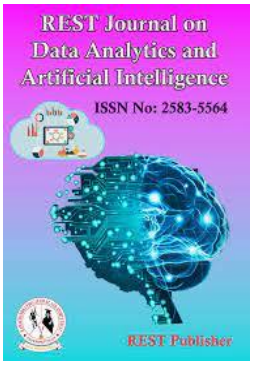
REST Journal on Data Analytics and Artificial Intelligence

Vol: 2(1), March 2023

REST Publisher; ISSN: 2583-5564

Website: http://restpublisher.com/journals/jdaai/

DOI: https://doi.org/10.46632/jdaai/2/1/5



Alzheimer's Disease Classification Using Deep Learning with Gabor Filter

*** Uma Maheshwari, S. Saranya, S. Bobby, M Suguna**

St.Joseph's College of Arts and Science for Women, Hosur, Tamil Nadu, India.

*Corresponding author Email: **umamahe996@gmail.com**

Abstract: *Alzheimer's disease (AD) is a gradual and irreversible neurodegenerative disorder with progression marked by lateralized brain atrophy. The hippocampus is the first part of the brain to experience atrophy in AD, which is also a prelude to the wider asymmetrical development of the human brain, albeit to a lesser level. Magnetic resonance imaging (MR) for structural purposes can identify the disease-induced structural alterations in the brain that helped identify AD. MR image attributes collected from the hippocampus regions are frequently employed for the AD classification task. Hippocampal asymmetries are not generally investigated in published approaches for picture classification, though. In this article, we suggest a novel method for classifying MRI images for AD by relying solely on hippocampal asymmetry characteristics. Alzheimer's disease (AD), the most prevalent type of dementia, is the main cause of brain problems with memory. The prodromal stage of this illness, termed as Mild Cognitive Impairment (MCI), requires appropriate detection and diagnosis, classification procedure.*

Key words: *Alzheimer's disease, Mild cognitive impairment, Gabor filter, Convolutional Neural Network.*

1. INTRODUCTION

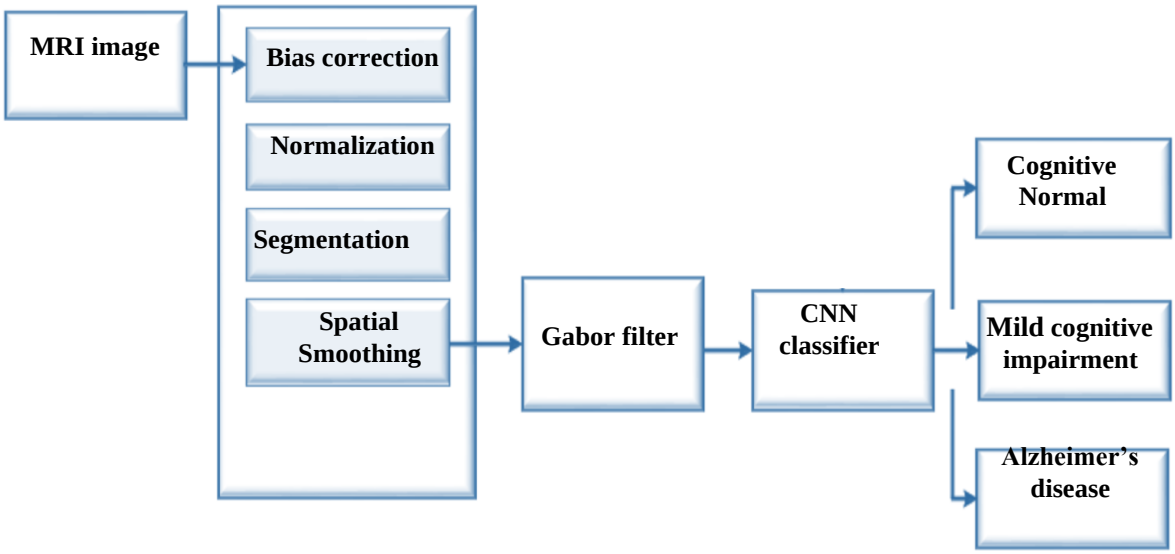
Alzheimer's disease (AD) is a progressive and irreversible neurodegenerative disease predominantly affecting the elderly and corresponding up to 80% of all dementia cases [1]. As advancing age is the most significant risk factor for developing AD, with the increase in life expectancy, this disease has become one of the most significant health problems in the world [2,1]. Histologically, AD is associated with an excessive accumulation of amyloid-b protein on extracellular plaques and deposition of hyperphosphorylated tau protein in intracellular neurofibrillary tangles [3], which can lead to the death of the neurons. The human brain exhibits a high level of structural hemispherical symmetry that decreases with aging [4,5], and it is even more acutely affected by the presence of pathological conditions [6], which is the case of AD. The structural hemispherical asymmetry progression in AD is often characterized by regional gray matter loss with the degradation process affecting first and more severely, the left-hemisphere regions [7]. In Alzheimer's, several studies have been exploring the degree of brain symmetry loss in magnetic resonance (MR) images. The AD diagnosis procedure has been enhanced by the introduction of a non-invasive approach known as the computer-Aided. Diagnosis (CAD) system [11]. With good performance, CAD systems provide more accurate diagnosis and early information. In clinical practice, neurologists benefit greatly from the CAD system [25]. Furthermore, in recent years, accurate CAD results have become critical for providing neurodegeneration care in the early stages of AD. Previously, the CAD is designed to extract the low-level features from neuroimaging data also it considered as The main impact of this paper is the design of a CAD system to estimate the classification performance on the grey matter of structural 3D MRI for AD. The SPM tool is used to initially bias correct, normalize, and segment MR images. After smoothing, the Gabor filter is used to extract texture features from grey matter images of the brain. Finally, an optimal DNN for classification is proposed in order to achieve maximum classification accuracy. The optimal DNN is created by selecting the optimal weight with an ESSA and dynamically adjusting the parameter with fuzzy logic.

2. RELATED WORKS

A multivariate approach was developed by Yudong et al. [30] to detect AD. They aimed to diagnose the brain's MR images automatically using a new machine learning system. In which, a stationary wavelet entropy was used to extract the textural information of the brain image. This method utilized four-stage decomposition to provide thirteen stationary wavelet entropy (SWE) features. Then, the Neural Network with a single hidden layer was used to classify the image. PP-PSO (Predator-Prey Particle Swarm Optimization) increased the stability of this method. Ruoxuan Cui and Manhua Liu [7] used the benefits of both convolutional and recurrent neural networks to diagnose AD by longitudinal analysis of structural MR images. Initially, they constructed Convolutional Neural Network (CNN) to perform classification by learning MRI's spatial features. Next, a recurrent Neural Network (RNN) was constructed with a cascade structure of three bidirectional gated recurrent units (BGRU) layers to extract longitudinal features for AD classification. The optimal performance was achieved by joining the spatial and longitudinal disease classifiers. Additionally, the longitudinal analysis with RNN was modeled at various time points using imaging data information on genotype and phenotype. In particular, feature-wise importance was discovered and structured feature selection and fusion from diverse modalities were made easier. The kernels were classified in accordance with the modalities, and each feature was then represented by a distinct kernel. The best possible kernel presentation of multimodal elements was combined using a data-driven methodology. Using data from the ANDI database, the scientists assessed the proposed research and clearly identified the brain areas and SNPs associated with AD. Alzheimer's disease diagnosis using an MRI scan. Yet, the Gabor features have very high dimensions. So, by calculating the statistics of mean and standard deviation for each of the three projections of the MRI image, the dimensionality of the Gabor feature vector is decreased. This effectively conveys the MRI image's texture feature. & An ideal DNN is suggested to increase the Alzheimer's disease diagnosis system's classification accuracy. Because of their direct connection to the objective function, the weight parameters of the DNN model must be carefully chosen to ensure maximum efficacy. The categorization accuracy in this work

3. PROPOSED METHODOLOGY

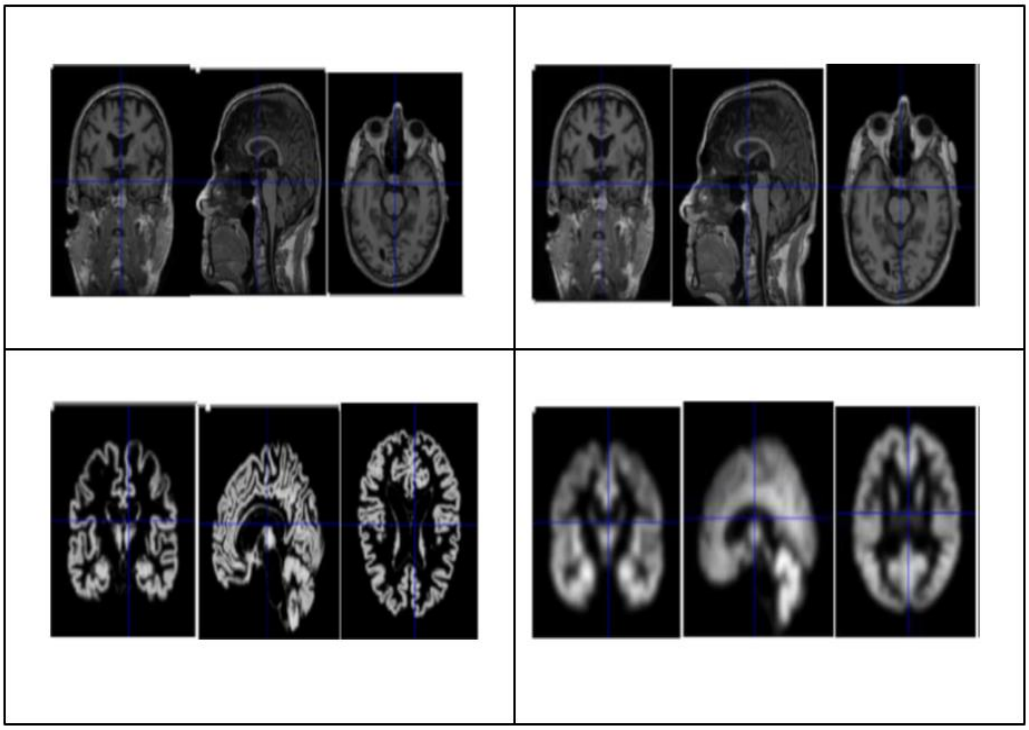
A computer-aided diagnosis (CAD) is proposed in this paper to detect AD in the early stage. This system involves three levels of processing Initially, MRI data pre-processing is done by Statistical Parameter Mapping (SPM) tool. All images are corrected for bias field in similarities also they are normalized and segmented into the cerebrospinal fluid (CSF), white matter (WM), and Gray matter (GM). Most of the higher-order functions of the brain are linked by the network within GM. The brain damage caused by Alzheimer's are related to higher-order parts of the brain. Next to the segmentation, spatial smoothing of GM images is done by Gaussian filtering. This work only uses GM images for further processing. Gabor filter in three scales and eight orientations is used to extract



Pre-processing phase: In this study, we used the Non-Local Means technique [41] to reduce noise in all MR images, followed by bias field correction with the N4-ITK technique [42] and image intensity standardization with the histogram matching algorithm was proposed in [43], with the T1-w template image from the NAC dataset [39] used as a reference image. We then used spatial affine transformations provided by the Nifty-Reg image registration tool [44] to align the study (ADNI) images to the NAC T1-w template image. Then, using the ROBEX [45] technique, we extracted the brain from all of the images. Finally,

we performed a deformable image registration [46] between the NAC T1-w framework and all research images to properly delimit the hippocampal regions. Unlike the previous image registration, we used each study image as a reference to obtain the transformation, which we then applied to the presented adult neurogenesis mesh designs to define the regions of interest.

Gabor filter: To identify the characteristics of the GM image, a 3D Gabor filter with three scales and eight orientations is used [12]. To represent texture features on a slice-by-slice basis, the standard deviation and mean of Gabor magnitude are calculated. A linear filter is already known as a Gabor filter. This Gabor filter modulates complex sinusoidal signals in conjunction with a Gaussian envelope. The Gabor filter provides frequency resolution and optimal joint space.



To avoid artifacts on the resultant filtered image caused by the abrupt boundary truncation, the sorting process was performed using the brain hemispheres encephalon (right and left flipped). The hippocampal binary mask was also used to limit the analysis's region of interest

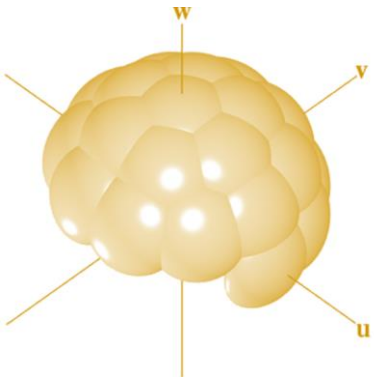
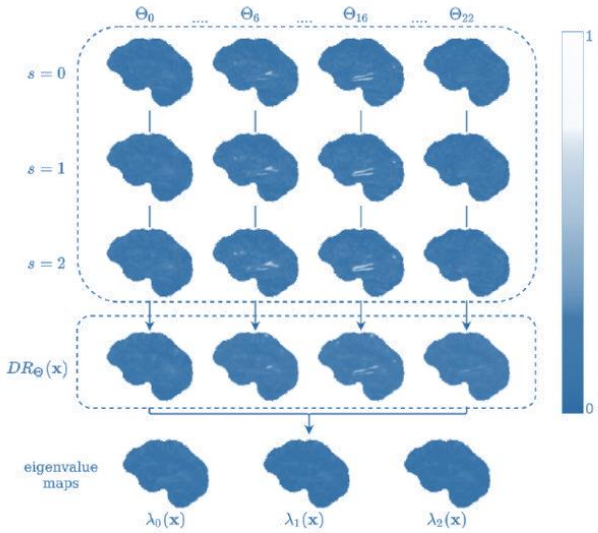


Illustration of the bank of 3-D log-Gabor filters used in this work

Image classification: We used asymmetrical attributes computed for each statistical measure and passed the ANOVA test to train SVM classifiers with different kernel types (linear, polynomial, and radial basis function (RBF)) for image classification in the CN MCI and CN AD diagnosis groups. We classified the attributes individually and with all possible combinations of horizontal concatenations. Furthermore, because we have a slightly unbalanced Fig. 3. The sagittal brain view's filter responses are represented visually. Using the class weight4 parameter from the scikit-learn python library, we automatically adjusted the

model weights to be inversely proportional to class frequencies in the input data in K.M. Poloni et al. Neurocomputing 419 (2021) 126-135 130 dataset



Our statistical analysis of the attribute measures revealed no statistically significant mean differences between groups; thus, because our goal was to demonstrate the predictive power of asymmetry attributes, we conducted our classification experiments using only the statistical measures that survived ANOVA, namely the mean, variance, and kurtosis measures. Furthermore, we restricted our classification to CN MCI and CN AD classes because variance was the only measure that revealed a significant mean difference between the MCI AD classes.

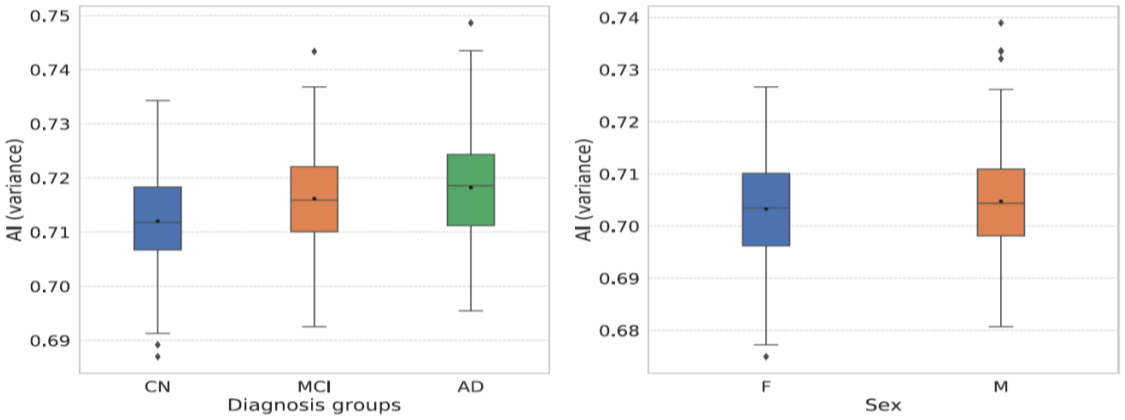
Experimental results and discussions: In this part, the experimental design and its results are briefly explained. This part is divided into three subsections: performance evaluations, evaluation metrics, and explanation of the data collection. The first one provides information on the experimental dataset that we used in our research and the performance prediction measures. The second subsection of the suggested method is explained, and the third one discusses the quantitative results and comparisons with more sophisticated methods.

Statistical analysis

Asymmetry				**ANOVA**	
Index	**CN**	**MCI**	**AD**	**p-value**	**post hoc**
Mean	0:6332 0:0099	0:6389 0:0073	0:6382 0:0075	< 0:001	CN < MCI, CN < AD
Variance	0:7120 0:0083	0:7162 0:0088	0:7182 0:0095	< 0:001	CN < MCI, MCI <
Kurtosis	0:6776 0:0716	0:7099 0:0803	0:7165 0:0869	< 0:001	AD, CN < AD CN <
Skewness	0:3198 0:0313	0:3235 0:0321	0:3209 0:0315	0:399	MCI, CN < AD Not significant

We tested the significant differences of our AI statistical measures for diagnosis groups and sex differences.

AI vs. diagnosis groups: The AI values, the ANOVA p-values, and the conclusions after performing the Tukey's HSD post hoc test, we summarise the ANOVA results for each statistical measure in the diagnosis groups. These analyses revealed that the skewness has a p-value greater than 0:05, indicating that there was no significant difference in mean values between the diagnosis groups according to this statistical measure. The pairwise diagnosis groups CN MCI and CN AD displayed statistically significant differences in all cases, but the skewness, according to Turkey's HSD comparison. Only the variance measure revealed statistically significant differences for the MCI AD case in the ANOVA test. In light of our post-roc findings, the variance measure demonstrated a clear asymmetrical trend,



AI vs. sex: gives the mean and SD of the AI values for sex analysis. The p-values by gender have statistically significant results. Except for the skewness (p-value > 0.05), there was a difference in every instance (p-value 0.05). Additionally, we see that for measures passing the ANOVA test, female group AI values are marginally lower. The boxplot of the variance measure for the population divided by sex is shown down

CONCLUSIONS AND FUTURE WORK

In this paper, we propose a new method for classifying MR images for AD by only using structural white matter asymmetrical attributes from directional Gabor filtration. To do this, we created a new asymmetry index and tested each proposed statistical attribute using it to see if it could be useful for determining white matter asymmetries and, consequently, if it could help with the diagnosis of AD In our research, the CAD is designed with the best DNN classifier to classify Alzheimer's disease, MCI, and cognitive normal. The MRI's texture features are extracted using the Gabor filter following preprocessing. This filter picks up image details at various frequencies and orientations. The best DNN classifier uses these features to diagnose AD. ESSA with dynamic parameter adaptation improves performance by selecting the best weight parameter. The suggested method successfully identifies a patient's AD, increasing the effectiveness of medical care.

REFERENCES

[1]. Ahmed OB, Benois-Pineau J, Allard M, Amar CB, Catheline G, Alzheimer's Disease Neuroimaging Initiative (2015) Classification of Alzheimer's disease subjects from MRI using hippocampal visual features. Multimed Tools Appl 74(4):1249–1266

[2]. Altaf T, Anwar SM, Gul N, Majeed MN, Majid M (2018) Multi-class Alzheimer's disease classification using image and clinical features. Biomed Sig Process Control 43:64–74

[3]. Babulal GM, Quiroz YT, Albensi BC, Arenaza-Urquijo E, Astell AJ, Babiloni C, Bahar-Fuchs A et al (2019) Perspectives on ethnic and racial disparities in Alzheimer's disease and related dementias: Update and areas of immediate need. Alzheimer's Dement 15(2):292–312

[4]. Bartos A, Gregus D, Ibrahim I, Tintěra J (2019) Brain volumes and their ratios in Alzheimer´ s disease on magnetic resonance imaging segmented using Freesurfer 6.0. Neuroimaging, Psychiatry Research

[5]. Bilderbeck AC, Penninx BWJH, Arango C, van der Wee N, Kahn R, Rossum I W-v, Hayen A, Kas MJ, Post A, Dawson GR (2019) Overview of the clinical implementation of a study exploring social withdrawal in patients with schizophrenia and Alzheimer's disease. Neurosci Biobehav Rev 97:87–93

[6]. Çevik A, Weber G-W, Eyüboğlu BM, Oğuz KK, Alzheimer's Disease Neuroimaging Initiative (2017) Voxel-MARS: a method for early detection of Alzheimer's disease by classification of structural brain MRI. Ann Oper Res 258(1):31–57

[7]. Cui R, Liu M, Initiative A's DN (2019) RNN-based longitudinal analysis for diagnosis of Alzheimer's disease. Comput Med Imaging Graph 73:1–10

[8]. Alzheimer's Association, Alzheimer's disease facts and figures, Alzheimer's & Dementia: The Journal of the Alzheimer's Association 15 (3) (2019) 321–387.

[9]. J. Zhang, M. Liu, L. An, Y. Gao, D. Shen, Alzheimer's disease diagnosis using landmark-based features from longitudinal structural MR images, IEEE Journal of Biomedical and Health Informatics 21 (5) (2017) 1607–1616.

[10]. H.S. Bassiony, M.B. Zickri, H.G. Metwally, H.A. Elsherif, S.M. Alghandour, W. Sakr, Comparative histological study on the therapeutic effect of green tea and stem cells in Alzheimer's disease complicating experimentally induced diabetes, International Journal of Stem Cells 8 (2) (2015) 181–190.

[11]. [R.M. Lucarelli, R.T. P., R. McColl, K. Hulsey, C. Ayers, A.R. Whittemore, K.S. King MR imaging of hippocampal asymmetry at 3T in a multiethnic, populationbased sample: results from the Dallas Heart Study, American Journal of Neuroradiology 34 (4) (2013) 752–757.

[12]. X. Long, L. Zhang, W. Liao, C. Jiang, B. Qiu, Alzheimer's Disease Neuroimaging Initiative, Distinct laterality alterations distinguish mild cognitive impairment and Alzheimer's disease from healthy aging: statistical parametric mapping with high resolution MRI, Human Brain Mapping 34 (12) (2013) 3400–3410.
[13]. S.X. Liu, Symmetry and asymmetry analysis and its implications to computer-aided diagnosis: A review of the literature, Journal of Biomedical Informatics 42 (6) (2009) 1056–1064.
[14]. A.W. Toga, P.M. Thompson, Mapping brain asymmetry, Nature Reviews Neuroscience 4 (1) (2003) 37–48.
[15]. B.A. Ardekani, S.A. Hadid, E. Blessing, A.H. Bachman, Sexual dimorphism and hemispheric asymmetry of hippocampal volumetric integrity in normal aging and Alzheimer's disease, American Journal of Neuroradiology 40 (2) (2019) 276–282.