Alzheimer Disease MRI Preprocessed Images: A Machine Intelligent Based Approach for Classification and Analysis

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ABSTRACT

Purpose: *Alzheimer's disease (AD) is considered as one of the most dangerous diseases in the present scenario. It is a brain disorder disease which leads to the destruction of the thinking skills and memory of human beings. It is very much essential for the early classification of AD magnetic resonance imaging (MRI) preprocessed images (ADMPIs) into several categories such as Mild_Demented (MID), Moderate_Demented (MOD), Non_Demented (ND), Very_Mild_Demented (VMD), etc. so that preventive measures can be taken at the earliest.*

Approach: *In this work, a machine intelligent (MI) based approach is proposed for the classification of ADMPIs into the MID, MOD, ND and VMD types. This approach is focused on machine learning (ML) based methods such as Logistic Regression (LRG), Support Vector Machine (SVMN), Random Forest (RFS), Neural Network (NNT), Decision Tree (DTR), AdaBoost (ADB), Naïve Bayes (NBY), K-Nearest Neighbor (KNNH) and Stochastic Gradient Descent (SGDC) to carry out such classification.*

Result: *The ML based methods have been implemented using Python based Orange 3.26.0. In this work, 1564 ADMPIs having 500, 64, 500 and 500 numbers of each type such as MID, MOD, ND and VMD respectively are taken from the Kaggle source. The performance of all the methods is assessed using the performance parameters such as classification accuracy (CA), F1, Precision (PR) and Recall (RC). From the results, it is found that the NNT method is capable of providing better classification results in terms of CA, F1, PR and RC as compared to other ML based methods such as SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGD.*

Originality: *In this work, a MI based approach is proposed to carry out the classification of ADMPIs into several types such as MID, MOD, ND and VMD types. The NNT method performs better in terms of CA, F1, PR and RC as compared to LRG, SVMN, RFS, DTR, ADB, NBY, KNNH and SGDC methods.*

Paper Type: *Conceptual Research.*

Keywords: Alzheimer's disease, Machine learning, Classification accuracy, Recall (RC)

1. INTRODUCTION :

Alzheimer's disease (AD) [1-17] is considered as a major concern throughout the globe in this era. It is considered as a very dangerous disease as it leads to brain disorder. The brain disorder leads to the destruction of the thinking skills and memory of human beings. It is very much essential for the early classification of ADMPIs into several categories such as MID, MOD, ND, VMD, etc. so that the diagnosis process can be initiated accordingly at the earliest.

Machine Learning (ML) [18-23] can be considered as a solution for the classification of ADMPIs into several categories. The ML based methods can be broadly classified as supervised and unsupervised. The supervised ML [19, 20, 22] based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, etc. play a significant role to accomplish the classification mechanism. However, each ML based method is not capable of providing better classification results in several situations. The performance of each ML based method varies from one scenario to another scenario. So, it is a very challenging task to perform the classification mechanism accurately in different scenarios.

In this work, the main focus is given to the classification of ADMPIs into several categories such as MID, MOD, ND and VMD types [24] in a better way. Here, a MI [1-23] based approach is proposed to carry out the classification of ADMPIs into several types. Here, the NNT method is able to perform better in terms of CA, F1, PR and RC than LRG, SVMN, RFS, DTR, ADB, NBY, KNNH and SGDC methods.

The contributions in this work are mentioned as follows:

(1) In this work, a MI based approach is proposed for the classification of ADMPIs into MID, MOD, ND and VMD types.
(2) This approach is focused on the ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGD to carry out such classification mechanisms.
(3) All the methods are accessed using the performance parameters such as CA, F1, PR and RC.
(4) The Simulation of this work is accomplished using python based Orange 3.26.0.
(5) From the results, it is found that the NNT method is capable of providing better classification results than other ML based methods in this scenario.

The rest of this work is presented as follows. Section 2 to Section 7 describes the related works, the objective of the work, methodology, results and discussion, recommendation and conclusion respectively.

2. RELATED WORKS :

Many research works have been carried out related to the ADMPIs [1-17] processing and analysis. Some of the works are described as follows. Turkson et al. [1] focused on deep convolutional spiking NNT for the classification of AD. Zhang et al. [2] emphasized on the classification of AD using a 3D densely connected convolutional NNT with a connection wise attention process. Janghel et al. [3] focused on the early diagnosis of AD using a deep convolutional NNT based system. Nawaz et al. [4] emphasized on the stage recognition of AD using a deep feature based real time system. Liu et al. [5] focused on the diagnosis of AD with the help of attention based multi scale convolutional NNT. Leming et al. [6] emphasized on the categorization of AD by focusing on the mass general Brigham system. Han et al. [7] focused on the diagnosis of AD by focusing on multi scale 3D convolution feature based broad learning system with the analysis of MRI images. Lama et al. [8] emphasized on the categorization of AD with the help of multilayer extreme learning machine by focusing on the core large scale brain network. Sreelakshmi et al. [9] emphasized on the categorization of AD by focusing on cross sectional brain MRI based deep learning (DL) process. Feng et al. [10] focused on the identification of AD with the help of structural MRI images by analyzing the features of brain region of interest based individual network. The review of some articles related to the categorization of ADMPIs is mentioned in Table 1.

Table 1: Review of some articles related to ADMPIs classification Source: [1-8]

S. No	Field of Research	Focus	Outcome	Reference
1	Image Processing	Deep convolutional NNT	Categorization of AD	Turkson et al. (2021). [1]
2	Image Processing	3D densely connected convolutional NNT	Categorization of AD	Zhang et al. (2021). [2]
3	Image Processing	Deep convolutional NNT	Early diagnosis of AD	Janghel et al. (2021). [3]

4	Image Processing	Deep feature based real time system	Stage recognition of AD	Nawaz et al. (2021). [4]
5	Image Processing	Multi scale convolutional NNT	Diagnosis of AD	Liu et al. (2022). [5]
6	Image Processing	Mass general Brigham system	Categorization of AD	Leming et al. (2022). [6]
7	Image Processing	Convolution feature based broad learning system	Diagnosis of AD	Han et al. (2022). [7]
8	Image Processing	Multilayer extreme learning machine	Categorization of AD	Lama et al. (2022). [8]

3. RESEARCH GAP :

From the literature survey, it is observed that a single method may not be efficient enough to accomplish the classification process of ADMPIs in all scenarios. A method which is working well in a scenario may not perform well in other scenarios. So, accurate classification of ADMPIIs into several categories by applying different methods is a challenging task. So, more analysis is required by applying several methods to carry out the categorization mechanism in a better way to solve the mentioned issues.

4. RESEARCH AGENDA :

The main focus of the research agenda is mentioned as follows.
(1) To apply different existing ML based methods for the categorization of ADMPIs into several types.
(2) To compare different MI based method by focusing on the categorization of ADMPIs.
(3) To analyze the performance of all the methods in terms of CA, F1, PR and RC.

5. OBJECTIVES :

The key objectives of this work are presented as follows.
(1) To implement several ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGD for the classification of ADMPIs into MID, MOD, ND and VMD types in a better way.
(2) To compare LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGD methods in terms of CA, F1, PR, RC.

6. METHODOLOGY :

In this work, a MI [1-23] based approach is proposed for the classification of ADMPIs [24] into MID, MOD, ND and VMD types. This approach is focused on several ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC to carry out the classification mechanism. All the methods are accessed using the performance parameters such as CA, F1, PR and RC for performance analysis. The methodology is described in Fig. 1.

In this work, at first, the ADMPIs are imported to Orange 3.26.0 [25] through the Import Images option. Afterwards, the image embedding (IED) process is accomplished on the ADMPIs to extract the essential features such as height, width, etc. For IED, several embedders such as SqueezeNet, Inception v3, DeepLoc, etc. can be used. In this work, SqueezeNet (local) embedder is considered for processing. After the completion of the IED process, test and score computation will be performed by considering the ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC and the proposed method to find out the CA, F1, PR and RC values in units. The test and score computation can be performed by considering cross validation (CRV) as well as random sampling mechanisms. In this work, the CRV process is focused. The CRV process can be carried out by recognizing the number of folds (NF) as 2, 3, 5, 10, 20, etc. But, in this work, the NF value is considered as 5 to accomplish the classification mechanism.

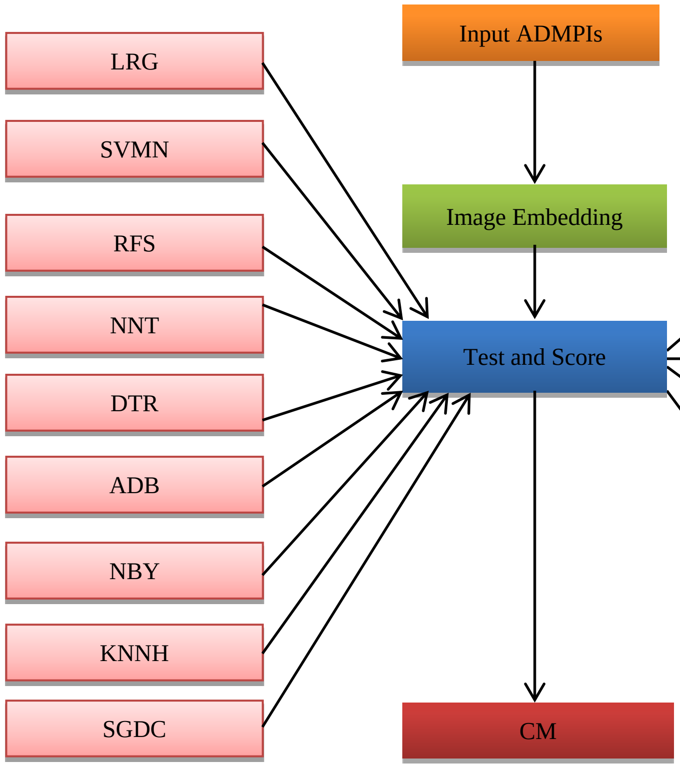

Fig. 1: Methodology [25]

In this work, the parameter setup for each method is described as follows. For LRG, the regularization type can be considered as Lasso (L1) and Ridge (L2). İn this work, Ridge (L2) is considered for processing. The strength value (SV) for this work is considered as per equation (1).

$$SV=1 \qquad \text{-----} \qquad (1)$$

For SVMN, the kernel can be considered as Linear, Polynomial, RBF and Sigmoid. In this work, the kernel is considered as a radial basis function and the iteration limit is taken as 100. Here, the numerical tolerance (NTL) value is taken for processing as per equation (2).

$$NTL=0.0010 \qquad \text{-----} \qquad (2)$$

In this work, for RFS the number of trees (NBTR) considered for processing is mentioned in equation (3).

$$NBTR=50 \qquad \text{----} \qquad (3)$$

For NNT, the activation function can be considered as ReLu, Logistic, tanh, etc. The solver can be considered as Adam, SGDC, L-BFGS-B, etc. In this work, the activation function is considered as ReLu and the solver is considered as Adam with the maximal number of iterations as 100. The neurons (NR) in hidden layers and regularization (RE) value are considered in this work as per equation (4) and equation (5) respectively.

$$NR=200 \qquad \text{---} \qquad (4)$$

$$RE=0.0001 \qquad \text{----} \qquad (5)$$

For DTR, the maximum tree depth (MTDPT) is considered as per equation (6) with the minimum number of instances in leaves as 4.

$$MTDPT=100 \qquad \text{----} \qquad (6)$$

For KNNH, the metric can be considered as Euclidean, Manhattan, Chebyshev and Mahalanobis and the weight(WT) can be considered as distance (ds) and uniform (u). In this work, for KNNH weight value is mentioned in equation (7) by considering the number of neighbors as 10 and the metric as Manhattan.

$$WT=ds \qquad \text{----} \qquad (7)$$

At the test and score computation, the CA, F1, PR and RC values (in units) are computed. Then, the confusion matrix (CM) representation can be carried out. The CM can be represented by considering the number of instances, proportion of predicted and proportion of actual values. However, in this work, the number of instances is considered for processing. The methodology used in this work for the classification of ADMPIs into MID, MOD, ND and VMD types is described in Algorithm 1.

Algorithm 1: ADMPI Classification
Input: ADMPIs
Output: MID, MOD, ND and VMD Type

Step 1: Start
Step 2: Input ADMPIs
Step 3: Image embedding (ADMPIs)
Step 4: Test and Score (LR, SVM, RF, NN, DT, AB, NB, KNN, SGD)
Step 5: Compute CA, F1, PR and RC by applying LR, SVM, RF, NN, DT, AB, NB, KNN, SGD
Step 6: Create (CM) for each method to analyze the classification results
Step 7: Stop

7. RESULTS AND DISCUSSION :

The simulation of this work is accomplished using Python based Orange 3.26.0 [25]. In this work, 1564 ADMPIs having 500, 64, 500 and 500 numbers of each type such as MID, MOD, ND and VMD respectively are taken from the source [24].The Orange workflow setup diagram is mentioned in Fig. 2. The sample representation of MID, MOD, ND and VMD types are mentioned in Fig. 3 to Fig. 6 respectively. The ADMPIs are processed using several ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC when the NF value is recognized as 5. The performance of all the methods is accessed using performance parameters such as CA, F1, PR and RC which are described as follows.

- **CA:** It refers to the rate of correct classification. It is represented in equation (8) by considering the number of corrected predictions (CP) and the total number of input samples (IS).

$$\textbf{CA} = CP / IS \qquad \text{-----} \qquad (8)$$

- **F1:** It is the harmonic mean of PR and RC. It is mentioned in equation (9).

$$\textbf{F1} = 2 * (PR * RC) / (PR + RC) \qquad \text{----} \qquad (9)$$

- **PR:** It is represented in equation (10) by considering the true positives (TP) and false positives (FP).

$$\textbf{PR} = TP / (TP+FP) \qquad \text{----} \qquad (10)$$

- **RC:** It is represented in equation (11) by considering the TP and false negatives (FN).

$$\textbf{RC} = TP / (TP+FN) \qquad \text{----} \qquad (11)$$

The classification results are better when the CA,F1, PR and RC values are higher. Table 2 describes the CA, F1, PR and RC computed values (in units) of the proposed method and other methods. Fig. 7 to Fig. 10 represents the comparison results of all methods graphically in terms of CA, F1, PR and RC respectively. This work is also focused on CM representation. The CM represents the actual and predicted values by showing the number of instances for each of these methods. The CM representation for LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC methods are mentioned in Fig. 11 to Fig. 19 respectively. In CM, the actual values are represented using light blue color and the predicted values are represented using light pink color.

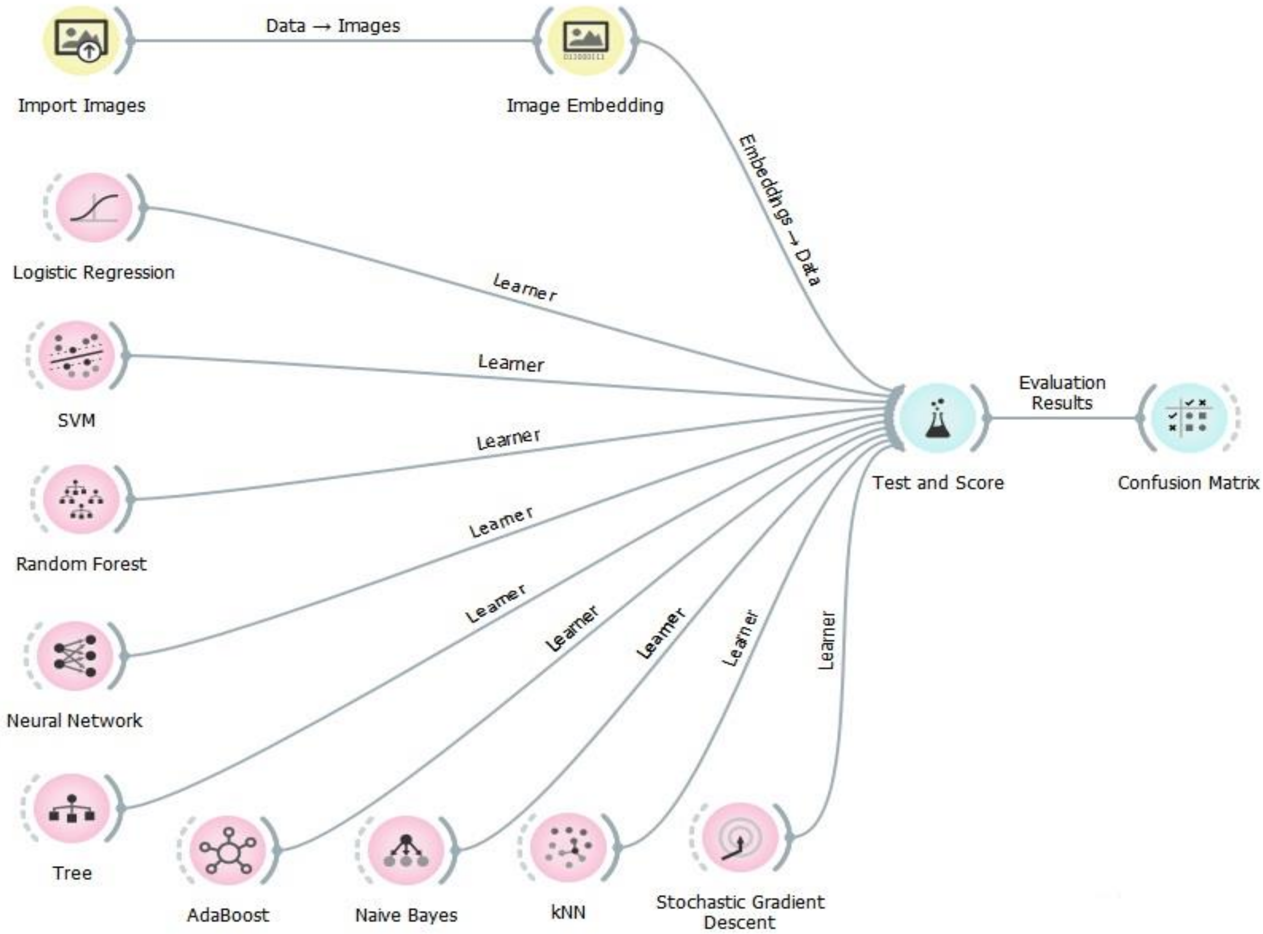

Fig. 2: Orange workflow setup diagram [25]

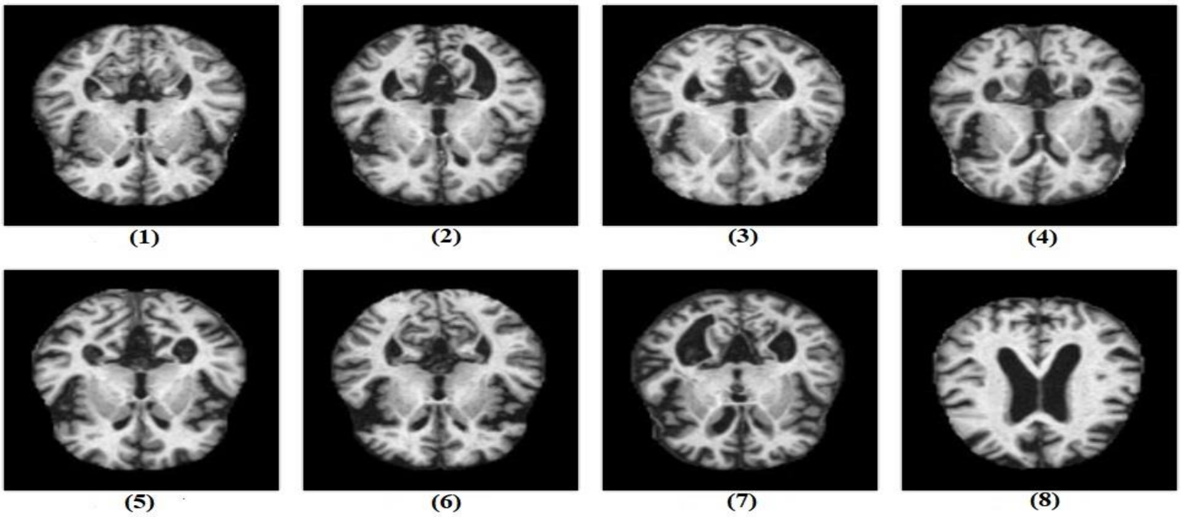

Fig. 3: Sample depiction of MID type [24]

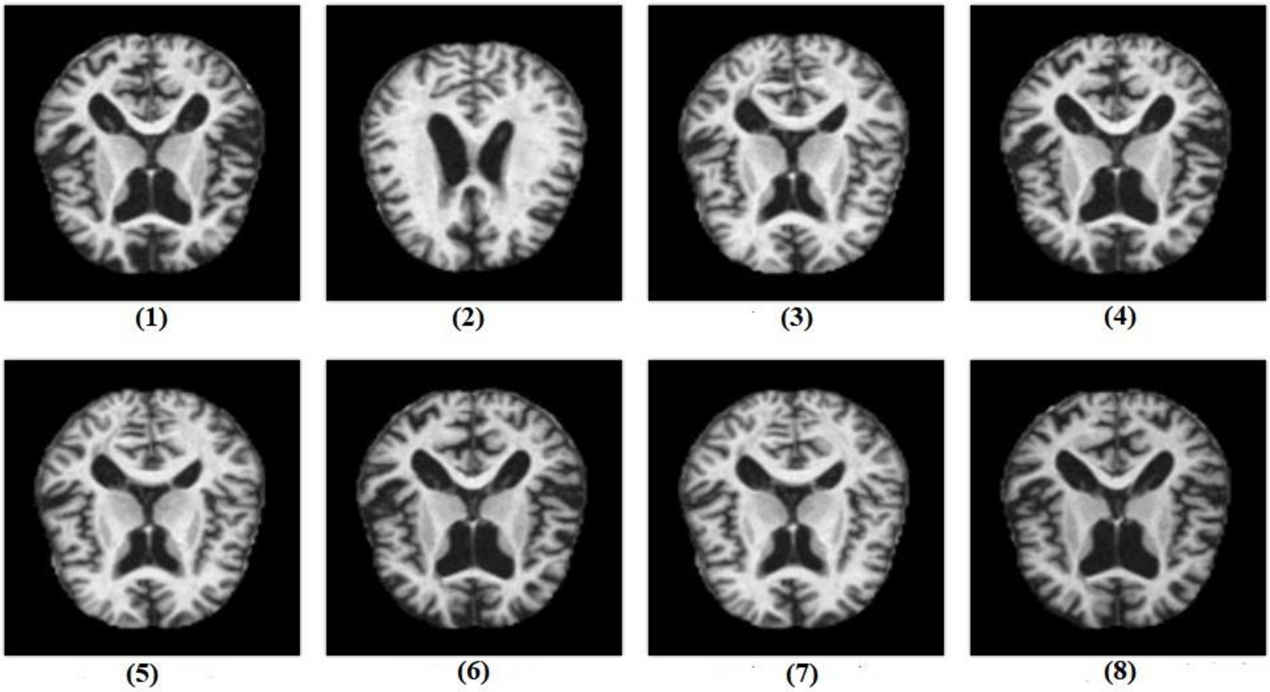

Fig. 4: Sample depiction of MOD type [24]

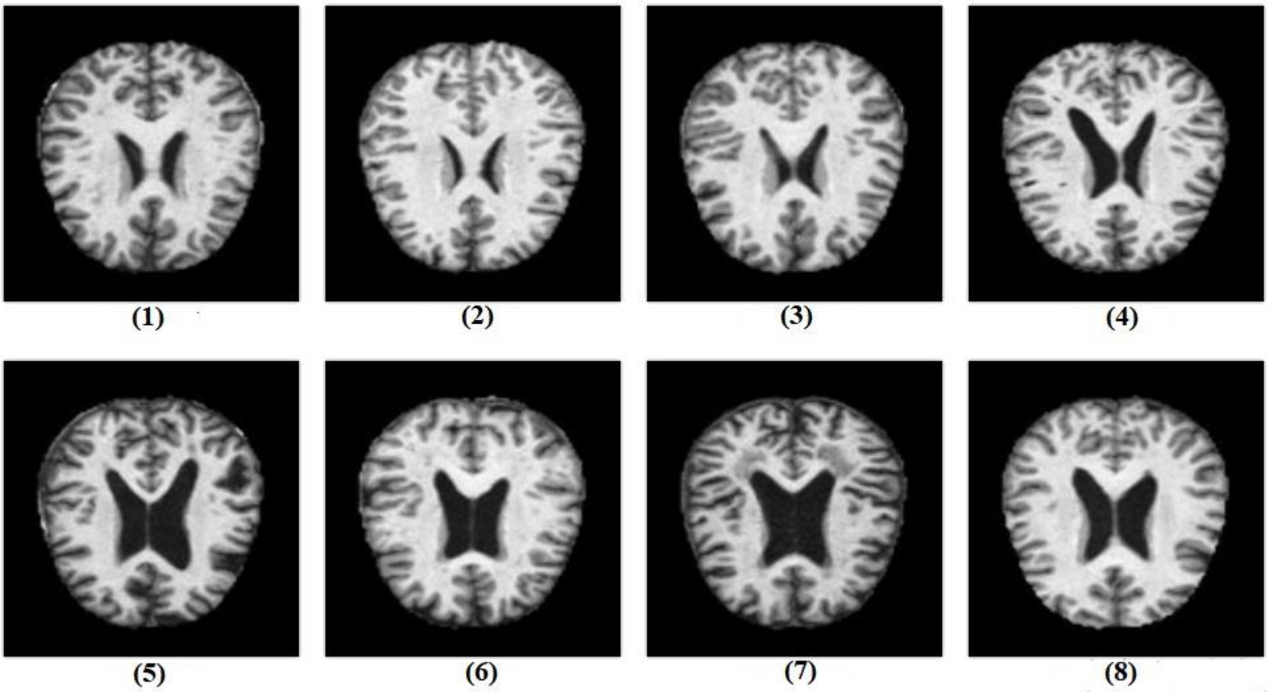

Fig. 5: Sample depiction of ND type [24]

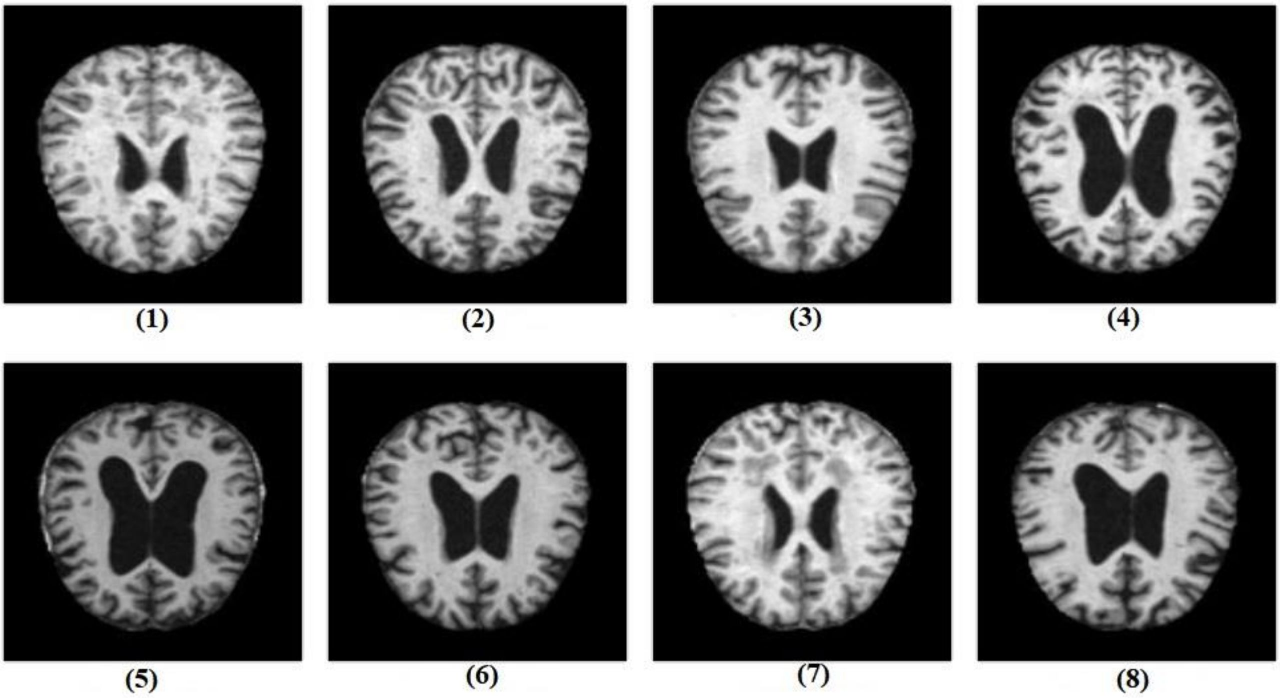

Fig. 6: Sample depiction of VMD type [24]

Table 2: Comparison of MI based methods [25]

Method	CA	F1	PR	RC
LRG	0.710	0.710	0.711	0.710
SVMN	0.777	0.778	0.784	0.777
RFS	0.744	0.742	0.756	0.744
NNT	0.868	0.868	0.868	0.868
DTR	0.613	0.613	0.613	0.613
ADB	0.619	0.619	0.619	0.619
NBY	0.598	0.604	0.623	0.598
KNNH	0.801	0.797	0.807	0.801
SGDC	0.726	0.726	0.726	0.726

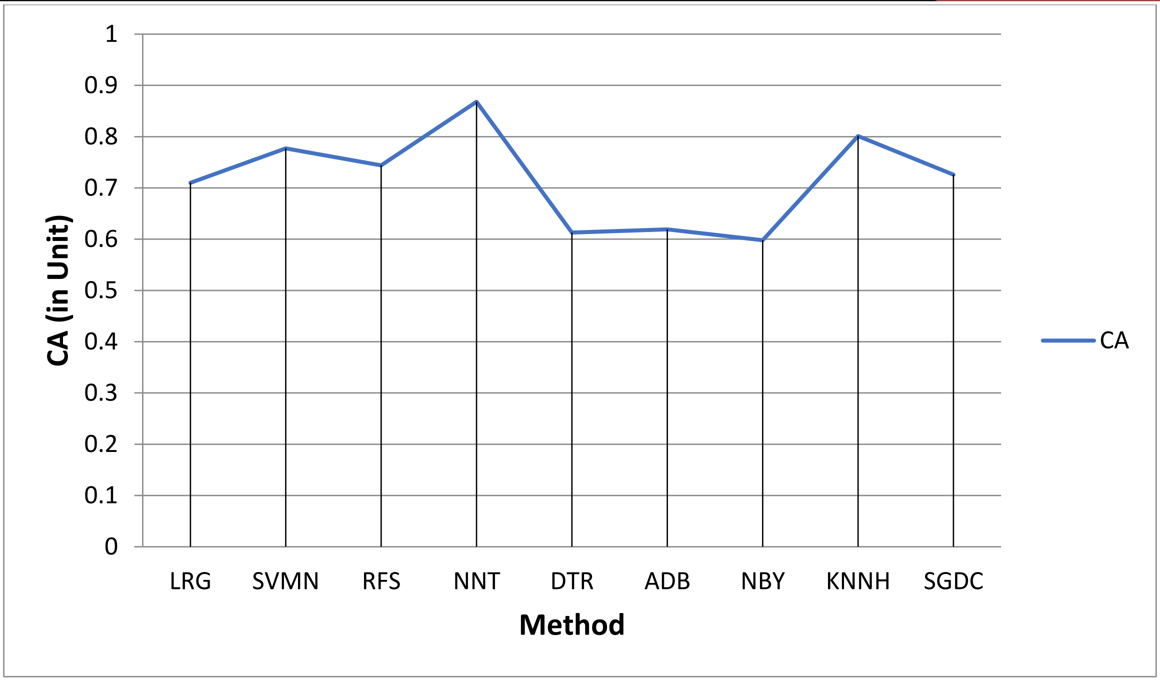

Fig. 7: Comparison results representation of all methods in terms of CA [25]

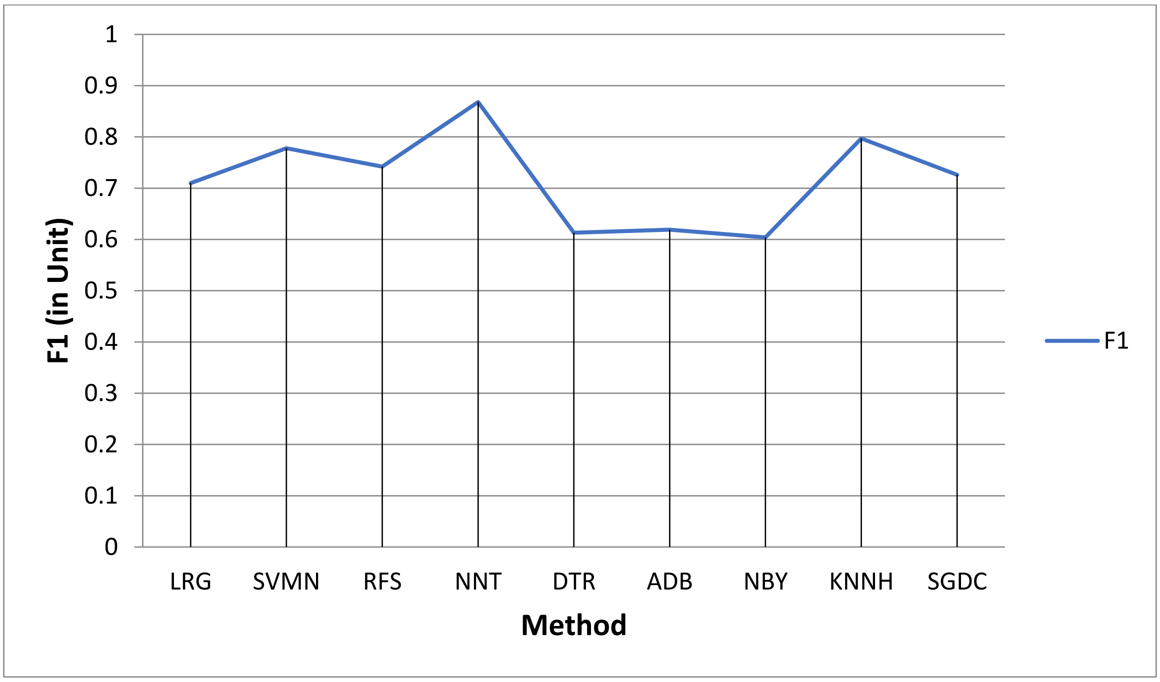

Fig. 8: Comparison results representation of all methods in terms of F1 [25]

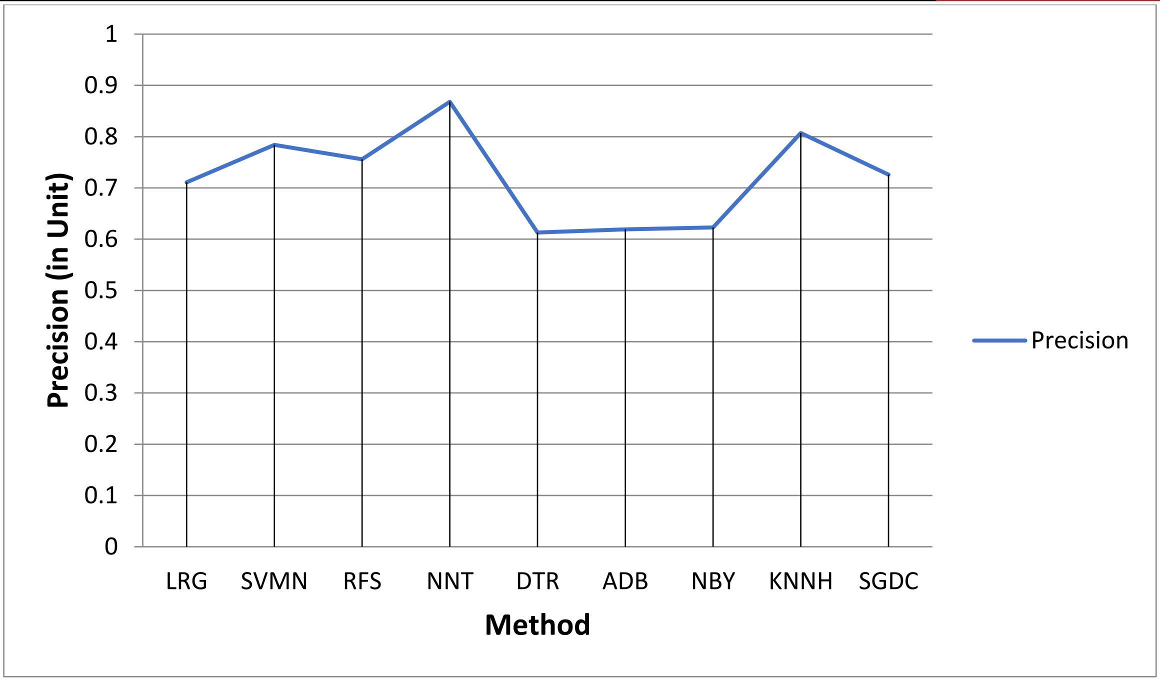

Fig. 9: Comparison results representation of all methods in terms of PR [25]

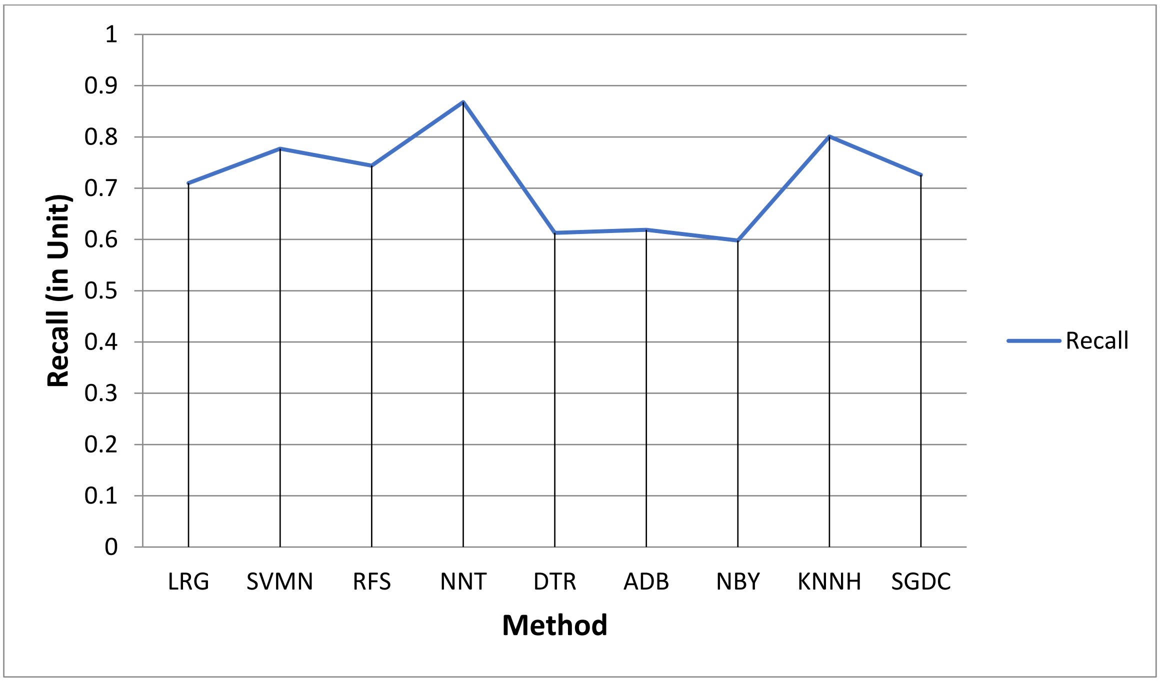

Fig. 10: Comparison results representation of all methods in terms of RC [25]

Actual \ Predicted	Mild_Demented	Moderate_Demented	Non_Demented	Very_Mild_Demented	Σ
Mild_Demented	375	7	37	81	500
Moderate_Demented	11	46	1	6	64
Non_Demented	28	0	371	101	500
Very_Mild_Demented	73	3	106	318	500
Σ	487	56	515	506	1564

Fig. 11: CM of LRG [25]

Actual \ Predicted	Mild_Demented	Moderate_Demented	Non_Demented	Very_Mild_Demented	Σ
Mild_Demented	427	0	19	54	500
Moderate_Demented	11	42	0	11	64
Non_Demented	16	0	370	114	500
Very_Mild_Demented	60	0	64	376	500
Σ	514	42	453	555	1564

Fig. 12: CM of SVMN [25]

Actual \ Predicted	Mild_Demented	Moderate_Demented	Non_Demented	Very_Mild_Demented	Σ
Mild_Demented	380	0	32	88	500
Moderate_Demented	25	23	2	14	64
Non_Demented	9	0	399	92	500
Very_Mild_Demented	40	0	99	361	500
Σ	454	23	532	555	1564

Fig. 13: CM of RFS [25]

Actual \ Predicted	Mild_Demented	Moderate_Demented	Non_Demented	Very_Mild_Demented	Σ
Mild_Demented	448	2	16	34	500
Moderate_Demented	4	57	0	3	64
Non_Demented	6	0	440	54	500
Very_Mild_Demented	45	1	42	412	500
Σ	503	60	498	503	1564

Fig. 14: CM of NNT [25]

Actual \ Predicted	Mild_Demented	Moderate_Demented	Non_Demented	Very_Mild_Demented	Σ
Mild_Demented	344	26	46	84	500
Moderate_Demented	17	33	7	7	64
Non_Demented	36	2	328	134	500
Very_Mild_Demented	106	13	127	254	500
Σ	503	74	508	479	1564

Fig. 15: CM of DTR [25]

Actual \ Predicted	Mild_Demented	Moderate_Demented	Non_Demented	Very_Mild_Demented	Σ
Mild_Demented	353	13	47	87	500
Moderate_Demented	21	28	5	10	64
Non_Demented	45	9	318	128	500
Very_Mild_Demented	85	15	131	269	500
Σ	504	65	501	494	1564

Fig. 16: CM of ADB [25]

Predicted

Actual	Mild_Demented	Moderate_Demented	Non_Demented	Very_Mild_Demented	Σ
Mild_Demented	297	30	26	147	500
Moderate_Demented	13	34	3	14	64
Non_Demented	2	9	340	149	500
Very_Mild_Demented	58	11	167	264	500
Σ	370	84	536	574	1564

Fig. 17: CM of NBY [25]

Predicted

Actual	Mild_Demented	Moderate_Demented	Non_Demented	Very_Mild_Demented	Σ
Mild_Demented	423	1	41	35	500
Moderate_Demented	18	33	6	7	64
Non_Demented	6	0	451	43	500
Very_Mild_Demented	55	0	100	345	500
Σ	502	34	598	430	1564

Fig. 18: Confusion matrix of KNNH [25]

Predicted

Actual	Mild_Demented	Moderate_Demented	Non_Demented	Very_Mild_Demented	Σ
Mild_Demented	380	11	42	67	500
Moderate_Demented	9	50	2	3	64
Non_Demented	30	5	380	85	500
Very_Mild_Demented	66	12	96	326	500
Σ	485	78	520	481	1564

Fig. 19: CM of SGDC [25]

From Table 2 and Fig. 7 to Fig. 19, it is observed that LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC methods are able to provide 0.710, 0.777, 0.744, 0.868, 0.613, 0.619, 0.598, 0.801 and 0.0.726 CA values (in unit) respectively. LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and proposed method are able to provide 0.710, 0.778, 0.742, 0.868, 0.613, 0.619, 0.604, 0.797 and 0.726 F1 values (in unit) respectively. LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC methods are able to provide 0.711, 0.784, 0.756, 0.868, 0.613, 0.619, 0.623, 0.807 and 0.726 PR values (in unit) respectively. LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH, SGDC and proposed method are able to provide 0.710, 0.777, 0.744, 0.868, 0.613, 0.619, 0.598, 0.801 and 0.726 RC values (in unit) respectively. So, the NNT method is capable of providing better classification results as compared to LRG, SVMN, RFS, DTR, ADB, NBY, KNNH and

SGDC methods and it is having 0.868 CA, F1, PR and RC values in units. However, the NBY method is not capable of providing better categorization results than other methods and it is having 0.598, 0.604, 0.623 and 0.598 CA, F1, PR and RC values in units respectively. The decreasing order of performance of these methods is NNT, KNNH, SVMN, RFS, SGDC, LRG, ADB, DTR and NBY.

8. RECOMMENDATIONS :

This work can be extended to analyze the ADMPIs and other types of images in terms of CA, F1, PR and RC by applying DL based methods.

9. CONCLUSION :

This paper focused on the MI based approach for the classification of ADMPIs into MID, MOD, ND and VMD types. In this work, the performance of different ML based methods such as LRG, SVMN, RFS, NNT, DTR, ADB, NBY, KNNH and SGDC are analyzed. From the results, it is found that the NNT is capable of providing better classification results in terms of CA, F1, PR and RC as compared to other ML based methods such as LRG, SVMN, RFS, DTR, ADB, NBY, KNNH and SGDC. The CA, F1, PR and RC values in units using the NNT method are computed as 0.868 which is higher as compared to other ML based methods. However, in this scenario, the NBY method is unable to perform better than other methods. The CA, F1, PR and RC values in units using the NBY method are computed as 0.598, 0.604, 0.623 and 0.598 respectively which are lower than other ML based methods in this scenario. This approach can help the researchers to carry out the image classification mechanism in a better way for several applications.

REFERENCES :

[1] Turkson, R. E., Qu, H., Mawuli, C. B., & Eghan, M. J. (2021). Classification of Alzheimer's disease using deep convolutional spiking neural network. *Neural Processing Letters*, *53*(4), 2649-2663. Google Scholar

[2] Zhang, J., Zheng, B., Gao, A., Feng, X., Liang, D., & Long, X. (2021). A 3D densely connected convolution neural network with connection-wise attention mechanism for Alzheimer's disease classification. *Magnetic Resonance Imaging*, *78(1)*, 119-126. Google Scholar

[3] Janghel, R. R., & Rathore, Y. K. (2021). Deep convolution neural network based system for early diagnosis of Alzheimer's disease. *Irbm*, *42*(4), 258-267. Google Scholar

[4] Nawaz, H., Maqsood, M., Afzal, S., Aadil, F., Mehmood, I., & Rho, S. (2021). A deep feature-based real-time system for Alzheimer disease stage detection. *Multimedia Tools and Applications*, *80*(28), 35789-35807. Google Scholar

[5] Liu, Z., Lu, H., Pan, X., Xu, M., Lan, R., & Luo, X. (2022). Diagnosis of Alzheimer's disease via an attention-based multi-scale convolutional neural network. *Knowledge-Based Systems*, *238 (1)*, 1-11. Google Scholar

[6] Leming, M., Das, S., & Im, H. (2022). Construction of a confounder-free clinical MRI dataset in the Mass General Brigham system for classification of Alzheimer's disease. *Artificial Intelligence in Medicine*, *129(1)*, 1-11. Google Scholar

[7] Han, R., Liu, Z., & Chen, C. P. (2022). Multi-scale 3D convolution feature-based Broad Learning System for Alzheimer's Disease diagnosis via MRI images. *Applied Soft Computing*, *120(1)*, 1-14. Google Scholar

[8] Lama, R. K., Kim, J. I., & Kwon, G. R. (2022). Classification of Alzheimer's Disease Based on Core-Large Scale Brain Network Using Multilayer Extreme Learning Machine. *Mathematics*, *10*(12), 1-20. Google Scholar

[9] Sreelakshmi, S., Malu, G., & Sherly, E. (2022, March). Alzheimer's Disease Classification from Cross-sectional Brain MRI using Deep Learning. In *2022 IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES)* (Vol. 1, pp. 401-405). IEEE. Google Scholar

[10] Feng, J., Zhang, S. W., Chen, L., Zuo, C., & Alzheimer's Disease Neuroimaging Initiative. (2022). Detection of Alzheimer's disease using features of brain region-of-interest-based individual network constructed with the sMRI image. *Computerized Medical Imaging and Graphics*, *98(1)*, 1-13. Google Scholar

[11] Zhang, Y., Teng, Q., Liu, Y., Liu, Y., & He, X. (2022). Diagnosis of Alzheimer's disease based on regional attention with sMRI gray matter slices. *Journal of neuroscience methods*, *365(1)*, 1-8. Google Scholar

[12] Sudharsan, M., & Thailambal, G. (2022, April). A Hybrid Learning Approach for Early-Stage Prediction and Classification of Alzheimer's Disease Using Multi-Features. In *2022 6th International Conference on Trends in Electronics and Informatics (ICOEI)* (pp. 1373-1380). IEEE. Google Scholar

[13] Li, J., Wei, Y., Wang, C., Hu, Q., Liu, Y., & Xu, L. (2022). 3-D CNN-Based Multichannel Contrastive Learning for Alzheimer's Disease Automatic Diagnosis. *IEEE Transactions on Instrumentation and Measurement*, *71(1)*, 1-11. Google Scholar

[14] Goenka, N., Goenka, A., & Tiwari, S. (2022, March). Patch-Based Classification for Alzheimer Disease using sMRI. In *2022 International Conference on Emerging Smart Computing and Informatics (ESCI)* (pp. 1-5). IEEE. Google Scholar

[15] Ding, Z., Liu, Y., Tian, X., Lu, W., Wang, Z., Zeng, X., & Wang, L. (2022). Multi-resolution 3D-HOG feature learning method for Alzheimer's Disease diagnosis. *Computer Methods and Programs in Biomedicine*, *214(1)*, 1-8. Google Scholar

[16] Loddo, A., Buttau, S., & Di Ruberto, C. (2022). Deep learning based pipelines for Alzheimer's disease diagnosis: a comparative study and a novel deep-ensemble method. *Computers in Biology and Medicine*, *141(1)*, 1-15. Google Scholar

[17] Zhang, F., Pan, B., Shao, P., Liu, P., Shen, S., Yao, P., & Alzheimer's Disease Neuroimaging Initiative. (2022). A Single Model Deep Learning Approach for Alzheimer's Disease Diagnosis. *Neuroscience*, *491(1)*, 200-214. Google Scholar

[18] Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. *SN Computer Science*, *2*(3), 1-21. Google Scholar

[19] Thomas, L., & Bhat, S. (2021). Machine Learning and Deep Learning Techniques for IoT-based Intrusion Detection Systems: A Literature Review. *International Journal of Management, Technology and Social Sciences (IJMTS)*, *6*(2), 296-314. Google Scholar

[20] Rangi, P. K., & Aithal, P. S. (2021). Literature Survey and Research Agenda of Risk Determinants in Indian Equities and Machine Learning. *International Journal of Management, Technology, and Social Sciences (IJMTS)*, *6*(1), 83-109. Google Scholar

[21] Pulluparambil, S. J., & Bhat, S. (2021). Medical Image Processing: Detection and Prediction of PCOS–A Systematic Literature Review. *International Journal of Health Sciences and Pharmacy (IJHSP)*, *5*(2), 80-98. Google Scholar

[22] Pulluparambil, S. J., & Bhat, S. (2021). Application of Machine Learning in Google Services-A Case Study. *International Journal of Case Studies in Business, IT and Education (IJCSBE)*, *5*(2), 24-37. Google Scholar

[23] Puneeth, B. R., & Nethravathi, P. S. (2021). A literature review of the detection and categorization of various arecanut diseases using image processing and machine learning approaches. *International Journal of Applied Engineering and Management Letters (IJAEML)*, *5*(2), 183-204. Google Scholar

[24] Retrieved from https://www.kaggle.com/datasets/sachinkumar413/alzheimer-mri-dataset?select=Dataset on 04 June 2022.

[25] Retrieved from https://orangedatamining.com/ on 04 June 2022.