ORIGINAL ARTICLE

A Deep Learning Approach: Effective Multi-Class Classification of Alzheimer's Disease using Unified Integration in the Tri-Branch Network with Efficient Net

Kumar Prasun [1*], Santosh Kumar Sharma [2]

[1] *Computer Application Program, PadmaKanya Multiple Campus, Kathmandu, Nepal*

[2] *Nepal College of Information Technology, Kathmandu, Nepal*

*Corresponding Author: Kumar Prasun
Email: kumar.prasun@pkmc.tu.edu.np

Received: 23 March 2024 / Accepted: 24 February 2025

Abstract

Purpose: One of the increasing neurological disorders is Alzheimer's, which progressively weakens brain cells and leads to critical cerebral impairments like memory loss. The present diagnostic techniques comprise PET scans, MRI scans, CSF biomarkers, and others that frequently need manual power and time-consuming process which might not offer appropriate results. This emphasizes the requirement for more precise and potential diagnostic solutions.

Materials and Methods: The proposed model utilizes AI-based Deep Learning (DL) techniques for effective multi-class classification of AD such as Early Mild Cognitive Impairment (EMCI), Late Mild Cognitive Impairment (LMCI), Mild Cognitive Impairment (MCI), Cognitive Normal (CN) and Alzheimer's Disease (AD) using Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. The proposed study utilizes Tri Branch Attention Network (TBAN) with Unified Component Incorporation (UCI) by capturing both spatial and channel attention information, by replacing the Squeeze and Excitation (SE) component in the conventional EfficientNet model and helps in addressing the concerns associated to imbalanced spatial feature distribution in images. Further, the incorporation of the proposed TBAN module in the Conv Layer helps, not only in terms of capturing the long-term dependence between the different channels of the network but also helps in retaining the specific location information to enhance the performance of the model. Similarly, the proposed UCI which is used in the MBConv layer deals with regularization, as the accuracy of the model can be dropped due to unbalanced regularization, hence the incorporation of UCI advocates strong regularization for combatting the concerns associated with overfitting and aids in providing better accuracy.

Results: Eventually, the proposed framework is evaluated with different metrics and the accuracy value obtained by the proposed model is 0.95. Likewise, precision, recall, and F1 scores gained by the proposed work are 0.95, 0.95, and 0.95.

Conclusion: The proposed research resolves significant gaps in the present diagnostic practices by implementing emerged AI techniques to improve the efficacy and accuracy of Alzheimer's diagnosis by medical imaging. Through enhancing the abilities of early detection, this proposed model holds the prospective to majorly affect treatment tactics for people affected with Alzheimer's. Finally, it led to better patient consequences and life quality.

Keywords: Alzheimer's Disease; Classification; Multi-Class Classification; EfficientNet; Alzheimer's Disease Neuroimaging Initiative Dataset; Performance Metrics.

DOI:

1. Introduction

Alzheimer's Disease is considered one of the most frequent forms of dementia. AD is a progressive brain disease that can extremely deleterious influence on an individual and the social life of humans. As AD is a severe neurodegenerative brain disorder with a wide-reaching global impact, it has been revealed that the number of patients suffering from AD will be escalated to 300 million by 2050 [1]. Further, About 1 out of 85 people in the world are suspected to have AD by 2050 [2]. AD can damage the brain permanently which affects the cognitive part as well as the memory part of the brain [3]. Therefore, the loss of nerve cells in the brain results in Alzheimer's [4]. AD can destructively distress the functionality of the emblematic health activities such as reading, writing, speaking, and many more [5, 6]. Patients who are in the cognitive stage are very much vulnerable to idiosyncrasies, on the other hand, patients who are in the final stage of AD suffer from heart failure. However, the patient's health can be enhanced by early treatment and diagnosis. Typically, the brain contains millions and millions of neurons and these cells aid in organization of the memory aspect, learning, and personality aspects of an individual. In people with AD, many processes affect the cells and chemicals, which include factors like amyloid plaque deposits and neurofibrillary tangles, in which amyloid plaques deposit outside the brain cells and neurofibrillary tangles [7] are deposited inside the brain cells.

Further, AD can be classified into three different stages such as mild, moderate, and severe [8]. The early stages of Alzheimer's can do most of things self-sufficiently and can communicate socially. The person may find specific tasks like driving, and managing medications as a challenging task, however, these symptoms may be noticeable to the individual affected and the people who are close to the patients, conversely, middle-stage Alzheimer can remember significant details despite the loss of memory [9]. However, late-stage Alzheimer's is the most challenging part to handle as the individual loses their ability and respond and communicate or control movement [10], as a result, memory and cognitive skills become worse, therefore extensive care needs to be taken. There are different symptoms of AD for different stages, however, some of the common signs of AD include memory loss which disrupts the tasks of daily life, taking longer time to complete normal tasks, having trouble thinking, misplacing items, gradual loss of speech, significant issues with long and short term memory, loss of weight, hard to complete familiar tasks [11]. As AD is considered a deadly and terrifying disease, it is important to identify the symptoms and proceed in carrying out the treatment for the problem. Therefore, different techniques like cognitive and memory tests like MMSE (Mini Mental State Examination), and MoCA (Montreal Cognitive Assessment) are used for evaluating the memory and problem-solving abilities of a patient [12]. Likewise, imaging methods like PET scans can be used for detecting the structural and functional changes in the brain, moreover, Genetic tests can be used for identifying certain gene mutations associated with a specific condition.

However, these manual techniques are not effective enough for precise identification and classification of AD [13], as these techniques can result in inconsistent diagnoses due to their inability to detect the subtle changes in cognitive function. Moreover, these manual techniques can be time-consuming and relatively labor intensive as they often require extensive training and expertise from the healthcare professional. Occasionally, manual techniques may not deliver comprehensive insights into the underlying biological mechanism of AD. Therefore, technological advancements such as AI approaches can aid in delivering better performance for early identification and precise classification as these technological advancements uses different approaches like image analysis techniques, NLP (Natural Language Processing), predictive modeling, and many more for obtaining better and desired outcomes for classification of AD. Hence, various existing studies use different ML and DL approaches for early identification and precise classification of AD. Recommended study [14] has used a DSC (Depth wise Separable Convolution) combined CNN model for classification of AD, as the conventional CNN model gas delivered an accuracy rate of 78% for detecting and classifying AD. Though the outcome of the model has delivered considerable accuracy, the study primarily focuses on increasing the classification of accuracy by combining other pre-trained model with DSC for better results. Likewise, a suggested study has used TL (transfer learning) to achieve precise outcome for the classification of AD [15]. Correspondingly, an existing study [16] has used the LSTM approach to develop a robust and precise approach for the classification of AD. Though the model has delivered satisfactory outcomes for the classification of AD, it only perform binary classification of AD, further, the model was restricted to less number of samples.

Though the existing studies have delivered considerable performance for the classification of AD, there are certain pitfalls that needs to be addressed such as low accuracy rate, prerequisite of a huge number of training images, performing only binary classification of AD, and inability to work with huge datasets. Therefore, to overcome these results, the proposed model uses the TBAN-UCI model for multi-class classification of AD to obtain a precise and better outcome that helps medical professionals. ADNI dataset is implemented for the study. In the image dataset, some features might be overlooked because of their prominence or frequency in the training set. To overcome this problem, the proposed research employs TBAN by multiple attention mechanisms which permits the proposed model to dynamically alter its focus over diverse spatial regions of the brain images. This means, fewer features are given sufficient attention throughout training, allowing the proposed model to acquire a more widespread depiction of the data. By equalizing the significance of different spatial features, the proposed TBAN improves the capability of the model to simplify over diverse classes. Eventually, the proposed model uses different evaluation metrics for assessing the performance of the proposed model for multi-class classification of AD. Therefore, the objectives of the proposed framework,

- To pre-process the dataset using the Image resizing technique and Feature extraction method
- To perform Multi-class classification of AD using the proposed TBAN-UCI method as TBAN helps in improving the capability of the model for extracting the features and aids in capturing both spatial and channel attention information
- To utilize the proposed UCI model in the EfficientNet for stabilizing regularization as unbalanced regularization can degrade the performance of the model.
- To measure the efficacy of the proposed framework by utilizing various evaluation metrics like F1 score, value of precision, accuracy, and recall rate.

1.1. Paper Organization

Section 2 deals with existing works deliberated by authors for the classification of AD, section 3 deals with the approaches used for the proposed framework, section 4 discusses the results obtained by the model by using the proposed framework for multiclass classification of AD, and section 5 deals with the summary of the proposed framework and discusses the future work.

1.2. Literature Review

Different prevailing studies associated with the detection and classification of AD using various AI techniques are reviewed in the subsequent section

AD is a progressive brain disease, in which the demise of the brain cells can result in memory loss. Therefore, the study has focused on employing DL techniques for classifying patients with AD. CNN-based end-to-end mechanism with comprehensive steps starting from image acquisition has performed for classifying the scanned MRI images for predicting whether patients have Alzheimer's or not. In CNN, Glorot Uniform weight initializer was used to prevent activation of neuron function from starting in saturated or in a dead region which resulted in a quicker convergence rate and aided in providing better accuracy for the model. Moreover, Adam optimizer was also used for the optimization process in order to achieve quick convergence. However, from the experimental outcome, it was identified that classification accuracy of the framework has resulted in better outcomes for the classification of AD. Though the model has delivered better accuracy, it has only focused on binary classification [17]. Similarly, binary classification was carried out by the study for effective classification of AD. sMRI (Structural MRI) played a huge role in comprehending the anatomical changes associated to AD in its early stages. Different features from local brain images were obtained using 2D-CNN. Further, features were learned automatically by using 2 TL (Transfer Learning) models such as Xception and Inception V3. Experimental outcomes delivered a better performance for the classification of AD [18]. According to the source [19], it was revealed that Alzheimer's disease "fourth killer" as the survival time for AD patients is 5.5 years. Due to this aspect, SVM has been used for the classification and prediction of AD, which was extracted from MRI. SVM was primarily used for its robust objectivity and good generalization ability [19].

Existing studies have considered classifying three different classifications of AD, which include AD vs NC, AD vs, MCI, and MCI vs NC. Around 450 MRI images were used. The process carried out includes pre-processing the images and classifying the obtained pre-processed images. Skull striping, segmentation, registration, and outlining the ROI were some of the pre-processing techniques used for pre-processing the input images in the approached study. These techniques have helped to separate the brain tissues from the skull images and they reduce the misclassification during the segmentation. The Accuracy obtained for three binary classification tasks with spike pre-training technique were 90.15%, 87.30%, and 83.90%. However, the accuracy obtained by three binary classifications without spike was 86%, 83%, and 76%. Therefore, the incorporation of ANN for extraction of the relevant features of AD helped in the satisfactory classification of AD [20]. The model used by the study for the classification of AD was ResNet50-based CNN model. The study has focused on classifying AD as moderately demented, very mild demented, Non- demented, and Mild demented. The implementation of ResNet50-based CNN model aided in increasing the accuracy from 78% to 90% [21]. Usually, single and multi-modal imaging features were used for the classification of AD, however, very few studies have considered brain imaging with genetic features for diagnosing the disease. Therefore, the study has used integrated Fisher score and multi-modal multitask-feature to categorize the most related features, particularly 5 genetic and 5 imaging characteristics. The approached Fisher score has aided in dimensionality reduction, resolving variance in scales among two data kinds. The Linear SVM has been carried out for the classification process which results in enhanced diagnostic accuracy [22].

Likewise, the motto of the study [23] was to design a framework for the primary discovery of Alzheimer's disease and the classification of medical images of different stages of AD. Therefore, the study has used CNN. Two different methods were used for the classification of AD, in which the first method utilized simple CNN architecture, which dealt with 2D and 3D structural brain scans. In the second method, TL was used with the help of VGG-19 for medical image classification. Nine different metrics were used for evaluating the model, in which satisfactory outcome was obtained for 2D and 3D classification of AD. Though the model has used considerable pre-trained models for classification, better pre-trained models such as EfficientNet will be focused for improving the performance [23]. Similarly, a study [24] has focused on employing a hybrid model for the classification of AD, where two manageable modalities like fNIRS (Functional Near Infrared Spectroscopy) and EEG (Electroencephalography) for classifying 4 classes of AD, in which the four classes of subjects which includes MCI, HC (Health Control) and two AD patients group. The process proceeded by utilizing PCCFS (Pearson Correlation Co-Efficient Based Feature Selection) to optimize the process of feature selection and aided in accomplishing better classification accuracy. Experimental outcomes have revealed that MCI and mild AD groups have delivered comparatively lower accuracy than other models. Moreover, the accuracy obtained by hybrid EEG-fNIRS was 79.31%, however, without integrating the models together, the accuracy obtained by EEG was 65% and fNIRS was 58%.

An 8-layer CNN model called CNN-BN-DO-DA has been utilized by the study [25] for the classification of AD, in which batch normalization and dropout techniques were used along with the CNN model. Initially, the data augmentation technique was used by fragmenting the training data for the original data, then batch normalization was used for normalizing the inputs of the layer into mini-groups to solve the issues associated with continuous training change. Eventually, the dropout method was used to alleviate the issues associated with computational consumption and overfitting. OASIS dataset was used. The result of the study has indicated that better techniques will be used in the future to speed up convergence rate and will be aided in improving the efficacy of the model.

Like hybrid models, ensemble approaches were also carried for examining the classification of AD. Hence, recommended study has used amalgamation of techniques like linearSVM, LR based classifiers. The model has used ensemble based techniques for building a predictive model which could identify the subjects of MCI easily. The advantage of employing an ensemble approach resulted in cost-effectiveness of the model and the ability to predict the early stages of AD [26]. Similarly, study [27] has used ensemble strategy for classification of AD. Computationally effective ensemble of Deep CNN trained TL (Transfer Learning) has implemented. TL was used for reducing the complexity of the model as it aided in creating more computationally effective DL ensemble model. The ensemble model resulted in delivering satisfactory outcome for the model however, the model lacked in providing a suitable weightage to each individual on the basis of its efficacy in the ensemble.

1.3. Research Gap

From the review of various existing studies, central concerns are depicted as follows,

Most of the prevailing methods involve binary classification, by limiting the capability for identifying various phases of Alzheimer's Disease (AD). Since the VGG19 [28] has performed better, several methods like EfficientNetB0- B7 have not involved, which has been a gap for enhancing the accuarcy in the classification within the multi tasks. As the deep convolutional spiking NN [29] has provided enhanced accuracy using various assets since there is a need of enhanced methods for increaisng the precision diagnosis. The existing models have struggled in their performance on less diverse datasets by restricting their clinical applicability which has highlighted the need of robust models that adapts to varying dataset sizes without decreasing the accuracy [25]. In addressing the limitations faced by the existing studies, the proposed model has achieved enhanded accuracy of 95% in efficiently classifying the five distinct stages of AD which improves the diagnostic precision compared to existing binary-focused models, fulfilling the need in AD diagnosis. Additionally, with the use of TBAN and UCI, the proposed model has recognized spatial and channel attention information for tackling imbalances in feature distribution. The proposed research has demonstrated better outcomes in reliability by using an advanced tool for early AD detection. The implementation of the UCI results in regularization which leads to enhanced performance with several variations in the size of the data.

2. Materials and Methods

AD is considered one of the most dreadful diseases in the world, thus, it is important to classify the disease as timely as possible. In order to identify AD, different manual techniques were used which included cognitive assessment, brain imaging approaches like MRI, PET scans, and other techniques. However, the traditional approaches are prone to errors, time-consuming, and laborious. Therefore, AI methods are used for precise identification and classification of AD which makes it easier and functional for medical professionals for effective classification. Hence, the proposed study uses EfficientNet which incorporates TBAN with UCI for effective and precise classification of AD and is depicted in Figure 1.

Figure 1 represents the overall procedure of the framework, in which the process starts by loading the ADNI dataset. Once the dataset is loaded, images present in the dataset are pre-processed using different techniques like image resizing and feature extraction. After pre-processing, the data is splitted as train test split, in which the train test split is divided as 80% train and 20% test. Once the model is fragmented as train and test split, a classification process is carried out, in which TBAN and UCI methods are used for the proposed classification process. The diverse channels in an NN may signify various perspectives of the input image, such as texture, color, and particular anatomical features in medical imaging. Considering how these channels relate over several layers is significant for efficient classification. The proposed TBAN seizures long-term dependencies by empowering the proposed model to evaluate the significance of features from diverse channels over the network. This is obtained by an attention mechanism that deliberates the relationship among channels at different depts., empowering the proposed model to acquire how features impact others. Further, the incorporation of the classification of image, and the feature's location plays a crucial role in determining their significance. To preserve the spatial context,

Figure 1. Mechanism of Proposed Framework

TBAN is incorporated into the spatial attention mechanisms to enable the model to focus the image. This spatial awareness enhances the model's ability to accurately contrast the classes by maintaining the location of the features. Eventually, the model is assessed by using different metrics.

2.1. Dataset Description

The dataset used for the proposed model is an MRI dataset of 5 stages of AD from the ADI repository. The dataset comprises 5 stages of AD already split into 2 directories for training and testing and the 5 stages of AD are classified as [30]. Table 1 represents the types of datasets and their counts employed in the proposed research.

Table 1. Dataset Description

Dataset	Image counts
AD	933
CN	792
MCI	800
LMCI	1717
EMCI	1060

2.1.1. Performance Metrics

Performance metrics are used for measuring the effectiveness of the proposed framework since it is important to assess the effectiveness and reliability of the proposed model. Therefore, diverse metrics are also used, such as:

a) Accuracy

Accuracy is represented as a metric that describes the performance of the proposed model across all classes. Equation 1 depicts the mathematical formula for accuracy,

$$\text{Accuracy} = \frac{\text{True\_Neg} + \text{True\_Pos}}{\text{True\_Neg} + \text{False\_Neg} + \text{True\_Pos} + \text{False\_Pos}} \quad (1)$$

Where True_Neg is denoted as true negative, True_Pos is denoted as true positive, False_Neg is defined as false negative and False_Pos is defined as false positive.

b) Recall

The recall is indicated as the reclusive of the production metric that assesses the total of correct positive categories made out of all the optimistic classes. Equation 2 shows the formula for the recall rate.

$$\text{Recall} = \frac{\text{True\_Pos}}{\text{False\_Neg} + \text{True\_Pos}} \quad (2)$$

c) Precision

Precision is implied as the covariance unit of the method which is ensured by the suitably recognized cases (True_Pos) to the overall group of cases that are precisely characterized (True_Pos + False_Pos). Equation 3, depicts the formula for precision.

$$\text{Precision} = \frac{\text{True\_Pos}}{\text{False\_Pos} + \text{True\_Pos}} \quad (3)$$

d) F1-Score

F1-score is represented as a measure of the harmonic mean of recall and precision value. The mathematical equation for the F1 score is depicted in Equation 4,

$$\text{F1} - \text{score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \quad (4)$$

2.2. Pre-Processing

Pre-processing is primarily used for improving the accuracy and reliability of the model, by removing the inconsistent data and noisy data from the images.

- Image Resizing – Image resizing is used for changing the process of dimensions of an image by altering the number of pixels in the image, thereby upholding the aspect ratio of the images.
- Normalization – Normalization aims to reduce the dimensionality of the data by converting the pixel values into floating data which is needed for the model.

2.3. Classification – TBAN and UCI

Different CNNs are used for automatically learning and extracting meaningful features from the given data, which makes the usage of CNN exceedingly useful for effective classification. Likewise, CNN is one of the popularly used techniques for classification, however, the major drawback of employing CNN is that, the parameters of the model such as the number of neurons (width), and number of layers (depth) in each layer are accustomed arbitrarily. This can eventually lead to ineffective classification of AD. Therefore, in order to overcome these issues, the proposed framework incorporates EfficientNet for effective multi-class classification of AD by evenly adjusting the parameters of the network such as width, depth, and resolution. The EfficientNet is characterized by two principles, the first principle deals with faster training, and the second principle deals with scaling technique, as the performance of the scaling technique helps with assuring the depth of the network while maintaining the accuracy of the model.

In general, EfficientNet comprises MBConv (Mobile Inverted Bottleneck Convolutions) which combines depth-wise separable convolutions that aid in reducing the number of parameters and computations of the model. Furthermore, the scaling technique employed is one of the key aspects of the EfficientNet model over CNN. In addition, the proposed model focuses on incorporating EfficientNet due to its ability to obtain better accuracy as it employs a compound scaling approach that uniformly scales the width, depth, and resolution of the network. In addition, compound scaling of EfficientNet facilitates the model to work with larger datasets. Despite having various advantages of using the EfficientNet model, there few disadvantages like unbalanced regularization which hinders the efficacy of the model. Therefore, the proposed model utilizes TBAN and UCI methods for classification. The proposed TBAN contains three footprints such as physical, anatomical and pathological. The physical footprints are the observable characteristics in MRI images, which represent the structural integrity of brain tissues, aiding in diagnosing conditions like multiple sclerosis, Alzheimer's disease, or traumatic brain injuries. The anatomical footprints are the specific brain structures identified through imaging, allowing for targeted analysis and a better understanding of brain functionality and pathology through accurate detection. The pathological footprints are abnormalities in the brain that indicate disease processes, crucial for diagnosis, treatment planning, and disease progression monitoring. The rationale for the Selected Network Structure includes the network structure such as TBAN which is selected for its ability to effectively capture the difficult patterns in high dimensional data like MRI images and the adaptations made are the modifications to the base architecture, such as adding layers, adjusting kernel sizes, or integrating UCI, aim to enhance feature extraction and model sensitivity to desired footprints. The changes in the detection system include enhanced feature learning, enabling the network to learn complex features and relationships between brain regions, and strong regularization techniques, such as UCI, to avoid overfitting to noise and capture essential pathological features, ensuring good generalization to new data. Figure 2 depicts the proposed approach for multi-class classification of AD. The figure shows the process involved in the effective multi-class classification of AD, where the image features are initially fed to EfficientNet input layers, the TBAN

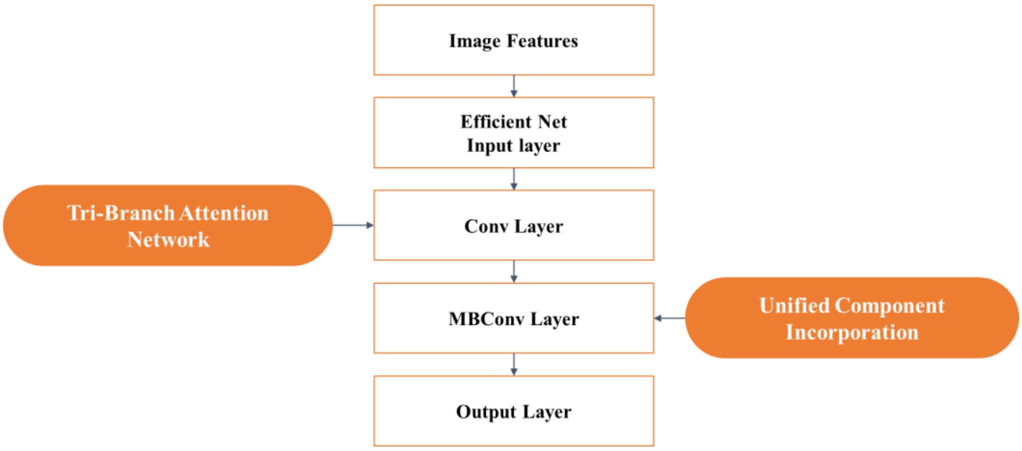


Figure 2. Multi-class classification of AD using TBAN and UCI

model is implemented in the Conv layer and UCI is incorporated in the MBConv layer.

In Figure 2, the image features are fed to the EfficientNet input layer initially, where the EfficientNet input layer performs in resizing the input images to a specific size. The major purpose of implementing the EfficientNet input layer is to prepare and pre-process the input data for the upcoming layers present in the EfficientNet model. The input layer plays an important role in shaping the data and setting the initial parameters of the model. The proposed research uses a TBAN, which is incorporated with EfficientNet, a CNN architecture that is popular for its potential scaling and performance in the task of image categorization. This is robustly seizure of both spatial and channel attention that is significant for precisely recognizing the different stages of Alzheimer's. The proposed TBAN includes the following layers in which the initial process is performed in the Input layer where the MRI images are resized to identical dimensions. A further process is proceeded by the Branch layers which involve the spatial, channel, and combined branches. The spatial branches seize spatial features from the MRI images, the channel branch highlights the information relevant to the channel wise and improves feature representation and the combined features incorporate the outcomes from spatial and channel for widespread feature extraction. The next process is continued by the EfficientNet backbone in which the process of stabilization of width, resolution, and depth is performed and enhances the performance of proposed model. Then the attention mechanism is involved for the modification of the focus on diverse features, confirming that the proposed model highlights related information throughout the classification. The process is concluded in the output layer which contains a softmax activation function that results in possibilities for each class. After that, the features are fed to the Conv layer, where the proposed TBAN is used. TBAN is used to capture channel and spatial attention information by replacing the SE module with the traditional EfficientNet. Utilization of TBAN enhances the capability to extract effective features of the AD images. In addition to assigning weights to the input features, TBAN also assigns weights to different spatial positions on each channel, which makes the model effective for the classification of AD. The implementation of TBAN helps in addressing the concerns associated with imbalanced spatial feature distribution in images and assists in improving the capability of the model for extracting the features. Since the uneven applications may result in some features being excessively penalized, regularization is essential for preventing overfitting and influencing model performance on test or validation data. This problem is solved by the MBConv layer's UCI, which guarantees uniform regularization for every feature. Also, the UCI enhances the model's capacity to generalize new data and reduces the possibility of performance deterioration. During this process, overfitting happens when a model fits the training data too closely, including noise and outliers, resulting in poor performance on new data. Strong regularization is essential to prevent this. The UCI enhances the regularization by uniformly applying across all features, by preventing the model from becoming overly complex. This balanced approach ensures the model by focusing on meaningful patterns rather than memorizing the training data, which improves its ability to generalize and reduce overfitting, which leads to better classification performance. Eventually, in the output layer, desired predictions are obtained. Figure 3 depicts the process of TBAN.

In Figure 3, TBAN model encompasses three parallel branches, where CD is denoted as channel dimension, HI is denoted as spatial height. Initially, the modules are passed to each attention branch for capturing the cross-dimension interaction information among $CD, HI,$ and W. In the first division, the TBAN builds interaction between HI and CD. In order to build an interaction between CD and HI, the input is rotated to 90 degrees counterclockwise. After that, $1\ X\ HI\ X\ CD$ passed via the sigmoid function for generating the resultant attention weights. C-Pool utilized in the model is denoted as compound pooling and BN is denoted as batch normalization. In the second division, the input images are rotated to 90 degrees to obtain a rotated tensor, then the rotated tensor is passed as input for generating weighted feature maps. In the third and final division, rotation does not proceed, however, weighted feature maps are generated directly. Hence, the working mechanism of the model results in obtaining better quality images, which is required for enhancing the accuracy of classification of Alzheimer's disease as EMCI, LMCI, MCI, AD, and CN. Initially, the process starts with data pre-processing that enhances the variability of the proposed model by image resizing, normalization and efficiently augmenting the dataset. Then the data is split into train (80%) and test (20%). The train data includes the images for training and the test dataset includes the images for evaluating the performance of the proposed model in the unseen dataset. The proposed research employs TBAN incorporated with EfficientNet. To enhance the ability of feature extraction, AMI in EfficientNet is swapped with a triple attention module. Followed by, different classifiers are included, which encompass a fully connected layer, 1x1 convolutional layer, softmax classifier and pooling layer configured to resultant possibilities for five different classes showcasing diverse stages of Alzheimer's disease. After, the accomplishment of the proposed model architecture, the training phase starts with distinct hyperparameters such as a number of epochs, learning rate, and batch size with 1000, 0.001, and 32. The proposed research employs an early-stopping approach which ends the epoch in 545 when the process is accomplished, which aids to time consumption during the process. Throughout the training process, the images are constantly mounted to the dimensions of 224x224x3 to confirm similar input sizes. Based on labeled examples, the proposed model acquires to segment diverse classes over several epochs. Once the training is completed, the last model is stored for future usage. To evaluate the model's performance, unsymmetrically chosen images from the test data are used in the trained model, based on its training phase it permits an assessment regarding the classification of unseen data.

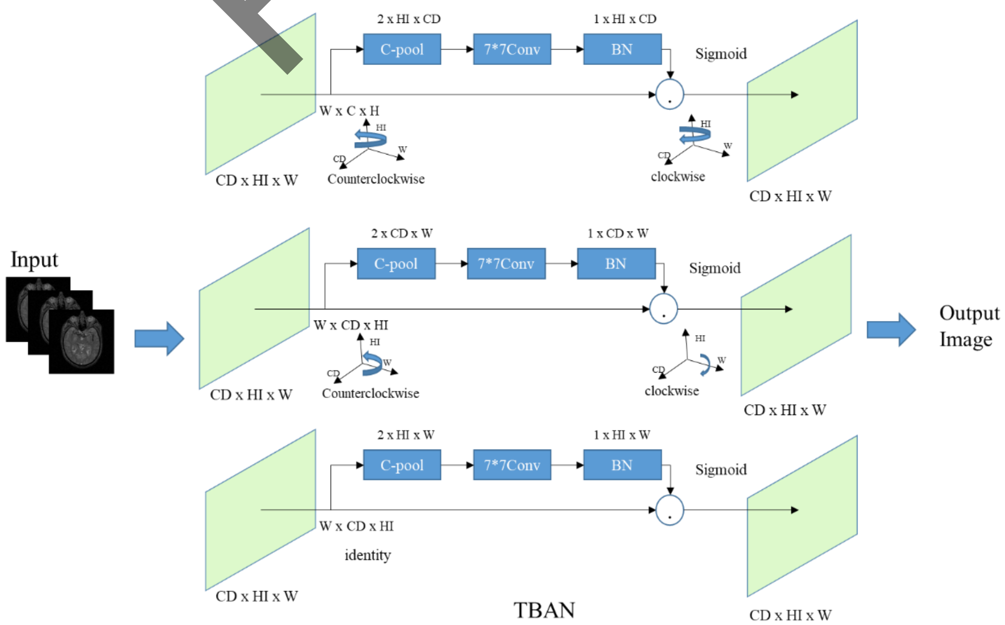


Figure 3. Architecture of TBAN

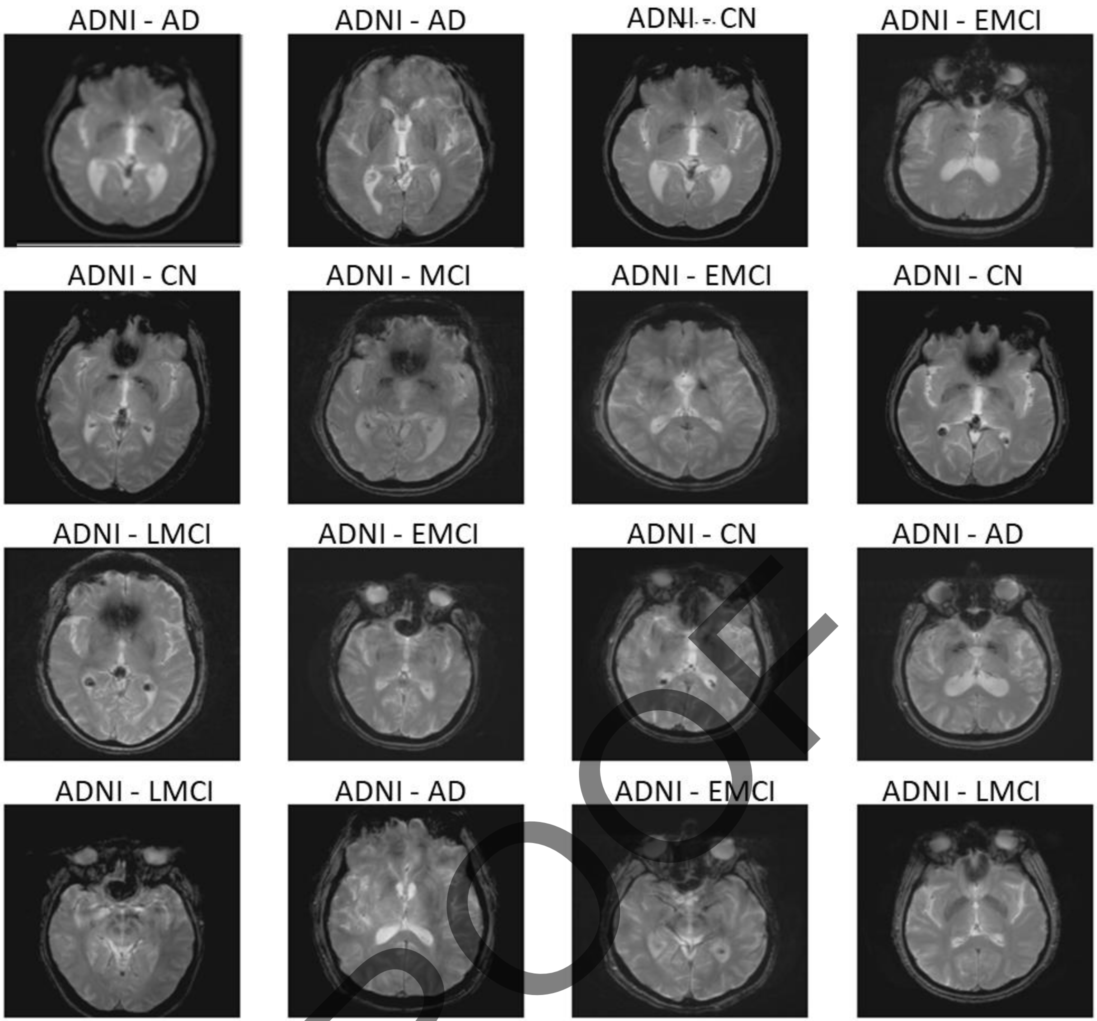


Figure 4. Dataset Images

3. Results

This section deals with the outcome obtained by the proposed model for the multi-class classification of AD. In order to achieve this, different metrics are used. Hence, the following section encompasses dataset description, performance metrics, EDA, performance analysis, and comparative analysis of the model.

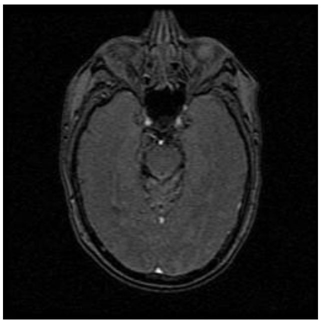
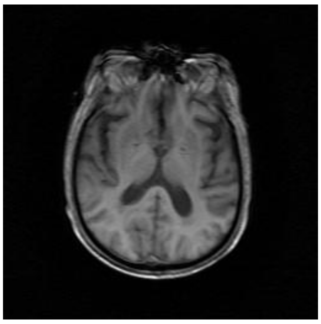
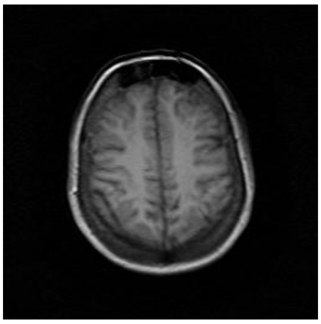
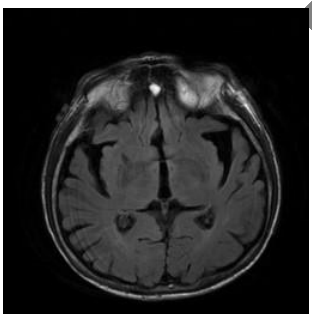
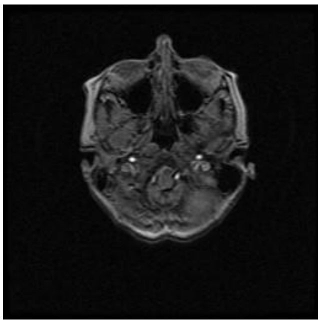
3.1. Exploratory Data Analysis

EDA is defined as an analysis method that recognizes the general pattern in the data. The pattern comprises different outliers and features of the data which might be considered as unexpected data. The main purpose of employing EDA is to detect errors and outliers as it aids in building precise and reliable models. Figure 4 shows the dataset images used in the proposed research.

Figure 4 depicts the dataset images of the brain images, where different sizes and images of the brain images are shown. This process depicts which types of brain images are employed in the proposed model. These EDA images are projected to show what kinds of sample images are used for the detection process. Likewise, Table 2 shows the Alzheimer's Disease image and Cognitive Normal brain images.

Similarly, EDA of Early mild cognitive impairment, Late Mild Cognitive Impairment, and Mild Cognitive Impairment brain images are depicted in the EDA section of Table 2. The table represents the 5 classes of samples with their counts from the ADNI dataset. Therefore, this section discusses about EDA of the proposed multi-class classification model. The subsequent section discusses the performance of the projected study, where numerous metrics are used for assessing the performance of the model.

Table 2. Five Classes of MRI Images AD, CN, EMCI, LMCI, and MCI

Sample Images	Class Name
	Alzheimer's Disease brain image (AD) - Number of samples - 171
	Cognitive Normal brain images (CN) - Number of samples - 580
	Early mild cognitive impairment (EMCI) - Number of samples - 240
	Late Mild Cognitive Impairment (LMCI) - Number of samples - 72
	Mild Cognitive Impairment brain images (MCI) - Number of samples - 233

3.2. Performance Analysis

Analyzing the performance of the model is important for evaluating the efficacy of the proposed framework. Therefore, various metrics are utilized for assessing the usefulness of the proposed work such as F1 score, accuracy value, recall rate, and value of precision. Figure 5 depicts the confusion matrix of the multiclass classification of AD likewise, Figure 6 also shows the loss and validation loss of the proposed model (Table 3).

Table 3. Labels of the classes

Class	Disease
AD	Alzheimer's Disease images
LMCI	Late Mild Cognitive Impairment brain images
EMCI	Early mild cognitive impairment
CN	Cognitive Normal brain images
MCI	Mild Cognitive Impairment Brain images

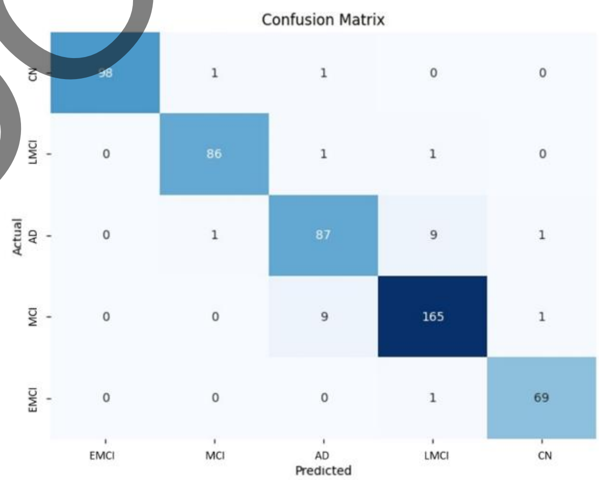


Figure 5. Confusion Matrix

Table 4. Performance Metrics

Performance Metrics	Proposed Model
Accuracy	0.95
Precision	0.95
Recall	0.95
f1-score	0.95

Table 4 depicts the different performance metrics obtained by the proposed model, where the accuracy attained by the proposed model is 95%, the precision obtained by the model is 95%, and similarly, the F1 score and recall attained by the proposed framework are 95%.

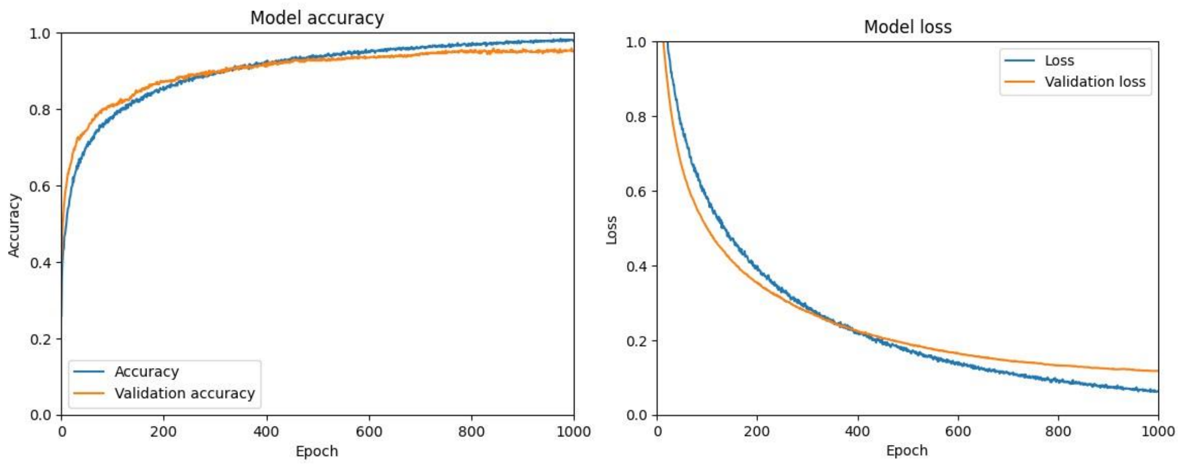


Figure 6. Model accuracy and model loss

Though the proposed model has delivered effective outcomes for the multi-class classification of AD, different existing studies are compared with the proposed framework with the aim of examining the effectiveness of the projected study. Therefore, the subsequent section deals with the comparative analysis of the proposed framework.

3.3. Comparative Analysis

Comparative analysis primarily deals with comparing the metrics of the proposed work with the prevailing works,

Table 5 shows the accuracy obtained by the existing and proposed model for classification of AD, in which the accuracy attained by the existing model is 0.79% and the accuracy obtained by the proposed model is 0.95%.

Table 5. Comparison of Proposed Model with Existing Model based on Accuracy [31]

Model	Accuracy
Inception and ResNet V2 model	0.79
Proposed Model	0.95

Table 6. Comparative Analysis Proposed Model Performance with Existing Model [32]

Performance Metrics	Proposed Model	CNN Model
Accuracy	0.95	0.88
Precision	0.95	0.88
Recall	0.95	0.88
f1-score	0.95	0.9

Likewise, Table 6 depicts the accuracy, recall, F1 score, and precision of the proposed model with the existing works. In which the accuracy, recall rate, and precision value of the existing model is 0.88% and eventually the F1 score obtained by the existing model is 0.90%. However, different metrics like Accuracy value, the value of F1 score, the value of precision, and the recall rate attained by the projected study is 0.95%.

Consequently, the proposed framework is compared with the existing Extra tree classifier approach in Table 7, where accuracy, precision, recall, and F1 score obtained by the existing model were 0.86%, 0.79%, 0.77%, and 0.78%, on the other hand, the proposed model deliver accuracy, F1 score, recall and precision value of 0.95%.

Table 7. Comparative Analysis Proposed Model Performance with Existing Model [33]

Performance Metrics	Proposed Model	Extra Tree Classifier Model
Accuracy	0.95	0.86
Precision	0.95	0.79
Recall	0.95	0.77
f1-score	0.95	0.78

From the experimental result, it can be identified that a projected study has delivered better performance metrics than the existing models for multi-class classification of AD. The proposed model was compared with existing models which consist of 5 sets of AD images such as AD, CN, MCI, EMCI, and LMCI models. Though different studies have considered the multi-class classification of AD, proposed model has the ability to deliver precise and effective accuracy for identifying and classifying Alzheimer's disease. This is primarily due to the incorporation of TBAN and UCI in the proposed EfficientNet model. TBAN is performed for effective multi-class classification of AD such as EMCI, LMCI, MCI, AD, and CN, by capturing both spatial and channel attention information and helping in addressing the concerns associated with imbalanced spatial feature distribution in images. Further, the incorporation of the Proposed TBAN module in the Conv Layer helps, not only in terms of capturing the long-term dependence between the different channels of the network but also helps in retaining the detailed location information with the aim to enhance the accuracy of classification of AD (Table 8).

4. Discussion

AD is a progressive brain disease that can enormously harmful influence the individual and social life of humans. To detect this the proposed research employs EfficientNet with the integration of TBAN and UCI. As AD is a dangerous neurodegenerative brain disorder with an extensive accomplishment on global impression, it has been exposed that which number of patients enduring AD will be worsened to 300 million by 2050 [1]. However, many existing studies have employed diverse methodologies to detect AD in MRI images. Similarly, [20] the utilization of DCNN skewering NN can leverage difficulties which makes the existing model more complex to implement and interpret in a clinical environment. The outcome might not be generalizable over different populations because of its efficient bias in the train data that may impact the performance of the model in the real world. Likewise, the existing study [21] has attained an average performance of accuracy rate of 78% to 90% with ResNet with CNN. Similarly, the existing study hybrid EEG-fNIRS was 79.31% with PCCFS for optimizing the process of feature selection and assisted in achieving better classification accuracy for MCI and mild AD. Similarly, the prevailing study [23] described average accuracy which can be an important instabilities in identification rates which depends on the usability of the dataset that might weaken its consistency for clinical usage. Employing pre-trained DL models like VGG 19 could restrict the adaptation and innovation to new datasets and efficiently foremost to average performance when used in diverse imaging or population conditions. Literally, the study [24] depends on EEG-fNIRS hybridization which restricts its pertinence which might not seize all related neurophysiological variations combined with AD. While feature selection is improved, the procedure may static be subjective and can manage significant biomarkers which are not comprised in the analysis. When compared to these existing studies the proposed EfficientNet model attains extraordinary performance with 95% accuracy by identifying 5 distinct classes from the dataset, which majorly outperforms well than existing research. By incorporating UCI and TBAN, the proposed model resolves the problems relevant to imbalanced datasets that frequently led to precision falls in other studies. The proposed model represents the best performance when compared to existing models such as ResNet V2 and Inception. The capability to categorize diverse stages of AD improves its diagnostic abilities which permits for adapted interventions on the basis of disease progression.

Table 8. Overall Comparative Analysis of the Proposed Model with Existing Models

Performance Metrics	Accuracy	Precision	Recall	f1-score
Inception and ResNet V2 model	0.79			
CNN Model	0.88	0.88	0.88	0.9
Extra Tree Classifier Model	0.86	0.79	0.77	0.78
Proposed Model	**0.95**	**0.95**	**0.95**	**0.95**

5. Conclusion

AD is one of the most dreadful diseases in the work, therefore, it is important to detect AD as timely as possible. Therefore, various techniques are used for identifying and classifying AD, however manual techniques like MRI, and PET scans are considered to be time-consuming, labor-intensive, and result in imprecise classification of AD. Therefore, the proposed model focused on using AI techniques for the effective classification of AD. The proposed model utilized was TBAN with UCI in EfficientNet. TBAN was performed by apprehending both spatial and channel attention information and helped in addressing the distresses associated with imbalanced spatial feature distribution in images. Further, the incorporation of the Proposed TBAN module in the Conv Layer helps, not only in terms of capturing the long-term dependencies between the different channels of the network but also in retaining the exact location information with the aim of enhancing the accuracy of classification of AD. Moreover, the proposed UCI used in the MBConv layer dealt with regularization, as the accuracy of the model can be dropped due to unbalanced regularization, hence the incorporation of UCI upholds strong regularization for combatting the concerns associated with overfitting and aids in providing better accuracy. The incorporation of the proposed model resulted in achieving better outcomes by attaining an accuracy rate of 0.95%, recall, precision, and F1 score of 0.95%. The future work of the proposed study involves considering DL algorithms for obtaining much better outcomes for classification.

References

1- Zhi Yang *et al.*, "An Alzheimer's Disease classification network based on MRI utilizing diffusion maps for multi-scale feature fusion in graph convolution." Vol. 21 (No. 1), pp. 1554-72, (2024).

2- Sitara Afzal *et al.*, "Alzheimer disease detection techniques and methods: a review." (2021).

3- Daniel Lamontagne-Kam, Anosha Kiran Ulfat, Vincent Hervé, Tra-My Vu, and Jonathan %J Frontiers in Neuroscience Brouillette, "Implication of tau propagation on neurodegeneration in Alzheimer's disease." Vol. 17(2023).

4- Mehdi Jorfi, Anna Maaser-Hecker, and Rudolph E %J Genome Medicine Tanzi, "The neuroimmune axis of Alzheimer's disease." Vol. 15 (No. 1), pp. 1-25, (2023).

5- Morteza Rohanian, "Multimodal Assessment of Cognitive Decline: Applications in Alzheimer's Disease and Depression." (2023).

6- Vishal Thakur, Mansi Sharma, Vishal Sharma, Akriti Singh, and Suhaib Farooq, "NEURODEGENERATIVE DISEASE: ALZHEIMER'S DISEASE." (2023).

7- Haitao Ding, Zhiqian Li, Kui Luo, Qiyong Gong, and Xiaohe %J TrAC Trends in Analytical Chemistry Tian, "Application of biomarker-derived fluorescent probes for the detection of Alzheimer's disease." p. 117369, (2023).

8- Marco Calabrò, Carmela Rinaldi, Giuseppe Santoro, and Concetta %J AIMS neuroscience Crisafulli, "The biological pathways of Alzheimer disease: A review." Vol. 8 (No. 1), p. 86, (2021).

9- Anil Kumar, Jaskirat Sidhu, Amandeep Goyal, Jack W Tsao, and Chaddie Doerr, "Alzheimer disease (nursing)." (2021).

10- Fariba Mirakhori, Mina Moafi, Maryam Milanifard, and Hossein %J Journal of Pharmaceutical Negative Results Tahernia, "Diagnosis and Treatment Methods in Alzheimer's Patients Based on Modern Techniques: The Orginal Article." pp. 1889-907, (2022).

11- Jenny %J TRACEY-Drawing Wright and Visualisation Research, "Drawing and Memory Loss: Mapping and Recording the Journey Through Alzheimer's Disease." Vol. 16 (No. 1), (2022).

12- Giovanna Furneri *et al.*, "The combined use of Mini-Mental State Examination with Montreal Cognitive Assessment to evaluate the clinical efficacy of cholinesterase inhibitors in Mild Alzheimer's disease patients." p. 95.

13- Mosleh Hmoud %J Soft Computing Al-Adhaileh, "Diagnosis and classification of Alzheimer's disease by using a convolution neural network algorithm." Vol. 26 (No. 16), pp. 7751-62, (2022).

14- Junxiu Liu *et al.*, "Alzheimer's disease detection using depthwise separable convolutional neural networks." Vol. 203p. 106032, (2021).

15- Alejandro Puente-Castro, Enrique Fernandez-Blanco, Alejandro Pazos, Cristian R %J Computers in biology Munteanu, and medicine, "Automatic assessment of Alzheimer's disease diagnosis based on deep learning techniques." Vol. 120p. 103764, (2020).

16- Waleed Salehi *et al.*, "An approach to binary classification of alzheimer's disease using LSTM." Vol. 10 (No. 8), p. 950, (2023).

17- Yousry AbdulAzeem, Waleed M Bahgat, Mahmoud %J Neural Computing Badawy, and Applications, "A CNN based framework for classification of Alzheimer's disease." Vol. 33pp. 10415-28, (2021).

18- Ahsan Bin Tufail, Yong-Kui Ma, and Qiu-Na %J Journal of digital imaging Zhang, "Binary classification of Alzheimer's disease using sMRI imaging modality and deep learning." Vol. 33pp. 1073-90, (2020).

19- Zhao Fan, Fanyu Xu, Xuedan Qi, Cai Li, Lili %J Neural Computing Yao, and Applications, "Classification of Alzheimer's disease based on brain MRI and machine learning." Vol. 32pp. 1927-36, (2020).

20- Regina Esi Turkson, Hong Qu, Cobbinah Bernard Mawuli, and Moses J %J Neural Processing Letters Eghan, "Classification of Alzheimer's disease using deep convolutional spiking neural network." Vol. 53pp. 2649-63, (2021).

21- Muhammed Yildirim and Ahmet %J Ingénierie des Systèmes d Inf. Cinar, "Classification of Alzheimer's Disease MRI Images with CNN Based Hybrid Method." Vol. 25 (No. 4), pp. 413-18, (2020).

22- Jinhua Sheng, Yu Xin, Qiao Zhang, Luyun Wang, Ze Yang, and Jie %J Scientific Reports Yin, "Predictive classification of Alzheimer's disease using brain imaging and genetic data." Vol. 12 (No. 1), p. 2405, (2022).

23- Hadeer A Helaly, Mahmoud Badawy, and Amira Y %J Cognitive computation Haikal, "Deep learning approach for early detection of Alzheimer's disease." pp. 1-17, (2021).

24- Pietro A Cicalese *et al.*, "An EEG-fNIRS hybridization technique in the four-class classification of alzheimer's disease." Vol. 336p. 108618, (2020).

25- Xianwei Jiang, Liang Chang, Yu-Dong %J Journal of Medical Imaging Zhang, and Health Informatics, "Classification of Alzheimer's disease via eight-layer convolutional neural network with batch normalization and dropout techniques." Vol. 10 (No. 5), pp. 1040-48, (2020).

26- Asif Hassan Syed, Tabrej Khan, Atif Hassan, Nashwan A Alromema, Muhammad Binsawad, and Alhuseen Omar %J IEEE Access Alsayed, "An ensemble-learning based application to predict the earlier stages of Alzheimer's disease (AD)." Vol. 8pp. 222126-43, (2020).

27- Muhammad Tanveer *et al.*, "Classification of Alzheimer's disease using ensemble of deep neural networks trained through transfer learning." Vol. 26 (No. 4), pp. 1453-63, (2021).

28- Hadeer A Helaly, Mahmoud Badawy, and Amira Y %J Cognitive computation Haikal, "Deep learning approach for early detection of Alzheimer's disease." Vol. 14 (No. 5), pp. 1711-27, (2022).

29- Regina Esi Turkson, Hong Qu, Cobbinah Bernard Mawuli, and Moses J %J Neural Processing Letters Eghan, "Classification of Alzheimer's disease using deep convolutional spiking neural network." Vol. 53 (No. 4), pp. 2649-63, (2021).

30- [Online]. Available: https://www.kaggle.com/datasets/madhucharan/alzheimersdisease5classdatasetadni/data.

31- RC Suganthe *et al.*, "Multiclass classification of Alzheimer's disease using hybrid deep convolutional neural network." pp. 145-53, (2021).

32- SM Hasan Mahmud *et al.*, "Detection of Different Stages of Alzheimer's Disease Using CNN Classifier." Vol. 76 (No. 3), (2023).

33- Mohammed Raza Syed, Neel Kothari, Yash Joshi, Aruna %J International Journal of Intelligent Systems Gawade, and Applications in Engineering, "EADDA: Towards Novel and Explainable Deep Learning for Early Alzheimer's Disease Diagnosis Using Autoencoders." Vol. 11 (No. 4), pp. 234-46, (2023).