Efficient Alzheimer's Disease Segmentation on MRI Image Classification Using ML

Mohammad Aftab Ahmed[1], Meka Kesavardhan [2], Dr.S.Jancy[3], Dr.L.Sujihelen[4], Dr.Mercypaulselvan [5], Dr. Viji Amutha Mary.A[6]
[1,2]Student,Computer science and Engineering,
Sathyabama Institute of Science and Technology, Chennai, India
[3,4,5]Assistant Professor, Department of Computer Science and Engineering,
Sathyabama Institute of Science and Technology, Chennai, India
Mailid: jancy.cse@sathyabama.ac.in

Article Info
Page Number: 550 - 561
Publication Issue:
Vol 71 No. 3s2 (2022)

Abstract

In the recent past, Computer Aided Diagnosis (CAD) technologies plays vital role in computer vision in the field of medical diagnosis. Few nervous disorders and describing compulsive area are analyzed, and structural human organ brain is undergone for research with the support of magnetic resonance imaging (MRI) imaging. Standard classification machine learning algorithms are being used in analysis for the automated diagnosis of Alzheimer's disease (AD), and machine learning-based methods have become a common alternative for AD diagnosis. State-of-the-art approaches that take diagnosis into account have been shown to be more accurate than conventional evaluation. Obtaining information from various approaches, on the other hand, is time-consuming and costly, and certain methodologies could have energy adverse effects. Our research is based on computerized automated Magnetic Resonance Imaging (MRI). In this research, automatic object segmentation and classification of Alzheimer disease (AD) is proposed. The collected MRI brain images contain various noises such as salt and pepper noise, speckle noise and Gaussian noise. The 2D Adaptive Median Filter (AMF) is proposed to filter all types of noises. The filtered image is further enhanced to improve the quality of image. The significant Edge Preservation-Contrast Limited Adaptive Histogram Equalization (EP-CLAHE) algorithm is used to improve the quality of image in terms of contrast and brightness. The AD region from MRI brain image is further clustered using Efficient Fuzzy based C Means Clustering (EFCMC). The clustered AD region is further segmented using Adaptive Otsu Thresholding (AOT). The significant features are calculated using Gray Smooth Co-occurrence Vector (GSCV). The 1 Dimensional Iterative Convolutional Neural Network (1D I) is used to classify the AD stages. The experimental results show that the proposed methodology performance is better than conventional methodologies.

Article History
***Article Received**: 28 April 2022*
***Revised**: 15 May 2022*
***Accepted**: 20 June 2022*
***Publication**: 21 July 2022*

Keywords: - Computer Aided Diagnosis (CAD), Alzheimer's disease (AD), magnetic resonance imaging (MRI), 2D Adaptive Median

I. INTRODUCTION

In human disorder Alzheimer's disease (AD) and moderate cerebral dysfunction, a prodromal level of human AD, the brain area is one of the first to be affected. Hippocampal hypertrophy is a commonly used and approved screening tool for AD diagnosis. The majority of existing approaches for hippocampus analysis use magnetic resonance imaging images to measure structure and volume characteristics (MRI). The areas around the brain, on the other hand, may be related to Alzheimer's disorder, and the sensory characteristics of the hippocampal area are crucial for disease detection [1]. One of the deep learning techniques is the ability to find out AD based on automated digital imaging techniques. We are attempting to classify convolutional neural network (CNN) behaviors as they transition from 2D to 3D structure by taking into account theoretical framework from existing researches. The objective of this image analysis is to inspect the concert from a quantity of CNN methodologies used in MRI or PET segmentation and classification responsibilities for AD estimation, as well as to summaries its properties using a range of variables that can be tweaked and modified. There are several frameworks to choose from; nevertheless, we are evaluating a simple architecture with a transition in the processing location depends on the matrix and strides of the convolution operation [2]. Three structural MR image factors are provided in the implemented procedure with protocol: brain image region based on GSCV vector, and Gabor function. These technologies can extract both 2D and 3D data from brains, and the research findings suggest that feature diffusion can improve accuracy. We also look at features mixture association approaches and use the regression coefficients principle to develop the SVM-RFE algorithm. The suggested method's efficacy is shown by comparative tests on the public AD Neuroimaging Initiative registry [3]. AD is a progressive and curable neuro-developmental disorder, and accurate intervention is important for care professionals to respond successfully. Noninvasive in human brain imaging including MRI and CT are frequently applied to diagnose or control disorder development and medication effects. In this regard, the question of developing computer-aided diagnostic (CAD) approaches to distinguish human AD images from those of healthy brains has received much interest in coming days [4]. Object segmentation is one method for determining these disabilities from an MRI. Object analysis is the division of dividing an image into distinct regions. Different tissues on the image are defined by these areas. As a result, a fascinating method for neurological analyses emerges. As a result, studying the segmented picture will help determine the diagnosis of certain brain diseases. A segmentation approach based on a controlled version of the Self-Organizing Maps is used in this analysis (SOM). In addition, a possibility segmentation approach is proposed in order to increase the differentiated image's quality [5]. Machine learning methods are increasingly being used to identify and/or forecast the occurrence of certain neurological diseases, including AD; this may be due to the availability of data and efficient processors available. The aim of this project was to develop a reliable classification scheme for Alzheimer's disease (AD) and cognitive decline that could be used to compare safe monitors in a low-cost network with deep structure and computation. The databases used in this analysis were obtained from the AD neuroimaging scheme [6]. Cells eventually do not die as human regular control synthesis ceases, and these irregular cells form a lump of tissue known as a cancer. Big biochemical devices like MRI, PET-CT, and MG devices are used to detect tumors. There have been several experiments in the last generation on the discovery of tumors using MRI. Brain cancer diagnosis detects the exact location of the cancer as well as its size. On Image features, methodologies are used to retain information data. Deterioration, contrast adjustment, and wiener filter are three of these methods. The aim of investigate is to create an image analysis algorithm for detecting cancer on Image data [7]. Technological advancements and artificial intelligence may aid surgeons in tumor diagnosis without the use of invasive procedures. The deep neural network is a computer algorithm that has shown significant results in object classification and segmentation (DNN). We propose a new Classification algorithm for classifying three different types of tumors. The built network was checked on T1-weighted contrast-enhanced MRI images, and it was found to be simpler than pre-existing pre-trained networks. The network's accuracy was assessed using four techniques: two repositories and a hybrid of two 10-fold border approaches [8]. The benefits of MRI technology include no radiation exposure to the human body, successful imaging of complex systems, and the ability to do computed tomography imaging in any position. As a result, MRI brain tumor images are often used by doctors to compile and analyze brain tumors [9]. A modern threshold-based segmentation approach is used to present an automated brain tumor detection scheme. The suggested segmentation approach is built on a beta-mixture model and training automata working together (LA). Each Beta functions represents a single segment class, and the input parameters for differentiation are calculated by intersecting two neighboring Beta compounds. Texture parameters are used to extract features. As classification models, support vector machines (SVM), K-nearest neighboring (KNN), and random forests (RF) are used [10].

II Related Works

Tinu Varghese etl al [11] has proposed to estimate better differentiate between treated patients and MCI and aged monitors, researchers are evaluating the precision of GM and CSF full model. Using real MR frames, we investigated the potential of BP-ANN to detect physical differences in various regions of brain images. The technique uses texture features for skull shedding and the Gabor filter to data comprises. In comparison, it is found significant trend toward increased GM harmonic distortion in the MCI community. Jyoti Islam et. al

[12] has proposed brain MRI data mining and developed a DNN for AD diagnosis. About the fact that most standard systems use classification model, our model can differentiate between different stages of Alzheimer's disease and produces excellent early intervention outcomes. MRI is a common practice in research experiments for diagnosing Alzheimer's disease. The relationship among AD MRI data and regular healthy MRI data in older people causes AD complicated to comprehend. Kanghan Oh et al. [13] presented their analysis, which uses MRI to include a method for allowing end-to-end learning of a regression convolutional neural network (RCNN) system for visual feature image recognition (AD vs. control samples, mild brain loss vs. controlled brain disorders, controlled moderate mental retardation) and visualizes the outcomes in terms of t. The suggested approach uses directed supervised learning for the binary classification and fully connected layers layers auto-encoder (CAE)-based unattended testing for the AD vs. NC classification task. U. Rajendra Acharya [14] has proposed this research to create a Computer-Aided-Brain-Diagnosis (CABD) device that can tell whether a brain scan indicates AD. The approach classifies images using MRI and other data mining techniques. MRI is a non-invasive technique that is often used in laboratories to investigate neurological issues. The T2 scanning

series is used to collect images. Smoothing, image segmentation, Normal distribution dependent feature collection, and k-Nearest Neighbor (KNN) based grouping are among the numerical techniques used in the framework. Ben Ahmed et. al [15] has proposed the graphical encoding system and pattern recognition study were used to distinguish three types of subject areas: normal corrections (NC), mild neurological problems, and D). In each piece of all three brain representations, the technique uses circular harmonic features to derive image patterns from the cancer's most active areas: hip-pocampus and posterior gran canaries. The characteristics are calculated using the Bag-of- Visual-Words methodology to establish one attribute by the brain (subject). A full 3D description of brain ROIs is converted into a 1D symbol, a matrix multiplication histogram. Spectrum mathematics, suggested by Ali M. Hasan et al. [16], validates the concept of balance obeisance articulated in terms of the Marsaglia method (usually used to represent two different objects, etc.). The result is then used to extend local features in order to acquire the LBP's essential entropy (FELBP). QELBP and modeling protocols DL operations are combined in the proposed study to derive characteristics from MRI neuro-imaging. The QELBP–DL feature approximation of the brain in MRI brain activity is used to improve the detection of MRI brain imaging because of its superior performance. Hong Zheng et. al [17] has proposed to enhance the margins of brain MRI by integrating kernel function from another better contrast object. In a relevant impacts, multi-contrast artifacts are thought to have the same modulation orientation. We decided to create a regression value relation model among similar images obtained in order to recover a high-resolution image from its high production. Image patches' resemblance is used to approximate strength parameters, resulting in a more reliable restored image. To improve the image quality even further, an iterative back-projection lter is added to the restored image.

D. Poornima et. al [18] has proposed hybrid K means Fuzzy C Means clustering techniques to segment the bone cancer region from the x ray images. The method of modifying a photographic image so that the effects are best suited for viewing is known as image improvement. It's used to increase the image's accuracy. To improve the graphic, the PCA is used. Adaptive Mean Adjustment (AMA) is a digital image processing method for enhancing contrast enhancement. K means and Fuzzy C Means (FCM) convergence are two clustering algorithms that can be used in imaging techniques. K means and FCM properties are combined in the hybrid segmentation. Following the automated automatic seed collection, K indicates clustering is used. In hybrid segmentation, the various frequency pixels are grouped together using FCM. Following clustering, a standard is used to determine the region of interest for bone cancer segmentation. Vedanarayanan et. al [19] has proposed a Precise Medical Bed (PMB) can be used to provide an effective alternative for the most difficult problems in a precise and reliable manner, based on time and expense considerations. PMB could guide itself across the route and conquer any challenges in the healthcare facility using the suggested approach. PMB's front motors assist the bed in turning right or left, while the handlebars assist the bed in moving forward and reverse. To detect any obstacles, ultrasonic wireless sensors are mounted on front side. The PMB is run on a path in the laboratory, and the pace of the PMB is adjustable. G. Arulselvi et. al [20] has proposed an innovative algorithm PA-PIC (Precision Agriculture for Pest Identification and Classification) is a proposal for identifying and classifying harmful pests and beneficial insects in farming practices without causing crop damage. Using a sensors to detect and recording device, the frequency response of various pests and insects is measured for PA-PIC. The noise that occurs in conjunction with the accelerator sensor must be correctly filtered. Evolutionary audio signal amplification is used to increase the efficiency of the acoustic signal by restoring and enhancing it, and responsive filters are used to eliminate whole noise harmonic currents from noisy sound source.

The experts are also working on predicting brain Alzheimer's disease and patients' odds of recovery. Prognostication, grouping, and segmentation analysis are all possible with MRIs in the field of cognitive AD science. There are two types of AD defects in the brain: benign or malignant defects. In panel data regression models for estimating overall survival in individuals with severe cortical AD, the 3D- convolutional neural network model is effective. For improved precision, a 1D CNN is combined with a Support Vector Classifier. During the analysis, the structure, position, strength, and deep features of AD cells are examined. Simple, full back, and task duration times for elevated gliomas AD patients vary. A hybrid method integrating CNN and classification techniques achieves the highest prediction precision. Deep function discovery and description is a critical step in predicting and diagnosing Alzheimer's disease using radiation MRIs. The picture attributes are specifically linked to relevant biological features that provide contextual details that radiologists are acquainted with. The aim of brain AD differentiation is to remove the AD area from images for diagnosis and detection of brain AD. For MRI brain segmentation, the DL approach is recommended. Some of these machine learning techniques rely on various image data for testing, which is expensive, moment, and requires medical knowledge. Deep learning techniques for segmentation are trained using two data sets: completely compiled and poorly compiled data.

For brain cancer or tumor segmentation on MR images, the traditional fuzzy c-means (FCM) clustering approach is the most commonly used unsupervised regularization technique. The traditional FCM, on the other hand, has a high computation time frame and is vulnerable to cluster centers. To overcome the disadvantages of traditional FCM, an innovative FCM method was used. The model is created by combining the image's grey level dissemination of information with a new optimization problem that guarantees cluster consistency and compact size. **Disadvantages of existing methodology** K-Value is hard to estimate, It won't match well with the large group, The total groups may vary depending on the initial clusters, It does not fit well for groups of various sizes and densities (in the original information). Many reviews are presented in literature by many researchers with respect to ecommerce applications in different domain [21][22][23]. This analysis will surely enable the researchers with the idea of deep learning technique in different applications [24][25][26][27]. Different issues also discussed in machine learning applications [28][29][30].

III PROPOSED METHODOLOGIES

It is presumed that early detection of neurodegenerative disorders in the human brain is critical for optimal diagnosis and services. This could include identifying anatomical and functional differences in the brain, such as asymmetric information between the cerebral hemispheres. Computational algorithms can predict changes and be used to diagnose dementia and Alzheimer's disease (AD) in its initial stages, as well as to control the disease's progression.

Proposed Algorithm 1 – Image Restoration, Image De-noising using 2D Adaptive Median Filter

Proposed Algorithm 2 – Image Segmentation , Efficient Fuzzy based C Means Clustering (EFCMC) and Otsu Thresholding (AOT)

Proposed Algorithm 3 – Image Feature Extraction,Gray Smooth Co-occurrence Vector (GSCV)
Proposed Algorithm 4 – Classification, Classification using Convolutional Neural Network

The MRI brain image consist of various noises such as salt and pepper noise, speckle noise, random noise and Gaussian noise. All the noises should be adaptively filtered using proposed filtered called 2D Adaptive Median Filter (2D-AMF). The filtered image is enhanced to improve quality. The contrast and brightness are improved by applying Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm. The Efficient Fuzzy based C Means Clustering (EFCMC) technique is applied to cluster AD affected region from the MRI brain image. The clustered pixels are segmented using Adaptive Otsu Thresholding (AOT). The statistical features are calculated from the segmented image using Gray Smooth Co-occurrence Vector (GSCV).

SYSTEM MODEL

To remove mixed noise, a 2D Adaptive Median Filter (2D AMF) is more efficient than a window function. For a standardized or Gaussian noise model, linear processing techniques are optimal, implying that the noise composition in actual signals is simplified. Where the length of the window size is less than half the length of the window size, 2D AMF effectively suppresses noise from the signal. A valuable signal is a non-changing data set (in the case of a one-D signal) or data series (in the event of two-dimensional monitoring). The 2D AMF algorithm is used to manipulate time measurements in a sliding window that contains a certain amount of signal samples locally. The samples that are distributed in each location of the window size are ranked and according rising or reducing values. In a ranking list, the average is a set of observations in the beginning of the page.

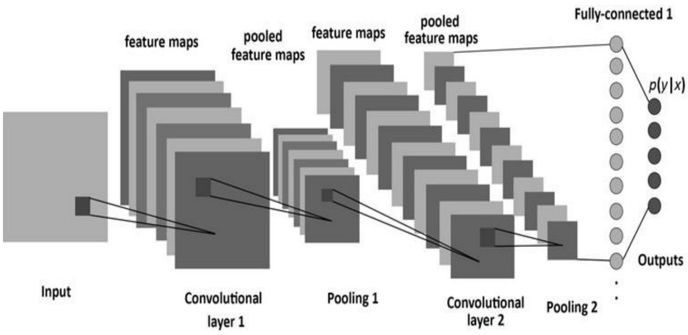

Figure 1: Proposed architecture diagram

Figure 1 shows proposed architecture diagram. In MRI images, standard noise appeared as a slight random change in the amplitude of a single pixel or a select minority of pixels. These variations may be significant enough to cause incorrect segmentation. A spatial domains low-pass filter has been used, which had a detrimental impact on the noise smoothing linear picture improvement responds. As a result of the Gaussian filter's ideally low value for, its output was assessed visually.

To obtain the best differentiation in a spatial domain with differing cluster levels of intensity and configurations, the Efficient Fuzzy based C Means Clustering (EFCMC) with Adaptive Otsu

Thresholding (AOT) approaches are used. Fuzzy clustering divides a group of data objects from an Image captured (p1, p2, p3,..., pm) into k (m) clusters, reducing overall variance. Each piece of data in the feature vector has an extent of belonging to its own category (aij). In comparison to the positions in the group edge, the points nearest to the centroids have a greater degree.

The aij correlation coefficient by being in the jth region is given for a data set I allocated to group j. The aij parameter number is always one. The fuzzy aided clustering technique is based on the prioritisation of the corresponding optimization problem (Fw) with respect to A (fuzzy k separation) and B (k set of groups):

$$F_w(A,B)=\sum_{j=1}^{m}\sum_{i=1}^{k}(a_{ij})^w d^2(P_j,B_i);\ k\leq m \quad (1)$$

where, w(>1), is the allowance proponent performances as a regulator factor for the fuzziness in a_{ij}, P_j is the j[th] argument in the feature selection matrix of N-dimensional domain, B_i could be the middle point for grouping i, a_{ij} is the high degree of clustering membership of the image pixel P_j in group i, $d^2(P_j,B_i)$ is the distance quantity among P_j and B_i, m and k signify the quantity of information stragegy points and the quantity of groups, correspondingly.

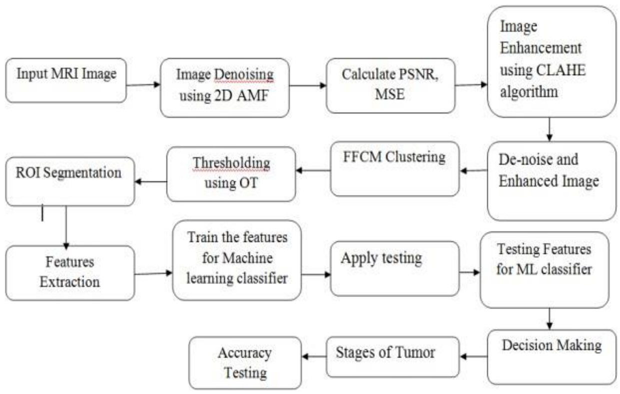

Figure 2 shows the architecture diagram of 1D Convolutional Neural Network

As previously stated, the proposed CNN and output data were made using an ensemble classification methodology with the slice train/test subgroups specified in the database. The proposed classifier was tested for a total of 80 iterations from each fold initialization using an Extreme Gradient Descent (SGD) optimization method with a beginning kernel function of 0.005 and an acceleration factor of 0.9 on each fold approximation. In comparison, every 20 epochs, we used an empirical back propagation decline. The value for absenteeism was set to 0.5.

IV RESULTS AND DISCUSSION

In this section, various results obtained using MRI brain image processing proposed algorithms. All of the information we used in our research came from a public archive. T1 weighted MRI and a 1.5 T detector were used to create the data samples. A total of 170 people were participated in this study, including 54 people with Alzheimer's disease (AD), 58 people with moderate cognitive problems (MCI), and 58 healthy people.

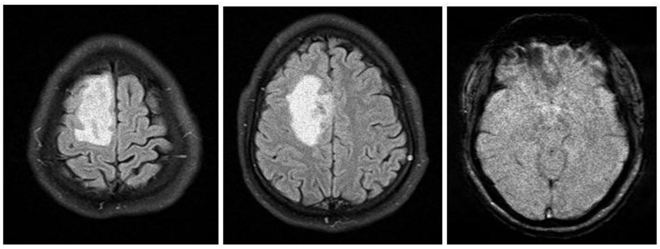

Figure 3. Input images of MRI brain image database

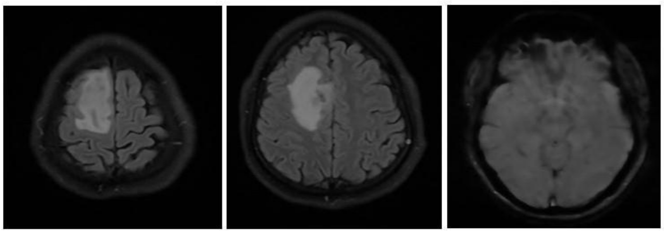

Figure 4 . Filtered image using 2D-Adaptive Median Filter

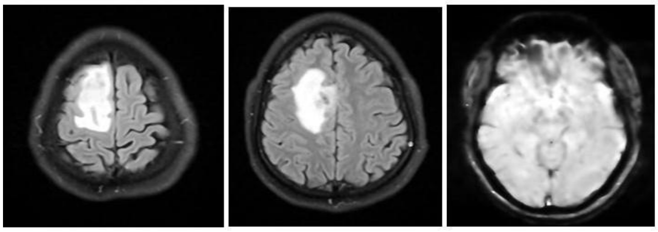

Figure 5. Enhanced images using CLAHE algorithm

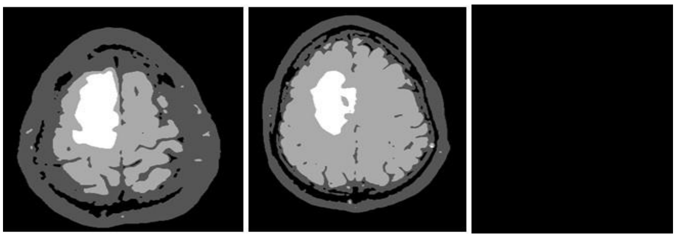

Figure 6: Clustered images using Efficient Fuzzy based C Means Clustering (EFCMC)

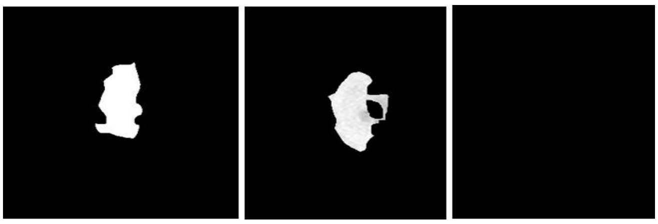

Figure 7: Thresholding (Segmented) image using Adaptive Otsu Thresholding technique

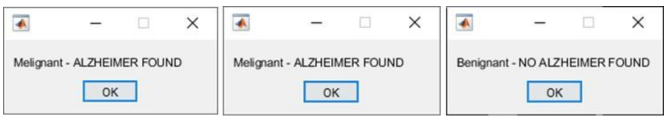

Figure 8: Classifier Output

Figure 3 show input images of MRI brain image database. The proposed approach has positive success for AD diagnosis, as shown by research observations and comparisons on weighted functional MR images from the MRI database. Figure 4 show filtered images. Figure 5 show quality improved image. The contrast and brightness are improved. The importance of MR object per-processing in creating positive effect of the image for further analysis cannot be overstated. Typically, the captured images in the database are of such low quality that they involve noise reduction and quality evaluation. The acquired image in the database is transformed into a two-dimensional vector and the object is transformed from RGB to grey scale image in the pre- processing stage. A 2D Adaptive median filter is used to exclude the image's distortion. Figure 6 shows the AD affected pixels clustered images. Figure 7 shows threshold image of AD region. EFCMC is conducted for 13 clusters based on the grey level pressure. Clustered images are those that have the smallest grey level and are distinguished from one another by their image intensity. The CNN is used to classify the given image benign of malignant. These can be assessed using the true positive, false positive, true negative, and false negative values. Both photos in the collection were checked in this study to determine the system's precision, sensitivity, and specificity. The following four characteristics are used in the estimation of the device precision, sensitivity, and specificity.

TABLE 1 QUALITY MEASUREMENT FOR IMAGE

S. No	**Methodology Used**	**PSNR in dB**	**MSE**
Image 1	2D Median Filter	36.39	10.39
Image 1	2D Hybrid Median Filter	38.76	4.39
Image 1	2D Adaptive Median Filter	52.387	0.03

TABLE 2 GSCV FEATURE EXTRACTION

S. No	**GSCV Features**	**Alzheimer Disease (AD) Image**	**Normal Image**
4	Cross Correlation	0.9387	0
5	Cluster Prominence	4.3989	8.3989
6	Cluster shade	4.9543	7.3989
7	Energy	4.9896	7.3987
8	Homogeneity	2.3989	8.3987
9	Dissimilarity	8.3989	9.3986
10	Energy	3.9877	8.3878
11	Maximum Probability	0	1

TABLE 3: QUALITY MEASURE OF CLASSIFIERS

Types of methodology	**Accuracy in %**	**Specificity in %**	**Sensitivity in %**
Back Propagation Neural Network	78.2989	78.3656	75.3989
K Nearest Neighbor	82.4989	81.3878	85.3989
Convolutional Neural Network	92.3987	93.3878	94.3989

V CONCLUSION AND FUTURE WORK

In this research, a novel segmentation and classification methodologies are implemented for identifying and classifying AD. The MRI images are undergone for preprocessing based on image filtering using 2D AMF and enhancement using CLAHE algorithm. The preprocessed images are given to clustering technique using EFCMC and thresholding using Adaptive Otsu Thresholding (AOT) technique. CNN, like ANN, is a semi-supervised linear classifier that just doesn't require extensive function engineering prior, and its identity standardized extracting features property is used to classify Alzheimer's disease. In future, we will observe the concert of intended machine learning techniques, as well as enhanced ones, on other MRI and CT images.

REFERENCES

[1] Cui, Ruoxuan, and Manhua Liu. "Hippocampus Analysis by Combination of 3-D DenseNet and Shapes for Alzheimer's Disease Diagnosis." *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 5, Sept. 2019, pp. 2099–107. *DOI.org (Crossref)*, doi:10.1109/JBHI.2018.2882392.

[2] Khagi, Bijen, and Goo-Rak Kwon. "3D CNN Design for the Classification of Alzheimer's Disease Using Brain MRI and PET." *IEEE Access*, vol. 8, 2020, pp. 217830–47. *DOI.org (Crossref)*, doi:10.1109/ACCESS.2020.3040486.

[3] Xiao, Zhe, et al. "Brain MR Image Classification for Alzheimer's Disease Diagnosis Based on Multifeature Fusion." *Computational and Mathematical Methods in Medicine*, vol. 2017, 2017, pp. 1–13. *DOI.org (Crossref)*, doi:10.1155/2017/1952373.

[4] Lahmiri, Salim, and Mounir Boukadoum. "Alzheimer's Disease Detection in Brain Magnetic Resonance Images Using Multiscale Fractal Analysis." *ISRN Radiology*, vol. 2013, Oct. 2013, pp. 1–7. *DOI.org (Crossref)*, doi:10.5402/2013/627303.

[5] Andres Ortiz1, Juan M. Gorriz2, Javier Ramirez2, and Diego Salas-Gonzalez2, "MRI Brain Image Segmentation with Supervised SOM and Probability-Based Clustering Method", Springer 2011.

[6] Marzban, Eman N., et al. "Alzheimer's Disease Diagnosis from Diffusion Tensor Images Using Convolutional Neural Networks." *PLOS ONE*, edited by Stephen D. Ginsberg, vol. 15, no. 3, Mar. 2020, p. e0230409. *DOI.org (Crossref)*, doi:10.1371/journal.pone.0230409.

[7] Dimililer, Kamil, and Ahmet İlhan. "Effect of Image Enhancement on MRI Brain Images with Neural Networks." *Procedia Computer Science*, vol. 102, 2016, pp. 39–44. *DOI.org (Crossref)*, doi:10.1016/j.procs.2016.09.367.

[8] Badža, Milica M., and Marko Č. Barjaktarović. "Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network." *Applied Sciences*, vol. 10, no. 6, Mar. 2020, p. 1999. *DOI.org (Crossref)*, doi:10.3390/app10061999.

[9] Liu, Li, et al. "Multimodal MRI Brain Tumor Image Segmentation Using Sparse Subspace Clustering Algorithm." *Computational and Mathematical Methods in Medicine*, vol. 2020, July 2020, pp. 1–13. *DOI.org (Crossref)*, doi:10.1155/2020/8620403.

[10] Edalati-rad, Akram, and Mohammad Mosleh. "Improving Brain Tumor Diagnosis Using MRI Segmentation Based on Collaboration of Beta Mixture Model and Learning Automata." *Arabian Journal for Science and Engineering*, vol. 44, no. 4, Apr. 2019, pp. 2945–57. *DOI.org (Crossref)*, doi:10.1007/s13369-018-3320-1.

[11] Varghese, Tinu, et al. "Discrimination between Alzheimer's Disease, Mild Cognitive Impairment and Normal Aging Using ANN Based MR Brain Image Segmentation." *Proceedings of the International Conference on Frontiers of Intelligent Computing: Theory and Applications (FICTA) 2013*, edited by Suresh Chandra Satapathy et al., vol. 247, Springer International Publishing, 2014, pp. 129–36. *DOI.org (Crossref)*, doi:10.1007/978-3- 319-02931-3_16.

[12] Islam, Jyoti, and Yanqing Zhang. "Brain MRI Analysis for Alzheimer's Disease Diagnosis Using an Ensemble System of Deep Convolutional Neural Networks." *Brain Informatics*, vol. 5, no. 2, Dec. 2018, p. 2. *DOI.org (Crossref)*, doi:10.1186/s40708-018-0080-3.

[13] Oh, Kanghan, et al. "Classification and Visualization of Alzheimer's Disease Using Volumetric Convolutional Neural Network and Transfer Learning." *Scientific Reports*, vol. 9, no. 1, Dec. 2019, p. 18150. *DOI.org (Crossref)*, doi:10.1038/s41598-019-54548-6.

[14] Acharya, U. Rajendra, et al. "Automated Detection of Alzheimer's Disease Using Brain MRI Images– A Study with Various Feature Extraction Techniques." *Journal of Medical Systems*, vol. 43, no. 9, Sept. 2019, p. 302. *DOI.org (Crossref)*, doi:10.1007/s10916-019-1428-9.

[15] Ben Ahmed, Olfa, et al. "Alzheimer's Disease Diagnosis on Structural MR Images Using Circular Harmonic Functions Descriptors on Hippocampus and Posterior Cingulate Cortex." *Computerized Medical Imaging and Graphics*, vol. 44, Sept. 2015, pp. 13–25. *DOI.org (Crossref)*, doi:10.1016/j.compmedimag.2015.04.007.

[16] Hasan, Ali M., et al. "MRI Brain Classification Using the Quantum Entropy LBP and Deep-Learning-Based Features." *Entropy*, vol. 22, no. 9, Sept. 2020, p. 1033. *DOI.org (Crossref)*, doi:10.3390/e22091033.

[17] Zheng, Hong, et al. "Multi-Contrast Brain MRI Image Super-Resolution With Gradient-Guided Edge Enhancement." *IEEE Access*, vol. 6, 2018, pp. 57856–67. *DOI.org (Crossref)*, doi:10.1109/ACCESS.2018.2873484.

[18] D. Poornima, et al. "Bone Cancer Identification and Classification Using Hybrid Fuzzy Clustering With Deep Learning Classification." *Journal of Advanced Research in Dynamical*

and Control Systems, vol. 11, no. 10-SPECIAL ISSUE, Oct. 2019, pp. 88–98. *DOI.org (Crossref)*, doi:10.5373/JARDCS/V11SP10/20192779.

[19] V., Vedanarayanan. “Autonomous Integrated Precise Medical Bed (PMB) Using Secured IOT.” *Journal of Advanced Research in Dynamical and Control Systems*, vol. 12, no. SP4, Mar. 2020, pp. 1125–36. *DOI.org (Crossref)*, doi:10.5373/JARDCS/V12SP4/20201586.

[20] D., Poornima. “Precision Agriculture for Pest Management on Enhanced Acoustic Signal Using Improved Mel- Frequency Cepstrum Coefficient and Deep Learning.” *Journal of Advanced Research in Dynamical and Control Systems*, vol. 12, no. SP3, Feb. 2020, pp. 50–65. *DOI.org (Crossref)*, doi:10.5373/JARDCS/V12SP3/20201238.

[21] Kanyadara Saakshara, Kandula Pranathi, R.M. Gomathi, A. Sivasangari, P. Ajitha, T. Anandhi, "Speaker Recognition System using Gaussian Mixture Model", 2020 International Conference on Communication and Signal Processing (ICCSP), pp.1041-1044, July 28 - 30, 2020.

[22] R. M. Gomathi, P. Ajitha, G. H. S. Krishna and I. H. Pranay, "Restaurant Recommendation System for User Preference and Services Based on Rating and Amenities," 2019 International Conference on Computational Intelligence in Data Science (ICCIDS), 2019, pp. 1-6, doi: 10.1109/ICCIDS.2019.8862048.

[23] Subhashini R , Milani V, "IMPLEMENTING GEOGRAPHICAL INFORMATION SYSTEM TO PROVIDE EVIDENT SUPPORRT FOR CRIME ANALYSIS", Procedia Computer Science, 2015, 48(C), pp. 537–540

[24] Harish P, Subhashini R, Priya K, "Intruder detection by extracting semantic content from surveillance videos", Proceeding of the IEEE International Conference on Green Computing, Communication and Electrical Engineering, ICGCCEE 2014, 2014, 6922469

[25] Sivasangari, A., Krishna Reddy, B.J., Kiran, A., Ajitha, P.(2020), “ Diagnosis of liver disease using machine learning models”, ISMAC 2020, 2020, pp. 627–630, 9243375

[26] Sivasangari, A., Nivetha, S., Pavithra,, Ajitha, P., Gomathi, R.M. (2020),” Indian Traffic Sign Board Recognition and Driver Alert System Using CNN”, 4th International Conference on Computer, Communication and Signal Processing, ICCCSP 2020, 2020, 9315260

[27] Ajitha, P., Lavanya Chowdary, J., Joshika, K., Sivasangari, A., Gomathi, R.M., "Third Vision for Women Using Deep Learning Techniques", 4th International Conference on Computer, Communication and Signal Processing, ICCCSP 2020, 2020, 9315196

[28] Ajitha, P.Sivasangari, A.Gomathi, R.M.Indira, K."Prediction of customer plan using churn analysis for telecom industry",Recent Advances in Computer Science and Communications,Volume 13, Issue 5, 2020, Pages 926-929.

[29] Gowri, S. and Divya, G., 2015, February. Automation of garden tools monitored using mobile application. In International Confernce on Innovation Information in Computing Technologies (pp. 1-6). IEEE.

[30] Gowri, S., and J. Jabez. "Novel Methodology of Data Management in Ad Hoc Network Formulated Using Nanosensors for Detection of Industrial Pollutants." In International Conference on Computational Intelligence, Communications, and Business Analytics, pp. 206-216. Springer, Singapore, 2017.