



**IJIRCCCE**

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 9, Issue 4, April 2021

**ISSN** INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA

**Impact Factor: 7.488**

 9940 572 462

 6381 907 438

 [ijircce@gmail.com](mailto:ijircce@gmail.com)

 [www.ijircce.com](http://www.ijircce.com)

# Segmentation and Classification of Alzheimer's Disease Using Deep Learning

Mrs.V. Vidyalakshmi<sup>1</sup>, P.Thangalakshmi<sup>2</sup>, S.Kreshmi<sup>2</sup>, G.Aishwarya<sup>2</sup>, P.G.Sakthi Saranya<sup>2</sup>

Assistant Professor, Dept of ECE, Velammal Engineering College, Chennai, Tamilnadu, India<sup>1</sup>

B.E, Dept of ECE, Velammal Engineering College, Chennai, Tamilnadu, India<sup>2</sup>

**Abstract:** In recent years, the diagnosis of Alzheimer's disease (AD) has become one of the most of diagnosis for AD. In the proposed method, the accuracy of classification is improved by using deep learning Network classifier, are selected by using region masking. The Convolutional Neural Network classifier is used for the diagnosis of AD. The data set will be discussed in this project contains normal and AD subjects. The empirical results show that the proposed method significantly improves the accuracy of the diagnosis of AD in comparison with previous methods. The Alzheimer's disease become one of challenging problems in medical fields. This project proposes a new segmentation method, region masking which is used for selecting the useful properties of affected parts in the human brain and Convolutional Neural Network Classifier for improving the accuracy of detection and classification. The functional MRI technology is used for investigation and detection of Alzheimer disease. The Alzheimer disease is detected at different levels like normal ,medium and severe stage in order to differentiate stages and the stages are displayed in the LCD.

**KEYWORDS:** AD, regionmasking, Filtering Enhancement, MATLAB, MRI.

## I. INTRODUCTION

The problems associated with the aging population are becoming increasingly serious as people live longer and fertility rates decline in most countries. Furthermore, because a greater proportion of individuals are elderly, more people are at high risk of developing dementia. Alzheimer's disease (AD) is the most common form of dementia diagnosed in elderly people and significantly reduces their quality of life. Alzheimer's disease (AD) is an irreversible neurodegenerative disorder that leads to progressive loss of memory and cognition function. Its early and accurate diagnosis is not only challenging but also crucial for future treatments and risk reduction. Over the past decade, several imaging modalities have been used in AD diagnosis, including diffusion tensor imaging (DTI), structural magnetic resonance imaging (MRI) and positron emission tomography (PET). Among these modalities, functional MRI (fMRI) plays an important role in monitoring brain activity and exploring the functional connectivity among different brain regions; therefore, fMRI is a promising methodology for the investigation and detection of brain disease. The Alzheimer's disease is diagnosed with

the help of MRI images by image processing system and classified using convolutional neural network and region masking.

## II. LITERATURE SURVEY

[1]Ensemble distributed classification of presenile dementia Manhua Liu a,b, Daoqiang Zhang a,c, Dinggang Shen a, and therefore the presenile dementia Neuroimaging Initiative-2019. rather than building one international classifier, an area patch-based topological space ensemble methodology was planned , that builds multiple individual classifiers supported totally different subsets of native patches then combines them for a lot of correct and sturdy classification. Specifically, to capture the native spatial consistency, every brain image is partitioned off into variety of native patches and a set of patches is willy-nilly designated from the patch pool to make a weak classifier. Here, the distributed representation-based classifier (SRC) methodology, that has shown to be effective for classification of image knowledge (e.g., face), is employed to construct every weak classifier. Then, multiple weak classifiers square measure combined to form the ultimate call. Furthermore, A random patch based mostly topological space ensemble classification framework with the SRC was given. rather than willy-nilly sampling the voxels, the native patches square measure extracted from the relevant regions to capture the native spatial consistency and square measure willy-nilly

sampled to construct a feature topological space for style of individual weak classifier. Then, multiple classifiers square measure combined to form a lot of correct and sturdy classification. The experimental results on ADNI info show that SRC continues to perform well once the spatiality will increase. It achieves higher classification performance than SVM classifier once a lot of options square measure used for classification. The random patch based mostly topological space ensemble classification will additional improve the classification accuracy by combining multiple weak classifiers and exploitation native patches to capture spatial consistency. [2]Attention-based 3D Convolutional Network Biomarkers Exploration Dan Jin<sup>1,2</sup>, Jian Xu<sup>2,3</sup>, Kun Zhao<sup>1,4</sup>, Fangzhou Hu<sup>1,5</sup>, Zhengyi Yang<sup>1,2</sup>, Bing Liu<sup>1,2,6</sup>, Tianzi Jiang<sup>1,2,6</sup>, Yong Liu<sup>1,2</sup>,-2019. a completely unique attention-based 3D ResNet design was planned to diagnose explore potential biological markers. By introducing the eye mechanism, the planned approach additional improves the classification performance and identifies necessary brain regions for AD classification at the same time. while not sophisticated feature extraction and have choice, our easy finish-to- end network achieved exceptional classification performance. the foremost advantage of the present work is that the incorporated attention mechanism not solely improved the classification performance however conjointly captured the numerous brain regions for AD classification. It ought to even be noted that our attention-based network is simply transferred to classification of alternative brain diseases wherever adult male imaging is obtainable.[3]Neuroimaging markers of world knowledge in early Alzheimer's disease: A resonance imaging– electroencephalography study Markus Waser<sup>1,2,3</sup> | Thomas Benke<sup>4</sup> | Peter Dal-Bianco<sup>5</sup> | Heinrich Garn<sup>3</sup> | Jochen A. Mosbacher<sup>6</sup> | Gerhard Ransmayr<sup>7</sup> | Reinhold Schmidt<sup>6</sup> | Stephan Seiler<sup>6</sup> | Helge B. D. Sorensen<sup>1</sup> | Poul J. Jennum<sup>2</sup>-2019. The cross-sectional study consistently investigated the link between imaging and graph markers and therefore the international psychological feature standing in early AD. The joint modalities would determine psychological feature deficits with higher accuracy than the individual modalities. in a very cohort of 111 AD patients, combined method of imaging measures of plant tissue thickness and regional brain volume with graph measures of cadent activity, information science and purposeful coupling in a very generalized multivariate analysis model. Machine learning classification was wont to value the markers' utility in accurately separating the topics consistent with their psychological feature score. [4] Sleep-wake rhythm fragmentation relates a lot of powerfully than age and the other far-famed risk to medial lobe atrophy Eus J.W. Van Someren<sup>1,2</sup>, J.M. Oosterman<sup>3</sup>, B. Van Harten<sup>4</sup>, R.L.Vogels<sup>4</sup>, A.A. Gouw<sup>5</sup>, H.C.Weinstein<sup>4</sup>, A. Poggesi<sup>6</sup>, Ph. Scheltens<sup>5</sup> and E.J.A. Scherder-2019. A contribution of the everyday age-related sickness is hypothesized in sleep-wake rhythm fragmentation to medical lobe atrophy. resonance imaging and actigraphy in 138 aged people showed that individual variations in sleep-wake rhythm fragmentation accounted for a lot of (19%) of the variance in medial lobe atrophy than age did (15%), or any of a listing of health and brain structural indicators. The findings recommend a task of sleep-wake rhythm fragmentation in age-related medial lobe atrophy, which may partly be prevented or reversible. [5] associate degree Ontology-Based Annotation of viscus Implantable Electronic Devices to sight medical aid Changes in a very National written record Arnaud Rosier, Member, IEEE, Philippe Mabo, Michel Chauvin, and Anita Burgun-2019. This study introduces a tool annotation methodology that supports the consistent description of the purposeful attributes of viscus devices and evaluates however this methodology will sight device changes from a CIED written record. we have a tendency to designed the viscus Device metaphysics, associate degree metaphysics of CIEDs and device functions. we have a tendency to annotated 146 viscus devices with this metaphysics and used it to sight medical aid changeswith relevance chamber pacing, viscus resynchronization medical aid, and medical aid capability in a very French national written record of patients with implants (STIDEFIX).

### III. EXISTING SYSTEM

In this paper, the correct diagnosing of Alzheimer's disease (AD) plays a vital role in patient treatment, particularly at the disease's early stages, as a result of risk awareness permits the patients to endure preventive measures even before the incidence of irreversible brain harm. though several recent studies have used computers to diagnose AD, most machine detection ways area unit restricted by nonheritable observations. AD may be diagnosed-but not predicted-at its early stages, as prediction is merely applicable before the unwellness manifests itself. Deep Learning (DL) has become a typical technique for the first diagnosing of AD

### IV. PROPOSED SYSTEM

In this project, a brand new segmentation technique, region masking that is employed for choosing the helpful properties of affected elements within the human brain for up the accuracy of designation for AD. within the projected technique, the accuracy of classification will be improved by deep learning Network classifier, square measure elite by mistreatment region masking. what is more, the Convolutional Neural Network classifier is employed for the designation of AD. the info set contains traditional and AD subjects. The empirical results show that the projected technique considerably improves the accuracy of the designation of AD compared with previous strategies

## V. BLOCK DIAGRAM

### A. MATLAB Unit

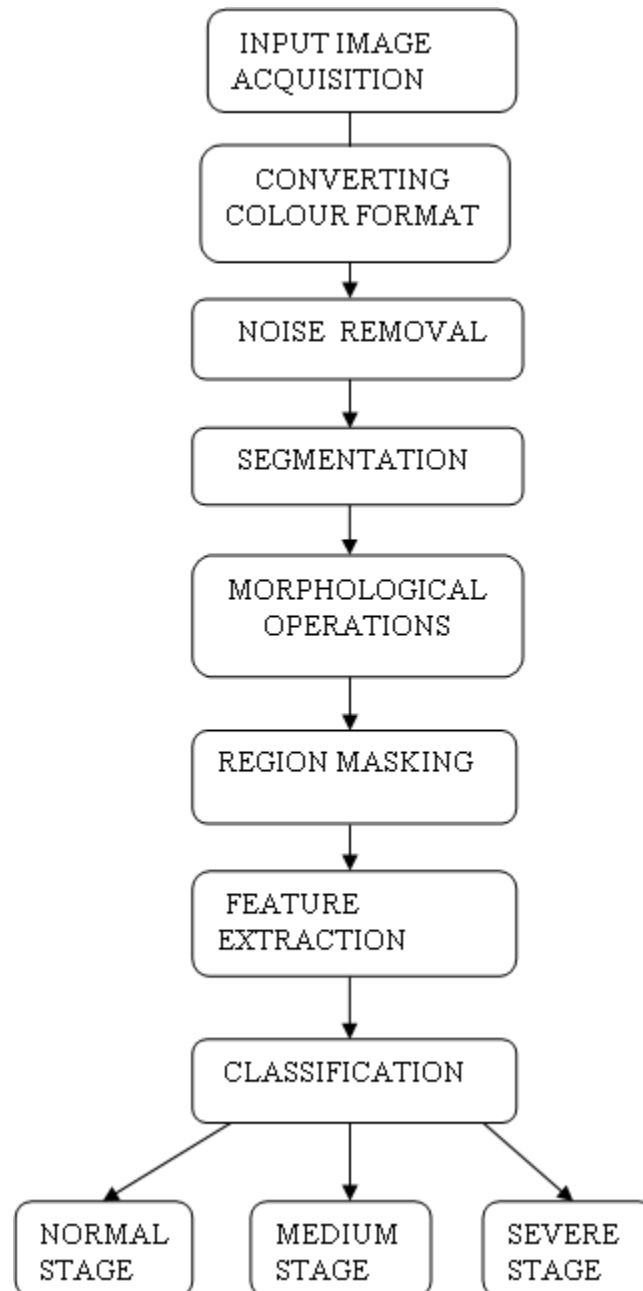


Fig. 1. MATLAB unit

### MODULE DESCRIPTIONS

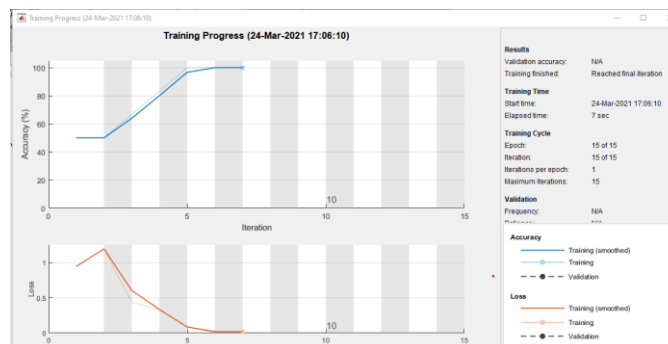
1. INPUT IMAGE scan associated show an input Image. scan a picture into the space, victimisation the imread command. In image process, it's outlined because the action of retrieving a picture from some supply, typically a hardware-based supply for process. it's the primary step within the advancement sequence as a result of, while not a picture, no process is feasible. The image that's noninheritable is totally unprocessed.

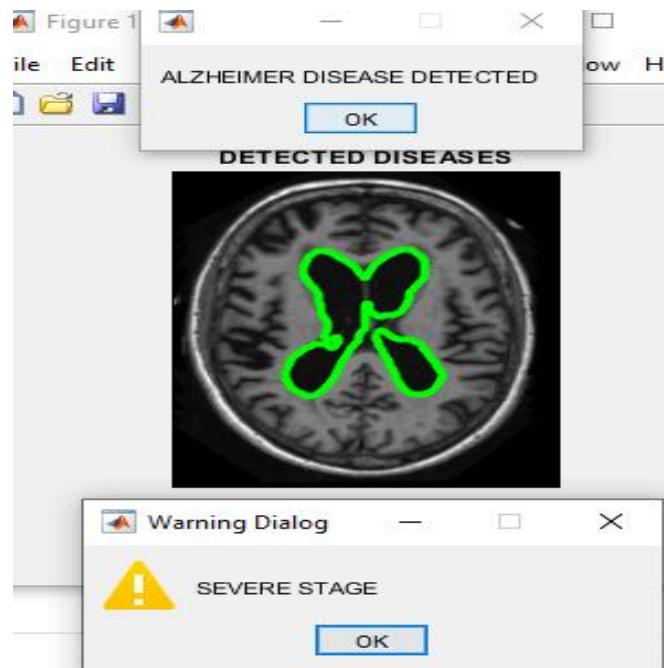


2. PREPROCESSING Pre-processing may be a common name for operations with pictures at rock bottom level of abstraction each input and output ar intensity pictures. The aim of pre-processing is associate improvement of the image knowledge that suppresses unwanted distortions or enhances some image options necessary for more process. Image pre-processing ways use the right smart redundancy in pictures. Neighboring pixels resembling one object in real pictures have primarily an equivalent or similar brightness worth. therefore distorted element will usually be remodeled as a median worth of neighboring pixels. 1. changing color FORMAT for several applications of image process, color data does not facilitate US. If you get into the business of making an attempt to differentiate colours from each other, then one reason for changing RGB image to BLACK AND WHITE or GRAYSCALE formats in image.

RGB COLOR IMAGE: The RGB color model is associate additive color model during which red, inexperienced and blue lightweight ar additional along in varied ways that to breed a broad array of colours. The name of the model comes from the initials of the 3 additive primary colours red, green, and blue. The main purpose of the RGB color model is for the sensing, illustration, and show of pictures in electronic systems, like televisions and computers, tho' it's additionally been employed in typical photography. Before the electronic age, the RGB color model already had a solid theory behind it, based mostly in human perception of colours. RGB may be a device-dependent color model: completely different devices observe or reproduce a given RGB worth otherwise, since the colour parts (such as phosphors or dyes) and their response to the individual R, G, and B levels vary from manufacturer to manufacturer, or maybe within the same device over time. therefore associate RGB worth doesn't outline an equivalent color across devices while not some quite color management. Typical RGB input devices ar colour TV and video cameras, image scanners, and digital cameras. Typical RGB output devices ar TV sets of assorted technologies (CRT, LCD, plasma, etc.), laptop and transportable displays, video projectors, colorful LED displays, and enormous screens like large Tron. Fig Example of RGB color image GRAYSCALE IMAGE: In photography and computing, a grayscale or gray scale digital image is a picture during which the worth of every element may be a single sample, that is, it carries solely intensity data. pictures of this kind, additionally referred to as black-and-white, ar composed solely of reminder grey, varied from black at the weakest intensity to white at the strongest. Grayscale pictures ar distinct from one-bit bi-tonal black-and-white pictures, that within the context of laptop imaging ar pictures with solely the 2 colours, black, and white (also referred to as bi-level or binary images). Grayscale pictures have several reminder grey in between. Grayscale pictures also are referred to as monochromatic, denoting the presence of only 1 (mono) color (chrome). Grayscale pictures ar usually the results of mensuration the intensity of sunshine at every element in a very single band of the spectrum (e.g. infrared, light, ultraviolet, etc.), and in such cases they're monochromatic correct once solely a given frequency is captured. however additionally they will be synthesized from a full color image. Fig Example of grey scale image 2. NOISE REMOVAL Filtering may be a technique for modifying or enhancing a picture. as an example, you'll be able to filter a picture to stress sure options or take away different options. Image process operations enforced with filtering embody smoothing, sharpening, and edge sweetening

## VI. RESULT AND DISCUSSION





## VII. CONCLUSION

In this paper, we demonstrated that the AD detection and classification task using a small dataset can be better solved using different image processing techniques with deep learning concepts. This method can effectively improve the accuracy of the classification in small sample sets. Researchers can use this method to relieve the challenge of extremely limited sample size, particularly when collecting neuroimaging data is difficult and computer-aided diagnoses with limited samples are required. Our work may also assist researchers to make better use of shared data and promote the exchange of collected data. In future, with more time and with more comprehensive research the proposed system can be made more accurate. Also new Alzheimer's disease detection algorithms can be added so as to give the doctor a wider variety of options to choose from

## REFERENCES

- [1] M. Prince, A. Wimo, M. Guerchet, A. Gemma-Claire, Y.-T. Wu, and M. Prina, "World Alzheimer Report 2015: The Global Impact of Dementia - An analysis of prevalence, incidence, cost and trends," *Alzheimer's Dis. Int.*, p. 84, 2015.
- [2] M. Graña et al., "Computer Aided Diagnosis system for Alzheimer Disease using brain Diffusion Tensor Imaging features selected by Pearson's correlation," *Neurosci. Lett.*, vol. 502, no. 3, pp. 225–229, 2011.
- [3] M. Dyrba et al., "Combining DTI and MRI for the automated detection of Alzheimer's disease using a large European multicenter dataset," in *International Workshop on Multimodal Brain Image Analysis*, 2012, pp. 18–28.
- [4] S. Haller et al., "Individual classification of mild cognitive impairment subtypes by support vector machine analysis of white matter DTI," *Am. J. Neuroradiol.*, vol. 34, no. 2, pp. 283–291, 2013.
- [5] W. Lee, B. Park, and K. Han, "Classification of diffusion tensor images for the early detection of Alzheimer's disease," *Comput. Biol. Med.*, vol. 43, no. 10, pp. 1313–1320, 2013.
- [6] T. M. Nir et al., "Diffusion weighted imaging-based maximum density path analysis and classification of Alzheimer's disease," *Neurobiol. Aging*, vol. 36, no. S1, pp. S132–S140, 2015.
- [7] R. Cuingnet et al., "Automatic classification of patients with Alzheimer's disease from structural MRI: A comparison of ten methods using the ADNI database.," *Neuroimage*, vol. 56, no. 2, pp. 766–81, 2010.
- [8] E. Westman, J.-S. Muehlboeck, and A. Simmons, "Combining MRI and CSF measures for classification of Alzheimer's disease and prediction of mild cognitive impairment conversion," *Neuroimage*, vol. 62, no. 1, pp. 229–238, 2012.
- [9] C. Aguilar et al., "Different multivariate techniques for automated classification of MRI data in Alzheimer's disease and mild cognitive impairment," *Psychiatry Res. - Neuroimaging*, vol. 212, no. 2, pp. 89–98, 2013.

- [10] A. Ortiz, J. M. Górriz, J. Ramírez, F. J. Martínez-Murcia, and A. D. N. Initiative, “LVQ-SVM based CAD tool applied to structural MRI for the diagnosis of the Alzheimer’s disease,” *Pattern Recognit. Lett.*, vol. 34, no. 14, pp. 1725–1733, 2013.
- [11] L. Khedher, J. Ramírez, J. M. Górriz, A. Brahim, and F. Segovia, “Early diagnosis of Alzheimer’s disease based on partial least squares, principal component analysis and support vector machine using segmented MRI images,” *Neurocomputing*, vol. 151, no. P1, pp. 139–150, 2015.
- [12] F. de Vos et al., “Combining multiple anatomical MRI measures improves Alzheimer’s disease classification,” *Hum. Brain Mapp.*, vol. 37, no. 5, pp. 1920–1929, 2016.
- [13] N. L. Foster et al., “FDG-PET improves accuracy in distinguishing frontotemporal dementia and Alzheimer’s disease,” *Brain*, vol. 130, no. 10, pp. 2616–2635, 2007.
- [14] K. Herholz, S. F. Carter, and M. Jones, “Positron emission tomography imaging in dementia,” *Br J Radiol*, vol. 80, no. Special\_Issue\_2, pp. S160-167, 2007.
- [15] D. Zhang, Y. Wang, L. Zhou, H. Yuan, and D. Shen, “Multimodal classification of Alzheimer’s disease and mild cognitive impairment,” *Neuroimage*, vol. 55, no. 3, pp. 856–867, 2011.
- [16] D. Zhang and D. Shen, “Multi-modal multi-task learning for joint prediction of multiple regression and classification variables in Alzheimer’s disease,” *Neuroimage*, vol. 59, no. 2, pp. 895–907, 2012.
- [17] E. L. Dennis and P. M. Thompson, “Functional brain connectivity using fMRI in aging and Alzheimer’s disease,” *Neuropsychology Review*, vol. 24, no. 1, pp. 49–62, 2014.
- [18] J. L. O’Brien et al., “Longitudinal fMRI in elderly reveals loss of hippocampal activation with clinical decline,” *Neurology*, vol. 74, no. 24, pp. 1969–1976, 2010.
- [19] E. Challis, P. Hurley, L. Serra, M. Bozzali, S. Oliver, and M. Cercignani, “Gaussian process classification of Alzheimer’s disease and mild cognitive impairment from resting-state fMRI,” *Neuroimage*, vol. 112, pp. 232–243, 2015.
- [20] X. Chen, H. Zhang, Y. Gao, C. Y. Wee, G. Li, and D. Shen, “High-order resting-state functional connectivity network for MCI classification,” *Hum. Brain Mapp.*, vol. 37, no. 9, pp. 3282–3296, 2016.
- [21] A. Khazaei, A. Ebrahimzadeh, and A. Babajani-Feremi, “Classification of patients with MCI and AD from healthy controls using directed graph measures of resting-state fMRI,” *Behav. Brain Res.*, 2016.
- [22] S. H. Hojjati, A. Ebrahimzadeh, A. Khazaei, and A. Babajani-Feremi, “Predicting conversion from MCI to AD using resting-state fMRI, graph theoretical approach and SVM,” *J. Neurosci. Methods*, vol. 282, pp. 69–80, 2017.
- [23] R. Armananzas, M. Iglesias, D. A. Morales, and L. Alonso-Nanclares, “Voxel-based diagnosis of Alzheimer’s disease using classifier ensembles,” *IEEE J Biomed Heal. Inf.*, vol. XX, no. X, pp. 1–7, 2016.
- [24] K. Supekar, V. Menon, D. Rubin, M. Musen, and M. D. Greicius, “Network analysis of intrinsic functional brain connectivity in Alzheimer’s disease,” *PLoS Comput. Biol.*, vol. 4, no. 6, 2008.
- [25] X. Zhao et al., “Disrupted small-world brain networks in moderate Alzheimer’s disease: A resting-state fMRI study,” *PLoS One*, vol. 7, no. 3, 2012.
- [26] E. J. Sanz-Arigita et al., “Loss of ‘Small-World’ Networks in Alzheimer’s Disease: Graph Analysis of fMRI Resting-State Functional Connectivity,” *PLoS One*, vol. 5, no. 11, 2010.
- [27] S. J. Teipel et al., “Multicenter stability of resting state fMRI in the detection of Alzheimer’s disease and amnesic MCI,” *NeuroImage Clin.*, vol. 14, pp. 183–194, 2017.
- [28] C. G. Yan, R. C. Craddock, X. N. Zuo, Y. F. Zang, and M. P. Milham, “Standardizing the intrinsic brain: Towards robust measurement of inter-individual variation in 1000 functional connectomes,” *Neuroimage*, vol. 80, pp. 246–262, 2013.
- [29] R. Gopalan, R. Li, and R. Chellappa, “Unsupervised adaptation across domain shifts by generating intermediate data representations,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 36, no. 11, pp. 2288–2302, 2014.
- [30] H. V. Nguyen, H. T. Ho, V. M. Patel, and R. Chellappa, “DASH-N: Joint Hierarchical Domain Adaptation and Feature Learning,” *IEEE Trans. Image Process.*, vol. 24, no. 12, pp. 5479–5491, 2015.
- [31] V. M. Patel, R. Gopalan, R. Li, and R. Chellappa, “Visual Domain Adaptation: A survey of recent advances,” *IEEE Signal Process. Mag.*, vol. 32, no. 3, pp. 53–69, 2015.



**INNO SPACE**  
SJIF Scientific Journal Impact Factor

Impact Factor:  
7.488

**ISSN** INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

 9940 572 462  6381 907 438  [ijircce@gmail.com](mailto:ijircce@gmail.com)



[www.ijircce.com](http://www.ijircce.com)

Scan to save the contact details