ISSN 2347 - 3983
Volume 7, No. 11 November 2019
International Journal of Emerging Trends in Engineering Research
Available Online at http://www.warse.org/IJETER/static/pdf/file/ijeter397112019.pdf
https://doi.org/10.30534/ijeter/2019/397112019

Evaluating the performance metrics of different machine learning classifiers by combined feature extraction method in Alzheimer's disease detection

Dinu A.J.*, Ganesan R#1 Kumar S.S#2
*Research Scholar, Noorul Islam University, Kumaracoil, Thuckalay, Tamil Nadu, India
[1,2]Professor, Department of EIE, Noorul Islam University, India
*dinubhagya@gmail.com, [1]dr.ganesh.jass@gmail.com, [2]kumarss@live.com

ABSTRACT

The rapid growth of machine learning technology has a great advantage in developing high performance neural network algorithms which can extract low-to-high-level features in human MRI images. Classification of clinical data for Alzheimer's disease has always been challenging as currently there is no clinical test for Alzheimer's disease. Doctors diagnose it by conducting assessments of patients' cognitive decline. But it's particularly difficult for them to identify mild cognitive impairment at an early stage when symptoms are less obvious. Also, it is difficult to predict whether patients will develop Alzheimer's disease or not. The accurate diagnosis of Alzheimer's disease in the early stage is important to take preventive measures and to reduce the severity and progression before irreversible brain damages occur. The effectiveness of abnormality detection depends on the accuracy and robustness of the algorithm used. Different machine learning techniques with different levels of sensitivity, specificity, and accuracy have been developed. In this paper, performance measures of different classification algorithms like Support Vector Machine, k-Nearest-Neighbor, Discriminant Analysis Model Pseudo Linear, Discriminant Analysis Model Pseudo Quadra and Binary Decision Tree are compared and analyzed to obtain the most accurate classification method for the early prediction of Alzheimer's disease.

Key words: Machine Learning, Feature Extraction, Feature selection, Alzheimer's disease, Mild Cognitive Impairment, Normal Cognitive, Magnetic Resonance Imaging, Supervised Learning, Alzheimer's Disease Neuroimaging Initiative

1. INTRODUCTION

Alzheimer's disease is an accelerating and irremediable neurologic brain disease that slowly destroys brain cells and thereby resulting in memory losses, and ultimately loss of the ability to carry out even the basic tasks. The cognitive decline caused by this syndrome ultimately leads to dementia. It is the most common form of dementia in elderly people who is more than 65 years of age. The disease begins with mild degeneration in memory and gets worse. Magnetic Resonance Imaging (MRI) is an efficient imaging method to detect Alzheimer's disease without using harmful radiations. It is possible to find the shape, size and position of abnormalities using MRI. Detecting Alzheimer's disease by doctors requires diligent medical analysis along with other physical and neurological exams [1]. It is a strenuous job for the technicians to categorize and analyze these images manually. Hence the use of automatic detection methods became popular. Abnormalities can be easily identified using various neural network methods.

In Alzheimer disease, death of brain cells and development of tangles and plaques in brain results in memory loss. Early diagnosis of AD is crucial to control the growth of the disease and for preventing the loss of ability to carry out even the basic human tasks. Machine learning techniques uses various algorithms to obtain the required data from MRI images and parse it, learn from it, and make a prediction out of the input data given. So, to accomplish a specific task, the system is "trained" using algorithms, which provides the ability to learn and perform the task. It uses cascade chains of different processing units for feature extraction and transformation [2,3]. Each of the successive layers utilizes the output from the previous layer as inputs. The algorithms used may be supervised for pattern analysis applications and unsupervised for applications include classifications.

Earlier various biomarkers are used to evaluate the biological changes carried due to Alzheimer's disease. The different biomarkers like cerebrospinal fluid (CSF) biomarker in MRI brain images was utilized to detect Alzheimer's disease and to track the progression of the disease. Here variations in the level of biomarkers are used for the diagnosis of AD. A set of serum markers have been discovered which may occur due to inflammatory actions in the central nervous system during the early course of AD. This technique is the most acceptable method to diagnose AD with high specificity and sensitivity. But Biomarkers are not useful for early diagnosis of the disease. Moreover, it must use an intra cerebral ventricular injection. To collect the CSF the clinical employees, must take utmost care without damage brain tissues and spinal card. This is one among the foremost important mechanism to estimate the Alzheimer's where they estimate the tangle and plague of the brain tissues for Alzheimer's analysis [4].

Recently volumetric analysis is used for analyzing manually or semi-automatic techniques using SPM-5 in MATLAB Environment [5,6]. There the neurologist needs to calculate the total volume of the different regions such as white matter, gray matter, CSF and sum together come to conclusion about the stage of the disease.

2. PRINCIPLES OF DIFFERENT MACHINE LEARNING ALGORITHMS

Different powerful machine learning algorithms that extract different features from MRI images for detection of Alzheimer disease have been developed by Scientists. In this paper, performance measures of different classification algorithms like Support Vector Machine, k Nearest Neighbor, Discriminant Analysis Model Pseudo Linear, Discriminant Analysis Model Pseudo Quadra and Binary Decision Tree are compared and analyzed.

2.1 Support Vector Machine

A Support Vector Machine is a supervised learning technique which is used to solve classification and regression problems. It is defined by a separating optimal hyperplane in an N dimensional space (where N is the number of features), in a maximized margin. Then will extend the same for non-linearly separable problems. It will have a penalty term for misclassifications [7,8]. Also map the data to high dimensional space to classify with linear decision surfaces and explicate the problem so that data is mapped implicitly to this space. To define an optimal hyperplane, the width of the margin (w) should be maximized.

$$\frac{w}{||w||}.(x2-x1) = width = \frac{2}{||w||}$$
$$w.x2+b=1$$
$$w.x1+b=1$$
$$w.x2+b-(w.x1-b)=1-(-1)$$
$$w.x2-w.x1=2$$
$$\frac{w}{||w||}.(x2-x1) = \frac{2}{||w||} \qquad (2)$$
$$min\frac{1}{2}||w||^2$$
$$s.t.\, yi(w.xi+b)\geq 1; \forall xi$$

Figure 1: Dimensional space of Support Vector Machine

2.2 k Nearest Neighbor

The KNN classifier distinguishes the ailment by examination of components that determines the data vectors by considering the classes [9]. Here we map the original feature into the target space to identify the informative and predictive features by k-Nearest Neighbor classifier. k-Nearest Neighbor learning algorithm assumes all instances correspond to points in the n-dimensional space R^n. The nearest neighbors of an instance are defined in terms of Euclidean distance. Euclidean distance between the instances Xi = <Xi1,…,Xin>and Xj = <Xj1,…,Xjn> is given by

$$d(Xi-Xj) = \sum_{r=1}^{n}\sqrt{(Xi+Xj)^2} \qquad (1)$$

For a given query instance Xq, f(Xq) is calculated as the function values of k-Nearest Neighbor of Xq. For k-Nearest Neighbor, locate k nearest training examples, and estimate f(Xq). If the target function is real-valued, take mean of f-values of k-Nearest Neighbor. If the target function is discrete valued, take a vote among f-values of k Nearest Neighbour.

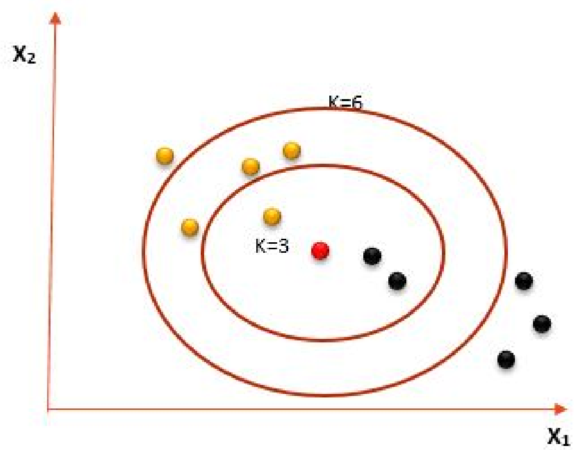

Figure 2: Target space of k-Nearest Neighbor

2.3 Discriminant Analysis Model-Pseudo Linear

In Discriminant Analysis -Pseudo Linear model, we assume that the covariance matrix is identical for different k classes. The classifier becomes linear by making this assumption [10].

$$f_k(x) = \frac{1}{(2\pi)^{p/2}|\Sigma k|^{1/2}} e^{-1/2(x-\mu_k)^T\Sigma_k^{-1}(x-\mu_k)} \qquad (3)$$

For LDA
$\Sigma k = \Sigma, \forall k$

2.4 Discriminant Analysis Model-Pseudo Quadra

In Discriminant Analysis -Pseudo Quadra model, we do not assume that the covariance matrix is identical for different k classes. In this case, the decision boundary is obtained from a quadratic Gaussian function [11].

$$f_k(x)=\frac{1}{2\pi^{\frac{p}{2}}|\Sigma_k|^{\frac{1}{2}}}e^{\frac{-1}{2}(x-\mu k)^T\Sigma_k^{-1}(x-\mu k)} \quad (4)$$

Here Σ_k represents the covariant matrix

2.5 Binary Decision Tree

A binary decision tree classifier is mainly used for multiclass classification [12].

3. MATERIALS AND METHODS USED

In this study MRI images of AD and non-AD patients and collected are classified into 3 different stages such as AD, MCI and No Disease, which serves as the data source. The performance parameters of the MRI images are evaluated in terms of the classification accuracy, sensitivity, specificity and time consumption for the comparison of different machine learning techniques [13, 14]. The Figure 3 represents different stages in detection of Alzheimer Disease by using different Machine Learning Classification algorithms.

The input datasets comprise of MRI images of patients having Normal Brain, Mild cognitive Impairment (MCI), and the Alzheimer's disease (AD). At first the MRI input image is fed to a pre-processing unit. The pre-processing techniques involves data collections and processing the information. Feature extraction methods includes the separation of the redundant and non-redundant information from the MRI image and then extracts the useful information for analysis. In our work the feature extraction methods used are SURFF, BRISK, FAST and Harris algorithms [15, 16].The different features obtained from the SURFF, BRISK, FAST and Harris algorithms are combined, and the strongest points are obtained to get the adequate number of features. The Principal Component Analysis method is used for Feature Selection [17, 18]. The different classification techniques used for the study are Discriminant Analysis Model-Pseudo Linear, Discriminant Analysis Model-Pseudo Linear, Discriminant Analysis Model-Pseudo Quadra and Binary Decision Tree classifiers. A voting process is done after the classification method to increase the accuracy of the classifications.

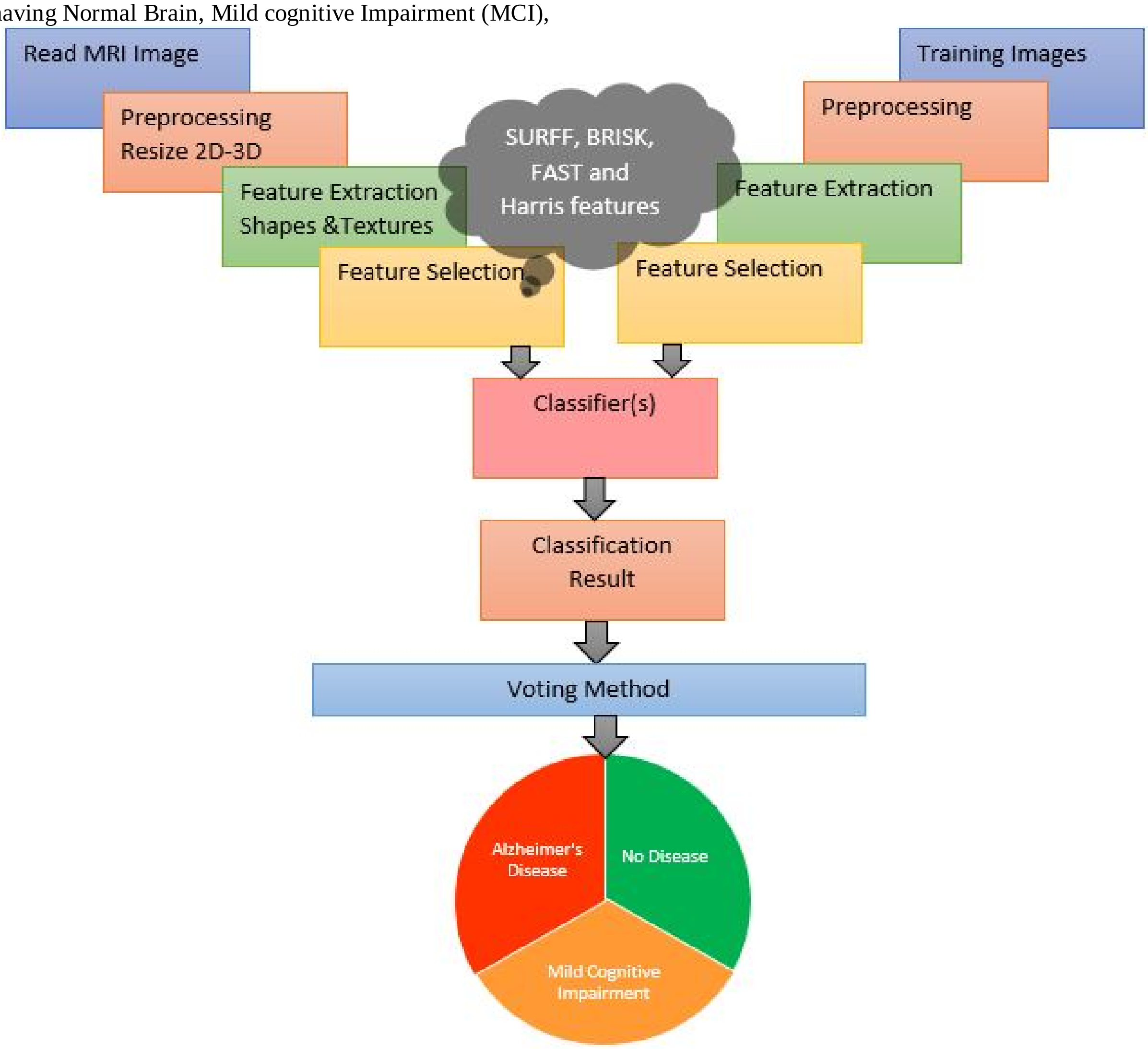

Figure 3: Work Flow of a Machine Learning Classifier System

PERFORMANCE ANALYSIS

In this work, three classes are separated for the analysis

- Class 1-Alzheimer's Disease (AD)
- Class 2- Mild Cognitive Impairment (MCI)
- Class 3- No Disease

The four parameters deliberate such as TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) is used to classify the AD, MCI and No Diseased images present in the datasets.

True positive (TP) = the number of cases correctly identified as AD patient
True negative (TN) = the number of cases correctly identified as healthy person
False positive (FP) = the number of cases incorrectly identified as AD patient
False negative (FN) = the number of cases incorrectly identified healthy person

These findings suggest that this approach is efficient and may be promising for clinical applications.

4.1 Classification Accuracy

The closeness of a measured value to the standard or known value is termed as classification accuracy.
Classification Accuracy=TP+TN/ (TP+TN+FP+FN) (5)

4.2 Sensitivity

The closeness of a measured value to the standard or known value is termed as classification accuracy.
Sensitivity=TP/ (TP+FN) (6)

4.3 Specificity

The closeness of a measured value to the standard or known value is termed as classification accuracy.
Specificity=TN/(TN+FP) (7)

4.4 Time Consumption

Time taken to obtain the result is available from MATLAB results viewer and it is measured in Seconds.

4. RESULTS AND DISCUSSIONS

The input images used for the research is taken from Alzheimer's Disease Neuroimaging Initiative (ADNI) database that consists of 100 samples those between ages 18 to 87. The parameters such as TP, TN, FP and FN are determined for calculating performance metrics such as classification accuracy, sensitivity, specificity and time consumption. Table 1 shows the parameters measurements of different neural network architecture. It was seen from the investigational results that; the accuracy of classification is found to be high for SVM classifier and the execution time is found to be low for Binary Decision Tree classifier. Hence the performance of the Support Vector Machine classification method outperforms other techniques in the early classification and detection of Alzheimer's disease in terms of accuracy and efficiency. Also, the Binary Decision Tree classifier is found to be the fastest method compared to other methods.

Table 1: Parameters measurements of different neural network architecture

Neural Network Architecture	Number of Samples	Accuracy	Sensitivity	Specificity	Execution Time (Seconds)
Support Vector Machine	50	90.42	0.68	0.11	0.42
	75	90.70	0.74	0.14	0.53
	100	91.3	0.85	0.27	0.64
k Nearest Neighbor	50	83.42	0.63	0.09	0.47
	75	86.30	0.69	0.11	0.58
	100	87.24	0.81	0.17	0.69
Discriminant Analysis Model-Pseudo Linear	50	84.53	0.64	0.07	0.51
	75	87.40	0.72	0.13	0.68
	100	88.13	0.82	0.2	0.76
Discriminant Analysis Model-Pseudo Quadra	50	85.42	0.63	0.1	0.55
	75	88.31	0.69	0.15	0.7
	100	89.20	0.81	0.19	0.82
Binary Decision Tree	50	90.36	0.64	0.12	0.39
	75	89.63	0.71	0.16	0.47
	100	91.22	0.87	0.24	0.54

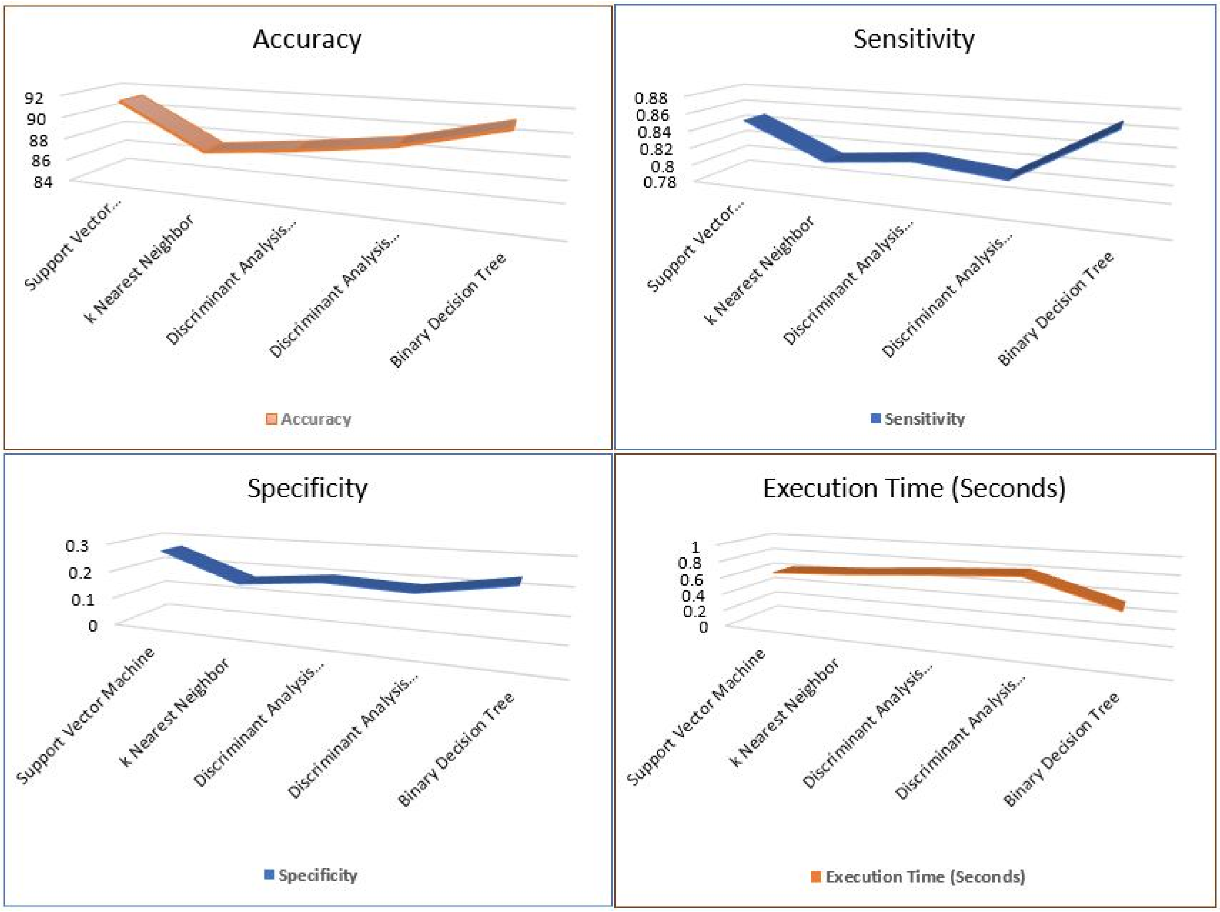

Figure 4: Accuracy, Sensitivity, Specificity and Execution Time obtained from different classification methods

5. CONCLUSION

In this work, the performance metrics of different neural network algorithms like Support Vector Machine, k Nearest Neighbor, Discriminant Analysis Model Pseudo Linear, Discriminant Analysis Model Pseudo Quadra and Binary Decision Tree that are used for the classification of different stages of Alzheimer's disease is studied. The results have been analyzed and compared in terms of as classification accuracy, sensitivity, specificity and time consumption. From the study, the accuracy of classification is found to be high for SVM classifier and the execution time is found to be low for Binary Decision Tree classifier. Hence from the analysis results it is evident that the performance of the Support Vector Machine classification method outperforms other techniques in the early classification and detection of Alzheimer’s disease in terms of accuracy and efficiency, and the Binary Decision Tree classifier is found to be the fastest method compared to other methods. These findings suggest that this approach is efficient and may be promising for clinical applications. The future work intends to combine the different feature extracting methods based on selecting the more distinguishing features along with the appropriate classification algorithm to yield better classification accuracy with optimal time consumption.

REFERENCES

1. Jesia Mathew, Lasitha Mekkayil, Hariharan Ramasangu, B.Ramaswamy Karthikeyan, Aditya G Manjunath, **Robust Algorithm for Early Detection of Alzheimer’s Disease using Multiple Feature Extractions**, *India Conference (INDICON) IEEE*, 2016
https://doi.org/10.1109/INDICON.2016.7839026
2. Jun Zhang, YueGao, YaozongGao, Brent C. Munsell, DinggangShen, **Detecting Anatomical Landmarks for Fast Alzheimer’s Disease Diagnosis**, *IEEE Transactions on Medical Imaging*, Volume: 35, Issue: 12, pp.2524 - 2533,2016
3. Tong, Qinquan Gao, Ricardo Guerrero, Christian Ledig, Liang Chen, Daniel Rueckert**, A Novel Grading Biomarker for the Prediction of Conversion From Mild Cognitive Impairment to Alzheimer's Disease**, *IEEE Transactions on Biomedical Engineering*, Volume: 64, Issue: 1,pp. 155 – 165, Jan. 2016
4. E. Moradi, A. Pepe, C. Gaser, H. Huttunen, and J. Tohka, **Machine learning framework for early MRI-based Alzheimer's conversion prediction in MCI subjects**, *NeuroImage*, vol. 104, pp. 398-412, 2015.
https://doi.org/10.1016/j.neuroimage.2014.10.002

5. S. Q. Liu, S. D. Liu, W. D. Cai, H. Y. Che, S. Pujol, R. Kikinis, D. Feng, M. J. Fulham, and ADNI, **Multimodal neuroimaging feature learning for multiclass diagnosis of Alzheimer's disease**, *IEEE Trans. Biomed. Eng.*, vol. 62, pp. 1132-1140, 2015. https://doi.org/10.1109/TBME.2014.2372011
6. R. Min, G. Wu, J. Cheng, Q. Wang, and D. Shen, **Multi-atlas-based representations for Alzheimer's disease diagnosis**, *Hum Brain Mapp*, vol. 35, pp. 5052-5070, 2014.
7. K. R. Gray, P. Aljabar, R. A. Heckemann, A. Hammers, and D. Rueckert, **Random forest-based similarity measures for multi-modal classification of Alzheimer's disease**, *NeuroImage*, vol. 65, pp. 167–175, Jan. 2013
8. Dinu A.J. and Ganesan R, **Early detection of Alzheimer's disease using predictive k-NN instance based approach and T-Test Method**, International Journal of Advanced Trends in Computer Science and Engineering ,Volume 8 No. 1.4, pp.29 – 37, 2019 https://doi.org/10.30534/ijatcse/2019/0581.42019
9. D. Zhang, Y. Wang, L. Zhou, H. Yuan, and D. Shen, **Multimodal classification of Alzheimer's disease and mild cognitive impairment**, *NeuroImage*, vol. 55, pp. 856-867, 2011
10. A J Dinu, R Ganesan, J Felix, V Balaji, **A study on Deep Machine Learning Algorithms for diagnosis of diseases**, *International Journal of Applied Engineering Research (IJAER)*, Volume 12, pp. 6338-6346, Number 17 (2017).
11. A J Dinu, R Ganesan, J Felix, V Balaji, **Quality Analysis of Various Deep Learning Neural Network Classifiers for Alzheimer's Disease Detection, Journal of Engineering and Applied Sciences**, pp.8334-8339,2017.
12. D. Jha, J. I. Kim, G. R. Kwon, **Diagnosis of Alzheimer's Disease Using Dual-Tree Complex Wavelet Transform, PCA, and Feed-Forward Neural Network**, *Journal of Healthcare Engineering.*, 2017 https://doi.org/10.1155/2017/9060124
13. B. Kapur, N. Ahluwalia, and R. Sathyaraj, **Comparative Study on Marks Prediction using Data Mining and Classification Algorithms**, *International Journal of Advanced Research in Computer Science*, 2017.
14. BijenKhagi,Goo-Rak Kwon, **Alzheimer's disease detection from Brain MRI using Feature extraction from CNN network and classification by KNN**, *Proceedings of Symposium of the Korean Institute of communications and Information Sciences*, 1039-1041, 2018.
15. A J Dinu, R Ganesan, J Felix, V Balaji, A Kebede, **Performance Analysis and Comparison of Medical Image Compression Techniques**, Control, Instrumentation, Communication and Computational Technologies (ICCICCT), 2016 IEEE International Conference, pp. 738 – 745, Dec 2016. https://doi.org/10.1109/ICCICCT.2016.7988050
16. A J Dinu, R Ganesan, R T Amruth, **Analysis of Various Medical Image Compression Methods**, International Journal of Control Theory and Application, pp.109-119, July 2017.
17. ZiadSankari, HojjatAdeli, **Probabilistic neural networks for diagnosis of Alzheimer's disease using conventional and wavelet coherence**, Journal *of Neuroscience Methods*, 197(1): pp.165-170, 2011. https://doi.org/10.1016/j.jneumeth.2011.01.027
18. Baiying Lei, Peng Yang, Tianfu Wang, Siping Chen, Dong Ni, **Relational-Regularized Discriminative Sparse Learning for Alzheimer's Disease Diagnosis**, *IEEE Transactions on Cybernetics*, Volume: 47, Issue: 4,pp.1102-1113, April 2017 https://doi.org/10.1109/TCYB.2016.2644718