuracy across 2400 samples. The model performs with uniform value of 0.9958 for precision, recall, and F1-scores, it demonstrates balance classification and robust reliability. The consistent support of 600 samples for each class provides unfair classification, and ensure the minimal diagnostic error in early stage dementia detection.

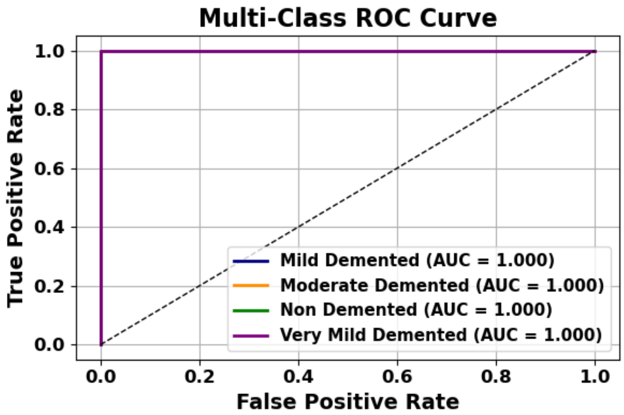

Figure 13: *ROC-AUC curve*

Figure 13 displays the Multi-Class ROC curve for the Attention DenseNet 121 model for AD classification. All four classes of Alzheimer shows the good Area Under Curve (AUC) value of 1.000, which indicates the good classification performance that all cases without error.

4.3 Comparative Analysis

Table 3: *Comparison of accuracy of existing studies of AD disease*

Method	Accuracy (%)
ResNet3D –CNN-LSTM [21]	96.5
CNN [22]	99.30
R–CNN [23]	98.91
CNN- TL-DenseNet [24]	97.84
SVM [25]	90.5
CNN-ResNet50 [26]	94.53
Conv-Swinformer [27]	93.56
CNN [28]	98.9
Proposed Method	99.58

The table 3 demonstrates a comparison analysis of accuracy of different existing studies for AD classification. When compared to the existing model, the Attention DenseNet 121 achieves the higher accuracy of 99.58% for highly accurate early diagnosis of Alzheimer Disease.

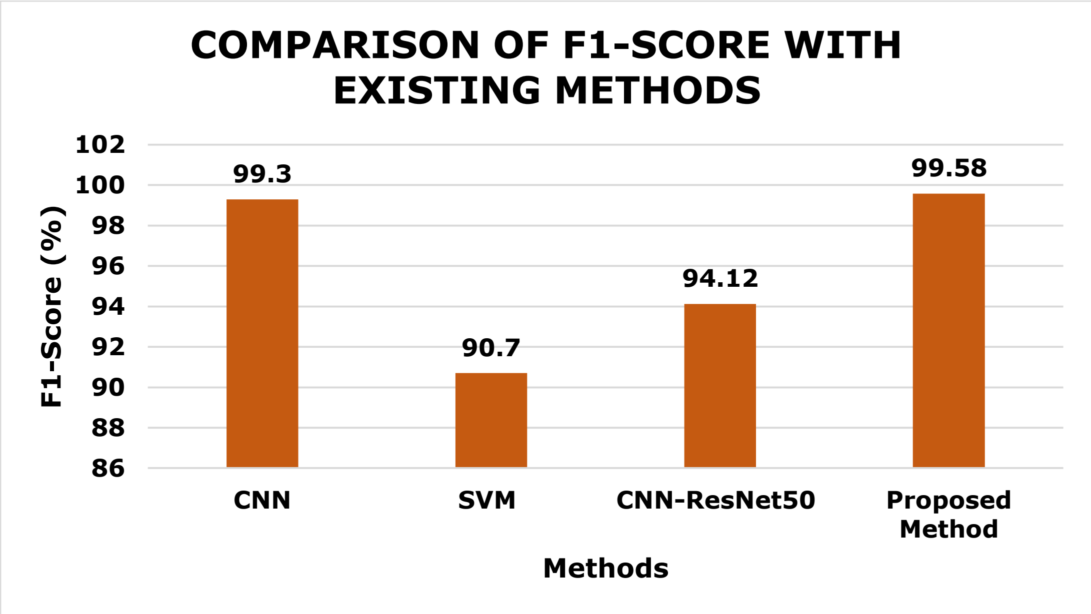

Figure 14: *Comparison with F1-Score of existing methods*

The comparison F1-Score of Attention DenseNet 121 with existing methods is shown in Figure 14. The proposed model achieves the 99.58% of F1-Score. The Attention DenseNet 121 model have better performance classifying the AD disease when compared to other method.

Table 4: *Comparison with specificity of various studies for AD classification*

Study	Specificity (%)
R–CNN [23]	87.98
CNN- TL-DenseNet [24]	97.76
CNN-ResNet50 [26]	98.21
Conv-Swinformer [27]	93.31
CNN [28]	99.2
Proposed Method	99.58

The table 4 compares the specificity of different studies for AD classification. CNN- TL-DenseNet [24], and CNN [28] methods shows lower the specificity of 87.98 % and 93.31 % respectively, meanwhile the proposed method achieves the higher specificity of 99.58% for precise classification of AD classification.

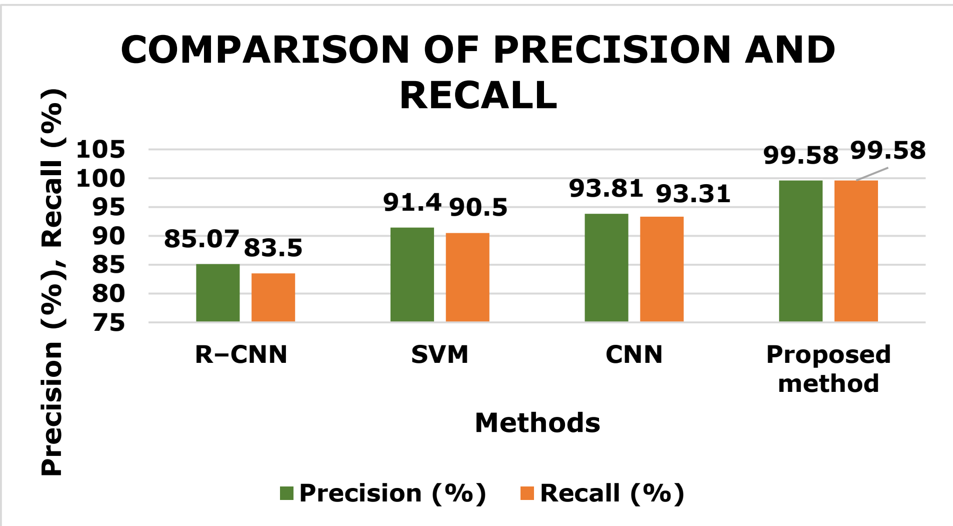

Figure 15: *Comparison of Precision and Recall*

The comparative analysis of precision and recall for AD classification is shown in Figure 15. The proposed method achieves the precision and recall of 99.58 % and 99.58 %. While comparing with other methods, the Attention DenseNet model have better performance for classifying the AD disease.

5. Conclusion

In this work, the Attention-based DenseNet 121 is proposed to classify the early stages of AD. The pre-processing step is significantly reduced the noise and increase the image quality by using the NLM filter. Next, the Adaptive Mean Thresholding technique is accurately segmented the relevant brain regions in image. Moreover, GLCM based feature extraction is performed well in quantify textural information from the MRI images. Finally, the proposed method effectively classified the Alzheimer disease with higher accuracy. DenseNet121 achieved a higher uniform value of 99.58% across the accuracy, precision, recall and F1-Score which is highly efficient compared to the existing method. The Attention DenseNet 121 is precise and effective for classifying the AD.

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