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Research Article

Alzheimer's Disease Detection using Gaussian Kernel Based Fuzzy C-Means Clustering Algorithm

Aswathy Aravindan [a] and Dr. N. Kavitha [b]

[a] *Research Scholar, Department of Computer Science, Nehru Arts and Science College, Coimbatore*
[b] *Head of the Department and Associate Professor, Department of Computer Science, Nehru Arts and Science College, Coimbatore*

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Abstract: The most prevalent cause of dementia in older people is Alzheimer's disease (AD). Dementia is a neurological disease that severely limits a person's capacity to do everyday tasks. The importance of early Alzheimer's disease diagnosis can be attributed to several factors. Most of them provide for Alzheimer's disease therapies that can slow down the disease's development. The CT scan reveals a degree of generalized cortical atrophy in Alzheimer's disease patients. As a result, CT scan picture processing is critical in the early detection of Alzheimer's disease. Here, image processing is used to detect the objects in CT pictures. Edge detection is a critical first phase in image processing since it defines the discontinuities in gray-level images. The majority of them are clinic-based structural MRI images with small sample size and few scanning layers. Deep learning, on the other hand, necessitates a large amount of annotated details. This paper suggests a dataset increment approach based on a weighted mixture of positive and negative tests and a learning method with a limited number of samples to meet the realistic requirements of clinical evaluation of Alzheimer's disease. It produces a GKFCM Clustering model that can collect more image feature details and boost the model's generalization ability.

Keywords: GKFCM, AD, CT, MRI, Disease Prediction

1. Introduction

Alzheimer's (AHLZ-high-Merz) is a brain disorder that causes memory, thought, and behavior problems. It's not a common feature of aging. Over time, Alzheimer's grows stronger. The disease may lead someone to get confused, lost in familiar locations, misplaced, or language difficulties. Early Alzheimer's diagnosis requires reversible signs to be treated promptly. This also contributes to improved neurological conditions like memory problems (Al-Jibory, W. K., 2013).

Magnetic resonance imaging (MRI) is used frequently for AD diagnosis. Earlier reports have found that grey matter and hippocampus concentrations are lower in AD patients than in healthy people. However, regional brain volumes are challenging to measure because minor image registration discrepancies and cross-sections of cut pictures have significantly affected volume (Fuse, H., 2018).

In recent years, several automated AD diagnostic experiments have been carried out using various approaches. Most of the research focused on the identification of AD from neuro imaging results. However, early symptom identification is essential because condition-modifying medications would be most successful. If they are delivered early in the disease before permanent brain harm. It is also very important to use automatic techniques to prevent signs of AD from being observed from such data (Gunawardena, K. A. N. N. P., 2016).

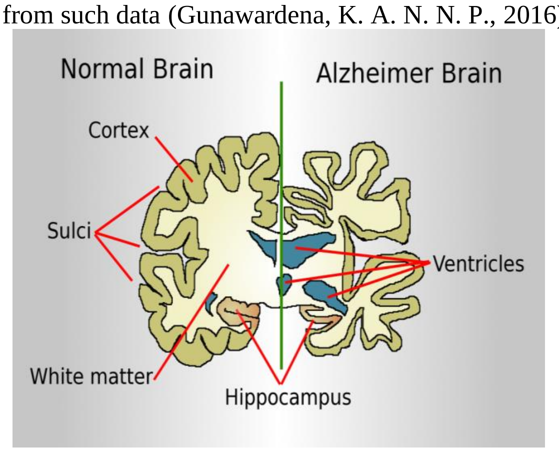

Figure 1: Difference between Normal Brain and Alzheimer Brain

Medical Imagery is the mechanism and procedure used by medical intervention and clinical analyses to provide abstract images of the body'score. Computer learning techniques and manipulating medical videos may enable neurologists to determine how Alzheimer's disorder progresses. Alzheimer's disease is a progressive neurodegenerative disease that causes tissue damage in the brain, and nerve cell death normally begins progressively and becomes with time. The disorder of Alzheimer is predicted to impact rising numbers of people by 2050. It is also anticipated that the costs of caring for AD patients will increase**.** Currently, AD is the sixth cause of mortality in the United States. Individual computer-aided systems are required to diagnose this disease accurately and at an early stage (Vengatesan, K., 2019).

The remainder of this article is arranged accordingly. Section 2 presents some scholars presenting Alzheimer's methods of diagnosis. Section 3 shows the proposed device model. Section 4 shows the study results. Finally, in section 5, this paper discusses the thesis and possible work.

2 Background Study

Researchers also implemented machine learning strategies for clinical measurements and imaging data for AD diagnostics to create classifiers. These findings have reported significant anatomical variations between the brain with AD and the healthy brain in regions such as entorhinal cortex and hippocampus entorhinal cortex.

(Al-Jibory, W. K., & El-Zaart, A 2013) Smoothing is an initial stage to remove as many noises as possible in every edge detection operation. The first derivative's edge detection depends on how well the image works when it contains sharp intensity and low noise. LOG edge detection improves the location, particularly if the edges are not quite sharp. The authors were proposed a new method that uses the Weibull distribution to create masks for the first and second derivative picture instead of the Gaussian distribution.

(Krashenyi, I. 2016) Fuzzy inference method (FIS) was a system using fuzzy set theory for mapping outputs to inputs (features) (classes). The first one has to choose numerical input variables that are crisp and specify their ranges for each word to construct FIS. Then the correspondence between input values and each fuzzy set should be described during the fuzzification stage. It was achieved with the aid of membership functions, representing each class member's parameter meaning degree. After that, it was suggested to specify a series of FIS rules that classify FIS decisions using logical operators and the rule for integrating fuzzy output from each rule.

(He, G. 2017) Imagery of the brain focused on PET and MRI will detect Alzheimer's disease efficiently. However, practical clinical implementations have several practical issues, such as restricted image records, few image scanning layers, and PET data difficulties. A convolutionary neural network model to diagnose Alzheimer's disease was developed to implement clinical diagnosis based on original MRI imagery with only 18 scanning levels as datasets. An incremental data set approach is suggested for the weighted combination of positive and negative samples to obtain valuable incremental knowledge. A DenseNet Classification Model for 3D CNN complete convolution was developed. It has better picture knowledge and boost model generalization.

(Lodha, P. 2018) To identify Alzheimer's subjects and evaluate photographs of brain regions associated with Alzheimer's disorders, the authors were used MRI images and process them using machine learning algorithms to process numerical data. The Random Forest and Neural Network function far more accurately than other approaches. This approach was implemented to provide immediate and reliable results.

(N P, K. T., & Varghese, D. 2019) Alzheimer's disease remains a significant clinical science problem. Machine learning has main area in computer science and has demonstrated promise for future advances. Here a device with a machine learning methodology named the SVM was used for early AD estimation in health care. The improved precision, sensitivity, and specificity of these methods suggested this procedure was a promising option for the clinical evaluation of brain changes correlated with moderate cognitive dysfunction.

(Yang, S. J. 2020) Alzheimer's condition was an age-related neurological illness and it was useful to avoid early action through recognizing the development. The authors were suggested a linear regression function approach in this analysis and applied it to ADNI data to estimate the conversion period and show that CC atrophy facilitates AD progression. Viasimulation test, the proposed model would restore the failure period correctly while censoring and working.

(Zhou, Q. 2014) The findings indicate that AD atrophy was common on both sides and its shown evenly**.** In comparison, a MCI and na MCI subjects are dominant both on the left and right, suggesting that hemisphere-dependent atrophy superiority is possible at various AD stages.

3 System Model

3.1 Preprocessing Stage

This stage is carried out by implementing several initial image processing procedures before some specific processing function. It increases the accuracy of the picture and eliminates noise. Because, brain images are more vulnerable than other medical images, minimal noise and optimum clarity should be provided.

3.2 Convolutional Shape Local Binary Texture:

This approach classifies a regular picture as grayscale and a sharp image, rendering the image a reshape that is sized to equal all pixel duration, strength and magnitude around the image. In that case, the image is in the same highlighted view of data where formulated image data are again preprocessed for a clustered region to start with the local binary bit pattern and textures classification such that each part of the image is clustered into a matrix format where all matrix structure data has a local and global cluster head that means that it is calculated as an In general, several local heads and clusters are created centered on the displaced territory. In this, we stress the central strength area dependent on the segregated matrix. Each average head of the area is measured in one such array and highlighted based on the high functional results. The related matrix strength core data was taken separately such that the area segmentation is separated for the impacted and usual sections.

3.3 Feature Description

Classification of function data based on the data generated and formulated by the binary texture pattern is recorded. Here, we have several data fields in which the average data is used as a basis and formulated from the full data of each classification part. To make the entire highlighted area more intensive and large as a function input.

3.4 Data Description

In this article, the images are taken as a brain image base with a full framework of brain and medullaoblungata that concentrate as an input structure. Several fields inside an image are different. In this case, the images are obtained from the uci data repository, where many Imagery are formulated differently. There are crucial facts for measuring the strength of the picture in various areas. Around 50 images of the different patients are taken. It is analyzed using an algorithm to ensure that the patient has standard and correct measures needed with precision and efficiency.

Figure 2: Input Image

Figure 2 shows the RAW Input image that is directly used, with preprocessing steps and sharpening of the data (Figure 2 shows the RAW Input image, that directly used with preprocessing steps and sharpening of the data.)

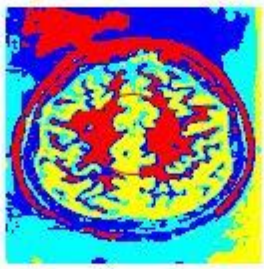

Figure 3: Cluster Region Separately

Clustering Part: figure 3 to identify every region separate between localization and to find out the normal and benign part Separately Cluster region:

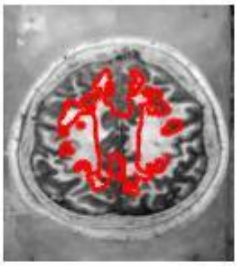

Figure 4: Clustering Level 1

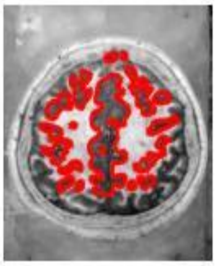

Figure 5: Clustering level 2

Figure 6: Clustering Level 3
Figure 4, 5, 6 represents the Clustering level by level.

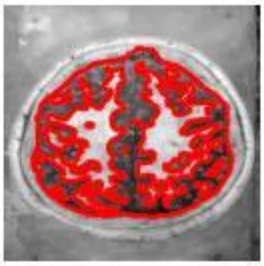

Figure 7: Image Segmentation

3.5 Image Segmentation

The area of interest's coordinated location is established, and the region chosen is planted and zoomed. This picture is used to change the intensity of the pixel. The pixels are labeled as white and black for the cropped picture depending on the pixel intensity. The White Area is the living tissue, and the Black Region is the dying tissue. The number of white pixels and black pixels are determined, and if the black pixel is very less, the patient is well. The patient is graded as a moderate cognitive disability, an Alzheimer's disorder, or a stable patient depending on the percentage of Black Pixels. Figure7 illustrates the image segmentation result

Clustering Methods: Clustering methods are uncontrolled segmentation methods that partition a picture into pixel/voxel clusters of equal intensity without the use of training images. Clustering techniques use the picture data accessible to practice themselves. The segmentation and preparation were carried out in tandem through two steps: Data clustering and estimation of tissue type characteristics.

$$j_m = \sum_{i=1}^{c} \sum_{j=1}^{N} u_{ij}^{m} \qquad (1)$$

where N is the number of image elements that need to be partitioned into C clusters, u_{ij} is the membership function of the element x_j (a feature vector at position j) belonging to the i^{th} cluster, m is the weighting exponent that controls the fuzziness of the resulting partition (most often is set to m = 2, if m = 1 we have the k-means clustering), and D_{ij} is the similarity measure between x_j and the i^{th} cluster center v_i.

Each area is illuminated separately depending on the clustered position. It is stored at a strong noise cancellation rate with low homogeneity data with a decent filter rate in morphological image at figure 8.

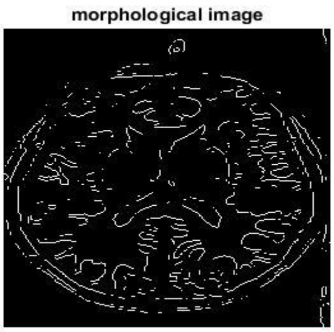

Figure 8: Morphological Image

Figure 9: Efficient LBP Features

Figure 9 shows the Preprocessed binary picture recognition describes binary patterns and forms of high-level characteristics and often sees more distinctly internal joints and movement lines.

Thresholding is one of the popular image segmentation mechanisms. In this picture segmentation technique, the grayscale or pixel strength segmentation is done. It also types as a two-level threshold for classifying pixels in two categories depending on the picture pixels' strength.

Algorithm 1-GKFCM

Step1: get input image to calculate the length and width and reshape it into a normal shape

Step2: select the fir filter to detect the window area of the image (rectangular window) to move the window in all shape to the removal of noise part

Step 3: dilate and erode the image with disk shape (5, 2) and apply it to a binary image.

Step 4: low-intensity image part is achieved in the highlighted region (0,1) in the range of (256,256)

Step 5: images are split into pieces of parts with different dimension (3,3) matrix, ascended in single dimension array.

Step 6: average mean of 1d array is retrieved (to have highly attractive region)

Step 7: every average mean is taken as reference (max(avg_mean)) then lbp is calculated

Step 8: generalize feature of GLCM is calculated for every w (window size), and high energize data is taken as reference

Step 9: based on window size data (newindex x =1 as a reference is taken to carry over in the image)

Step 10: sum of feature (f) is the input for the terminal of the image

Step 11: convolution neural network

A. Input layers → size of image structure is given as one of input
B. No of dimension → dimension of the image in the different category are categorized
C. Separate layers are trained in different fields from convolution layer, pooling layer, dense layer, output layer
D. Every layer of information feature with array matrix
E. Each array matrix has neurons and connected layers and which has equality label
F. The knowledge base and knowledge graph of the structure is defined, then the collective field as (s) is noted
G. Feature data s = i+o layer,

Step 12: end of the process

Algorithm 2: SWARM BASED OPTIMIZED SEARCH COMBINATION:

Step1: No of data for the alignment of SWARM mode

Step2: To track the data and predict the data, iteration of the data is necessary

Step3: No iteration is chosen from this input to the model (dataset)

Step4: Calculating the fitness function for the model

Step5: The iteration of the model will begin, and the objective function of the model will be chosen.

Step6: Increasing and decreasing energy to the test rat will be populated.

Step7: We are exploring data and random numbers, choosing to see the data within this range or not covering.

Step8: If the common data of the global fitness data search bit is getting matched, the model's energy calculation will be changed, with a random jump between the models.

Step9: There is a big OUTLAYER movement; calculation of high and hard data search (Which is organized to form a multiple data) key for the energy data used to check in the model.

Step10: Now complete data with high energy mode vector data is calculated ina highly effective manner based on the arrival of an optimized layer with key data retrieval.

Step11: As in outcome, the data's tolerance is getting calculated, and the maturity of finding the segmented part is calculated.

The brain consists of approximately 100 billion nerve cells; each nerve cell is linked to other nerve cells and constitutes a communications network. The brain forms plaques and tangles as one age. They first establish a region of memory in the hippocampus and then expand to other brain areas. These plaques and tangles deactivate or hinder signaling between nerve cells and affect their work. The nerve cells' distraction and death trigger cognitive loss, behavioural changes, everyday activity issues, and other Alzheimer's disease symptoms.

4 Results and Discussion

Our experiment used the evidence of neuro imaging as Brain MRIs to check brain atrophy, hippocampus area, and vascular enlargement to diagnose Alzheimer's disease with a variety of image segmentation techniques on Brain MRI. For this different technique of image segmentation pixel strength, image gradient is used. The procedure was conducted on 12 Alzheimer's MRI samples.

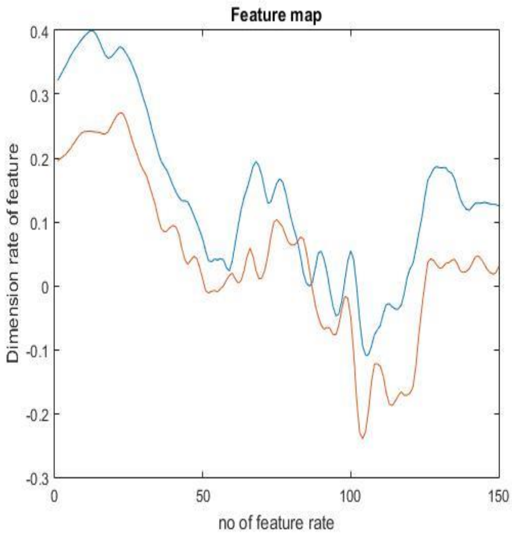

Figure 10: Proposed Feature Map

Figure 10 represents the feature map result, in x axis denotes the no of feature rate and y-axis denotes the dimension rate of feature.

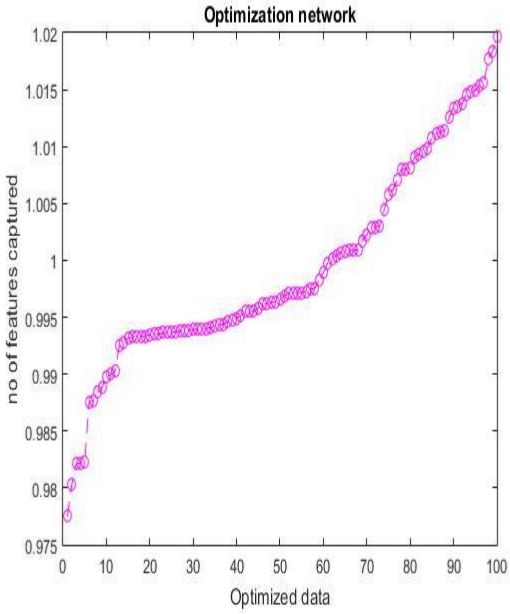

Figure 11: Proposed Optimization Network

Figure 11 shows the optimization network result, in x-axis denotes the optimized data volumes and Y-axis denotes the no of features captured

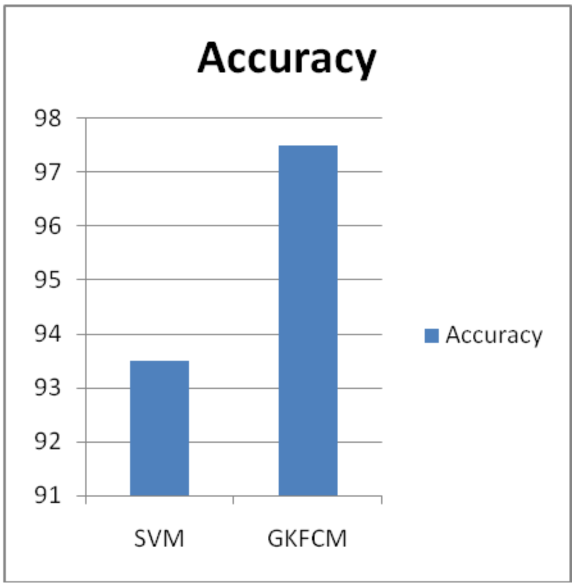

Figure 12: Comparison Chart

Figure 12 shows the comparison for the existing system [10] and proposed system GKFCM

5 Conclusions

The aim is to diagnose Alzheimer's disease early. Enlarged atrophy of the vascular and brain. Identification of the swollen vascular is achieved by utilizing picture segmentation. The patient is graded as a stable patient, first stage AD, second stage AD, and moderate cognitive disability instances by enlargement. Brain atrophy is another significant element in the diagnosis of AD. The GKFCM picture segmentation algorithm is used to diagnose brain atrophy. Picture gradient is used to verify atrophy of the cavity of the brain. This intuitive approach has a basic technique and low picture sophistication. The Proposed system overcomes the issue of early diagnosis without disruption to the brain and completes 97.2753% of the method suggested. The proposed system would enhance research in the field of medical imaging.

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