Using Advanced Computation Techniques for Alzheimer's Disease

Final Paper Presentation for 580: Topics for Computers in Biomedicine

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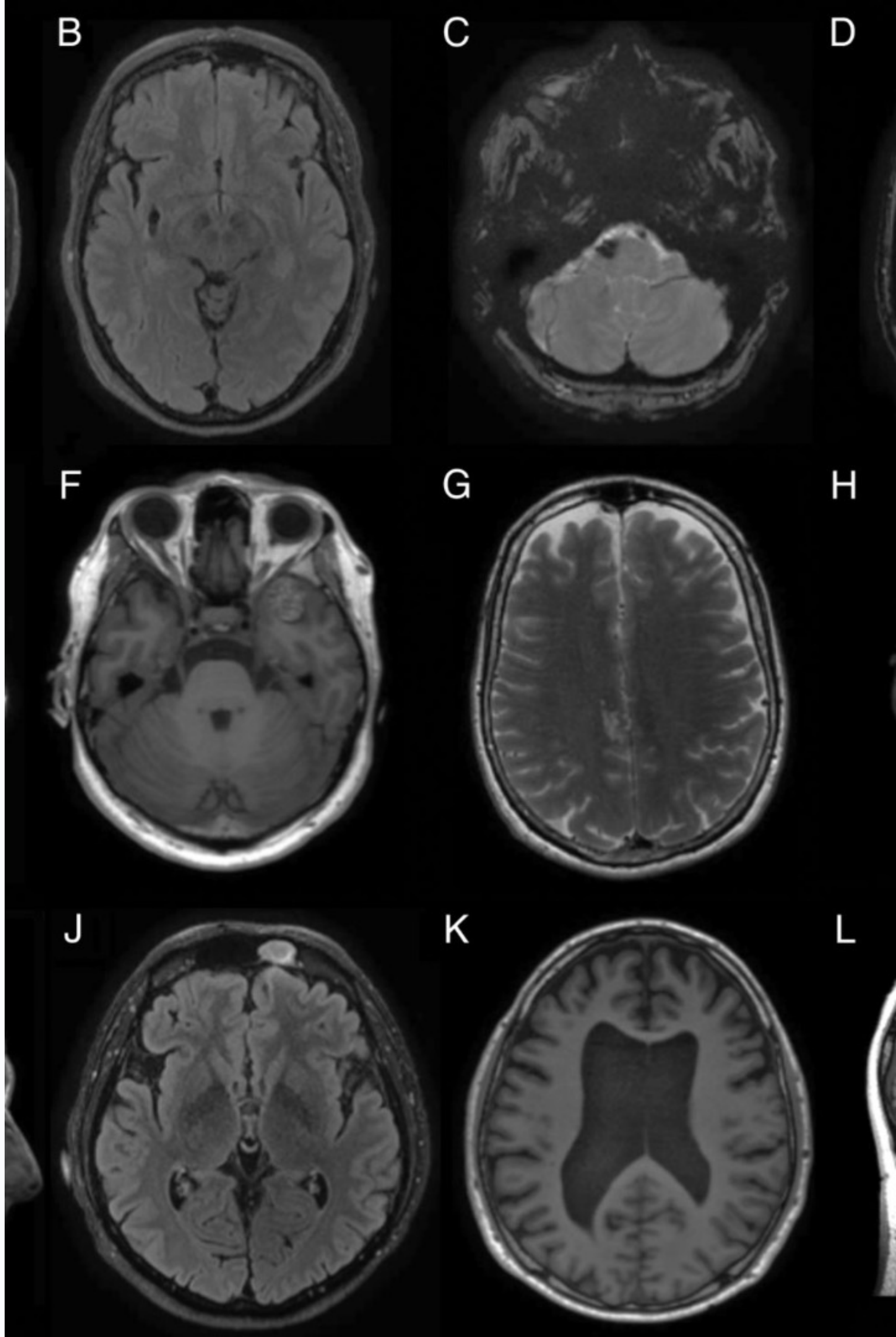


Understanding Alzheimer's Disease

1. ## What is Alzheimer's Disease (AD)?

   Alzheimer's Disease is a progressive neurodegenerative disorder affecting memory, thinking, and behavior.

2. ## Why Advanced Computation?

   Advanced computation is crucial for early detection, which is essential for effective intervention and treatment.

3. ## Early detection crucial for effective intervention and treatment.

   Early detection is crucial for effective intervention and treatment as it leads to impaired daily activities and a decline in overall mental function.

Paper 1

An Efficient Deep Neural Network Binary Classifier for Alzheimer's Disease Classification

Deep Neural Networks

Understanding Deep Learning and Deep Neural Networks (DNN):

Deep learning represents a sophisticated branch of artificial intelligence specifically designed to grapple with intricate and multifaceted datasets. At the heart of this technological realm lies the Deep Neural Network (DNN), a powerful computational tool akin to a highly intelligent computer program. DNNs excel in the rapid and precise analysis and interpretation of data, particularly when dealing with complex visual information, such as images of the brain.

Advantages of Deep Neural Networks (DNNs):

The advantages of employing DNNs in various applications are notable. These networks are recognized for their exceptional speed and efficiency in tasks encompassing classification, pattern recognition, and image analysis. What sets DNNs apart is their unique capability to directly handle raw data without necessitating extensive preprocessing. This quality allows them to efficiently glean insights from complex datasets, making them a formidable tool in the realm of artificial intelligence.

Data Splitting and Classification:

Scientists use a dataset, which is a collection of information, to teach the DNN. They usually divide the data into a training set (80% of the total data) and a testing set. During training, they often create a validation set from the training data. Once trained, the DNN is tested on new data for predictions.

Objective

Binary Classification and Advancements:

Scientists often concentrate on binary classification, such as distinguishing between Alzheimer's disease (AD) and conditions like Mild Cognitive Impairment (MCI) or Cognitively Normal (CN). Traditional methods like Support Vector Machines (SVM) or K-Nearest Neighbor (KNN) have struggled with handling abundant features in the data.

Innovative Approach:

In this study, scientists introduced a fresh perspective by crafting a specialized Deep Neural Network (DNN) featuring two hidden layers. They experimented with different activation functions—ELU, PReLU, and Leaky ReLU—in these layers to enhance the DNN's classification capabilities. Leveraging images from the Alzheimer's Disease Neuroimaging Initiative (ADNI), they built a dataset focusing on categorizing subjects into two groups: those with Alzheimer's disease (AD) and those who are cognitively normal (CN). The novel DNN model exhibited promising results, surpassing the accuracy of traditional methods.

Dataset

Dataset Overview:

The dataset used for this analysis comprises individuals sourced from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. Initiated in 2003 under the principal investigation of Michael W. Weiner, MD, ADNI operates as a collaborative effort between the public and private sectors.

ADNI's Primary Objective:

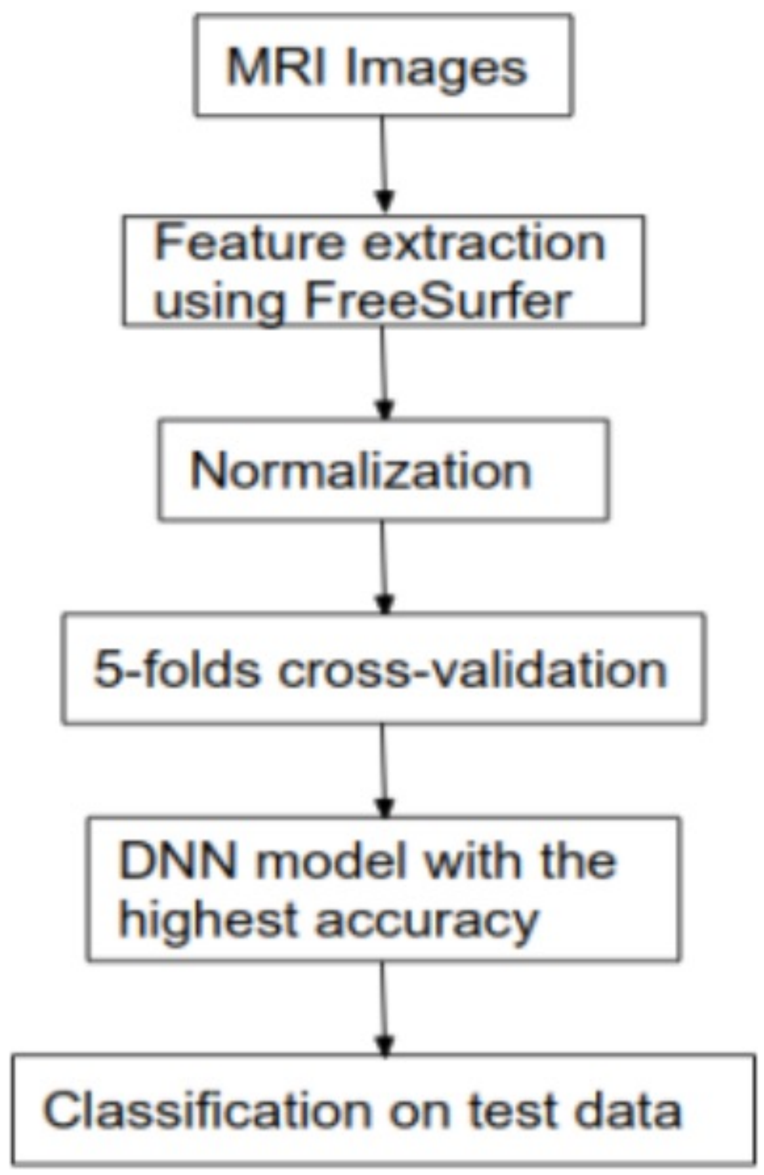
The overarching goal of ADNI is to explore the synergies of various imaging modalities, including MRI and PET scans, along with neuropsychological assessments, clinical evaluations, and biological markers. The collective aim is to develop a comprehensive understanding of Alzheimer's disease (AD), focusing on early detection and the progression of its prodromal stage, known as Mild Cognitive Impairment (MCI).

Group	AD	MCI	CN
Nos. of Subjects	58	48	73
Female/male	21/37	23/25	31/42
Age	75.3 ± 7.9	74.5 ± 6.2	76.6 ± 4.2
Education	15.1 ± 3.4	15.8 ± 2.7	15.7 ± 2.7
MMSE	24.5 ± 1.7	25.9 ± 1.5	28.1 ± 0.8
CDR	0.7 ± 0.2	0.5	0

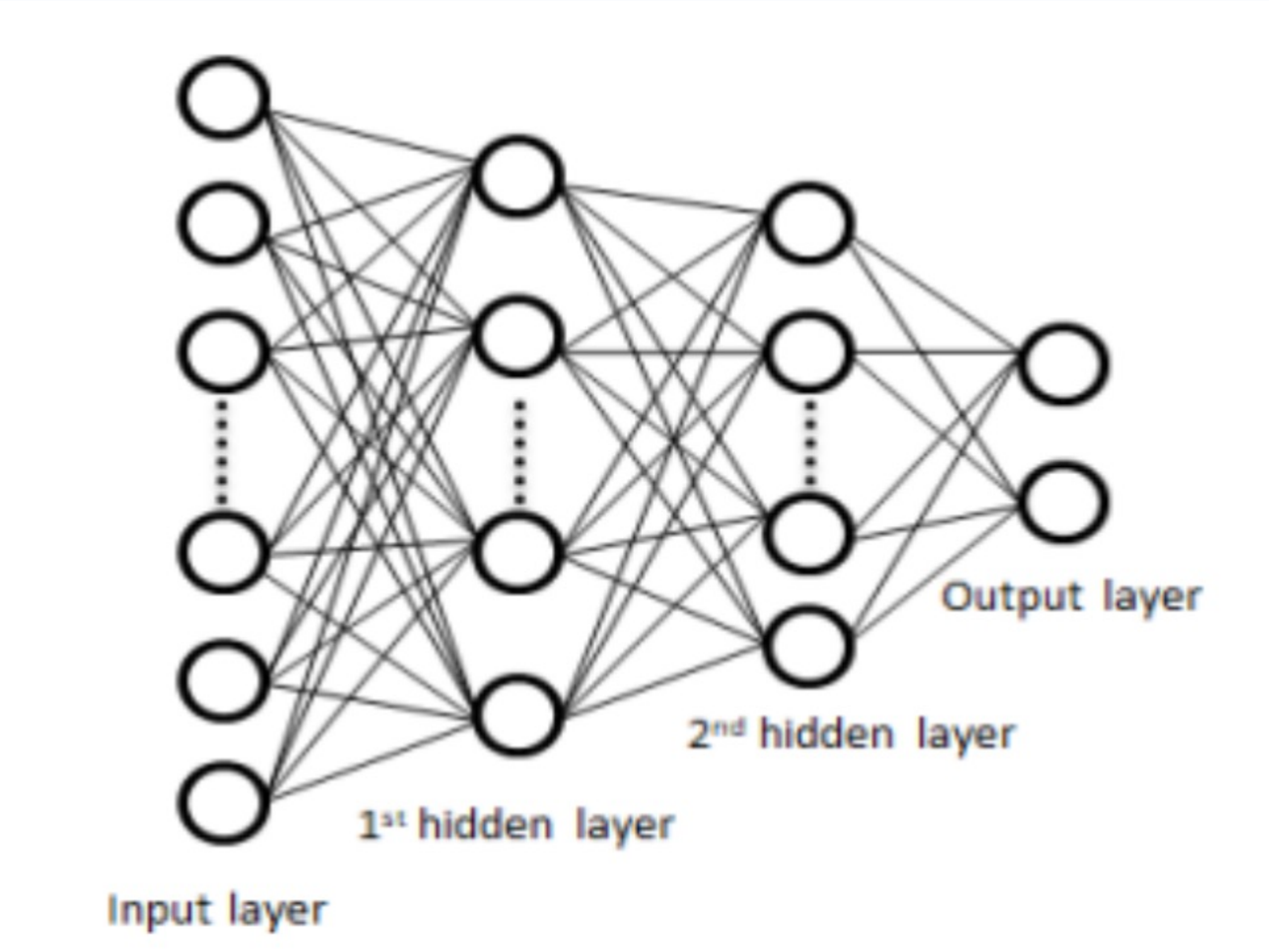
This study utilized the widely adopted FreeSurfer software for conducting automated surface-based cortical segmentation and subcortical volume-based segmentation.

Subjects' Desikan-Killiany-Tourville (DKT) atlas, a comprehensive map featuring 31 cortical surface labels per hemisphere, was generated. We specifically focused on both left and right hemisphere regions for model training, resulting in a total of 62 cortical surface labels serving as features.

Following feature extraction, the obtained data underwent a crucial normalization process. This step ensures that the features possess a zero mean and unit variance after normalization. By doing so, we aimed to minimize data redundancy and enhance data integrity between features, facilitating more effective subsequent analyses.



As the model serves as a binary classifier, the choice of loss function was binary cross-entropy. Employing a 5-fold cross-validation, we calculated the average accuracy score on the validation data. The accuracy of each model was assessed across varying numbers of epochs. The classification results from the model exhibiting the highest accuracy were then compared with those of traditional machine learning models.



Results

- The study involved the creation of a fully connected Deep Neural Network (DNN) with 2 hidden layers, focusing on the classification of the AD vs. CN group within the ADNI dataset. Importantly, this classification was carried out on a subset representing only 20% of the total data.
- Through meticulous experimentation involving various activation functions and epochs, the paper identified the optimal combination for each hidden layer. The highest accuracy was achieved by employing the Leaky ReLU activation function in the first hidden layer and PReLU in the second hidden layer.
- The resulting model demonstrated superior classification accuracy on the test data, outperforming traditional machine learning algorithms. Specifically, the model achieved accuracy scores of 85.19% for AD vs. CN, 76.93% for MCI vs. CN, and 72.73% for AD vs. MCI. These outcomes signify a notable advancement in accuracy compared to conventional approaches..

Paper 2

Deep Learning Approach for Early Detection of Alzheimer’s Disease

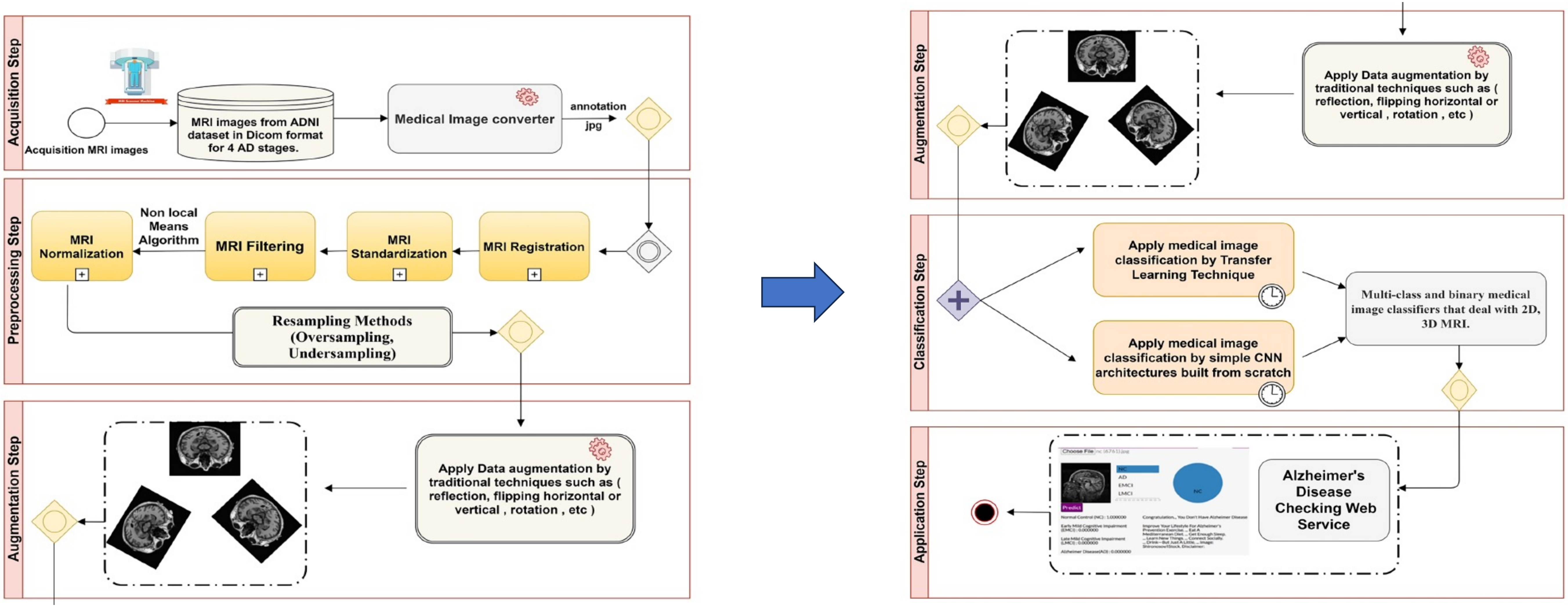
Introduction

Innovative Alzheimer's Disease Detection Using CNNs

This study presents a novel deep learning approach for Alzheimer's disease detection. Utilizing advanced convolutional neural networks (CNNs), the research delves into the classification of medical images from MRI scans, enhancing accuracy and offering a user-friendly web service for remote diagnostics.

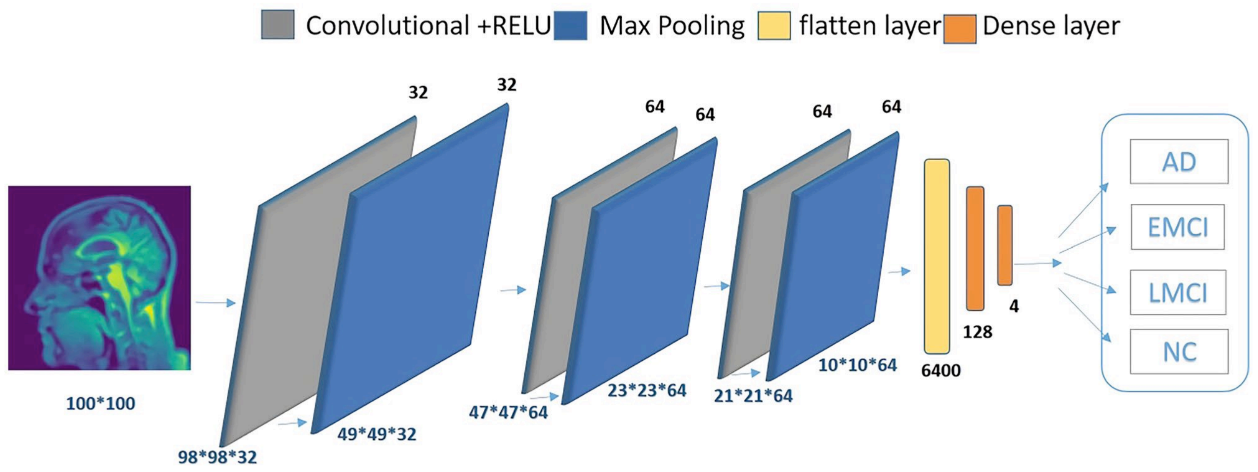
Deep Learning Techniques for Medical Imaging

The methodology encompasses the deployment of simple CNNs for both 2D and 3D MRI image analysis, as well as sophisticated transfer learning techniques utilizing the VGG19 model. Data augmentation and resampling strategies were implemented to address imbalances in the dataset.



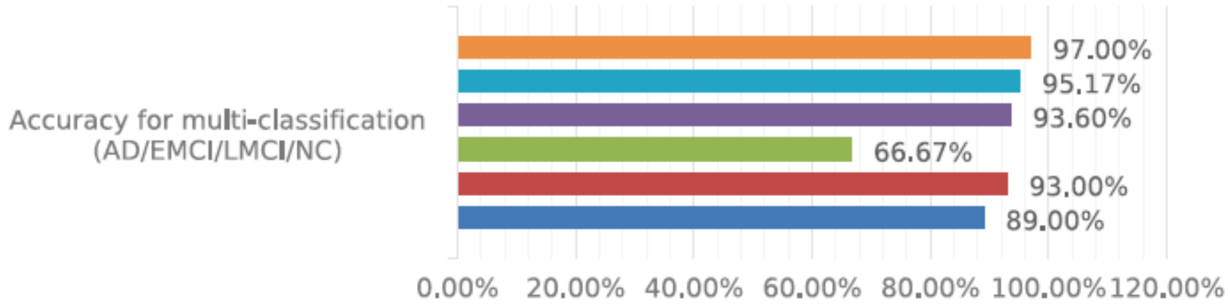
Dataset Overview for Alzheimer's Disease Detection

- **Source**: Alzheimer's Disease Neuroimaging Initiative (ADNI) database.
- **Purpose:** To facilitate the development and validation of Alzheimer's disease detection methods using MRI and PET scans.
- **Composition**: Rich compilation of neuroimaging data, clinical assessments, and biomarkers.
- **Subjects**: Individuals diagnosed with Alzheimer’s disease, Mild Cognitive Impairment, and cognitively normal controls.
- **Features**: Includes demographics, neuropsychological data, genetic profiles, and imaging data. The dataset format in this model is the 2D format with a size of (100 × 100) pixels
- **Data Augmentation:** Techniques employed to enhance the dataset and improve model training.
- **Impact**: The comprehensive dataset allows for robust training of CNN models, resulting in high accuracy for Alzheimer's disease stage classification.



Groundbreaking Results in Alzheimer's Disease Detection

- **Accuracy**: Achieved a landmark accuracy of 97% in classifying different stages of Alzheimer's disease.
- **Comparison**: Significantly outperformed traditional machine learning methods.
- **Validation**: Validated through robust 5-fold cross-validation to ensure reliability and generalizability.
- **Innovation**: Demonstrated the effectiveness of transfer learning with pre-trained VGG19 models on medical imaging data.
- **Contribution**: Introduced an operational web service for remote diagnostics, expanding access to Alzheimer's disease detection tools.



	Accuracy for multi-classification (AD/EMCI/LMCI/NC)
Song, TChowdhury [34]	89.00%
Harshit et al.[38]	93.00%
Juan Ruiz et al.[41]	66.67%
Proposed 2D-M2IC model	93.60%
Proposed 3D-M2IC model	95.17%
Proposed fine-tuned VGG19 model	97.00%

Paper 3

MRI Deep Learning-Based Solution for Alzheimer's Disease Prediction

Objective

- Assessment tests like MMSE and CDR are commonly used for Alzheimer's diagnosis, but their limitations lead to a reliance on MRI for definitive diagnosis.
- Conventionally, radiologists and physicists predict the CDR score (or the extent of Alzheimer's disease) using the MRI scans. However, this study suggests a novel approach for automatic Alzheimer's diagnosis using image processing and deep learning techniques.
- Deep learning methods come in two types: combining with traditional methods and full end-to-end solutions. Noteworthy results include a 93% accuracy with a full deep learning solution using the OASIS-1 dataset. However, some question the need for such complexity in the models. The goal is to make fair and unbiased comparisons between different methods in Alzheimer's diagnosis.

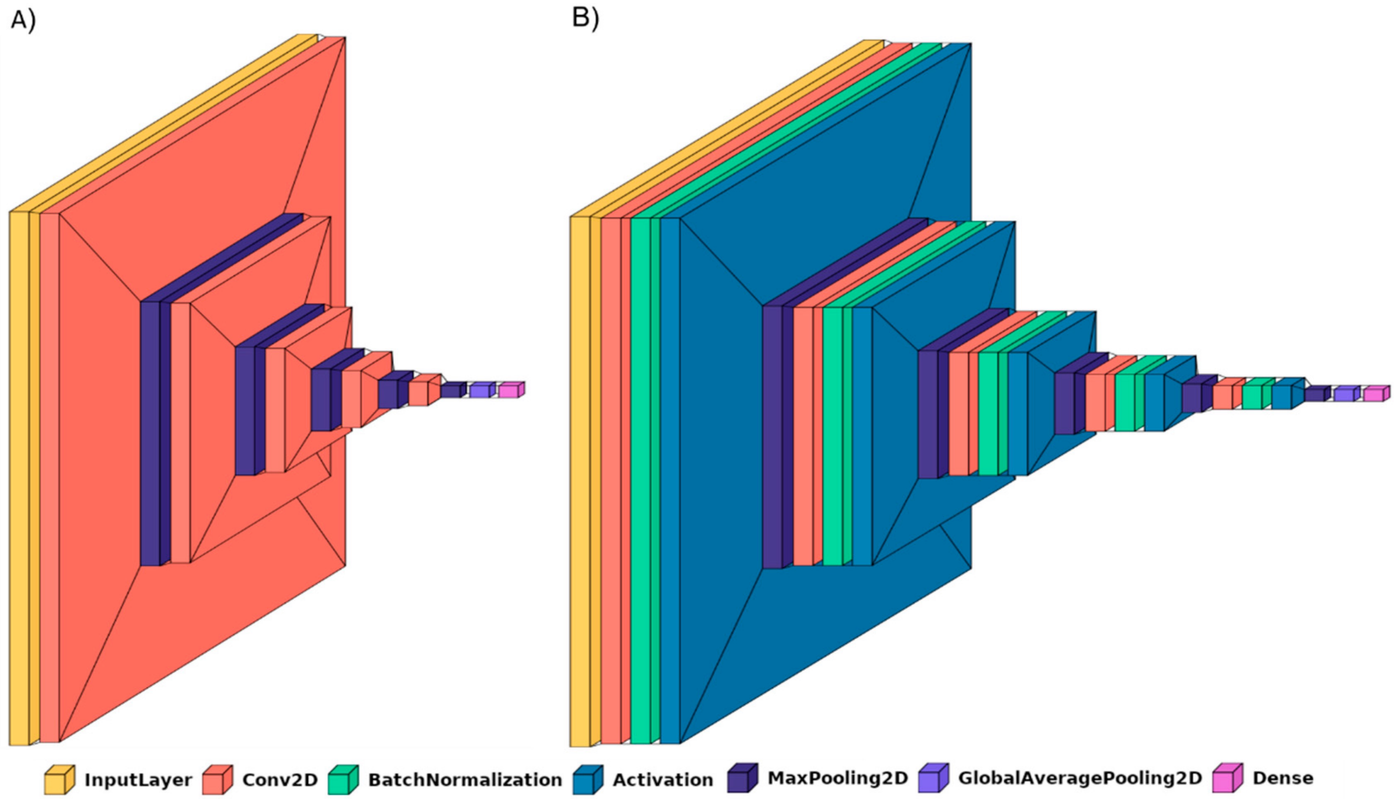
Methodology

1. **Data collection** involves obtaining MRI scans and CDR scores from individuals with varying degrees of Alzheimer's, providing quantitative measures of dementia severity.
2. **Preprocessing** enhances MRI data quality through normalization, noise reduction, and standardization
3. **Image processing** identifies relevant brain regions associated with Alzheimer's progression.
4. **Training:** A deep learning model, likely using CNNs, is trained on the dataset to associate patterns in MRI scans with CDR scores, integrating clinical annotations for improved diagnostic accuracy. The model is evaluated, comparing results with baseline diagnostic tools like MMSE and CDR.

Implementation

- OASIS collection datasets are chosen as a baseline for methodology validation due to their well-structured organization, enabling reproducibility and fair comparisons using standardized data.
- The classification problem involves labeling images into
  - two classes: CDR=0 (cognitive normal) and CDR=0.5, 1, or 2 (various stages of dementia)
  - three classes: CDR=0, CDR=0.5, and CDR=1, 2.
- Several architectures are considered:
  - **BrainNet2D** is a custom 2D neural network designed for analyzing MRI data with or without Batch Normalization.
  - **BrainNet3D** is a custom 3D neural network specifically tailored to consider the full 3D structure of MRI data.
  - **ResNet18** is a 2D Slice-level Network utilizing the ResNet18 architecture for individual slices, and the final output is determined by a majority vote over all slices.

- Two experimental strategies are considered:
  - Using the entire 3D volume for models with 3D convolutional layers
  - Utilizing a limited number (10) of slices for models with 2D convolutional layers.
- Training Strategies:
  - **Cyclical Learning Rate (CLR):** Optimizes the learning rate during training cycles, enhancing model tuning.
  - **Batch Normalization**: Stabilizes training and reduces overfitting.
  - **Metadata Integration**: Includes sex and age information in the network for better diagnosis.
  - **ImageNet Weights**: Pre-trained weights from ImageNet are used for some experiments, improving results and speeding up training.



Strategies

- Two experimental strategies are considered:
    - Using the entire 3D volume for models with 3D convolutional layers
    - Utilizing a limited number (10) of slices for models with 2D convolutional layers.
  - Training Strategies:
    - Cyclical Learning Rate (CLR): Optimizes the learning rate during training cycles, enhancing model tuning.
    - Batch Normalization: Stabilizes training and reduces overfitting.
    - Metadata Integration: Includes sex and age information in the network for better diagnosis.
    - ImageNet Weights: Pre-trained weights from ImageNet are used for some experiments, improving results and speeding up training.

Results

OASIS-1 Two-Class Classification:

2D models (BrainNet2D) outperformed 3D approaches (BrainNet3D, ResNet18) with BAC up to 0.84.

OASIS-2 Two-Class Classification:

Notable performance gains observed in 2D models (BrainNet2D reached 0.92, ResNet18 0.93).

OASIS-2 Three-Class Classification:

While BrainNet3D achieved a BAC of 0.76, it showed a lower improvement rate compared to 2D approaches.

Overall Deductions

1. 2D models consistently outperformed 3D models across datasets and classification tasks.
2. Specific strategies like Batch Normalization and CLR triangular learning rate contributed to performance gains.
3. In OASIS-2, both BrainNet2D and ResNet18 achieved notable improvements, surpassing state-of-the-art results in two-class classification.

Paper 4

Computation Modeling of Dementia Prediction using Deep Learning Model

Objective

•Hierarchical Analysis for Dementia Prediction

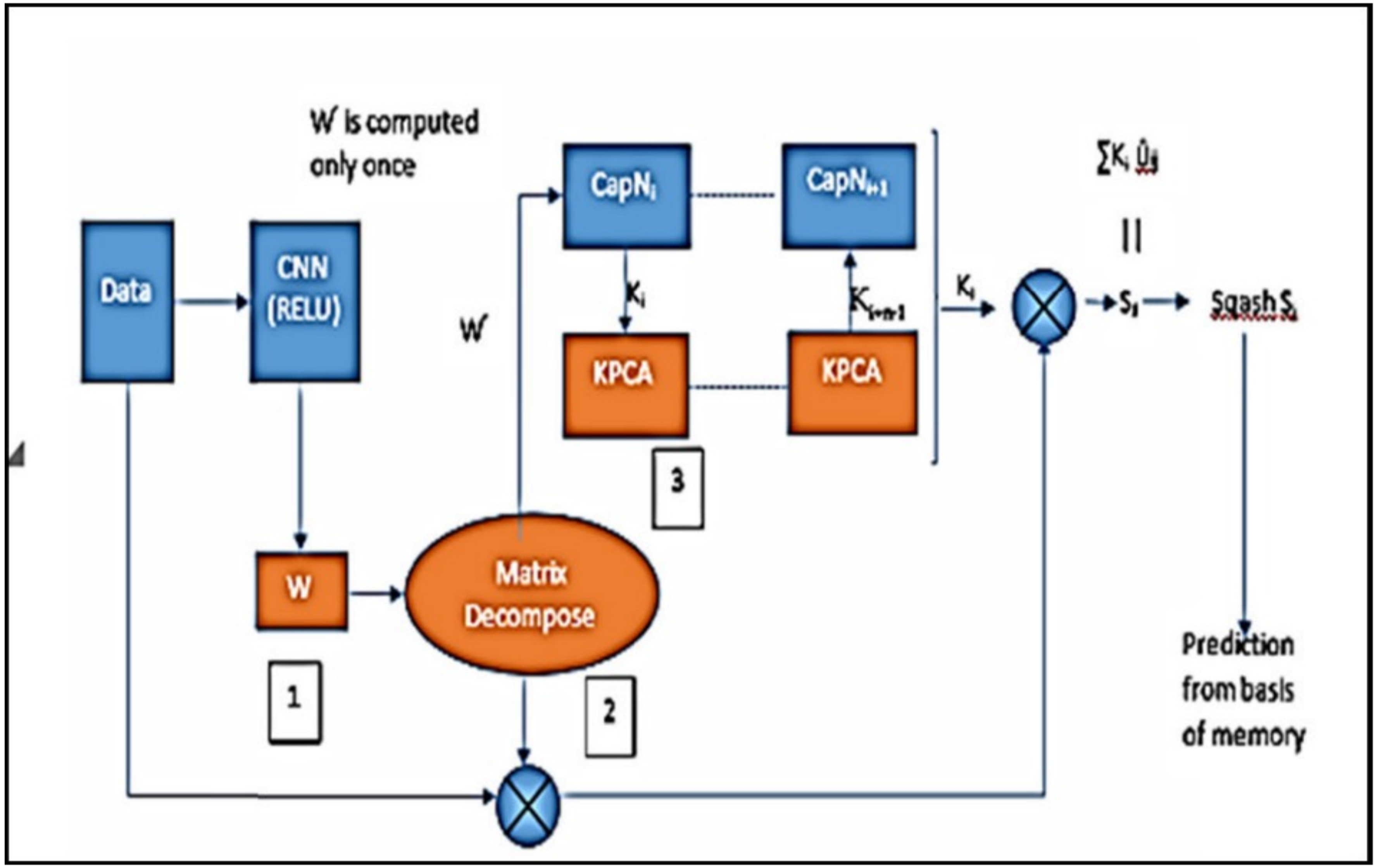
•Exploratory Data Analysis (EDA) and Feature Importance Assessment

•Implementation of Modified Capsule Networks (M-CapNet)

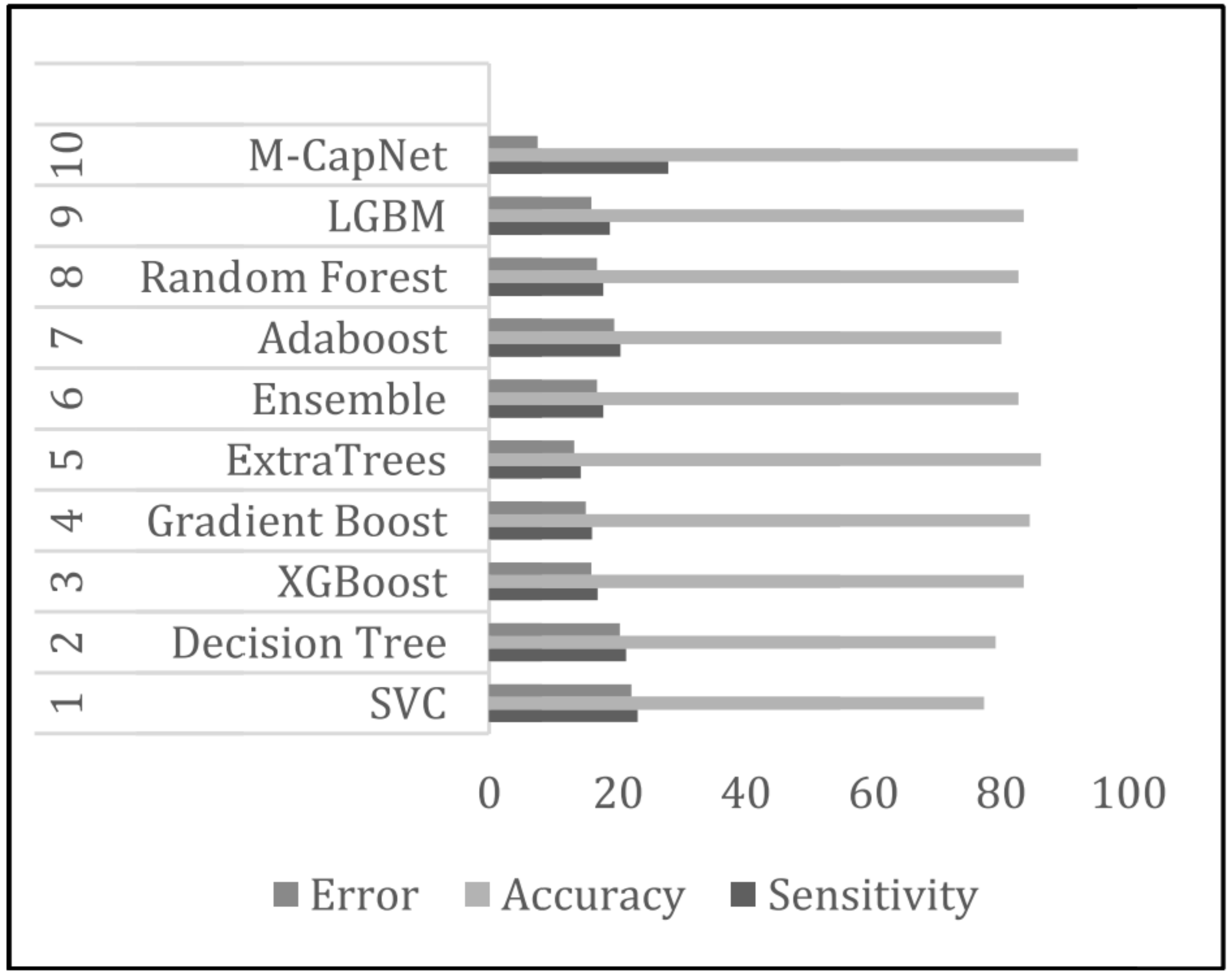
•Evaluation of M-CapNet's Accuracy for Dementia Prediction

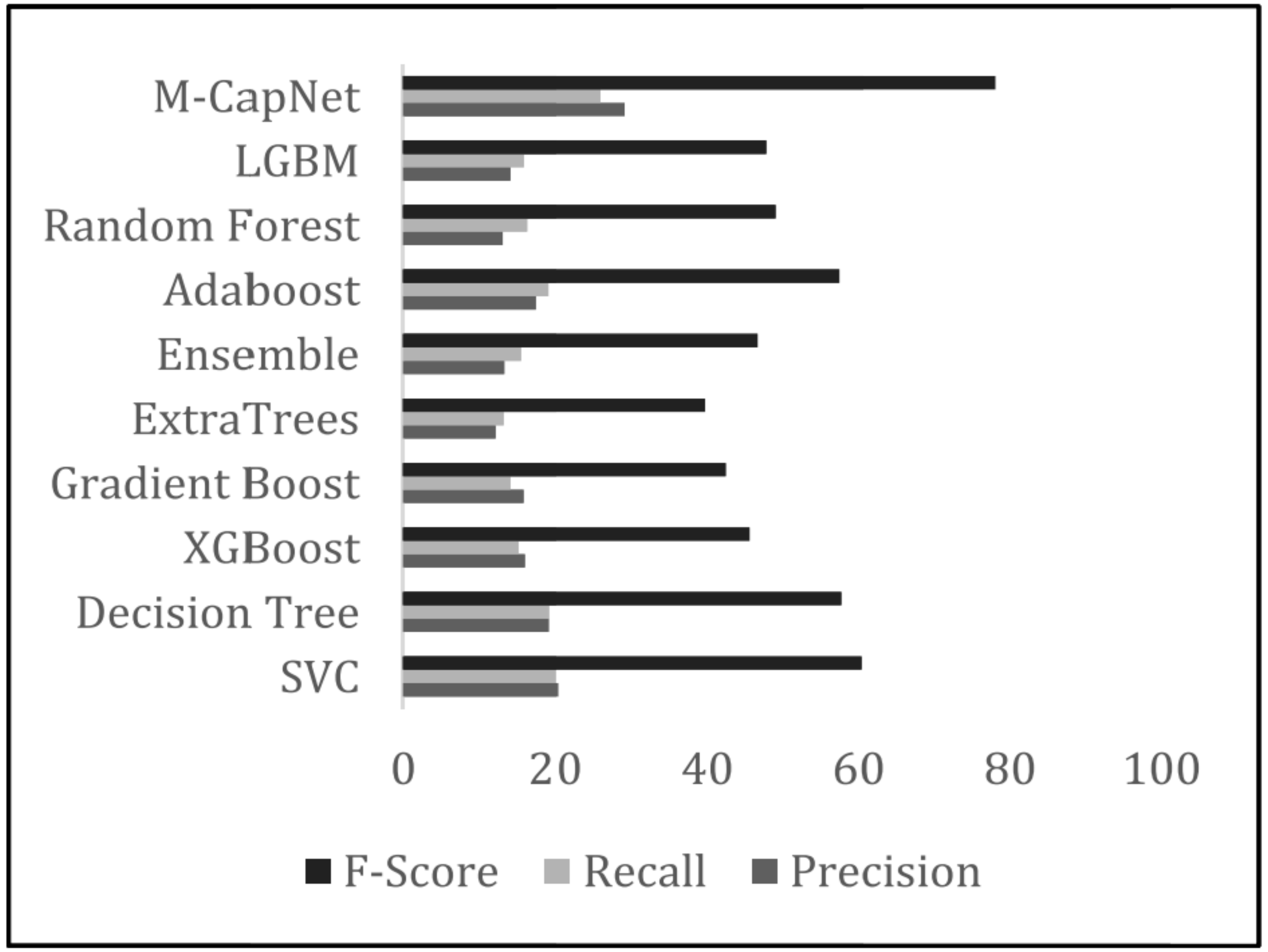
•Comparative Analysis with State-of-the-Art Deep Learning Classifiers

Proposed Methodology

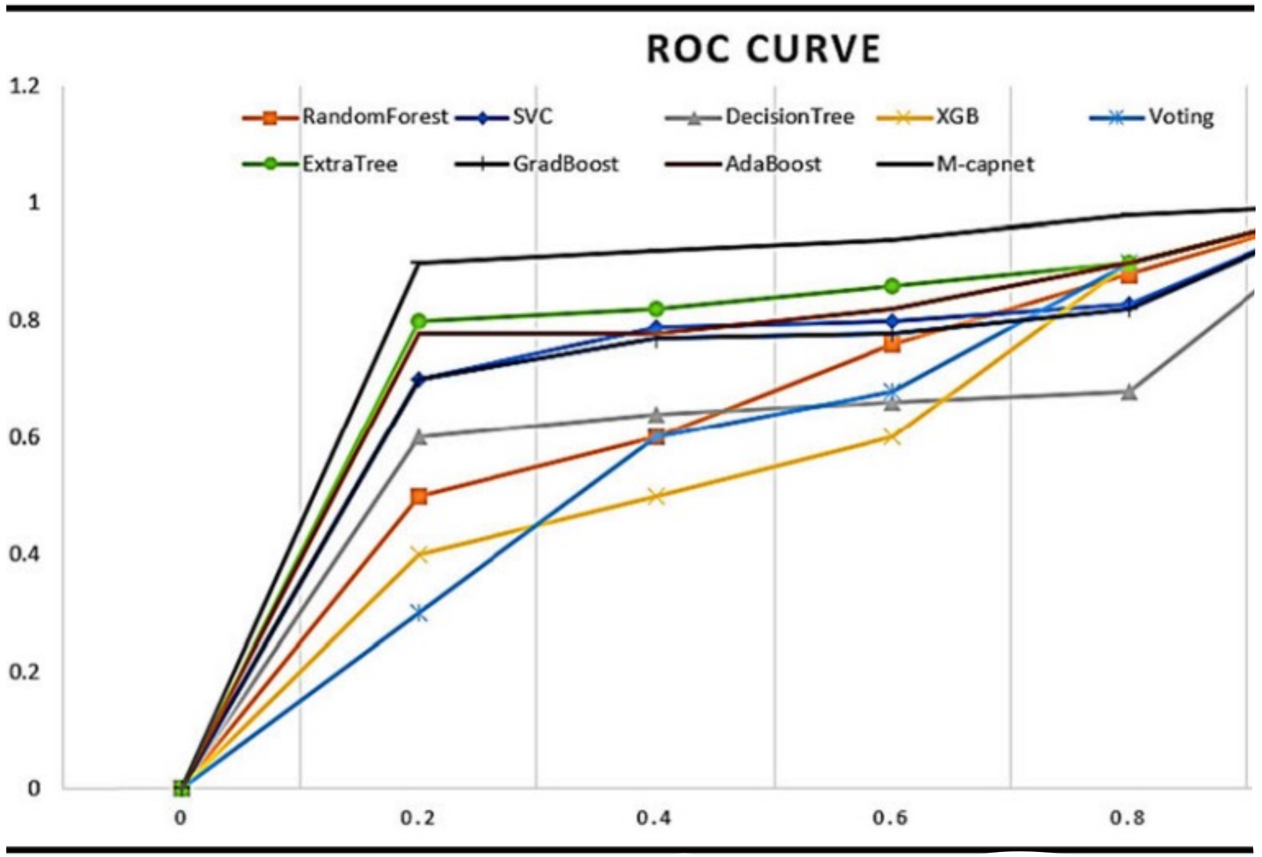


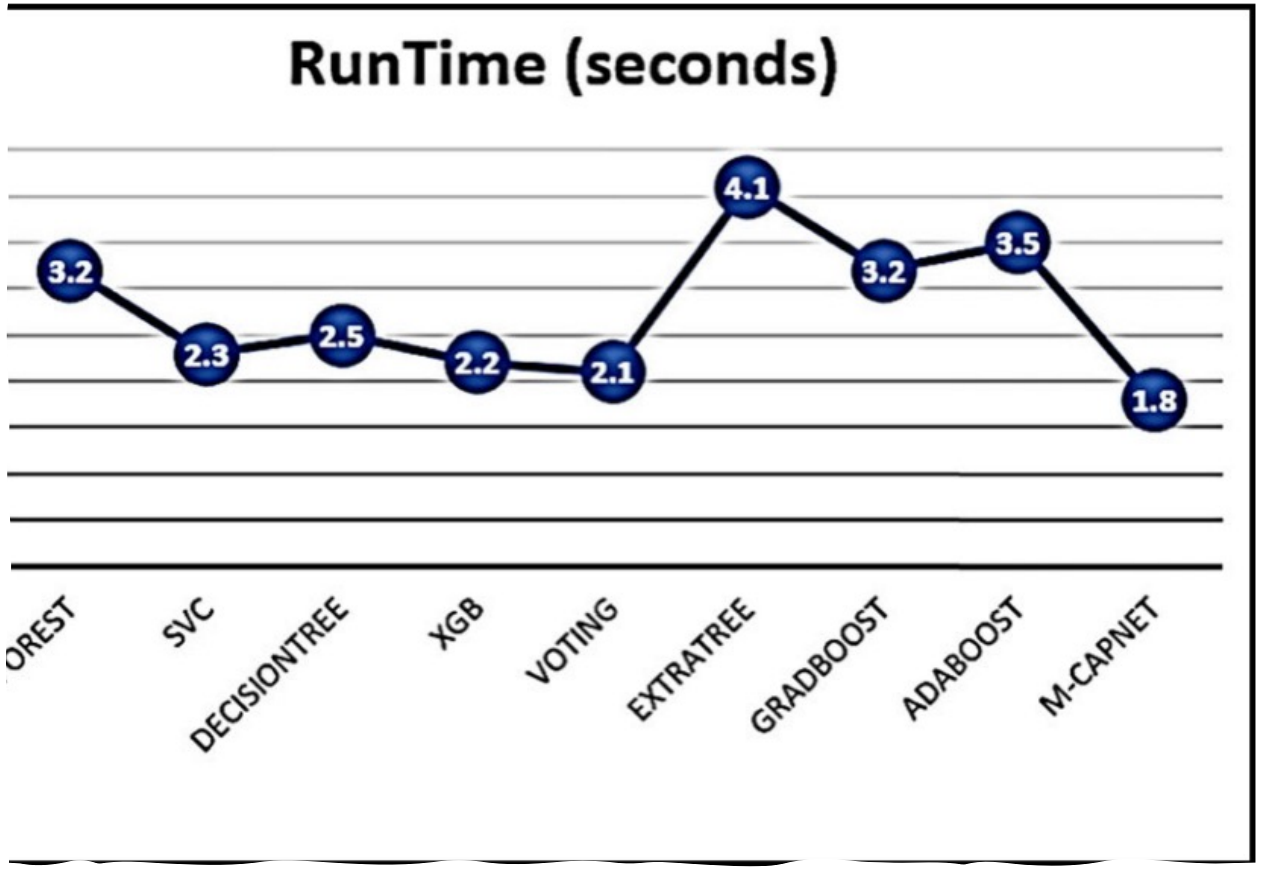
Why M-CapNet?


10 M-CapNet
9 LGBM
8 Random Forest
7 Adaboost
6 Ensemble
5 ExtraTrees
4 Gradient Boost
3 XGBoost
2 Decision Tree
1 SVC
0 20 40 60 80 100
Error Accuracy Sensitivity


M-CapNet
LGBM
Random Forest
Adaboost
Ensemble
ExtraTrees
Gradient Boost
XGBoost
Decision Tree
SVC
0 20 40 60 80 100
F-Score Recall Precision

Why M-CapNet?


ROC CURVE
RandomForest
SVC
DecisionTree
XGB
Voting
ExtraTree
GradBoost
AdaBoost
M-capnet
1.2
1
0.8
0.6
0.4
0.2
0
0
0.2
0.4
0.6
0.8


RunTime (seconds)
3.2
2.3
2.5
2.2
2.1
4.1
3.2
3.5
1.8
OREST
SVC
DECISIONTREE
XGB
VOTING
EXTRATREE
GRADBOOST
ADABOOST
M-CAPNET

Results

Conducted an ablation study to evaluate the impact of individual features on the model's accuracy using Sets A, B, C, and D, partitioning the OASIS dataset. Removing 'age' drastically reduced accuracy from 92.3% to 71.1%, highlighting its crucial role in dementia prediction. Further exclusion of 'age' and 'gender' lowered accuracy to 69.9%, emphasizing their significant impact on predictive performance. Comprehensive data (Set A) with all features achieved the highest accuracy (92.39%), underscoring their collective importance.

Study Label	Accuracy	Recall	F1 Score
A	92.3	82.3	88.81
B	71.1	23.2	62.63
C	69.9	34.1	54.52
D	88.1	79.2	84.82

Thank you