DL-EPAD: A DEEP LEARNING APPROACH TO EARLY PREDICTION FOR ALZHEIMER'S DISEASE DETECTION USING MGKFCM

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Abstract

In Alzheimer's disease (AD), memory and cognitive abilities deteriorate, ultimately affecting the capacity to do basic activities. In and around brain cells, aberrant amyloid and tau protein accumulation is believed to cause it. Amyloid deposits create plaques surrounding brain cells, whereas tau deposits form tangles inside brain cells. The plagues and tangles harm healthy brain cells, causing shrinkage. This damage seems to be occurring in the hippocampus, a brain region involved in memory formation. There are presently no methods that provide the most accurate outcomes. The current techniques do not identify AD early. The proposed DL-EPAD method achieves excellent clustering quality using MGKFCM (Modified Gaussian Kernel Fuzzy C-means Clustering) method. The MGKFCM utilizes an Elbow Method to determine the number of clusters in a dataset. Unlike other medical pictures, brain scans are extremely sensitive. The pictures should be visible, and the noise should be minimal. The study utilizes Deep Learning, which outperforms other conventional machine learning techniques. Convolutional Neural Networks (CNN) utilizes neuroimaging data without pre-processing to pick AD classification features. The suggested approach outperforms current techniques (98%).

Keywords: AD, MGKFCM, CNN, MRI, DL-EPAD, Deep Learning

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1. INTRODUCTION

The brain is one of the most important parts of our bodies. The brain is in charge of all the actions and reactions that enable us to think and believe. It also gives us more control over our feelings and memories [1]. AD is an irreversible and untreatable condition of the brain. Every four seconds, a new case of AD is discovered throughout the globe. Slowly, but surely, it builds up and destroys an individual's memory, making it impossible for them to think clearly. Nerve cells degenerate and die as a result of this degenerative condition. There is only a four to eight-year average life expectancy after an Alzheimer's diagnosis [3]. This disorder affects around one in every ten persons over the age of 65, although it has been identified in many people as early as their 20s. Dementia in the elderly is almost often brought on by this illness. AD is the most common cause of dementia, which causes 60 to 80 percent of all cases [4]. In this disorder, the brain develops plaques and tangles, and brain cells die off one at a time. After she died, the doctor performed a postmortem brain scan and discovered many clumps in her cortex. We determined that these two factors are responsible for causing this condition [6]. They disrupted the brain's ability to communicate with other areas of the body. As a result, regular tasks like driving, cooking, and other household chores become more difficult for those who suffer from this condition. An early indication of AD is a lack of ability to remember names or key items. [7]. In the middle stage of Alzheimer's, symptoms may include significant mood swings, confusion, impulsivity and short attention spans as well as a lack of object recognition [9] The worst is still to come in the last stage.

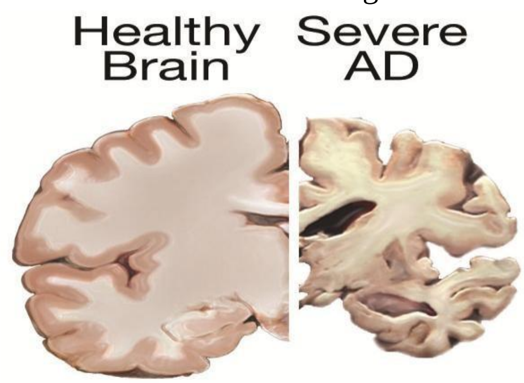

Figure 1 Image representing a Healthy Brain vs. Severe AD Brain

The most obvious signs are a lack of social skills, an increased risk of infection, a shaky sense of direction, and memory loss. AD affects an estimated 50 million individuals globally, according to a recent poll. Scientists and doctors now have a major issue in identifying this ailment since patients' cognitive symptoms are typically attributed to ageing, which makes it difficult to diagnose until patients are in the terminal stages of the disease. The danger posed by this illness will only grow until improved treatment options are made available [11]. As a result, the illness has a higher incidence among the elderly. Although there is no cure for this condition, early management may help delay the progression of dementia [10]. A balanced diet, physical exercise, social interaction, avoiding head traumas, reading, playing an instrument, and engaging in intellectual pursuits have all been linked to a decreased risk of AD [12]. These activities may improve brain health and cognitive ability in general.

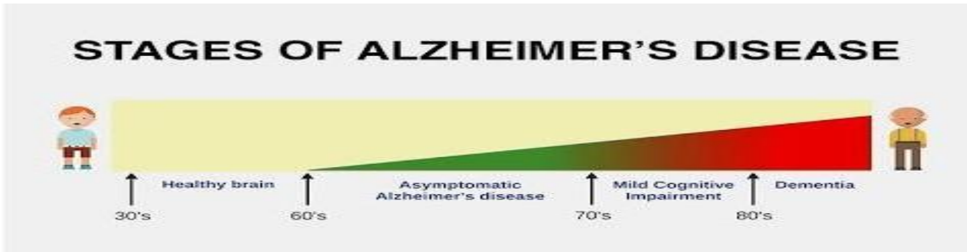

Figure 2: Stages of AD

Medical imaging is the technique and process by which visual representations of the inside of the body are created for the purpose of medical intervention and clinical analysis. Neurologists may use machine learning and medical image processing to determine if an individual develops AD. AD is a chronic neurodegenerative disease that results in tissue loss throughout the brain. Nerve cell death often begins slowly and progresses over time. By the year 2050, AD is predicted to impact an increasing number of individuals. Additionally, the expense of caring for people with AD is predicted to increase. AD is now the sixth leading cause of mortality in the United States. As a result, customised computer-assisted solutions are required for the accurate and timely identification of this condition [6].

The rest of this article is organized in the same manner. Section 2 has many writers that discuss various approaches for diagnosing AD. The suggested model is shown in Section 3. Section 4 summarizes the study's findings. Finally, Section 5 outlines the conclusion and future work.

2. BACKGROUND STUDY

Armstrong et al. [1] suggested how cell telephone devices should be incorporated in people with AD. The author proposed how a cell phone may be used to control blood pressure and heart rate, particularly for Alzheimer's patients. There are currently no devices allowing the unlimited usage of cell phones in the wellness tracking scheme.

Babalola *et al.* [2] proposed four completely automatic segmentation tests segment subcortical structures: volumetric, overlapping, distance-based, and spatial measures. The respective approaches include profile active appearance models, regular segmentation, the classifier's atlas-based fusion, and Bayesian appearance models. It was emphasized that it is usually more difficult to segment subcortical structures, including the hippocampus, thalamus, putamen, and caudate. However, the signal amplitude is insufficient to differentiate between different structures of subcortical gray matter. The subcortical arrangements include typical forms and spatial interactions. Therefore, the segmentation procedures for these constructs typically provide details with a priori regarding their predicted shape and position from the brain atlas. In 270 participants, any approach tried to divide 18 subcortical structures, and the results were more identical.

Coppola et al. [3] proposed that music and photos play a vital function in AD. This research explores cognitive capacity and the quality of life of people with a technological diagnosis of dementia. Students created an easy-to-use tablet program to make technology easier for older adults with disabilities via service-learning classes. This study would explore smartphone apps created by students to enhance the quality of life of AD or dementia patients.

Gordillo et al. [4] proposed various categories of current segmentation of brain tumors depending on the degree of human involvement necessary to segment the tumor from MR photographs. Segmentation methods for a brain tumor may be differentiated widely into manual, semi-automatic, and completely automatic methods.

Jean et al. [5] presented a report addressing the social functioning and quality of living for technologically diagnosed individuals with dementia. The research focuses on advanced, popular, and easy-to-use technologies such as iPads and tablets, which may help assess the level of dementia and boost cognizance. The study hopes to explore the newly developed applications. Current aid software may reduce symptoms and enhance memory in older adults who have AD or other disorders associated with dementia.

Khan et al. [6] present a review that compares and assesses recent work on prognosis/diagnosis of AD by methods/techniques of machine learning. The suggested ML approach (three general algorithms for function selection, filter methods, wrapper, and embedded methods) deals with pathologically validated data. It resolves class differences and problems in overtraining. The precision is 96.6 percent.

Sandhya *et al.* [7] proposed an optimization approach that has been tried to find the right answer to a particular problem. Traditional optimization techniques were initially employed for engineering challenges but only for a single objective purpose. And there were meta-heuristic methods added. These methods are focused on nature or on swarming. These methods are mostly focused on swarm intelligence and solving optimization problems.

3. DL-EPAD MODEL

The suggested system's primary objective is to detect AD early. Brain atrophy is a crucial factor in the diagnosis of AD. To identify brain atrophy, the MGKFCM (Modified Gaussian Kernel Fuzzy C-means) image segmentation technique is utilised. The atrophy of the cerebral cavity was verified using image gradients. A gradient in a photograph refers to a variation in the colour or intensity of the image. This previous method employs a straightforward procedure and a modest level of visual complexity. The proposed technology eliminates the need for early detection without causing brain damage and completes 98 percent of the indicated procedure. The patient is classified as stable, first stage AD, second stage AD, or moderate cognitive dysfunction using Convolutional Neural Networks. The proposed system is a contribution to the field of medical imaging. It showed higher accuracy over performance when compared to other existing ones, in addition to MGKFCM, a dimensionality reduction technique known as LDA (Linear

Discriminant Analysis). It reduces the number of variables or dimensions in a dataset and retains the necessary information. Optimization techniques are also used in the proposed work to get the best solution without compromising the quality. The early detection and classification of AD are more accurate in the proposed system.

Data set collection

The proposed work aims at the early detection of AD. The data set play an important role. The training data is needed to train the model for performing needed actions. Most of the data in the data set used for training the model and data set is also separated into test data. In the proposed system, the algorithm is executed on AD-related datasets obtained from Kaggle.

Pre-processing Stage

The pre-processing phase improves the image's accuracy and lowers noise. Because brain images are more sensitive than other medical imaging, there must be as little noise as possible while maintaining optimum visibility. The Image conversion from color to grayscale, resizing the image, reshaping the image, sharpening the image, etc.

Image denoising - Ant Colony Optimization (ACO)

Techniques for pre-processing Magnetic Resonance Images increase the identification of suspicious regions (MRI). The technique of pre-processing and augmentation comprises of two steps: first, a tracking algorithm eliminates film artefacts from the MRI, such as labels and X-ray markers. Second, using the Ant Colony Optimization (ACO) approach, high-frequency components are deleted. Pre-processing with tracking functions that include noise reduction is often required prior to doing detailed data evaluation and extraction, and is commonly categorised as radiometric or geometric enhancements.

The choice of high-frequency elements is entirely determined by the pheromone content of the pathways and a heuristic evaluation. Nodes are created using MRI pixels. Throughout the construction, a specific ant k selects the next node using a probabilistic action selection rule that specifies the chance that ant k will choose to travel from current node *i* to next node j:

$$p_{ij}^{k} \frac{[T_{ij}]]^{\alpha}[n_{ij}]^{\beta}}{\sum_{k} [T_{ij}]^{\alpha}_{N_i}[n_{ij}]^{\beta}} \text{ if } j \in N_{i}^{k} \text{ ----(1)}$$

Where T_{ij} represents the essence of the arc from node i to node j, N_i^k represents the region nodes for a specific ant k, provided that it is on node i. The neighborhood only comprises nodes that the exact ant k has not visited. The constants α and β indicate the influence of content and heuristic correspondingly. At last n_{ij} denotes the heuristic details for going from node i to node j.

Data Description

The photographs taken have been completely concentrated in the brain and medulla oblongata in the proposed work. Several fields are different inside a picture. The photographs are obtained in the UCI data archive, containing several different images in this scenario. There are important facts for the measurement of image intensity in different fields. Around 50 pictures of the various patients were taken. An algorithm assures that the patient's steps and performance are normal and correct.

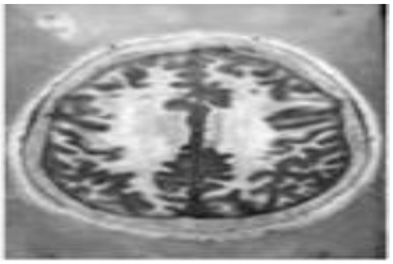

Figure 3Input image

The RAW input picture shown in Figure 3 is immediately utilised for pre-processing and sharpening the data.

Image Segmentation

The orchestrated position of the area of interest is identified, and the selected region is planted and zoomed in. This picture is used to alter the intensity of the pixels. For the image, pixels are referred to as white or black, depending on their brightness. The White Area represents living tissue, whereas the Black Area represents dead tissue. The number of white and black pixels is computed, and if the black pixel is very little, the patient is OK. According to the Black Pixels ratio, the patient is characterised as having a slight learning impairment, having AD, or being healthy. Thresholding is a widely used technique for picture segmentation. The grayscale or pixel power segmentation is achieved in this image segmentation technique. It is two-tier thresholding for classifying pixels in two groups, based on the intensity of the image pixels.

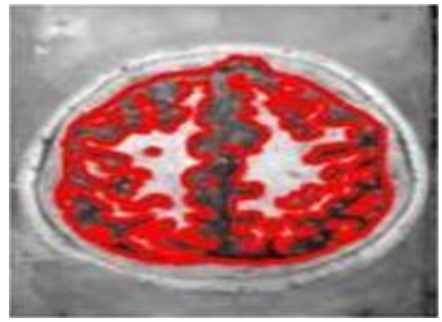

Figure 4 Image Segmentation

The Image segmentation is shown in figure 4, in which an image is partitioned into multiple regions or categories. Once the segmentation is done, only the important segment of the image needs to be processed.

Figure 5 Morphological Image

The morphological image is shown in figure 5. Here the images are processed based on shapes. Basic morphological operations are erosion, dilation, etc.

Figure 6 Efficient LBP Features

Figure 6 displays the pre-processed binary image identification, identifying the binary trends and modes of higher-level characteristics.

Clustering

Clustering methods are uncontrolled segmentation techniques that separate an image into comparable intensity pixel/voxel clusters in the absence of training images. Clustering algorithms make use of accessible picture data for self-practice. The segmentation and planning were conducted in two steps: Data clustering and tissue sort estimation features.

$$\mathrm{j}_m = \sum_{\mathrm{i}=1} \sum_{\mathrm{j}=1}^{N} u_{\mathrm{ij}D_{\mathrm{ij}}}^{m} \text{--------------} (2)$$

Each region is lighted independently, depending on the cluster's position. It is processed at a high rate of noise cancellation with poor homogeneity figures and a high rate of morphologic image filtering.

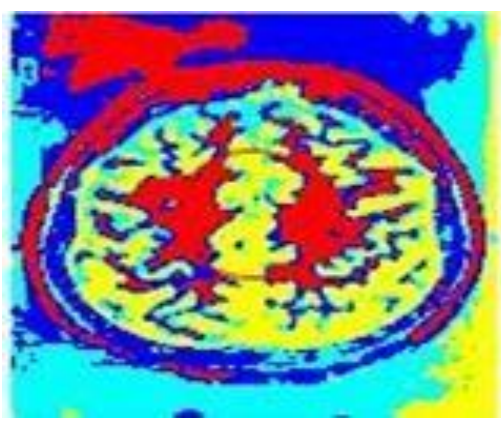

Figure 7 Cluster Region Separately

Figure 7 separates each area between localizations and distinguishes the normal and benign portions. Separately.

3.6 Feature Description:

The points, edges, objects, etc., are the most common features seen in an image. A feature may be thought of as a piece of information about the content of a picture; the information shows whether or not a certain portion of the image has specific attributes. The classification of the feature details based on generated and formulated information is registered with the binary texture pattern. The proposed method has many data fields that base the average data on the complete data for the classified part.

Optimization

A swarm-based optimization technique is used in the proposed system. An optimization technique is needed if the needed area is not identified properly. Using this optimization technique, the area can be identified clearly and accurately

MGKFCM system

The proposed MGKFCM (Modified Gaussian Kernel Fuzzy C-Means Clustering) detects AD early. Vascular and brain atrophy are exacerbated. The implementation is accomplished by the use of picture segmentation for the purpose of identifying larger Vascular. The extent of enlargement will determine whether the patient is classified as healthy, in the first stage of AD, in the second stage of AD, or has mild cognitive impairment. Another critical element in the identification of AD is brain shrinkage. Brain atrophy is detected using the MGKFCM image segmentation technique. The image's gradient is used to assess Cavity in Brain atrophy. This automated approach employs a straightforward process and produces images with a minimal time complexity. This solves the issue of early detection while causing no harm to the brain. This will bolster medical imaging research.

Algorithm Steps-MGKFCM

Given, X= $\{x_1, \ldots x_n\} \subset R^p$, the MGKFCM partitions X into c fuzzy subsets by resucing the following objective function

$J(U,V) = \sum_{i=1} \sum_{k=1}^{n} U_i^m \; X - V_i \; ^2$ ----(3)

Where c is the number of clusters and selected as a specified value in this paper, n is the number of data points, U_{ik} is the membership of X_k in class t, satisfying $\sum_{i=1}^{c} u_{ik} = 1, m$ the quantity controls clustering fuzziness, and v the set of cluster centers or prototype (vi€ Rp). A famous alternate iterative algorithm minimizes the function Jm.

Now consider the proposed MGKFCM algorithm. Define a nonlinear map as $\emptyset x \rightarrow \emptyset(x) \in F$, where x € X, X denotes the data space, and F, the transformed feature space with higher even infinite dimension. MGKFCM reduces the subsequent objective function.

$J(U,V) = \sum_{i=1} \sum_{k=1}^{n} U_i^m \; \emptyset(X) - \emptyset(V_i) \; ^2$ --(4)

$\| \emptyset(X_K) - \emptyset(V_i) \|^2 = K(X_K, X_K) + K(V_i, V_i) - 2K(X_K, V_i)$ ---- (5)

Where $K(x,y) = \emptyset(x)^T \emptyset(y)$ is an inner product kernel function. If we adopt the Gaussian function as a kernel function, i.e.,

$K(x,y) = \exp(-\| x - y \|^2 / \sigma^2)$, then K(x,x) = 1, according to equation (4), equation (5) can be rewritten as

$J(U,V) = 2 \sum_{i=1}^{c} \sum_{k=1}^{n} U_i^m \, (1 - K(X_k, V_i))$ ---(6)

Reducing formula (6) under the constraint of μ_{ik}, we have

$$\mu_{ik} = \frac{(1/(1-K(x_K,v_i)))^{\frac{1}{m-1}}}{\sum_{j=1}^{c}(1/(1-K(x_K,v_i)))^{\frac{1}{m-1}}} \text{ ------- (7)}$$

$$V_i = \frac{\sum_{k=1}^{n} U_{ik}^m K(x_K, v_i) x_k}{\sum_{k=1}^{A} U_{ik}^m K(x_K, v_i)} \text{ ----(8)}$$

Here we just use the Gaussian Kernel function for simplicity. If we use other kernel functions, corresponding modifications will be in equations (7) and (8). Equation (4) can be viewed as a kernel-induced new metric in the data space, defined as the following.

$d(x,y) = \| \emptyset(x_k) - \emptyset(v_i) \| = \sqrt{2(1 - k(x,y))}$ ---- (9)

If k(x,y) is the Gaussian Kernel function, then d(x,y) described in equation (9) is a metric in the original space.

According to equation (8), the information point x_k is endowed with an additional credence k(x_k , v_i) , which measures the parallel between x_k and v_i , and when x_k, is an outlier, i.e., $x_k$is far from other information points, then k(x_k,v_i) will be very small. So the biased sum of information points shall be more robust.

Convolutional shape local binary texture using CNN:

In this method, a normal image is classified as grayscale and sharpened scaled of the image, making the image a reshape scaled one to have all scales as same pixel length and intensity and magnitude of the image throughout the image. This is the same data as when you start with local binary bit pattern and texture classification. Then, the formulated data of an image again is pre-processed with the grouped region, so that every part of the image is clustered into such a matrix format, where every piece of data on the matrix structure will have a local and global cluster head, which means it is the average of all data from the whole cycle.

Overall many local and cluster heads will be generated based on the region displaced.

4. DISCUSSION

The performance of the proposed model needs to be analyzed. The accuracy, precision, etc., were used for classification result evaluation. The MGKFCM algorithm was chosen to solve the problem. MATLAB 2015 was used for the implementation of the proposed work. To diagnose AD, the test utilizes neuroimaging data to assess brain atrophy, hippocampal shrinkage, and vascular expansion. This is accomplished via the use of several pixel intensity segmentation algorithms and the colour gradient. The procedure was carried out on 12 MRI samples.

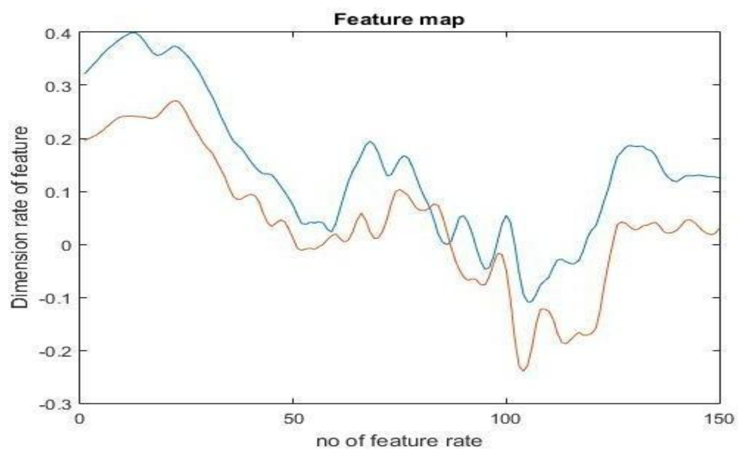

Figure 8: Proposed Feature Map

The resulting feature map is shown in Figure 8. The x-axis represents the number of feature rates, while the y-axis represents the feature's dimension rate. By applying feature detectors or filters to the input picture or previous layer output, feature maps are formed.

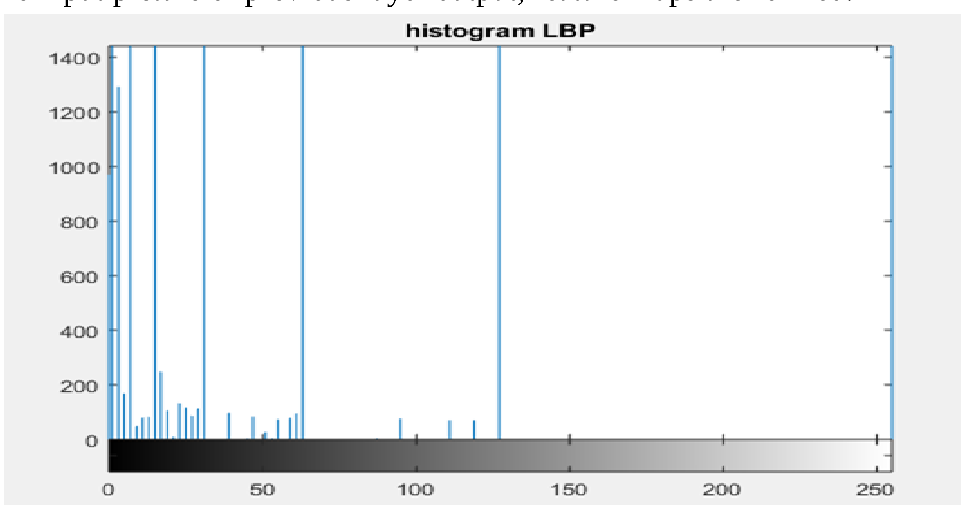

Figure 9: Histogram LBP

The Local Binary Pattern (LBP) histogram is shown in figure 9. LBP is a texture operator. Its function is to label the pixel images. The labeling is done by thresholding. The result will be a binary number.

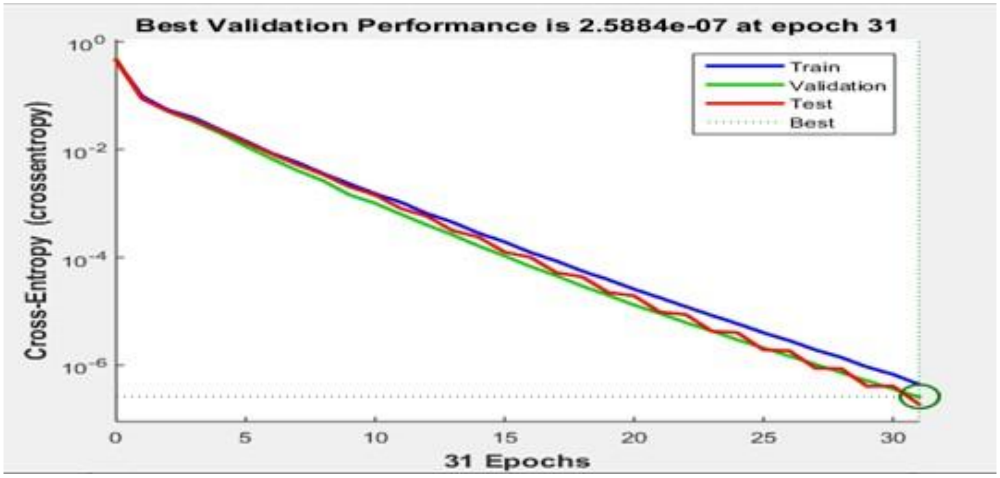

Figure 10: Validation Performance

The best validation performance is computed using 31 Epochs is shown in figure 10. The performance is checked at every stage. This is done to check whether the performance is at the desired level.

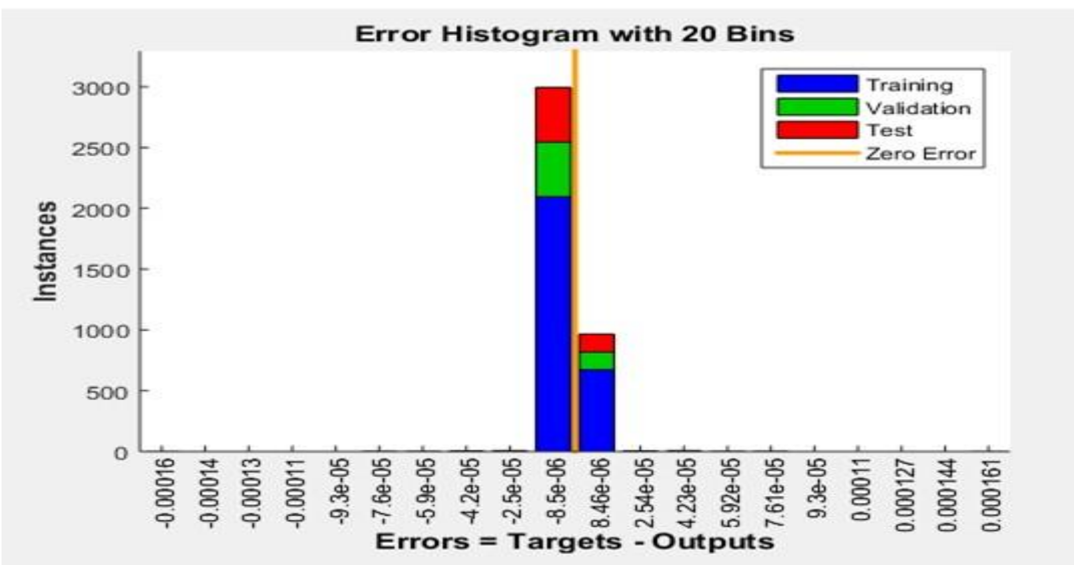

Figure 11: Error Histogram with 20 Bins

The error histogram with 20 binary values is represented in figure 11. This histogram shows the error between target values and predicted values. This diagram makes it very easy to understand whether the predicted value is the same as the target value. The 20 bins indicate the number of vertical bars observed in the graph.

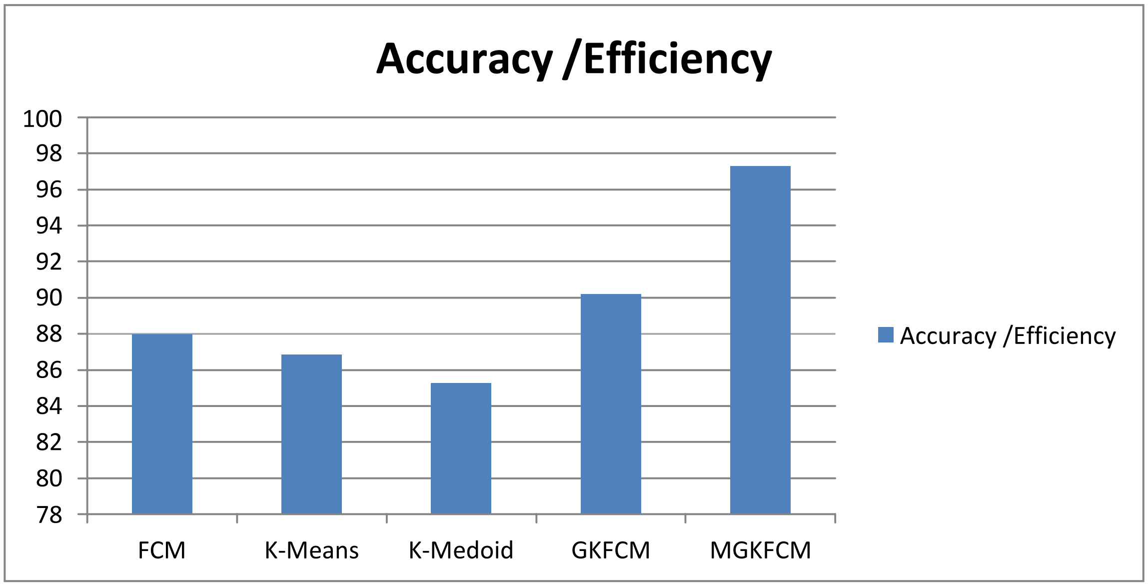

Figure 12: Proposed Algorithm Accuracy Result

The overall performance and accuracy of MGKFCM are better than other algorithms. Figures 12 given above show various comparison charts.

5. Conclusion

Worldwide, research is underway to detect and diagnose Alzheimer's. The study's goal is to detect and diagnose this disease early. We proposed the DL-EPAD model for Early Prediction for AD using MGKFCM. The performance of MGKFCM is compared to K-Means, K-Medoid, FCM, and GKFCM. This model is the fastest and most accurate 98%. In particular, the purported connection between MRI volume decrease and gravity is elusive. Textural characteristics of amyloid-beta and tau may be derived from MRI images. The study shows how to utilize wavelet, wave atom, and MGKFCM in MRI images. This improves categorization accuracy. Correct MRI image segmentation requires pre-processing. It is suggested that wave atoms shrink. The suggested technique was evaluated on both synthetic and clinical MR images. Testing the technique on various degrees of noise validates it. An MRI picture is segmented to extract textural features. Labeling the lateral ventricles locates the MRI seed site. a Gaussian histogram with the highest third peak. Level separates MRI images. The proposed segmentation method improves similarity and spatial overlap. Pre-processing the picture using wave atom shrinking increases accuracy. An early Alzheimer's detection objective Cerebral and vascular. The extended vascular is segmented in pictures. The patient is classified as healthy, early-stage AD, or mild cognitively impaired. Brain shrinkage is another indicator of AD. It identifies brain atrophy via picture segmentation. A gradient picture shows brain shrinkage. For Further, we improve the accuracy for Early Prediction of AD.

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