Brain Tumor Detection using Integrated Learning Process Detection (ILPD)

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***Abstract*—Brain tumor detection becomes more complicated process in medical image processing. Analyzing brain tumors is very difficult task because of the unstructured shape of the tumors. Generally, tumors are of two types such as cancerous and non-cancerous. Cancerous tumors are called malignant and non-cancerous are called benign tumors. Malignant tumors are more complex to the patients if these are not detected in the early stages. Precancerous are the other types of tumors that may become cancerous if the treatment is not taken in the early stages. Machine Learning (ML) approaches are most widely used to detect complex patterns but ML has various disadvantages such as time taking process to detect brain tumors. In this paper, integrated learning process detection (ILPD) is introduced to detect the tumors in the brain and analyzes the shape and size of the tumors, and find the stage of the tumors in the given input image. To increase the tumor detection rate advanced image filters are adopted with Deep Convolutional Neural Networks (D-CNN) to improve the detection rate. A pre-trained model called VGG19 is applied to train the MRI brain images for effective detection of tumors. Two benchmark datasets are collected from Kaggle and BraTS 2019 contains MRI brain scan images. The performance of the proposed approach is analyzed by showing the accuracy, f1-score, sensitivity, dice similarity score and specificity.**

Keywords—Machine learning (ML); deep convolutional neural network (D-CNN); brain-tumor-detection; integrated learning process detection (ILPD)

I. Introduction

A tumor is a type of irregular tissue or cell that didn't have any shape or size [1]. Tumors will grow irregularly and can cause more damage to health if they are not detected in the early stages. These tumors may convert into cancerous or non-cancerous. Generally, the human brain is closed with a strong skull. Skull is a very small area, if it is extended this will become more complicated. Abnormal cells grow more heavily than normal cells and this may transform tumors [2]. It is very tedious to recognize tumors in the brain by using MRI images. This is based on the experience of the doctor and some methods are selected from the treatment of the patient for fast recovery. One of the tough tasks in this context is to detect the particular type of tumor in the early stages; this will help the experts treat the patient accordingly [3]. Hybrid feature extraction is one of the approaches which is used to extract the accurate features that show the huge impact on brain tumor detection [4].

Glioma is one type of brain tumor that shows severe damage to the brain. The properties of glioma are entirely different compared with other types of tumors. This consists of three types of tumors such as whole tumor (WT), tumor core (TC), and enhancing tumor (ET) [5]. Some tumors are very complicated like glioma because to reduce the impact of these tumors surgery is required. Segmentation is one of the most difficult tasks to detect tumors using MRI scan images. In MRI brain image analysis modality gives the unique and key details that belong to every piece of the tumor. The four modalities that are present in the segmentation are T1, T1c, T2, and FLAIR [6]. Multi-atlas segmentation (MAS) is the approach that segments the brain tumor images. To recover the brain image into a normal-looking image the low-rank approach is used. MAS approach is an iterative approach that recovered the image and increases the segmentation accuracy [7]. Brain tumor segmentation has many unsolved issues. Brain tumor segmentation considers every label as one unit [8]. In general, the segmentation of brain images didn't contain the tumor tissue or other anomalies [9]. In brain images, several types of segmented images are present such as gray matter and white matter. Gray matter consists of necrotic cells. White matter consists of militated axons called tracts.

In this paper, Integrated Learning Approach (ILA) is introduced to detect the tumor regions by using advanced filtering techniques and a Deep Convolutional Neural Network (D-CNN).

II. Literature Survey

Several authors discussed about the brain tumors detection using MRI images. In this section, various methodologies are discussed about brain tumors detection and also discussed about traditional image processing and DL approaches.

V. Shreyas et al., [10] proposed a novel approach that shows the rapid runtime compared with traditional approaches. The proposed approach Brain Tumor Segmentation (BraTS) achieved better performance by showing a dice score of 83% in the full tumor region, 75% in the core region, and 72% in the intensified tumor region. The proposed BraTS is 18 times faster than the other existing approaches. M. Ali et al., [11] introduced the two new segmentation approaches such as 3D CNN and U-Net are merged to give the better accurate results. The training is given by using the BraTS-19 challenge dataset that gives the segmentation of the brain input images. This system segments the tumor sub-regions that are used to predict the final output.

A. Kumar et al., [12] developed the ML approach to recognize tumors in brain by using the MRI images. This approach uses the Particle Swarm Optimization (PSO) for feature selection and Support Vector Machine (SVM) for classification of tumors. This approach achieved better results in classification of input images.

Zhang, D et al., [13] proposed the unique segmentation approach called a task-structured brain tumor segmentation network (TSBTS net). This approach mainly focused on predicting the tumor regions in the given dataset images. From the modality data the weights are also extracted in this approach. The proposed approach achieved better segmentation performance compared with existing approaches. Zhou C et al., [14] proposed the One-pass Multi-task Network (OM-Net) be used to solve the irrelevant issues in detecting the tumor regions. The OM-Net is the combination of segmentation and DL model that consists of shared parameters and used to learn the merged features. This is also the task specific parameters to learn preferential features. Badrinarayanan V., [15] proposed the novel deep fully segmented approach called as SegNet. SegNet is one of the decoder networks which is mapped with the low-resolution encoder that uses pixel-wise classification. Hu, K. et al., [16] proposed the novel tumor segmentation technique based on a multi-cascaded convolutional neural network (MCCNN) and fully connected conditional random fields (CRFs). This technique is a combination of MCCNN and CRFs. Each feature has its properties to detect the brain. The proposed technique finds the image patches that are extracted from axial, coronal, and sagittal used to train the three segmentation approaches. This will gives the final segmented output.

III. Role of Deep Learning (DL)

In recent years, CNN becomes more popular in the classification of images. Pereira S et al., [17] introduced the dynamic partition approach that uses the CNN that has a 3 x 3 core size. This approach will follow the steps such as preprocessing, training, and validation of the dataset. The dataset used to analyze the algorithm is BraTS 2015. Hao et al., [18] proposed the automatic segmentation approach that uses the U-net D-CNN. This is applied to BraTS 2015 dataset. Better segmentation is applied in this to get accurate results. Wang et al., [19] introduced the cataract network. The proposed network follows several steps for tumor segmentation. Secondly, the bounding box is implemented on tumor image, and the segmented region is shown. By using the multi-view fusion techniques the false positives are reduced. Myronenko A [20] introduced the 3D tumor segmentation approach that uses the auto-encoder to redesign the brain tumor images. The dataset is the 2018 BraTS Challenge used for result analysis. Xue F et al., [21] introduced the 3D MRI tumor segmented technique. The input uses the encoder and decoder defines several block sizes and weight loss. The training is also increased in this paper. Zhou X et al., [22] introduced 3D approach for segment the brain tumor images. To achieve high performance the 3D shuffleNetV2 as encoder, and decoder with residual blocks are used. Saman S et al., [23] introduced the active lineation model for the MRI brain tumor images with segmentation. This approach is mainly used to extract the features that belong to tumor parts in MRI. Liu et al., [24] discussed the DL approach that learns the set of convolution and deep supervision. This technique is replaced with the feature extraction that leans with group convolution. The dataset is collected from BraTS2018 and the proposed technique detects the segmented region of an input image.

M. Rizwan et al., [25] introduced a new approach called Gaussian Convolutional Neural Network (GCNN). CNN applied two benchmark datasets to classify the multiple tumor diseases. This is mainly focused on finding the grades of the tumor. The accuracy of GCNN is 99.8% for one dataset and 97.15% for another dataset. Bhuiyan et al., [26] proposed an automated approach to finding the cancer cells present in the human brain. The proposed approach is combined with several ground-truth-level approaches giving better approaches than existing approaches. Compare with all the existing models, the proposed approach achieved the 98.6% of accuracy. Yazdan SA et al., [27-32] proposed the automated diagnostic approach called as Multi-Scale CNN (MSCNN) to classify [32-36] the brain tumors. Compare with AlexNet and ResNet the proposed MSCNN achieved the accuracy of 91.2%.

IV. VGG 19 for MRI Brain Images

Visual Geometry Group (VGG) is the CNN architecture which consists of number of layers. Transfer learning is one of the domains that reduce the training set size and computation time when deep learning models are built. This domain helps us to transfer the pre-trained learning to a new model. This is utilized in the segmentation of tumors, classifications of tumor images, etc. The proposed approach is integrated with advanced image filters with VGG-19 and Deep CNN. In this paper, VGG-19 is used as the pre-trained model which contains 19 layers. VGG19 is mainly used to recognize the brain tumors. From the ImageNet database, the training is done with huge number of predefined brain tumors and other types of brain images. Based on this pre-trained model the tumor and non tumor images are classified. The input size of brain images are converted to 224 by 224.

The VGG contains very small convolutional filters. VGG-19 contains 19 convolutional layers and three are fully connected layers (see Fig. 1).

Input: The input brain image size is 224x224. For this tumor detection, the image is cropped to the center of the image for maintaining consistency.

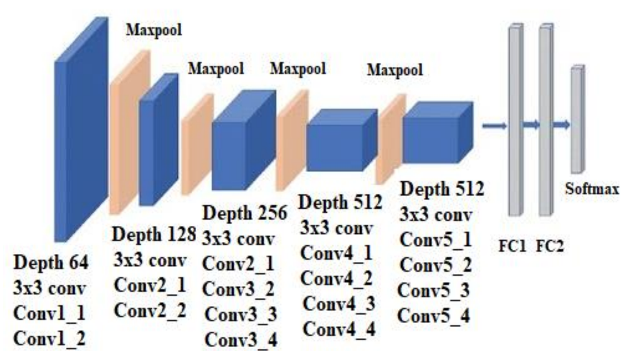

Fig. 1. Shows the Architecture of VGG19 with Total Number of Layers Present in this Process.

Convolutional Layers: This layer contains the minimal responsive field, i.e., 3×3, very small size catches the up/down and left/right. In this scenario, the 1x1 filters also act as the linear transformation of the input. The continuation of this is done by the ReLu function, which reduces the training time by using the AlexNet.

Hidden Layers: These layers used the ReLu in VGG. To reduce the memory consumption and training time ReLu is used by the VGG. This will show the huge impact on overall accuracy.

Fully-Connected Layers: In VGG-19 there are three fully connected layers. Among these, two layers contain 4096 and 3rd contains 1k channels and one for every class.

V. Image Filtering and Pre-Processing of Input Brain Image

Image filtering is one of the significant tasks that will analyze the specific features of the image. There are various operations that show impact on image filtering such as smoothing and sharpening. The properties of the image filters are represented as:

$$f(a) = \propto a + \beta \quad (1)$$

The result of the integer is rounded and fixes the range [0, 255]. The color component value (R, G, or B) is represented as x. α is the contrast with the range (α>1 initializes high contrast and 0<α<1 low contrast). To make it easy for making changes in "brightness" and "contrast" the formula is given as:

$$f(x) = \propto (a - 128) + 128 + b \quad (2)$$

Where b controls brightness.

More complex contrast adjustments can be done using arbitrary "curves" f:[0,255]→[0,255], which are be provided by the user of the image processing software using graphical tools.

By using the linear smoothing layer the quality of the input image is improved as shown in Fig. 2. These are very good filters that can easily remove the noise from the images. By using the weighted sum of the pixels the linear filter is implemented. In every window, this weighted sum is implemented using a convolution mask. A filter that does not have the weighted sum of pixels then is considered non-linear filters.

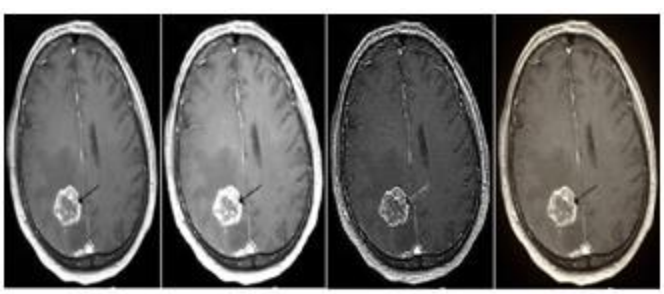

Fig. 2. (A) Input Image, (B) Filtered Image, (C) Sharpen Image and (D) Pre-Processed Image.

A. Mean Filtering

This is one of the better filtering approaches which are used in this paper. By using the local averaging operation (LAP), the filtering approach is implemented. In this context, the pixels are replaced with all the nearest values of the input image.

$$h(a, b) = \frac{1}{M} \sum_{(k,l) \in N} f(k, l) \quad (3)$$

Where 'M' represents the total pixels in the nearest 'N'.

B. Region based Segmentation for Finding the Statistical Information of the Input Image

Region based mathematical model is used to find the statistical information of the image. For example, the region in the image u of the image domain calculates the intensity of the mean of X with u.

$$\mu_u = \frac{1}{|X|} \int_u X(a) da \quad (4)$$

Where $|X| = f_u da$ (the measure if X, or the variance within X.

$$\sigma_u^2 = \frac{1}{|X|} \int_u (\mu_u - X(a))^2 da \quad (5)$$

Equation 4 and 5 combined to show the hybrid model.

$$u_t + F\|\nabla_u\| = 0 \quad (6)$$

Where, u=u (a, t) initializes the level sets of curves of family C (a, t). F is used to combine the equations.

C. Preprocessing

In this step, the input images subtracts the mean "μ" for every sample image "i" and standard deviation (SD) "σ" divides to extract "i_0" output image as:

$$i_o = \frac{i - \mu}{\sigma} \quad (7)$$

D. Deep CNN

Deep CNN is focused on finding the important patterns from the MRI dataset. Deep CNN or CNN works better on brain MRI image classification for detecting the tumor or non-tumor images. The D-CNN takes the input image and classifies the image based on specific types such as tumor or abnormality is present or not. This classification of tumor images is based on image resolution. Image resolution mainly considers the height (h), width (w), dimension (d). For this brain image segmentation, two types of images are present such as RGB and grayscale images. RGB image contains 8 x 8 x 3 array of matrix and the grayscale image contains a 6 x 6 x 1 array of the matrix. To segment the image into two parts the threshold-based segmented approach is integrated with the input image. Based on the pixel values the segmentation is done. For every image, the pixel values are different for the tumors and background of the image. The system will set the threshold value. The threshold value is based on pixel values are between low and high. According to this, the classification is done.

E. Non Linearity (ReLU)

Rectified Linear Unit (ReLU): This is utilized to analyze output and shows result as positive or zero. Positive represents the tumor is present and zero represents no tumor. In general, ReLu is very fast and easy to implement on MRI brain images. The output of the ReLu is given below.

$$f(x) = \max(0, x) \quad (8)$$

F. Pooling Layer

This layer mainly reduces the size of the input image without losing any pixels. This layer consists of two pooling hidden layers contains five nodes at each pool and this will help the proposed algorithm to limit the iterations. MRI brain image is reduced by size and extracts only tumor affected image which is most important for classification.

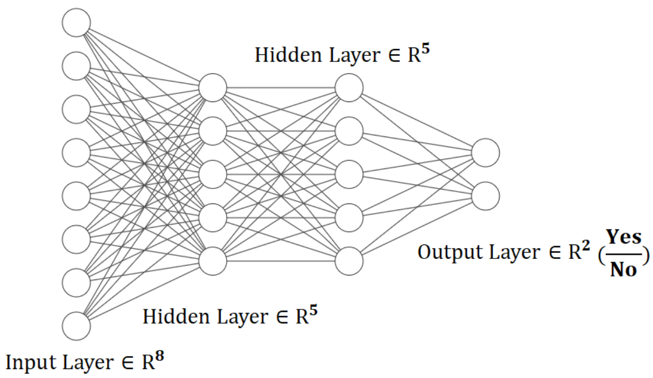

Fig. 3. The Overall Process of MRI Input Image and Output of the Image.

Fig. 3 shows the number of layers that are used to process the MRI input images. The input layer consists of eight nodes and one pooling layer consists of two hidden layers with five nodes each. Finally, the output layer shows the final output of the input image which is tumor present or not.

VI. Dataset Description

Two datasets used for experimental analysis are Brain Tumor Segmentation Challenge (BraTS) 2019 [17] (see Fig. 7 and Fig. 8) and Kaggle dataset (see Fig. 5 and Fig. 6). These datasets contain two folders such as training and testing. BraTS 2019 contains 259 high and low-grade glioma patient samples. From these samples, 125 are unknown status [18]. This dataset contains five types of images namely T1, T1ce, T2, and FLAIR images as shown in the Fig. 4. The dimensions are 240 x240 x155 with 1mm3 resolution. The algorithm shows the three-segmented regions such as deep segmented region, normal region, and light segmented region (see Tables I to III).

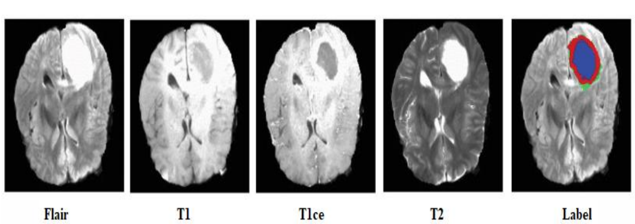

Fig. 4. Types of Images Present in Dataset.

A. Limitations and Challenges

- Finding the accurate location of tumor becomes more challenging task.
- Finding the abnormal cells becomes more complex by using the state-of-art approaches.
- Accurate classification of tumors and cancer cells is detected using MRI scan images.
- Two types of datasets are used to diagnose the MRI scan images.

VII. Performance Metrics

The performance of the proposed models is analyzed by using the confusion matrix (CM). This is the advanced representation to predict the accurate prediction of diseases. This presents the actual value and predicted value of the given inputs. To count the overall values the following are the attributes used to find the accurate values.

True Positive (TP)-This initializes the actual value as positive (tumor identified) and the predicted value is also positive (tumor identified).

True Negative (TN)-This initializes the actual value as negative (No tumor) and the predicted value is also negative (No tumor).

False Positive (FP)-This initializes the actual value as positive (tumor identified) and the predicted value is negative (No tumor).

False Negative (FN)-This initializes the actual value as negative (No tumor) and the predicted value is also positive (tumor identified).

Specificity: This parameter mainly detects the total number of TP and FP and this parameter has more potential to predict the background region.

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (9)$$

Sensitivity This parameter mainly detects the total number of TP and FN and this parameter has more potential to predict the segmented region.

$$\text{Sensitivity or Recall} = \frac{TP}{TP+FN} \quad (10)$$

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

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN} \quad (11)$$

Precision: The percentage of quality of predictions is defined as:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (12)$$

TABLE I. TRAINING AND TESTING TIME (SEC) FOR TWO DATASETS

Algorithms	Training Time (Sec)	Testing Time (Sec)
EffecientNetB0 [28]	66.78	69.12
YOLO5 (You Only Look Once) [29]	74.67	75.78
ILPD	49.89	56.89

TABLE II. PERFORMANCE OF EXISTING AND PROPOSED ALGORITHMS APPLIED ON NAVONEEL BRAIN TUMOR IMAGES

Algorithms	Specificity	Sensitivity	Accuracy	Precision
YOLO5 (You Only Look Once) [28]	90.2%	91%	93.1%	91.6%
EffecientNetB0 [29]	99.2%	99.5%	98.8%	99.4%
ILPD	99.45%	99.71%	99.23%	99.6%

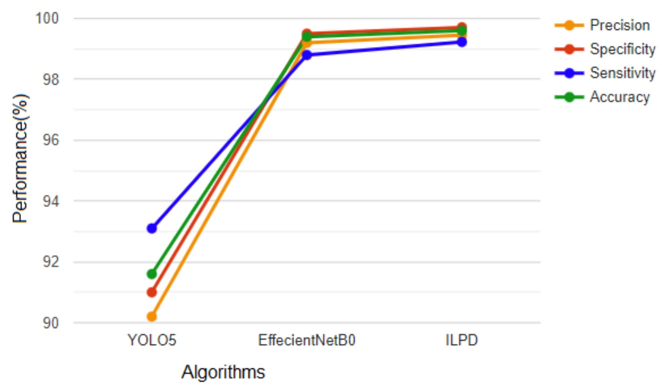

Fig. 5. Line Graph Representation for Kaggle Dataset.

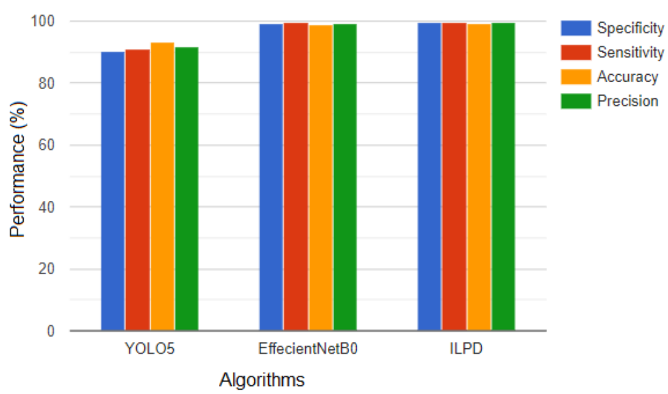

Fig. 6. Bar Graph Representation for Kaggle Dataset.

TABLE III. PERFORMANCE OF EXISTING AND PROPOSED ALGORITHMS APPLIED ON BRATS 2017 BRAIN TUMOR IMAGES

Algorithms	Specificity	Sensitivity	Accuracy	Precision
YOLO5 (You Only Look Once) [28]	91.2%	92%	92.1%	92.9%
EffecientNetB0 [29]	98.12%	99.1%	98.1%	99.1%
ILPD	99.7%	99.5%	99.9%	99.1%

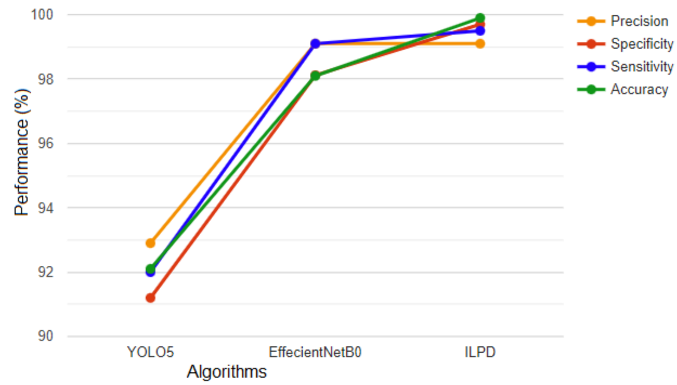

Fig. 7. Line Graph Representation for BraTS Dataset.

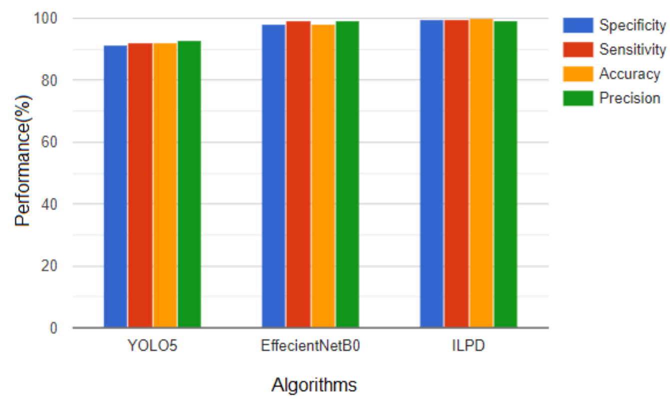

Fig. 8. Bar Graph Representation for BraTS Dataset.

VIII. CONCLUSION

In this paper, the ILPD is the efficient approach for finding tumors in the given MRI images. The MRI image is preprocessed and filtered by utilizing the advanced filtering approach. The classification is mainly focused on detecting the tumors or healthy images by using Integrated Learning Process Detection (ILPD). The final output consists of two neurons that belong to tumor or normal image. Two segmented images are represented by showing red and green color regions. From these images the features are extracted from last convolution layer. The ILPD focused on solving various issues in detecting brain tumors by using the segmentation approach and advanced image filters with the preprocessing method. Advanced image filters eliminate the noise from the MRI images and segment the images and represent the tumors with the green and red colors. Red represents the deep tumors and the green represents the tumors with low density. The performance of the existing and proposed approach shows the results based on the parameters. The ILPD achieved precision (99.67%), dice score (98.87), sensitivity (97.89%), specificity (99.12%), and accuracy (98.45%). The dice score shows the efficiency of the segmented image. In the future, the deeply segmented approach is used to increase the performance in terms of detecting the density of the image.

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