Detecting Brain Diseases using Hyper Integral Segmentation Approach (HISA) and Reinforcement Learning

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***Abstract*—Medical Images are most widely done by the various image processing approaches. Image processing is used to analyze the various abnormal tissues based on given input images. Deep learning (DL) is one of the fast-growing field in the computer science and specifically in medical imaging analysis. Tumor is a mass tissue that contains abnormal cells. Normal tumor tissues may not grow in other places but if it contains the cancerous (malignant) cells these tissues may grow rapidly. It is very important to know the cause of brain tumors in humans and these should be detected in the early stages. Magnetic Resonance Imaging (MRI) images are most widely used to detect the tumors in the brain and these are also used to detect the tumors all over the body. Tumors are of various types such as noncancerous (benign) and cancerous (malignant). Sometimes tumors may convert into cancer cells based on the stage of the tumor. In this paper, a hyper integral segmentation approach (HISA) is introduced to detect cancerous tumors and non-cancerous tumors. Detecting cancerous cells in the tumors may reduce the life threat to the affected persons. The agent based reinforcement classification (ABRC) is used to classify the Alzheimer's disease (AD) and cancerous and non-cancerous cells based on the abnormalities present in the MRI images. Two publically available datasets are selected such as MRI images and AD-affected MRI images. Performance is analyzed by showing the improved metrics such as accuracy, f1-score, sensitivity, dice similarity score, and specificity.**

Keywords*—Benign; malignant; magnetic resonance imaging; Alzheimer's disease

I. Introduction

The brain is one of the most important organs that play a major role in the human body. This organ controls the whole body by giving instructions to the rest of the body parts. In the world, the second cause of human death is caused by brain disease if the people are not identified in the early stages [1]. From the computer point of view, many applications are developed to analyze brain tumors and other brain disorders by using MRI, CT scans, and X-rays. Very fast and timely recognition and detection of brain tumors are required for curing the tumor. This depends on the experts and professionals to treat the patients. It is a very tedious task to predict the type of the tumors present in the brain for the proper treatment [2]. Segmentation of brain tumors is mainly based on a few important factors such as removing noise, missing borders, and contrast. MRI segmentation is one of the better strategies for recognizing brain images. Based on the density functions the parametric approaches are used for selecting the tumors [3]. Some of the basic modalities used to detect and analyze brain tumors are positron emission tomography (PET), magnetic resonance imaging (MRI), and computed tomography (CT) [4].

Generally various types of tumors are present. Tumors may convert into cancer and non-cancerous cells. After the heart disease, most of the people causing deaths are cancer patients. Among all the types of cancers, brain cancers become more complex to detect and analyze in the early stages [5]. MRI is one of the popular approaches for detecting the cancerous tissues in brain tumors [6]. Traditional segmentation of analysis is a very tedious and time-consuming process for experts also [7] [8]. Thus an automated and dynamic detection and recognition of tumors belong to cancerous or not.

Reinforcement learning (RL) [9] is used to increase the performance of the existing approaches by using agent-based learning. The RL agent mainly controls the behavior of the policy mapping from given inputs to actions. RL mainly uses the labeled training with the expected output. This also uses the unique optimal action that receives the updated sample to indicate the accurately selected action. RL is used to solve the classification tasks in DCNN. Instead of the traditional classification process, the advanced RL classification works better on same brain datasets are straightly generated by using the classifier with estimated class labels. The agent plays the major role in RL to communicate with the input and takes the required action to process the MRI brain image classification (Fig. 1).

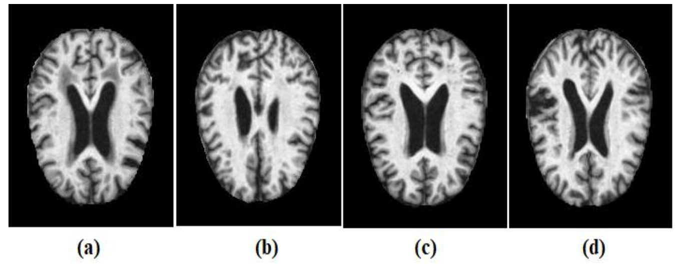

Fig. 1. Sample Images of AD (a) Mild Demented, (b) Moderate Demented, (c) Non Demented (d) Very Mild Demented.

The proposed approach is also used to detect the AD and also types of AD based on the given brain samples. This approach finds the shape and curves of the cancer cells present in the brain. It consists of multi-layered approach that contains multiple layers to get accurate results. A powerful deep learning training model is used to train the types of tumor images. Fig. 2 shows the classification of tumor cells and cancer cells present in the input image. In Fig. 2(a) is the normal MRI brain image, Fig. 2(b) is the tumor image which is represented in red color and 2(c) represents in blue color with cancer cells region.

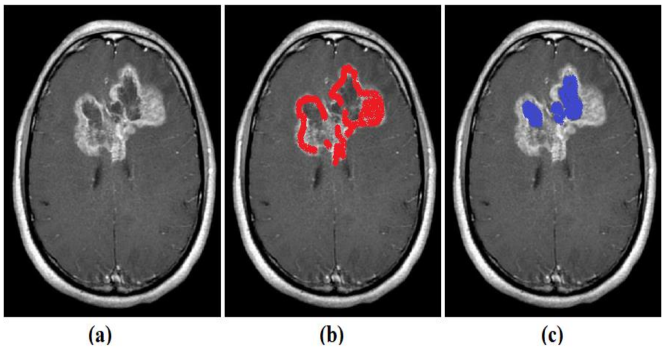

Fig. 2. (a) Tumor Image (b) Tumor Cells (c) Cancer Cells.

II. Literature Survey

Z. Jia et al., [10] proposed the FAHS-SVM to segment the brain images. This approach is focused on detecting the cerebral venous system by using MRI images. This approach also contains one or more layers belonging to hidden nodes. M. S. Majib et al., [11] introduced the dynamic approach to classifying tumor-affected images without the interference of humans. The proposed approach VGG-SCNet's achieved a better performance for the detection of the tumor. M. N. Islam et al., [12] introduced a new approach to predicting the stage of childbirth accurately. S. Pereira et al., [13] developed the automated segmented approach by integrating CNN. Several steps are used to detect brain tumors by using the advanced segmentation approach. The normalization step is also utilized to remove the clamor from the image. Shakeel et al., [14] proposed the ML-based NN approach that analysis the tumor images by using infrared sensor imaging technology. Fractal dimension algorithm (FDA) is used for features extraction. This approach is mainly used to reduce the difficulties of tumor detection. Mallick, P. K et al., [15] proposed the improved compression approach that consists of a deep wavelet auto-encoder (DWA) for the feature reduction property. This approach also finds the size of the tumors. Li, G et al., [16] discussed various issues that are identified in the present pedestrian detection methods.

Zhang, D. et al., [17] proposed a novel approach to extract the features from the tumor images and these are called weights. This approach detects the tumor affected regions of the tumor images. Zhou, C et al., [18] proposed the lightweight model to solve several complex issues based on the detection of tumors. The post-processing method is also used to get the segmented outputs. Badrinarayanan, V., [19] presented a novel approach that deeply worked on a pixel-based segmented approach called as SegNet. The decoder network is also used to analyze the resolution of the brain images by using the feature maps. Hu, K. et al., [20] proposed a variety of segmentation approach that combines the two deep learning models such as MCCNN and CRFs. The proposed segmentation approach process the MRI images in two stages, in the first stage MCCNN is used to merge the components that take dependencies on multi-scale features segmentation. In the second stage, CRF is applied to get accurate segmentation by using spurious outputs. The proposed approach shows better results in detecting the tumors. Almahfud et al., [21] discussed several issues in detecting the brain tumors by using the optimal and nearest outliers based on the sensitive color variations. This approach is the combination of K-Means and Fuzzy C-Means. This is applied to MRI brain image datasets. This approach achieved better results compared with K-Means and FCM. K. Muhammad et al., [22] introduced the survey on various DL algorithms such as BTC models. These approaches discussed pre-processing, feature extraction, and classification. The existing approaches are applied to various benchmark datasets. M. Rizwan et al., [23] proposed the distinctive brain tumor approach that detects the tumors from the given quality MRI brain images. The proposed approach classifies the types of tumors such as pituitary, glioma, and meningioma. This approach is also focused on separating the tumor grades. A. Saleh et al., [24] aim to improve the tumor detection rate by using the DL algorithms. Various DL algorithms such as ANN, CNN, and D-CNN are applied to several approaches [35-37]. N. Noreen et al., [25] proposed the DL-based approach that contains the integrated approach to classify the tumors from MRI brain images. Several pre-trained models are used for training and feature extraction approaches are also used. All these features are combined and sent to the soft-max layer for the classification of tumors and non-tumors. The proposed approach achieved the accuracy of 99.35% with Inception-v3 and 99.56% with DensNet201. Zhou SK et al., [26] proposed the deep reinforcement learning (DRL) model that teaches the group of actions that increases the performance of the output. DRL utilizes the agent based approach that increases the accuracy of brain tumor detection. Chao Yu et al., [27] discuss several RL approaches that are applied on various medical and healthcare diagnosis. Al Walid Abdullah et al., [28] proposed the policy based redesigning the partial policies that ensures the robust and effective localization using the sub-agents by solving the several decision based approaches [29-34]. The proposed approach shows the optimal solution for the actual behavior learning framework.

III. Feature Extraction Methods to Remove the Noise from the MRI Images

This step is mainly based on changing the pixel intensity values based on range. This approach will improve the contrast of the input image that helps image for better tumor detection. This is also called contrast stretching. This approach will transfer the n-dimensional MRI gray-scale image. The two types of MRI images such as cancer tumor image and AD based image are used to process. The following mathematical equation is used to analyze the pixels of the image.

$$\widehat{X}[:,i] = \frac{X[:,i]-\min(X[:,i]}{\max(X[:,i])-\min(X[:,i])} \quad (1)$$

For every brain image, the pixel numbers are positive and the range of normalized data is [0, 1] or [0, 255].

IV. Image Classification using Deep-Convolutional Neural Network (D-CNN)

Classification of brain MRI scan images is used to segment the various types of features. The MRI images have some features such as edges, intensity pixels, pixel value changes, and the size of the image. After the training and preprocessing the D-CNN is integrated with the feed-forward neural network (FFNN) and analyzes the normal and abnormal tissues based on the threshold values and processes the data in the grid-based topology. This is also called as ConvNet. Based on the types of tumors the classification is done by DCNN. Fig. 3 shows the processing of layers present in the DCNN. This is also shows the classification of AD images and normal images. Fig. 4 shows the execution flow for detecting AD and NON-AD images. This shows the functionality of every step and process the images for classification.

This consists of various hidden layers which are used to extract the data from the MRI scan images. This contains four layers such as:

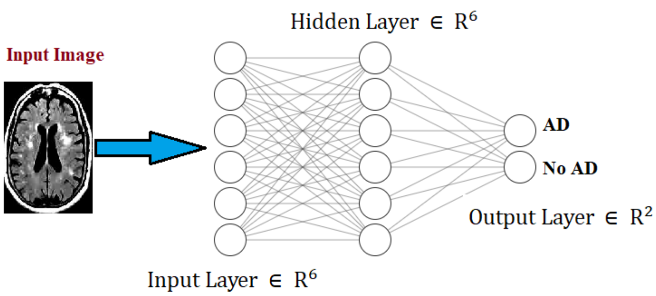

Fig. 3. D-CNN to Find the AD or Not.

A. Convolution Layer

This is one of the significant layers and this consists of the first layer and this will extract the highly valuable features from the MRI images. These layers contain the filters that use the convolution operation. Every image initializes the matrix pixel value. The range of these pixel values is 0 or 1. 3x3 filter matrix is utilized. The dot product is calculated to get the accurate feature matrix.

$$Z^l = h^{l-1} * W^l \quad (2)$$

1) ReLU layer: ReLU (Rectified Linear Unit): This is used to extract the feature maps.

This operation performs the component wise operation and the negative pixels are represented as 0. This is also used the non-linearity network and generates the output as feature map. Graph represents the ReLU function:

The MRI scan image is analyzed with no of convolutions and ReLU layers are used to locate the features. Fig. 5 shows the range values among the ReLU layers.

$$R(z) = \max(0, z) \quad (3)$$

2) Pooling layer: This layer is utilized to reduce the dimensions of feature maps. This layer creates the pooled feature map.

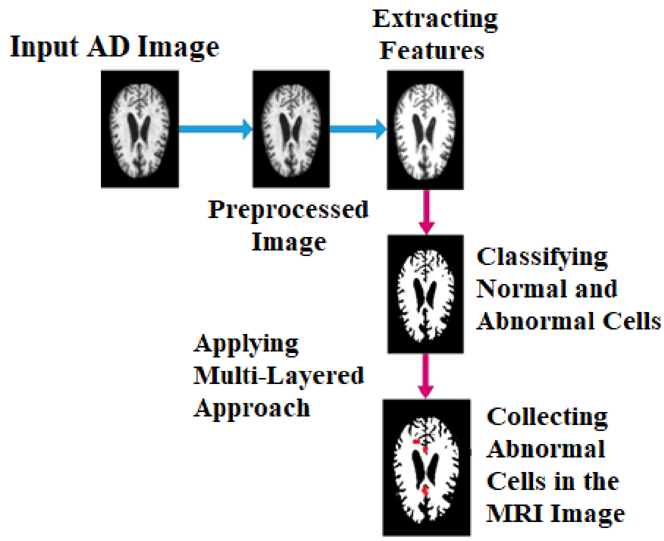

Fig. 4. AD Detection Process using Proposed Approach.

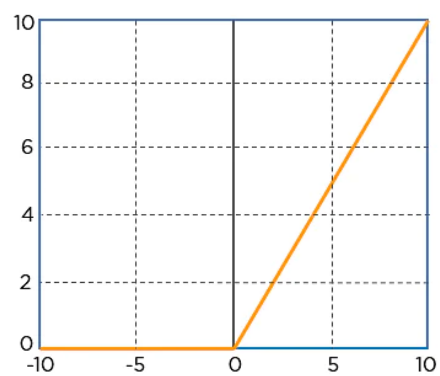

Fig. 5. Showing the Range Values 0-10.

This layer contains several filters that are used to find the significant regions such as normal and abnormal cells in the MRI scan images.

Every neuron is fully connected with all the neurons in the upper layer, the main aim of this layer is to transform the dimensions, and is also used to turn the high-dimensional features into low-dimensional every neuron in this system has activation function to get the final output.

$$h^l_{ab} = \max_{i=0,\ldots,s,j=0,\ldots,s} h^{l-1}_{(a+i)(b+j)} \quad (4)$$

$z^l \to$ pre − activation output of layer l

$h^l \to$ activation of layer l

$* \to$ discrete convolution operator

$W, \gamma, \beta \to$ Learnable parameters

B. Steps for Agent Based Reinforcement Classification (ABRC)

The proposed classification is applied on two benchmark datasets.

Step 1: In the initial stage, the agent utilizes the Softmax exploration policy to find the strong values for original classes and low values for the wrong classes that are lies in the utilized exploration policy. The proposed approach is on-policy learning approach. Based on the changed actions the initial state is represented by.

$$P(x) = \frac{e^{\frac{P_i^x(s_t)}{\tau}}}{\sum_b e^{\frac{P_i^y(s_t)}{\tau}}} \quad (5)$$

Step 2: From the above equation the negative values shows the wrong classes and these are passed by TDlearning at the initial state. Here, 1 represents the errors (cancerous/AD affected) and 0 represents the 1 (non-cancerous/AD not effected). The testing approach calculates all the values $V_i(s0)$ for all the classes i and agents belongs to AC_i belongs to these classes. The predicted class y_p belongs to agent with high state value:

$$y_p = \operatorname{argmax}_i V_i\,(s_0) \quad (6)$$

Output: The result shows that patient have affected with AD or Not and Cancerous tumors or not.

C. Segmentation

Edge-based segmentation is the technique that finds the accurate edges of the brain input images. This technique focused on detecting the edges based on the gray levels, image color, texture, etc. The gray level may change if the system moves from one region to another. If any abnormality is present then finding the edge is easy task. Different functions are used to get the image with edge segmentation and this output should not be confused with the final segmented image.

These edges are mainly connected with the "Magnitude" and "Direction". The edge detection used in this paper used both directions. This approach is represented with the following equations. To calculate the g the 7 or 8 or 9 formulas are used to calculate the g and theta. By using this strong edges are identified based on magnitude and direction.

$$g = (g_a^2 + g_b^2) \quad (7)$$

$$g = |g_a| + |g_b| \quad (8)$$

$$g = \max(|g_a| + |g_b|) \quad (9)$$

$$\theta = \arctan\frac{g_a}{g_b} \quad (10)$$

Where g_a = Magnitude of a

Where g_b = Magnitude of b

V. Dataset Description

For the experimental results, three datasets are used two datasets for brain tumor detection and one for AD detection. Two MRI brain tumor datasets are BraTS-2019 [12] [20] and the Kaggle dataset. Another AD dataset is collected from the Kaggle dataset and this contains 10000 MRI samples with four classes shown in Fig. 1. The training set contains 5000 images and testing contains 5000 images.

VI. Performance Metrics

The performance is evaluated by calculating various metrics such as dice score, precision, sensitivity, specificity, accuracy. The segmentation of brain image result is analyzed by using dice score.

$$\text{Dice Score} = \frac{2TP}{FN + FP + 2TP}$$

Specificity: This parameter mainly detects the total number of TP and FP and this is used to calculate the model which is more ability to predict the background area.

$$\text{Specificity} = \frac{TN}{TN + FP}$$

Sensitivity This parameter mainly detects the total number of TP and FN and this is used to calculate the model which is more ability to predict the segmented area.

$$\text{Sensitivity or Recall} = \frac{TP}{TP + FN}$$

Accuracy is one metric that measures the reliability of the classification result. The formula is give below.

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN}$$

Precision: The overall percentage of the output results are defined as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Table I and Fig. 6 show the performance of training and testing in terms of time. Among all the existing models the proposed model achieved the low training and testing time (Sec).

TABLE I. TRAINING AND TESTING TIME (SEC) FOR MRI IMAGE DATASET

Algorithms	***Training Time (Sec)***	***Testing Time (Sec)***
K-means and FCM [21]	74.67	75.78
CNN	72.21	78.89
ILPD	49.89	56.89
ISA	43.12	51.21

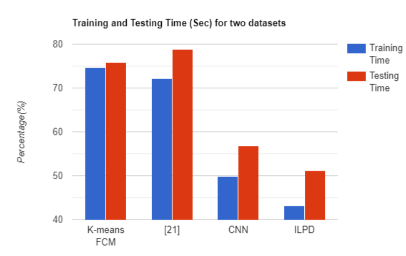

Fig. 6. Training and Testing Time (Sec) for Two Datasets.

TABLE II. TRAINING AND TESTING TIME (SEC) FOR AD BASED MRI IMAGES

Algorithms	Training Time (Sec)	Testing Time (Sec)
Vanilla DNN	72.34	73.80
CNN	71.89	74.34
CNN-DNN	48.78	54.34
ISA	41.55	49.43

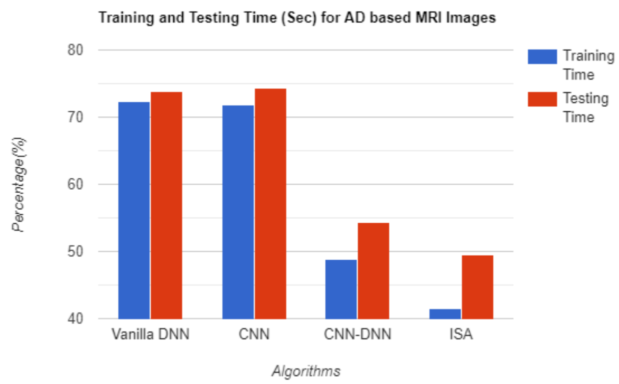

Fig. 7. Training and Testing Time (Sec) for AD based MRI Images.

Table II and Fig. 7 show the performance of AD based MRI images based on training and testing in terms of computation time (Sec).

TABLE III. RESULTS OF ON NAVONEEL BRAIN TUMOR IMAGES

Algorithms	Dice Score	Specificity	Sensitivity	Accuracy	Precision
K-means and FCM [29]	56.4%	53.12%	57.56%	53.12%	56.32%
CNN	82.53 %	81.98%	84.12%	83.54%	85.43%
ILPD	97.87 %	98.12%	97.43%	98.23%	98.67%
ISA	99.12 %	99.56%	99.1%	99.67%	99.89%

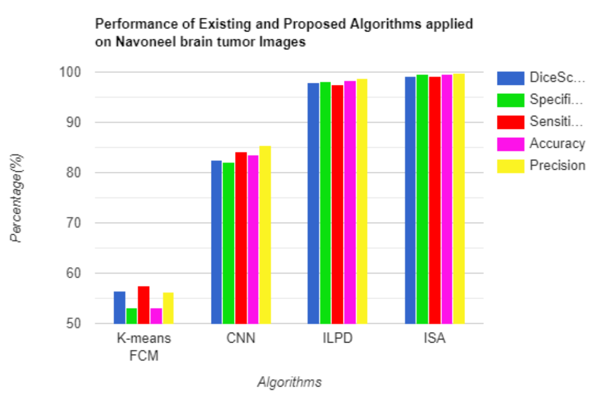

Fig. 8. Performance of Existing and Proposed Algorithms Applied on Navoneel Brain Tumor Images.

Table III and Fig. 8 show the performance and comparison between existing and proposed algorithms by applying the confusion matrix parameters to analyze the performance. This is applied on navoneel brain tumors datasets.

TABLE IV. RESULTS ON BRATS 2017 BRAIN TUMOR IMAGES

Algorithms	Dice Score	Specificity	Sensitivity	Accuracy	Precision
K-means and FCM [29]	56.4%	51.42%	56.34%	54.42%	57.42%
CNN	83.63 %	82.56%	83.42%	85.74%	86.43%
ILPD	98.87 %	99.12%	97.89%	98.45%	99.67%
ISA	99.56 %	99.96%	99.78%	99.45%	100%

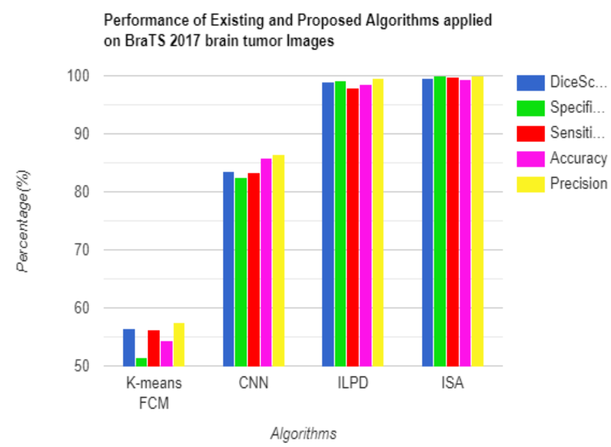

Fig. 9. Performance of Existing and Proposed Algorithms Applied on BraTS 2017 Brain Tumor Images.

Table IV and Fig. 9 show the performance and comparison between existing and proposed algorithms by applying the confusion matrix parameters to analyze the performance. This is applied on BRATS 2017 brain tumors datasets.

Table V and Fig. 10 show the performance and comparison between existing and proposed algorithms by applying the confusion matrix parameters to analyze the performance. This is applied on AD based MRI image datasets.

TABLE V. RESULTS ON AD BASED MRI IMAGES

Algorithms	Dice Score	Specificity	Sensitivity	Accuracy	Precision
Vanilla DNN	72.34	75.80	83.12	87.12	90.12
CNN	78.98	83.24	85.34	88.34	91.12
CNN-DNN	82.56	85.64	87.67	91.67	92.34
ISA	89.34	97.87	98.56	99.67	99.45

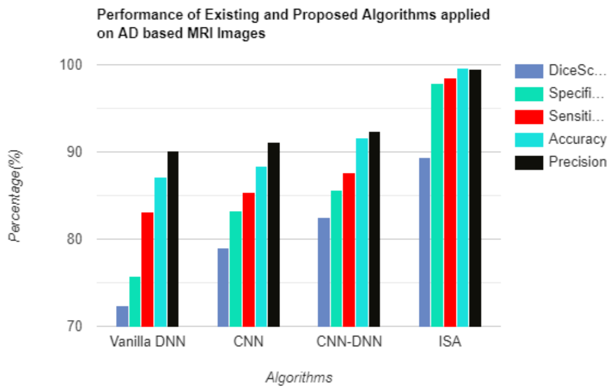

Fig. 10. Graph Representation on AD based MRI Images.

VII. Conclusion

An integrated segmentation approach (ISA) is developed to detect the cancerous cells in MRI images and also work on AD detection. The proposed approach is integrated with various advanced steps to get accurate results. Generally detecting the AD from the MRI scan images is a very difficult task. But the proposed approach becomes very easy to detect the AD and also cancer cells in the MRI scan images. Advanced training and preprocessing approaches improve the performance. The proposed approach increases the performance for the detection of MRI scan images in terms of parameters such as Dice Score-99.12%, Specificity-99.12%, Sensitivity-99.56%, Accuracy-99.1%, Precision-99.67%. AD detection performance is Dice Score-89.34%, Specificity-97.87%, Sensitivity-98.56%, Accuracy-99.67%, Precision-99.45%.

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