Journal of Theoretical and Applied Information Technology
15th March 2025. Vol.103. No.5

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

EARLY-STAGE DETECTION AND CLASSIFICATION OF ALZHEIMER'S DISEASE USING CUTTING EDGE TECHNOLOGIES

NASSER NAMMAS ALBOGAMI[1]
[1]Information technology department, Faculty of computing and information technology, King Abdulaziz University, Saudi Arabia.
E-mail: nalbugami@kau.edu.sa

ABSTRACT

Alzheimer's disease has emerged as a significant global health issue in recent decades. However, low- and middle-income countries have been slow to acknowledge its severity. According to reports, the global prevalence of Alzheimer's disease is expected to exceed 55 million individuals by the end of 2023, with projections suggesting this figure will triple by 2050. Early detection and appropriate treatment plans can mitigate the risks associated with Alzheimer's disease. Yet, only 10 percent of affected individuals in developing nations receive a formal diagnosis from healthcare professionals. In this study, we propose a novel computer-aided diagnostic (CAD) based Alzheimer's disease detection and classification system that provides precise classification of the disease's current stage. The proposed scheme assists medical professionals to diagnose the Alzheimer's disease with maximum accuracy level 99.8%. Furthermore, the proposed approach improves the existing neuroimaging datasets by conducting analysis and preprocessing techniques such as annotation and labeling. To best of our knowledge, our proposed scheme is the the most appropriate and feasible approach that alleviate the timely detection of Alzheimer's disease, enabling patients to receive appropriate medical treatment and slow the progression of the condition.

Keywords: *Artificial Intelligence; Deep learning; Alzheimer's disease (AD); computer-aided diagnostic (CAD).*

1. INTRODUCTION

Alzheimer's disease (AD) represents the most prevalent form of dementia, typified by a progressive decline in neurocognitive function, predominantly afflicting the elderly population. This neurodegenerative condition is marked by substantial deterioration in memory and cognitive capabilities relative to the individual's baseline, indicative of primary dementia syndrome. In Saudi Arabia, AD is responsible for approximately two-thirds of cases of progressive cognitive decline among the geriatric demographic, with an estimated prevalence exceeding 130,000 individuals [1]. Globally, the prevalence of AD was estimated at 26.6 million individuals in 2006, with projections indicating this figure will double every two decades, potentially affecting about 1.2% of the global population by 2046 [2].

The early detection of Alzheimer's disease is frequently linked to the identification of mild cognitive impairment (MCI), an incipient phase of AD. Although the cognitive deficits and memory complaints associated with MCI do not substantially impair daily functioning, there is robust evidence suggesting a high probability of MCI progressing to Alzheimer's disease or other dementias. Timely and precise identification of Alzheimer's disease, particularly the transition from MCI to AD, allows patients to comprehend the severity of their condition and implement preventive strategies, such as lifestyle modifications and pharmacotherapy [3].

Diagnosing Alzheimer's disease in its prodromal stages is challenging, yet accurate prognostication can mitigate its impact. Neuronal degeneration and subsequent apoptosis within the brain culminate in profound amnesia. In 2017, approximately 50 million individuals worldwide were afflicted by Alzheimer's disease. The progression of Alzheimer's can be stratified into four distinct stages [4]. Pre-dementia, or mild cognitive impairment, represents a phase of cognitive decline preceding the overt manifestation of the illness, often characterized by short-term memory loss that may be misattributed to normal aging. In the early stages, dementia can be accurately diagnosed, with long-term memories generally preserved while the

capacity to form new memories deteriorates. As the disease advances, it profoundly affects various facets of life, impairing motor functions and impacting speech, memory retention, and literacy skills. The terminal stage of Alzheimer's results in total dependency on a caregiver and eventual death, frequently exacerbated by comorbid conditions such as infections or pneumonia.

Deep learning algorithms have demonstrated high accuracy in computer-aided diagnoses of severe diseases. However, the efficacy of these algorithms is constrained by the availability of annotated datasets for training. Furthermore, the high dimensionality or class imbalance of existing datasets can impede the performance of conventional machine learning algorithms. Research teams and companies often encounter difficulties in obtaining a diverse array of medical images for studies due to limited access to images from a restricted pool of patients or geographic locations. This limitation compromises the broad applicability and accuracy of solutions. Many researchers concentrate solely on the binary classification of Alzheimer's disease without providing insights into the disease's severity stages. There is an increasing demand for deep learning-based solutions capable of prognosticating the current stage of Alzheimer's disease to deliver intensive care tailored to the condition's severity [5], [6], [7].

The primary objective of our study is to detect and diagnose Alzheimer's disease (AD) in its nascent stages. We propose a methodology to ascertain the presence of Alzheimer's and classify the disease into the four previously described stages. This project emphasizes early diagnosis and offers a comprehensive classification of the disease's severity, from the initial to the terminal stage.

Our methodology involves acquiring magnetic resonance imaging (MRI) scans, followed by preprocessing for normalization and smoothing to eliminate anomalies. The MRI images are then converted into binary (black and white) format. Using the advancements of Convolutional Neural Network (CNN) model, we train our model to to classify AD stages categorized as early stage also called initial stage, moderate stage (recommended to admit at hospital with appropriate treatment), and advanced stage (ending stage of human live). Further, the contributions of our study can be summarized as follows:

- We examine the constraints of conventional ML/DL techniques to diagnosis Alzheimer's disease, and identify the primary obstacles that must be addressed.
- Analyze existing neuroimaging datasets with respect to annotation and labeling.
- We implement both binary and multiclass classification of Alzheimer's disease utilizing advanced CNN algorithms.
- We assess the performance of proposed scheme, and compare with existing well known approaches using both simulated and real-world datasets.

Rest of the paper is organized in such way that section II present a comprehensive literature review followed by technology background and related work. Section III presents the proposed our proposed scheme framework in details. Further, in section IV we describe the implementation and results of proposed model, and compare with existing state-of-the-art methods. Lastly, we conclude our study in section V.

2. LITERATURE REVIEW

In this section we present background knowledge of emerging technologies used in proposed our proposed scheme approach followed by a comprehensive related work in section 2.2.

2.1. Technology Background

A. Computer-aided diagnostic (CAD)

Computer-aided diagnostic (CAD) systems for Alzheimer's disease (AD) leverage deep learning techniques to enhance diagnostic accuracy and early detection. A prevalent approach involves the use of Convolutional Neural Networks (CNNs), denoted as CNN_{AD} to analyze magnetic resonance imaging (MRI) scans. Given an input MRI scan $X \in R^{n*n}$, the CNN model $F \in R^{n*n} \rightarrow \{0, 1, 2, 3\}$ maps the scan to one of four stages of Alzheimer's disease: 0 as non-AD, 1 as early stage, 2 as moderate stage, and 3 as advanced stage. The process begins with preprocessing steps, including normalization and smoothing, represented as X' = g(X) where g is a function that standardizes the image data. The transformed image X' is then input into the CNN, which comprises multiple layers L_i (convolutional, pooling, and fully connected layers) that extract hierarchical features $\phi(X')$. The final layer outputs the predicted stage y = argmax ($\phi(X')$), optimizing the cross-entropy loss function L, (y, y^) during training. The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, denoted D (X_i, y_i), is commonly used to train and validate the model, where X_i are MRI scans and y_i are the corresponding labels. By integrating deep learning frameworks such as TensorFlow or PyTorch, the CAD system

significantly improves the accuracy and reliability of Alzheimer's disease diagnostics [8], [9], [10].

B. Deep learning

Deep learning methodologies for diagnosing and classifying Alzheimer's disease (AD) primarily utilize Convolutional Neural Networks (CNNs) due to their efficacy in image processing tasks. Given an MRI scan $X \in R^{h*w*d}$ where h is height, w is width, and d is the number of channels, the CNN model $X \in R^{h*w*d} \rightarrow \{c_0,c_1,c_2,c_3\}$. The preprocessing step X' = g(X) involves normalization and smoothing, where g is a function that adjusts the image data for consistency. The CNN architecture consists of multiple layers *L_i*, where each layer transforms the input feature map to a higher-level representation. The feature extraction process captures essential characteristics of the MRI scan through convolutional and pooling operations. The final output layer of the CNN uses a softmax function to produce a probability distribution over the class labels. The predicted class indicates the stage of AD. The model is trained by minimizing the cross-entropy loss function Through iterative optimization techniques such as stochastic gradient descent (SGD), the CNN model learns to accurately classify the stages of Alzheimer's disease, leveraging deep learning frameworks like TensorFlow or PyTorch for implementation [11], [12].

C. ResNet-50

The ResNet-50 model, a variant of the Residual Network architecture, is widely employed across various domains for tasks such as image classification, object detection, and feature extraction. With its 50 layers, including residual blocks, the ResNet-50 model addresses the challenge of vanishing gradients in deep neural networks, allowing for the training of extremely deep architectures. This model's usage spans diverse applications, from identifying objects in images to diagnosing medical conditions from scans. In image classification tasks, ResNet-50 achieves state-of-the-art performance due to its ability to learn intricate features from data. Moreover, its pertained weights on large-scale image datasets, such as ImageNet, make it highly suitable for transfer learning, where the model can be fine-tuned on smaller, domain-specific datasets. In healthcare, ResNet-50's feature extraction capabilities have been leveraged for disease diagnosis and medical image analysis, aiding in the detection of abnormalities and assisting healthcare professionals in making informed decisions. Overall, the ResNet-50 model's versatility and effectiveness make it a go-to choice for a wide range of machine learning and computer vision tasks [13], [14].

D. Alax Net

AlexNet, introduced by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton in 2012, marked a significant milestone in the field of deep learning as the winner of the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in that year. The architecture of AlexNet comprises eight layers, including five convolutional layers and three fully connected layers as shown in figure 1.

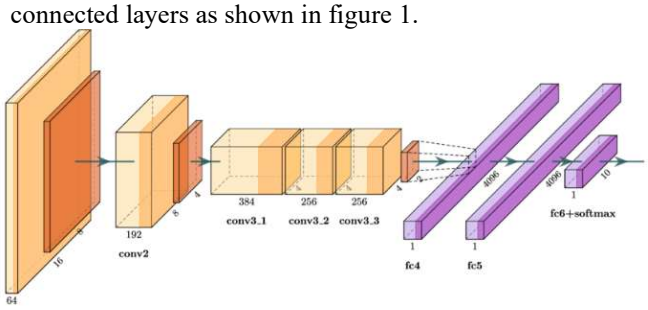

Figure 1. Fundamental architecture of Alex Net model.

It features a novel design with large kernel sizes, local response normalization, and dropout regularization, which were groundbreaking at the time. The convolutional layers in AlexNet are followed by max-pooling layers to down sample the feature maps and increase the network's receptive field. The fully connected layers serve as a classifier, mapping the high-level features extracted by the convolutional layers to class labels. AlexNet's architecture demonstrated superior performance in image classification tasks, significantly advancing the state of the art and paving the way for the widespread adoption of deep convolutional neural networks in computer vision. Its impact extended beyond academic research, influencing the design of subsequent architectures and catalyzing the rapid progress of deep learning in various domains [15], [16].

2.2. Related Work

Alzheimer's is a neurodegenerative condition set apart by the slow demise of neuronal cells, prompting mental deterioration, hindered mental capabilities, social changes, and disintegrating language abilities. Around 5.4 million individuals in the US are impacted by this condition, with 5.2 million being older. Various examination studies underline the significance of speedily and precisely diagnosing Alzheimer's infection, as this empowers opportune mediation, compelling side effect the board, execution of wellbeing measures, and cost-productive treatments. Endeavors in diagnosing Alzheimer's sickness have investigated different PC

helped multi-class symptomatic strategies, making changing degrees of progress. Most exploration in PC helped determination (computer aided design) for Alzheimer's sickness centers around twofold grouping, principally deciding if a patient has Alzheimer's or not. In their review, Karami et al. [18] give a thorough examination of flow philosophies utilized in computer aided design frameworks for Alzheimer's illness using neuroimaging procedures. Dementia alludes to a decrease in mental capacities and cerebrum capability, with Alzheimer's sickness (Promotion) being a type of dementia that frequently creates in adulthood. Promotion is described by its moderate and degenerative nature, prompting a consistent loss of memory capability. The test lies in the way that Promotion conclusion frequently happens in the later stages, decreasing the viability of expected medicines. The rising worldwide populace of Alzheimer's patients has elevated the emphasis on the early recognition of the infection. Mind neuroimaging examination is a critical part of the exhaustive indicative interaction for Alzheimer's illness.

Many countries are encountering a segment shift towards a maturing populace. In this unique situation, Alzheimer's illness has turned into a main source of mental degradation, with its commonness firmly corresponding with propelling age. In contemporary times, PC helped plan (computer aided design) programming has gotten some forward momentum among engineers and has arisen as a crucial area of examination inside clinical imaging and symptomatic radiology [19], [20], [21]. M.M. Fareed., et al, [22] proposed ADD-Net a deep learning-based pipeline using a shallow CNN architecture and MR brain images for accurate diagnosis and stratification of Alzheimer's disease stages. The study achieves a high accuracy of 99.68% and highlights the importance of early diagnosis and improving patient care. However, it's important to consider the limitations of the study, such as the need for further validation on larger datasets and the generalizability of the proposed pipeline in real-world clinical settings. A deep learning-based pipeline using a shallow CNN architecture and MR brain images for accurate diagnosis and stratification of Alzheimer's disease stages. The study achieves a high accuracy of 96.68% and highlights the importance of early diagnosis.

M. Odusami, R. Maskeliunas, and R. Damaševičius [23] aimed to address the limitations of deep learning algorithms in identifying changes in functional connectivity in patients with mild cognitive impairment (MCI) and Alzheimer's disease (AD). They used randomized concatenated deep features from pre-trained models and experimented with ResNet18 and DenseNet201 for AD multiclass classification. The proposed model achieved impressive results with 97.86% accuracy, 93.94% precision, and 95.89% recall. This demonstrates the potential of advanced deep learning with MRI images for classifying and predicting neurodegenerative brain diseases like AD.

Similarly, A. M. Alhassan [24] focused on improving the efficiency of Alzheimer's disease (AD) diagnosis using structural MRI (sMRI) and segmentation techniques. You addressed the limitations of the OTSU segmentation method by implementing enhanced fuzzy elephant herding optimization (EFEHO) and proposed a dual attention multi-instance deep learning network (DA-MIDL) for timely diagnosis of AD and mild cognitive impairment (MCI). Your tests showed that this approach achieves faster convergence and reduced processing time without compromising segmentation performance. This study provides a valuable tool for efficient and real-time picture segmentation. Authors in [25] also emphasized on the usage of 3D CNN models for neuroimaging-based Alzheimer's disease diagnosis. It discusses the fundamental concepts and algorithms of 3D CNN models and highlights recent applications in AD diagnosis. While there are promising results, the clinical application of 3D CNN models still faces challenges, such as generalizability and interpretability issues, as well as the need for large and diverse datasets. Computational complexity and resource requirements are also considerations in real-world clinical settings. In this regard, IGnet approach developed in [26] using deep learning model for automated Alzheimer's disease (AD) classification. It integrated computer vision and natural language processing techniques, using MRI data and genetic sequencing data. The approach achieved an accuracy of 83.78% and an AUC-ROC of 0.924 on the ADNI dataset. This shows the potential of using multi-disciplinary AI approaches for AD.

N. Song et al., [27] aimed to improve the efficiency of Alzheimer's disease (AD) diagnosis using structural MRI (sMRI) and segmentation techniques. By implementing enhanced fuzzy elephant herding optimization (EFEHO) and proposing a dual attention multi-instance deep learning network (DA-MIDL), the project addresses the limitations of the OTSU segmentation method. The tests conducted show that this approach achieves faster convergence and reduced processing time without compromising segmentation performance. It's an innovative and valuable tool for efficient and real-time picture

segmentation in AD diagnosis. Another method proposed in [28] aimed to improve the efficiency of Alzheimer's disease (AD) diagnosis using structural MRI (sMRI) and segmentation techniques. By addressing the limitations of the OTSU segmentation method, the system implements enhanced fuzzy elephant herding optimization (EFEHO) to achieve faster convergence and reduced processing time without compromising segmentation performance. Additionally, a dual attention multi-instance deep learning network (DA-MIDL) is proposed to provide efficient and real-time picture segmentation. This system offers a promising approach for timely and accurate AD diagnosis.

N. I. El-Aal [29] proposed model focuses on improving classification accuracy and reducing time by selecting the optimal subset of features. It utilizes pre-trained DL models, ResNet-101 and DenseNet-201, to extract features and applies the Rival Genetic algorithm (RGA) and Pbest-Guide Binary Particle Swarm Optimization (PBPSO) to select the best features. The results show that PBPSO selected features achieved high accuracies of 87.3% and 94.8% with shorter execution times of 46.7 sec and 32.7 sec for ResNet-101 and DenseNet-201 features, respectively. Overall, the research aims to enhance the efficiency and accuracy of Alzheimer's disease diagnosis using deep learning techniques. D. AlSaeed and S. F. Omar [30] introduced a classification model that uses the AlexNet framework to diagnose Alzheimer's disease at the Mild Cognitive Impairment (MCI) level. You tested the model using the OASIS Brain dataset, which includes different views of the human brain. With over 100,000 MRI images, your model achieved an impressive accuracy of 98.35%. This research has the potential to contribute significantly to the early detection of Alzheimer's disease.

Authors [31] proposed a deep learning architecture for classifying MRI to predict different stages of Alzheimer's disease (AD). The paper utilizes pre-trained CNN models and optimization algorithms for feature selection. The results show efficient accuracies using the selected features. However, it's important to consider limitations such as dataset size, availability of imaging techniques, and the need for further research and validation. Overall, the project and research paper contribute to the advancement of AD diagnostics and classification using deep learning and optimization techniques.

According to above literature on early-stage Alzheimer's disease detection through deep learning explores various methodologies and techniques. Researchers have investigated diverse models, including multimodal attentive translators, text-conditional attention models, and LSTM networks with external memories. Efforts have also been made to integrate textual context, entity-awareness, and attribute-driven attention into the detection process. Commonly employed architectures include Encoder-Decoder and Merge Model. Furthermore, approaches such as multi-task learning, inverse reinforcement learning, and guiding decoding have been explored to enhance the quality of Alzheimer's detection. The review underscores the significance of large-scale datasets and robust evaluation methods. However, existing models often struggle to achieve an accuracy above 0.5, and numerous comparative studies have been conducted on various CNN algorithms. A notable limitation in previous models is the lack of object relativity, leading to difficulties in establishing relationships between relevant factors. Addressing this issue is pivotal to improving the effectiveness of early-stage Alzheimer's detection models, thus enhancing their clinical utility.

Table 1. Comparative Analysis Of Existing State Of The Art Methods For Detection Of AD

[Ref]	Proposed Model	Used Techniques	Accuracy	Limitation
[18]	CAD Systems for AD	Neuroimaging techniques	N/A	Focuses mainly on binary classification (AD vs. Non-AD)
[22]	ADD-Net	Shallow CNN with MR brain images	93.68%	Needs further validation on larger datasets and real-world clinical settings
[23]	Deep Learning for AD Classification	ResNet18, DenseNet201 with randomized concatenated	97.86%	Functional connectivity changes in MCI need more exploration
[24]	DA-MIDL	Structural MRI, Enhanced Fuzzy	Faster convergence	Does not compromise segmentation but needs real-world validation

[25]	3D CNN Models	3D Convolutional Neural Networks	Promising results	Generalizability, interpretability, large dataset requirement
[26]	IGnet	Deep learning integrating computer vision and NLP (MRI + genetic sequencing data)	83.78% (AUC-ROC: 0.924)	Requires multi-disciplinary validation, dataset diversity
[27]	DA-MIDL	sMRI, EFEHO, dual attention mechanism	Faster convergence	Needs validation for real-time segmentation effectiveness
[28]	DA-MIDL	sMRI, EFEHO for segmentation	Faster processing	Real-time efficiency needs clinical validation
[29]	Feature Selection Model	ResNet-101, DenseNet-201, RGA, PBPSO	87.3%	Feature selection dependency on dataset
[30]	AlexNet-based AD Classifier	AlexNet framework using OASIS dataset	98.35%	Requires more diverse dataset testing
[31]	Deep Learning Model for AD	Pre-trained CNN, optimization algorithms	Efficient accuracies	Dataset size, imaging technique availability, validation needed

Despite significant advancements in deep learning-based Alzheimer's disease (AD) diagnosis, several challenges remain unresolved. Existing studies have primarily focused on binary classification (AD vs. Non-AD), limiting their applicability to real-world clinical scenarios that require multi-class stratification of disease stages. While models such as ADD-Net and IGnet have demonstrated promising accuracy, their generalizability is restricted due to the reliance on small, homogeneous datasets, necessitating further validation on larger and more diverse populations. Additionally, methods employing neuroimaging techniques, such as DA-MIDL and 3D CNN models, face challenges related to computational complexity, segmentation accuracy, and dataset annotation quality. Feature selection techniques, including Rival Genetic Algorithm (RGA) and Pbest-Guide Binary Particle Swarm Optimization (PBPSO), have shown improved classification performance, but they require extensive preprocessing and optimization efforts. Furthermore, current research lacks comprehensive comparative analyses using both simulated and real-world datasets, making it difficult to evaluate the practical feasibility of proposed solutions.

To bridge this gap, we examine the constraints of conventional machine learning and deep learning techniques in diagnosing Alzheimer's disease and identify the primary obstacles that hinder their effectiveness. We analyze existing neuroimaging datasets concerning annotation and labeling quality to ensure robust data-driven insights. Our approach integrates both binary and multi-class classification of AD using advanced CNN architectures, addressing the need for early-stage detection and accurate disease progression tracking. Additionally, we assess the performance of our proposed scheme and compare it with well-known existing models, utilizing both simulated and real-world datasets to enhance its clinical applicability and reliability. By tackling these limitations, our research aims to develop a more precise, scalable, and clinically viable solution for Alzheimer's disease diagnosis.

3. PROPOSED MODEL

In this section, we explain how the proposed CNN model predicts Alzheimer's using fMRI images. Here, CNN serves as the encoder extracting image features, while LSTM acts as the decoder taking the feature vector as input and generating corresponding text output. The model is trained using these two components, followed by testing on the proposed model. The flow diagram of the methodology for research development is depicted in Figure 2.

Journal of Theoretical and Applied Information Technology
15th March 2025. Vol.103. No.5

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

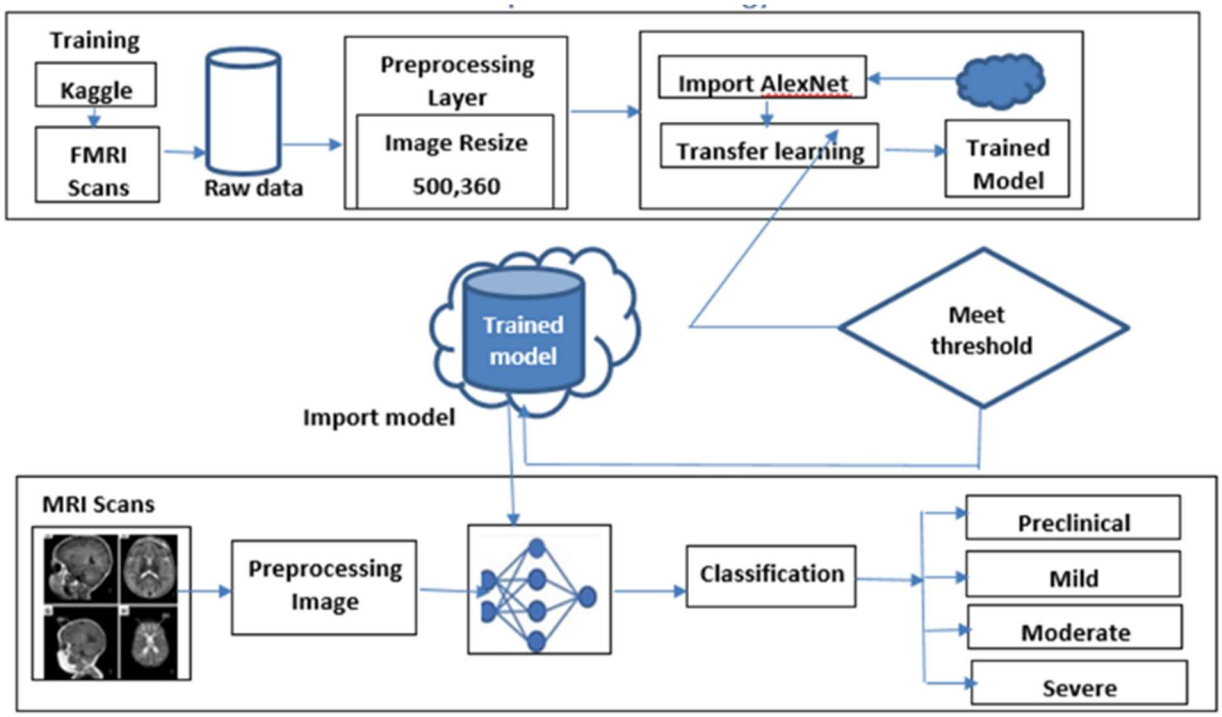

Figure 2: Architecture Diagram Of Proposed Methodology

Input the fMRI images with a nifty extension. Functional Magnetic Resonance Imaging (fMRI) comprises imaging methods designed to illustrate regional, time-varying changes in brain metabolism. These changes can arise from task-induced cognitive state changes or unregulated processes in the resting brain.

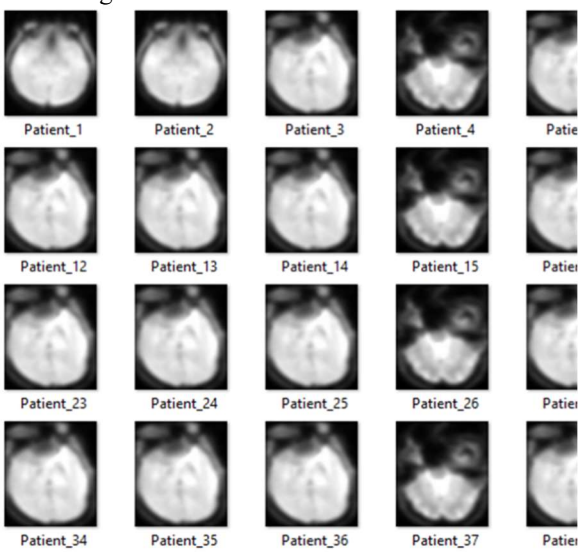

Figure 3. Sample Images From Dataset.

Image Resizing involves adjusting all images to a uniform size (e.g., 64x64 pixels) to ensure consistency across the dataset. Normalization follows, scaling pixel values to the range [0, 1] by dividing each value by 255. Data Augmentation techniques such as shear, zoom, and flip are then applied to enhance dataset diversity artificially, improving the model's ability to generalize. Moving to model definition and fitting, the defined architecture includes Conv2D and MaxPooling2D layers for feature extraction, followed by a flatten layer to prepare features for dense (fully connected) layers. The model is compiled using the adam optimizer, binary cross-entropy loss suitable for binary classification tasks, and accuracy as the metric. Training (model.fit) utilizes generators created from the prepared image data (train_generator and validation_generator), iterating over a specified number of epochs (e.g., 10 epochs), with validation conducted on separate validation data after each epoch.

Further, the training process entails passing batches of data through the model, calculating gradients to adjust model parameters, and systematically refining the model's performance across numerous epochs. It is crucial to meticulously monitor and adjust hyperparameters to ensure the model converges effectively to an optimal solution and demonstrates strong generalization capabilities on new data.

Primarily the proposed model containing the four fundamental steps described as follows:

Step 1: Data Collection, where Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) scan images are retrieved from

the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. These images are then split into training, validation, and test sets in an 80:10:10 ratio respectively to ensure adequate data for model development and evaluation. To address potential class imbalances in the training data, data augmentation techniques are applied, enhancing the dataset's diversity without acquiring new data.

Moving to Step 2: Data Preprocessing, each image in the augmented training set undergoes preprocessing. First, the MRI images are normalized and subjected to noise reduction using nonlinear filtering techniques. Subsequently, all images are resized to a fixed size of 64x64 pixels with 3 color channels (RGB), ensuring uniformity and compatibility with the subsequent model architecture.

Step 3 focuses on Model Training, where a Convolutional Neural Network (CNN) architecture is defined and trained. The CNN model is constructed with layers including convolutional layers for feature extraction with Rectified Linear Unit (ReLU) activation, max-pooling layers for spatial downsampling, and dropout layers to mitigate overfitting. The flattened output is fed into dense layers with ReLU activation for feature aggregation, concluding with an output layer utilizing softmax activation for multi-class classification. The model is compiled with the Adam optimizer and trained on the augmented training dataset, iteratively updating its weights based on computed gradients during backpropagation.

In Step 4: Results, the trained CNN model's performance is evaluated on the validation and test sets to assess its accuracy in classifying Alzheimer's disease. The validation accuracy and test accuracy metrics are computed and displayed, providing insights into the model's effectiveness in disease detection and classification. The results are analyzed to interpret the model's strengths and potential areas for improvement in Alzheimer's disease detection using neuroimaging data.

Overall, this structured approach ensures systematic data handling, rigorous preprocessing to enhance data quality, robust model training leveraging deep learning techniques, and thorough evaluation of model performance, thereby contributing to advancements in Alzheimer's disease diagnosis through computational methods.

```
Epoch 1/25
500/500 [==============================] - 26s 49ms/step - loss: 0.7841 - accuracy: 0.5100 - val_loss: 0.8023 - val_accuracy: 0.3000
Epoch 2/25
500/500 [==============================] - 24s 49ms/step - loss: 0.7131 - accuracy: 0.5240 - val_loss: 0.6898 - val_accuracy: 0.8000
Epoch 3/25
500/500 [==============================] - 25s 51ms/step - loss: 0.6984 - accuracy: 0.5050 - val_loss: 0.6967 - val_accuracy: 0.5000
Epoch 4/25
500/500 [==============================] - 25s 51ms/step - loss: 0.6924 - accuracy: 0.5280 - val_loss: 0.8567 - val_accuracy: 0.3000
Epoch 5/25
500/500 [==============================] - 26s 51ms/step - loss: 0.6843 - accuracy: 0.5310 - val_loss: 0.6869 - val_accuracy: 0.5000
Epoch 6/25
500/500 [==============================] - 26s 51ms/step - loss: 0.6693 - accuracy: 0.5730 - val_loss: 0.7029 - val_accuracy: 0.4000
Epoch 7/25
500/500 [==============================] - 24s 47ms/step - loss: 0.6704 - accuracy: 0.5700 - val_loss: 0.5915 - val_accuracy: 0.8000
Epoch 8/25
500/500 [==============================] - 25s 49ms/step - loss: 0.6623 - accuracy: 0.5660 - val_loss: 0.4749 - val_accuracy: 0.7000
Epoch 9/25
500/500 [==============================] - 23s 46ms/step - loss: 0.6391 - accuracy: 0.6170 - val_loss: 0.6095 - val_accuracy: 0.7000
Epoch 10/25
500/500 [==============================] - 24s 49ms/step - loss: 0.6073 - accuracy: 0.6500 - val_loss: 0.7247 - val_accuracy: 0.7000
Epoch 11/25
500/500 [==============================] - 25s 50ms/step - loss: 0.6035 - accuracy: 0.6570 - val_loss: 0.5074 - val_accuracy: 0.8000
Epoch 12/25
500/500 [==============================] - 27s 53ms/step - loss: 0.5899 - accuracy: 0.6580 - val_loss: 0.6708 - val_accuracy: 0.7000
Epoch 12: early stopping
```

Figure 4: Loss Rate Against The Epochs

3.1. Dataset

The Alzheimer's disease Neuroimaging Initiative (ADNI) dataset serves as a cornerstone in contemporary research aimed at advancing the understanding and diagnosis of Alzheimer's disease (AD). This comprehensive dataset encompasses a wealth of neuroimaging, clinical, genetic, and biomarker data collected from over a decade of rigorous longitudinal studies. It includes MRI and PET scans, providing detailed insights into structural and functional brain changes associated with AD progression. The ADNI dataset is meticulously curated, offering a diverse cohort of participants spanning healthy controls, individuals with mild cognitive impairment (MCI), and those diagnosed with AD. Researchers leverage this rich resource to develop and validate machine learning algorithms and predictive models aimed at early detection, progression tracking, and treatment efficacy assessment in Alzheimer's disease. The ADNI dataset's longitudinal nature and extensive multidimensional data make it invaluable for studying the complex neurobiological mechanisms

underlying AD and developing innovative diagnostic and therapeutic strategies to combat this debilitating condition.

Algorithm 1: Proposed algorithm for Alzheimer's Detection and classification Using CNN

- Load MRI and PET scan images: Let MRI_images = {MRI_1, MRI_2, ..., MRI_N} and PET_images = {PET_1, PET_2, ..., PET_N} from ADNI database.
- Split the dataset into training (Train), validation (Val), and test (Test) sets: - Train, Val, Test = Split({MRI_images, PET_images}, 0.8, 0.1, 0.1)
- Apply data augmentation techniques to up-sample the training dataset:- Augmented_Train = DataAugmentation(Train)
- For each image in the balanced training dataset (Augmented_Train):
- Preprocessed_MRI = NonlinearFiltering(MRI_image)
- Normalized_MRI = Normalize(Preprocessed_MRI)
- Resized_Image = Resize(Normalized_MRI, 64x64x3)
- Define a new CNN base model:
- CNN_model = {

  Input layer (64x64x3),
  Convolutional layers with ReLU activation,
  Max-pooling layers,
  Dropout layers (3 layers, dropout rate = 0.5),
  Flatten layer,
  Fully connected dense layer with ReLU activation,
  Fully connected output layer using softmax activation for multi-class classification
  }
- Compile(CNN_model, loss_function = CrossEntropyLoss, optimizer = AdamOptimizer)
- Train the model using the balanced training dataset:
- Trained_model = Train(CNN_model, Augmented_Train)
- Validation_accuracy = Evaluate(Trained_model, Val)
- Test_accuracy = Evaluate(Trained_model, Test)
- Display the performance metrics.
- interpret the AD results.

End Algorithm

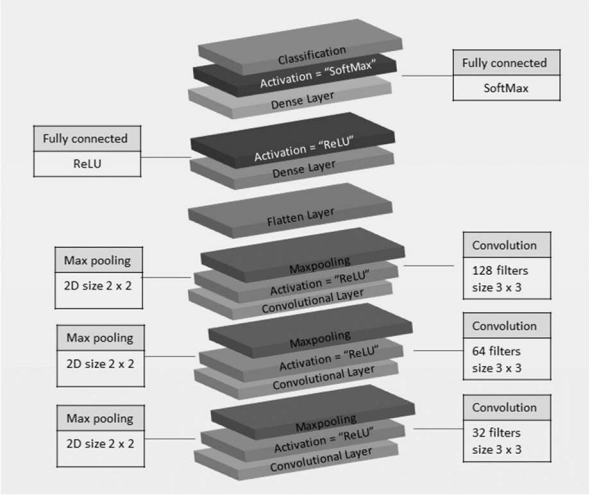

Figure 5: Layers Of The Proposed Convolution Neural Network Architecture.

Table 2: Dataset Details For Binary Classification

Class Label	No. of Samples
Demented	2561
Non Demented	2560

Table 3 provides details of the dataset used for binary classification, where the task involves distinguishing between individuals with dementia (Demented) and those without (Non Demented). The table indicates that there are 2561 samples labeled as Demented and 2560 samples labeled as Non Demented, ensuring a balanced distribution between the two classes. This dataset is crucial for training and evaluating machine learning models aimed at detecting dementia based on various features, such as neuroimaging data or clinical assessments.

In contrast, Table 4 Table 4 presents the dataset details for multi-class classification, where samples are classified into four distinct classes: Very Mild Demented, Mild Demented, Moderate Demented, and Non-Demented.

Table 3: Dataset Details For Multi Classification

Class Label	No. of Samples
Very Mild Demented	1792
Mild Demented	717
Moderate Demented	52
Non Demented	2560

The table specifies the number of samples corresponding to each class label, revealing that there are 1792 samples labeled as Very Mild Demented, 717 samples labeled as Mild Demented, 52 samples labeled as Moderate Demented, and 2560 samples labeled as Non-Demented, summing up to 5121 samples in total. This dataset provides a

more nuanced understanding of the severity of dementia, enabling machine learning models to differentiate between different stages of the disease with varying degrees of impairment.

3.2. Performance evaluation Metrics

A. Accuracy

In the realm of deep learning, accuracy serves as a crucial metric to assess the performance of a model in classification tasks. Mathematically, accuracy represents the proportion of correctly classified instances over the total number of instances in the dataset. It is typically expressed as a percentage. Let *TP* denote the number of true positive predictions (correctly classified instances), *TN* denote the number of true negative predictions (correctly rejected instances), *FP* denote the number of false positive predictions (incorrectly classified instances), and *FN* denote the number of false negative predictions (incorrectly rejected instances). The accuracy *Acc* is calculated using the following formula 1:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

B. Precision

In deep learning, precision is a vital metric used to evaluate the quality of a classification model, particularly in scenarios where the focus is on minimizing false positive predictions. Mathematically, precision represents the proportion of true positive predictions over the total number of positive predictions made by the model. Let *TP* denote the number of true positive predictions (correctly classified instances), and *FP* denote the number of false positive predictions (incorrectly classified instances). Precision *P* is computed using the following equation 2:

$$P = \frac{TP}{TP + FP} \quad (2)$$

4. IMPLEMENTATION AND RESULTS

The proposed our proposed scheme model was developed using Python programming language, specifically version 3.11 on Dell XPS 15, RAM 32 GB, HD 1 TB, processor core i9 12th generation, and NVIDIA GPU 3050 Ti 4 GB. We conducted different experiments using ADNI dataset on variety of classifiers including Softmax, VGG-16, reLU, Sigmoid, SVM, and RF. First we apply the TL on ResNet-50 with AlexNet architecture, and remove the fully connected layers from ResNet-50, retaining only the convolutional layers. Once the ResNet-50 and AlexNet architectures are integrated, we fine-tune the combined model using transfer learning that allow us to initialize the model with pre-trained weights from both ResNet-50 and AlexNet. Leveraging the parallel processing capabilities of the GPU, we employ the CUDA programming model, which allows us to exploit the parallel processing capabilities of NVIDIA GPUs. Below figure 6, and 7 present the training and testing accuracy, and loss level respectively observed during the experiments.

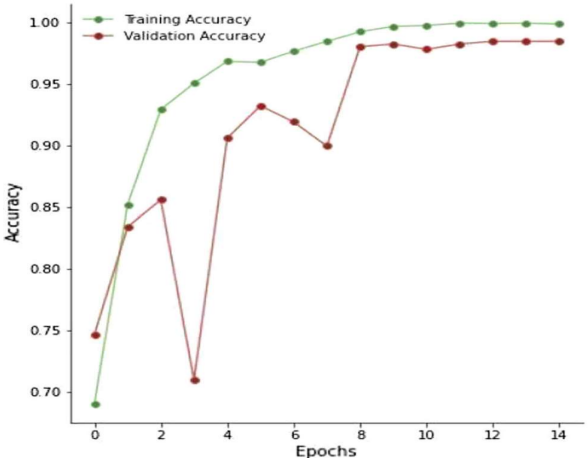

Figure 6. Training And Validation Accuracy

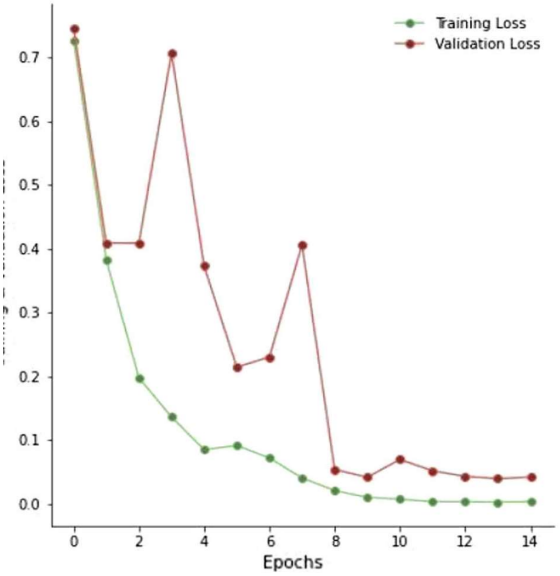

Figure 7. Training And Validation Loss

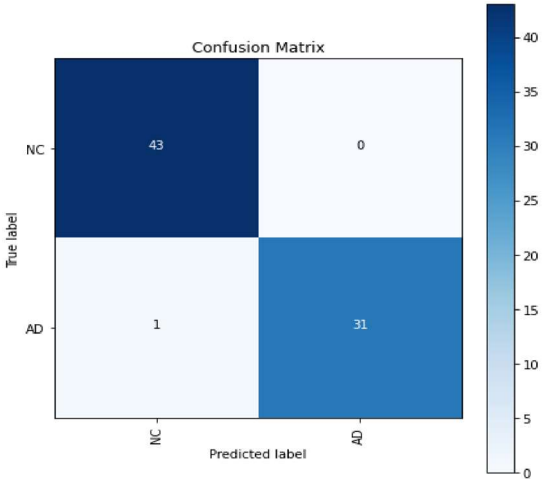

Figure 8. Confusion Matrix

Further, we compare the performance metrics with exiting state-of-the-art methods [15], [16], [17], [18], [19] and [20] that were evaluated using the similar ADNI dataset. Most of the existing methods used only for binary classification but not multi-classification for Alzheimer. Only [19] method used for multi-classification for Alzheimer's disease detection. Therefore, with the same objective and datasets, we observed that our proposed our proposed scheme approach achieve the highest accuracy 99.87 whereas [19] attained maximum 83. 69 as shown in figure 9.

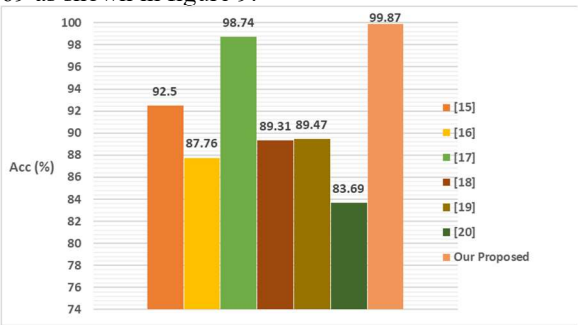

Figure 9. Accuracy Comparison Of Existing State-Of-The-Art Methods With Proposed Scheme

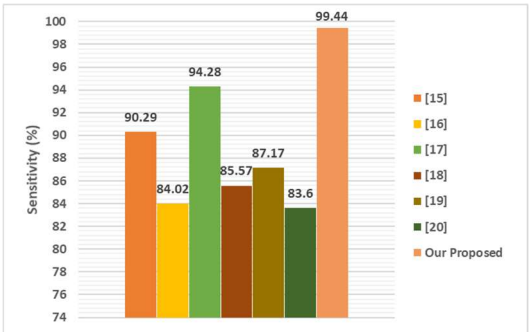

Figure 10. Sensitivity Comparison Of Existing State-Of-The-Art Methods With Proposed Scheme

According to figure 10, the highest sensitivity 99.44% obtained by our approach indicates its remarkable ability to accurately detect positive instances, making it a promising approach for various classification tasks. This analysis underscores the effectiveness of our proposed method in achieving high sensitivity, a crucial aspect in tasks where correctly identifying positive instances is paramount, such as medical diagnosis or anomaly detection.

5. CONCLUSION

This study introduces a system designed for medical image classification and the recognition of Alzheimer's disease. Referred to as Neuro-imaging based Early Detection of Alzheimer's disease using Deep Learning (our proposed scheme), this paper presents a computer-aided diagnostic (CAD) approach aimed at precisely categorizing the stages of Alzheimer's disease, thus enhancing diagnostic accuracy. By employing advanced analysis and preprocessing techniques, including annotation and labeling, our proposed scheme surpasses existing methods in processing neuro-imaging datasets. Notably, the architecture of our proposed scheme utilizes depthwise separable convolutions, reducing parameter numbers compared to traditional models and resulting in more lightweight neural networks. we train the proposed model using ResNet-50 with AlexNet architecture Leveraging the parallel processing capabilities of the GPU, we employ the CUDA programming model, which allows us to exploit the parallel processing capabilities of NVIDIA GPUs. We decompose the neural network operations into parallelizable tasks, such as matrix multiplications and convolutions, which are then executed concurrently on multiple GPU cores. This parallelism is achieved by launching threads, organized into blocks and grids, to perform computations on different subsets of the input data simultaneously. Various performance metrics including accuracy, sensitivity (SEN), F1-score, and specificity (SPC) are employed to evaluate our proposed scheme model with different classifiers such as ReLU, Softmax, and Sigmoid, SVM, and RF, and attained highest accuracy of 99.57% by Softmax classifier with ResNet-50. Future work involves implementing additional pre-trained models for classification and investigating patient progression between Alzheimer's disease stages. Additionally, efforts will be made to expand the dataset size for enhanced accuracy and explore different augmentation methods, such as down sampling.

REFERENCES:

[1]. Alhazzani, A. A., Alqahtani, A. M., Alqahtani, M. S., Alahmari, T. M., & Zarbah, A. A. (2020). Public awareness, knowledge, and attitude toward Alzheimer's disease in Aseer region, Saudi Arabia. *The Egyptian Journal of Neurology, Psychiatry and Neurosurgery*, *56*, 1-7.

[2]. Kerwin, D., Abdelnour, C., Caramelli, P., Ogunniyi, A., Shi, J., Zetterberg, H., & Traber, M. (2022). Alzheimer's disease diagnosis and management: perspectives from around the world. Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring, 14(1), e12334.

[3]. Rajan, K. B., Weuve, J., Barnes, L. L., McAninch, E. A., Wilson, R. S., & Evans, D. A. (2021). Population estimate of people with clinical Alzheimer's disease and mild cognitive impairment in the United States (2020–2060). Alzheimer's & dementia, 17(12), 1966-1975.

[4]. Lane, C. A., Hardy, J., & Schott, J. M. (2018). Alzheimer's disease. European journal of neurology, 25(1), 59-70.

[5]. Salehi, A. W., Baglat, P., & Gupta, G. (2020). Alzheimer's disease diagnosis using deep learning techniques. Int. J. Eng. Adv. Technol, 9(3), 874-880.

[6]. Liu, S., Liu, S., Cai, W., Pujol, S., Kikinis, R., & Feng, D. (2014, April). Early diagnosis of Alzheimer's disease with deep learning. In 2014 IEEE 11th international symposium on biomedical imaging (ISBI) (pp. 1015-1018). IEEE.

[7]. Al-Shoukry, S., Rassem, T. H., & Makbol, N. M. (2020). Alzheimer's diseases detection by using deep learning algorithms: a mini-review. IEEE Access, 8, 77131-77141.

[8]. Gupta, S., Saravanan, V., Choudhury, A., Alqahtani, A., Abonazel, M. R., & Babu, K. S. (2022). [Retracted] Supervised Computer-Aided Diagnosis (CAD) Methods for Classifying Alzheimer's Disease-Based Neurodegenerative Disorders. Computational and Mathematical Methods in Medicine, 2022(1), 9092289.

[9]. Sathiyamoorthi, V., Ilavarasi, A. K., Murugeswari, K., Ahmed, S. T., Devi, B. A., & Kalipindi, M. (2021). A deep convolutional neural network based computer aided diagnosis system for the prediction of Alzheimer's disease in MRI images. Measurement, 171, 108838.

[10]. Ruiz, E., Ramirez, J., Górriz, J. M., Casillas, J., & Alzheimer's Disease Neuroimaging Initiative. (2018). Alzheimer's disease computer-aided diagnosis: histogram-based analysis of regional MRI volumes for feature selection and classification. Journal of Alzheimer's Disease, 65(3), 819-842.

[11]. Venugopalan, J., Tong, L., Hassanzadeh, H. R., & Wang, M. D. (2021). Multimodal deep learning models for early detection of Alzheimer's disease stage. Scientific reports, 11(1), 3254.

[12]. Helaly, H. A., Badawy, M., & Haikal, A. Y. (2022). Deep learning approach for early detection of Alzheimer's disease. Cognitive computation, 14(5), 1711-1727.

[13]. Fulton, L. V., Dolezel, D., Harrop, J., Yan, Y., & Fulton, C. P. (2019). Classification of Alzheimer's disease with and without imagery using gradient boosted machines and ResNet-50. Brain sciences, 9(9), 212.

[14]. Islam, F., Rahman, M. H., Hossain, M. S., & Ahmed, S. (2023). A novel method for diagnosing Alzheimer's disease from MRI scans using the ResNet50 feature extractor and the SVM classifier. International Journal of Advanced Computer Science and Applications, 14(6).

[15]. Kumar, L. S., Hariharasitaraman, S., Narayanasamy, K., Thinakaran, K., Mahalakshmi, J., & Pandimurugan, V. (2022). AlexNet approach for early stage Alzheimer's disease detection from MRI brain images. Materials Today: Proceedings, 51, 58-65.

[16]. Liu, J., Li, M., Luo, Y., Yang, S., Li, W., & Bi, Y. (2021). Alzheimer's disease detection using depthwise separable convolutional neural networks. Computer Methods and Programs in Biomedicine, 203, 106032.

[17]. Ebrahimi, A., Luo, S., & Disease Neuroimaging Initiative, F. T. A. S. (2021). Convolutional neural networks for Alzheimer's disease detection on MRI images. Journal of Medical Imaging, 8(2), 024503-024503.

[18]. Karami, V., Nittari, G., & Amenta, F. (2019). Neuroimaging computer-aided diagnosis systems for Alzheimer's disease. International Journal of Imaging Systems and Technology, 29(1), 83-94.

[19]. Kerwin, D., Abdelnour, C., Caramelli, P., Ogunniyi, A., Shi, J., Zetterberg, H., & Traber, M. (2022). Alzheimer's disease diagnosis and management: perspectives from around the world. Alzheimer's & Dementia: Diagnosis,

Assessment & Disease Monitoring, 14(1), e12334.
[20]. Podhorna, J., Winter, N., Zoebelein, H., Perkins, T., & Walda, S. (2020). Alzheimer's diagnosis: real-world physician behavior across countries. Advances in therapy, 37, 883-893.
[21]. Roth, S., Burnie, N., Suridjan, I., Yan, J. T., & Carboni, M. (2023). Current diagnostic pathways for Alzheimer's disease: a cross-sectional real-world study across six countries. Journal of Alzheimer's Disease Reports, 7(1), 659-674.
[22]. Fareed, M. M. S., Zikria, S., Ahmed, G., Mahmood, S., Aslam, M., Jillani, S. F., ... & Asad, M. (2022). ADD-Net: an effective deep learning model for early detection of Alzheimer disease in MRI scans. IEEE Access, 10, 96930-96951.
[23]. Odusami, M., Maskeliūnas, R., & Damaševičius, R. (2022). An intelligent system for early recognition of Alzheimer's disease using neuroimaging. Sensors, 22(3), 740.
[24]. Alhassan, A. M., Alzheimer's Disease Neuroimaging Initiative, & Australian Imaging Biomarkers and Lifestyle Flagship Study of Ageing. (2022). Enhanced fuzzy elephant herding optimization-based OTSU segmentation and deep learning for Alzheimer's disease diagnosis. Mathematics, 10(8), 1259.
[25]. Xu, X., Lin, L., Sun, S., & Wu, S. (2023). A review of the application of three-dimensional convolutional neural networks for the diagnosis of Alzheimer's disease using neuroimaging. Reviews in the Neurosciences, 34(6), 649-670.
[26]. Wang, J. X., Li, Y., Li, X., & Lu, Z. H. (2022). Alzheimer's disease classification through imaging genetic data with IGnet. Frontiers in Neuroscience, 16, 846638.
[27]. Song, X., Mao, M., & Qian, X. (2021). Auto-metric graph neural network based on a meta-learning strategy for the diagnosis of Alzheimer's disease. IEEE Journal of Biomedical and Health Informatics, 25(8), 3141-3152.
[28]. Murugan, S., Venkatesan, C., Sumithra, M. G., Gao, X. Z., Elakkiya, B., Akila, M., & Manoharan, S. (2021). DEMNET: A deep learning model for early diagnosis of Alzheimer diseases and dementia from MR images. Ieee Access, 9, 90319-90329.
[29]. Shereen A El-Aal, N. I. G. (2021). A proposed recognition system for Alzheimer's disease based on deep learning and optimization algorithms. Journal of Southwest Jiaotong University, 56(5).
[30]. AlSaeed, D., & Omar, S. F. (2022). Brain MRI analysis for Alzheimer's disease diagnosis using CNN-based feature extraction and machine learning. Sensors, 22(8), 2911.
[31]. Bhasin, H., Agrawal, R. K., & Alzheimer's Disease Neuroimaging Initiative. (2020). A combination of 3-D discrete wavelet transform and 3-D local binary pattern for classification of mild cognitive impairment. BMC Medical Informatics and Decision Making, 20, 1-10.