UtilitasMathematica

ISSN 0315-3681 Volume 122, 2025

"Advancing Alzheimer's Disease Detection: A Multi-Modal Deep Learning Approach for Streamlined Clinical Diagnosis"

Heena Panjwani[1, a)] and Mehul Parikh[2, b)]

[1]*Ph.D Scholar, Gujarat Technological University, Computer Engineering, Ahmedabad, 382424, India*
[2]*Lalbhai Dalpatbhai College of Engineering, Information Technology, Ahmedabad, 380015, India*

[a)] *panjwaniheena067@gmail.com*
[b)]*mehulcparikh@ldce.ac.in*

Abstract

Alzheimer’s disease (AD) stands as the most prevalent chronic ailment among the elderly, exhibiting a high incidence rate [1]. Accurate early-stage identification of Alzheimer's disease is crucial for successful treatment and recovery, presenting a significant research challenge in precise diagnosis.Researchers have used different approaches to; diagnose AD but these approaches lack prediction accuracy by various researchers. In recent years, deep learning has become more successful and popular in the area of medical imaging, becoming the method of choice for imaging the medical images and fast growing interest to identify AD. Deep models have improved precision and efficiency in approaching this investigation compared to regular machine learning technologies. This review paper analyses the difference between other research approaches that aim at the early identification of AD; incorporation of ConvNets with Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI). The finding is that the networks trained on multi-modal images are more accurate than the networks trained on single-modal images at generalization. The performance of the suggested strategy has been tested using the data set from the Alzheimer’s Disease Neuroimaging Initiative. Accuracy (AUC),Specificity (SPE) and sensitivity (SEN) were the parameters used to assess the performance of the model and all the results obtained were 83.81%,87.50%,75.76% respectively.

Keywords:

Alzheimer’s Disease-Diagnosis, Magnetic Resonance Imaging (MRI),Deep Learning, Positron-Emitted Tomography (PET) and Convolution Neural Network(CNN).

1. Introduction:

Alzheimer's disease (AD) stands as the most predominant neurodegenerative brain disorder that affects elderly individuals globally, ranking among the primary causes of dementia [13]. AD represents an untreatable, degenerative neurological condition that gradually leads to the death of brain cells, causing a decline in memory, reasoning abilities, and ultimately hindering the performance of even the most basic daily routine tasks. This cognitive deterioration eventually culminates in dementia. The disease progresses from the early stage of normally controlled (NC) to mild cognitive impairment (MCI), ultimately reaching the impactful stage of AD.

The significance of early identification arises from the projected global disease burden of AD, estimated to exceed $2 trillion by 2030 [14]. Thus, significant efforts have been made with a focus on developing ways to delay or halt the disease's progression, particularly during pre-symptomatic stages. A wide array of techniques has been employed for AD diagnosis and over the past decades, machine learning methods have displayed promising results in AD classification. However, a revolutionary shift has occurred with the advent of deep learning, surpassing traditional machine learning approaches in terms of performance in classification and regression tasks. Consequently, DL based methodologies have become the best choice available for next-generation applications.to be used to identify Alzheimer's disease.

There is a high level of dependence on the biomarkers in assessing the accuracy of diagnosing AD. Biomarkers play a significant contribution towards understanding of the prediction,the diagnosis, progression, regression and reversal of the disease. the prognosis of the disease and the treatment outcomes of the disease [15]. For the screening of AD, several neuroimaging techniques such as Of these, the Modality MRI and PET, have been researched in-depth. MRI gives good structural imaging of the anatomy. and structure of the human brain which will enable measurement and investigation of the biological. the progression of AD pathologic features of brain atrophy. On the other hand, PET enables the determination of the numerical density of the various tissue types. Metabolic processes in tissues and organs of the human body and deviations from norm in view of displaying the data and images. These neuroimaging techniques go a long way in helping towards early diagnosis of appreciation as to the nature of Alzheimer's disease.

Most of the earlier conventions in machine learning require feature extraction which is most often done by hand.tedious, error-prone, confirmative and directly dependent on the specialist's knowledge and may take several cycles to accomplish the best outcome in the lab experiments. However to respond to these challenges and spur the mentioned improvements the following measures needed to be taken. and for improved performance, convolutional neural networks (CNNs) provide a great opportunity and have been shown to provide accurate diagnosis of AD. CNNs can also learn more relevant features from input data that require no human intervention, unlike setting up features on your own. This automated feature extraction capability not only minimizes the necessity of such knowledge but it also helps in extracting different features.
However the use of graphical display also increases the efficiency and accurate diagnosis of AD. Therefore, CNNs have become important because of a competent and promising strategy that may help develop effective tools for diagnosing Alzheimer's disease.

CNNs have shown impressive performance in several applications mainly in image such as image recognition, objects' identification and natural language processing concerns. Their ability to achieve feature learning in an automated manner with features that are at some level hierarchical. That is why they are so suitable for a large number of machine learning issues.

CNNs are a type of neural networks which are especially suitable for processing data organized in grids such as images and audio information. As discussed earlier a normal CNN comprises three kinds of layers. of layers: [16]

1. Convolutional Layer: Computation of convolutional layer takes place in a CNN. It processes the input data with the help of a set of linear learnable transformations (called kernels) to detect relevant features in the data. Each individual filter moves over the data set and for each point in the set, element by element multiplication occurs. and summations and then passing these values to the corresponding feature maps with regards to the feature maps desired.

2. Pooling Layer: It downsizes the size of the feature maps from the convolutional layer in terms of spatial size. This is done on the feature maps and is typically done by a down sampling operation such as max-pooling or average-pooling. The idea used in pooling is that it reduces the dimensionality of the network as well as the number of parameters used in this network making the whole network more efficient.

3. Fully Connected Layer: The fully connected layer is a classical type of a neural network layer where each neuron within the previous layer connects with every neuron of the current layer.[17] In other words, it is the final step of deep learning; where it is expected to take the extracted features of the previous layers and make a prediction of what it has been trained for. The fully connected layer is usually applied at the last step of the CNN in order to bring out meaningful features to particular classes of the problem in hand.

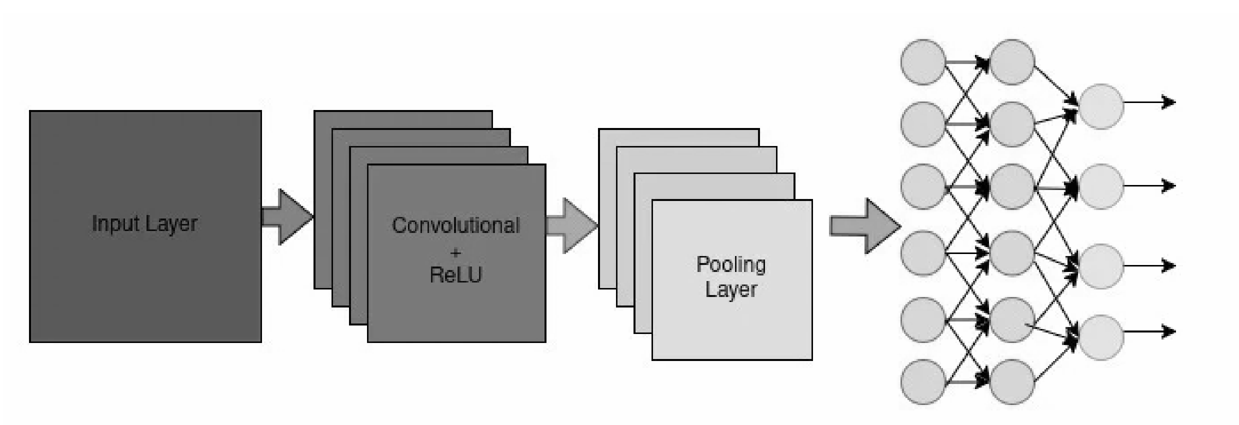

Fig 1: CNN Model

Table 1: Assessment of Different Methodologies Used For AD Detection

Sr. No.	Title	Dataset	Research Gap	Conclusion
1	Multimodal deep learning models for early detection of Alzheimer's disease stage.[6]	ADNI dataset	The assessment utilized solely CN and AD images, which limited the developed model's ability to establish an effective stage-wise classification platform for the three stages, namely CN, MCI, and AD.	Within the framework of the carried out research the authors intended to draw public attention to the possible opportunities.Deep Learning (DL) for MMDF for short, which involves the integration of multiple modes of data. on the following key findings: 1) It was found that deep penetration to the patient's skin is not necessary for obtaining a positive treatment outcome. models outperformed shallow models when it comes to single-modality sub- stage of Alzheimer's prediction. 2) They proposed a novel DL framework scoped for its use in particular. which is the focus of this paper, is the ability to fuse multimodality data.have shown the ability to perform better than the company.compared with the so-called single-modality DL approaches. 3) The authors introduced innovative perturbation and There are the clustering based feature extraction. trends to assist in analysis of the difficult to obtain illustrations. of DL models, as well as their ability to demonstrate the efficiency for Alzheimer's disease patients stage prediction. 4) The research involved the application of a 3D convolutional We introduce a novel neural network architecture for MRI. image data indicating a probability for moving forward with Alzheimer's disease diagnosis and classification.

2	Ensembles of Patch-Based Classifiers for Diagnosis of Alzheimer Diseases.[10]	GARD dataset	Due to the limited size of the dataset used, the training of the model was impeded, leading to a reduction in its overall efficiency and performance.	The diagnosis of Alzheimer's disease using brain MRI data. Authors specifically focused on the hippocampus, a clinically large area largely studied for AD detection. The the strategy they used include engineering Convolutional Neural Network (CNN) classifiers based on Temporal Voxel Patterns (TVPs) extracted from semi-randomly generated locations within the hippocampus region. This effective approach lets them develop the necessary amount of training data effectively. The authors, after a great training, successfully combined the models, which led to significant individual models, hence global accuracy which could be matched up against the results of models which are only developed for MRI data. This indicates that their approach achieved promising.The given results and demonstrated promising abilities in being accurate in diagnosing AD using brain MRI scans with emphasis to hippocampus region.
3	Multimodal multi task deep learning model for Alzheimer's disease progression detection based on time series data. [7]	ADNI dataset	The paper primarily focused on voxel feature extraction which processes brain data uniformly, and proved to be advantageous for some aspects of analysis. However, this approach has its limitations as well. By processing the brain uniformly, the model may overlook important local information that could be crucial for accurate AD diagnosis. The uniform processing may not fully capture the spatial	In their paper the authors suggested a creative group of modes or ways of operating the multi task deep learning model that combined Convolutional Neural (CNN) and Bidirectional Americas nations Ownership A global attitude and a flag of Europe indicated a pull towards acquisition and conquest. Long Short-Term Memory (BiLSTM) networks. This model was developed to aim at learning two tasks: AD multiclass classification and regression of four cognitive processes. scores. To accomplish this, the CNN subnetworks were employed to extract local features from marketing and pediatric within an individual case Each modality. This allowed the model to capture specific patterns and knowledge from the input data in a localized manner. On the other hand, the BiLSTM subnetworks are the two dedicated to capturing structural information.By using BiLSTM, the model could effectively capture the time trends both for single cases and for groups of subjects. the data over time.

			relationships between voxels, potentially missing out on significant patterns or details present in localized regions. Moreover, dealing with a large number of voxels can lead to increased complexity in the model. The sheer volume of voxels requires substantial computational resources and can result in longer training times. To address this challenge, the authors may have employed pre-selection techniques to reduce the number of voxels considered for analysis. However, this additional step adds complexity to the overall model and may introduce the risk of omitting relevant information during the pre-selection process.	CNN and its advantages will be enhanced by the following improvements: and BiLSTM, the proposed ensemble multimodal multitask deep learning model aimed to acquire better performance for both AD classification and cognitive score regression. The model's capacity to pull out local and longitudinal features from multimodal data made it a rich and promising approach that offers an avenue of attacking the complexity of AD diagnosis and understanding the relationship between cognitive scores and disease progression.

4	Deep Learning Framework for Alzheimer's Disease Diagnosis via 3D-CNN and FSBi-LSTM[11].	ADNI dataset		In this paper, the authors introduced a novel framework for diagnosing Alzheimer's disease (AD) that utilized a combination of 3D Convolutional Neural Network (CNN) and Fused Spatial Bidirectional Long Short-Term Memory (FSBi-LSTM). The key Innovation process was shifted with the substitution of Fully Connected (FC) layer in the 3D-CNN with a new LSTM network framework. The authors assumed that this modification was an advantage to their model because retain and preserve spatial feature maps information to a greater extent. By leveraging Lim et al. 's capabilities of FSBi-LSTM The model would also be able to capture and Understand the temporal structures You've to analyze the temporal dependencies. Indeed, in order to assess the effectiveness of their proposed method, the authors have performed variety of experiments using the Alzheimer's Disease Neuroimaging Initiative-consortium ADNI dataset. The results demonstrated as to the efficaciousness of their strategy in accurately diagnosing AD, demonstrating the possibilities of the 3D-CNN and FSBi-LSTM framework for enhancing the diagnostic capabilities of AD classification models. In general, the paper provided an competent and ground-breaking approach to AD identification, quarrying the power of 3D-CNN and FSBi-LSTM for it to be possible to learn spatial and pulsations and oscillations of time from the data as well as Limited to achieving the possible state of art in terms of performance.on the ADNI dataset.

5	Early Diagnosis of Alzheimer's Disease Using Deep Learning[12].	ADNI dataset		The authors of this study seem to have postulated the following hypotheses: an ensemble learning method on using deep learning methodologies for the early diagnosis of Alzheimer's disease (AD). The proposed approach involved training of a base classifier that consists of many classifiers as a whole, of the end and end process in enhance the model's fitting capabilities and overall performance. The authors conducted their evaluations by in the context of the ADNI database, and the results proving that their collection That is, the member of the ensemble learning method outperformed conventional machine learning strategies for early diagnosing of AD. The advantage of their approach intended that deep learning-based ensemble methods have the possibilities of providing more accuracy. and testing efficiency of AD diagnosis. which provides a basis for achieving a more reliable and timely identification of the illness.
6	Development and validation of an interpretable deep learning framework for Alzheimer's disease classification.[8]	ADNI dataset and MMSE score.		The approach of the learning framework showed great efficiency and effectiveness in its endeavor of high accuracy in Alzheimer's disease diagnosis based on MRI data. The model's performance was compared with some information from different groups of people, neuropathological Based on the described findings, and expert and professional evaluations. The authors expect positive outcomes that if their model is validated in the treatment of tumors that have exact edges or is small and can be easily extirpated, there should be less postoperative cell migration with their technique than with the current standard technique. In clinical context, it would result in long overdue revolutionary enhancements in care and outcomes compared to the neurological function tests conducted in the current month. As the search for disease-modifying treatments of neurological disorders progress; approaches for Alzheimer's disease treatment continue, the successful validation of hypotheses that support the theory of consumption location,

				and also the validation of the h1 , h2 and h3 tested in this study. As to their method maybe they promote a certain way that was paving the path. in order to achieve better and concrete treatment strategies.
7	Early-Stage Identification and Pathological Development of Alzheimer's Disease Using Multimodal MRI[9].	Clinical data of the Neurology Department of Xuan Wu Hospital, Beijing and MMSE score.	SVM algorithm is not suitable for large datasets owing to which only around 200 images were used for training and testing purpose keeping the model undertrained.	The authors conducted a comprehensive study using multimodal MRI data to investigate the follow-up of Alzheimer's disease (AD) pathology and potential biomarkers at the early stages of the disease. Through their studies, they conducted three group experiments and succeeded with impressive accuracy rates of 80.24% for the Subjective HF with reduced Cognitive Decline (SCD) group. 97.76% for the amnestic Mild Cognitive Impairment (aMCI) group, and 98.58% for the AD group. Furthermore, the authors described the twenty most superior portions of the brain which revealed the highest level of discrimination their counterparts in four other countries of the study.power between the groups. A lot of useful information can be gained large as to the regions. most affected by AD pathology towards the beginning of the study, pointing out possible candidates to serve as biomarkers in the early diagnosis.pathology, offering important facts to identify the initial onset of the disease. clarifying the existing knowledge about disease's mechanisms. This research has added to the intensifying pool of Knowledge with an envisaged end of enhancing the identification of the problem and a measure to prevent its occurrence in the future Alzheimer's disease.
8	A deep learning model for early prediction of Alzheimer's disease dementia	ADNI and AIBL dataset.	Studying hippocampus as the only ROI limits the ability to extract features as there are many unknown regions in the distribution of abnormal regions in the brain which may also lead to the loss of useful	The authors model showed that patients has Mild Cognitive Impairment (MCI) with various progress algorithms detecting those who were more likely to develop AD dementia. This approach holds great potential that can be harnessed to be reliable and affordable.The authors are using deep learning method holds a potential of being of high value tool in the management and understanding of AD dementia,which gives an insight of the opportunities for improving patient care, cost-effective

	based on hippocampal magnetic resonance imaging data.[17]		information.	prognosis, and potential progresses in the development of effective treatments and therapies.
9	Diagnosis and monitoring of Alzheimer's patients using classical and deep learning techniques.[20]	OASIS and ADNI dataset		This paper proposed a machine-based analysis of the Broadly, such ALD-like diseases which provided more accurate diagnoses in other than comparison to state of the art. To further assist the Alzheimer's patients and caretakers, a post-diagnosis monitoring system was proposed to log the daily life activities of the patients, thus, enabling future systems to develop suggestions and activities plan for the patients to extend the healthy living and minimize human assistance for AD patients.In the proposed system, for both diagnosis and post-diagnosis ADL monitoring systems, relatively higher accuracy is achieved.
10	Hippocampus segmentation on epilepsy and Alzheimer's disease studies with multiple convolutional neural networks [46]	ADNI dataset		These authors proposed a hippocampus segmentation method including consensus of multiple U-Net based CNNs and traditional post processing, successfully using a new optimizer and loss function from the literature. The presented method achieves state-of-the-art performance on the public HarP hippocampus segmentation benchmark. The hypothesis was raised that current automatic hippocampus segmentation methods, including our own, would not have the same performance on our in-house epilepsy dataset, with many cases of hippocampus removal. Quantitative and qualitative results show failure from those methods to take into account hippocampus removal, in unseen epilepsy data. This raises the concern that current automatic hippocampus segmentation methods are not ready to deal with hippocampus resection due to epilepsy treatment. We show that training in the epilepsy data does improve results, but there is still room for improvement. In future work, improvements can be made to our methodology to detect the removal of the hippocampus as a pre-processing step.

11	Multimodal deep learning for Alzheimer's disease dementia assessment[8]	AIBL and OASIS dataset	The study had several limitations.To Begin, in cases of mixed dementia, the present models default to a diagnosis of AD whenever this condition is present, thus attributing a single diagnosis to participants with multiple comorbidities.	The authors concluded that their interpretable, multimodal deep learning framework was able to obtain high accuracy signatures of dementia status from routinely collected clinical data, which was validated against data from independent cohorts, neuropathological findings, and expert-driven assessment. Their approach has the potential to expand the scope of machine learning for AD detection and management, and ultimately serve as an assistive screening tool for healthcare practitioners.
12	Deep Learning Approach for Early Detection of Alzheimer's Disease[9]	ADNI dataset		The proposed framework was based on deep-learning CNN architectures. Four AD stages were multi-classified. Besides, separate binary classifications were implemented between each two-pair class. The experimental results prove that the proposed architectures are suitable simple structures that reduce computational complexity, memory requirements, overfitting, and provide manageable time. They also achieved very promising accuracy in multi-class AD stage classifications.

2. Data Collection:

The dataset serves as the foundation for conducting our research and analysis. We outline its key characteristics, such as the number of samples, the nature of the data (e.g., images, text, numerical data) and any relevant information about its source and origin.

Additionally, we elucidate the preprocessing steps that were applied to the dataset before using it in our study. Preprocessing is an essential phase that aims to clean and transform the raw data into a suitable format for analysis. This may involve tasks such as data cleaning (removing duplicates or missing values), data normalization (scaling data to a common range), feature extraction (selecting relevant features), and data augmentation (increasing the size of the dataset through techniques like rotation or flipping for image data).

The dataset is also described along with every step of preprocessing to make the research more transparent to enable the readers to appreciate how the data was collected and processed for analysis based on the given research methodology. and to this end provide a significant contribution to the success and validity of replication studies in our field.

3. Dataset:

In developing the information for this article we used a resource information base derived from Alzheimer's Disease. Imaging archive used in the current study: Alzheimer's Disease Neuroimaging Initiative (ADNI) which can be accessed at adni.loni.usc.edu. The main goal of ADNI has therefore been to explore the application of longitudinal. Biological markers, clinical assessment MRI, PET scans diagnosis and treatment.
neuropsychological assessments for following the course of mild cognitive impairment (MCI)
prostate cancer and early Alzheimer's disease (AD). That is why the launch of this initiative is targeted at understanding how these various data Bussing et al 2009 describe biomarkers using PET scans and other biochemical tests, clinical assays and neuropsychological assessments or examinations, can be used synergistically for improved analysis of the nature and progression of. advancement of MCI and AD. The amount of data collected within ADNI has been crucial in the discovery and moving the research field and our knowledge forward in Alzheimer's disease-related conditions.

These were 126 PET images from CN, 160 PET scans from sMCI, 96 PET scans from AD.
chosen from the ADNI dataset. Likewise, 458 MRI images of all three classes of AD used for purposes of training and validation.
NeuroImaging data that organizes the results of the analysis of the subject's structural and functional organisation of the brain offer the possibility to achieve this task.
Alzheimer's disease; it also helps in the early identification of Alzheimer patients and specific strategies formulated for them. affected individuals. These include Clinical Rating Dementia and Mini mental state examinations among others Psychological assessment;_displaying cognition problems of patients such as the Clinical Dementia Rating (CDR) and the Mini-Mental.

Alzheimer's disease (AD) assessment is greatly supported by the use of Mini Mental State Examination (MMSE) and State Examination (MMSE). These tests assess cognitive functions that include learning, memory, attention, language, and many more, learning, memory, and attention. They are widely used in clinical practice to detect the signs of ASD and also track disease progression to support proper rankings of AD and to help define its stages and follow the changes that happen over time.

Therefore, a combination of this neuroimaging technique and the neuropsychological techniques discussed in this paper will be useful. greatly improve the identification rate and efficiency of AD from current rate. By integrating information between neuroimaging approaches, including MRI and PET, and clinical-cognitive tests. Patients, researchers, and clinicians receive a better understanding of the disease's evolution and its effect on the higher mental processes.

4. Methodology:

As shown in the framework presented in figure 2 below is intended to capture an ROI (Region of Interest) filter and feature extraction method called Interest Based feature extraction method and an effective system for the management of data on the data files obtained from Alzheimer's Disease Neuroimaging Initiative (ADNI) [21].

The pipeline starts with obtaining neuroimaging data from the ADNI database and then forms the basis of our dataset, to which other sources may be added during the data analysis phase. The next step is one which involves coming up with the definitions and identification of. psychologically concrete ROIs within the neuroimaging data. ROIs are regions in the brain that are of special interest for AD analysis, as they might reveal a certain shift or pathology linked with the disease.

After identification of the ROIs, our feature extraction technique is applied on these regions to extract features that would be discerning between them, features that are relevant. These features embrace basic facts about the brain morphology and organization pertinent to AD diagnosis and prognosis given ischaemia as of basal forebrain survival.

The data management component is essential, as it is the component that is used in managing the extracted features depending on the above five components. the best way of arranging the dataset in order to achieve great results. Some of the activities encountered under this step include data cleansing. cleaning, transformations, and sorting, making certain that it is in the proper format for the following analysis.

After data management, the extracted features are passed through our selected classification or prediction model. The learned patterns and relations from patterns contributed to extract the features of the proposed model. interactions between AD and non-AD cases, which in turn makes it possible to create accurate and reliable.grouping of subjects into categories which actually makes it classification of subjects into different groups.

In summary, the proposed pipeline learnt here encompasses ROI-based feature extraction with generally reliable data. management methods and offering an exhaustive and efficient tool to evaluate. the sample data in this study of longitudinal neuroimaging data from the ADNI database. It is believed that this pipeline will generate significant business value proofs and progresses obtained in AD research to help solve the early diagnosis and the general comprehension of the disease.

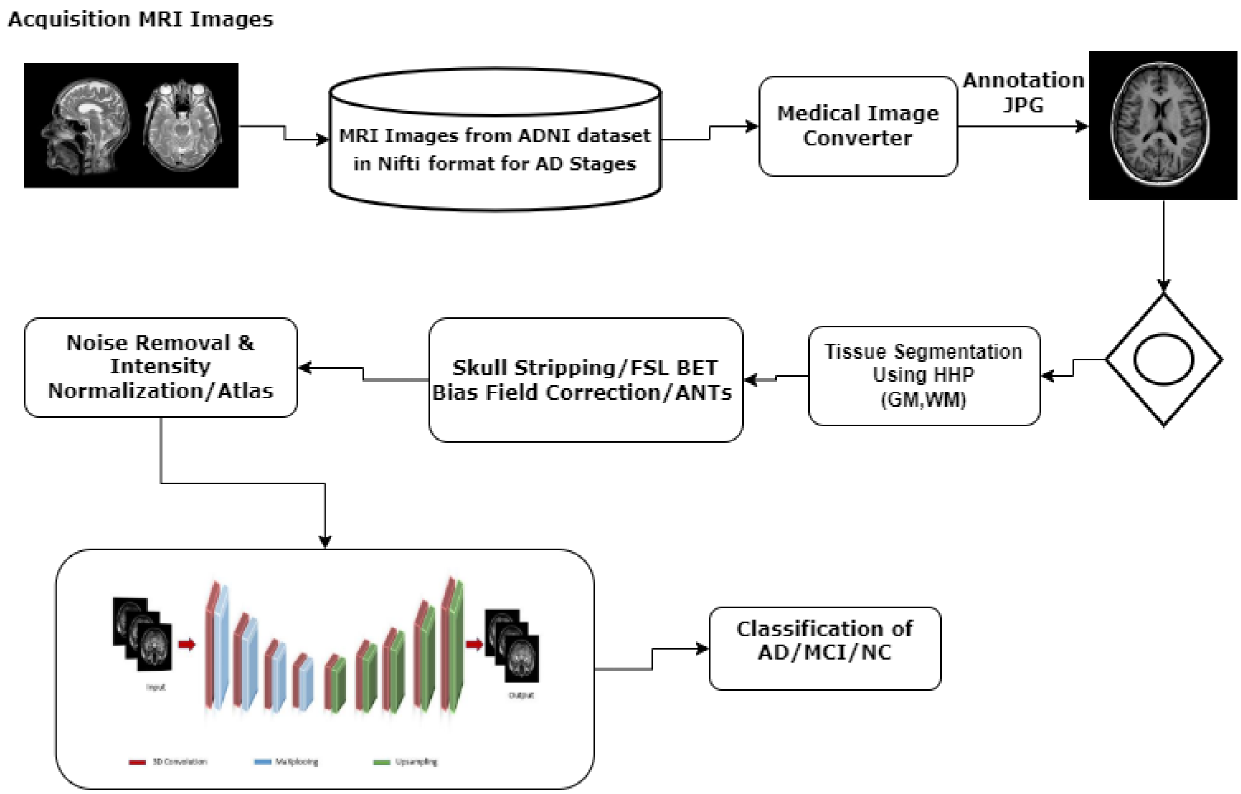

Fig 2: Proposed Workflow

The four broad categories as depicted in the image above are:

1) Data (Input):
The first type of data pertains to the data which is actually used in the study. The bio markers linked with Alzheimer's disease detection are MRI and PET-CT. The study will use MRI and PET-CT data collected from the participants.
Furthermore, data collected from Neuropsychological tests were collected from ADNI and OASIS. referenced from online databases for purposes of testing and validation.

2) Pre-Processing:
The second category is data pre-processing, as the pre-processing step is crucial for data clean and improve the quality. improve the cases inside the model trying to be learned. Smoothing and segmentation of tissue analyses will be used for pre-processing the raw data with the result of minimizing the variability of the measurement for a given variable. Tissue segmentation requires the removal of the skull and contains an image to subdivide the brain so that treatment can be targeted on sure areas of the mind, such as the hippocampus. affected early in AD. For noise reduction operation on the data set, the process of Smoothing will be applied. quality of the data [43].

It is crucial to consider that in this study, neuroimaging data come from different sources

and acquisition protocols, several problems arise mainly because of differences in equipment from different manufacturers and due to differences.
guidelines observed by working personnel in the medical field. Besides, conditions such as the protracted acquisition time means that the subject can move slightly thereby creating distortions into the desired position. acquired images [2].
To overcome these problems for the purpose of making the data more accurate and reliable the following preprocessing has been done.
To clarify, such operations are conceived to enhance the equality of images acquired and provide them ready for other analysis operations like feature extraction, feature selection and experiments.
Some of the key preprocessing steps include:
1. Intensity Normalization: This process involves a process of standardizing the luminance values of the given images to keep them the same across scans and devices more often than not. This way the images are ensured in a way that the conventional methods of safety have not been able to provide. equivalent and have concluded that variations in intensity due to different acquisition parameters are mitigated [35].

2. Registration: Registration techniques are used to map images from various sources or even to remove offsets. coordinates, and also for possible transformation: shift, rotation and scaling. This ensures that companion structural formations are co-located which is fundamental to precise evaluation [44].

3. Skull Dissection: To conclude, it is frequently valuable to reshape the specimen, that is to remove what is called “skull-stripping”: the outer layers of non-brain tissue. focusing the analysis on structures and features of the brain, and excluding all the rest.

4. Motion Correction: Forging movement artifacts that are usually from the subject's movement during imaging. measures that would be useful in correcting the effect of the acquisition on the data can be obtained. It becomes especially important in the context of preserving the spatial relations of the images [42].

By following these preprocessing procedures, the researchers can further process the obtained images into a unified and harmonized format that will in the process partly eliminate variability due to different acquisitions procedures. This in turn enables high reliable analysis performance for activities like features.
learning stages such as extraction, feature selection and classification and thus help in the improvement of the accuracy and results in neuroimaging analysis and derived from neuroanatomical information.

ISSN 0315-3681 Volume 122, 2025

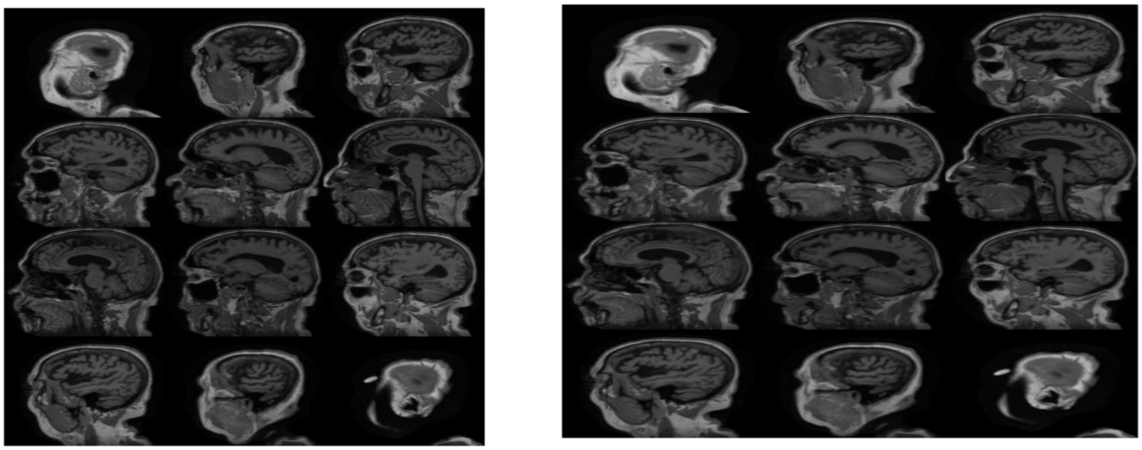

Fig 3: Output of each stage of the preprocessing pipeline for a cognitively normal subject
{1➔2➔3➔4}.

Input scan Dimensions: (256, 256, 150) Spacing: (0.9375, 0.9375, 1.2)
Origin: (88.6399, -116.532, -112.1136).
Output scan Dimension: (182, 218, 182) Spacing: (1.0, 1.0, 1.0)
Origin: (-90.0, 126.0, -72.0)

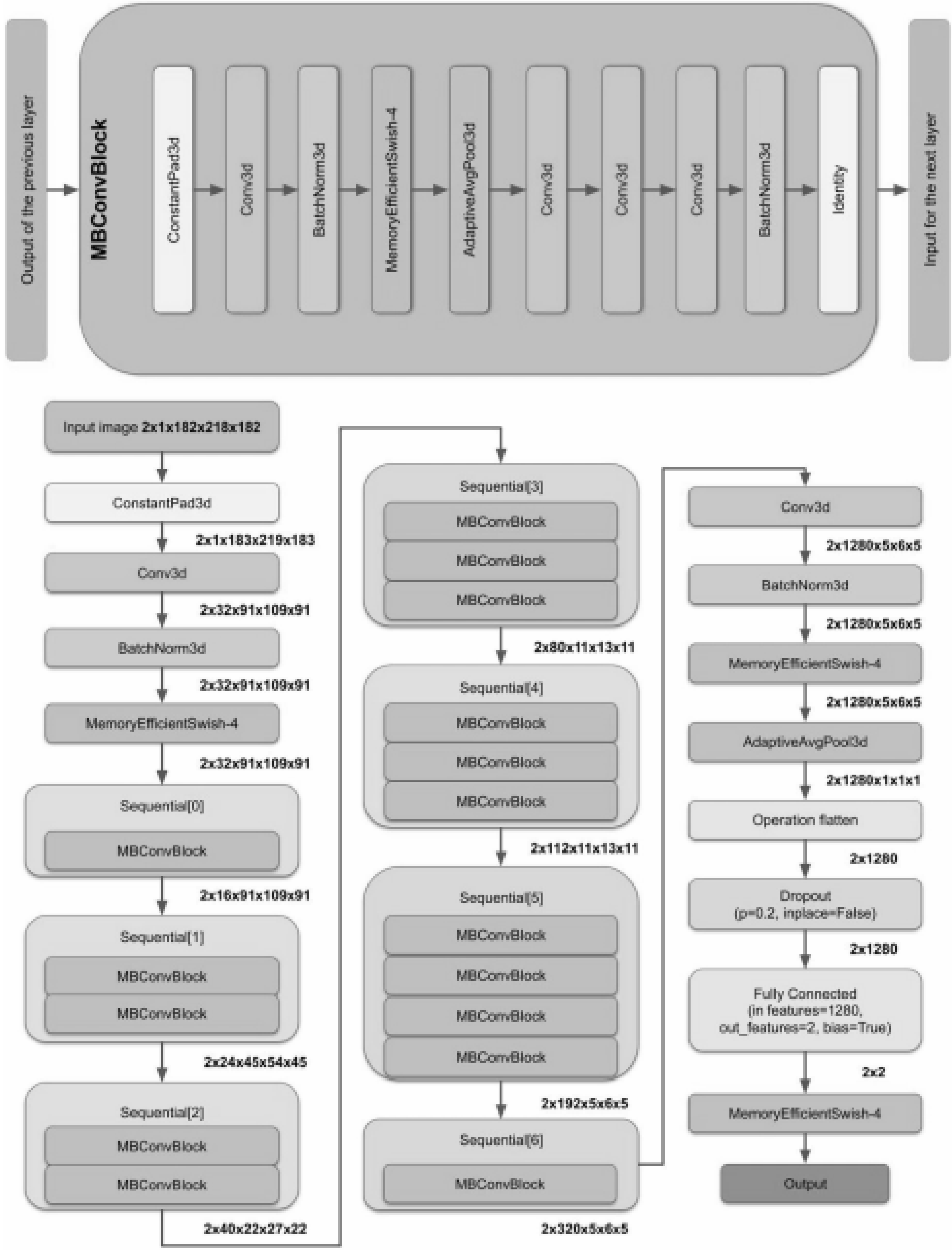

Fig 4: Structural layout

3) Feature Extraction:
The third category focuses on feature extraction. The study employs convolutional layers, pooling layers, and fully connected layers for extracting in-depth features from the pre-processed data. These layers are key components of convolutional neural networks (CNNs) and are particularly effective for processing neuroimaging data.

Hyperparameter tuning along with an n-fold cross validation technique was used for the purpose of feature extraction. A fine tuning between learning rate (lr) and number of epochs was carried out to bring the best possible outcome. A combination with lr=0.001 and epochs=50 carved out the best result from the model. [1]

T1 Weighted MRI scans are the most anatomical of scans providing the most accurate representation of tissues like WM, GM and CSF. MP-RAGE is the most widely used sequence for structural brain imaging in the clinics and research centers as these structures capture good tissue contrast and offer great spatial resolution with coverage of the whole brain [33].

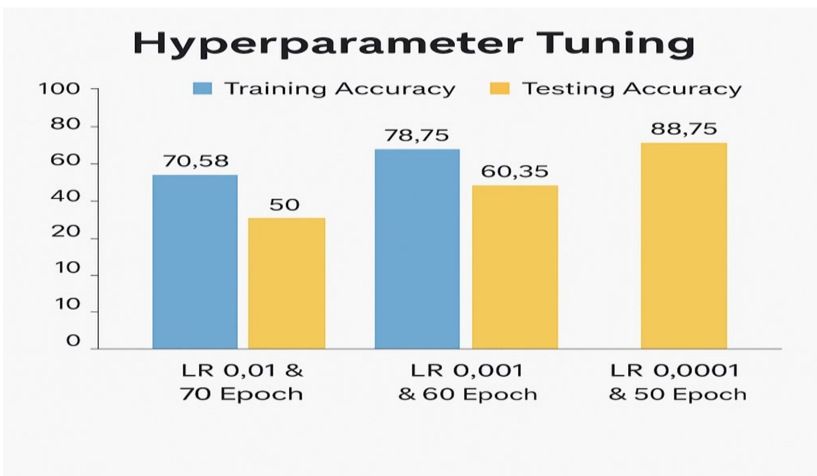

Fig. 5: Tuning of the learning rate and number of epochs using a random search procedure and performance evaluation

Require: Pre-processed T1 MPRAGE MRI scans of AD and stable MCI
Ensure: A trained and validated 3D CNN model for improved inference:

- batchsize = 2, workers = 2 ▷ Parameters for Data Loaders
- trainloader = DataLoader(trainingdataset[])
- validationloader = DataLoader(validationdataset[])
- testloader = DataLoader(testingdataset[])
- explicit_dims = 3 ▷ Parameters for the model
- explicit_dims = 3 ▷ for 3D Input
- output_class = 2 ▷ Number of output classes
- loss_function = CrossEntropyLoss() ▷ Tuned Hyper-parameter

- train_metric = ROCAUCMetric()
- model = EfficientNetBN("efficientnet-b0")
- NO. epoch = 50, C = 1 ▷ Tuned Hyper-parameter
- NO. epoch = 50, C = 1 ▷ 5-fold stratified CV

while C < 6 do ▷ Begin a 5-Fold Training Loop

- epoch = 0, NO. epoch = 50 ▷ Training for the 50 epochs
- while epoch < NO. epoch do
    - for i, data in trainloader do ▷ sets the model to train
        - inputsAdataA = batch.data
        - inputsBdataB = batch.data
        - model.train() ▷ Consider the model to do the model in terms of training
        - outputs, labels = model(inputsA, inputsB)
        - loss = loss_function(outputs, labels) ▷ Determine the loss
        - optimizer.zero_grad() ▷ set the gradients to zero
        - loss.backward() ▷ Computes the gradients
        - optimizer.step() ▷ Update the model
        - epoch_loss += loss
    - end for
    - with torch.no_grad() ▷ sets the model to evaluate
        - for i, data in validationloader do ▷ evaluation loop
            - val_inputsAdataA = val.data
            - val_inputsBdataB = val.data
            - val_outputs, val_labels = model(val_inputsA, val_inputsB)
        - end for
        - roc = train_metric.add() and auc_metric() values
    - if auc_metric > best_metric then
        - save model (save the model)
        - best_metric = auc_metric

  - end if
  - epoch++

- end while
- C++ ▷ Training Completed for FOLD C end while

draw_confusion_matrix(A,B), drawROC(A,B) ▷ sets the model to test
model.eval() ▷ using test only new MRI scans
for i, data in testloader do
- test_inputsAdataA = test.data
- test_inputsBdataB = test.data
- test_output = model(test_inputs) end for

draw_confusion_matrix(test_pred, test_labels), drawROC(test_pred, test_labels)
traindataloader = DataLoader(trainingdataset[C + 1])
C = C + 1 ▷ if the fold is not reset; current fold learning will be applied in the following fold.

Total params: 4,690,942
Trainable params: 4,690,942
Non-trainable params: 0
Input size (MB): 27.55
Forward/backward pass size (MB): 7754.59
Params size (MB): 17.89
Estimated Total Size (MB): 7800.03

4) Classifier:

The final category involves the classifier used to classify the extracted features. The study will use the Softmax classifier, which is commonly used for multi-class classification tasks. It will provide the classified output, allowing researchers to evaluate the reliability and performance of the model.

By following these four categories, the study aims to develop an effective and reliable model for Alzheimer's disease detection, leveraging neuroimaging data and neuropsychological information to enhance early diagnosis and understanding of the disease.

Results:

The performance of the model was analyzed with an aim to understand its potential.

The parameters of the confusion matrix are as follows.
- True positive (TP)
- True negative (TN)
- False positive (FP).
- False negative (FN).

While TP and TN refer to the person being diagnosed correctly, FP and FN mean misdiagnosed. Accordingly, the confusion matrix is formed Accuracy, Precision and Recall were used for evaluating the effectiveness of the model.

Accuracy:
Accuracy evaluates the correctness level of the model's predictions for AD diagnosis. It calculates the number of MRIs accurately classified among the total inputs of MRIs.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

Precision:
Precision is defined as the ratio of correctly labeled positive AD records by the model to the entirety of positive records labeled by the model.

$$\text{Precision: } TP/(TP+FP)$$

Recall:

Recall specifically focuses on the model's ability to correctly identify all positive cases.

$$\text{Recall: } TP/(TP+FN)$$

F1-score:
The harmonic mean of precision and recall, providing a single metric that balances both.

$$\text{F1-score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$$

In the first fold the validation accuracy peaked at 88.75% indicating that the model was learning adequately. The accuracy increased in succeeding folds because of the application of transfer learning from prior folds. Maximum testing accuracy reached at 93.10% in fold 5 while overall accuracy reached 92.29%.

Confusion matrix was used for the assessment of the efficiency of a classification model. Accuracy, precision, recall, and F1-score may all be calculated via a confusion matrix.

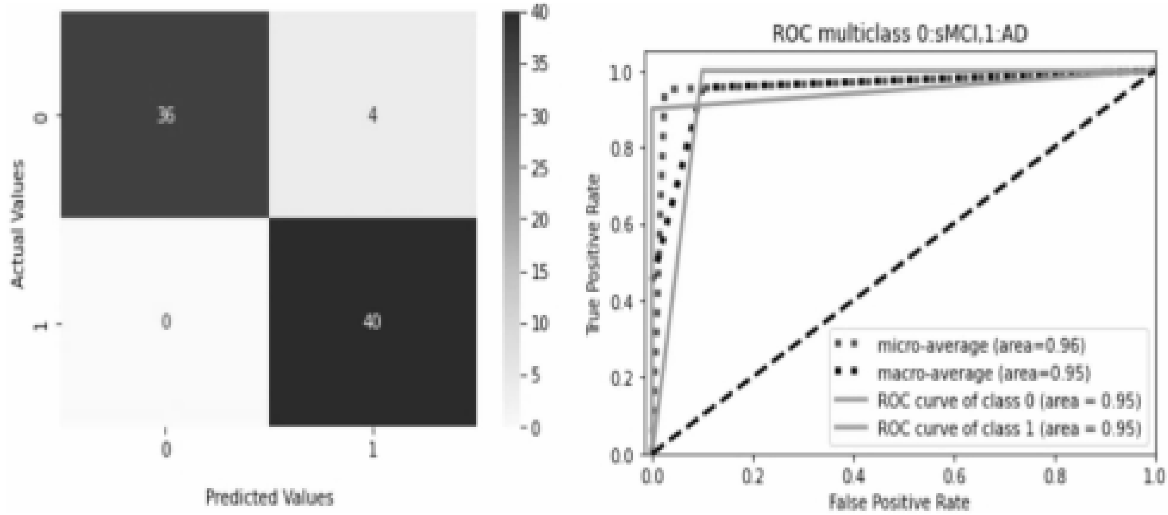

Fig 6: ROC AUC curve and the Confusion Matrix [0-sMCI,1-AD,2-CN] for the optimal training fold for the AD vs. CN vs. sMCI task

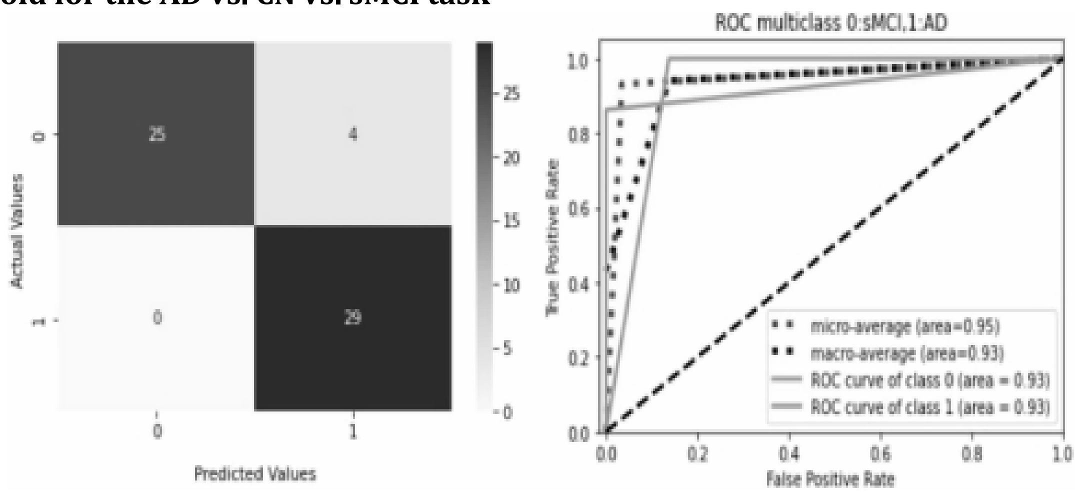

Fig 7: ROC AUC curve and the Confusion Matrix [0-sMCI,1-AD] for the optimal testing fold for the AD vs. sMCI task

DL Model	ACC	SPE	SEN
3D CNN [EfficientNet] [26]	73.10%	86.20%	73.00%
3D CNN [DenseNet 264]	82.50%	82.50%	82.50%

3D CNN [39]	72.50%	82.50%	61.00%
2D CNN (Proposed Model)	83.81%	87.50%	75.76%
AlexNet+SVM 2D CNN[18]	78.56%	77.63%	91.02%

We achieved an accuracy of 83.81%, Specificity of 87.50% and Sensitivity of 75.76% at the evaluation of unseen data for the multiclass classification task. This is significantly better than the early AD prediction accuracy reported by state-of-the-art methods in the last five years. Although our models are suitable to use in clinical settings to aid neuroradiologists, further training with more high-quality MRI scans from a diverse range of sources is required to ensure reproducibility.

5. Challenges and Future Work:

Although deep learning techniques have shown promising results, there are still many limitations and obstacles in the field of AD.

1. Lack of Sufficient Data: The scarcity of large and well-labeled datasets is a significant hindrance to training and optimizing deep learning models effectively. Adequate data samples
are important for constructing high-quality models, and such data is likely to be rather limited.
of the measures included in the study, its performance and generalizability of the model [4].

2. Biomarker Combination and Explanation: Finding out the best mix of the various prognostic biomarkers for AD diagnosis is that it calls for elaborate explanations and confirmations. The depth of the model, benchmarking platforms, as well as others, are major factors that contribute to success. combinations, which may then help determine the best biomarker accuracy.

3. Cost and Medical Efficiency: However, deep learning models are seen to have prospects in achieving the above goal. diagnostics, the effectiveness of costs and general medical effectiveness of these models remains need thorough verification. The use of high-quality models of artificial intelligence in healthcare contexts entails awareness of the resource investment and possible benefits.

4. External Validation and Transfer Learning: In order to evaluate the model’s stability and extension of the findings across different data sets, further validation through transfer of

learned models becomes crucial [45]. That is why, by passing it through training and testing which involve different datasets, the researchers can determine the performance of the model. measures in different situations and environments.

Nonetheless, many challenges have been named that researchers keep trying to enhance deep learning. techniques in AD diagnosis. Remedying these limitations will be critical in order to provide confidence in the practical and wide usage of AI models for the early diagnosis of AD, patients' outcomes enhancement and supporting progress in the research of Alzheimer's Disease.

6. CONCLUSION:

As a matter of fact, the purpose of this research was to focus on the applicability of Convolutional Neural Networks to practical tasks. For the detection of Alzheimer's disease (AD), the present work used CNN regarded as a deep learning tool. The work proposed an accurately designed deep learning system that incorporates the T1 weighted MRI brain scans and PET scan images for diagnosis of AD. To improve the reducing the model's efficiency, a Region of Interest (ROI) based feature extraction technique was used. that was available in the form of the dataset collected by Alzheimer's Disease Neuroimaging Initiative (ADNI).

The study addressed a detection algorithm based on CNN that presents a simplistic and low computational good set of features from the publicly available set of features. These extracted features are applied to train as well as test the model, with the objective of making the AD detection more resilient.

The potential of CNs in the diagnosis of AD as well as the feature extraction technique as proposed here offer understanding. improving the performance of AD diagnosis based on information derived from neuroimages. Such improvements and the growth of deep learning based approaches can facilitate improved early identification of AD and hence help to improve the overall patients' care and management in various settings.

7. REFERENCES:

1. Fan Zhang, Zhenzhen Li, Boyan Zhang, Haishun Dua, Binjie Wang and Xinhong Zhang, "Multi-modal deep learning model for auxiliary diagnosis of Alzheimer's disease", 0925-2312/© 2019 Elsevier B.V.
2. Xin Bi, Xiangguo Zhao, Hong Huang, Deyang Chen and Yuliang Ma, "Functional Brain Network Classification for Alzheimer's Disease Detection with Deep Features and Extreme Learning Machine", Springer Science+Business Media, LLC, part of Springer Nature 2019.
3. Xiuli Bi, Shutong Li, Bin Xiao, Yu Li, Guoyin Wang and Xu Ma, "Computer Aided Alzheimer's Disease Diagnosis by An Unsupervised Deep Learning Technology", NEUCOM 20664 2018.
4. Farheen Ramzan, Muhammad Usman Ghani Khan, Asim Rehmat, Sajid Iqbal, Tanzila Saba, Amjad Rehman and Zahid Mehmood, "A Deep Learning Approach for

Automated Diagnosis and Multi-Class Classification of Alzheimer's Disease Stages Using Resting-State fMRI and Residual Neural Networks" , Springer Science+Business Media, LLC, part of Springer Nature 2019.
5. Shuang Shuang Gao, Dimas Lima, "A review of the application of deep learning in the detection of Alzheimer's disease", 2666-3074/KeAi, 2021.
6. JananiVenugopalan, LiTong, Hamid Reza Hassanzadeh and May D. Wang, "Multimodal deep learning models for early detection of Alzheimer's disease stage, Scientific Reports 2021.
7. Shaker El-Sappagh, Tamer Abuhmed , S.M. Riazul Islam, Kyung Sup Kwak, "Multimodal multi task deep learning model for Alzheimer's disease progression detection based on time series data", 0925-2312/ 2020 The Authors. Published by Elsevier B.V.
8. Shangran Qiu, Prajakta S. Joshi, Matthew I. Miller, Chonghua Xue, Xiao Zhou, Cody Karjadi, Gary H. Chang, Anant S. Joshi, "Development and validation of an interpretable deep learning framework for Alzheimer's disease classification", The Author(s) (2020). Published by Oxford University Press on behalf of the Guarantors of Brain.
9. Tianyi Yana, Yonghao Wanga, Zizheng Wengb, Wenying Duc, Tiantian Liua, Duanduan Chena, Xuesong Lid, Jinglong Wue and Ying Hanc, "Early-Stage Identification and Pathological Development of Alzheimer's Disease Using Multimodal MRI", ISSN 1387-2877/19/2019 – IOS Press and the authors.
10. Samsuddin Ahmed, Kyu Yeong Cho, Jang Jae Lee, Byeong C. Kim, Goo-Rak Kwon, Kun Ho Lee And Ho Yub Jung "Ensembles Of Patch-Based Classifiers For Diagnosis Of Alzheimer Diseases", 2169-3536, 2019-IEEE.
11. Chiyu Feng 1, Ahmed Elazab 1,2, Peng Yang1, Tianfu Wang1, Feng Zhou3 Huoyou Hu4, Xiaohua Xiao4, And Baiying Lei 1, (Senior Member, Ieee) Deep Learning Framework For Alzheimer's Disease Diagnosis Via 3d-Cnn And Fsbi-Lstm, 2021-IEEE.
12. Huanhuan Ji, Zhenbing Liu, Wei Qi Yan Reinhard Klette Early Diagnosis of Alzheimer's Disease Using Deep Learning ICCCV'19, June 15–18, 2019, Jeju Island, South Korea.
13. Alzheimer's Association. 2016 Alzheimer's disease facts and figures. Alzheimers Dement. 12(4), 459–509 (2016).
14. Patterson, C. World Alzheimer Report 2018—The State of the Art of Dementia Research: New Frontiers. (Alzheimer's Disease, International (ADI), London, 2018).
15. T. K. Khan, ''Introduction to Alzheimer's disease biomarkers,'' in Biomarkers in Alzheimer's Disease, 1st ed. New York, NY, USA: Academic, 2016, p. 13.
16. MK Gurucharan, "Basic CNN Architecture: Explaining 5 Layers of Convolutional Neural Network", 2022, upGrad.
17. Hongming Lia , Mohamad Habesa,b , David A. Wolkb, Yong Fana, "A deep learning model for early prediction of Alzheimer's disease dementia based on hippocampal magnetic resonance imaging data" , 2019, Elsevier.
18. Wang, S.H.; Phillips, P.; Sui, Y.; Liu, B.; Yang, M.; Cheng, H. Classification of Alzheimer's disease based on eight-layer convolutional neural network with leaky rectified linear unit and max pooling. J. Med. Syst. 2018, 42, 1–11. [CrossRef]
19. Karasawa, H.; Liu, C.L.; Ohwada, H. Deep 3d convolutional neural network architectures for Alzheimer's disease diagnosis. In Asian Conference on Intelligent

Information and Database Systems; Springer: Cham, Switzerland, 2018; pp. 287–296.
20. Yue, L.; Gong, X.; Chen, K.; Mao, M.; Li, J.; Nandi, A.K.; Li, M. Auto-detection of Alzheimer's disease using deep convolutional neural networks. In Proceedings of the 2018 14th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD), Huangshan, China, 28–30 July 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 228–234.
21. Jain, R.; Jain, N.; Aggarwal, A.; Hemanth, D.J. Convolutional neural network based Alzheimer's disease classification from magnetic resonance brain images. Cogn. Syst. Res. 2019, 57, 147–159.
22. Huang, Y.; Xu, J.; Zhou, Y.; Tong, T.; Zhuang, X. Diagnosis of Alzheimer's disease via multi-modality 3D convolutional neural network. Front. Neurosci. 2019, 13, 509.
23. Goceri, E. Diagnosis of Alzheimer's disease with Sobolev gradient-based optimization and 3D convolutional neural network. Int. J. Numer. Methods Biomed. Eng. 2019, 35, e3225.
24. Zhang, F.; Li, Z.; Zhang, B.; Du, H.; Wang, B.; Zhang, X. Multi-modal deep learning model for auxiliary diagnosis of Alzheimer's disease. Neurocomputing 2019, 361, 185–195.
25. Basheera, S.; Ram, M.S.S. Convolution neural network–based Alzheimer's disease classification using hybrid enhanced independent component analysis based segmented gray matter of T2 weighted magnetic resonance imaging with clinical valuation. Alzheimer's Dement. Transl. Res. Clin. Interv. 2019, 5, 974–986. [CrossRef]
26. Spasov, S.; Passamonti, L.; Duggento, A.; Lio, P.; Toschi, N.; Alzheimer's Disease Neuroimaging Initiative. A parameter-efficient deep learning approach to predict conversion from mild cognitive impairment to Alzheimer's disease. Neuroimage 2019, 189,276–287.
27. Mehmood, A.; Maqsood, M.; Bashir, M.; Shuyuan, Y. A deep siamese convolutional neural network for multi-class classification of Alzheimer disease. Brain Sci. 2020, 10, 84.
28. Raju, M.; Gopi, V.P.; Anitha, V.S.; Wahid, K.A. Multi-class diagnosis of Alzheimer's disease using cascaded three dimensional convolutional neural network. Phys. Eng. Sci. Med. 2020, 43, 1219–1228.
29. Liu, M., et al., A multi-model deep convolutional neural network for automatic hippocampus segmentation and classification in Alzheimer's disease. NeuroImage. 208:116459, 2020 https://doi.org/10.1016/j.neuroimage.2019.116459.
30. Basaia, S., et al., Automated classification of Alzheimer's disease and mild cognitive impairment using a single MRI and deep neural networks. NeuroImage Clin. 21:101645, 2019. https://doi.org/10.1016/j.nicl.2018.101645.
31. "Welcome to ANTsPyNet's documentation! — ANTsPyNet 0.0.1 documentation"https://antsx.github.io/ANTsPyNet/docs/build/html/index.html. (Accessed May 06, 2022).
32. Wang, J., He, L., Zheng, H., and Lu, Z.-L., Optimizing the mag netization-prepared rapid gradient-echo (MP-RAGE) sequence. PLoS ONE. 9(5):e96899, 2014. https://doi.org/10.1371/journalpone.0096899.
33. Gaillard, F., "MRI sequences (overview) | Radiology Reference Article | Radiopaedia.org," Radiopaedia. https://radiopaedia.org/articles/mri-sequences-overview. (Accessed Dec. 10, 2022).

34. Bhagwat, N., et al., Understanding the impact of preprocessing pipelines on neuroimaging cortical surface analyses. GigaScience.10(1):giaa155, 2021. https://doi.org/10.1093/gigascience/giaa155.
35. Tustison, N. J., et al., N4ITK: improved N3 bias correction. IEEE Trans. Med. Imaging. 29(6):1310–1320, 2010. https://doi.org/10.1109/TMI.2010.2046908.
36. "Denoise an image — denoiseImage."https://antsx.github.io/ANTsRCore/reference/denoiseImage.htm (Accessed May 15, 2022).
37. Agarwal, D., Berbis, M. A., Martín-Noguerol, T., Luna, A., Garcia, S. C. P., and de la Torre-Díez, I., End-to-end deep learning architectures using 3D neuroimaging biomarkers for early Alzheimer's diagnosis. Mathematics. 10(15):Art. no. 15, 2022. https://doi.org/10.3390/math10152575.
38. Droste, B., "Google Colab Pro+: Is it worth $49.99?," Medium, 2022. https://towardsdatascience.com/google-colab-pro-is-it-worth-49-99-c542770b8e56 (accessed May 22, 2022).
39. Dyrba, M., et al., Improving 3D convolutional neural network comprehensibility via interactive visualization of relevance maps: evaluation in Alzheimer's disease. Alzheimers Res. Ther.13(1):191, 2021. https://doi.org/10.1186/s13195-021-00924-2.
40. Suk, H.-I., Lee, S.-W., Shen, D., and Alzheimer's disease neuro-imaging initiative, Deep ensemble learning of sparse regression models for brain disease diagnosis. Med. Image Anal. 37:101–113,2017.https://doi.org/10.1016/j.media.2017.01.008.
41. Hardy, J., Amyloid, the presenilins and Alzheimer's disease. Trends Neurosci. 20(4):154–159,1997.https://doi.org/10.1016/S0166-2236(96)01030-2.
42. "Trained models," Apr. 25, 2022. https://github.com/neuronets/trained-models. (Accessed May 16, 2022).
43. Manjón, J. V., MRI Preprocessing. In: Martí-Bonmatí, L., and Alberich-Bayarri, A., (Eds.), Imaging Biomarkers: Development and Clinical Integration. Cham: Springer International Publishing, pp. 53–63, 2017.https://doi.org/10.1007/978-3-319-43504-6_5
44. "Atlases-NIST."https://nist.mni.mcgill.ca/atlases/. (Accessed Oct. 22, 2022).
45. Oh, K., Chung, Y.-C., Kim, K. W., Kim, W.-S., and Oh, I.-S., Classification and visualization of Alzheimer's disease using volumetric convolutional neural network and transfer learning. Sci. Rep. 9(1), Art. no. 1, 2019. https://doi.org/10.1038/s41598-019-54548-6.
46. Diedre Carmo, Bruna Silva b, Alzheimer's Disease Neuroimaging Initiative, Clarissa Yasuda b,Letícia Rittner a and Roberto, Heliyon, Science Direct,Vol.7,2021,https://doi.org/10.1016/j.heliyon.2021.e06226.