COMPARATIVE ANALYSIS ON RESEARCH PAPERS

Presented by:

Binary_Girls

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Summery

- The first paper proposes Multi-Level Stacking Ensemble for Detection of Alzheimer's Disease and application of SHAP Analysis in this field

- The second paper is actually a review paper of almost 47 authentic papers. It introduces a new approach to research and provides a summary of all the completed research methodologies proposed so far in the detection of Alzheimer's Disease.

Explainable Artificial Intelligence of Multi-Level Stacking Ensemble for Detection of Alzheimer’s Disease Based on Particle Swarm Optimization and the Sub-Scores of Cognitive Biomarkers

Authors :

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and Hager Saleh

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Problem Statement:

- Existing machine learning techniques for Alzheimer's disease (AD) detection often rely on single-modal data, limiting their ability to fully capture the complexity of AD progression. These approaches lack robust feature selection and interpretability, which hinders their effectiveness in leveraging diverse cognitive biomarkers for accurate and early-stage diagnosis.

Objectives:

- Enhance early Alzheimer’s disease detection
- Optimize feature selection with Particle Swarm Optimization
- Integrate heterogeneous modalities efficiently
- Advance interpretability in AI diagnostics
- Demonstrate superior performance of multi-level stacking

Introduction

Alzheimer's Disease (AD) is a leading cause of dementia, marked by progressive memory loss and cognitive decline, affecting over 50 million people globally—a number projected to triple by 2050. Mild Cognitive Impairment (MCI), a precursor to AD, presents an opportunity for early intervention, as approximately 10-15% of MCI patients transition to AD annually. Despite the lack of a cure, early detection and intervention can significantly reduce AD progression.

Introduction

Limitations of Previous Studies (Research Gap)

- Most studies relied on single-modal data or summary scores.
- Few integrated cost-effective cognitive sub-scores for AD detection.
- Explainability of black-box models remains under explored.

The Proposed Framework:

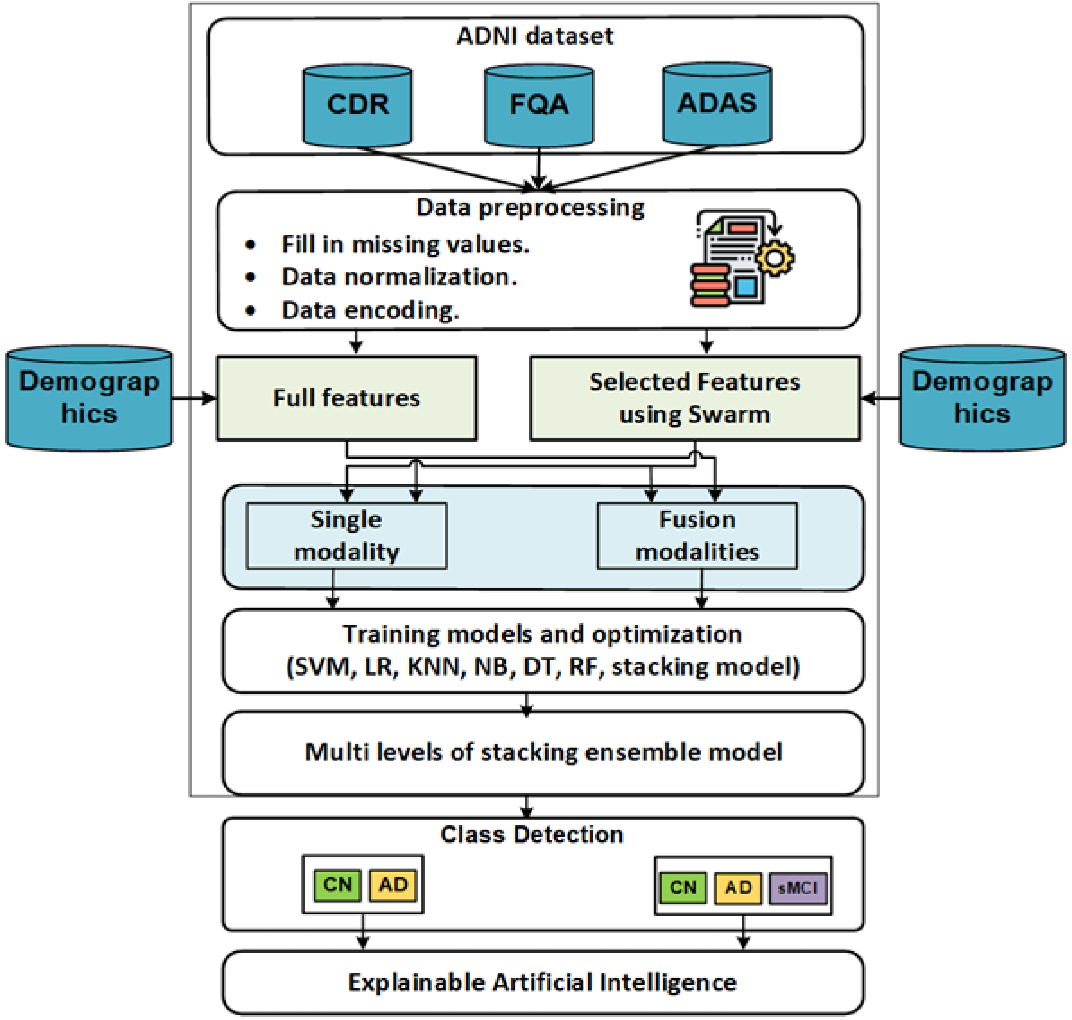

Figure : The Proposed Framework

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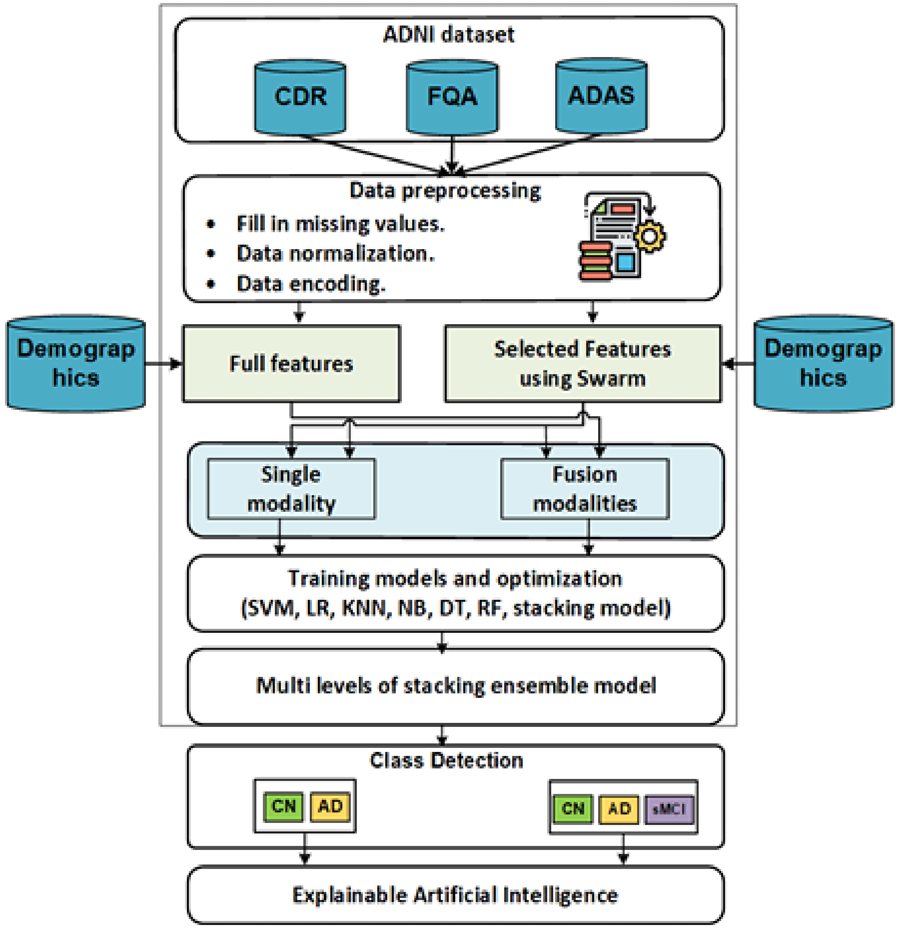

Figure : The Proposed Framework

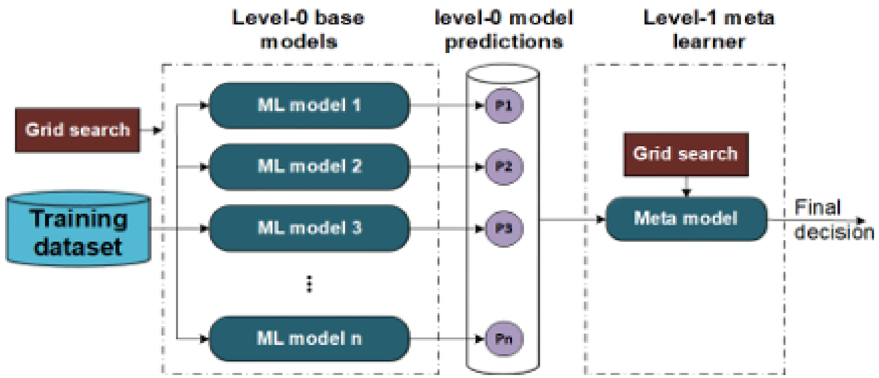

Figure : Single Level Stacking Ensemble

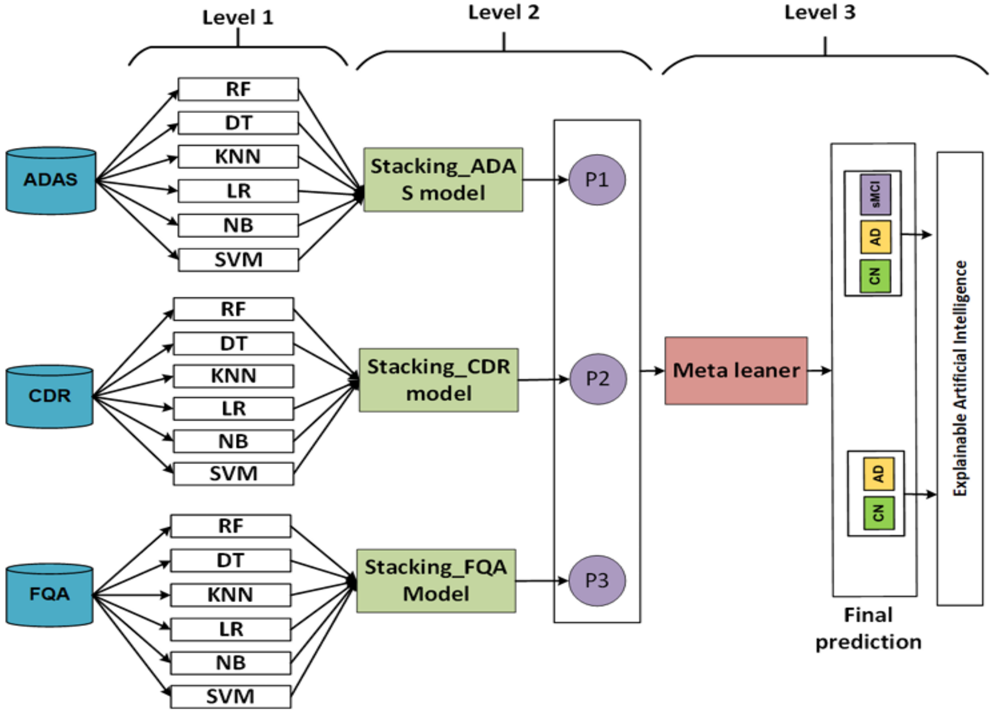

Figure : The Multi-Level Stacking Ensemble

Materials & Methods:

- **Particle Swarm Optimization (PSO)**

Algorithm

Input: N: sample size

p:problem dimension

M:Maximum iterations

LS:the lower bound of the search space

US:the upper bound of the search space

Output: S_{best} :the best solution

1 Start

2 Initialize the search process randomly.

Materials & Methods:

➢ **Particle Swarm Optimization (PSO)**

3 for i←1 to N do

4 v_i^0← random volicty vector [LS∪US]^p

//initialize the practical velocity

5. x_i^0←random position [LS∪US]^p

//initialize position

6. p_{best}^0←x_i^0

initialize the best solution

7. Apply Precision performance matrix to get g_{best}^0

8. m←1

Materials & Methods:

- **Particle Swarm Optimization (PSO)**

9. While m ≤ M do

10. For i=1 to N do

11. r^1 r^2 ← are two independent vectors that

 generated randomly $[0.1]^D$

12. Apply Recall performance matrix //update the velocity.

13. Apply F-score performance matrix//update the position.

Materials & Methods:

- **Particle Swarm Optimization (PSO)**

14. **If** $f(x^{t}_{i})<f(x^{t-1}_{best})$ then

15. $(x^{t}_{best\_i})\leftarrow f(x^{t}_{best\_i})$

16. Apply precision performance matrix to get the best solution //update the over all best position.

17. $m \leftarrow m+1$

Materials & Methods:

Single Level Stacking Ensemble

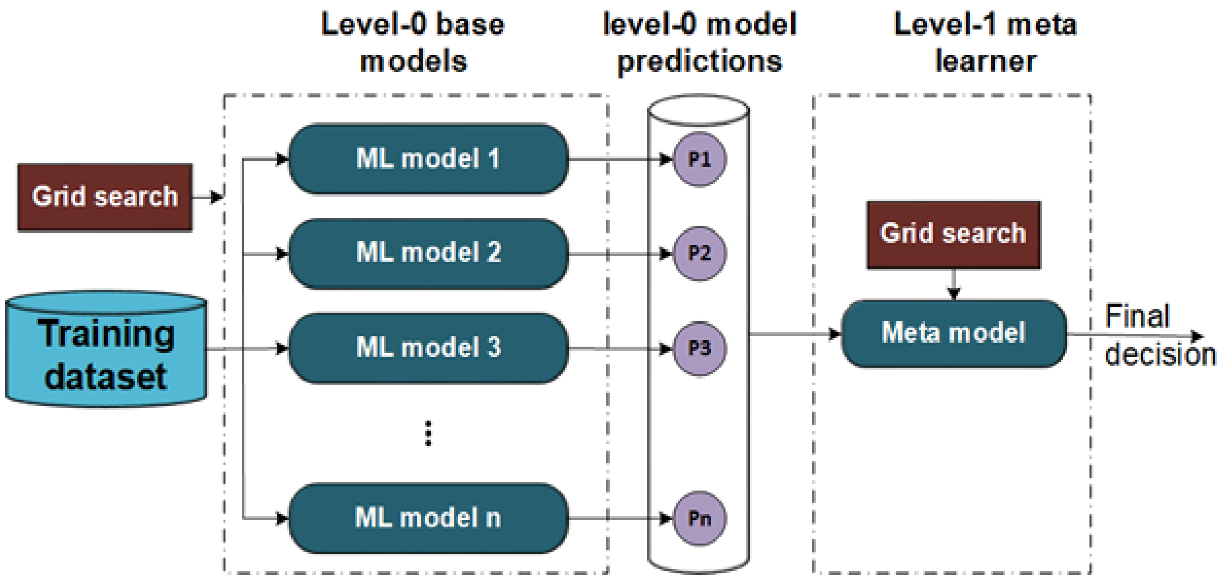

Figure : Single Level Stacking Ensemble

Materials & Methods:

Multi-level stacking ensemble model Development

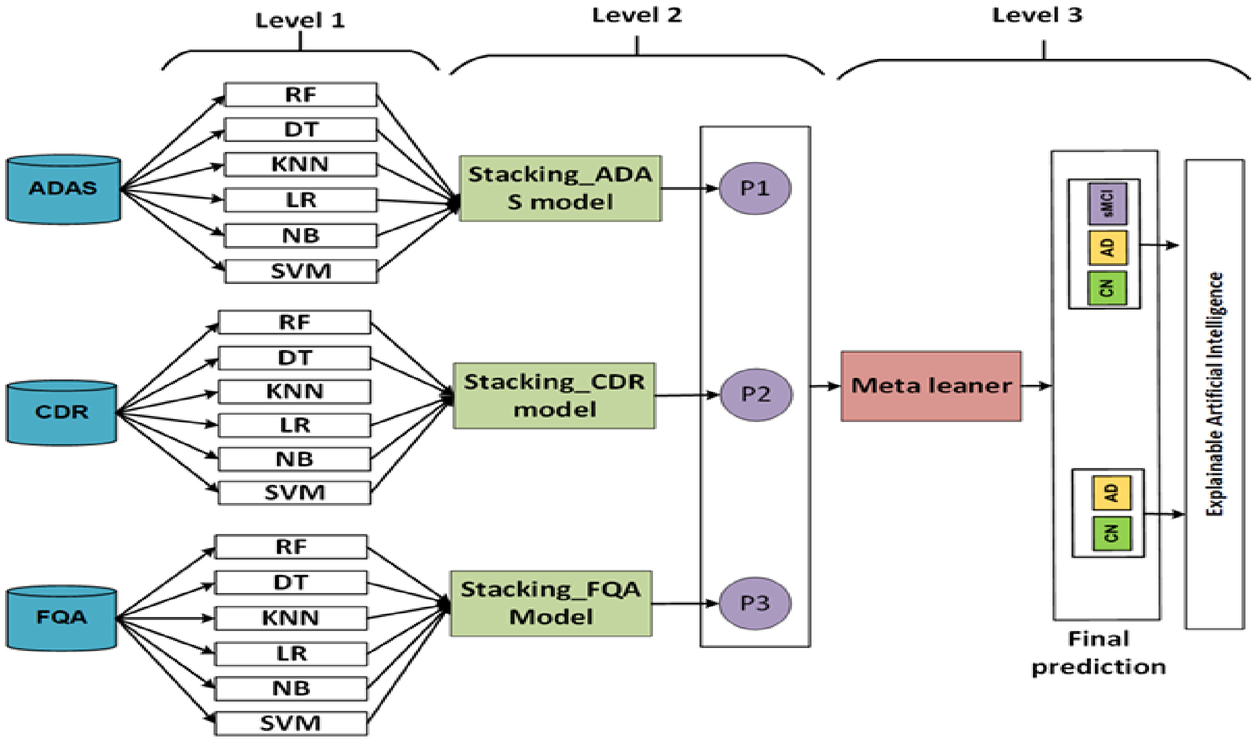

FIGURE 3. Multi-level stacking ensemble learners for predicting Alzheimer's disease.

Results and Analysis:

TABLE 2. The performance of models with the two classes and full features.

Datasets	Approaches	Models	Testing results			
			ACC	PRE	REC	F1
ADAS	Regular ML classifiers	RF	85.97	85.08	85.97	85.47
		LR	85.60	85.65	85.60	85.46
		DT	83.07	83.56	83.07	83.15
		SVM	85.60	85.59	85.60	85.47
		KNN	84.04	84.12	84.04	84.82
		NB	84.25	84.36	84.25	84.93
	Stacking model	Stacking_ADAS	86.21	86.20	86.21	86.04
CDR	Regular ML classifiers	RF	86.51	87.55	86.51	85.81
		LR	86.15	86.38	86.15	86.87
		DT	83.51	83.55	83.51	83.81
		SVM	86.68	86.07	86.68	86.27
		KNN	85.56	85.61	85.56	85.33
		NB	85.27	85.40	85.27	85.98
	Stacking model	Stacking_CDR	87.56	87.85	87.56	87.23
FAQ	Regular ML classifiers	RF	83.87	84.45	83.87	83.07
		LR	82.10	82.16	82.10	82.78
		DT	80.70	80.73	80.70	80.71
		SVM	83.80	83.97	83.80	83.42
		KNN	83.34	83.21	83.34	83.25
		NB	82.63	82.64	82.63	82.26
	Stacking model	Stacking_FAQ	85.56	85.61	85.56	85.33
ADAS_CDR	Regular ML classifiers	RF	86.87	86.45	86.87	86.07
		LR	85.15	85.09	85.15	85.02
		DT	84.70	84.73	84.70	84.71
		SVM	86.86	86.80	86.86	86.71
		KNN	85.74	85.78	85.74	85.56
		NB	85.68	85.62	85.68	85.49
	Stacking models	Stacking_ADAS_CDR	88.15	88.17	88.15	88.96
	Muti-level Stacking model	PMS_ ADAS_CDR	89.03	89.97	89.03	89.94
ADAS_FAQ	Regular ML classifiers	RF	86.58	86.70	86.58	86.96
		LR	85.26	85.34	85.26	85.11
		DT	84.31	84.29	84.31	84.63
		SVM	86.46	86.61	86.46	86.24
		KNN	85.28	85.29	85.28	85.08
		NB	85.97	85.67	85.97	85.51
	Stacking models	Stacking_ADAS_FAQ	87.56	87.85	87.56	87.23
	Muti-level Stacking model	PMS_ADAS_FAQ	88.91	88.90	88.91	88.80
CDR_FAQ	Regular ML classifiers	RF	87.39	87.95	87.39	86.90
		LR	89.15	89.22	89.15	88.93
		DT	85.51	85.55	85.51	85.81
		SVM	88.27	88.40	88.27	87.98
		KNN	87.10	87.01	87.10	87.89
		NB	86.92	86.83	86.92	86.66
	Stacking models	Stacking_CDR_FAQ	88.56	88.68	88.56	88.30
	Muti-level Stacking model	PMS_CDR_FAQ	89.15	89.22	89.15	89.93
ADAS_CDR_FAQ	Regular ML classifiers	RF	88.44	88.65	88.44	88.19
		LR	88.44	88.41	88.44	88.30
		DT	85.39	85.34	85.39	85.17
		SVM	88.56	88.61	88.56	88.33
		KNN	87.10	86.98	87.10	86.99
		NB	86.80	86.70	86.80	86.61
	Stacking model	Stacking_ADAS_CDR_FAQ	89.86	89.78	89.86	89.79
	Muti-level Stacking model	PMS_ADAS_CDR_FAQ	90.27	90.18	90.27	90.14

TABLE 3. The performance of models with the two classes and selected features by swarm.

Datasets	Approaches	Models	Testing results			
			ACC	PRE	REC	F1
ADAS	Regular ML classifiers	RF	85.97	85.08	85.97	85.47
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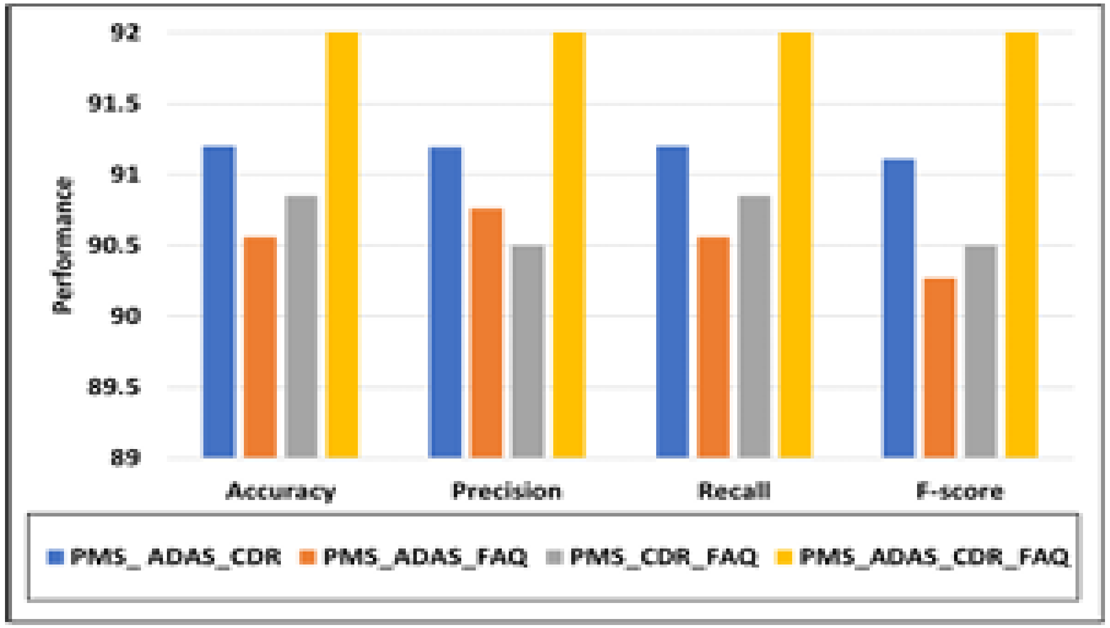
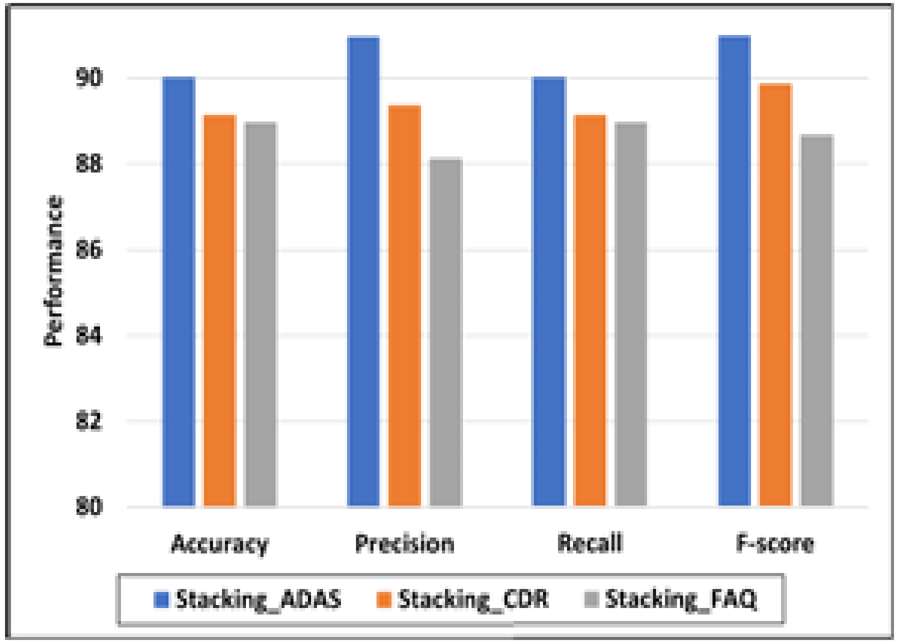
Visual Comparison:

- The results of two classes AD and CN

  The best models for each modality



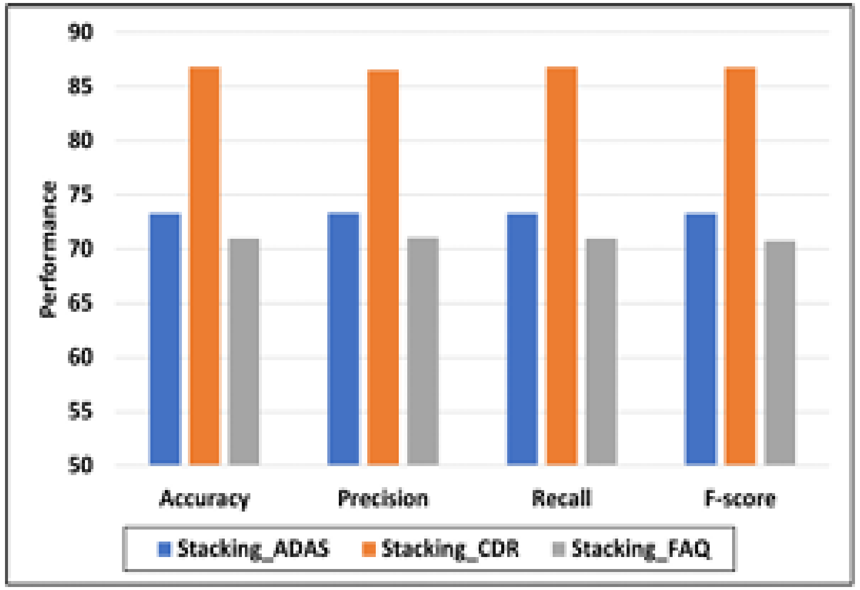
(b) two classes, multi modalities



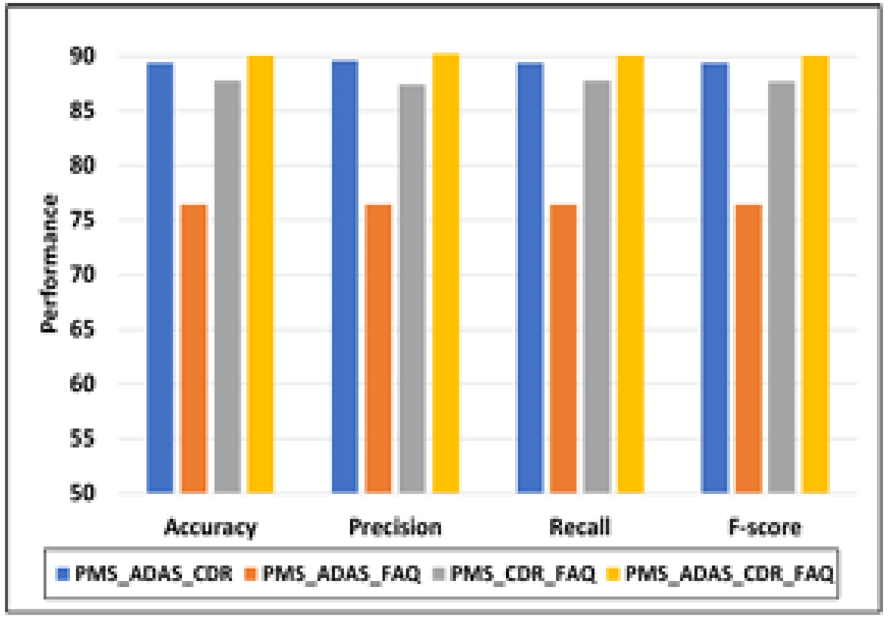
(a) two classes, single modality

Figure : The best models for each modality with two classes and selected features

Visual Comparison:



(a) two classes, single modality



(b) two classes, multi modalities

Figure : The best models for each modality with three classes and selected features

Comparison

TABLE 6. comparing with previous studies that used different datasets to detect AD.

Research study	Dataset	Models	Classes	The performance
[37]	OASIS	XBoost	non-demented demented	ACC=85.12, PRE=83, REC=83 and F1=85
[38]	OASIS	SVM	non-demented demented	ACC=92 and REC=91.89
[39]	OASIS dataset	CHFS+SVM	non-demented demented	ACC=96.50%, REC=96.5
[45]	ADNI	Deep CNN	CN, EMCI, LMCI and AD	ACC=93
[46]	ADNI	SVM	CN, EMCI, LMCI and AD	REC=75 F1=72
[47]	ADNI	GLM	CN, EMCI, LMCI, SMC and AD	ACC=88.24
[48]	MRI and PET	XGB	NC, MCI, and AD	ACC=98.06%
[39]	Multi-modality (MRI,FDG, and PET)	ML models	AD and CN	ACC= 94.8%
Our work	Sub-scores of fusion (FQA, CDR, and ADAS)	Muti-level of stacking models	AD and CN	ACC=92.08 PRE=92.07 REC=92.08 F1=92.01

SHAP AnalysisSHAP (SHapley Additive exPlanations)

SHAP (SHapley Additive exPlanations) values are a way to explain the output of any machine learning model.

- **Model Interpretability**

  Used to make the machine learning model interpretable

- **Transparency in Black-Box Models**

  Explains the model’s predictions, making them easier for doctors to interpret

SHAP Analysis:

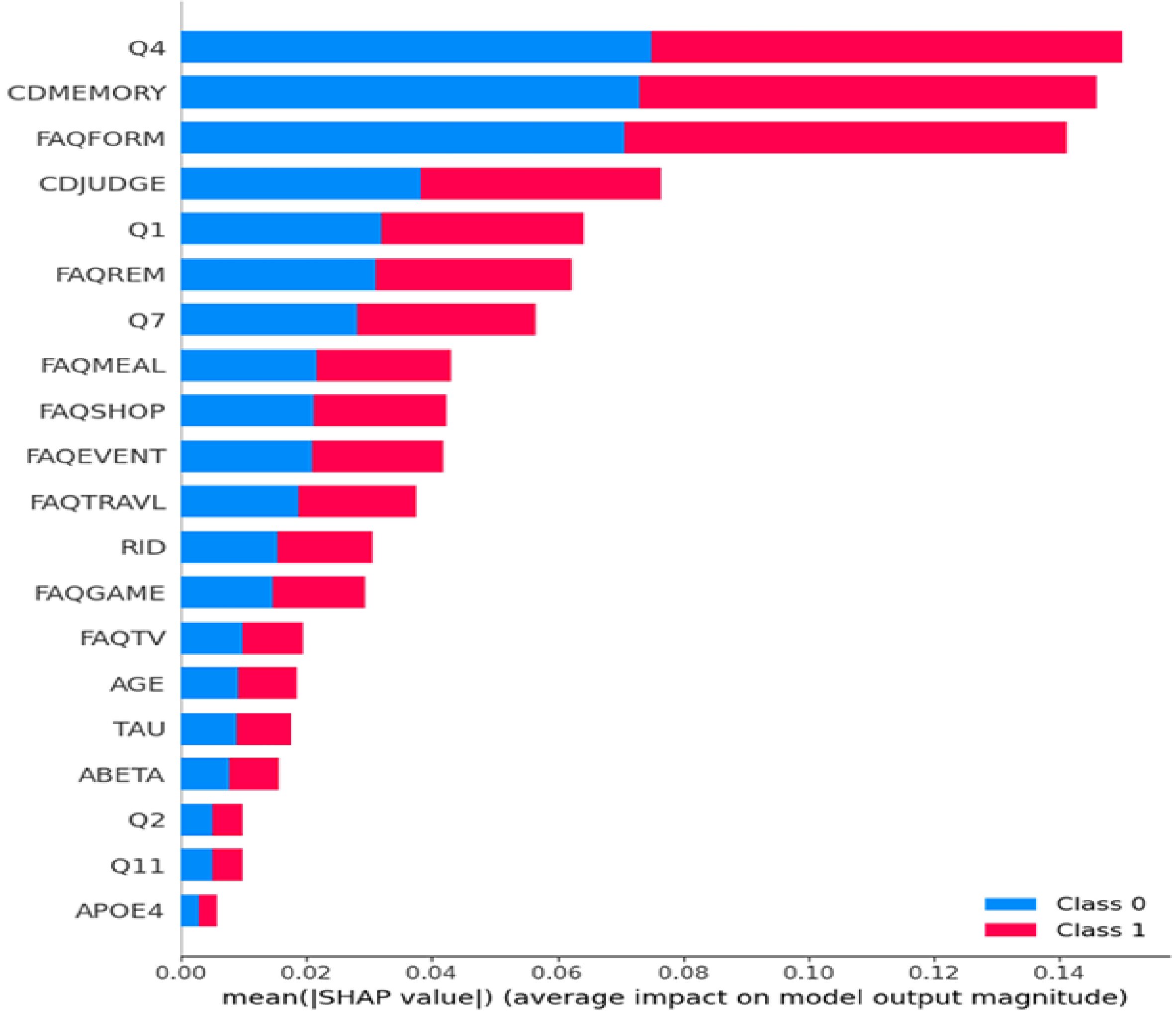


FIGURE 12. **Summary plot for two class problems (0=AD, 1=CN).**

SHAP Analysis

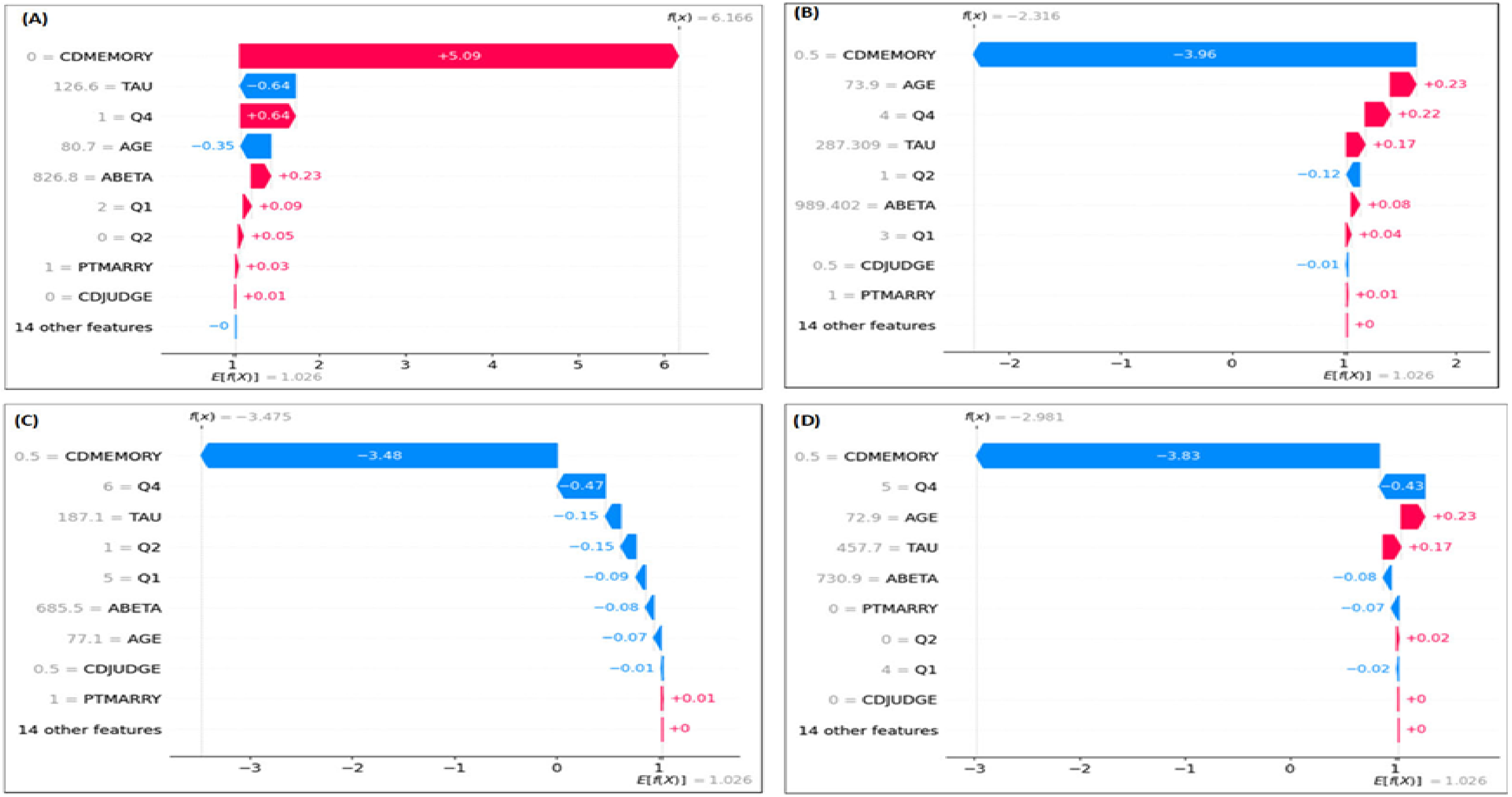


Figure : Waterfall for three classes problem

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[1] A.Association, “2018 Alzheimer’s disease facts and figures,” Alzheimer’s Dementia, vol. 14, no. 3, pp. 367–429, Mar. 2018.

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[6] M. S. Albert, S. T. DeKosky, D. Dickson, B. Dubois, H. H. Feldman, N. C. Fox, A. Gamst, D. M. Holtzman, W. J. Jagust, and R. C. Petersen, “The diagnosis of mild cognitive impairment due to Alzheimer’s disease: Recommendations from the national institute on aging-Alzheimer’s asso ciation workgroups on diagnostic guidelines for Alzheimer’s disease,” Focus, vol. 11, no. 1, pp. 96–106, 2013.

Conclusion:

- A new multi-level stacking model has been proposed to predict Alzheimer's Disease (AD) with higher accuracy.
- The study addresses classification problems with two classes (AD, CN) and three classes (AD, CN, sMCI).
- The proposed multi-level stacking model outperformed single-level stacking and classical ML models, achieving the highest performance with selected features for both two-class (accuracy = 92.08%) and three-class (accuracy = 90.03%) problems.
- Multi-modalities demonstrated superior results compared to single modalities.

A systematic review on machine learning and deep learning techniques in the effective diagnosis of Alzheimer’s disease

Authors:

Akhilesh Deep Arya,

Sourabh Singh Verma,

Prasun Chakarabarti,

Tulika Chakrabarti,

Ahmed A. Elngar,

Ali-Mohammad Kamali and

Mohammad Nami

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Introduction:

- Overview of Alzheimer's Disease (AD):
  - Progressive neurodegenerative condition
  - Primarily affects cognitive and memory functions in the elderly
  - Most cases of this disease are observed in people aging 65 and above
  - It is observed that people with higher education are at less risk

- Early detection is crucial for:
  - Delaying mental health effects
  - Improving patient quality of life

Different Stages of MCI/AD:

Stage No	Stage Name
1	Pre-clinical Alzheimer's disease
2	Mild cognitive impairment (MCI)
3	Mild dementia
4	Moderate dementia
5	Severe dementia due to Alzheimer's disease

- Current State of Research:
  - Advanced Diagnostics:
    a) MRI and PET scans
    b) Integration of machine learning and deep learning models for better diagnostic accuracy

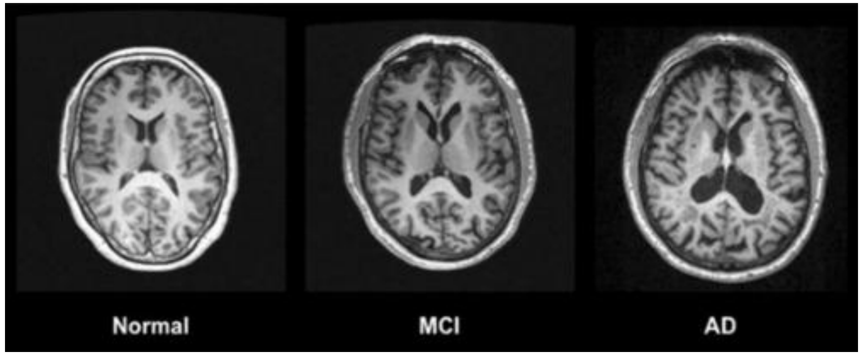


Figure 1: MRI scans images of different stages of AD

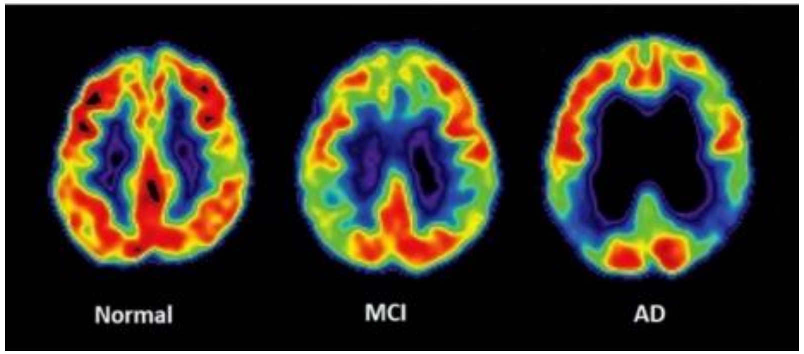
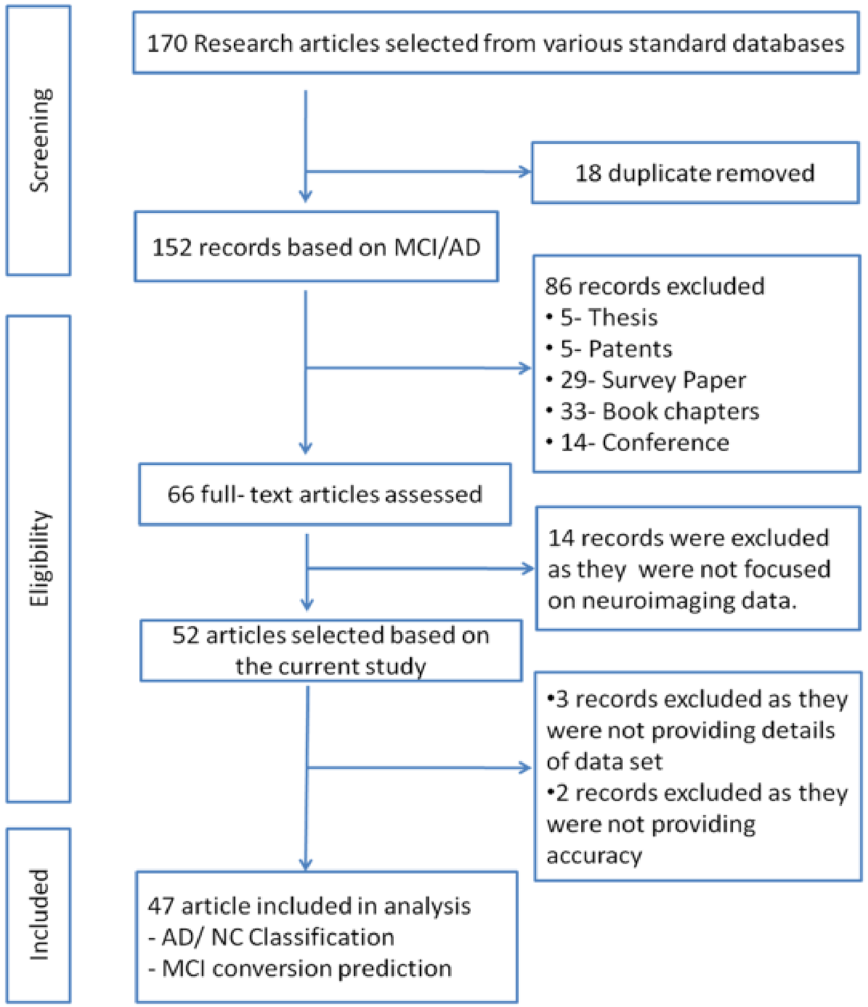


Figure 2: PET scans images of different stages of AD

Objectives:

- To analysis the models and methods used in different papers
- Compare the accuracy of the models
- Provide an overview about all the research works

Literature selection:



Methodes and Models:

Pre-processing methods:

1. Image normalization
2. Image cropping and resizing
3. Image augmentation
4. Feature extraction
5. Data augmentation

Methodes and Models

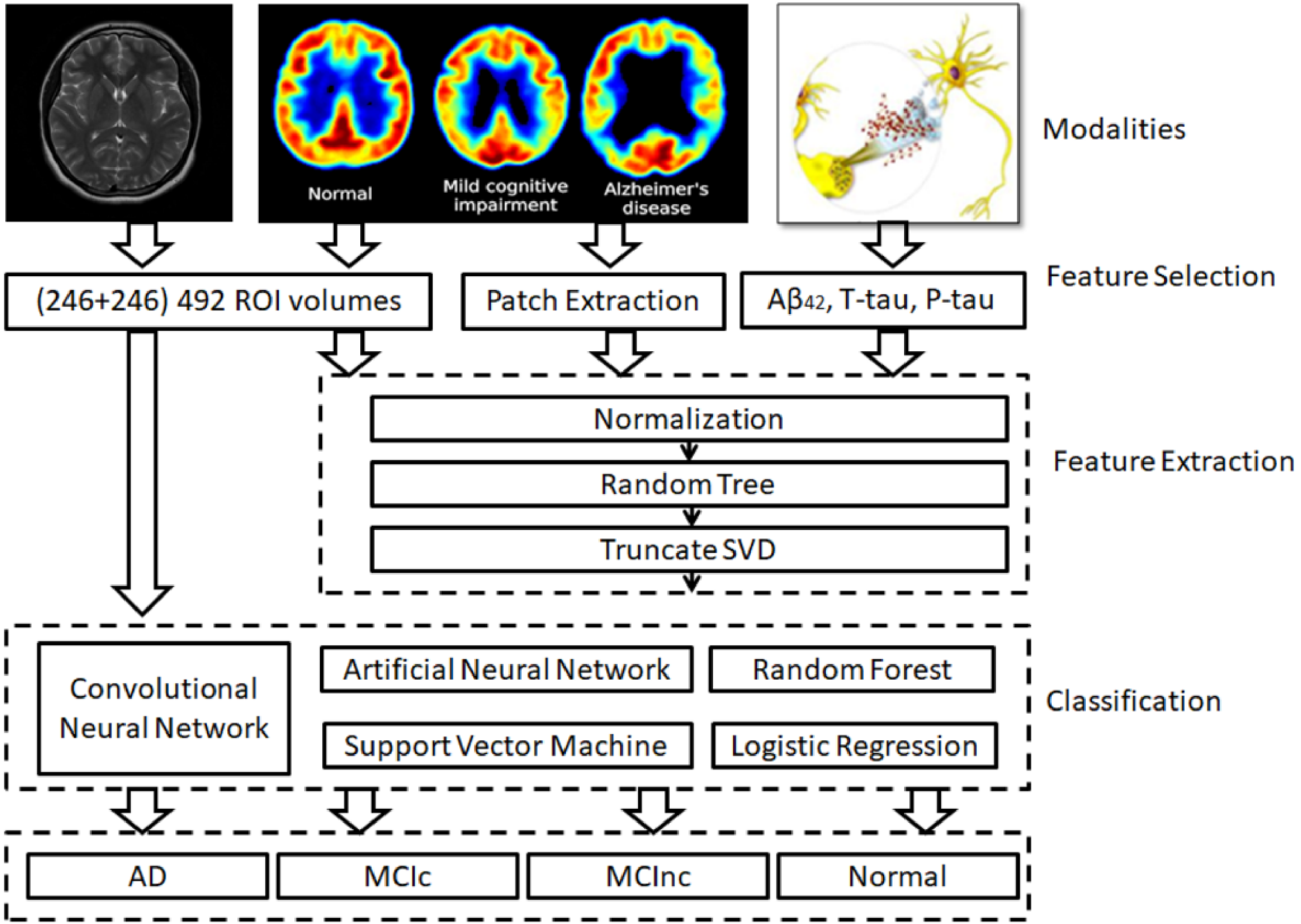


Figure: Description of modalities, feature selection, feature extraction, and classification algorithms used to predict AD and NC cases

Methodes and Models

Machine Learning Models:

- Logistic Regression
    - Predicts the probability of a binary outcome (e.g., disease vs. no disease)
    - Works well for linear relationships
- Support Vector Machine
    - Separates data into categories using a hyperplane
    - Effective for both linear and non-linear data
- Random Forest
    - Uses multiple decision trees for predictions
    - Reduces overfitting and improves accuracy
- Linear Discriminant Analysis (LDA):
    - Useful for classification tasks with multiple categories
    - Assumes data is normally distributed
    - Projects data into lower-dimensional space while maximizing class separability

Methodes and Models

Deep Learning Models:

- ANN
  - A basic neural network with 1-2 hidden layers
- DNN
  - A neural network with multiple hidden layers (deep architecture)
  - Learns hierarchical representations of data
- RNN
  - Retains information from previous inputs (memory)
  - Can analyze progression over time, useful for disease progression prediction

Methodes and Models

- CNN
  - Designed for image processing and pattern recognition
  - Captures spatial features like edges, shapes, and textures.
  - Widely used in medical imaging tasks

  There are some specific CNN models used in prediction of Alzheimer's disease. Some models which provide better accuracy are given below:

  - ResNet101
    - Deep CNN with 101 layers
    - Excels in processing complex and detailed images
  - VGG
    - Deep CNN with a simple architecture (e.g., 16 or 19 layers)
    - Performs well on image classification tasks

Methodes and Models

- VoxCNN
  - A CNN specifically designed for volumetric data (e.g., 3D brain scans)
  - Captures spatial and volumetric features effectively

- DenseNet
  - Deep CNN where each layer connects to every other layer
  - Reduces redundancy and enhances feature propagation

Visual Comparison

Comparison chart of accuracy derived from different articles:

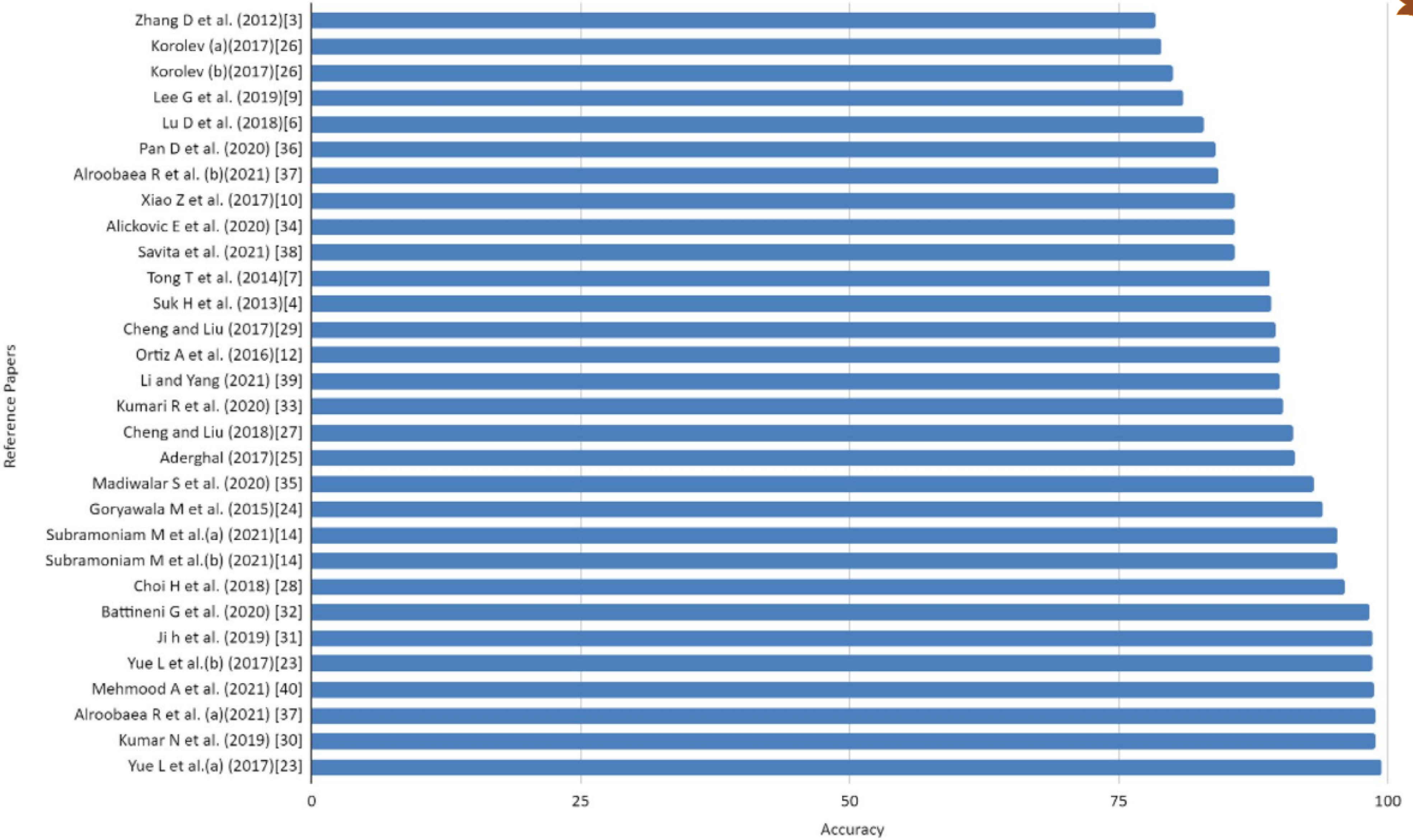
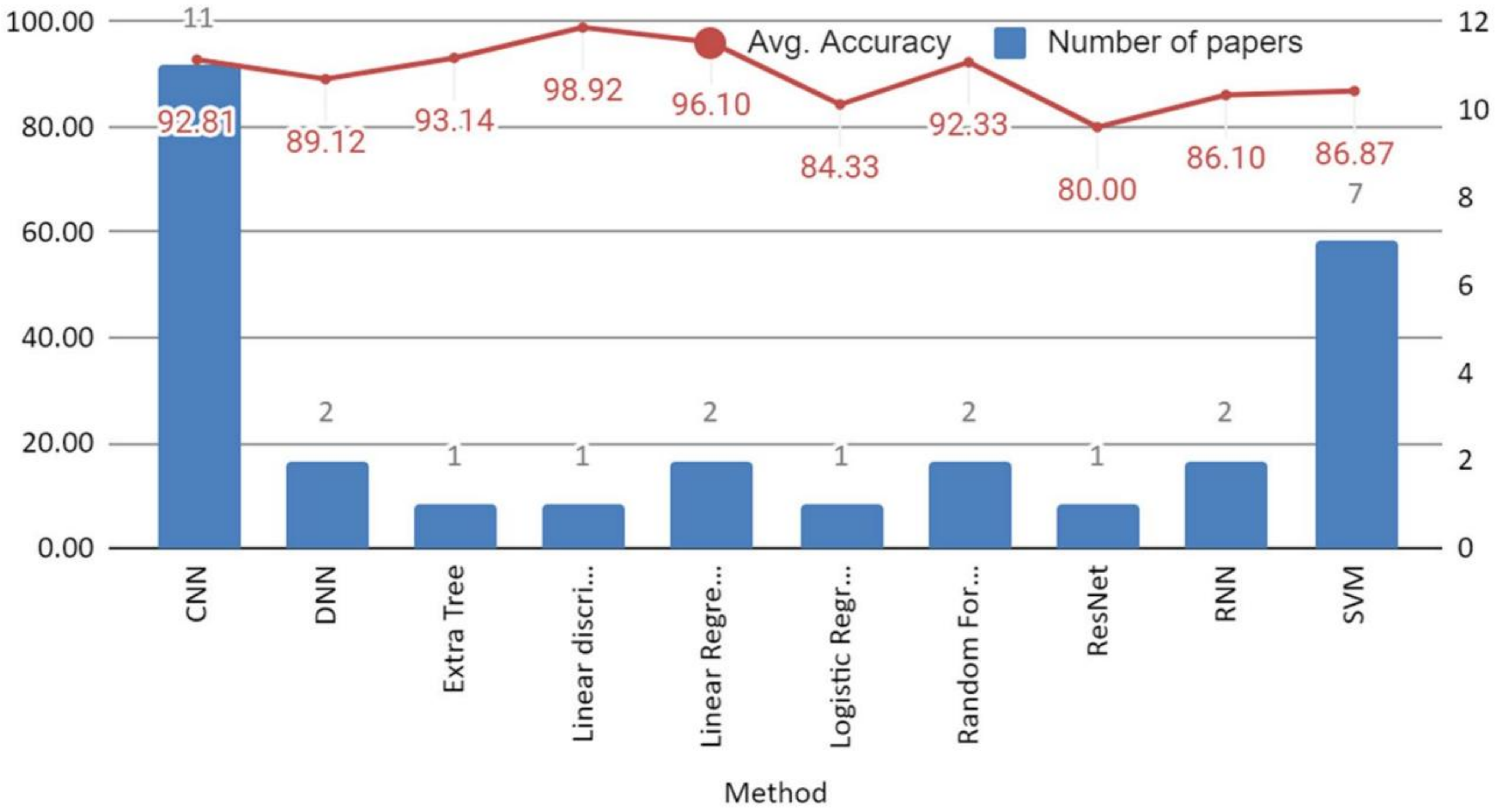


Table to represent Methodes and accuracy of the papers:

References	Method	AD:NC Acc	SEN recall	SPE	Precision	AUC
Zhang D et al. [3]	Multi-kernel SVM	78.40	79.00	78.00	–	76.80
Suk H et al. [4]	Group sparse representation + SVM	89.19	91.00	88.00	–	95.60
Lu D et al. [6]	DNN	82.93	79.69	83.84	–	–
Tong T et al. [7]	Multiple instance learning + SVM	89.00	–	–	–	–
Lee G et al. [9]	Multi- model deep learning + RNN	81.00	84.00	80.00	–	86.00
Xiao Z et al. [10]	SVM-REF with covariance	85.71	79.63	91.38	–	–
Ortiz A et al. [12]	Deep belief network (SVM)	90.00	86.00	94.00	–	95.00
Subramoniam M et al.(a) [14]	Vanilla DNN	95.31	–	–	–	–
Subramoniam M et al.(b) [14]	CNN	95.32	–	–	–	–
Yue L et al.(a) [23]	CNN	99.40	100	–	98.80	97.20
Yue L et al.(b) [23]	CNN	98.60	97.20	–	100	98.60
Goryawala M et al. [24]	Linear regression model + LDA	93.90	96.30	89.50	93.80	–
Aderghal [25]	2D CNN	91.41	93.75	89.60	–	–
Korolev (a) [26]	3D CNN	79.00	–	–	–	88.00
Korolev (b) [26]	ResNet	80.00	–	–	–	87.00
Cheng and Liu [27]	RNN	91.20	91.40	83.84	95.30	–
Choi H et al. [28]	3D CNN	96.00	–	–	–	91.00
Cheng and Liu [29]	3D CNN	89.60	87.10	92.00	–	94.45
Kumar N et al. [30]	Linear discriminant analysis	98.92	–	–	–	–
Ji h et al. [31]	CNN	98.59	97.22	100	–	–
Battineni G et al. [32]	Linear regression model	98.30	97.40	–	98.60	99.70
Kumari R et al. [33]	CNN	90.25	85.53	–	–	–
Alickovic E et al. [34]	Random forest	85.77	54.17	97.44	–	–
Madiwalar S et al. [35]	Extra tree	93.14	85.00	–	85.00	–
Pan D et al. [36]	CNN	84.00	–	–	–	92.00
Alroobaea R et al. (a) [37]	Random forest	98.89	99.19	–	98.89	–
Alroobaea R et al. (b) [37]	Logistic regression	84.33	84.14	–	84.54	–
Savita et al. [38]	SVM	85.80	–	–	87.83	–
Li and Yang [39]	SVM	90.00	93.90	85.10	–	97.00
Mehmood A et al. [40]	CNN	98.73	98.19	99.09	–	–

Frequency of methods used in different articles taken in the study, and average accuracy using different classifiers:



Limitations

- Only worked with image data
- XAI can be added

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Conclusion

- In the paper, authors tried to provide a review of all the research works published
- By studying the paper, researchers can easily understand about all the published research works and get idea about proposed methodologies
- This paper makes it easier for the researchers to grasp where they can contribute and how they can contribute


THANK
YOU