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Temporal Change Analysis Based Recommender System for Alzheimer Disease Classification

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Abstract*: *The development of recommender systems gathered momentum due to its relevance and application in providing a personalized recommendation on a product or a service for customer relations management. It has proliferated into medicine and its allied domains for the recommendations on disease prediction/detection, medicine, treatment, and other medical services. This chapter describes a new composite and comprehensive recommender system named Temporal Change Analysis based Recommender System for Alzheimer Disease Classification (TCA-RS-AD) using a deep learning model. Its performance is evaluated on the dataset with T1-weighted MRI clinical temporal data of OASIS and the results were recorded in terms of Precision, Recall, F1-Score and Accuracy, Hamming Loss, Cohens Kappa Coefficient, and Matthews Correlation Coefficient. The improved accuracy of this recommendation model endorses its suitability for its application in the classification of AD.

Keywords* : *Deep Learning Models, Confusion Matrix, Matthews Correlation Coefficient, Hamming Loss, Cohens Kappa, OASIS dataset.

I. INTRODUCTION

The semi-automated brain image analysis aims to discover or diagnose Alzheimer's disease due to brain disorders. The prognosis of AD is essential for providing timely treatments to the patients at an early stage. The Magnetic Resonance Imaging (MRI) Clinical Data is a comprehensive dataset that contains high-resolution and high contrast images for the gray and white matter of the brain. The novelty of Machine Learning (ML) classification techniques has been vastly explored for many applications in medical diagnosis [1]. Machine learning predictive capabilities are suitable for many medical applications. These methods find application in neuroimaging research for early detection and diagnosis of AD.

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Deep learning is an offshoot of machine learning. Deep Neural Networks (DNN) is a type of neural network with more than two layers. The TCA-RS-AD is designed to have multiple hidden layers.

Content-based and collaborative filtering are the most common approaches for creating a recommendation system framework. A good amount of information is required about the functionality of the objects in the content-based approach rather than using experiences and suggestions from users. Collaborative filtering is the process of filtering or evaluating items using the opinions of other people.

This chapter presents a new prediction and recommender scheme termed as, "Temporal Change Analysis based recommender System for Alzheimer Disease Classification (TCA-RS-AD)". This system uses MRI clinical temporal data for experimental analysis and validation. The proposed model is designed to classify and predict the early stage of AD.

II. RELATED WORK

Zhe Wang et al., [2] developed a new method named Resting-State fMRI based Network Connectivity Analysis (RS-fMRINC) using the feature vector-based classification method. This model could detect AD and Mild Cognitive Impairment (MCI).

Naganandhini et al., [3] developed a new detection method for identifying various stages of AD using ML algorithms. This model is designed to perform feature extraction and classification using the association between the data attributes.

Sajna et al., [4] developed a new method for the two-stage Convolutional Neural Network (CNN) model for prediction and early diagnosis of the AD. In the first stage, image patches were taken as input to learning inherent associations between local image patches and target landmarks. In the second stage, the entire image is considered as input to detect AD.

Lebedev et al., [5] developed a new method for Computed Aided Diagnosis (CAD) of AD. The Random Forest Classifier was trained using different structural MRI measure constraints to improve the performance of detection and prediction of AD.

Jyoti Islam et al., [6] designed a new method for AD diagnosis using an ensemble of deep CNN models. Their model used the clinical dataset to identify the different stages of AD for early diagnosis. Xia-an Bi et al., [7] developed the random neural network cluster, composed of multiple neural networks to improve the performance of feature selection and classification.

Sixty-one subjects comprising of 25 AD and 36 Healthy Control were acquired from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset to validate their method.

Abnaya Kumar et al., [8] developed a deep learning-based recommendation system for health using collaborative filtering, which was designed to implement an effective health recommendation engine. This model was evaluated with Mean Absolute Error (MAE).

Raid Lafta et al., [9] developed a smart recommendation system based on a short-term heart disease risk prediction. This system offers a solution to reduce the time and cost factor involved in taking the frequent medical test for medical intervention. The experimental results showed that the proposed system yields satisfactory accuracy.

Sivapalanet al.,[10] devised a new recommender system for classification, regression and time series using different types of classification models, including decision tree inference, Bayesian classification, Neural Networks, Support Vector Machine (SVM) and Association.

III. PROPOSED MECHANISM

The TCA-RS-AD method involves three phases: preprocessing, prediction, and recommendation. In the preprocessing phase, the clinical data is read and subjected to data imputation, transformations, and grouping. In the prediction phase, the training dataset is trained by tuning the hyperparameters to predict the different stages of AD. In the recommendation phase, a recommendation is performed by using a rating scale based on accuracy. Experimental Dataset: The TCA-RS_AD algorithm is tested on the magnetic resonance imaging (MRI) dataset comprising of normal and stages of AD chosen from OASIS Longitudinal Neuroimaging [11] are used. The vital attributes are as follows: Sex, Hand, Educ, SES, CDR, eTIV, nWBV, Group, Visit, MR Delay. The performance of TSA-RS-AD experimented on the OASIS dataset with 448 data, 112 data are of Mild AD, 112 data are Moderate AD, 112 data are Non-Demented, and 112 data are Very Mild AD-affected.

Table 1 displays the demographic characteristics in clinical data and Table 2 depicts the clinical information of the datasets.

Table 1: Demographic Characteristics

Descriptor	Explanation	Datatype
M/F	Gender	Categorical
Hand	Handedness (this item can be omitted as all are right-handed subjects)	Categorical
Age	years	Numerical
EDUC	Education Years	Numerical
SES	Socio-economic status as assessed by the Hollings head Index of Social position and classified from 1 (highest rank) to 5 (lowest status)	Numerical

Table 2: Clinical Information of OASIS Dataset

Descriptor	Explanation
MMSE	Mini-Mental State Examination Score; Range: 0 (Worst) to 30 (Best)
CDR	Clinical Dementia Rating (0: No dementia; 0.5: Very Mild AD; 1: Mild AD; 2: Moderate AD)

The TCA-RS-AD used data imputation, one-hot encoding, and normalization to prepare the dataset for training. One hot encoding is the most widely used and common technique and works very well unless there is a large number of the categorical attribute. This coding creates new (binary) columns, stating the existence of each possible value from the original data. The most commonly used coding system is one-hot coding. It compares every level to a specified reference point of the categorical variable. The coding with dichotomous values 0 and 1 is suitably used to code gender and hand as shown in Fig 1.

MRI ID	Gender	Hand
OASIS _MR_01	M	R
OASIS _MR_02	F	L
OASIS _MR_03	M	R
OASIS _MR_04	F	L

→

MRI ID	Gender	Hand
OASIS _MR_01	0	0
OASIS _MR_02	1	1
OASIS _MR_03	0	0
OASIS _MR_04	1	1

Fig 1: Illustration of One-Hot Encoding for Categorical Data

The dataset used in this work is a time-series data that provides insight into the perceivable changes useful for the early detection or prediction of any disorder or ailment. Table 3 shows the sample time series data in the OASIS dataset. The visit attribute helps to harness the information for AD classification based on the count of patients' visits for diagnosis.

Table 3: Sample Time Series OASIS Dataset

Subject ID	MRI ID	Visit	CDR	Group
OAS2_0048	OAS2_0048_MR5	5	1	Mild AD
OAS2_0048	OAS2_0048_MR4	4	1	Mild AD
OAS2_0048	OAS2_0048_MR3	3	1	Mild AD
OAS2_0048	OAS2_0048_MR2	2	1	Mild AD
OAS2_0048	OAS2_0048_MR1	1	1	Mild AD
OAS2_0007	OAS2_0007_MR4	4	1	Mild AD
OAS2_0007	OAS2_0007_MR3	3	1	Mild AD
OAS2_0007	OAS2_0007_MR2	2	0.5	Very Mild AD
OAS2_0007	OAS2_0007_MR2	1	0.5	Very Mild AD

The schematic description of TCA-RS-AD is given in Fig 2, which explains the stages of computation for AD recommendation.

To compute group analysis for making recommendations on AD detection, the proposed method used groupby() function on the visit attribute thus performed collaborative filtering for collection of items. The resultant aggregation of data is illustrated in Table 4. This table showed the sample grouped data based on visit attribute on the OASIS dataset. The train/test split for DNN is then applied to such grouped data.

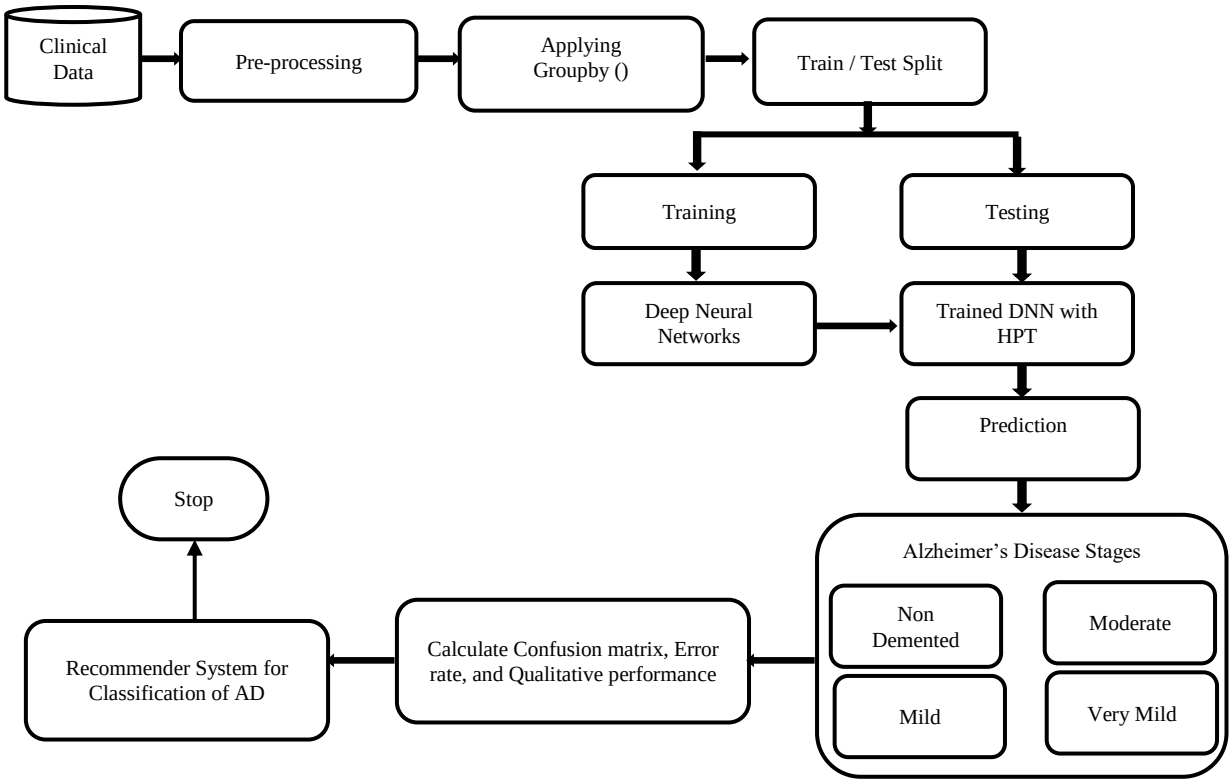

Fig 2: Flowchart of TCA-RS-AD

Algorithmic Description of TCA-RS-AD
Input: Clinical Data
Output: Classification and Recommendation on AD stages

Begin

Phase I: Pre-Processing

Step 1: Read the Clinical Data

Step 2: Preprocess Clinical Data using

A. Data Imputation

B. Transformation

C. Collaborative Filtering using groupby()

Step 3: Partition the dataset for training and testing

Phase II: Training &Prediction

Step 4: Train the Deep Neural Network model with hyperparameters tuning

Step 5: Test the model with the Test dataset

Step 8: Predict AD stages

Step 9: Measuring the model performance by calculating Confusion Matrix, Cohens Kappa, MCC, Hamming Loss, and Accuracy, Mean Absolute Error, MSE, BAS, Median Absolute Error in Training and Testing Data.

Step 10: Measure accuracy rating and error rating

Step 11: Make recommendations

End

Table 4: Sample Time-series Data using *groupby()* Function

Visit	Subject ID	CDR	Group
1	OAS2_0048	1	Mild AD
	OAS2_0007	0.5	Very Mild AD
2	OAS2_0007	0.5	Very Mild AD
	OAS2_0058	0.5	Very Mild AD
	OAS2_0048	1	Mild AD
3	OAS2_0048	1	Mild AD
	OAS2_0007	1	Mild AD
4	OAS2_0007	1	Mild AD
	OAS2_0048	1	Mild AD
5	OAS2_0048	1	Mild AD
	OAS2_0017	0	Non Demented
	OAS2_0073	0	Non Demented
	OAS2_0127	0.5	Very Mild AD

IV. NEURAL NETWORKS

Neural Networks (NN) is an ML algorithm that is built on the concept of biological neural network and its functions. The NN consists of discrete elements called neurons. Fig 3 depicts the basic NN structure and its elements.

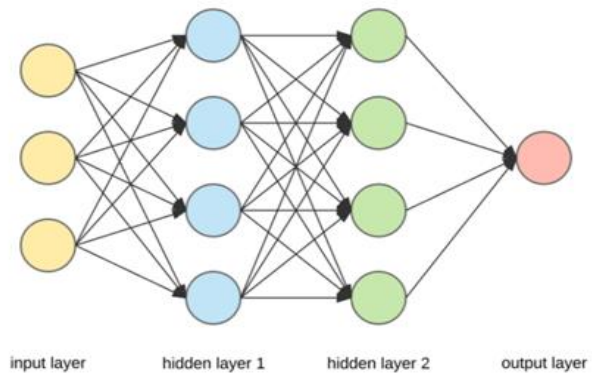

Fig 3: Basic Neural Network Model

After splitting into the train/test set, the proposed method uses three types of layers for training the data: dense layer, activation layer, and dropout layer.

The input size of the first dense layer is 168.It is representing the number of one-hot encoded input features. Since all the inputs from the dataset are categorical, the one-hot encoding scheme was used to transform those inputs to numeric and vector type. The essential elements of a DNN are described herein under:

- *Dense Layer*: It is the input layer. The first dense layer is connected by weight to each output. So, there are $n_{inputs} * n_{output}\ weights$.
- *Activation Layer (ReLU):* A non-linear activation function, namely ReLU (Rectified Linear Unit), which performs non-linear operation follows the dense surface, as shown in Eqn.(1).

  $$f(x) = max(0, x) \quad (1)$$

  The ReLUactivation function performs non-linearity in the DNN model.
- *Dropout:* This layer is used to avoid overfitting in the DNN model. In this method, a dropout of 0.8 is used.
- *Fully-Connected Layer:* The final output layer is typically a fully connected neural network layer. the Dense layer, ReLU are repeated from a network with a known Deep neural network.
- The proposed optimal DNN uses a fully connected layer with SoftMax, which is a non-linear activation function used for multiclass classification.

The model summary of the TCA-RS-AD is given in Table 5, wherein Layer type, Output Shape and Param# denote the functionality of the layer, dimension of the output and the number of trained parameters respectively.

Table 5: Model Summary of the TCA-RS-AD

Layer Type	Output Shape	Param #
Dense_1 (Dense)	(None, 64)	768
Dense_2 (Dense)	(None, 64)	4160
Dropout_1(Dropout)	(None, 64)	0
Dense_3 (Dense)	(None, 50)	3250
Dense_4 (Dense)	(None, 100)	5100
Dropout_2 (Dropout)	(None, 100)	0
Dense_5 (Dense)	(None, 4)	404
Total Params:13,682		
Trainable Params: 13,682		
Non-Trainable Params: 0		

The hyperparameters tuning is performed on the TCA-RS-AD model to improve performance accuracy. The hyperparameters used for tuning are listed in Table 6.

Table 6: Hyperparameters for TCA-RS-AD

Hyper Parameters	Default Value
Epochs	1500
Batch Size	16
Optimizer	Adam
Learning Rate	0.001
First Moment	0.09
Loss Function	Categorical_Cross_entropy
Last Moment	0.999

V. RESULT & PERFORMANCE ANALYSIS

The performance metrics used in this study are described in Table 7. The efficiency of classification is measured using Precision, Recall, F1-Score, Hamming Loss, Cohen's Kappa Coefficient, Matthews Correlation Coefficient (MCC), Mean Absolute Error (MAE), Mean Square Error(MSE), Balanced Accuracy Score (BAS), Median Absolute Error (MdAE).

The below-mentioned metrics were applied to both the DNN model and DNN with a hyperparameter tuning model called TCA-RS-AD. The computational potential of DNN and TCA-RS-AD has experimented on the OASIS dataset and the obtained results are furnished in Table 8.

It is apparent from Table 8 that the DNN model produced the Support value for the Very Mild AD detection. Its performance was relatively moderate for Non-demented and Mild AD. It is also worth noting that this model has failed to handle a Moderate AD class. It could be observed that this model exhibits inconsistent Precision, Recall, F1-Score, and Support in classifying Mild and Moderate AD as well as the testing accuracy is low. These measures are graphically depicted in Fig 4. This disadvantage offers scope to modify the basic DNN into TCA-RS-AD, to obtain enhanced accuracy on all the classes of data. A support value of zero for Moderate AD indicates a shallow performance of the model. The classification accuracy of DNN on AD classification is not promising. As a part of improving the performance of the model, data imputation and hyperparameter tuning were applied to the OASIS data.

Table 7: Description of Performance Metrics

S.No	Metric	Formula	Notational Definitions	Remarks
1.	Precision	$\frac{TP}{(TP + FP)}$	TP: True Positive FP: False Positive	The measure of Correctness. High value denotes higher accuracy and vice-versa.
2.	Recall	$\frac{TP}{(TP + FN)}$	FN: False Negative	The measure of prediction accuracy.

3	F1-Score	$\frac{(1+\beta)^2 * Recall * Precision}{\beta^2 * Recall * Precision}$	F1 score can be interpreted as a weighted and average of the precision and recall	The F1 score best value is 1 and the worst score is 0
4	Hamming Loss (HL)	$\frac{1}{NL}\sum_{i=1}^{L}\sum_{j=1}^{N} Y_{i,j} \oplus X_{i,j}$	The fraction of labels that are incorrectly predicted	Its always between 0 and 1, lower is better.
5	Cohen's Kappa Coefficient	$\frac{P_0 - P_e}{1 - P_e} = 1 - \frac{1 - P_0}{1 - P_e}$	The degree of acceptance of a classification problem between two annotators.	The number between -1 and 1. The maximum value means complete agreement zero or lower means change agreement.
6	Matthews Correlation Coefficient	$\frac{TP * TN - FP * FN}{\sqrt{(TP+FP)*(TP+FN)*(TN+FP)*(TN+FN)}}$	The MCC is essence a correlation coefficient value	The coefficient of +1 represents a perfect prediction, 0 an average random prediction and -1 an inverse prediction.
7	Mean Absolute Error	$\frac{\sum_{i=1}^{n} \lvert y_i - x_i \rvert}{n} = \frac{\sum_{i=1}^{n} \lvert e_i \rvert}{n}$	calculating the loss function	The output is a non-negative floating-point. The best value is 0.0
8	Mean Square Error	$\frac{1}{n}\sum_{i-1}^{n}(y_i - y_i^{\wedge})^2$	calculating the loss function	The best value is 0.0
9	Balanced Accuracy Score	$\frac{(Sensitivity + Specificity)}{2}$	Multiclass classification problems to deal with imbalanced dataset	Random performance would score is 0 and perfect performance score 1.
10	Median Absolute Error	$\sum_{i=1}^{j} f_i \geq \frac{n+1}{2}$	calculating the loss function of the positive floating-point value	The best value is 0.0

Table 8: Result & Performance Analysis of DNN and TCA-RS-AD Model

Group	Precision		Recall		F1-Score		Support	
	DNN	TCA-RS-AD	DNN	TCA-RS-AD	DNN	TCA-RS-AD	DNN	TCA-RS-AD
Non-Demented	0.53	1.00	0.62	0.81	0.57	0.90	13	15
Moderate AD	0.00	0.00	0.00	0.01	0.00	0.01	0	1
Very Mild AD	0.96	0.99	0.90	1.00	0.93	0.99	61	69
Mild AD	0.74	0.90	0.76	096	0.75	0.93	37	27
Classification Model Report								
Macro Avg	0.56	0.96	0.54	0.93	0.56	0.94	112	112
Weighted Avg	0.83	097	0.81	0.96	0.82	0.96	112	112
Accuracy (DNN): 0.8125 (81.25%)			**Accuracy (TCA-RS-AD): 0.9642 (96.42%)**					

DNN and TCA-RS-AD are good for the Moderate AD classification, while DNN alone is excellent for both non-demented and Very Mild AD. DNN and TCA-RS-AD reveal very good performance for demented and non-demented classes when using the Recall and F1-Score metrics. Also, on the classification of Moderate AD, except TCA-RS-AD, these classifiers uniformly model scant or poor performance. It is evident TCA-RS-AD that consistently outruns its counterparts, in the Mild AD, Very Mild AD, Moderate AD, Non-Demented while DNN and the performance of TCA-RS-AD are far below average.

It can also be inferred from the results presented in Table 6 that TCA-RS-AD better than the rest of the classifiers. It believed that the excellent performance of TCA-RS-AD may be attributed to the process of boosting in TCA-RS-AD. It minimizes over fitting and variance.

The prediction accuracy for Non-Demented and Very Mild AD has increased approximately by 8%. Moreover, its overall accuracy increased to 96.42% against that of DNN which was 81.25%. This performance augmentation of about 15% is attributed to the data imputation and fine-tuning of the hyperparameters.This improvement is endorsed by the Support values shown in Figure 5. The accuracy of the classification in both training and testing samples were recorded, by varying the epochs, batch sizes, and the optimizers.

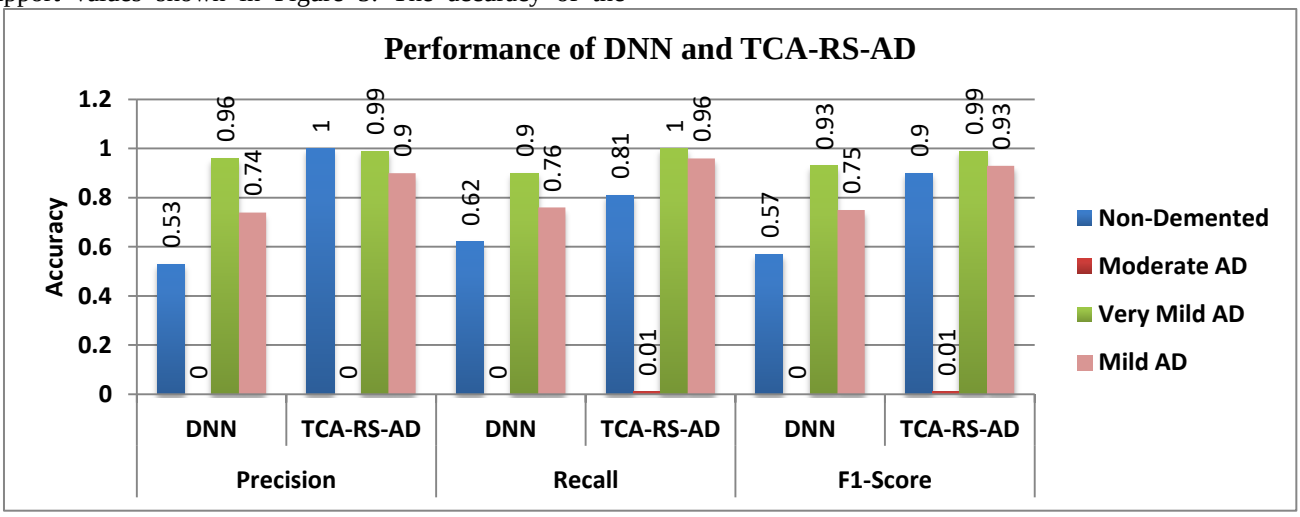

Fig 4: Performance of DNN and TCA-RS-AD

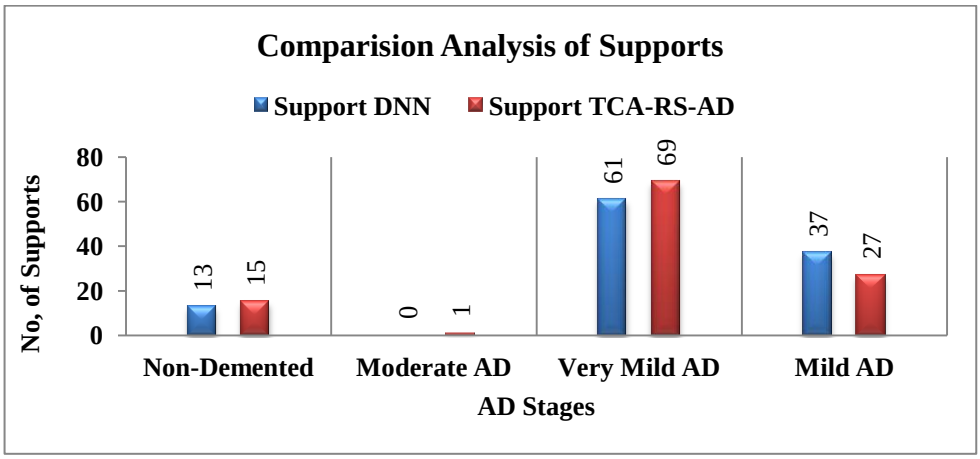

Fig 5: Comparison Analysis of support for DNN and TCA-RS-AD

In addition to the accuracy metrics, the merits of the proposed model are demonstrated by the error rate metrics namely MAE, MSE, BAS and MdAE listed in Table 9. These observations confirmed that the error rate is significantly minimized and accuracy is maximized in AD detection.

Table 9: Comparison Analysis of Error Rate Metrics

Model	Error Rate Metrics				Accuracy		
	MAE	MSE	M_dAE	HL	Cohens Kappa	MCC	BAS
DNN Model	0.392	1.0357	0.1	0.142857	0.743744	0.76485	0.5645
TCA-RS-AD Model	0.0893	0.2500	0.0	0.035714	0.933363	0.93440	0.9251

Fig 6 shows the comparative analysis of the recorded error and accuracy metrics for both models. It clearly illustrates the superiority of TCA-RS-AD in AD detection over DNN.

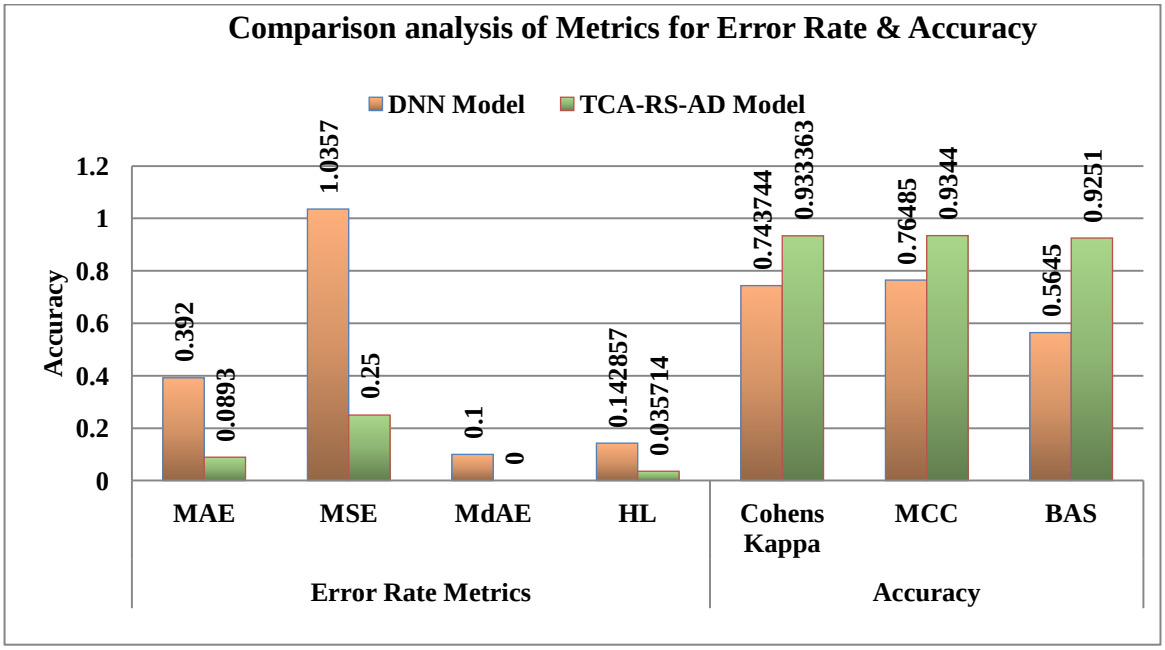

Fig 6: Comparative analysis of Metrics for Error Rate & Accuracy

Based on the performance measures of TCA-RS-AD, the degree of recommendation on AD classification is given a 6-point scale [Excellent, High, Moderate, Low, Poor and Scant] and the respective performance mapping is given below:

S: Scant performance (0–9%);
P: Poor performance (10–29%);
L: Low performance (30–49%);
M: Moderate performance (50–69%);
H: High performance (70–89%);
E: Excellent performance (90–99%)

Table 10: Classifiers with their Performance

Metrics / Classifiers	Precision				Recall				F1-Score			
	VM	M	MAD	ND	VM	M	MAD	ND	VM	M	MAD	ND
DNN	E	H	S	M	E	H	S	M	E	H	S	M
TCA-RS-AD	E	E	S	E	E	E	S	H	E	E	S	E
AD Stages	VM: Very Mild AD; M: Mild AD; ND: Non-Demented; MAD: Moderate AD											
Recommender Scale	Excellent: E; High: H; Moderate: M; Low: L; Poor: P; Scant: S											

Table 10 summarizes the performance rating of DNN and TCA-RS-AD for the three prominent metrics namely precision, recall and F1-Score, in terms of the 6-point Recommender scale. It is observed that the TCA-RS-AD exhibits its novelty and robustness in the prediction of very mild and Mild AD which is a vital factor for the early detection of AD. In all other classes except Moderate AD, the TCA-RS-AD is confirmed to recommend better than the basic DNN. These observations vouch for its merits and applicability over its counterpart. These inferences are pictorially depicted in Fig 7, for precision, recall, and F1-Score.

Fig 8 revealed the overall rating comparison of Error ratings for DNN and TCA-RS-AD models. This showed that the error rating of TCA-RS-AD is highest when compared to the DNN model.

From the above results, it is recommended that the proposed TCA-RS-AD Model works better for the detection of AD.

VI. CONCLUSION

The Temporal Change Analysis based Recommender System for Alzheimer Disease Classification (TCA-RS-AD) works on the principle of deep learning. This intelligent model exhibits its potential in the classification of Alzheimer's disease and provides a recommendation on a 6-point scale using the accuracy of classification. The performance of this system is exceptionally good in the time-series based early-stage prediction of AD, as evidenced by its results. The results of this model may serve as a supplementary tool for AD detection for clinical trials. This model is designed to be computationally light and hence it can be effortlessly deployed in edge devices.

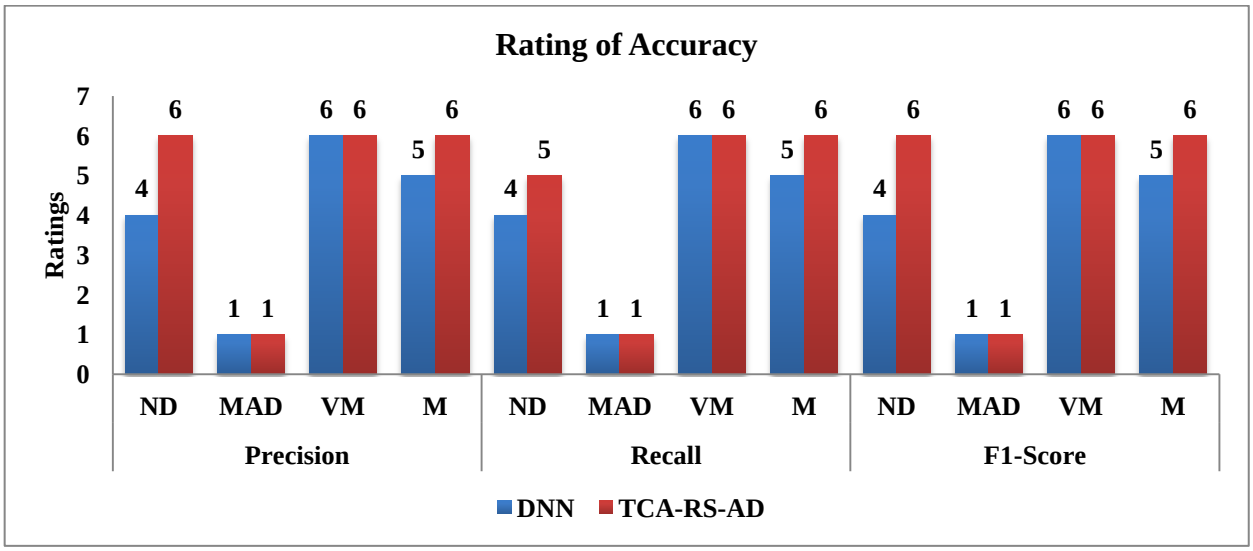

Fig 7: Accuracy Rating for DNN and TCS-RS-AD

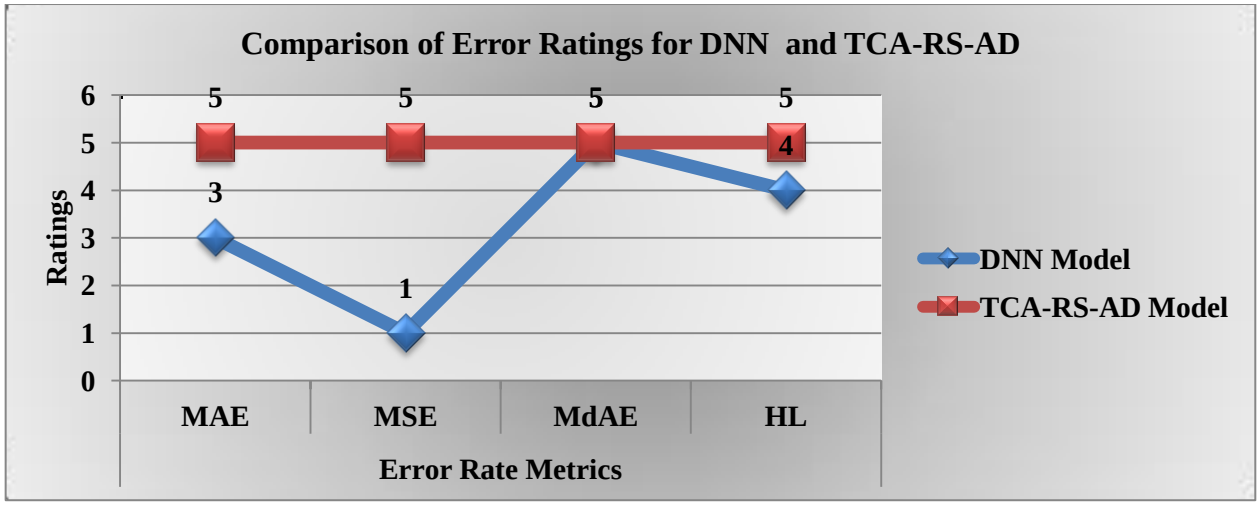

Fig 8: comparison of Error ratings for DNN and TCA-RS-AD models

REFERENCES

1. Ashby-Mitchell, K., Burns, R., Shaw, J., & Anstey, K. J. (2017). The proportion of dementia in Australia explained by common modifiable risk factors. Alzheimer's research & therapy, 9(1), 11.
2. Arnold, L., Rebecchi, S., Chevallier, S. and Paugam-Moisy, H. (2011). An Introduction to Deep Learning. ESANN 2011 Proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence, and Machine Learning, Bruges, Belgium, 27(29) 477-488.
3. Naganandhini S, Shanmugavadivu P, Asaithambi A, MansoorRoomi M.M. (2019). Alzheimer's Disease Classification Using Machine Learning Algorithms, Advances in Computerized Analysis in Clinical and Medical Imaging, Taylors and Francis, CRC Press, 1-18.
4. Sajna, T, Anish Kumar, B. (2018). Land Mark Detection and Alzheime*r's disease Prediction using two-stage CNN and Landmark Features. International Journal of Advances in Electronics and computer sciences. 5(6). ISSN: 2393-2835, 72-75.
5. Lebedev, A. V., Westman, E., Van Westen, G. J. P., Kramberger, M. G., Lundervold, A., Aarsland, D., ... &Vellas, B. (2014). Random Forest ensembles for detection and prediction of Alzheimer's disease with good between-cohort robustness. NeuroImage: Clinical, 6, 115-125.
6. Islam, J., & Zhang, Y. (2018). Brain MRI analysis for Alzheimer's disease diagnosis using an ensemble system of deep convolutional neural networks. Brain informatics, 5(2), 2-7.
7. Bi, X. A., Jiang, Q., Sun, Q., Shu, Q., & Liu, Y. (2018). Analysis of Alzheimer's disease based on the random neural network cluster in fMRI. Frontiers in neuroinformatics, 12, 60.
8. Sahoo, A. K., Pradhan, C., Barik, R. K., &Dubey, H. (2019). DeepReco: Deep Learning Based Health Recommender System Using Collaborative Filtering. Computation, 7(2), 1-18.
9. Lafta, R., Zhang, J., Tao, X., Li, Y., & Tseng, V. S. (2015). An intelligent recommender system based on short-term risk prediction for heart disease patients. In 2015 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT), 3,102-105.
10. Schafer, J. B., Konstan, J., &Riedl, J. (1999). Recommender systems in e-commerce. In Proceedings of the 1st ACM conference on Electronic commerce, ACM, 158-166.
11. OASIS: Longitudinal: Principal Investigators: D. Marcus, R, Buckner, J. Csernansky, J. Morris; P50 AG05681, P01 AG03991, P01 AG026276, R01 AG021910, P20 MH071616, U24 RR021382.

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